data_cleaning_and_feature_selection

August 6, 2025

# 1 Introduction

## 1.1 Improting required libraries

[1]:
```
# Core libraries for data manipulation
import numpy as np              # For numerical operations
import pandas as pd             # For structured data (DataFrame) manipulation

# Regular expressions for pattern matching
import re

# Visualization libraries
import matplotlib.pyplot as plt   # For basic plotting
import seaborn as sns             # For statistical plots and visual styles

# Dask for out-of-core and parallel data processing (large datasets)
import dask.dataframe as dd

# Glob for file path matching (e.g., loading multiple CSV files at once)
import glob
```

## 1.2 Code to check and review each CSV

[2]:
```
def eval_df(dataframe):
    """
    Evaluate the structure and quality of a pandas DataFrame.

    This function prints:
    - Data types and memory usage
    - Columns with missing values
    - Count of duplicate rows
    - Summary statistics (numeric and categorical)

    Parameters:
    -----------
    dataframe : pd.DataFrame
        The DataFrame to evaluate.
    """
```

```python
    # Display data types and basic memory usage
    print("\n DATA TYPES & MEMORY USAGE")
    print("-" * 40)
    print(dataframe.info())

    # Check and display missing values per column
    print("\n MISSING VALUES PER COLUMN")
    print("-" * 40)
    missing_values = dataframe.isnull().sum()
    print(missing_values[missing_values > 0])

    # Check for duplicate rows
    duplicates = dataframe.duplicated().sum()
    print("\n DUPLICATE ROWS FOUND")
    print("-" * 40)
    print(f"{duplicates} duplicate rows found.")

    # Display summary statistics (for both numeric and object types)
    print("\n SUMMARY STATISTICS")
    print("-" * 40)
    print(dataframe.describe())
```

### 1.3 Get the sample countries

- this would include those that have mobility data, policy data, covid data and country statistics data

[3]:
```python
# To get a common code for the countries I would use the ISO 3166-1 alpha-3
# Load country and country code reference data
COUNTRY_CODE = pd.read_csv("data/country_codes.csv")

# Preview the first few rows
COUNTRY_CODE.head()
```

[3]:

| | id | alpha2 | alpha3 | en |
|---|---|---|---|---|
| 0 | 4 | af | afg | Afghanistan |
| 1 | 8 | al | alb | Albania |
| 2 | 12 | dz | dza | Algeria |
| 3 | 20 | ad | and | Andorra |
| 4 | 24 | ao | ago | Angola |

[4]:
```python
len(COUNTRY_CODE)
```

[4]: 193

[5]:
```python
# Capitalise all codes in alpha2 and alpha3
COUNTRY_CODE['alpha2'] = COUNTRY_CODE['alpha2'].str.upper()
```

```
COUNTRY_CODE['alpha3'] = COUNTRY_CODE['alpha3'].str.upper()
```

[6]:
```
COUNTRY_CODE = COUNTRY_CODE.rename(columns = {
    'alpha2': 'code2',
    'alpha3' : 'Code',
    'en' : 'Country'
})
```

### 1.3.1 Get the mobility data

[7]:
```
# Columns to include (mobility trends + region info + date)
usecols = [
    "country_region_code",
    "country_region",
    "sub_region_1",
    "sub_region_2",
    "metro_area",
    "date",
    "retail_and_recreation_percent_change_from_baseline",
    "grocery_and_pharmacy_percent_change_from_baseline",
    "parks_percent_change_from_baseline",
    "transit_stations_percent_change_from_baseline",
    "workplaces_percent_change_from_baseline",
    "residential_percent_change_from_baseline"
]

# Explicit dtypes to avoid Dask inference issues
dtype_fix = {
    'sub_region_1': 'object',
    'sub_region_2': 'object',
    'metro_area': 'object',
}

# Load the dataset with parsing and type fixes
df = dd.read_csv(
    'data/global_mobility_report.csv',
    usecols=usecols,
    dtype=dtype_fix,
    parse_dates=['date'],
    assume_missing=True
)

# Filter: only country-level data + dates up to the end of 2022
missing_cols = ['sub_region_1', 'sub_region_2', 'metro_area']
filtered = df[
    df[missing_cols].isnull().all(axis=1) &
    (df['date'] <= '2022-12-31')
```

```
]

# Safely preview the filtered result
print(filtered.sample(frac = 0.0001, random_state = 1).compute())
```

```
       country_region_code country_region sub_region_1 sub_region_2  \
18274                   AR      Argentina         <NA>         <NA>
456350                  BJ          Benin         <NA>         <NA>
109303                  CL          Chile         <NA>         <NA>
497226                  FR         France         <NA>         <NA>
19372                   GT      Guatemala         <NA>         <NA>
160328                  LI  Liechtenstein         <NA>         <NA>
91450                   KG     Kyrgyzstan         <NA>         <NA>
268085                  ML           Mali         <NA>         <NA>
480291                  NP          Nepal         <NA>         <NA>
533080                  RW         Rwanda         <NA>         <NA>
450650                  TJ     Tajikistan         <NA>         <NA>
532980                  US  United States         <NA>         <NA>
410679                  UY        Uruguay         <NA>         <NA>

       metro_area       date  \
18274        <NA> 2020-11-28
456350       <NA> 2022-02-22
109303       <NA> 2022-03-22
497226       <NA> 2020-08-08
19372        <NA> 2021-08-02
160328       <NA> 2021-06-06
91450        <NA> 2021-07-08
268085       <NA> 2021-10-05
480291       <NA> 2021-07-08
533080       <NA> 2020-08-13
450650       <NA> 2020-04-29
532980       <NA> 2021-01-03
410679       <NA> 2021-10-12

        retail_and_recreation_percent_change_from_baseline  \
18274                                               -44.0
456350                                               38.0
109303                                               -6.0
497226                                              -22.0
19372                                                -6.0
160328                                                NaN
91450                                               -19.0
268085                                               43.0
480291                                              -11.0
533080                                              -14.0
450650                                              -32.0
```

```
532980                                               -27.0
410679                                               -15.0

        grocery_and_pharmacy_percent_change_from_baseline  \
18274                                                -11.0
456350                                               113.0
109303                                                19.0
497226                                                -7.0
19372                                                 17.0
160328                                                 NaN
91450                                                 -4.0
268085                                                86.0
480291                                                33.0
533080                                               -12.0
450650                                               -20.0
532980                                               -16.0
410679                                                 4.0

        parks_percent_change_from_baseline  \
18274                                -65.0
456350                               156.0
109303                               -11.0
497226                               155.0
19372                                 -9.0
160328                                 NaN
91450                                 -4.0
268085                               114.0
480291                                 3.0
533080                                 3.0
450650                               -22.0
532980                               -24.0
410679                               -39.0

        transit_stations_percent_change_from_baseline  \
18274                                           -38.0
456350                                           -4.0
109303                                           13.0
497226                                            2.0
19372                                           -21.0
160328                                          -52.0
91450                                            -5.0
268085                                           62.0
480291                                           -3.0
533080                                           -9.0
450650                                          -37.0
532980                                          -33.0
410679                                            0.0
```

```
        workplaces_percent_change_from_baseline  \
18274                                      -5.0
456350                                     35.0
109303                                     32.0
497226                                    -14.0
19372                                     -18.0
160328                                      NaN
91450                                     -44.0
268085                                      3.0
480291                                    -21.0
533080                                    -25.0
450650                                    -12.0
532980                                    -17.0
410679                                     23.0

        residential_percent_change_from_baseline
18274                                       11.0
456350                                       6.0
109303                                       5.0
497226                                      -2.0
19372                                        7.0
160328                                       NaN
91450                                       -6.0
268085                                     -11.0
480291                                       8.0
533080                                       9.0
450650                                       8.0
532980                                       7.0
410679                                       1.0
```

[8]:

```python
# --- New Code to Check Latest Date per Country ---
# Group by country and find the maximum (latest) date for each
latest_dates = filtered.groupby('country_region')['date'].max()

# Compute the result (this triggers the Dask computation)
latest_dates_computed = latest_dates.compute()

# Optional: Sort the results by date to see which countries have the most␣
↪recent data
print("\n--- Latest Date per Country (Sorted) ---")
print(latest_dates_computed.sort_values(ascending=False))
```

```
--- Latest Date per Country (Sorted) ---
country_region
Cambodia      2022-10-15
Sri Lanka     2022-10-15
Slovakia      2022-10-15
```

```
Singapore    2022-10-15
Senegal      2022-10-15
                …
Benin        2022-10-15
Barbados     2022-10-15
Bangladesh   2022-10-15
Australia    2022-10-15
Ukraine      2022-02-23
Name: date, Length: 135, dtype: datetime64[ns]
```

[9]:
```
# --- New Code to Check Latest Date per Country ---
# Group by country and find the maximum (latest) date for each
latest_dates = filtered.groupby('country_region')['date'].min()

# Compute the result (this triggers the Dask computation)
latest_dates_computed = latest_dates.compute()

# Optional: Sort the results by date to see which countries have the most␣
↪recent data
print("\n--- Earliest Date per Country (Sorted) ---")
print(latest_dates_computed.sort_values(ascending=False))
```

```
--- Earliest Date per Country (Sorted) ---
country_region
Cambodia              2020-02-15
Panama                2020-02-15
Trinidad and Tobago   2020-02-15
Slovakia              2020-02-15
Singapore             2020-02-15
                         …
Brazil                2020-02-15
Benin                 2020-02-15
Barbados              2020-02-15
Bangladesh            2020-02-15
Jordan                2020-02-15
Name: date, Length: 135, dtype: datetime64[ns]
```

[10]:
```
# I woul like to get what happened in the first two years of the pandemic
filtered = filtered[
    filtered['date'] <= '2022-02-15'
]
```

[11]:
```
print(filtered.sample(frac = 0.0001, random_state = 1).compute())
```

```
       country_region_code      country_region sub_region_1 sub_region_2  \
35060                   AU           Australia         <NA>         <NA>
177745                  CM            Cameroon         <NA>         <NA>
```

```
157822                  DO  Dominican Republic         <NA>          <NA>
212703                  HU             Hungary         <NA>          <NA>
130970                  LB             Lebanon         <NA>          <NA>
266250                  MD             Moldova         <NA>          <NA>
58358                   PT            Portugal         <NA>          <NA>
431777                  SV         El Salvador         <NA>          <NA>
430657                  VE           Venezuela         <NA>          <NA>

       metro_area       date  \
35060        <NA> 2021-10-18
177745       <NA> 2021-06-21
157822       <NA> 2020-12-05
212703       <NA> 2021-12-07
130970       <NA> 2020-07-17
266250       <NA> 2022-01-26
58358        <NA> 2020-08-17
431777       <NA> 2020-05-17
430657       <NA> 2020-12-23

        retail_and_recreation_percent_change_from_baseline  \
35060                                               -15.0
177745                                                6.0
157822                                              -29.0
212703                                                7.0
130970                                              -10.0
266250                                              -14.0
58358                                                -1.0
431777                                              -82.0
430657                                                6.0

        grocery_and_pharmacy_percent_change_from_baseline  \
35060                                                6.0
177745                                              33.0
157822                                              -4.0
212703                                              24.0
130970                                               4.0
266250                                               3.0
58358                                               12.0
431777                                             -65.0
430657                                              44.0

        parks_percent_change_from_baseline  \
35060                                -17.0
177745                               -11.0
157822                               -32.0
212703                                22.0
130970                                28.0
266250                               -29.0
```

```
58358                                93.0
431777                              -74.0
430657                                9.0

        transit_stations_percent_change_from_baseline  \
35060                                           -53.0
177745                                           35.0
157822                                          -23.0
212703                                           -9.0
130970                                          -42.0
266250                                          -19.0
58358                                           -35.0
431777                                          -76.0
430657                                           19.0

        workplaces_percent_change_from_baseline  \
35060                                     -18.0
177745                                    -12.0
157822                                    -17.0
212703                                    -12.0
130970                                    -23.0
266250                                    -32.0
58358                                     -44.0
431777                                    -48.0
430657                                    -20.0

        residential_percent_change_from_baseline
35060                                        9.0
177745                                      -2.0
157822                                       8.0
212703                                       5.0
130970                                       1.0
266250                                       1.0
58358                                       11.0
431777                                      23.0
430657                                       9.0
```

[12]:
```
# rename country_region_code and country_region
filtered = filtered.rename(columns = {
    'country_region_code' : 'code2',
    'country_region' : 'Country'
})
```

[13]:
```
# get a dataframe for the unique countries in the mobility data
countries_in_mob = filtered[['code2', 'Country']].drop_duplicates().compute()
countries_in_mob
```

[13]:
```
        code2                   Country
308409     BA  Bosnia and Herzegovina
547709     JO                    Jordan
161748     LT                 Lithuania
222006     LU                Luxembourg
253027     LY                     Libya
…       …                      …
53823      KE                     Kenya
317749     MY                  Malaysia
578462     NL               Netherlands
242319     PY                  Paraguay
504341     ZM                    Zambia

[135 rows x 2 columns]
```

[14]:
```
# check if there are missing
countries_in_mob[countries_in_mob['code2'].isna()]
```

[14]:
```
        code2  Country
355842   <NA>  Namibia
```

Python has read NA code for Nambia as an empty cell

[15]:
```
# Create the condition
condition = (filtered['Country'] == 'Namibia') & (filtered['code2'].isna())

# Use .where to replace values where the condition is False
# This means: keep 'code2' where condition is False, otherwise use 'NA'
# Note: .where keeps the original where the condition is FALSE, and replaces␣
↪where it's TRUE
# So we need to negate the condition for .where, or use .mask
# .mask is the opposite of .where: it replaces where the condition is TRUE
filtered['code2'] = filtered['code2'].mask(condition, 'NA')
```

[16]:
```
# get a dataframe for the unique countries in the mobility data
countries_in_mob = filtered[['code2', 'Country']].drop_duplicates().compute()
# check if there are missing
countries_in_mob[countries_in_mob['code2'].isna()]
```

[16]:
```
Empty DataFrame
Columns: [code2, Country]
Index: []
```

[17]:
```
# Get unique code2 that is in countries_in_mob but not in COUNTRY_CODE
not_in_cc = np.setdiff1d(countries_in_mob['code2'].unique(),␣
↪COUNTRY_CODE['code2'].unique())
not_in_cc
```

[17]:
```
array(['AW', 'HK', 'PR', 'RE', 'TW'], dtype=object)
```

[18]:
```
countries_in_mob[countries_in_mob['code2'].isin(not_in_cc)]
```

[18]:
```
       code2      Country
307435    AW        Aruba
261599    RE      Réunion
128171    HK    Hong Kong
498936    PR  Puerto Rico
460440    TW       Taiwan
```

[19]:
```
# Check if there are items Country in countries_in_mob and COUNTRY_CODE that␣
↪have the same code2 but different name
```

All of the five are either not a country, not a soverign nation, or not recognised as independent so for this analysis I would remove them for now

[20]:
```
# Check if there are items in countries_in_mob and COUNTRY_CODE that have the␣
↪same 'code2' but different 'Country' names

# Perform an inner join on 'code2' to find matching codes
merged_check = countries_in_mob[['code2', 'Country']].merge(
    COUNTRY_CODE[['code2', 'Country']],
    on='code2',
    how='inner',
    suffixes=('_mob', '_cc')  # Add suffixes to distinguish the 'Country'␣
↪columns
)

# Filter for rows where the country names are different
mismatched_names = merged_check[merged_check['Country_mob'] !=␣
↪merged_check['Country_cc']]

# Display the results
if not mismatched_names.empty:
    print("Found entries with the same 'code2' but different 'Country' names:")
    print(mismatched_names[['code2', 'Country_mob', 'Country_cc']])
else:
    print("No entries found with the same 'code2' but different 'Country' names.
↪")
```

```
Found entries with the same 'code2' but different 'Country' names:
   code2     Country_mob                                        Country_cc
9     MD         Moldova                               Moldova, Republic of
20    VE       Venezuela                  Venezuela, Bolivarian Republic of
24    BO         Bolivia                   Bolivia, Plurinational State of
28    TZ        Tanzania                      Tanzania, United Republic of
30    GB  United Kingdom  United Kingdom of Great Britain and Northern I…
```

```
38      LA            Laos                  Lao People's Democratic Republic
60      VN         Vietnam                                          Viet Nam
68      MM  Myanmar (Burma)                                         Myanmar
76      TR          Turkey                                          Türkiye
86      KR     South Korea                               Korea, Republic of
100     BS     The Bahamas                                          Bahamas
105     US   United States                         United States of America
109     RU          Russia                               Russian Federation
123     CV      Cape Verde                                       Cabo Verde
```

[21]:
```
COUNTRY_CODE.head(10)
```

[21]:
```
   id code2 Code              Country
0   4    AF  AFG          Afghanistan
1   8    AL  ALB              Albania
2  12    DZ  DZA              Algeria
3  20    AD  AND              Andorra
4  24    AO  AGO               Angola
5  28    AG  ATG  Antigua and Barbuda
6  32    AR  ARG            Argentina
7  51    AM  ARM              Armenia
8  36    AU  AUS            Australia
9  40    AT  AUT              Austria
```

Based on the output, the countries are the same

[22]:
```
# create a version of the COUNTRY_CODE the has no country to be merged to the␣
↪filtered dask dataframe
country_code_wo_country = COUNTRY_CODE[['code2', 'Code']]

# merge the COUNTRY_CODE to the filtered dataframe to add the three letter code
filtered_mobility = dd.merge(
    filtered,
    country_code_wo_country,
    on = 'code2',
    how = 'left'
)

# Get a dataframe for the unique countries in the mobility data, excluding rows␣
↪with <NA> in 'code2'
countries_in_mob = (
    filtered_mobility[['Code', 'Country']]
    .drop_duplicates()
    .dropna(subset=['Code'])  # Remove rows where 'code2' is <NA>
    .compute()
)

countries_in_mob
```

[22]:
```
      Code               Country
2877   ARG             Argentina
2883   GNB         Guinea-Bissau
732    ITA                 Italy
5856   TUR                Turkey
2196   UKR               Ukraine
…     …                     …
2193   POL                Poland
0      ARE  United Arab Emirates
3609   AUT               Austria
732    KEN                 Kenya
2825   ROU               Romania

[130 rows x 2 columns]
```

[23]:
```python
# remove duplicates, and sort the results alphabetically by Country
result = (
    filtered_mobility[['code2', 'Code', 'Country']]
    .drop_duplicates()
    .compute()
    .sort_values(by='Country')  # Sort alphabetically by the 'Country' column
)

result.style.set_table_attributes(
    'style="height:300px; overflow-y:scroll; display:block;"'
)
```

[23]:
```
<pandas.io.formats.style.Styler at 0x7625caeadca0>
```

[24]:
```python
# It seems that there might be missing code
result[result['Code'].isna()]
```

[24]:
```
      code2  Code      Country
732      AW  <NA>        Aruba
3590     HK  <NA>    Hong Kong
2925     PR  <NA>  Puerto Rico
2196     RE  <NA>      Réunion
732      TW  <NA>       Taiwan
```

[25]:
```python
print(filtered_mobility.sample(frac = 0.0001, random_state = 1).compute())
```

```
      code2             Country sub_region_1 sub_region_2 metro_area  \
611      AU           Australia         <NA>         <NA>       <NA>
2688     CM            Cameroon         <NA>         <NA>       <NA>
1758     DO  Dominican Republic         <NA>         <NA>       <NA>
7179     HU             Hungary         <NA>         <NA>       <NA>
6009     LB             Lebanon         <NA>         <NA>       <NA>
```

```
12385    MD            Moldova         <NA>         <NA>       <NA>
184      PT           Portugal         <NA>         <NA>       <NA>
3020     SV        El Salvador         <NA>         <NA>       <NA>
1044     VE          Venezuela         <NA>         <NA>       <NA>

            date  retail_and_recreation_percent_change_from_baseline  \
611   2021-10-18                                              -15.0
2688  2021-06-21                                                6.0
1758  2020-12-05                                              -29.0
7179  2021-12-07                                                7.0
6009  2020-07-17                                              -10.0
12385 2022-01-26                                              -14.0
184   2020-08-17                                               -1.0
3020  2020-05-17                                              -82.0
1044  2020-12-23                                                6.0

       grocery_and_pharmacy_percent_change_from_baseline  \
611                                                  6.0
2688                                                33.0
1758                                                -4.0
7179                                                24.0
6009                                                 4.0
12385                                                3.0
184                                                 12.0
3020                                               -65.0
1044                                                44.0

       parks_percent_change_from_baseline  \
611                                 -17.0
2688                                -11.0
1758                                -32.0
7179                                 22.0
6009                                 28.0
12385                               -29.0
184                                  93.0
3020                                -74.0
1044                                  9.0

       transit_stations_percent_change_from_baseline  \
611                                            -53.0
2688                                            35.0
1758                                           -23.0
7179                                            -9.0
6009                                           -42.0
12385                                          -19.0
184                                            -35.0
3020                                           -76.0
1044                                            19.0
```

```
       workplaces_percent_change_from_baseline  \
611                                      -18.0
2688                                     -12.0
1758                                     -17.0
7179                                     -12.0
6009                                     -23.0
12385                                    -32.0
184                                      -44.0
3020                                     -48.0
1044                                     -20.0

       residential_percent_change_from_baseline Code
611                                          9.0  AUS
2688                                        -2.0  CMR
1758                                         8.0  DOM
7179                                         5.0  HUN
6009                                         1.0  LBN
12385                                        1.0  MDA
184                                         11.0  PRT
3020                                        23.0  SLV
1044                                         9.0  VEN
```

