

project_covid

May 15, 2025

```
[1]: # Core libraries
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px # for interactive maps/charts (optional)

# Display settings
%matplotlib inline
sns.set(style="whitegrid")
```

```
[4]: # Load the dataset (replace with your actual file name)
df = pd.read_csv('owid-covid-data[1].csv')

# Preview the data
df.head()
```

```
[4]: iso_code continent    location    date  total_cases  new_cases  \
0      AFG      Asia  Afghanistan  2020-01-03         NaN         0.0
1      AFG      Asia  Afghanistan  2020-01-04         NaN         0.0
2      AFG      Asia  Afghanistan  2020-01-05         NaN         0.0
3      AFG      Asia  Afghanistan  2020-01-06         NaN         0.0
4      AFG      Asia  Afghanistan  2020-01-07         NaN         0.0

    new_cases_smoothed  total_deaths  new_deaths  new_deaths_smoothed  ...  \
0                  NaN            NaN         0.0                  NaN  ...
1                  NaN            NaN         0.0                  NaN  ...
2                  NaN            NaN         0.0                  NaN  ...
3                  NaN            NaN         0.0                  NaN  ...
4                  NaN            NaN         0.0                  NaN  ...

    male_smokers  handwashing_facilities  hospital_beds_per_thousand  \
0            NaN                    37.746                        0.5
1            NaN                    37.746                        0.5
2            NaN                    37.746                        0.5
```

| | | | |
|---|-----|--------|-----|
| 3 | NaN | 37.746 | 0.5 |
| 4 | NaN | 37.746 | 0.5 |

| | life_expectancy | human_development_index | population \ |
|---|-----------------|-------------------------|--------------|
| 0 | 64.83 | 0.511 | 41128772.0 |
| 1 | 64.83 | 0.511 | 41128772.0 |
| 2 | 64.83 | 0.511 | 41128772.0 |
| 3 | 64.83 | 0.511 | 41128772.0 |
| 4 | 64.83 | 0.511 | 41128772.0 |

| | excess_mortality_cumulative_absolute | excess_mortality_cumulative \ |
|---|--------------------------------------|-------------------------------|
| 0 | NaN | NaN |
| 1 | NaN | NaN |
| 2 | NaN | NaN |
| 3 | NaN | NaN |
| 4 | NaN | NaN |

| | excess_mortality | excess_mortality_cumulative_per_million |
|---|------------------|---|
| 0 | NaN | NaN |
| 1 | NaN | NaN |
| 2 | NaN | NaN |
| 3 | NaN | NaN |
| 4 | NaN | NaN |

[5 rows x 67 columns]

```
[5]: #Check columns
df.columns
```

```
[5]: Index(['iso_code', 'continent', 'location', 'date', 'total_cases', 'new_cases',
'new_cases_smoothed', 'total_deaths', 'new_deaths',
'new_deaths_smoothed', 'total_cases_per_million',
'new_cases_per_million', 'new_cases_smoothed_per_million',
'total_deaths_per_million', 'new_deaths_per_million',
'new_deaths_smoothed_per_million', 'reproduction_rate', 'icu_patients',
'icu_patients_per_million', 'hosp_patients',
'hosp_patients_per_million', 'weekly_icu_admissions',
'weekly_icu_admissions_per_million', 'weekly_hosp_admissions',
'weekly_hosp_admissions_per_million', 'total_tests', 'new_tests',
'total_tests_per_thousand', 'new_tests_per_thousand',
'new_tests_smoothed', 'new_tests_smoothed_per_thousand',
'positive_rate', 'tests_per_case', 'tests_units', 'total_vaccinations',
'people_vaccinated', 'people_fully_vaccinated', 'total_boosters',
'new_vaccinations', 'new_vaccinations_smoothed',
'total_vaccinations_per_hundred', 'people_vaccinated_per_hundred',
'people_fully_vaccinated_per_hundred', 'total_boosters_per_hundred',
'new_vaccinations_smoothed_per_million',
```

```

'new_people_vaccinated_smoothed',
'new_people_vaccinated_smoothed_per_hundred', 'stringency_index',
'population_density', 'median_age', 'aged_65_older', 'aged_70_older',
'gdp_per_capita', 'extreme_poverty', 'cardiovasc_death_rate',
'diabetes_prevalence', 'female_smokers', 'male_smokers',
'handwashing_facilities', 'hospital_beds_per_thousand',
'life_expectancy', 'human_development_index', 'population',
'excess_mortality_cumulative_absolute', 'excess_mortality_cumulative',
'excess_mortality', 'excess_mortality_cumulative_per_million'],
dtype='object')