[26]:

```
# Drop unnecessary columns in filtered_mobility
filtered_mobility = filtered_mobility.drop(columns = [
    'code2',
    'sub_region_1',
    'sub_region_2',
    'metro_area'
], axis = 1)

# Rename columns to be shorter
filtered_mobility = filtered_mobility.rename(columns = {
    'retail_and_recreation_percent_change_from_baseline' :␣
 ↪'retail_and_recreation',
    'grocery_and_pharmacy_percent_change_from_baseline' :␣
 ↪'grocery_and_pharmacy',
    'parks_percent_change_from_baseline' : 'parks',
    'transit_stations_percent_change_from_baseline' : 'transit_stations',
    'workplaces_percent_change_from_baseline' : 'workplaces',
    'residential_percent_change_from_baseline' : 'residential',
    'date' : 'Date'
})

print(filtered_mobility.sample(frac = 0.0001, random_state = 1).compute())
```

```
                 Country       Date  retail_and_recreation  \
611            Australia 2021-10-18                  -15.0
```

```
2688            Cameroon 2021-06-21                    6.0
1758  Dominican Republic 2020-12-05                  -29.0
7179             Hungary 2021-12-07                    7.0
6009             Lebanon 2020-07-17                  -10.0
12385            Moldova 2022-01-26                  -14.0
184             Portugal 2020-08-17                   -1.0
3020         El Salvador 2020-05-17                  -82.0
1044           Venezuela 2020-12-23                    6.0

      grocery_and_pharmacy  parks  transit_stations  workplaces  residential  \
611                    6.0  -17.0             -53.0       -18.0          9.0
2688                  33.0  -11.0              35.0       -12.0         -2.0
1758                  -4.0  -32.0             -23.0       -17.0          8.0
7179                  24.0   22.0              -9.0       -12.0          5.0
6009                   4.0   28.0             -42.0       -23.0          1.0
12385                  3.0  -29.0             -19.0       -32.0          1.0
184                   12.0   93.0             -35.0       -44.0         11.0
3020                 -65.0  -74.0             -76.0       -48.0         23.0
1044                  44.0    9.0              19.0       -20.0          9.0

     Code
611   AUS
2688  CMR
1758  DOM
7179  HUN
6009  LBN
12385 MDA
184   PRT
3020  SLV
1044  VEN
```

### 1.3.2 Get national policy

[27]:
```
# Check the oxford covid19 government response tracker
national_policy = pd.read_csv('data/oxcgt.csv')
national_policy.head()
```

[27]:
```
  CountryName CountryCode  RegionName  RegionCode Jurisdiction      Date  \
0       Aruba         ABW         NaN         NaN    NAT_TOTAL  20200101
1       Aruba         ABW         NaN         NaN    NAT_TOTAL  20200102
2       Aruba         ABW         NaN         NaN    NAT_TOTAL  20200103
3       Aruba         ABW         NaN         NaN    NAT_TOTAL  20200104
4       Aruba         ABW         NaN         NaN    NAT_TOTAL  20200105

   C1M_School closing  C1M_Flag  C2M_Workplace closing  C2M_Flag  …  \
0                   0       NaN                      0       NaN  …
1                   0       NaN                      0       NaN  …
```

```
2                    0       NaN                        0       NaN  …
3                    0       NaN                        0       NaN  …
4                    0       NaN                        0       NaN  …

   V3_Vaccine Financial Support (summary)  V4_Mandatory Vaccination (summary)  \
0                                      0                                 NaN
1                                      0                                 NaN
2                                      0                                 NaN
3                                      0                                 NaN
4                                      0                                 NaN

   ConfirmedCases  ConfirmedDeaths  MajorityVaccinated  PopulationVaccinated  \
0             0.0              0.0                  NV                   0.0
1             0.0              0.0                  NV                   0.0
2             0.0              0.0                  NV                   0.0
3             0.0              0.0                  NV                   0.0
4             0.0              0.0                  NV                   0.0

   StringencyIndex_Average  GovernmentResponseIndex_Average  \
0                      0.0                              0.0
1                      0.0                              0.0
2                      0.0                              0.0
3                      0.0                              0.0
4                      0.0                              0.0

   ContainmentHealthIndex_Average  EconomicSupportIndex
0                             0.0                   0.0
1                             0.0                   0.0
2                             0.0                   0.0
3                             0.0                   0.0
4                             0.0                   0.0

[5 rows x 56 columns]
```

[28]:
```
eval_df(national_policy)
```

```
 DATA TYPES & MEMORY USAGE
----------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 202760 entries, 0 to 202759
Data columns (total 56 columns):
 #   Column
Non-Null Count   Dtype
---  ------
--------------   -----
 0   CountryName
```

```
202760 non-null  object
 1   CountryCode
202760 non-null  object
 2   RegionName
0 non-null       float64
 3   RegionCode
0 non-null       float64
 4   Jurisdiction
202760 non-null  object
 5   Date
202760 non-null  int64
 6   C1M_School closing
202760 non-null  int64
 7   C1M_Flag
128263 non-null  float64
 8   C2M_Workplace closing
202760 non-null  int64
 9   C2M_Flag
133824 non-null  float64
 10  C3M_Cancel public events
202760 non-null  int64
 11  C3M_Flag
138576 non-null  float64
 12  C4M_Restrictions on gatherings
202760 non-null  int64
 13  C4M_Flag
125800 non-null  float64
 14  C5M_Close public transport
202760 non-null  int64
 15  C5M_Flag
67355 non-null   float64
 16  C6M_Stay at home requirements
202760 non-null  int64
 17  C6M_Flag
89648 non-null   float64
 18  C7M_Restrictions on internal movement
202760 non-null  int64
 19  C7M_Flag
70722 non-null   float64
 20  C8EV_International travel controls
202760 non-null  int64
 21  E1_Income support
202760 non-null  int64
 22  E1_Flag
99391 non-null   float64
 23  E2_Debt/contract relief
202760 non-null  int64
 24  E3_Fiscal measures
```

```
106288 non-null  float64
 25  E4_International support
106370 non-null  float64
 26  H1_Public information campaigns
202760 non-null  int64
 27  H1_Flag
191745 non-null  float64
 28  H2_Testing policy
202760 non-null  int64
 29  H3_Contact tracing
202760 non-null  int64
 30  H4_Emergency investment in healthcare
106245 non-null  float64
 31  H5_Investment in vaccines
198475 non-null  float64
 32  H6M_Facial Coverings
202760 non-null  int64
 33  H6M_Flag
167295 non-null  float64
 34  H7_Vaccination policy
202760 non-null  int64
 35  H7_Flag
126150 non-null  float64
 36  H8M_Protection of elderly people
202760 non-null  int64
 37  H8M_Flag
114519 non-null  float64
 38  V1_Vaccine Prioritisation (summary)
202760 non-null  int64
 39  V2A_Vaccine Availability (summary)
202760 non-null  int64
 40  V2B_Vaccine age eligibility/availability age floor (general population
summary)  118396 non-null  object
 41  V2C_Vaccine age eligibility/availability age floor (at risk summary)
120360 non-null  object
 42  V2D_Medically/ clinically vulnerable (Non-elderly)
127138 non-null  float64
 43  V2E_Education
127138 non-null  float64
 44  V2F_Frontline workers  (non healthcare)
127138 non-null  float64
 45  V2G_Frontline workers  (healthcare)
127138 non-null  float64
 46  V3_Vaccine Financial Support (summary)
202760 non-null  int64
 47  V4_Mandatory Vaccination (summary)
90957 non-null   float64
 48  ConfirmedCases
```

```
201664 non-null  float64
 49  ConfirmedDeaths
201664 non-null  float64
 50  MajorityVaccinated
200568 non-null  object
 51  PopulationVaccinated
200568 non-null  float64
 52  StringencyIndex_Average
202760 non-null  float64
 53  GovernmentResponseIndex_Average
202760 non-null  float64
 54  ContainmentHealthIndex_Average
202760 non-null  float64
 55  EconomicSupportIndex
202760 non-null  float64
dtypes: float64(30), int64(20), object(6)
memory usage: 86.6+ MB
None

  MISSING VALUES PER COLUMN
----------------------------------------
RegionName
202760
RegionCode
202760
C1M_Flag
74497
C2M_Flag
68936
C3M_Flag
64184
C4M_Flag
76960
C5M_Flag
135405
C6M_Flag
113112
C7M_Flag
132038
E1_Flag
103369
E3_Fiscal measures
96472
E4_International support
96390
H1_Flag
11015
H4_Emergency investment in healthcare
```

```
96515
H5_Investment in vaccines
4285
H6M_Flag
35465
H7_Flag
76610
H8M_Flag
88241
V2B_Vaccine age eligibility/availability age floor (general population summary)
84364
V2C_Vaccine age eligibility/availability age floor (at risk summary)
82400
V2D_Medically/ clinically vulnerable (Non-elderly)
75622
V2E_Education
75622
V2F_Frontline workers  (non healthcare)
75622
V2G_Frontline workers  (healthcare)
75622
V4_Mandatory Vaccination (summary)
111803
ConfirmedCases
1096
ConfirmedDeaths
1096
MajorityVaccinated
2192
PopulationVaccinated
2192
dtype: int64

  DUPLICATE ROWS FOUND
----------------------------------------
0 duplicate rows found.

  SUMMARY STATISTICS
----------------------------------------
       RegionName  RegionCode          Date  C1M_School closing  \
count         0.0         0.0  2.027600e+05       202760.000000
mean          NaN         NaN  2.021066e+07            1.193199
std           NaN         NaN  8.174621e+03            1.139102
min           NaN         NaN  2.020010e+07            0.000000
25%           NaN         NaN  2.020098e+07            0.000000
50%           NaN         NaN  2.021070e+07            1.000000
75%           NaN         NaN  2.022040e+07            2.000000
max           NaN         NaN  2.022123e+07            3.000000
```

```
          C1M_Flag  C2M_Workplace closing       C2M_Flag  \
count  128263.000000          202760.000000  133824.000000
mean        0.835268               1.149645       0.797630
std         0.370940               0.988767       0.401768
min         0.000000               0.000000       0.000000
25%         1.000000               0.000000       1.000000
50%         1.000000               1.000000       1.000000
75%         1.000000               2.000000       1.000000
max         1.000000               3.000000       1.000000

       C3M_Cancel public events       C3M_Flag  \
count             202760.000000  138576.000000
mean                   1.103250       0.858857
std                    0.851878       0.348170
min                    0.000000       0.000000
25%                    0.000000       1.000000
50%                    1.000000       1.000000
75%                    2.000000       1.000000
max                    2.000000       1.000000

       C4M_Restrictions on gatherings  …  \
count                   202760.000000  …
mean                         2.010209  …
std                          1.710198  …
min                          0.000000  …
25%                          0.000000  …
50%                          3.000000  …
75%                          4.000000  …
max                          4.000000  …

       V2G_Frontline workers  (healthcare)  \
count                        127138.000000
mean                              1.803316
std                               0.471447
min                               0.000000
25%                               2.000000
50%                               2.000000
75%                               2.000000
max                               2.000000

       V3_Vaccine Financial Support (summary)  \
count                           202760.000000
mean                                 3.100533
std                                  2.411897
min                                  0.000000
25%                                  0.000000
50%                                  5.000000
```

```
75%                                    5.000000
max                                    5.000000

       V4_Mandatory Vaccination (summary)  ConfirmedCases  ConfirmedDeaths  \
count                        90957.000000    2.016640e+05     2.016640e+05
mean                             0.278681    1.340886e+06     1.955307e+04
std                              0.448353    5.583371e+06     7.556113e+04
min                              0.000000    0.000000e+00     0.000000e+00
25%                              0.000000    5.146750e+03     6.400000e+01
50%                              0.000000    5.987900e+04     8.650000e+02
75%                              1.000000    5.218538e+05     7.470000e+03
max                              1.000000    1.007653e+08     1.092764e+06

       PopulationVaccinated  StringencyIndex_Average  \
count         200568.000000            202760.000000
mean              22.603420                42.675426
std               29.597555                24.930305
min                0.000000                 0.000000
25%                0.000000                22.220000
50%                2.330000                42.590000
75%               46.570000                62.040000
max              105.750000               100.000000

       GovernmentResponseIndex_Average  ContainmentHealthIndex_Average  \
count                    202760.000000                   202760.000000
mean                         44.857776                       46.699253
std                          19.649721                       19.865910
min                           0.000000                        0.000000
25%                          31.250000                       33.330000
50%                          46.880000                       48.720000
75%                          60.000000                       62.020000
max                          91.150000                       93.450000

       EconomicSupportIndex
count         202760.000000
mean              31.968029
std               32.962193
min                0.000000
25%                0.000000
50%               25.000000
75%               62.500000
max              100.000000

[8 rows x 50 columns]
```

[29]:

```python
# List of measures to focus on
measures_to_focus = [
```

```python
    'CountryName',
    'CountryCode',
    'Date',
    'ConfirmedCases',
    'ConfirmedDeaths',
    'PopulationVaccinated',
    'StringencyIndex_Average', # Index that encompasses containment and closure␣
 ↪policies and public information campaigns
    'ContainmentHealthIndex_Average', # Index that involve both␣
 ↪StringencyIndex_Average plus health system polices
    'EconomicSupportIndex' # Index encompasses by economic policies
]

# Filter national_policy to include only the selected high-priority measures
national_policy = national_policy[measures_to_focus]

# Convert the 'Date' column to datetime using .loc to avoid␣
 ↪SettingWithCopyWarning
# This explicitly targets the 'Date' column for all rows (:)
national_policy.loc[:, 'Date'] = pd.to_datetime(
    national_policy['Date'].astype(str),
    format='%Y%m%d'
)

# Rename the columns in the national_policy columns
national_policy = national_policy.rename(columns = {
    'CountryName' : 'Country',
    'CountryCode' : 'Code'
})

national_policy
```

[29]:

```
         Country Code       Date  ConfirmedCases  ConfirmedDeaths  \
0          Aruba  ABW 2020-01-01             0.0              0.0
1          Aruba  ABW 2020-01-02             0.0              0.0
2          Aruba  ABW 2020-01-03             0.0              0.0
3          Aruba  ABW 2020-01-04             0.0              0.0
4          Aruba  ABW 2020-01-05             0.0              0.0
…              …  …          …               …                …
202755  Zimbabwe  ZWE 2022-12-27        259981.0           5637.0
202756  Zimbabwe  ZWE 2022-12-28        259981.0           5637.0
202757  Zimbabwe  ZWE 2022-12-29        259981.0           5637.0
202758  Zimbabwe  ZWE 2022-12-30        259981.0           5637.0
202759  Zimbabwe  ZWE 2022-12-31        259981.0           5637.0

        PopulationVaccinated  StringencyIndex_Average  \
0                       0.00                     0.00
```

```
1                       0.00                     0.00
2                       0.00                     0.00
3                       0.00                     0.00
4                       0.00                     0.00
…                      …                       …
202755                 29.11                    29.48
202756                 29.11                    29.48
202757                 29.11                    29.48
202758                 29.11                    29.48
202759                 29.11                    29.48

        ContainmentHealthIndex_Average  EconomicSupportIndex
0                                 0.00                   0.0
1                                 0.00                   0.0
2                                 0.00                   0.0
3                                 0.00                   0.0
4                                 0.00                   0.0
…                                  …                    …
202755                           41.65                   0.0
202756                           41.65                   0.0
202757                           41.65                   0.0
202758                           41.65                   0.0
202759                           41.65                   0.0

[202760 rows x 9 columns]
```

[30]:

```
# To mirror the mobility data, I would limit the max date to 2022-02-15
national_policy = national_policy[
    national_policy['Date'] <= '2022-02-15'
]
```

[31]:

```
# Create a Country and Code of the national_policy
np_df = national_policy[['Code']].drop_duplicates()

# Get the intersection of np_df and the countries_in_mob
study_sample = pd.merge(
    countries_in_mob,
    np_df,
    how = 'inner',
    on = ['Code'])

print(study_sample.sort_values(by = 'Country'))
```

```
    Code      Country
50   AFG  Afghanistan
113  AGO       Angola
0    ARG    Argentina
```

```
29   AUS    Australia
124  AUT      Austria
..   …          …
110  VEN    Venezuela
4    VNM      Vietnam
70   YEM        Yemen
111  ZMB       Zambia
112  ZWE     Zimbabwe

[127 rows x 2 columns]
```

### 1.3.3 Get the country stats

[32]:
```
COUNTRY_CODE
```

[32]:
```
      id code2 Code                             Country
0      4    AF  AFG                         Afghanistan
1      8    AL  ALB                             Albania
2     12    DZ  DZA                             Algeria
3     20    AD  AND                             Andorra
4     24    AO  AGO                              Angola
..   …    …   …                                 …
188  862    VE  VEN  Venezuela, Bolivarian Republic of
189  704    VN  VNM                            Viet Nam
190  887    YE  YEM                               Yemen
191  894    ZM  ZMB                              Zambia
192  716    ZW  ZWE                            Zimbabwe

[193 rows x 4 columns]
```

[33]:
```
country_stat = COUNTRY_CODE
# Define path to folder containing country statistics CSVs
folder_path = 'data/country_stat/'
csv_files = glob.glob(folder_path + "*.csv")

# Merge each additional CSV file into the main country_stat DataFrame
# Handle potential encoding issues for each file
for file in csv_files:
    print(f"Attempting to read: {file}")
    try:
        # Try UTF-8 first (most common standard)
        df = pd.read_csv(file, encoding='utf-8')
    except UnicodeDecodeError:
        # If UTF-8 fails, try common alternatives
        try:
            df = pd.read_csv(file, encoding='latin1') # ISO 8859-1
            print(f"  Successfully read {file} with 'latin1' encoding.")
```

```python
        except UnicodeDecodeError:
            try:
                df = pd.read_csv(file, encoding='cp1252') # Windows-1252
                print(f"  Successfully read {file} with 'cp1252' encoding.")
            except UnicodeDecodeError:
                # If all common encodings fail, raise an error with the filename
                raise UnicodeDecodeError(f"Failed to read {file} with common␣
↪encodings (utf-8, latin1, cp1252). "
                                         "Please check the file's encoding.")

    # Drop 'Country' column if it's duplicated (assuming 'Code' is the unique␣
↪key)
    df.drop(columns=["Country"], inplace=True)

    # Merge on country code
    country_stat = pd.merge(country_stat, df, on="Code", how="outer")

# Evaluate the merged DataFrame for structure, completeness, and duplicates
eval_df(country_stat)
```

```
Attempting to read: data/country_stat/urbanization.csv
Attempting to read: data/country_stat/corruption_perception_index.csv
Attempting to read: data/country_stat/gdp_per_capita.csv
Attempting to read: data/country_stat/geographic_data.csv
Attempting to read: data/country_stat/hospital_beds.csv
  Successfully read data/country_stat/hospital_beds.csv with 'latin1' encoding.
Attempting to read: data/country_stat/unemployment.csv
Attempting to read: data/country_stat/political_regime.csv
Attempting to read: data/country_stat/gini_index.csv
Attempting to read: data/country_stat/population_density.csv
Attempting to read: data/country_stat/extreme_poverty.csv
Attempting to read: data/country_stat/median-age.csv
Attempting to read: data/country_stat/land-area-km.csv

 DATA TYPES & MEMORY USAGE
----------------------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 317 entries, 0 to 316
Data columns (total 19 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   id                           193 non-null    float64
 1   code2                        193 non-null    object
 2   Code                         247 non-null    object
 3   Country                      193 non-null    object
 4   urban_population             197 non-null    float64
 5   corruption_perception_index  180 non-null    float64
```

```
 6   gdp_per_capita              271 non-null    float64
 7   land_boundaries             312 non-null    float64
 8   coastline                   310 non-null    float64
 9   num_border_countries        310 non-null    float64
 10  border_countries            176 non-null    object
 11  hospital_beds_per_1000      167 non-null    float64
 12  unemployment                187 non-null    float64
 13  political_regime            174 non-null    object
 14  gini_index                  169 non-null    float64
 15  population_density          200 non-null    float64
 16  poverty                     159 non-null    float64
 17  median_age                  201 non-null    float64
 18  land_area_sqkm              196 non-null    float64
dtypes: float64(14), object(5)
memory usage: 47.2+ KB
None

 MISSING VALUES PER COLUMN
----------------------------------------
id                             124
code2                          124
Code                            70
Country                        124
urban_population               120
corruption_perception_index    137
gdp_per_capita                  46
land_boundaries                  5
coastline                        7
num_border_countries             7
border_countries               141
hospital_beds_per_1000         150
unemployment                   130
political_regime               143
gini_index                     148
population_density             117
poverty                        158
median_age                     116
land_area_sqkm                 121
dtype: int64

 DUPLICATE ROWS FOUND
----------------------------------------
0 duplicate rows found.

 SUMMARY STATISTICS
----------------------------------------
               id  urban_population  corruption_perception_index  \
count  193.000000        197.000000                   180.000000
```

```
mean   433.279793        59.427223                       43.166667
std    254.431053        23.161899                       18.960264
min      4.000000        13.250000                        9.000000
25%    212.000000        41.612000                       29.000000
50%    430.000000        60.308000                       39.500000
75%    659.000000        78.099000                       56.000000
max    894.000000       100.000000                       87.000000

       gdp_per_capita  land_boundaries      coastline  num_border_countries  \
count      271.000000       312.000000     310.000000            310.000000
mean     26985.167085      1747.996795    2602.079032              2.106452
std      26661.273006      3088.111848   12848.775646              2.548867
min        623.400000         0.000000       0.000000              0.000000
25%       6856.675700         0.000000      58.900000              0.000000
50%      18256.998000       156.000000     190.500000              1.000000
75%      42198.130000      2432.000000    1146.750000              4.000000
max     166907.800000     22457.000000  202080.000000             14.000000

       hospital_beds_per_1000  unemployment  gini_index  population_density  \
count              167.000000    187.000000  169.000000          200.000000
mean                 2.951976      7.293941    0.375518          294.578268
std                  2.679764      5.673796    0.079872         1414.506600
min                  0.170000      0.100000    0.232323            0.136699
25%                  1.110000      3.448000    0.317809           31.278362
50%                  2.300000      5.206000    0.356654           84.848432
75%                  4.055000     10.334500    0.425342          209.366408
max                 22.020000     28.468000    0.630258        18297.025000

          poverty  median_age  land_area_sqkm
count  159.000000  201.000000    1.960000e+02
mean    10.755403   29.041841    6.618971e+05
std     17.961751    9.253179    1.823404e+06
min      0.000000   14.368000    2.084000e+00
25%      0.266830   20.903000    2.308750e+04
50%      1.401915   28.361000    1.203750e+05
75%     15.240933   36.543000    5.151600e+05
max     78.942020   54.642000    1.637687e+07
```