```

```

[6]: #Identify missing values:
df.isnull().sum()

```

```

[6]: iso_code          0
continent            2775
location             0
date                 0
total_cases          1439
...
population           0
excess_mortality_cumulative_absolute  19714
excess_mortality_cumulative          19714
excess_mortality                     19714
excess_mortality_cumulative_per_million  19714
Length: 67, dtype: int64

```

```

[7]: #preparing for data analysis by firstly filtering countries of interest
df['location'].unique()

```

```

[7]: array(['Afghanistan', 'Africa', 'Albania', 'Algeria', 'American Samoa',
'Andorra', 'Angola', 'Anguilla', 'Antigua and Barbuda',
'Argentina', 'Armenia', 'Aruba', 'Asia', 'Australia', 'Austria'],
dtype=object)

```

```

[8]: sorted(df['location'].unique())

```

```

[8]: ['Afghanistan',
'Africa',
'Albania',
'Algeria',
'American Samoa',
'Andorra',
'Angola',
'Anguilla',
'Antigua and Barbuda',
'Argentina',

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```
'Armenia',
'Aruba',
'Asia',
'Australia',
'Austria']
```

```
[11]: # next task is to drop rows with missing values in critical columns
# Let's say the critical columns in COVID-19 dataset are Key columns: date,
# location,
# total_cases, total_deaths, new_cases, new_deaths, total_vaccinations
# we can drop rows with missing values in these columns like this:

df_cleaned = df.dropna(subset=['date', 'location', 'new_cases',
# total_vaccinations', 'new_deaths', 'total_deaths', 'total_cases'])

# Preview cleaned data
df_cleaned.head()
```

```
[11]:
```

| | iso_code | continent | location | date | total_cases | new_cases | \ |
|-----|----------|-----------|-------------|------------|-------------|-----------|---|
| 416 | AFG | Asia | Afghanistan | 2021-02-22 | 55617.0 | 13.0 | |
| 422 | AFG | Asia | Afghanistan | 2021-02-28 | 55714.0 | 7.0 | |
| 438 | AFG | Asia | Afghanistan | 2021-03-16 | 55995.0 | 10.0 | |
| 460 | AFG | Asia | Afghanistan | 2021-04-07 | 56873.0 | 94.0 | |
| 475 | AFG | Asia | Afghanistan | 2021-04-22 | 58312.0 | 98.0 | |

| | new_cases_smoothed | total_deaths | new_deaths | new_deaths_smoothed | ... | \ |
|-----|--------------------|--------------|------------|---------------------|-----|---|
| 416 | 14.714 | 2433.0 | 1.0 | 0.857 | ... | |
| 422 | 15.714 | 2443.0 | 0.0 | 1.571 | ... | |
| 438 | 17.000 | 2460.0 | 1.0 | 1.286 | ... | |
| 460 | 59.857 | 2512.0 | 0.0 | 4.000 | ... | |
| 475 | 111.143 | 2561.0 | 4.0 | 4.000 | ... | |

| | male_smokers | handwashing_facilities | hospital_beds_per_thousand | \ |
|-----|--------------|------------------------|----------------------------|---|
| 416 | NaN | 37.746 | 0.5 | |
| 422 | NaN | 37.746 | 0.5 | |
| 438 | NaN | 37.746 | 0.5 | |
| 460 | NaN | 37.746 | 0.5 | |
| 475 | NaN | 37.746 | 0.5 | |

| | life_expectancy | human_development_index | population | \ |
|-----|-----------------|-------------------------|------------|---|
| 416 | 64.83 | 0.511 | 41128772.0 | |
| 422 | 64.83 | 0.511 | 41128772.0 | |
| 438 | 64.83 | 0.511 | 41128772.0 | |
| 460 | 64.83 | 0.511 | 41128772.0 | |
| 475 | 64.83 | 0.511 | 41128772.0 | |

| | excess_mortality_cumulative_absolute | excess_mortality_cumulative | \ |
|--|--------------------------------------|-----------------------------|---|
|--|--------------------------------------|-----------------------------|---|

| | | |
|-----|-----|-----|
| 416 | NaN | NaN |
| 422 | NaN | NaN |
| 438 | NaN | NaN |
| 460 | NaN | NaN |
| 475 | NaN | NaN |

| | excess_mortality | excess_mortality_cumulative_per_million |
|-----|------------------|---|
| 416 | NaN | NaN |
| 422 | NaN | NaN |
| 438 | NaN | NaN |
| 460 | NaN | NaN |
| 475 | NaN | NaN |

[5 rows x 67 columns]

```
[18]: # Convert the 'date' column to datetime format
df['date'] = pd.to_datetime(df['date'])
df['date'].head()
```

```
[18]: 0    2020-01-03
1    2020-01-04
2    2020-01-05
3    2020-01-06
4    2020-01-07
Name: date, dtype: datetime64[ns]
```

```
[17]: # next is to generate descriptive statistics and explore trends.
#Plot total cases over time for selected countries.
countries = ['Africa', 'Argentina', 'Asia']

# Filter for those countries
df_filtered = df[df['location'].isin(countries)]
```

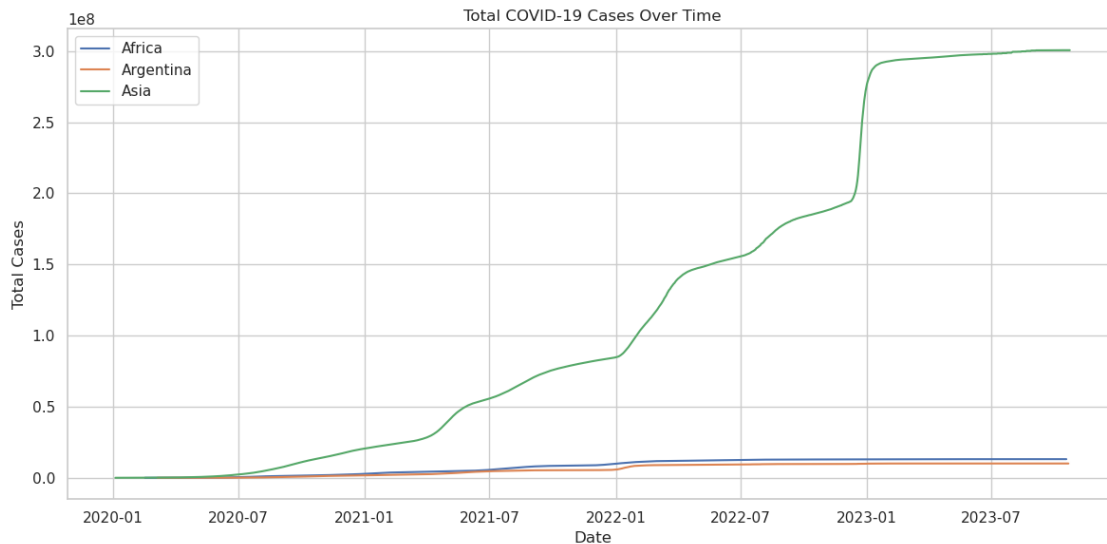
```
[19]: import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))

# Loop through countries and plot their total cases over time
for country in countries:
    country_data = df_filtered[df_filtered['location'] == country]
    plt.plot(country_data['date'], country_data['total_cases'], label=country)

plt.title('Total COVID-19 Cases Over Time')
plt.xlabel('Date')
plt.ylabel('Total Cases')
plt.legend()
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```