[34]:

```python
# Drop the id and code2 columns
country_stat = country_stat.drop(columns = ['id', 'code2'], axis = 1)
```

[35]:

```python
# Create a Country and Code of the country stat
cs_df = country_stat[['Code']].drop_duplicates()

# Get the intersection of np_df and the countries_in_mob
study_sample = pd.merge(
    study_sample,
```

```python
    cs_df,
    how = 'inner',
    on = ['Code'])

print(study_sample.sort_values(by = 'Country'))
```

```
    Code      Country
50   AFG  Afghanistan
113  AGO       Angola
0    ARG    Argentina
29   AUS    Australia
124  AUT      Austria
..   …          …
110  VEN    Venezuela
4    VNM      Vietnam
70   YEM        Yemen
111  ZMB       Zambia
112  ZWE     Zimbabwe

[127 rows x 2 columns]
```

[36]:
```python
country_stat = country_stat[country_stat['Code'].isin(study_sample['Code'])]
eval_df(country_stat)
```

```
 DATA TYPES & MEMORY USAGE
----------------------------------------
<class 'pandas.core.frame.DataFrame'>
Index: 127 entries, 1 to 246
Data columns (total 17 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Code                        127 non-null    object
 1   Country                     127 non-null    object
 2   urban_population            127 non-null    float64
 3   corruption_perception_index 124 non-null    float64
 4   gdp_per_capita              126 non-null    float64
 5   land_boundaries             127 non-null    float64
 6   coastline                   127 non-null    float64
 7   num_border_countries        127 non-null    float64
 8   border_countries            112 non-null    object
 9   hospital_beds_per_1000      126 non-null    float64
 10  unemployment                126 non-null    float64
 11  political_regime            124 non-null    object
 12  gini_index                  125 non-null    float64
 13  population_density          127 non-null    float64
 14  poverty                     115 non-null    float64
 15  median_age                  127 non-null    float64
```

```
 16  land_area_sqkm               127 non-null    float64
dtypes: float64(13), object(4)
memory usage: 17.9+ KB
None

  MISSING VALUES PER COLUMN
----------------------------------------
corruption_perception_index     3
gdp_per_capita                  1
border_countries               15
hospital_beds_per_1000          1
unemployment                    1
political_regime                3
gini_index                      2
poverty                        12
dtype: int64

  DUPLICATE ROWS FOUND
----------------------------------------
0 duplicate rows found.

  SUMMARY STATISTICS
----------------------------------------
       urban_population  corruption_perception_index  gdp_per_capita  \
count        127.000000                   124.000000      126.000000
mean          62.862701                    46.217742    29550.430979
std           22.370051                    19.204742    28943.024152
min           13.250000                    15.000000      623.400000
25%           47.401000                    30.750000     8125.092000
50%           66.177000                    41.000000    18379.695000
75%           81.456000                    60.000000    44282.128750
max          100.000000                    87.000000   166907.800000

       land_boundaries      coastline  num_border_countries  \
count       127.000000     127.000000            127.000000
mean       3190.928346    5059.715748              3.629921
std        3482.265985   19347.715515              2.448852
min           0.000000       0.000000              0.000000
25%         877.000000      62.250000              2.000000
50%        2237.000000     823.000000              4.000000
75%        4368.075000    2790.000000              5.000000
max       22407.000000  202080.000000             14.000000

       hospital_beds_per_1000  unemployment  gini_index  population_density  \
count              126.000000    126.000000  125.000000          127.000000
mean                 2.907857      6.571746    0.381391          227.507278
std                  2.433828      4.960589    0.083967          735.066124
min                  0.170000      0.100000    0.232323            2.075187
```

```
25%                       1.067500      3.433500    0.318931             33.333070
50%                       2.230000      4.968500    0.362465             84.937030
75%                       4.177500      8.730750    0.433141            208.888695
max                      12.880000     28.468000    0.630258           7896.325700

          poverty  median_age  land_area_sqkm
count  115.000000  127.000000    1.270000e+02
mean     8.515624   30.512756    8.072397e+05
std     15.720207    9.175992    2.070121e+06
min      0.000000   14.699000    1.600000e+02
25%      0.243869   22.996500    5.517500e+04
50%      1.040000   29.063000    2.300800e+05
75%      6.626446   39.189500    6.158150e+05
max     74.528350   47.262000    1.637687e+07
```

[37]:
```python
columns_w_missing = [
    'Code',
    'Country',
    'corruption_perception_index',
    'gdp_per_capita',
    'border_countries',
    'hospital_beds_per_1000',
    'unemployment',
    'political_regime',
    'gini_index',
    'poverty'
]
```

Evaluation of the Missing values:
No data for Liechtenstein, for the rest I used the value that is closest to the 2019 value.

[38]:
```python
# Create a copy to explore missing data safely
missing_df = country_stat[columns_w_missing]

# Add a column to count missing values per country
missing_df.loc[:, 'missing_count'] = missing_df.isna().sum(axis=1)

# Filter only countries with at least one missing value and sort by the number␣
↪of missing entries
missing_df = missing_df[missing_df['missing_count'] > 0].
↪sort_values(by='missing_count', ascending=True)

# Display in a scrollable format (useful for large result sets)
missing_df
```

```
/tmp/ipykernel_959/4263053850.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  missing_df.loc[:, 'missing_count'] = missing_df.isna().sum(axis=1)
```

[38]:

```
    Code                          Country  corruption_perception_index  \
1    AFG                      Afghanistan                         16.0
13   AUS                        Australia                         77.0
50   CPV                       Cabo Verde                         58.0
31   BRB                         Barbados                         62.0
121  KWT                           Kuwait                         40.0
117  KHM                         Cambodia                         20.0
113  JPN                            Japan                         73.0
110  JAM                          Jamaica                         43.0
125  LBY                            Libya                         18.0
128  LKA                        Sri Lanka                         38.0
144  MLT                            Malta                         54.0
235  VEN  Venezuela, Bolivarian Republic of                         16.0
188  SAU                     Saudi Arabia                         53.0
174  PHL                      Philippines                         34.0
167  OMN                             Oman                         52.0
152  MUS                        Mauritius                         52.0
72   FJI                             Fiji                          NaN
166  NZL                      New Zealand                         87.0
191  SGP                        Singapore                         85.0
22   BHR                          Bahrain                         42.0
221  TTO              Trinidad and Tobago                         40.0
23   BHS                          Bahamas                         64.0
27   BLZ                           Belize                          NaN
127  LIE                    Liechtenstein                          NaN

     gdp_per_capita                                   border_countries  \
1          2927.245  China 91 km; Iran 921 km; Pakistan 2,670 km; T…
13        56981.395                                                NaN
50         9111.630                                                NaN
31        18572.510                                                NaN
121       51122.332                 Iraq 254 km; Saudi Arabia 221 km
117        6448.885       Laos 555 km; Thailand 817 km; Vietnam 1158 km
113       44976.508                                                NaN
110       10216.065                                                NaN
125       14333.423  Algeria 989 km; Chad 1,050 km; Egypt 1,115 km;…
128       14637.444                                                NaN
144       54667.383                                                NaN
235             NaN  Brazil 2,137 km; Colombia 2,341 km; Guyana 789 km
188       56365.508  Iraq 811 km; Jordan 731 km; Kuwait 221 km; Oma…
174        9452.294                                                NaN
167       38292.387       Saudi Arabia 658 km; UAE 609 km; Yemen 294 km
```

| | | |
|---|---|---|
| 152 | 25739.355 | NaN |
| 72 | 13567.474 | NaN |
| 166 | 47523.230 | NaN |
| 191 | 119572.270 | NaN |
| 22 | 56749.960 | NaN |
| 221 | 34349.130 | NaN |
| 23 | 32495.334 | NaN |
| 27 | 11803.088 | Guatemala 266 km; Mexico 276 km |
| 127 | 166907.800 | Austria 34 km; Switzerland 41 km |

| | hospital_beds_per_1000 | unemployment | political_regime | gini_index | \ |
|---|---|---|---|---|---|
| 1 | 0.38 | 11.185 | electoral_autocracies | 0.410000 | |
| 13 | 3.84 | 5.159 | liberal_democracies | 0.343326 | |
| 50 | 1.97 | 12.128 | electoral_democracies | 0.423811 | |
| 31 | 5.74 | 8.412 | liberal_democracies | 0.340680 | |
| 121 | 2.00 | 2.251 | electoral_autocracies | 0.529000 | |
| 117 | 0.74 | 0.119 | electoral_autocracies | 0.454000 | |
| 113 | 12.88 | 2.351 | liberal_democracies | 0.329849 | |
| 110 | 1.73 | 4.987 | liberal_democracies | 0.356387 | |
| 125 | 3.20 | 19.050 | closed_autocracies | 0.441000 | |
| 128 | 4.00 | 4.670 | electoral_democracies | 0.376638 | |
| 144 | 4.11 | 3.616 | electoral_democracies | 0.310418 | |
| 235 | 0.93 | 5.876 | electoral_autocracies | 0.446984 | |
| 188 | 2.15 | 5.636 | closed_autocracies | 0.544000 | |
| 174 | 0.98 | 2.237 | electoral_autocracies | 0.378117 | |
| 167 | 1.10 | 2.040 | closed_autocracies | 0.443000 | |
| 152 | 3.63 | 6.331 | electoral_democracies | 0.367612 | |
| 72 | 1.89 | 4.373 | electoral_autocracies | 0.307069 | |
| 166 | 2.55 | 4.109 | liberal_democracies | 0.346000 | |
| 191 | 2.60 | 3.100 | electoral_autocracies | 0.337000 | |
| 22 | 1.74 | 1.223 | closed_autocracies | 0.557000 | |
| 221 | 1.90 | 3.523 | liberal_democracies | 0.533000 | |
| 23 | 2.70 | 9.336 | NaN | 0.533000 | |
| 27 | 1.03 | 9.053 | NaN | NaN | |
| 127 | NaN | NaN | NaN | NaN | |

| | poverty | missing_count |
|---|---|---|
| 1 | NaN | 1 |
| 13 | 0.497094 | 1 |
| 50 | 4.564231 | 1 |
| 31 | 1.677398 | 1 |
| 121 | NaN | 1 |
| 117 | NaN | 1 |
| 113 | 1.221445 | 1 |
| 110 | 0.056063 | 1 |
| 125 | NaN | 1 |
| 128 | 0.958613 | 1 |

```
144  0.304682            1
235  9.712060            1
188       NaN            1
174  5.057057            1
167       NaN            1
152  0.125314            1
72   1.318269            2
166       NaN            2
191       NaN            2
22        NaN            2
221       NaN            2
23        NaN            3
27   1.040000            3
127       NaN            6
```

[39]:

```
# Drop border countries
missing_df = missing_df.drop(columns = 'border_countries', axis = 1)

# Add a column to count missing values per country
missing_df.loc[:, 'missing_count'] = missing_df.isna().sum(axis=1)

# Filter only countries with at least one missing value and sort by the number␣
↪of missing entries
missing_df = missing_df[missing_df['missing_count'] > 0].
↪sort_values(by='missing_count', ascending=True)

# Display in a scrollable format (useful for large result sets)
missing_df
```

[39]:

```
    Code                         Country  corruption_perception_index  \
1    AFG                     Afghanistan                         16.0
121  KWT                          Kuwait                         40.0
117  KHM                        Cambodia                         20.0
125  LBY                           Libya                         18.0
235  VEN  Venezuela, Bolivarian Republic of                      16.0
188  SAU                    Saudi Arabia                         53.0
167  OMN                            Oman                         52.0
72   FJI                            Fiji                          NaN
166  NZL                     New Zealand                         87.0
191  SGP                       Singapore                         85.0
22   BHR                         Bahrain                         42.0
221  TTO             Trinidad and Tobago                         40.0
23   BHS                         Bahamas                         64.0
27   BLZ                          Belize                          NaN
127  LIE                   Liechtenstein                          NaN

     gdp_per_capita  hospital_beds_per_1000  unemployment  \
```

```
1        2927.245                    0.38         11.185
121     51122.332                    2.00          2.251
117      6448.885                    0.74          0.119
125     14333.423                    3.20         19.050
235           NaN                    0.93          5.876
188     56365.508                    2.15          5.636
167     38292.387                    1.10          2.040
72      13567.474                    1.89          4.373
166     47523.230                    2.55          4.109
191    119572.270                    2.60          3.100
22      56749.960                    1.74          1.223
221     34349.130                    1.90          3.523
23      32495.334                    2.70          9.336
27      11803.088                    1.03          9.053
127    166907.800                     NaN            NaN

          political_regime  gini_index   poverty  missing_count
1    electoral_autocracies    0.410000       NaN              1
121  electoral_autocracies    0.529000       NaN              1
117  electoral_autocracies    0.454000       NaN              1
125     closed_autocracies    0.441000       NaN              1
235  electoral_autocracies    0.446984  9.712060              1
188     closed_autocracies    0.544000       NaN              1
167     closed_autocracies    0.443000       NaN              1
72   electoral_autocracies    0.307069  1.318269              1
166    liberal_democracies    0.346000       NaN              1
191  electoral_autocracies    0.337000       NaN              1
22      closed_autocracies    0.557000       NaN              1
221    liberal_democracies    0.533000       NaN              1
23                     NaN    0.533000       NaN              2
27                     NaN         NaN  1.040000              3
127                    NaN         NaN       NaN              6
```

[40]:
```
# for this analysis we will remove all the rows that have missing
study_sample = study_sample[~study_sample['Code'].isin(missing_df['Code'])]
```

## 2 Create country stat, national policy and mobility data that includes only countries in the study sample

[41]:
```
country_stat = country_stat[country_stat['Code'].isin(study_sample['Code'])]
country_stat
```

[41]:
```
    Code               Country  urban_population  corruption_perception_index  \
2    AGO                Angola            66.177                         26.0
6    ARE  United Arab Emirates            86.789                         71.0
7    ARG             Argentina            91.991                         45.0
```

```
13   AUS           Australia           86.124                             77.0
14   AUT             Austria           58.515                             77.0
..   …                     …                …                          …
238  VNM            Viet Nam           36.628                             37.0
243  YEM               Yemen           37.273                             15.0
244  ZAF        South Africa           66.856                             44.0
245  ZMB              Zambia           44.072                             34.0
246  ZWE            Zimbabwe           32.210                             24.0

     gdp_per_capita  land_boundaries  coastline  num_border_countries  \
2         8274.5430          5369.00     1600.0                   4.0
6        68887.8400          1066.00     1318.0                   2.0
7        26629.5530         11968.00     4989.0                   5.0
13       56981.3950             0.00    25760.0                   0.0
14       65312.0230          2524.00        0.0                   8.0
..                …                …          …                     …
238      11628.6140          4616.00     3444.0                   3.0
243        623.4000          1601.00     1906.0                   2.0
244      14370.2380          5244.00     2798.0                   6.0
245       3591.5642          6043.15        0.0                   8.0
246       3294.8062          3229.00        0.0                   4.0

                                       border_countries  \
2    Democratic Republic of the Congo 2,646 km (of …
6                     Oman 609 km; Saudi Arabia 457 km
7    Bolivia 942 km; Brazil 1,263 km; Chile 6,691 k…
13                                                 NaN
14   Czech Republic 402 km; Germany 801 km; Hungary…
..                                                   …
238   Cambodia 1,158 km; China 1,297 km; Laos 2,161 km
243                 Oman 294 km; Saudi Arabia 1,307 km
244  Botswana 1,969 km; Lesotho 1,106 km; Mozambiqu…
245  Angola 1,065 km; Botswana 0.15 km; Democratic …
246  Botswana 834 km; Mozambique 1,402 km; South Af…

     hospital_beds_per_1000  unemployment       political_regime  gini_index  \
2                      0.75        16.497  electoral_autocracies    0.512640
6                      1.87         2.331     closed_autocracies    0.263990
7                      3.71         9.843  electoral_democracies    0.433141
13                     3.84         5.159    liberal_democracies    0.343326
14                     7.19         4.560    liberal_democracies    0.302104
..                        …             …                      …           …
238                    2.55         1.681  electoral_autocracies    0.367902
243                    0.71        17.202     closed_autocracies    0.367071
244                    2.30        28.468  electoral_democracies    0.630258
245                    2.00         5.542  electoral_autocracies    0.514831
246                    2.00         7.373  electoral_autocracies    0.502564
```

```
     population_density    poverty  median_age  land_area_sqkm
2             25.969065  31.122005      16.302       1246700.0
6            132.045270   0.000000      30.834         71020.0
7             16.433529   1.684649      30.763       2736690.0
13             3.312877   0.497094      36.543       7692020.0
14           107.620880   0.640639      42.433         82520.0
..                  …          …           …             …
238          310.034420   0.653778      30.586        313429.0
243           66.502680  19.802757      18.017        527970.0
244           49.120743  20.492558      26.873       1213090.0
245           24.904613  64.349754      16.763        743390.0
246           39.476223  39.754530      17.187        386850.0

[112 rows x 17 columns]
```

[42]:
```
national_policy = national_policy[national_policy['Code'].
 ↪isin(study_sample['Code'])]
national_policy
```

[42]:
```
          Country Code        Date  ConfirmedCases  ConfirmedDeaths  \
2192       Angola  AGO  2020-01-01             0.0              0.0
2193       Angola  AGO  2020-01-02             0.0              0.0
2194       Angola  AGO  2020-01-03             0.0              0.0
2195       Angola  AGO  2020-01-04             0.0              0.0
2196       Angola  AGO  2020-01-05             0.0              0.0
…             …    …           …              …                …
202436   Zimbabwe  ZWE  2022-02-11        231214.0           5374.0
202437   Zimbabwe  ZWE  2022-02-12        231299.0           5374.0
202438   Zimbabwe  ZWE  2022-02-13        231381.0           5374.0
202439   Zimbabwe  ZWE  2022-02-14        231603.0           5374.0
202440   Zimbabwe  ZWE  2022-02-15        231603.0           5374.0

        PopulationVaccinated  StringencyIndex_Average  \
2192                    0.00                     0.00
2193                    0.00                     0.00
2194                    0.00                     0.00
2195                    0.00                     0.00
2196                    0.00                     0.00
…                        …                       …
202436                 20.48                    51.45
202437                 20.51                    51.45
202438                 20.52                    51.45
202439                 20.53                    51.45
202440                 20.54                    51.45

        ContainmentHealthIndex_Average  EconomicSupportIndex
```

```
2192                            0.00                 0.0
2193                            0.00                 0.0
2194                            0.00                 0.0
2195                            0.00                 0.0
2196                            0.00                 0.0
…                                …                  …
202436                         61.05                 0.0
202437                         61.05                 0.0
202438                         61.05                 0.0
202439                         61.05                 0.0
202440                         61.05                 0.0

[87024 rows x 9 columns]
```

[43]:
```
filtered_mobility = filtered_mobility[filtered_mobility['Code'].
 ↪isin(study_sample['Code'])]
print(filtered_mobility.sample(frac = 0.0001, random_state = 1).compute())
```

```
           Country        Date  retail_and_recreation  grocery_and_pharmacy  \
2925      Barbados  2022-02-13                   32.0                  17.0
2688      Cameroon  2021-06-21                    6.0                  33.0
3070       Estonia  2020-07-06                   15.0                  14.0
637        Georgia  2021-12-28                   34.0                  76.0
3067   South Korea  2020-07-03                   -8.0                   5.0
17011       Mexico  2020-09-15                  -24.0                   1.0
3763        Serbia  2020-10-23                   -7.0                  13.0
3106   El Salvador  2020-08-11                  -47.0                 -24.0

       parks  transit_stations  workplaces  residential Code
2925    51.0               3.0        15.0         -3.0  BRB
2688   -11.0              35.0       -12.0         -2.0  CMR
3070   116.0              -3.0       -37.0          4.0  EST
637     30.0               9.0        -4.0         -3.0  GEO
3067    23.0              -5.0        -1.0          2.0  KOR
17011  -27.0             -40.0       -31.0          9.0  MEX
3763    18.0              -2.0       -15.0         -1.0  SRB
3106   -42.0             -56.0       -45.0         20.0  SLV
```

# 3 Evaluate each dataframe to get the features that would be used in the analysis

## 3.1 Mobility data

[44]:
```
# Basic info on the mobility data set
print(f'Shape: {filtered_mobility.shape[0].compute()} rows')
print(f'Columns: {filtered_mobility.columns.tolist()}')
print('Data types')
```

```
print(filtered_mobility.dtypes)
```

```
Shape: 81888 rows
Columns: ['Country', 'Date', 'retail_and_recreation', 'grocery_and_pharmacy',
'parks', 'transit_stations', 'workplaces', 'residential', 'Code']
Data types
Country                  string[pyarrow]
Date                      datetime64[ns]
retail_and_recreation            float64
grocery_and_pharmacy             float64
parks                            float64
transit_stations                 float64
workplaces                       float64
residential                      float64
Code                     string[pyarrow]
dtype: object
```

[45]:
```
# Check missing data patterns
missing_counts = filtered_mobility.isnull().sum().compute()
missing_percent = (missing_counts / len(filtered_mobility)) * 100

print("Missing data percentage:")
for col, pct in missing_percent.items():
    print(f"{col}: {pct:.2f}%")
```

```
Missing data percentage:
Country: 0.00%
Date: 0.00%
retail_and_recreation: 0.28%
grocery_and_pharmacy: 0.19%
parks: 0.67%
transit_stations: 0.44%
workplaces: 0.16%
residential: 0.08%
Code: 0.00%
```

[46]:
```
# Assuming 'Country' column exists in filtered_mobility
# Group by 'Country', calculate missing percentages for each group, and compute␣
↪the result
missing_percent_per_country = (
    filtered_mobility
    .groupby(['Country','Code'])  # Group the Dask DataFrame by 'Country'
    .apply(                 # Apply a function to each group
        lambda group: (group.isnull().sum() / len(group)) * 100,
        meta=dict([(col, 'f8') for col in filtered_mobility.columns]) # Provide␣
↪meta for Dask
    )
```

```
    .compute()            # Compute the result (triggers Dask execution)
)

# Filter the result to show only countries with at least one column having␣
↪missing data
# A country has missing data if the sum of missing percentages across its␣
↪columns is greater than 0
# Or, more simply, if the maximum missing percentage for the country is greater␣
↪than 0
countries_with_missing = missing_percent_per_country[
    missing_percent_per_country.max(axis=1) > 0
]

# Optional: Sort countries by the maximum percentage of missing data
sorted_by_max_missing = countries_with_missing.loc[countries_with_missing.
↪max(axis=1).sort_values(ascending=False).index]

# Display the results for countries with missing data
if not countries_with_missing.empty:
    print("Missing data percentage per Country (Countries with ANY missing␣
↪data):")
    print(sorted_by_max_missing)
else:
    print("No countries found with missing data in any column.")
```

```
Missing data percentage per Country (Countries with ANY missing data):
                       Country  Date  retail_and_recreation  \
Country          Code
Vietnam          VNM       0.0   0.0               0.000000
Gabon            GAB       0.0   0.0               3.415301
Cape Verde       CPV       0.0   0.0               3.017833
Papua New Guinea PNG       0.0   0.0               3.017833
Mongolia         MNG       0.0   0.0               2.595628
Benin            BEN       0.0   0.0               1.775956
Luxembourg       LUX       0.0   0.0               0.000000
Angola           AGO       0.0   0.0               0.000000
Burkina Faso     BFA       0.0   0.0               3.005464
Rwanda           RWA       0.0   0.0               3.415301
Zimbabwe         ZWE       0.0   0.0               0.000000
Botswana         BWA       0.0   0.0               3.415301
Haiti            HTI       0.0   0.0               3.415301
Barbados         BRB       0.0   0.0               0.409836
Mali             MLI       0.0   0.0               0.819672
Namibia          NAM       0.0   0.0               0.000000
Yemen            YEM       0.0   0.0               0.136612
Togo             TGO       0.0   0.0               0.000000
Zambia           ZMB       0.0   0.0               0.000000
```

| | | | | |
|---|---|---|---|---|
| Niger | NER | 0.0 | 0.0 | 3.415301 |
| Estonia | EST | 0.0 | 0.0 | 0.000000 |
| Malta | MLT | 0.0 | 0.0 | 0.000000 |
| Slovenia | SVN | 0.0 | 0.0 | 0.000000 |
| Lebanon | LBN | 0.0 | 0.0 | 0.000000 |
| Mauritius | MUS | 0.0 | 0.0 | 0.000000 |
| Norway | NOR | 0.0 | 0.0 | 0.000000 |
| Uganda | UGA | 0.0 | 0.0 | 0.000000 |
| Poland | POL | 0.0 | 0.0 | 0.000000 |
| Switzerland | CHE | 0.0 | 0.0 | 0.000000 |
| Latvia | LVA | 0.0 | 0.0 | 0.000000 |

| | | grocery_and_pharmacy | parks | transit_stations \ |
|---|---|---|---|---|
| Country | Code | | | |
| Vietnam | VNM | 0.000000 | 0.000000 | 0.000000 |
| Gabon | GAB | 0.683060 | 10.245902 | 3.415301 |
| Cape Verde | CPV | 3.017833 | 3.017833 | 3.017833 |
| Papua New Guinea | PNG | 3.017833 | 3.017833 | 3.017833 |
| Mongolia | MNG | 3.415301 | 3.551913 | 0.000000 |
| Benin | BEN | 0.000000 | 3.415301 | 3.415301 |
| Luxembourg | LUX | 0.273224 | 3.415301 | 0.000000 |
| Angola | AGO | 0.000000 | 3.415301 | 3.415301 |
| Burkina Faso | BFA | 0.000000 | 3.415301 | 3.415301 |
| Rwanda | RWA | 2.459016 | 3.415301 | 0.000000 |
| Zimbabwe | ZWE | 0.000000 | 3.415301 | 0.409836 |
| Botswana | BWA | 3.415301 | 3.415301 | 3.415301 |
| Haiti | HTI | 0.273224 | 0.000000 | 3.142077 |
| Barbados | BRB | 0.546448 | 3.415301 | 3.415301 |
| Mali | MLI | 0.000000 | 3.415301 | 3.415301 |
| Namibia | NAM | 0.000000 | 3.415301 | 3.415301 |
| Yemen | YEM | 0.000000 | 3.415301 | 3.415301 |
| Togo | TGO | 0.000000 | 3.415301 | 3.415301 |
| Zambia | ZMB | 0.000000 | 3.415301 | 0.000000 |
| Niger | NER | 3.415301 | 3.415301 | 3.415301 |
| Estonia | EST | 0.000000 | 2.459016 | 0.000000 |
| Malta | MLT | 0.000000 | 2.185792 | 0.000000 |
| Slovenia | SVN | 0.000000 | 1.912568 | 0.000000 |
| Lebanon | LBN | 0.000000 | 0.000000 | 1.912568 |
| Mauritius | MUS | 0.000000 | 0.546448 | 0.000000 |
| Norway | NOR | 0.409836 | 0.000000 | 0.000000 |
| Uganda | UGA | 0.000000 | 0.000000 | 0.000000 |
| Poland | POL | 0.136612 | 0.000000 | 0.000000 |
| Switzerland | CHE | 0.136612 | 0.000000 | 0.000000 |
| Latvia | LVA | 0.000000 | 0.136612 | 0.000000 |

| | | workplaces | residential | Code |
|---|---|---|---|---|
| Country | Code | | | |
| Vietnam | VNM | 16.256831 | 0.000000 | 0.0 |

```
Gabon            GAB     0.000000     0.000000    0.0
Cape Verde       CPV     0.000000     4.115226    0.0
Papua New Guinea PNG     0.411523     3.978052    0.0
Mongolia         MNG     0.000000     0.000000    0.0
Benin            BEN     0.000000     0.000000    0.0
Luxembourg       LUX     0.409836     0.273224    0.0
Angola           AGO     0.000000     0.000000    0.0
Burkina Faso     BFA     0.000000     0.000000    0.0
Rwanda           RWA     0.000000     0.000000    0.0
Zimbabwe         ZWE     0.000000     0.000000    0.0
Botswana         BWA     0.409836     0.000000    0.0
Haiti            HTI     0.000000     0.000000    0.0
Barbados         BRB     0.000000     0.546448    0.0
Mali             MLI     0.000000     0.000000    0.0
Namibia          NAM     0.000000     0.000000    0.0
Yemen            YEM     0.000000     0.000000    0.0
Togo             TGO     0.000000     0.000000    0.0
Zambia           ZMB     0.000000     0.000000    0.0
Niger            NER     0.000000     0.000000    0.0
Estonia          EST     0.000000     0.000000    0.0
Malta            MLT     0.000000     0.000000    0.0
Slovenia         SVN     0.000000     0.000000    0.0
Lebanon          LBN     0.000000     0.000000    0.0
Mauritius        MUS     0.000000     0.000000    0.0
Norway           NOR     0.000000     0.000000    0.0
Uganda           UGA     0.000000     0.273224    0.0
Poland           POL     0.000000     0.000000    0.0
Switzerland      CHE     0.000000     0.000000    0.0
Latvia           LVA     0.000000     0.000000    0.0
```

Based on this, it seems Vietnam and Gabon have more than 10% missing in one of their mobility features so I would look more into it

[47]:
```
# Check Vietnam and Gabon
vietnam = filtered_mobility[filtered_mobility['Code'] == 'VNM'].compute()
gabon = filtered_mobility[filtered_mobility['Code'] == 'GAB'].compute()
```

[48]:
```
vietnam
```

[48]:
```
      Country        Date  retail_and_recreation  grocery_and_pharmacy  parks  \
1464  Vietnam  2020-02-15                   -6.0                  -4.0  -11.0
1465  Vietnam  2020-02-16                   -9.0                  -7.0   -9.0
1466  Vietnam  2020-02-17                   -9.0                  -7.0   -7.0
1467  Vietnam  2020-02-18                  -11.0                  -4.0   -8.0
1468  Vietnam  2020-02-19                   -9.0                  -9.0   -9.0
…       …         …                     …                   …     …
2191  Vietnam  2022-02-11                   -9.0                   5.0  -10.0
2192  Vietnam  2022-02-12                   -9.0                   8.0  -11.0
```

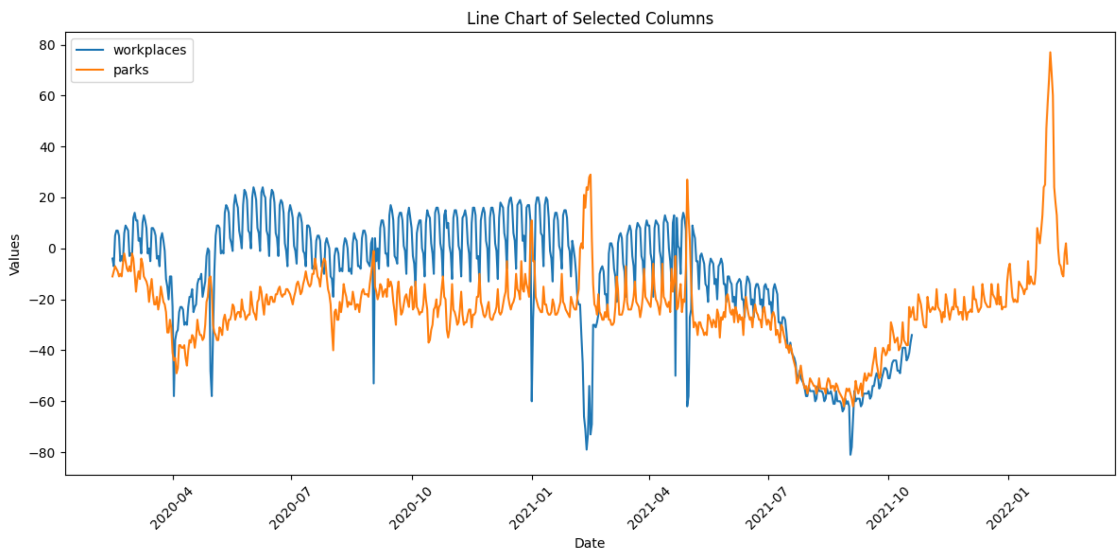
```
2193  Vietnam 2022-02-13                      -7.0                  10.0   -2.0
2194  Vietnam 2022-02-14                       1.0                  23.0    2.0
2195  Vietnam 2022-02-15                     -12.0                  16.0   -6.0

      transit_stations  workplaces  residential Code
1464              -9.0        -4.0          7.0  VNM
1465             -11.0        -7.0          7.0  VNM
1466             -11.0         5.0          6.0  VNM
1467              -9.0         7.0          6.0  VNM
1468             -12.0         7.0          4.0  VNM
…                  …         …           …   …
2191             -29.0         NaN          0.0  VNM
2192             -26.0         NaN          1.0  VNM
2193             -26.0         NaN          1.0  VNM
2194             -27.0         NaN         -4.0  VNM
2195             -27.0         NaN         -3.0  VNM

[732 rows x 9 columns]
```

[49]:
```
def plot_type(df, date_column, columns, type):
    """
    Plot selected columns from a DataFrame over time using line or stackplot.

    Parameters:
    - df: DataFrame with a 'date' column
    - date_column: a column for the date
    - columns: list of column names to plot
    - type: 'line' or 'stackplot'
    """
    plt.figure(figsize=(12, 6))

    if type == 'line':
        return [plt.plot(df[date_column], df[col], label=col) for col in␣
 ↪columns]

    elif type == 'stackplot':
        return plt.stackplot(df[date_column], *[df[col] for col in columns],␣
 ↪labels=columns)

def graph_columns(df, date_column, columns, type):
    """
    Generate a time series graph with title and styling.

    Parameters:
    - df: DataFrame
    - columns: list of columns to plot
    - type: 'line' or 'stackplot'
```

```
    """
    plot_type(df, date_column, columns, type)
    plt.title(f"{type.capitalize()} Chart of Selected Columns")
    plt.xlabel("Date")
    plt.ylabel("Values")
    plt.legend()
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

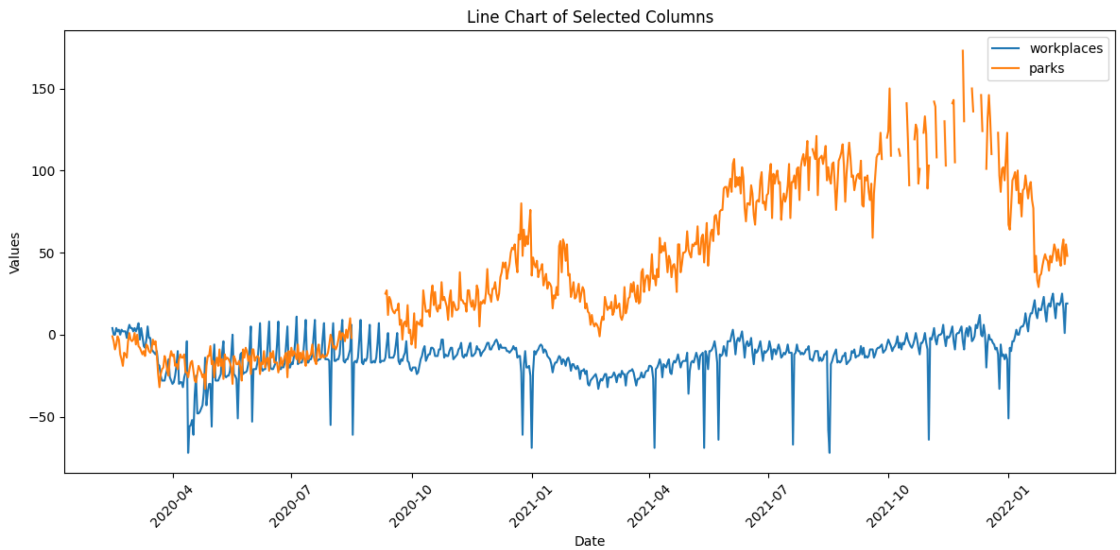
[50]:
```
print("Vietnam")
graph_columns(vietnam,'Date', ['workplaces', 'parks'], "line")
```

Vietnam




[51]:
```
print("Gabon")
graph_columns(gabon, 'Date', ['workplaces', 'parks'], "line")
```

Gabon




Based on the graphs, workplace data may not have been collected since around the last quarter of 2021 and parks are missing in some dates in Gabon. In addition, there seems to be a high degrea of day to day variabilty within the week as noticed by our reference study. With this I would use weekly median value to address the variability and might also address the missing values

### 3.1.1 Get the weekly median for the mobility values

[52]:
```
# 1. Extract year and week number from the 'date' column
# Using isocalendar() is the recommended way as it handles week boundaries␣
↪correctly
# This adds new columns 'year' and 'week'
filtered_mobility_with_week = filtered_mobility.assign(
    year=filtered_mobility['Date'].dt.isocalendar().year,
    week=filtered_mobility['Date'].dt.isocalendar().week
)

# Create the combined 'year_and_week' column (e.g., "2020-W01")
# Using string formatting for clarity and consistency
filtered_mobility_with_week = filtered_mobility_with_week.assign(
    year_and_week=(
        filtered_mobility_with_week['year'].astype(str) +
        "-W" +
        filtered_mobility_with_week['week'].astype(str).str.zfill(2) # Pad week␣
↪with leading zero
    )
)

# 2. Define the mobility columns to aggregate
mobility_cols = [
```

```python
    'retail_and_recreation',
    'grocery_and_pharmacy',
    'parks',
    'transit_stations',
    'workplaces',
    'residential'
]

# 3. Group by Country, Code, and year_and_week, then calculate the median for␣
 ↪mobility columns
# Select the relevant columns for grouping and aggregation
grouping_cols = ['Country', 'Code', 'year_and_week']
aggregation_dict = {col: 'median' for col in mobility_cols}

median_mobility_by_week = (
    filtered_mobility_with_week[grouping_cols + mobility_cols]
    .groupby(grouping_cols)
    .agg(aggregation_dict, split_out=1) # split_out can help with performance␣
 ↪on large groups
    # .median() # Alternative to .agg(), but .agg() is more explicit for␣
 ↪multiple columns
)

# 4. Reset index to make 'Country', 'Code', 'year_and_week' regular columns
median_mobility_by_week = median_mobility_by_week.reset_index()

# 5. Compute the result (triggers Dask execution)
# The result will be a pandas DataFrame
weekly_mobility = median_mobility_by_week.compute()

# Display the final result
print("Median mobility values by Country, Code, and Year-Week:")
print(weekly_mobility.head(20)) # Show first 20 rows as an example
```

```
Median mobility values by Country, Code, and Year-Week:
   Country Code year_and_week  retail_and_recreation  grocery_and_pharmacy  \
0    Japan  JPN      2020-W09                   -3.0                   7.0
1    Japan  JPN      2020-W10                  -10.0                   2.0
2    Japan  JPN      2020-W11                   -7.0                   3.0
3    Japan  JPN      2020-W12                   -3.0                   4.0
4    Japan  JPN      2020-W14                  -14.0                   6.0
5    Japan  JPN      2020-W18                  -35.0                  -5.0
6    Japan  JPN      2020-W19                  -34.0                  -5.0
7    Japan  JPN      2020-W20                  -32.0                  -1.0
8    Japan  JPN      2020-W21                  -27.0                  -1.0
9    Japan  JPN      2020-W23                  -18.0                   1.0
10   Japan  JPN      2020-W24                  -16.0                  -1.0
```

```
11   Japan   JPN     2020-W25              -11.0                     2.0
12   Japan   JPN     2020-W26              -11.0                     1.0
13   Japan   JPN     2020-W28              -12.0                    -1.0
14   Japan   JPN     2020-W31              -13.0                     1.0
15   Japan   JPN     2020-W35              -13.0                     0.0
16   Japan   JPN     2020-W36              -13.0                    -1.0
17   Japan   JPN     2020-W39              -12.0                     0.0
18   Japan   JPN     2020-W40               -9.0                     1.0
19   Japan   JPN     2020-W41              -11.0                    -2.0

    parks  transit_stations  workplaces  residential
0    -4.0             -10.0         1.0          2.0
1    -8.0             -18.0        -4.0          5.0
2    10.0             -17.0        -4.0          4.0
3    18.0             -15.0        -4.0          3.0
4     9.0             -25.0       -10.0          7.0
5     4.0             -50.0       -30.0         15.0
6     3.0             -56.0       -27.0         16.0
7     0.0             -44.0       -23.0         13.0
8    -8.0             -42.0       -21.0         12.0
9     2.0             -28.0       -13.0          8.0
10  -10.0             -27.0       -13.0          8.0
11    6.0             -23.0       -12.0          6.0
12   -7.0             -21.0       -12.0          6.0
13  -18.0             -22.0       -12.0          7.0
14   -3.0             -22.0       -12.0          6.0
15   -5.0             -24.0       -12.0          6.0
16  -10.0             -24.0       -12.0          6.0
17  -10.0             -20.0       -10.0          6.0
18    4.0             -17.0        -9.0          4.0
19   -4.0             -18.0        -9.0          4.0
```

[53]:
```python
len(weekly_mobility)
```

[53]: 11862

[54]:
```python
# Check missing data patterns
missing_counts = weekly_mobility.isnull().sum()
missing_percent = (missing_counts / len(weekly_mobility)) * 100

print("Missing data percentage:")
for col, pct in missing_percent.items():
    print(f"{col}: {pct:.2f}%")
```

```
Missing data percentage:
Country: 0.00%
Code: 0.00%
year_and_week: 0.00%
```

```
retail_and_recreation: 0.18%
grocery_and_pharmacy: 0.13%
parks: 0.46%
transit_stations: 0.34%
workplaces: 0.14%
residential: 0.00%
```

[55]:

```python
# Note: For pandas groupby.apply, we don't use the 'meta' argument.
missing_percent_per_group = (
    weekly_mobility
    .groupby(['Country', 'Code'])  # Group the pandas DataFrame by 'Country'␣
↪and 'Code'
    .apply(                 # Apply a function to each group
        lambda group: (group.isnull().sum() / len(group)) * 100
        # Do NOT include meta=... here for pandas
    )
    # No .compute() needed for pandas operations
)

# Filter the result to show only groups with at least one column having missing␣
↪data
# A group has missing data if the maximum missing percentage across its columns␣
↪is greater than 0
countries_with_missing = missing_percent_per_group[
    missing_percent_per_group.max(axis=1) > 0
]

sorted_by_max_missing = countries_with_missing.loc[countries_with_missing.
↪max(axis=1).sort_values(ascending=False).index]

# Display the results for groups with missing data
if not countries_with_missing.empty:
    print("Missing data percentage per Country-Code group (Groups with ANY␣
↪missing data):")
    print(sorted_by_max_missing)
else:
    print("No Country-Code groups found with missing data in any column.")
```

```
Missing data percentage per Country-Code group (Groups with ANY missing data):
                       Country  Code  year_and_week  retail_and_recreation  \
Country          Code
Vietnam          VNM       0.0   0.0            0.0               0.000000
Angola           AGO       0.0   0.0            0.0               0.000000
Benin            BEN       0.0   0.0            0.0               0.000000
Barbados         BRB       0.0   0.0            0.0               0.000000
Botswana         BWA       0.0   0.0            0.0               2.830189
Burkina Faso     BFA       0.0   0.0            0.0               0.000000
```

| | | | | | |
|---|---|---|---|---|---|
| Gabon | GAB | 0.0 | 0.0 | 0.0 | 2.830189 |
| Cape Verde | CPV | 0.0 | 0.0 | 0.0 | 2.830189 |
| Luxembourg | LUX | 0.0 | 0.0 | 0.0 | 0.000000 |
| Mali | MLI | 0.0 | 0.0 | 0.0 | 0.000000 |
| Mongolia | MNG | 0.0 | 0.0 | 0.0 | 0.000000 |
| Haiti | HTI | 0.0 | 0.0 | 0.0 | 2.830189 |
| Namibia | NAM | 0.0 | 0.0 | 0.0 | 0.000000 |
| Niger | NER | 0.0 | 0.0 | 0.0 | 2.830189 |
| Rwanda | RWA | 0.0 | 0.0 | 0.0 | 2.830189 |
| Papua New Guinea | PNG | 0.0 | 0.0 | 0.0 | 2.830189 |
| Togo | TGO | 0.0 | 0.0 | 0.0 | 0.000000 |
| Yemen | YEM | 0.0 | 0.0 | 0.0 | 0.000000 |
| Zambia | ZMB | 0.0 | 0.0 | 0.0 | 0.000000 |
| Zimbabwe | ZWE | 0.0 | 0.0 | 0.0 | 0.000000 |

| | | grocery_and_pharmacy | parks | transit_stations | \ |
|---|---|---|---|---|---|
| Country | Code | | | | |
| Vietnam | VNM | 0.000000 | 0.000000 | 0.000000 | |
| Angola | AGO | 0.000000 | 2.830189 | 2.830189 | |
| Benin | BEN | 0.000000 | 2.830189 | 2.830189 | |
| Barbados | BRB | 0.000000 | 2.830189 | 2.830189 | |
| Botswana | BWA | 2.830189 | 2.830189 | 2.830189 | |
| Burkina Faso | BFA | 0.000000 | 2.830189 | 2.830189 | |
| Gabon | GAB | 0.000000 | 2.830189 | 2.830189 | |
| Cape Verde | CPV | 2.830189 | 2.830189 | 2.830189 | |
| Luxembourg | LUX | 0.000000 | 2.830189 | 0.000000 | |
| Mali | MLI | 0.000000 | 2.830189 | 2.830189 | |
| Mongolia | MNG | 2.830189 | 2.830189 | 0.000000 | |
| Haiti | HTI | 0.000000 | 0.000000 | 0.943396 | |
| Namibia | NAM | 0.000000 | 2.830189 | 2.830189 | |
| Niger | NER | 2.830189 | 2.830189 | 2.830189 | |
| Rwanda | RWA | 0.000000 | 2.830189 | 0.000000 | |
| Papua New Guinea | PNG | 2.830189 | 2.830189 | 2.830189 | |
| Togo | TGO | 0.000000 | 2.830189 | 2.830189 | |
| Yemen | YEM | 0.000000 | 2.830189 | 2.830189 | |
| Zambia | ZMB | 0.000000 | 2.830189 | 0.000000 | |
| Zimbabwe | ZWE | 0.000000 | 2.830189 | 0.000000 | |

| | | workplaces | residential |
|---|---|---|---|
| Country | Code | | |
| Vietnam | VNM | 16.037736 | 0.0 |
| Angola | AGO | 0.000000 | 0.0 |
| Benin | BEN | 0.000000 | 0.0 |
| Barbados | BRB | 0.000000 | 0.0 |
| Botswana | BWA | 0.000000 | 0.0 |
| Burkina Faso | BFA | 0.000000 | 0.0 |
| Gabon | GAB | 0.000000 | 0.0 |
| Cape Verde | CPV | 0.000000 | 0.0 |

```
Luxembourg       LUX     0.000000          0.0
Mali             MLI     0.000000          0.0
Mongolia         MNG     0.000000          0.0
Haiti            HTI     0.000000          0.0
Namibia          NAM     0.000000          0.0
Niger            NER     0.000000          0.0
Rwanda           RWA     0.000000          0.0
Papua New Guinea PNG     0.000000          0.0
Togo             TGO     0.000000          0.0
Yemen            YEM     0.000000          0.0
Zambia           ZMB     0.000000          0.0
Zimbabwe         ZWE     0.000000          0.0
```

```
/tmp/ipykernel_959/2281753613.py:5: DeprecationWarning: DataFrameGroupBy.apply
operated on the grouping columns. This behavior is deprecated, and in a future
version of pandas the grouping columns will be excluded from the operation.
Either pass `include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  .apply(              # Apply a function to each group
```

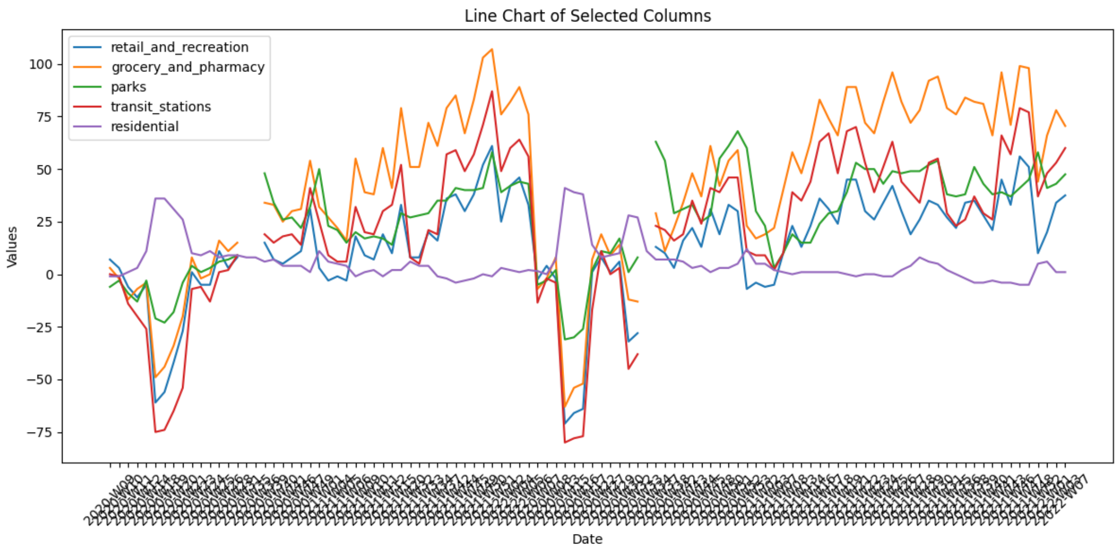
Vietnam still has attribute that has more that 16% missing so I will remove it for the analysis. There are still countries that have missing values in some of their parameters. I will check Botswana as it has 2.83% missing in three of its parameters

[56]:
```
to_keep = study_sample['Code'] != "VNM"
study_sample = study_sample[to_keep]
weekly_mobility = weekly_mobility[weekly_mobility['Code'].
 ↪isin(study_sample['Code'])]
print(weekly_mobility)
```

```
      Country Code year_and_week  retail_and_recreation  grocery_and_pharmacy  \
0       Japan  JPN      2020-W09                   -3.0                   7.0
1       Japan  JPN      2020-W10                  -10.0                   2.0
2       Japan  JPN      2020-W11                   -7.0                   3.0
3       Japan  JPN      2020-W12                   -3.0                   4.0
4       Japan  JPN      2020-W14                  -14.0                   6.0
…         …    …           …                     …                     …
11857  Jordan  JOR      2021-W48                   15.0                  50.0
11858  Jordan  JOR      2021-W52                   16.0                  47.0
11859  Jordan  JOR      2022-W01                   11.0                  46.0
11860  Jordan  JOR      2022-W03                    0.0                  33.0
11861  Jordan  JOR      2022-W07                   11.5                  41.5

       parks  transit_stations  workplaces  residential
0       -4.0             -10.0         1.0          2.0
1       -8.0             -18.0        -4.0          5.0
2       10.0             -17.0        -4.0          4.0
3       18.0             -15.0        -4.0          3.0
4        9.0             -25.0       -10.0          7.0
```

```
...      ...                ...          ...         ...
11857    8.0                4.0          3.0         3.0
11858    5.0              -10.0         -1.0         3.0
11859   10.0              -12.0          2.0         3.0
11860   -5.0              -30.0         -2.0         9.0
11861    5.5              -23.0         -1.5         6.0

[11756 rows x 9 columns]
```

[57]:
```
# Check Botswana
country_to_check = weekly_mobility[weekly_mobility['Code'] == 'BWA']
graph_columns(country_to_check, 'year_and_week', ['retail_and_recreation',
    'grocery_and_pharmacy', 'parks', 'transit_stations', 'residential'], "line")
```




Missing Data Handling: We identified short-term missing data periods (<3% of observations per country) in mobility variables, typically lasting 1-3 consecutive weeks. Given the low frequency and short duration of these gaps, we employed linear interpolation within each country to maintain data integrity while preserving sample size. This approach is appropriate because: (1) mobility patterns exhibit temporal smoothness, (2) the missing data percentage is minimal, and (3) interpolation preserves the temporal correlation structure of the data. We validated interpolated values to ensure they remained within reasonable bounds relative to surrounding observations.

### 3.1.2 Interpolate missing values

[58]:
```
def simple_mobility_interpolation(df):
    """Simple and robust interpolation for your mobility data"""

    # Define mobility variables
    mobility_variables = [
```

```
        'retail_and_recreation',
        'grocery_and_pharmacy',
        'parks',
        'transit_stations',
        'workplaces',
        'residential'
    ]

    # Create result dataframe
    result_df = df.copy()

    print("Starting interpolation...")
    print(f"Original missing values: {result_df[mobility_variables].isnull().
↪sum().sum()}")

    # Interpolate each variable using groupby transform (most reliable method)
    for var in mobility_variables:
        if var in result_df.columns:
            print(f"Interpolating {var}...")
            # This is the most robust approach for group-wise interpolation
            result_df[var] = result_df.groupby(['Country', 'Code'])[var].
↪transform(
                lambda x: x.interpolate(method='linear', limit_direction='both')
            )

    # Handle any remaining NAs (countries with all missing values for a␣
↪variable)
    for var in mobility_variables:
        if var in result_df.columns:
            result_df[var] = result_df[var].fillna(method='ffill').
↪fillna(method='bfill')

    final_missing = result_df[mobility_variables].isnull().sum().sum()
    print(f"Final missing values: {final_missing}")
    print("Interpolation complete!")

    return result_df

# Apply the simpler approach
interpolated_mobility_data = simple_mobility_interpolation(weekly_mobility)
```

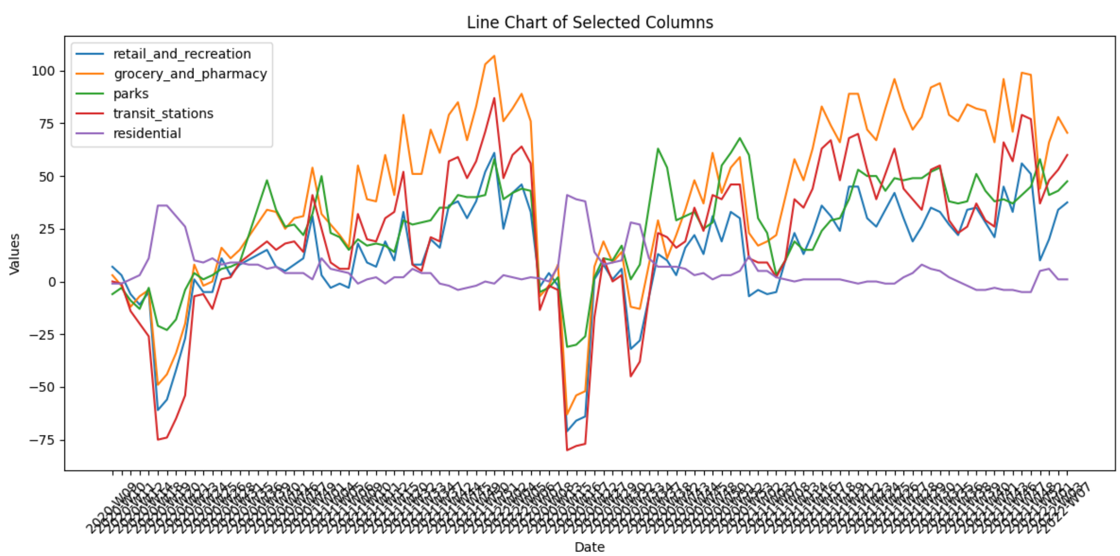
```
Starting interpolation…
Original missing values: 130
Interpolating retail_and_recreation…
Interpolating grocery_and_pharmacy…
Interpolating parks…
Interpolating transit_stations…
```

```
Interpolating workplaces…
Interpolating residential…
Final missing values: 0
Interpolation complete!
```

[59]:
```python
# Check missing data patterns
missing_counts = interpolated_mobility_data.isnull().sum()
missing_percent = (missing_counts / len(interpolated_mobility_data)) * 100

print("Missing data percentage:")
for col, pct in missing_percent.items():
    print(f"{col}: {pct:.2f}%")
```

```
Missing data percentage:
Country: 0.00%
Code: 0.00%
year_and_week: 0.00%
retail_and_recreation: 0.00%
grocery_and_pharmacy: 0.00%
parks: 0.00%
transit_stations: 0.00%
workplaces: 0.00%
residential: 0.00%
```

[60]:
```python
# Check Botswana
country_to_check = 
 ↪interpolated_mobility_data[interpolated_mobility_data['Code'] == 'BWA']
graph_columns(country_to_check, 'year_and_week', ['retail_and_recreation',
 ↪'grocery_and_pharmacy', 'parks', 'transit_stations', 'residential'], "line")
```



### 3.2 Checking for outliers

[61]:
```
# Check for extreme values in mobility variables
mobility_cols = [
    'retail_and_recreation',
    'grocery_and_pharmacy',
    'parks',
    'transit_stations',
    'workplaces',
    'residential'
]

# Compute quantiles for outlier detection
for col in mobility_cols:
    quantiles = interpolated_mobility_data[col].quantile([0.01, 0.25, 0.50, 0.
↪75, 0.99])
    print(f"{col} - 1st percentile: {quantiles[0.01]:.2f}, 1st quartile:
↪{quantiles[0.25]:0.2f}, median:{quantiles[0.50]:0.2f}, 3rd quartile:
↪{quantiles[0.75]:0.2f}, 99th percentile: {quantiles[0.99]:.2f}")

    # Winsorize extreme values or set reasonable bounds
    # Mobility changes rarely exceed ±100%
    #filtered_mobility[col] = filtered_mobility[col].clip(lower=-100, upper=100)
```

```
retail_and_recreation - 1st percentile: -78.00, 1st quartile:-26.00,
median:-10.00, 3rd quartile:3.00, 99th percentile: 70.00
grocery_and_pharmacy - 1st percentile: -54.45, 1st quartile:-5.00, median:5.00,
3rd quartile:22.00, 99th percentile: 120.00
parks - 1st percentile: -67.00, 1st quartile:-19.00, median:-1.00, 3rd
quartile:27.00, 99th percentile: 193.00
transit_stations - 1st percentile: -77.00, 1st quartile:-35.00, median:-17.00,
3rd quartile:1.00, 99th percentile: 67.00
workplaces - 1st percentile: -68.00, 1st quartile:-29.00, median:-18.00, 3rd
quartile:-6.00, 99th percentile: 36.45
residential - 1st percentile: -10.00, 1st quartile:1.00, median:6.00, 3rd
quartile:11.00, 99th percentile: 32.00
```

[62]:
```
outlier_threshold = 100

# 2. Initialize a dictionary to store results for each column
countries_with_outliers = {}

# 3. Check each mobility column for outliers and get max values
for column in mobility_cols:
    # Filter the DataFrame to rows where the value exceeds the threshold
    df_outliers_for_column = interpolated_mobility_data[
        interpolated_mobility_data[column] > outlier_threshold
```

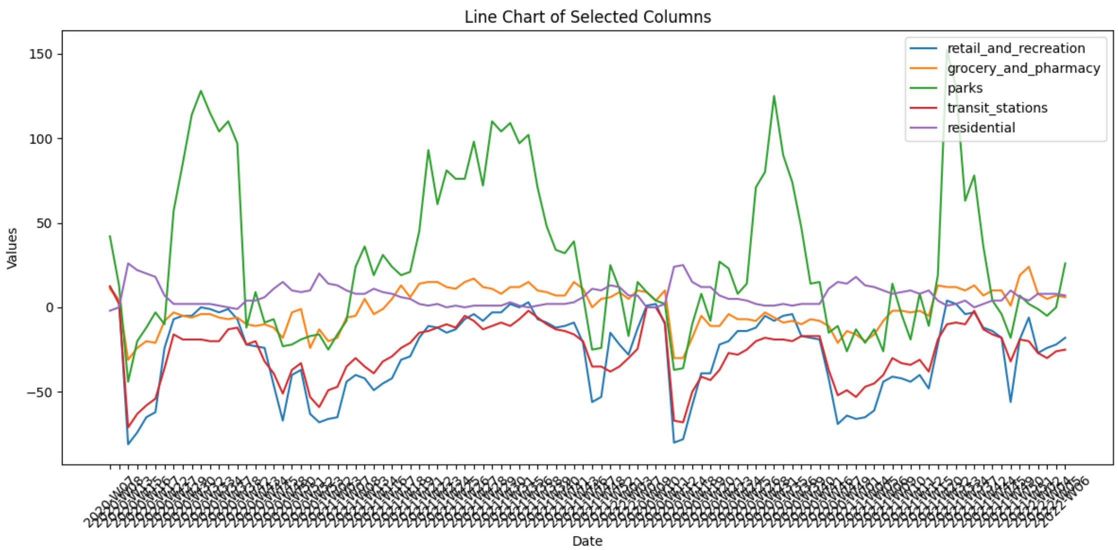
```
    ]

    # If there are outliers, find the max value and corresponding country code␣
 ↪for each country
    if not df_outliers_for_column.empty:
        # Group by 'Code' and find the maximum value for this column within␣
 ↪each group
        max_values_per_country = (
            df_outliers_for_column.groupby('Code')[column].max().reset_index()
        )
        # Convert to list of tuples (Country_Code, Max_Value)
        countries_with_outliers[column] = list(
            max_values_per_country.itertuples(index=False, name=None)
        )
    else:
        countries_with_outliers[column] = []

# 4. Display the results
print(f"Countries with outlier values (>{outlier_threshold}) in each mobility␣
 ↪parameter:")
print("-" * 80)
for column, country_data_list in countries_with_outliers.items():
    # Extract the base name of the column for cleaner display (optional)
    # display_name = column.replace('_percent_change_from_baseline', '')
    print(f"\n{column}:")

    if country_data_list:
        # Sort the list by Country Code for consistent output
        for country_code, max_value in sorted(country_data_list, key=lambda x:␣
 ↪x[0]):
            print(f"  - {country_code}: {max_value:.2f}")
    else:
        print("  - None found")
```

```
Countries with outlier values (>100) in each mobility parameter:
--------------------------------------------------------------------------------

retail_and_recreation:
  - IRQ: 103.00
  - MNG: 103.00
  - YEM: 106.00

grocery_and_pharmacy:
  - BEN: 129.00
  - BFA: 181.00
  - BWA: 107.00
  - CIV: 135.00
```

```
  - EGY: 118.00
  - IRQ: 172.00
  - MAR: 105.00
  - MNG: 194.00
  - NPL: 122.00
  - PNG: 120.00
  - YEM: 127.00
  - ZWE: 105.00

parks:
  - AGO: 102.50
  - AUT: 152.00
  - BEL: 142.00
  - BEN: 138.00
  - BFA: 143.00
  - BGR: 111.00
  - CAN: 183.00
  - CHE: 152.00
  - CZE: 134.00
  - DEU: 156.00
  - DNK: 389.00
  - ESP: 102.00
  - EST: 236.00
  - FIN: 368.00
  - FRA: 241.00
  - GAB: 151.50
  - GBR: 113.00
  - GRC: 308.00
  - HRV: 610.00
  - HUN: 170.00
  - IRL: 131.00
  - ITA: 209.00
  - LTU: 226.00
  - LUX: 161.00
  - LVA: 195.00
  - MLI: 150.50
  - MNG: 101.00
  - NLD: 251.00
  - NOR: 250.00
  - POL: 212.00
  - PRT: 160.00
  - SVK: 186.00
  - SVN: 221.00
  - SWE: 367.00
  - TGO: 135.00
  - TUR: 116.00
  - YEM: 136.00
```

```
transit_stations:
  - MNG: 131.50
  - ZWE: 101.00

workplaces:
  - None found

residential:
  - None found
```

[63]:
```python
# Check Botswana
country_to_check = interpolated_mobility_data[interpolated_mobility_data['Code'] == 'AUT']
graph_columns(country_to_check, 'year_and_week', ['retail_and_recreation', 'grocery_and_pharmacy', 'parks', 'transit_stations', 'residential'], "line")
```




Great question! Looking at your distributions, I can see some notable outliers, especially in grocery_and_pharmacy (120%) and parks (193%). Let me help you manage these outliers and understand their impact on your composite mobility variable.

Identifying Problematic Outliers Extreme Values Analysis: Parks: 99th percentile = 193% (very extreme!) Grocery & Pharmacy: 99th percentile = 120% (quite high) Others: Within reasonable ranges (-78% to 67%) Recommended Approach: Winsorization Winsorization is the best approach because it:

Caps extreme values rather than removing them Preserves sample size Maintains data distribution shape Reduces influence on composite index

[64]:
```python
def manage_mobility_outliers(df):
    """Manage outliers in mobility data using winsorization"""
```

```
    # Define reasonable caps based on your distributions
    outlier_caps = {
        'retail_and_recreation': (-80, 75),     # Slightly beyond 1st/99th␣
↪percentiles
        'grocery_and_pharmacy': (-60, 100),      # Cap the 120% extreme values
        'parks': (-70, 150),                    # Significantly cap the 193%␣
↪values
        'transit_stations': (-80, 70),
        'workplaces': (-70, 40),
        'residential': (-15, 35)
    }

    df_cleaned = df.copy()

    print("Managing outliers...")
    print("Variable                    Before Cap Range    After Cap Range    ␣
↪Observations Capped")
    print("-" * 75)

    for var, (lower_cap, upper_cap) in outlier_caps.items():
        if var in df_cleaned.columns:
            # Count observations that will be capped
            below_count = (df_cleaned[var] < lower_cap).sum()
            above_count = (df_cleaned[var] > upper_cap).sum()
            total_capped = below_count + above_count

            # Apply winsorization
            df_cleaned[var] = df_cleaned[var].clip(lower=lower_cap,␣
↪upper=upper_cap)

            # Show impact
            if total_capped > 0:
                print(f"{var:<30} [{df[var].min():4.0f}, {df[var].max():4.0f}] ␣
↪ [{lower_cap:4.0f}, {upper_cap:4.0f}]    {total_capped:>6}")

    return df_cleaned
```

[67]:
```
def manage_mobility_outliers_percentile(df):
    """Manage outliers in mobility data using percentile winsorization"""

    # Define reasonable caps based on your distributions
    variables = [
        'parks',
        'grocery_and_pharmacy'
    ]
```

```
    df_cleaned = df.copy()

    print("Managing outliers...")
    print("Variable                    Before Cap Range   After Cap Range   ␣
↪Observations Capped")
    print("-" * 75)

    for var in variables:
        lower_cap = df_cleaned[var].quantile(0.005)
        upper_cap = df_cleaned[var].quantile(0.995)
        # Count observations that will be capped
        below_count = (df_cleaned[var] < lower_cap).sum()
        above_count = (df_cleaned[var] > upper_cap).sum()
        total_capped = below_count + above_count

        # Apply winsorization
        df_cleaned[var] = df_cleaned[var].clip(lower=lower_cap, upper=upper_cap)

        # Show impact
        if total_capped > 0:
            print(f"{var:<30} [{df[var].min():4.0f}, {df[var].max():4.0f}]   ␣
↪[{lower_cap:4.0f}, {upper_cap:4.0f}]    {total_capped:>6}")

    return df_cleaned
```

[68]:
```
# Apply outlier management
mobility_data_cleaned =␣
↪manage_mobility_outliers_percentile(interpolated_mobility_data)
```

```
Managing outliers…
Variable                    Before Cap Range   After Cap Range    Observations
Capped
---------------------------------------------------------------------------
parks                          [ -93,   610]    [ -75,   241]       110
grocery_and_pharmacy           [ -87,   194]    [ -60,   139]       118
```

[73]:
```
len(mobility_data_cleaned)
```

[73]: 11756

[70]:
```
# Quick before/after comparison of key statistics
print("=== KEY IMPROVEMENTS ===")
print("Variable: Max Reduction | Std Dev Reduction")
print("-" * 45)

for var in mobility_cols:
    orig_max = interpolated_mobility_data[var].max()
```

```
    clean_max = mobility_data_cleaned[var].max()
    orig_std = interpolated_mobility_data[var].std()
    clean_std = mobility_data_cleaned[var].std()

    max_reduction = orig_max - clean_max
    std_reduction = orig_std - clean_std

    print(f"{var}: {max_reduction:>6.1f} | {std_reduction:>6.2f}")
```

```
=== KEY IMPROVEMENTS ===
Variable: Max Reduction | Std Dev Reduction
---------------------------------------------
retail_and_recreation:    0.0 |   0.00
grocery_and_pharmacy:   54.8 |   0.51
parks:  369.0 |   2.79
transit_stations:    0.0 |   0.00
workplaces:    0.0 |   0.00
residential:    0.0 |   0.00
```

[71]:
```
def compare_composite_before_after(df_before, df_after):
    """Compare composite mobility index before and after outlier management"""

    # Create composite indices
    weights = {
        'retail_and_recreation': 0.25,
        'grocery_and_pharmacy': 0.15,
        'parks': 0.10,
        'transit_stations': 0.20,
        'workplaces': 0.30
    }

    def create_composite(df_chunk):
        weighted_sum = sum(df_chunk[col] * weight for col, weight in weights.
 ↪items())
        return weighted_sum / sum(weights.values())

    composite_before = df_before.apply(create_composite, axis=1)
    composite_after = df_after.apply(create_composite, axis=1)

    # Compare distributions
    print("=== COMPOSITE MOBILITY INDEX COMPARISON ===")
    print("Metric           Before    After    Change")
    print("-" * 45)

    metrics = ['min', '25%', '50%', '75%', 'max', 'mean', 'std']

    for metric in metrics:
```

```python
        if metric == 'min':
            before_val = composite_before.min()
            after_val = composite_after.min()
        elif metric == 'max':
            before_val = composite_before.max()
            after_val = composite_after.max()
        elif metric == 'mean':
            before_val = composite_before.mean()
            after_val = composite_after.mean()
        elif metric == 'std':
            before_val = composite_before.std()
            after_val = composite_after.std()
        else:
            pct = float(metric.replace('%', '')) / 100
            before_val = composite_before.quantile(pct)
            after_val = composite_after.quantile(pct)

        change = after_val - before_val
        print(f"{metric:<12} {before_val:>8.2f} {after_val:>8.2f} {change:>8.
↪2f}")

    # Check extreme values
    extreme_before = (composite_before > 50) | (composite_before < -50)
    extreme_after = (composite_after > 50) | (composite_after < -50)

    print(f"\nExtreme composite values (>50 or <-50):")
    print(f"  Before: {extreme_before.sum()} observations")
    print(f"  After:  {extreme_after.sum()} observations")

# Run comparison
compare_composite_before_after(interpolated_mobility_data,␣
↪mobility_data_cleaned)
```

```
=== COMPOSITE MOBILITY INDEX COMPARISON ===
Metric            Before     After    Change
---------------------------------------------
min               -88.40    -83.38      5.02
25%               -22.00    -22.00      0.00
50%                -8.72     -8.72      0.00
75%                 3.70      3.70     -0.00
max               111.40    106.33     -5.07
mean               -8.42     -8.46     -0.05
std                23.78     23.63     -0.16

Extreme composite values (>50 or <-50):
  Before: 742 observations
  After:  731 observations
```

### 3.3 Compute Z-scores

[76]:
```
def get_zscore(df, cols):
    df = df.copy()
    for col in cols:
        mean = df[col].mean(skipna = True)
        sd = df[col].std(ddof = 0, skipna = True)
        # avoid division by zero
        sd = sd if sd > 0 else 1.0
        df[f'z_{col}'] = (df[col] - mean) / sd
        print(col)
        print(f'Mean: {mean}, Standard Deviation: {sd}')
    return df
```

[77]:
```
mobility_zscore = get_zscore(mobility_data_cleaned, mobility_cols)
mobility_zscore
```

```
retail_and_recreation
Mean: -10.790362368152433, Standard Deviation: 27.44330232611825
grocery_and_pharmacy
Mean: 10.97813882272882, Standard Deviation: 30.4071861471157
parks
Mean: 10.013865260292617, Standard Deviation: 48.35625961089843
transit_stations
Mean: -15.560224566178972, Standard Deviation: 29.194034738195462
workplaces
Mean: -17.67220993535216, Standard Deviation: 19.55509228163001
residential
Mean: 6.754295678802314, Standard Deviation: 8.280906480318396
```

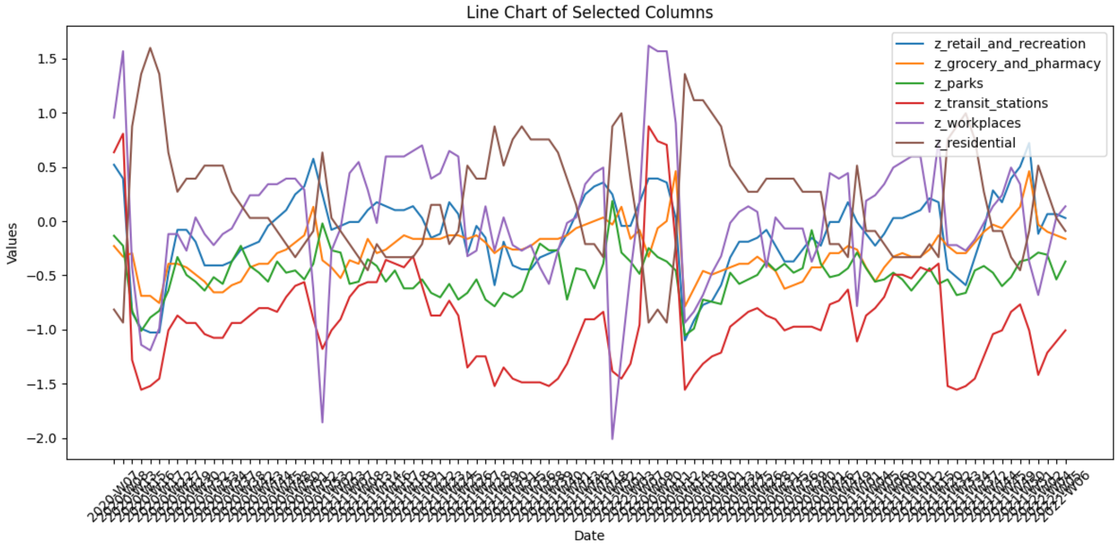
[77]:

| | Country | Code | year_and_week | retail_and_recreation | grocery_and_pharmacy | \ |
|---|---|---|---|---|---|---|
| 0 | Japan | JPN | 2020-W09 | -3.0 | 7.0 | |
| 1 | Japan | JPN | 2020-W10 | -10.0 | 2.0 | |
| 2 | Japan | JPN | 2020-W11 | -7.0 | 3.0 | |
| 3 | Japan | JPN | 2020-W12 | -3.0 | 4.0 | |
| 4 | Japan | JPN | 2020-W14 | -14.0 | 6.0 | |
| … | … | … | … | … | … | |
| 11857 | Jordan | JOR | 2021-W48 | 15.0 | 50.0 | |
| 11858 | Jordan | JOR | 2021-W52 | 16.0 | 47.0 | |
| 11859 | Jordan | JOR | 2022-W01 | 11.0 | 46.0 | |
| 11860 | Jordan | JOR | 2022-W03 | 0.0 | 33.0 | |
| 11861 | Jordan | JOR | 2022-W07 | 11.5 | 41.5 | |

| | parks | transit_stations | workplaces | residential | \ |
|---|---|---|---|---|---|
| 0 | -4.0 | -10.0 | 1.0 | 2.0 | |
| 1 | -8.0 | -18.0 | -4.0 | 5.0 | |
| 2 | 10.0 | -17.0 | -4.0 | 4.0 | |
| 3 | 18.0 | -15.0 | -4.0 | 3.0 | |

```
4        9.0              -25.0      -10.0          7.0
…       …                …        …          …
11857    8.0                4.0        3.0          3.0
11858    5.0              -10.0       -1.0          3.0
11859   10.0              -12.0        2.0          3.0
11860   -5.0              -30.0       -2.0          9.0
11861    5.5              -23.0       -1.5          6.0

       z_retail_and_recreation  z_grocery_and_pharmacy   z_parks  \
0                     0.283871               -0.130829 -0.289805
1                     0.028800               -0.295264 -0.372524
2                     0.138116               -0.262377 -0.000287
3                     0.283871               -0.229490  0.165152
4                    -0.116955               -0.163716 -0.020967
…                          …                      …        …
11857                 0.939769                1.283310 -0.041646
11858                 0.976208                1.184650 -0.103686
11859                 0.794014                1.151763 -0.000287
11860                 0.393187                0.724232 -0.310484
11861                 0.812233                1.003771 -0.093346

       z_transit_stations  z_workplaces  z_residential
0                0.190458      0.954852      -0.574127
1               -0.083571      0.699164      -0.211848
2               -0.049317      0.699164      -0.332608
3                0.019190      0.699164      -0.453368
4               -0.323346      0.392338       0.029671
…                     …            …            …
11857            0.670008      1.057127      -0.453368
11858            0.190458      0.852576      -0.453368
11859            0.121950      1.005989      -0.453368
11860           -0.494614      0.801439       0.271191
11861           -0.254839      0.827008      -0.091089

[11756 rows x 15 columns]
```

[79]:
```python
# Check Botswana
country_to_check = mobility_zscore[mobility_zscore['Code'] == 'AUS']
graph_columns(country_to_check, 'year_and_week', [
    'z_retail_and_recreation',
    'z_grocery_and_pharmacy',
    'z_parks',
    'z_transit_stations',
    'z_workplaces',
    'z_residential'], "line")
```




[ ]:

### 3.4 Create a composite mobility index

[80]:

```
import pandas as pd
import numpy as np
from numpy.linalg import eigh

MOB_Z_COLS = [
    "z_workplaces",
    "z_retail_and_recreation",
    "z_transit_stations",
    "z_grocery_and_pharmacy",
    "z_parks",
]

WEIGHTS = {  # your chosen weights
    "z_workplaces": 0.30,
    "z_retail_and_recreation": 0.25,
    "z_transit_stations": 0.20,
    "z_grocery_and_pharmacy": 0.15,
    "z_parks": 0.10,
}

def build_equal_weight_index(df: pd.DataFrame, cols=MOB_Z_COLS,␣
 ↪name="mob_index_eq"):
    out = df.copy()
    out[name] = out[cols].mean(axis=1)
```

```
    return out

def build_weighted_index(df: pd.DataFrame, weights=WEIGHTS, name="mob_index_w"):
    out = df.copy()
    # ensure only expected cols are used
    wcols = [c for c in weights.keys() if c in out.columns]
    wvec = np.array([weights[c] for c in wcols], dtype=float)
    wvec = wvec / wvec.sum()  # normalize in case they don't sum exactly to 1
    out[name] = out[wcols].to_numpy().dot(wvec)
    return out

def build_pc1_index(df: pd.DataFrame, cols=MOB_Z_COLS, name="mob_index_pc1"):
    """
    PCA via correlation matrix on the standardized inputs (z-scores).
    Returns PC1 score scaled to mean 0, sd 1. Sign is set so that
    it positively correlates with workplaces (i.e., "more out-of-home" =␣
↪higher).
    """
    out = df.copy()
    X = out[cols].to_numpy(dtype=float)
    # correlation matrix (since inputs are already z-scored, corr == cov)
    C = np.corrcoef(X, rowvar=False)
    # eigen-decomposition
    vals, vecs = eigh(C)            # ascending order
    pc1 = vecs[:, -1]               # last eigenvector (largest eigenvalue)
    # ensure sign matches workplaces direction
    if pc1[cols.index("z_workplaces")] < 0:
        pc1 = -pc1
    # PC1 scores
    scores = X.dot(pc1)
    # standardize PC1 scores to mean 0, sd 1 (optional but convenient)
    scores = (scores - np.nanmean(scores)) / (np.nanstd(scores) if np.
↪nanstd(scores) > 0 else 1.0)
    out[name] = scores
    return out, pc1, vals[-1] / vals.sum()  # also return loadings & variance␣
↪explained

def cronbach_alpha(df: pd.DataFrame, cols=MOB_Z_COLS):
    """
    Cronbach's alpha for internal consistency.
    Inputs should be standardized but it works regardless.
    """
    X = df[cols].to_numpy(dtype=float)
    k = X.shape[1]
    # item variances
    item_vars = np.nanvar(X, axis=0, ddof=1)
    total_var = np.nanvar(np.nansum(X, axis=1), ddof=1)
```

```
    if total_var <= 0:
        return np.nan
    alpha = (k / (k - 1.0)) * (1.0 - item_vars.sum() / total_var)
    return alpha

def build_all_indices(df: pd.DataFrame):
    out = df.copy()
    out = build_equal_weight_index(out, MOB_Z_COLS, "mob_index_eq")
    out = build_weighted_index(out, WEIGHTS, "mob_index_w")
    out, pc1_loadings, pc1_var = build_pc1_index(out, MOB_Z_COLS,␣
↪"mob_index_pc1")

    # Diagnostics
    alpha = cronbach_alpha(out, MOB_Z_COLS)
    corr = out[["mob_index_eq","mob_index_w","mob_index_pc1"]].corr()

    diags = {
        "cronbach_alpha": alpha,
        "pc1_loadings": dict(zip(MOB_Z_COLS, pc1_loadings)),
        "pc1_variance_explained": float(pc1_var),  # fraction (0-1)
        "index_correlations": corr,
    }
    # Optional sanity check vs residential (expect strong negative)
    if "residential" in out.columns:
        diags["corr_residential"] =␣
↪out[["mob_index_eq","mob_index_w","mob_index_pc1","residential"]].corr().
↪loc["residential"]

    return out, diags
```

[81]:
```
# df_weekly_z is your weekly DataFrame after winsorization + z-scoring
df_with_idx, diagnostics = build_all_indices(mobility_zscore)

# Peek diagnostics
alpha = diagnostics["cronbach_alpha"]
pc1_var = diagnostics["pc1_variance_explained"]          # e.g., 0.62 means 62%␣
↪variance
pc1_loads = diagnostics["pc1_loadings"]                  # each category's␣
↪loading
idx_corrs = diagnostics["index_correlations"]            # expect >0.95 among␣
↪indices
corr_res = diagnostics.get("corr_residential", None)     # optional

print("Cronbach alpha:", round(alpha, 3))
print("PC1 variance explained:", round(pc1_var*100, 1), "%")
print("PC1 loadings:", pc1_loads)
print(idx_corrs)
```

```
if corr_res is not None:
    print("\nCorrelations with residential (expect strong negative):\n",␣
 ↪corr_res)
```

```
Cronbach alpha: 0.891
PC1 variance explained: 71.4 %
PC1 loadings: {'z_workplaces': np.float64(0.4432371572721665),
'z_retail_and_recreation': np.float64(0.5048259748835973), 'z_transit_stations':
np.float64(0.48898075579385314), 'z_grocery_and_pharmacy':
np.float64(0.4764416969695046), 'z_parks': np.float64(0.2873894349975399)}
               mob_index_eq  mob_index_w  mob_index_pc1
mob_index_eq       1.000000     0.988901       0.997162
mob_index_w        0.988901     1.000000       0.995657
mob_index_pc1      0.997162     0.995657       1.000000

Correlations with residential (expect strong negative):
 mob_index_eq    -0.738544
mob_index_w     -0.737761
mob_index_pc1   -0.736568
residential      1.000000
Name: residential, dtype: float64
```

[82]:
```
df_with_idx
```

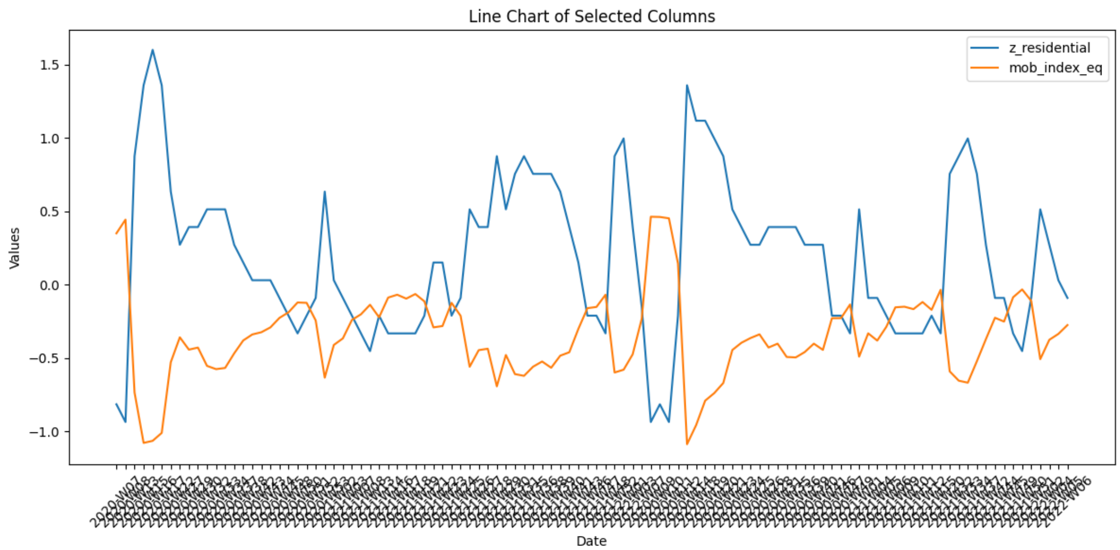
[82]:
```
      Country Code year_and_week  retail_and_recreation  grocery_and_pharmacy  \
0       Japan  JPN      2020-W09                   -3.0                   7.0
1       Japan  JPN      2020-W10                  -10.0                   2.0
2       Japan  JPN      2020-W11                   -7.0                   3.0
3       Japan  JPN      2020-W12                   -3.0                   4.0
4       Japan  JPN      2020-W14                  -14.0                   6.0
…         …   …           …                     …                   …
11857  Jordan  JOR      2021-W48                   15.0                  50.0
11858  Jordan  JOR      2021-W52                   16.0                  47.0
11859  Jordan  JOR      2022-W01                   11.0                  46.0
11860  Jordan  JOR      2022-W03                    0.0                  33.0
11861  Jordan  JOR      2022-W07                   11.5                  41.5

       parks  transit_stations  workplaces  residential  \
0       -4.0             -10.0         1.0          2.0
1       -8.0             -18.0        -4.0          5.0
2       10.0             -17.0        -4.0          4.0
3       18.0             -15.0        -4.0          3.0
4        9.0             -25.0       -10.0          7.0
…      …               …         …           …
11857    8.0               4.0         3.0          3.0
11858    5.0             -10.0        -1.0          3.0
11859   10.0             -12.0         2.0          3.0
```

```
11860   -5.0                -30.0        -2.0          9.0
11861    5.5                -23.0        -1.5          6.0

       z_retail_and_recreation  z_grocery_and_pharmacy   z_parks  \
0                     0.283871               -0.130829 -0.289805
1                     0.028800               -0.295264 -0.372524
2                     0.138116               -0.262377 -0.000287
3                     0.283871               -0.229490  0.165152
4                    -0.116955               -0.163716 -0.020967
…                          …                       …        …
11857                 0.939769                1.283310 -0.041646
11858                 0.976208                1.184650 -0.103686
11859                 0.794014                1.151763 -0.000287
11860                 0.393187                0.724232 -0.310484
11861                 0.812233                1.003771 -0.093346

       z_transit_stations  z_workplaces  z_residential  mob_index_eq  \
0                0.190458      0.954852      -0.574127      0.201709
1               -0.083571      0.699164      -0.211848     -0.004679
2               -0.049317      0.699164      -0.332608      0.105060
3                0.019190      0.699164      -0.453368      0.187577
4               -0.323346      0.392338       0.029671     -0.046529
…                     …            …             …            …
11857            0.670008      1.057127      -0.453368      0.781713
11858            0.190458      0.852576      -0.453368      0.620041
11859            0.121950      1.005989      -0.453368      0.614686
11860           -0.494614      0.801439       0.271191      0.222752
11861           -0.254839      0.827008      -0.091089      0.458965

       mob_index_w  mob_index_pc1
0         0.346910       0.271998
1         0.118693       0.018961
2         0.195029       0.121921
3         0.266647       0.212029
4        -0.002861      -0.067348
…              …              …
11857     0.874414       0.989510
11858     0.705245       0.792886
11859     0.697426       0.769906
11860     0.317392       0.300383
11861     0.541424       0.583846

[11756 rows x 18 columns]
```

[84]:

```
# Check Botswana
country_to_check = df_with_idx[df_with_idx['Code'] == 'AUS']
graph_columns(country_to_check, 'year_and_week', [
```

```
    #'retail_and_recreation',
    #'grocery_and_pharmacy',
    #'parks',
    #'transit_stations',
    #'workplaces',
    'z_residential',
    'mob_index_eq'], "line")
```




[85]:
```
# save to csv
df_with_idx.to_csv('data/cleaned/Mobility.csv')
```

## 4 National policy

[169]:
```
# update the national policy dataframe with changes on the study sample
national_policy = national_policy[national_policy['Code'].
 ↪isin(study_sample['Code'])]
national_policy
```

[169]:
```
          Country Code        Date  ConfirmedCases  ConfirmedDeaths  \
2192       Angola  AGO  2020-01-01             0.0              0.0
2193       Angola  AGO  2020-01-02             0.0              0.0
2194       Angola  AGO  2020-01-03             0.0              0.0
2195       Angola  AGO  2020-01-04             0.0              0.0
2196       Angola  AGO  2020-01-05             0.0              0.0
…            …    …          …              …                …
202436   Zimbabwe  ZWE  2022-02-11        231214.0           5374.0
202437   Zimbabwe  ZWE  2022-02-12        231299.0           5374.0
```

```
202438  Zimbabwe  ZWE 2022-02-13       231381.0          5374.0
202439  Zimbabwe  ZWE 2022-02-14       231603.0          5374.0
202440  Zimbabwe  ZWE 2022-02-15       231603.0          5374.0

        PopulationVaccinated  StringencyIndex_Average  \
2192                    0.00                     0.00
2193                    0.00                     0.00
2194                    0.00                     0.00
2195                    0.00                     0.00
2196                    0.00                     0.00
…                        …                        …
202436                 20.48                    51.45
202437                 20.51                    51.45
202438                 20.52                    51.45
202439                 20.53                    51.45
202440                 20.54                    51.45

        ContainmentHealthIndex_Average  EconomicSupportIndex
2192                              0.00                   0.0
2193                              0.00                   0.0
2194                              0.00                   0.0
2195                              0.00                   0.0
2196                              0.00                   0.0
…                                  …                    …
202436                           61.05                   0.0
202437                           61.05                   0.0
202438                           61.05                   0.0
202439                           61.05                   0.0
202440                           61.05                   0.0

[86247 rows x 9 columns]
```

#### 4.0.1 Check for missing

[171]:
```python
# Check missing data patterns
missing_counts = national_policy.isnull().sum()
missing_percent = (missing_counts / len(national_policy)) * 100

print("Missing data percentage:")
for col, pct in missing_percent.items():
    print(f"{col}: {pct:.2f}%")
```

```
Missing data percentage:
Country: 0.00%
Code: 0.00%
Date: 0.00%
ConfirmedCases: 0.00%
```

```
ConfirmedDeaths: 0.00%
PopulationVaccinated: 0.00%
StringencyIndex_Average: 0.00%
ContainmentHealthIndex_Average: 0.00%
EconomicSupportIndex: 0.00%
```

### 4.0.2 Check for outliers

[173]:
```python
# Check for extreme values in mobility variables
policy_cols = [
    'ConfirmedCases',
    'ConfirmedDeaths',
    'PopulationVaccinated',
    'StringencyIndex_Average',
    'ContainmentHealthIndex_Average',
    'EconomicSupportIndex'
]

# Compute quantiles for outlier detection
for col in policy_cols:
    quantiles = national_policy[col].quantile([0.01, 0.25, 0.50, 0.75, 0.99])
    print(f"{col} - 1st percentile: {quantiles[0.01]:.2f}, 1st quartile:
    ↪{quantiles[0.25]:0.2f}, median:{quantiles[0.50]:0.2f}, 3rd quartile:
    ↪{quantiles[0.75]:0.2f}, 99th percentile: {quantiles[0.99]:.2f}")
```

```
ConfirmedCases - 1st percentile: 0.00, 1st quartile:5064.00, median:82130.00,
3rd quartile:511385.00, 99th percentile: 20900049.88
ConfirmedDeaths - 1st percentile: 0.00, 1st quartile:91.00, median:1329.00, 3rd
quartile:10512.00, 99th percentile: 426153.38
PopulationVaccinated - 1st percentile: 0.00, 1st quartile:0.00, median:0.00, 3rd
quartile:9.49, 99th percentile: 80.01
StringencyIndex_Average - 1st percentile: 0.00, 1st quartile:37.96,
median:52.78, 3rd quartile:69.91, 99th percentile: 96.30
ContainmentHealthIndex_Average - 1st percentile: 0.00, 1st quartile:44.05,
median:56.37, 3rd quartile:66.37, 99th percentile: 83.45
EconomicSupportIndex - 1st percentile: 0.00, 1st quartile:0.00, median:50.00,
3rd quartile:75.00, 99th percentile: 100.00
```

[175]:
```python
national_policy
```

[175]:
```
          Country Code        Date  ConfirmedCases  ConfirmedDeaths  \
2192       Angola  AGO  2020-01-01             0.0              0.0
2193       Angola  AGO  2020-01-02             0.0              0.0
2194       Angola  AGO  2020-01-03             0.0              0.0
2195       Angola  AGO  2020-01-04             0.0              0.0
2196       Angola  AGO  2020-01-05             0.0              0.0
…             …    …           …               …                …
202436   Zimbabwe  ZWE  2022-02-11        231214.0           5374.0
```

```
202437  Zimbabwe  ZWE 2022-02-12       231299.0          5374.0
202438  Zimbabwe  ZWE 2022-02-13       231381.0          5374.0
202439  Zimbabwe  ZWE 2022-02-14       231603.0          5374.0
202440  Zimbabwe  ZWE 2022-02-15       231603.0          5374.0

        PopulationVaccinated  StringencyIndex_Average  \
2192                    0.00                     0.00
2193                    0.00                     0.00
2194                    0.00                     0.00
2195                    0.00                     0.00
2196                    0.00                     0.00
…                        …                       …
202436                 20.48                    51.45
202437                 20.51                    51.45
202438                 20.52                    51.45
202439                 20.53                    51.45
202440                 20.54                    51.45

        ContainmentHealthIndex_Average  EconomicSupportIndex
2192                              0.00                   0.0
2193                              0.00                   0.0
2194                              0.00                   0.0
2195                              0.00                   0.0
2196                              0.00                   0.0
…                                  …                   …
202436                           61.05                   0.0
202437                           61.05                   0.0
202438                           61.05                   0.0
202439                           61.05                   0.0
202440                           61.05                   0.0

[86247 rows x 9 columns]
```

There seems no outliers, since Covid and Vaccination statistics are different from policy, I would seperate them

[177]:
```python
covid_stats = national_policy[['Country', 'Code', 'Date','ConfirmedCases',␣
↪'ConfirmedDeaths', 'PopulationVaccinated']]
policy_index = national_policy[['Country', 'Code', 'Date',␣
↪'StringencyIndex_Average', 'ContainmentHealthIndex_Average',␣
↪'EconomicSupportIndex']]
```

### 4.0.3 Create a pure health systems index

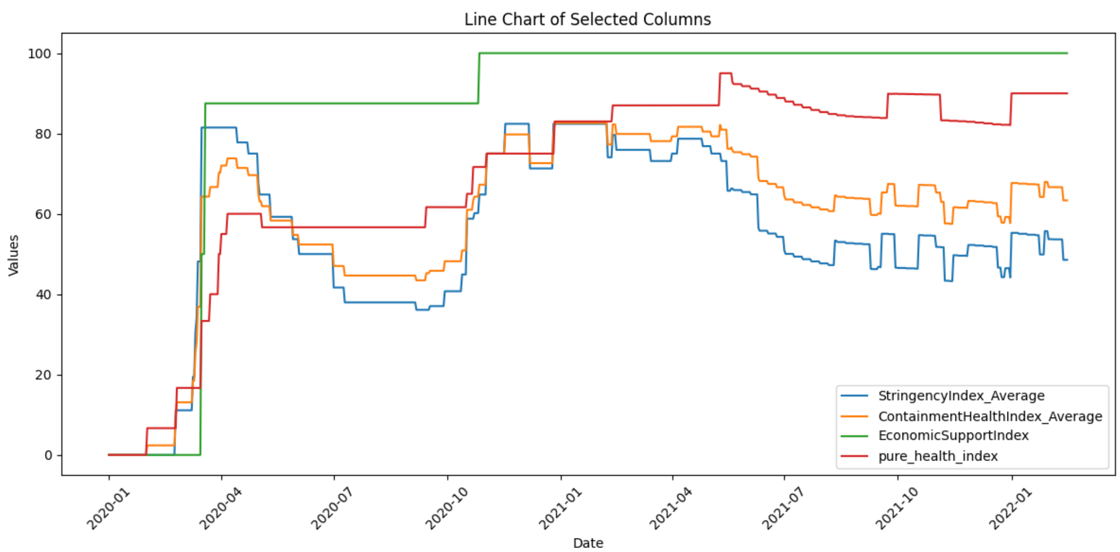
[180]:
```
def create_pure_health_index(df):
    """Create pure health index accounting for different indicator counts"""

    # Your mathematically correct formula
    df_result = df.copy()
    df_result['pure_health_index'] = (
        (df_result['ContainmentHealthIndex_Average'] * 14) -
        (df_result['StringencyIndex_Average'] * 9)
    ) / 5

    # Validate the results
    print("=== PURE HEALTH INDEX VALIDATION ===")
    print(f"Pure Health Index Range: {df_result['pure_health_index'].min():.2f}␣
↪to {df_result['pure_health_index'].max():.2f}")
    print(f"Pure Health Index Mean: {df_result['pure_health_index'].mean():.
↪2f}")
    print(f"Pure Health Index Std Dev: {df_result['pure_health_index'].std():.
↪2f}")

    # Check for negative values (should be minimal)
    negative_count = (df_result['pure_health_index'] < 0).sum()
    if negative_count > 0:
        print(f"Warning: {negative_count} negative values (likely rounding␣
↪errors)")
        # Clip negative values to 0
        df_result['pure_health_index'] = df_result['pure_health_index'].
↪clip(lower=0)

    # Verify the calculation makes sense
    countries_with_health_policies = (df_result['pure_health_index'] > 0).sum()
    print(f"Countries/periods with health policies:␣
↪{countries_with_health_policies}")

    return df_result

# Apply the formula
policy_data_with_pure_health = create_pure_health_index(policy_index)
```

```
=== PURE HEALTH INDEX VALIDATION ===
Pure Health Index Range: -0.02 to 97.49
Pure Health Index Mean: 53.92
Pure Health Index Std Dev: 22.95
Warning: 621 negative values (likely rounding errors)
Countries/periods with health policies: 81997
```

[181]:
```
# Since policies can not be negative and -0.02 most likely a rounding error, I␣
↪would clip it to 0
policy_data_with_pure_health['pure_health_index'] =␣
↪policy_data_with_pure_health['pure_health_index'].clip(lower=0)
```

### 4.0.4 Check for day to day variability

[183]:
```
# Check Botswana
country_to_check =␣
↪policy_data_with_pure_health[policy_data_with_pure_health['Code'] == 'AUT']
graph_columns(country_to_check, 'Date', [
    'StringencyIndex_Average',
    'ContainmentHealthIndex_Average',
    'EconomicSupportIndex',
    'pure_health_index'
    ], "line")
```




The indices appear relatively smooth over time, with no extreme outliers or heavy skewness. There are no visible outliers that would significantly distort the average.

### 4.0.5 Create a weekly policy indices

[185]:
```
# 1. Extract year and week number from the 'date' column
# Using isocalendar() is the recommended way as it handles week boundaries␣
↪correctly
# This adds new columns 'year' and 'week'
policy_with_week = policy_data_with_pure_health.assign(
    year=policy_data_with_pure_health['Date'].dt.isocalendar().year,
```

```
    week=policy_data_with_pure_health['Date'].dt.isocalendar().week
)

# Create the combined 'year_and_week' column (e.g., "2020-W01")
# Using string formatting for clarity and consistency
policy_with_week = policy_with_week.assign(
    year_and_week=(
        policy_with_week['year'].astype(str) +
        "-W" +
        policy_with_week['week'].astype(str).str.zfill(2) # Pad week with␣
↪leading zero
    )
)

# 2. Define the policy columns to aggregate
policy_cols = [
    'StringencyIndex_Average',
    'ContainmentHealthIndex_Average',
    'EconomicSupportIndex',
    'pure_health_index'
]

# 3. Group by Country, Code, and year_and_week, then calculate the mean for␣
↪policy columns
# Select the relevant columns for grouping and aggregation
grouping_cols = ['Country', 'Code', 'year_and_week']
aggregation_dict = {col: 'mean' for col in policy_cols}

mean_policy_by_week = (
    policy_with_week[grouping_cols + policy_cols]
    .groupby(grouping_cols)
    .agg(aggregation_dict, split_out=1) # split_out can help with performance␣
↪on large groups
    # .median() # Alternative to .agg(), but .agg() is more explicit for␣
↪multiple columns
)

# 4. Reset index to make 'Country', 'Code', 'year_and_week' regular columns
mean_policy_by_week = mean_policy_by_week.reset_index()

# Display the final result
print("Mean policy values by Country, Code, and Year-Week:")
print(mean_policy_by_week.head(20)) # Show first 20 rows as an example
```

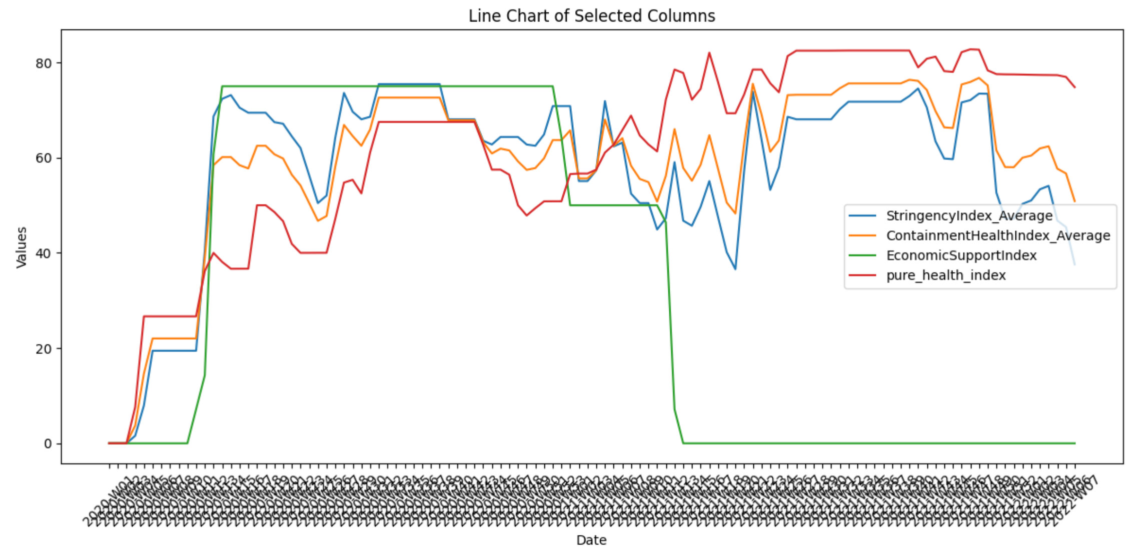
```
Mean policy values by Country, Code, and Year-Week:
   Country Code year_and_week  StringencyIndex_Average  \
0   Angola  AGO      2020-W01                 0.000000
```

```
1   Angola   AGO      2020-W02                0.000000
2   Angola   AGO      2020-W03                0.000000
3   Angola   AGO      2020-W04                0.000000
4   Angola   AGO      2020-W05                0.000000
5   Angola   AGO      2020-W06                3.177143
6   Angola   AGO      2020-W07                5.560000
7   Angola   AGO      2020-W08                5.560000
8   Angola   AGO      2020-W09                5.955714
9   Angola   AGO      2020-W10                8.330000
10  Angola   AGO      2020-W11                8.330000
11  Angola   AGO      2020-W12                9.521429
12  Angola   AGO      2020-W13               54.760000
13  Angola   AGO      2020-W14               90.740000
14  Angola   AGO      2020-W15               90.740000
15  Angola   AGO      2020-W16               90.740000
16  Angola   AGO      2020-W17               83.860000
17  Angola   AGO      2020-W18               78.700000
18  Angola   AGO      2020-W19               77.512857
19  Angola   AGO      2020-W20               76.722857

    ContainmentHealthIndex_Average  EconomicSupportIndex  pure_health_index
0                         0.000000              0.000000           0.000000
1                         0.000000              0.000000           0.000000
2                         0.000000              0.000000           0.000000
3                         0.000000              0.000000           0.000000
4                         0.000000              0.000000           0.000000
5                         2.040000              0.000000           0.000000
6                         3.570000              0.000000           0.000000
7                         3.570000              0.000000           0.000000
8                         5.525714              0.000000           4.755143
9                         7.740000              0.000000           6.678000
10                        7.740000              0.000000           6.678000
11                        8.502857              0.000000           6.669429
12                       37.582857              0.000000           6.664000
13                       62.417143              0.000000          11.436000
14                       66.157143             28.571429          21.908000
15                       68.450000             50.000000          28.328000
16                       64.027143             60.714286          28.328000
17                       60.710000             75.000000          28.328000
18                       59.947143             75.000000          28.328857
19                       59.440000             75.000000          28.330857
```

[201]:

```
# Check Botswana
country_to_check = mean_policy_by_week[mean_policy_by_week['Code'] == 'AUS']
graph_columns(country_to_check, 'year_and_week', [
    'StringencyIndex_Average',
    'ContainmentHealthIndex_Average',
```

```
    'EconomicSupportIndex',
    'pure_health_index'
    ], "line")
```




[192]:
```
len(mean_policy_by_week['Country'].unique())
```

[192]: 111

[199]:
```
mean_policy_by_week.groupby(['Country', 'Code']).count()
```

[199]:
```
                          year_and_week  StringencyIndex_Average  \
Country       Code
Angola        AGO                   112                      112
Argentina     ARG                   112                      112
Australia     AUS                   112                      112
Austria       AUT                   112                      112
Bangladesh    BGD                   112                      112
…                                  …                      …
United States USA                   112                      112
Uruguay       URY                   112                      112
Yemen         YEM                   112                      112
Zambia        ZMB                   112                      112
Zimbabwe      ZWE                   112                      112

                          ContainmentHealthIndex_Average  EconomicSupportIndex  \
Country       Code
Angola        AGO                                    112                   112
Argentina     ARG                                    112                   112
```

```
Australia     AUS                               112                     112
Austria       AUT                               112                     112
Bangladesh    BGD                               112                     112
…                                             …                     …
United States USA                               112                     112
Uruguay       URY                               112                     112
Yemen         YEM                               112                     112
Zambia        ZMB                               112                     112
Zimbabwe      ZWE                               112                     112

                    pure_health_index
Country       Code
Angola        AGO                 112
Argentina     ARG                 112
Australia     AUS                 112
Austria       AUT                 112
Bangladesh    BGD                 112
…                               …
United States USA                 112
Uruguay       URY                 112
Yemen         YEM                 112
Zambia        ZMB                 112
Zimbabwe      ZWE                 112

[111 rows x 5 columns]
```

[202]:
```python
# Save the policy data frame
mean_policy_by_week.to_csv('data/cleaned/National_policy.csv')
```

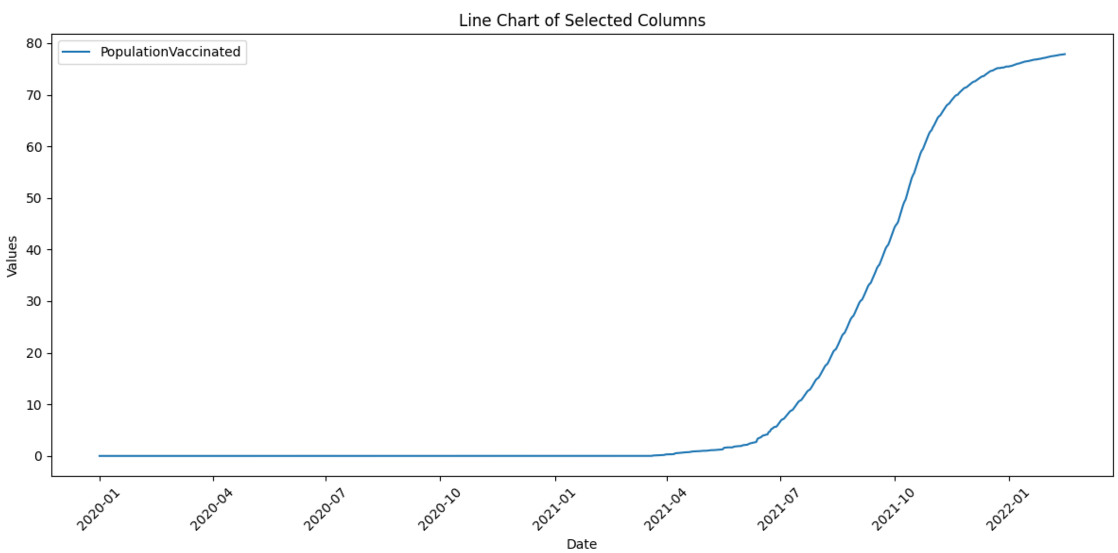
## 4.1 Covid stat

[203]:
```python
covid_stats
```

[203]:
```
         Country Code        Date  ConfirmedCases  ConfirmedDeaths  \
2192      Angola  AGO  2020-01-01             0.0              0.0
2193      Angola  AGO  2020-01-02             0.0              0.0
2194      Angola  AGO  2020-01-03             0.0              0.0
2195      Angola  AGO  2020-01-04             0.0              0.0
2196      Angola  AGO  2020-01-05             0.0              0.0
…            …   …          …             …               …
202436  Zimbabwe  ZWE  2022-02-11        231214.0           5374.0
202437  Zimbabwe  ZWE  2022-02-12        231299.0           5374.0
202438  Zimbabwe  ZWE  2022-02-13        231381.0           5374.0
202439  Zimbabwe  ZWE  2022-02-14        231603.0           5374.0
202440  Zimbabwe  ZWE  2022-02-15        231603.0           5374.0

        PopulationVaccinated
```

```
2192                    0.00
2193                    0.00
2194                    0.00
2195                    0.00
2196                    0.00
…                       …
202436                 20.48
202437                 20.51
202438                 20.52
202439                 20.53
202440                 20.54

[86247 rows x 6 columns]
```

[214]:
```
# Check Botswana
country_to_check = covid_stats[covid_stats['Code'] == 'AUS']
graph_columns(country_to_check, 'Date', [
    #'ConfirmedCases',
    #'ConfirmedDeaths',
    'PopulationVaccinated'
    ], "line")
```




[205]:
```
population = pd.read_csv('data/population.csv')
```

[206]:
```
population
```

[206]:
```
                    Country Name Country Code        2019
0                          Aruba          ABW    109203.0
```

```
1     Africa Eastern and Southern          AFE  675950189.0
2                     Afghanistan          AFG   37856121.0
3      Africa Western and Central          AFW  463365429.0
4                          Angola          AGO   32375632.0
..                            …          …            …
254                        Kosovo          XKX    1788891.0
255                   Yemen, Rep.          YEM   35111408.0
256                  South Africa          ZAF   59587885.0
257                        Zambia          ZMB   18513839.0
258                      Zimbabwe          ZWE   15271368.0

[259 rows x 3 columns]
```

[208]:

```
population = population.rename(columns = {
    'Country Name' : 'Country',
    'Country Code' : 'Code',
    '2019' : 'Population'
})

population = population[population['Code'].isin(study_sample['Code'])]

population = population.drop(columns = 'Country')

population
```

[208]:

```
    Code   Population
4    AGO   32375632.0
8    ARE    9445785.0
9    ARG   44973465.0
13   AUS   25334826.0
14   AUT    8879920.0
..   …            …
244  USA  330226227.0
255  YEM   35111408.0
256  ZAF   59587885.0
257  ZMB   18513839.0
258  ZWE   15271368.0

[111 rows x 2 columns]
```

[209]:

```
def create_weekly_covid_simple(covid_df, population_df):
    """Simplified approach using pandas resample"""

    # Prepare data
    covid_df['Date'] = pd.to_datetime(covid_df['Date'])

    # Merge with population
```

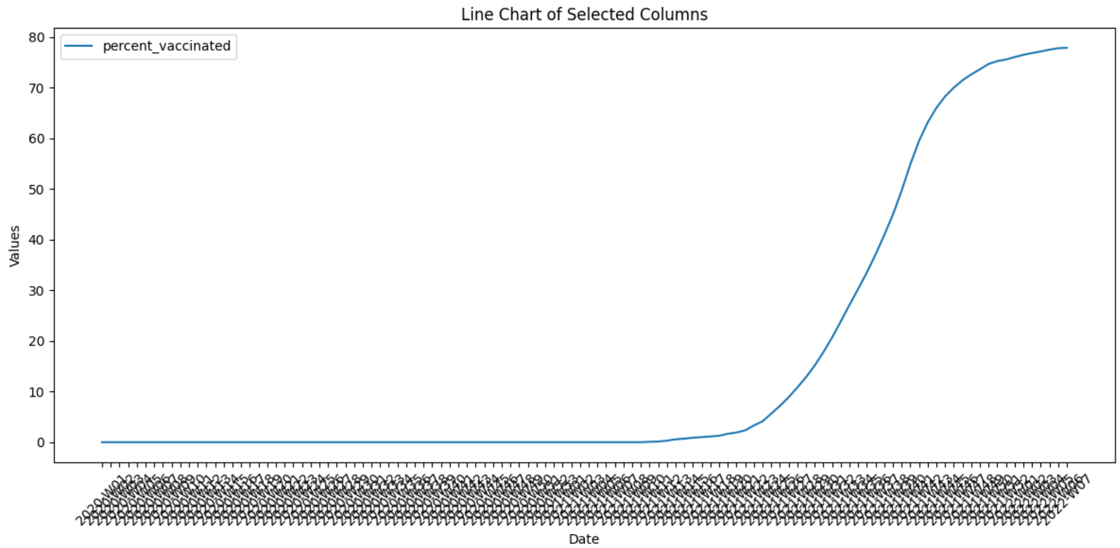
```python
    covid_merged = covid_df.merge(
        population_df[['Code', 'Population']],
        on='Code',
        how='left'
    )

    # Set date as index for resampling
    covid_indexed = covid_merged.set_index('Date')

    weekly_data_list = []

    # Process each country
    for country_code in covid_merged['Code'].unique():
        country_data = covid_indexed[covid_indexed['Code'] == country_code].copy()

        if len(country_data) > 0:
            # Resample to weekly (take last value of each week)
            weekly_country = country_data.resample('W').last()

            # Calculate differences for incidence
            weekly_country['case_incidence'] = weekly_country['ConfirmedCases'].diff()
            weekly_country['death_incidence'] = weekly_country['ConfirmedDeaths'].diff()

            # First week will be NaN, use the cumulative value
            weekly_country['case_incidence'].iloc[0] = weekly_country['ConfirmedCases'].iloc[0]
            weekly_country['death_incidence'].iloc[0] = weekly_country['ConfirmedDeaths'].iloc[0]

            # Calculate per 100k
            population = weekly_country['Population'].iloc[0]
            weekly_country['case_incidence_per_100k'] = (weekly_country['case_incidence'] / population) * 100000
            weekly_country['death_incidence_per_100k'] = (weekly_country['death_incidence'] / population) * 100000

            # Create year_and_week format
            weekly_country['year_and_week'] = (
                weekly_country.index.isocalendar().year.astype(str) +
                "-W" +
                weekly_country.index.isocalendar().week.astype(str).str.zfill(2)
            )
```

```
            # Clean and select columns
            weekly_country_clean = weekly_country.reset_index()[[
                'Country', 'Code', 'year_and_week',
                'case_incidence_per_100k', 'death_incidence_per_100k',
                'PopulationVaccinated'
            ]].rename(columns={'PopulationVaccinated': 'percent_vaccinated'})

            # Ensure non-negative values
            weekly_country_clean['case_incidence_per_100k'] =␣
↪weekly_country_clean['case_incidence_per_100k'].clip(lower=0)
            weekly_country_clean['death_incidence_per_100k'] =␣
↪weekly_country_clean['death_incidence_per_100k'].clip(lower=0)

            weekly_data_list.append(weekly_country_clean)

    return pd.concat(weekly_data_list, ignore_index=True)

covid19_final = create_weekly_covid_simple(covid_stats, population)
covid19_final
```

[209]:

```
        Country Code year_and_week  case_incidence_per_100k  \
0        Angola  AGO      2020-W01                 0.000000
1        Angola  AGO      2020-W02                 0.000000
2        Angola  AGO      2020-W03                 0.000000
3        Angola  AGO      2020-W04                 0.000000
4        Angola  AGO      2020-W05                 0.000000
…           …    …             …                       …
12427  Zimbabwe  ZWE      2022-W03                14.248887
12428  Zimbabwe  ZWE      2022-W04                 7.897131
12429  Zimbabwe  ZWE      2022-W05                 6.168406
12430  Zimbabwe  ZWE      2022-W06                 6.410690
12431  Zimbabwe  ZWE      2022-W07                 1.453701

       death_incidence_per_100k  percent_vaccinated
0                      0.000000                0.00
1                      0.000000                0.00
2                      0.000000                0.00
3                      0.000000                0.00
4                      0.000000                0.00
…                             …                 …
12427                  0.307765               20.04
12428                  0.281573               20.20
12429                  0.163705               20.37
12430                  0.078578               20.52
12431                  0.000000               20.54

[12432 rows x 6 columns]
```

[218]:
```
# Check Botswana
country_to_check = covid19_final[covid19_final['Code'] == 'AUS']
graph_columns(country_to_check, 'year_and_week', [
    #'case_incidence_per_100k',
    #'death_incidence_per_100k',
    'percent_vaccinated'
    ], "line")
```




[219]:
```
# Save Covid19_final
covid19_final.to_csv('data/cleaned/Covid_data.csv')
```

## 4.2 Country Stat

[223]:
```
country_stat = country_stat[country_stat['Code'].isin(study_sample['Code'])]
country_stat
```

[223]:
```
    Code                   Country  urban_population  \
2    AGO                    Angola            66.177
6    ARE      United Arab Emirates            86.789
7    ARG                 Argentina            91.991
13   AUS                 Australia            86.124
14   AUT                   Austria            58.515
..   …                         …               …
231  USA  United States of America            82.459
243  YEM                     Yemen            37.273
244  ZAF              South Africa            66.856
245  ZMB                    Zambia            44.072
246  ZWE                  Zimbabwe            32.210
```

```
     corruption_perception_index  gdp_per_capita  land_boundaries  coastline  \
2                           26.0       8274.5430          5369.00     1600.0
6                           71.0      68887.8400          1066.00     1318.0
7                           45.0      26629.5530         11968.00     4989.0
13                          77.0      56981.3950             0.00    25760.0
14                          77.0      65312.0230          2524.00        0.0
..                           …               …                …          …
231                         69.0      69511.7660         12002.00    19924.0
243                         15.0        623.4000          1601.00     1906.0
244                         44.0      14370.2380          5244.00     2798.0
245                         34.0       3591.5642          6043.15        0.0
246                         24.0       3294.8062          3229.00        0.0

     num_border_countries                                  border_countries  \
2                     4.0  Democratic Republic of the Congo 2,646 km (of …
6                     2.0                          Oman 609 km; Saudi Arabia 457 km
7                     5.0  Bolivia 942 km; Brazil 1,263 km; Chile 6,691 k…
13                    0.0                                                   NaN
14                    8.0  Czech Republic 402 km; Germany 801 km; Hungary…
..                    …                                                 …
231                   2.0  Canada 8,891 km (including 2,475 km with Alask…
243                   2.0                        Oman 294 km; Saudi Arabia 1,307 km
244                   6.0  Botswana 1,969 km; Lesotho 1,106 km; Mozambiqu…
245                   8.0  Angola 1,065 km; Botswana 0.15 km; Democratic …
246                   4.0  Botswana 834 km; Mozambique 1,402 km; South Af…

     hospital_beds_per_1000  unemployment       political_regime  gini_index  \
2                      0.75        16.497  electoral_autocracies    0.512640
6                      1.87         2.331     closed_autocracies    0.263990
7                      3.71         9.843  electoral_democracies    0.433141
13                     3.84         5.159    liberal_democracies    0.343326
14                     7.19         4.560    liberal_democracies    0.302104
..                      …             …                    …          …
231                    2.75         3.669    liberal_democracies    0.415335
243                    0.71        17.202     closed_autocracies    0.367071
244                    2.30        28.468  electoral_democracies    0.630258
245                    2.00         5.542  electoral_autocracies    0.514831
246                    2.00         7.373  electoral_autocracies    0.502564

     population_density    poverty  median_age  land_area_sqkm
2             25.969065  31.122005      16.302       1246700.0
6            132.045270   0.000000      30.834         71020.0
7             16.433529   1.684649      30.763       2736690.0
13             3.312877   0.497094      36.543       7692020.0
14           107.620880   0.640639      42.433         82520.0
..                  …          …           …               …
```

```
231            36.927360   0.999171      37.002      9147420.0
243            66.502680  19.802757      18.017       527970.0
244            49.120743  20.492558      26.873      1213090.0
245            24.904613  64.349754      16.763       743390.0
246            39.476223  39.754530      17.187       386850.0

[111 rows x 17 columns]
```

### 4.2.1 Check for missing

[224]:
```
# Check missing data patterns
missing_counts = country_stat.isnull().sum()
missing_percent = (missing_counts / len(country_stat)) * 100

print("Missing data percentage:")
for col, pct in missing_percent.items():
    print(f"{col}: {pct:.2f}%")
```

```
Missing data percentage:
Code: 0.00%
Country: 0.00%
urban_population: 0.00%
corruption_perception_index: 0.00%
gdp_per_capita: 0.00%
land_boundaries: 0.00%
coastline: 0.00%
num_border_countries: 0.00%
border_countries: 8.11%
hospital_beds_per_1000: 0.00%
unemployment: 0.00%
political_regime: 0.00%
gini_index: 0.00%
population_density: 0.00%
poverty: 0.00%
median_age: 0.00%
land_area_sqkm: 0.00%
```

border countries have more than 8% missing so I will drop it

[225]:
```
country_stat = country_stat.drop(columns = 'border_countries')
```

### 4.2.2 Check for outliers

[226]:
```
# Check for extreme values in numerical variables
num_cols = [
    'urban_population',
    'corruption_perception_index',
```

```python
    'gdp_per_capita',
    'land_boundaries',
    'coastline',
    'num_border_countries',
    'hospital_beds_per_1000',
    'unemployment',
    'gini_index',
    'population_density',
    'poverty',
    'median_age',
    'land_area_sqkm'
]

# Compute quantiles for outlier detection
for col in num_cols:
    quantiles = country_stat[col].quantile([0.01, 0.25, 0.50, 0.75, 0.99])
    print(f"{col} - 1st percentile: {quantiles[0.01]:.2f}, 1st quartile:
 ↪{quantiles[0.25]:0.2f}, median:{quantiles[0.50]:0.2f}, 3rd quartile:
 ↪{quantiles[0.75]:0.2f}, 99th percentile: {quantiles[0.99]:.2f}")
```

```
urban_population - 1st percentile: 16.60, 1st quartile:47.76, median:65.76, 3rd
quartile:80.50, 99th percentile: 97.78
corruption_perception_index - 1st percentile: 18.20, 1st quartile:31.00,
median:41.00, 3rd quartile:60.00, 99th percentile: 85.90
gdp_per_capita - 1st percentile: 1537.26, 1st quartile:7384.21, median:18106.02,
3rd quartile:41918.00, 99th percentile: 111515.05
land_boundaries - 1st percentile: 0.00, 1st quartile:1160.50, median:2420.00,
3rd quartile:4401.00, 99th percentile: 15919.30
coastline - 1st percentile: 0.00, 1st quartile:51.30, median:823.00, 3rd
quartile:2790.00, 99th percentile: 53009.70
num_border_countries - 1st percentile: 0.00, 1st quartile:2.00, median:4.00, 3rd
quartile:5.00, 99th percentile: 9.90
hospital_beds_per_1000 - 1st percentile: 0.21, 1st quartile:1.08, median:2.30,
3rd quartile:4.37, 99th percentile: 12.15
unemployment - 1st percentile: 0.42, 1st quartile:3.60, median:5.01, 3rd
quartile:8.63, 99th percentile: 20.33
gini_index - 1st percentile: 0.24, 1st quartile:0.32, median:0.35, 3rd
quartile:0.42, 99th percentile: 0.60
population_density - 1st percentile: 3.23, 1st quartile:37.46, median:88.66, 3rd
quartile:178.91, 99th percentile: 1205.61
poverty - 1st percentile: 0.00, 1st quartile:0.24, median:1.01, 3rd
quartile:6.63, 99th percentile: 65.02
median_age - 1st percentile: 15.09, 1st quartile:22.38, median:29.06, 3rd
quartile:39.77, 99th percentile: 45.89
land_area_sqkm - 1st percentile: 586.70, 1st quartile:65747.00,
median:230800.00, 3rd quartile:616035.00, 99th percentile: 9111548.00
```

[227]:

```
# Save the file
country_stat.to_csv('data/cleaned/Country_stat.csv')
```