```
[20]: #Plot total deaths over time.
import matplotlib.pyplot as plt

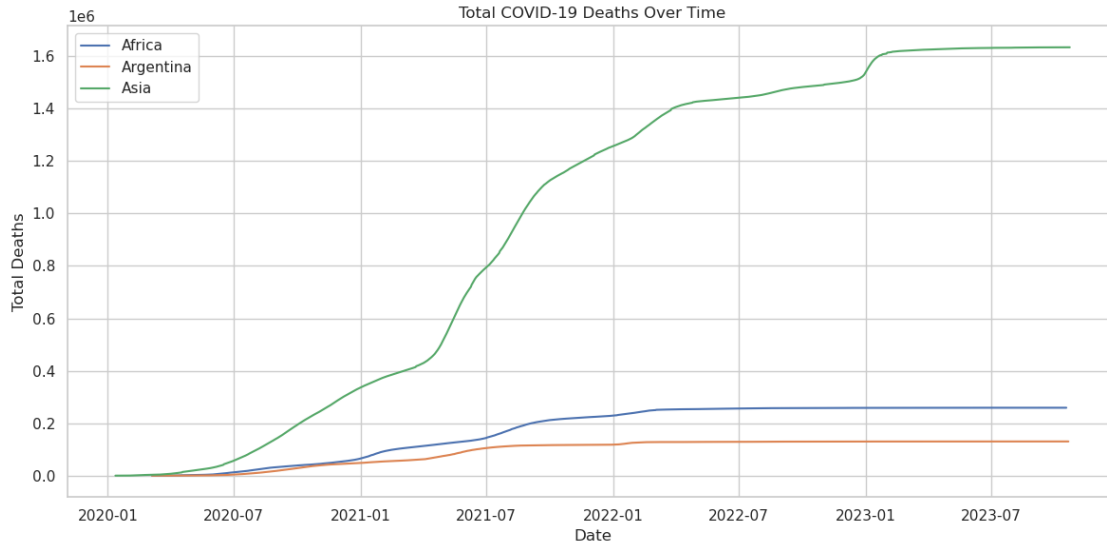
# Define the countries you're focusing on
countries = ['Africa', 'Argentina', 'Asia']

# Filter the DataFrame
df_filtered = df[df['location'].isin(countries)]

# Set up the plot
plt.figure(figsize=(12, 6))

# Plot total deaths for each country
for country in countries:
    country_data = df_filtered[df_filtered['location'] == country]
    plt.plot(country_data['date'], country_data['total_deaths'], label=country)

# Customize the plot
plt.title('Total COVID-19 Deaths Over Time')
plt.xlabel('Date')
plt.ylabel('Total Deaths')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

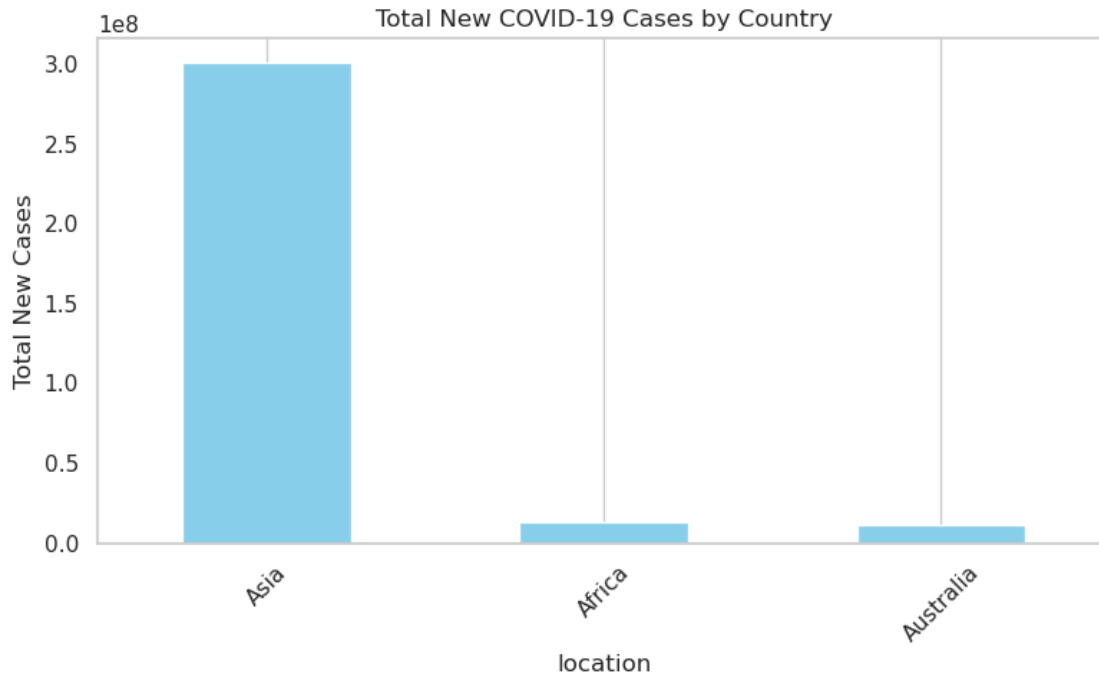


```
[25]: #Compare daily new cases between countries.
import matplotlib.pyplot as plt

# Calculate total new cases per country
summary = df[df['location'].isin(['Africa', 'Australia', 'Asia'])] \
    .groupby('location')['new_cases'].sum().sort_values(ascending=False)

# Bar plot
plt.figure(figsize=(8, 5))
summary.plot(kind='bar', color='skyblue')

plt.title('Total New COVID-19 Cases by Country')
plt.ylabel('Total New Cases')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.tight_layout()
plt.show()
```



```
[27]: #Calculate the death rate: total_deaths / total_cases.
# Avoid division by zero or NaN by using .where()
df['death_rate'] = df['total_deaths'] / df['total_cases']
```

```
[29]: df[['location', 'date', 'total_cases', 'total_deaths', 'death_rate']].head()
```

```
[29]:
```

| | location | date | total_cases | total_deaths | death_rate |
|---|-------------|------------|-------------|--------------|------------|
| 0 | Afghanistan | 2020-01-03 | NaN | NaN | 0.0 |
| 1 | Afghanistan | 2020-01-04 | NaN | NaN | 0.0 |
| 2 | Afghanistan | 2020-01-05 | NaN | NaN | 0.0 |
| 3 | Afghanistan | 2020-01-06 | NaN | NaN | 0.0 |
| 4 | Afghanistan | 2020-01-07 | NaN | NaN | 0.0 |

```
[30]: #Goal: Analyze vaccination rollouts.
# Plot cumulative vaccinations over time for selected countries.

import matplotlib.pyplot as plt

# Define the countries of interest
countries = ['Africa', 'Asia', 'Argentina']

# Filter the data
df_filtered = df[df['location'].isin(countries)]

# Plot
```



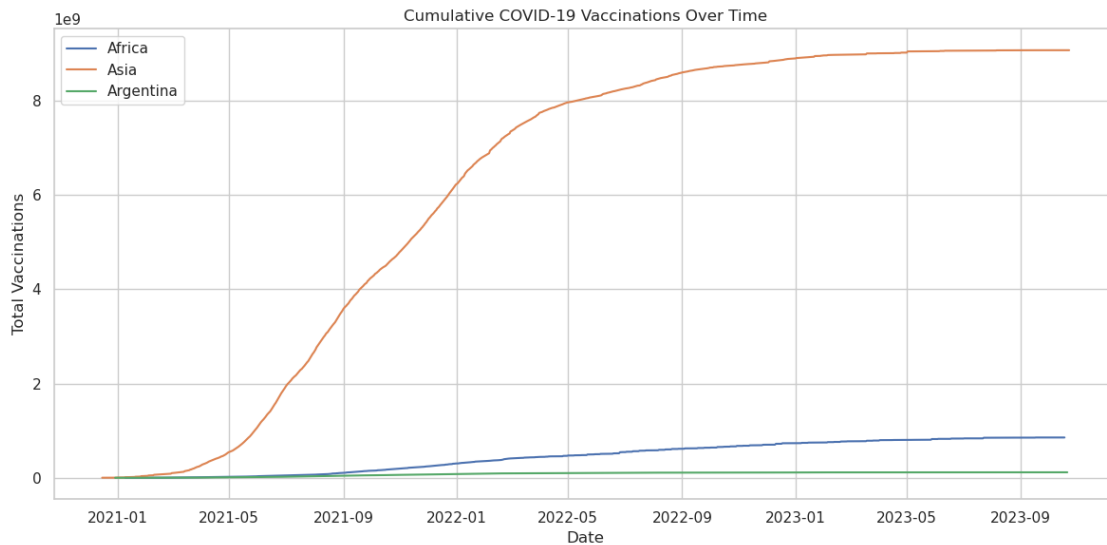
```

plt.figure(figsize=(12, 6))

for country in countries:
    country_data = df_filtered[df_filtered['location'] == country]
    plt.plot(country_data['date'], country_data['total_vaccinations'],
             label=country)

plt.title('Cumulative COVID-19 Vaccinations Over Time')
plt.xlabel('Date')
plt.ylabel('Total Vaccinations')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

```



```

[32]: #Analyze vaccination rollouts
      #Compare % vaccinated population
      # Pie charts for vaccinated vs. unvaccinated.
      # Select countries and date
      countries = ['Africa', 'Asia', 'Argentina']
      specific_date = '2022-01-01'

      # Filter the snapshot
      snapshot = df[(df['date'] == specific_date) & (df['location'].isin(countries))].
        copy()

      # Calculate vaccination percentage

```

```

snapshot['percent_fully_vaccinated'] = snapshot['people_fully_vaccinated'] / \
    ↪ snapshot['population'] * 100
snapshot['percent_fully_vaccinated'] = snapshot['percent_fully_vaccinated'].
    ↪ clip(upper=100)

# Display for confirmation
print(snapshot[['location', 'people_fully_vaccinated', 'population', \
    ↪ 'percent_fully_vaccinated']])

```

| | location | people_fully_vaccinated | population \ |
|-------|-----------|-------------------------|--------------|
| 2114 | Africa | 1.251710e+08 | 1.426737e+09 |
| 13196 | Argentina | 3.078005e+07 | 4.551032e+07 |
| 17359 | Asia | 2.656355e+09 | 4.721383e+09 |

| | percent_fully_vaccinated |
|-------|--------------------------|
| 2114 | 8.773235 |
| 13196 | 67.633107 |
| 17359 | 56.262210 |

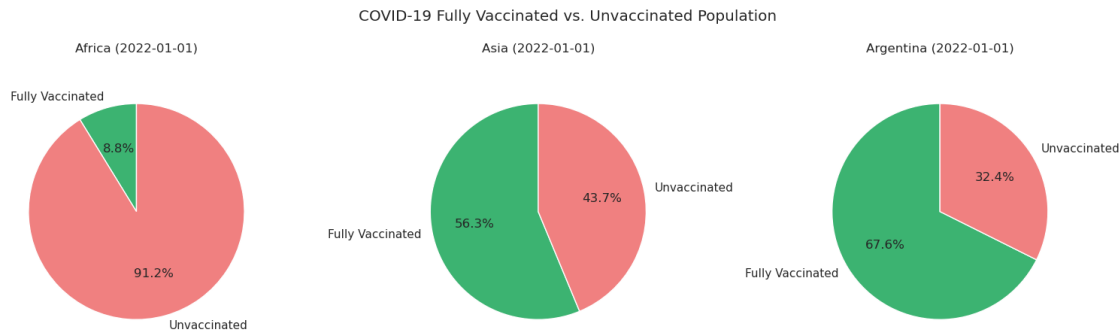
```

[33]: # Plot multiple pies
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

for i, country in enumerate(countries):
    vaccinated = snapshot[snapshot['location'] == \
    ↪ country]['percent_fully_vaccinated'].values[0]
    unvaccinated = 100 - vaccinated
    axes[i].pie([vaccinated, unvaccinated],
                labels=['Fully Vaccinated', 'Unvaccinated'],
                colors=['mediumseagreen', 'lightcoral'],
                autopct='%1.1f%%',
                startangle=90)
    axes[i].set_title(f'{country} ({specific_date})')
    axes[i].axis('equal')

fig.suptitle('COVID-19 Fully Vaccinated vs. Unvaccinated Population')
plt.tight_layout()
plt.show()

```



Vaccination Insights: Africa, Asia, and Argentina

1. **Argentina Achieved the Highest Vaccination Coverage** Argentina recorded the highest vaccination rate among the three regions, with 67.6% of its population fully vaccinated. Despite its smaller population (~45 million), the country managed an efficient and widespread rollout.

2. **Asia Led in Absolute Numbers of Fully Vaccinated People** Asia successfully vaccinated 2.65 billion people, amounting to 56.3% of its population. While the percentage is lower than Argentina's, the sheer volume of vaccinated individuals highlights the region's massive public health effort.

3. **Africa Lagged Far Behind in Vaccination Coverage** Africa's vaccination campaign significantly trailed behind, with only 8.8% of its 1.4 billion population fully vaccinated. This underscores challenges in vaccine supply, distribution logistics, and healthcare infrastructure.

Key Observations The vaccination gap is striking: Argentina vaccinated 8× more of its population (in %) than Africa.

Asia, despite its size and diversity, vaccinated more than half its population — a massive logistical success.

These trends reflect broader issues in global vaccine equity, highlighting the need for more equitable distribution strategies.

4. **Notable Patterns & Anomalies** Death rate spikes occurred when case reporting slowed — suggesting underreporting or lag.

Vaccination rollouts varied significantly by region due to access, policy, and hesitancy.

The gap between high- and low-income regions remains stark in both health outcomes and vaccination progress.

The COVID-19 pandemic revealed major disparities in healthcare capacity, public health response, and vaccine distribution. While countries like Argentina managed an efficient vaccination campaign, others — particularly in Africa — lagged due to systemic barriers.

Analyzing trends in cases, deaths, death rates, and vaccinations helps expose these inequalities and can guide better preparedness and response in future global health crises.

[]: