# FairScale

## Poverty Index Report

Prepared for SAP SE as part of CxC 2025

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# 1. Introduction

- Our task is to create a poverty index
- Poverty is defined as the ability to meet basic needs given the resources a person has
    - Wealth and poverty is usually exponentially distributed
    - Some have far fewer than they need, some have far more than they need
- We were given two widely-accepted indicators of poverty, provided by the World Bank and UNDP

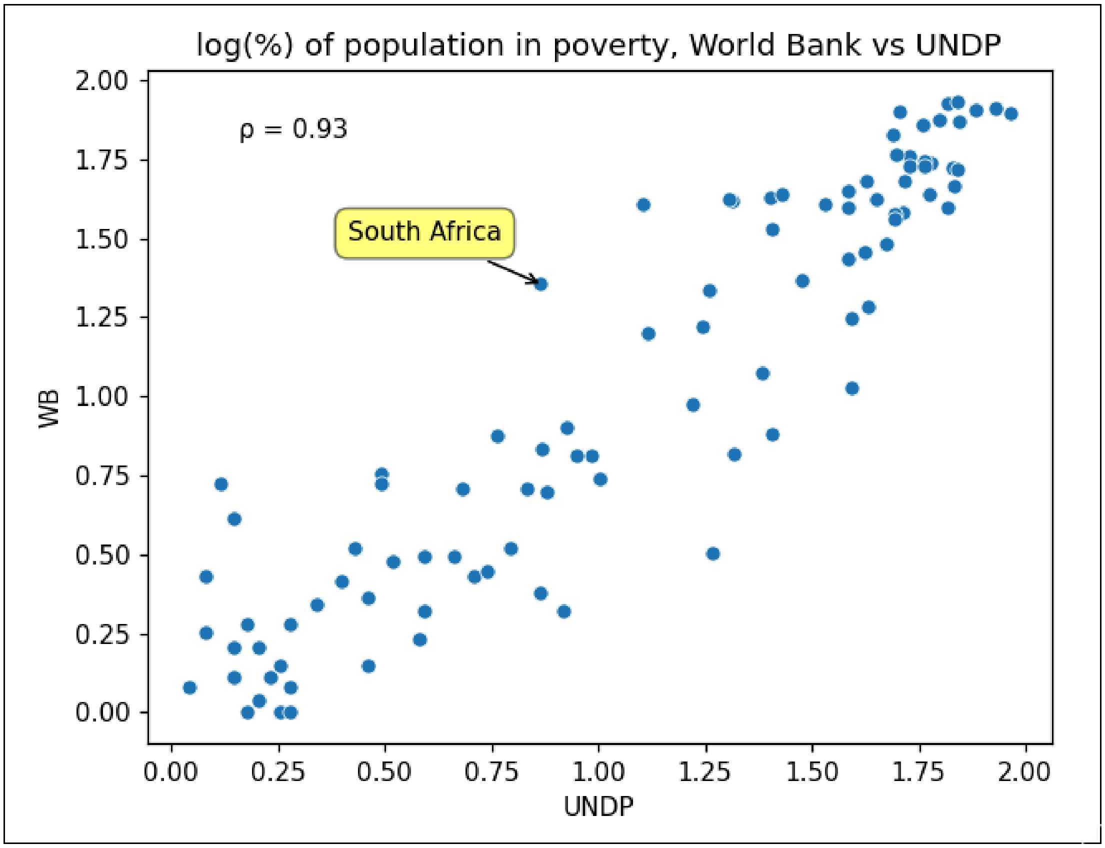



fig. 1: a scatterplot comparing the World Bank and UNDP poverty indicators

  - Each indicator accounts for $R^2$ = 86% of the variation in the other
- Our diagrams are interactive, but only on the jupyter notebook platform
    - Hovering over a data point allows you to see which country it represents
    - Open the repository locally for a live preview

# 2. Methodologies

- We did Principal Component Analysis (PCA) on the given dataset
    - PCA is a statistical method designed to capture as much of the variation in the data with as few dimensions as possible
    - The dataset mostly contained data corresponding to quality-of-life, basic needs, employment, social equity, health, and access to resources
    - We assume that, due to the choice of indicators, the principle components which captures

most of its variance will correspond to some measure of poverty

- Feature extraction
    - We were given time series data stretching from 2000 to 2023 for around 90 indicators
        - Many of those indicators were empty (NaN in python) because data could not be gathered at that time
        - If we fed the raw data into the PCA, the temporal relationship would be lost
    - We extracted the mean of the following: the data, its derivative, and its second derivative
        - The derivative communicates the speed which something is changing
        - The second derivative communicates the acceleration of the indicator, or to use a physics analogy, the pressure that outside powers put on the indicator
        - The NaNs were automatically excluded in the mean calculation
- Normalization (normal as in gaussian)
    - PCA works better when the data is gaussian
    - Due to the number of features, we normalized by inspection
    - We applied base-10 logarithmic scaling to most of the indicators
        - Since logarithms have an asymptote at zero and is undefined for all values under zero, we used the pseudo-logarithm instead, which is defined for all real values
        - We took the pseudo-logarithm for the derivatives also, as the derivative of an exponential function is still exponential
        - We applied the pseudo-log to the terms-of-trade indicator as well, but it may have been of limited use as local currency units might not been comparable with each other
    - Since many percentage-based indicators were heavily left-skewed, we divided the value (0-100) by 100 and squared it
        - Possible source of error: some indicators had many values at 100%
        - They were resistant to normalization, no matter how many times we raised it
        - Due to time constraints, we left them as either bimodal or right-skewed
    - We also applied the square root onto the total alcohol consumption indicator to normalize it
    - Although we did transform the distribution using non-linear functions, we made an effort to use functions that did not change the sign of each value
        - This is so that the weights generated by the PCA will have their sign preserved
        - e.g. if the weight is negative on an indicator, we can be confident that the score of the country on principal component will increase if the indicator is decreased
- Cleaning
    - We dropped all indices and columns with over half of the data missing (130 missing values)
    - We replaced all missing values and outliers (standard deviation over 2.5) in the set of extracted features with the mean of the feature
        - Possible source of error: a high peak at the mean impacts the standard deviation of the secondary normalization (see below) which impacts the result of the PCA
        - We originally tried generating representative data based on a gaussian model of the feature, but this resulted in the PCA being non-deterministic and we found that undesirable
            - The error would also be greater due to the sensitivity of PCA to outliers
    - The World Bank and UNDP poverty indicators were excluded from the PCA as to not impact

the results

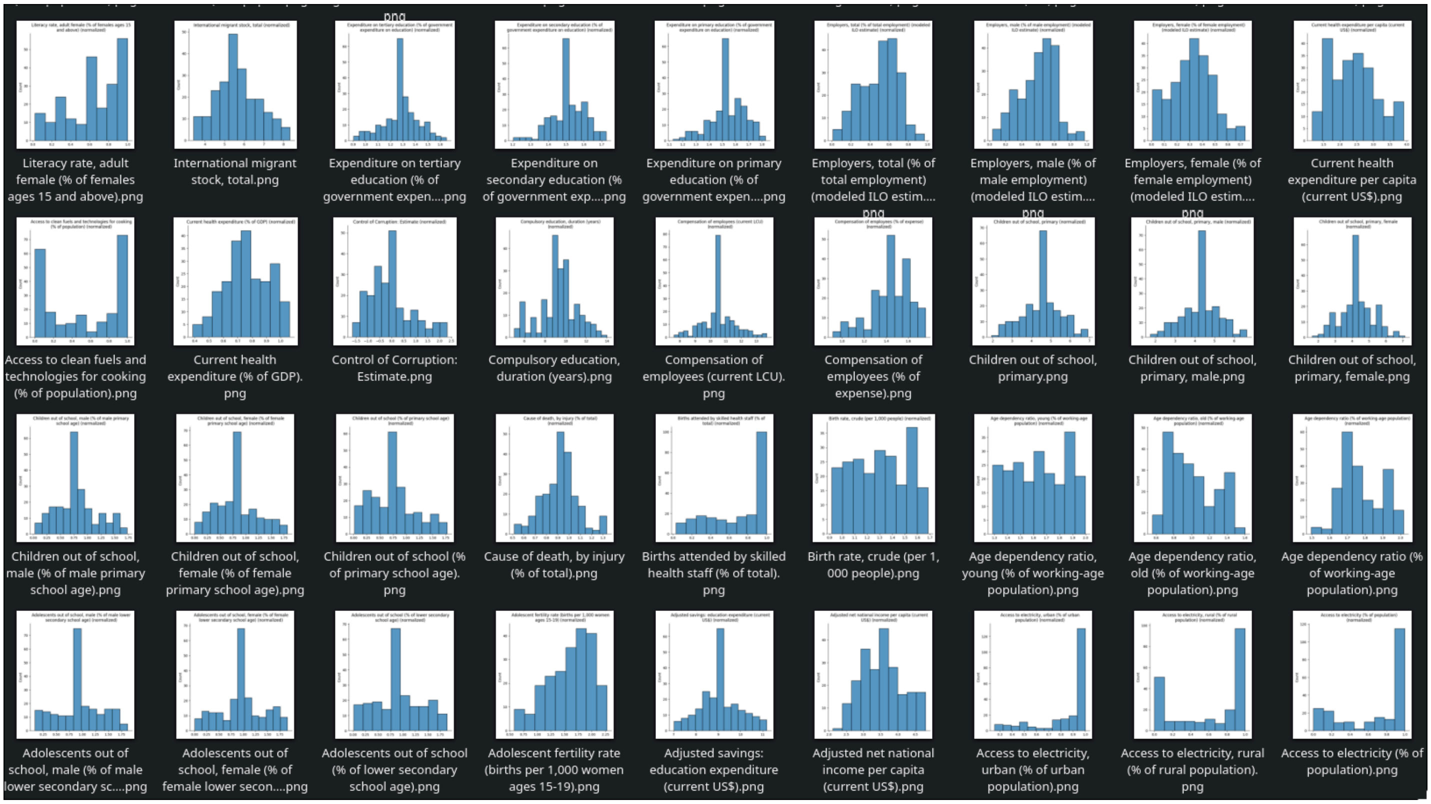



fig. 2: histograms of the normalized data

- the peaks are caused by the NaN values being replaced with the mean

| Indicator Name / Country Name | Access to clean fuels and technologies for cooking (% of population) | Access to clean fuels and technologies for cooking, rural (% of rural population) | Access to clean fuels and technologies for cooking, urban (% of urban population) | Access to electricity (% of population) | Access to electricity, rural (% of rural population) | Access to electricity, urban (% of urban population) | Adjusted net national income per capita (current US$) | Adjusted savings: education expenditure (current US$) | Adolescent fertility rate (births per 1,000 women ages 15-19) | Adolescents out of school (% of lower secondary school age) | ... | Terms of trade adjustment (constant LCU), SECOND DERIVATIVE | Total alcohol consumption per capita (liters of pure alcohol, projected estimates, 15+ years of age), SECOND DERIVATIVE | Unemployment with advanced education (% of total labor force with advanced education), SECOND DERIVATIVE | Unemployment with basic education (% of total labor force with basic education), SECOND DERIVATIVE | Unemployment with intermediate education (% of total labor force with intermediate education), SECOND DERIVATIVE |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Afghanistan | 0.044448 | 0.006470 | 0.425189 | 0.325942 | 0.316406 | 0.782840 | 2.702385 | 8.695612 | 2.057893 | 0.922540 | ... | 8.713281 | -0.000263 | -0.796659 | -0.684209 | -0.683001 |
| Africa Western and Central | 0.009573 | 0.000540 | 0.041347 | 0.197104 | 0.045300 | 0.605991 | 3.060213 | 9.086672 | 2.087651 | 0.922540 | ... | 1.445672 | -0.008555 | -0.051611 | -0.012649 | -0.002303 |
| Albania | 0.425189 | 0.205899 | 0.706623 | 0.994529 | 0.999131 | 0.975285 | 3.504623 | 8.530759 | 1.236911 | 0.438939 | ... | 9.120155 | -0.033684 | -0.058822 | -0.061096 | -0.021380 |
| Algeria | 0.978207 | 0.943897 | 0.997740 | 0.981995 | 0.959804 | 0.993142 | 3.460934 | 9.793755 | 1.036264 | 0.488767 | ... | 9.859411 | -0.003684 | -0.051611 | -0.012649 | -0.002303 |
| Angola | 0.205406 | 0.005763 | 0.607485 | 0.131674 | 0.001537 | 0.382139 | 3.186075 | 9.310128 | 2.199554 | 1.325245 | ... | -9.580800 | -0.107368 | 0.393280 | -0.012649 | 0.374428 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| West Bank and Gaza | 0.522369 | 0.439294 | 0.636055 | 0.994269 | 0.986222 | 0.997132 | 3.536888 | 8.679404 | 1.761598 | 0.965890 | ... | 6.134218 | -0.000168 | -0.062529 | -0.155708 | -0.115051 |
| World | 0.356941 | 0.120514 | 0.680017 | 0.718562 | 0.556290 | 0.924997 | 3.871600 | 9.086672 | 1.709903 | 0.922540 | ... | 1.445672 | -0.026870 | -0.051611 | -0.012649 | -0.002303 |
| Yemen, Rep. | 0.317777 | 0.159513 | 0.858644 | 0.387154 | 0.226836 | 0.878213 | 2.882514 | 8.927542 | 1.893741 | 1.594273 | ... | -8.638857 | 0.000842 | -0.051611 | -0.012649 | -0.002303 |
| Zambia | 0.019588 | 0.000436 | 0.108484 | 0.086871 | 0.005929 | 0.376409 | 2.917476 | 8.676742 | 2.127874 | 0.922540 | ... | 8.918997 | -0.012105 | -0.101312 | 0.422493 | -0.144131 |
| Zimbabwe | 0.096883 | 0.002925 | 0.669017 | 0.160418 | 0.030443 | 0.733629 | 2.866943 | 8.444791 | 2.013007 | 1.257741 | ... | 8.058335 | -0.050526 | -0.260459 | 0.124939 | 0.336266 |

221 rows × 200 columns

fig. 3: a sample of the normalized data

- Secondary normalization (normal as in magnitude)
  - In order for PCA to work effectively, all the values must be converted to Z-scores based on the mean and standard deviation of the feature distribution
  - We used StandardScaler from Scikit-learn, which did this automatically
- We used PCA to generate linear weights of each feature in the principal components. We then matrix-

multiplied it with the list of scaled Z-scores for each country to calculate its position in our index

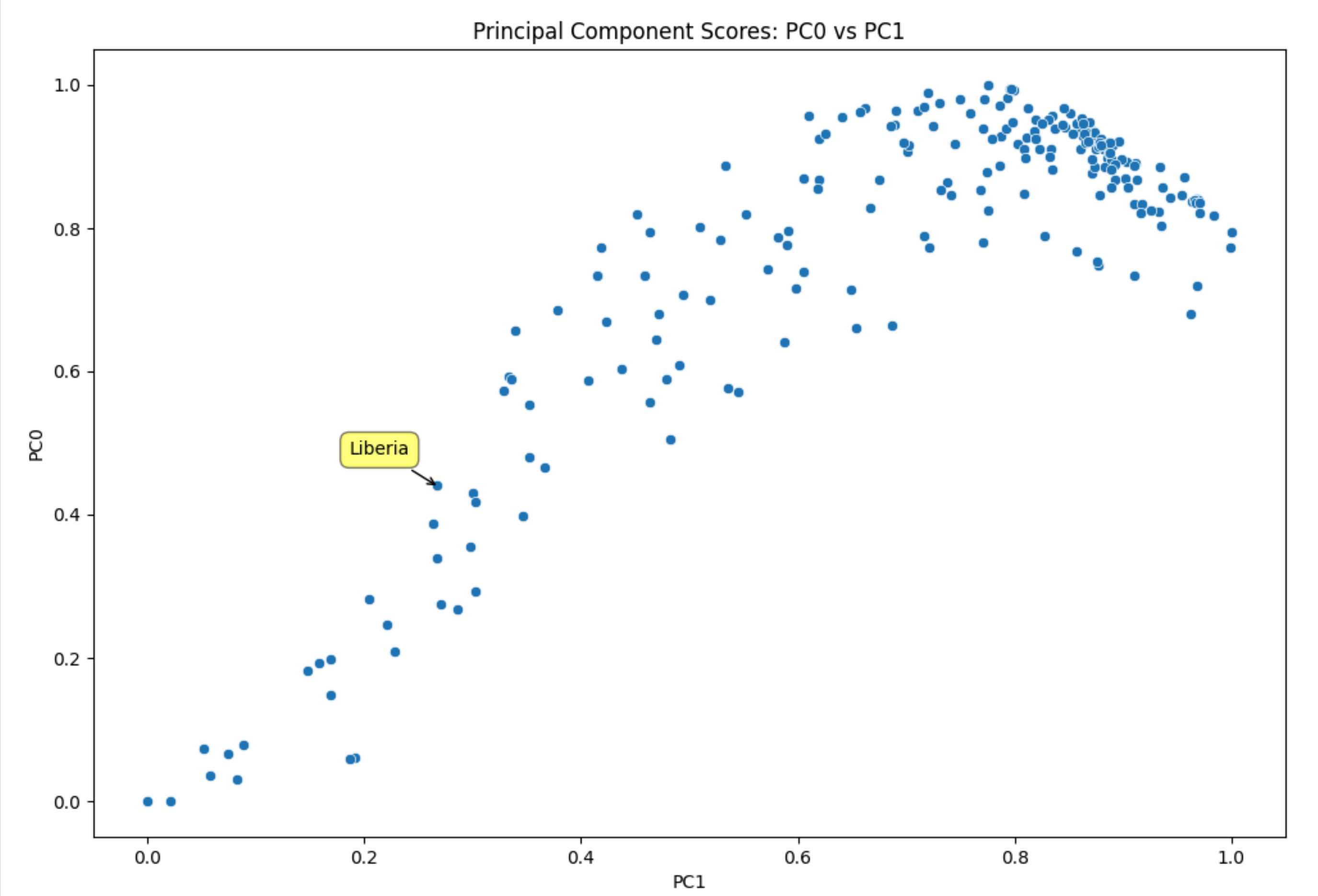
# 3. Data-Driven Insights & Analysis

- Data Retrieval
    - Using PCA, we took the 4 principal components that accounted for the most significant amount of the variation in the data
    - Since the last two components accounted for only around 1% of the variance, we chose to discard them
        - They are most likely just noise anyways
    - We then proceeded to normalize the principle component values between zero and one
        - We squared PC0 to distribute it more evenly
        - We negated PC1 to make it correlate positively with PC0

```
[10]: print(pca.explained_variance_ratio_) # how much of data does the pca explain?

[0.87572969 0.06357132 0.01399742 0.00982442]
```

fig.5: Amount of variance in the data each principal component explains




- fig.6: plot of the two principal components (normalized)

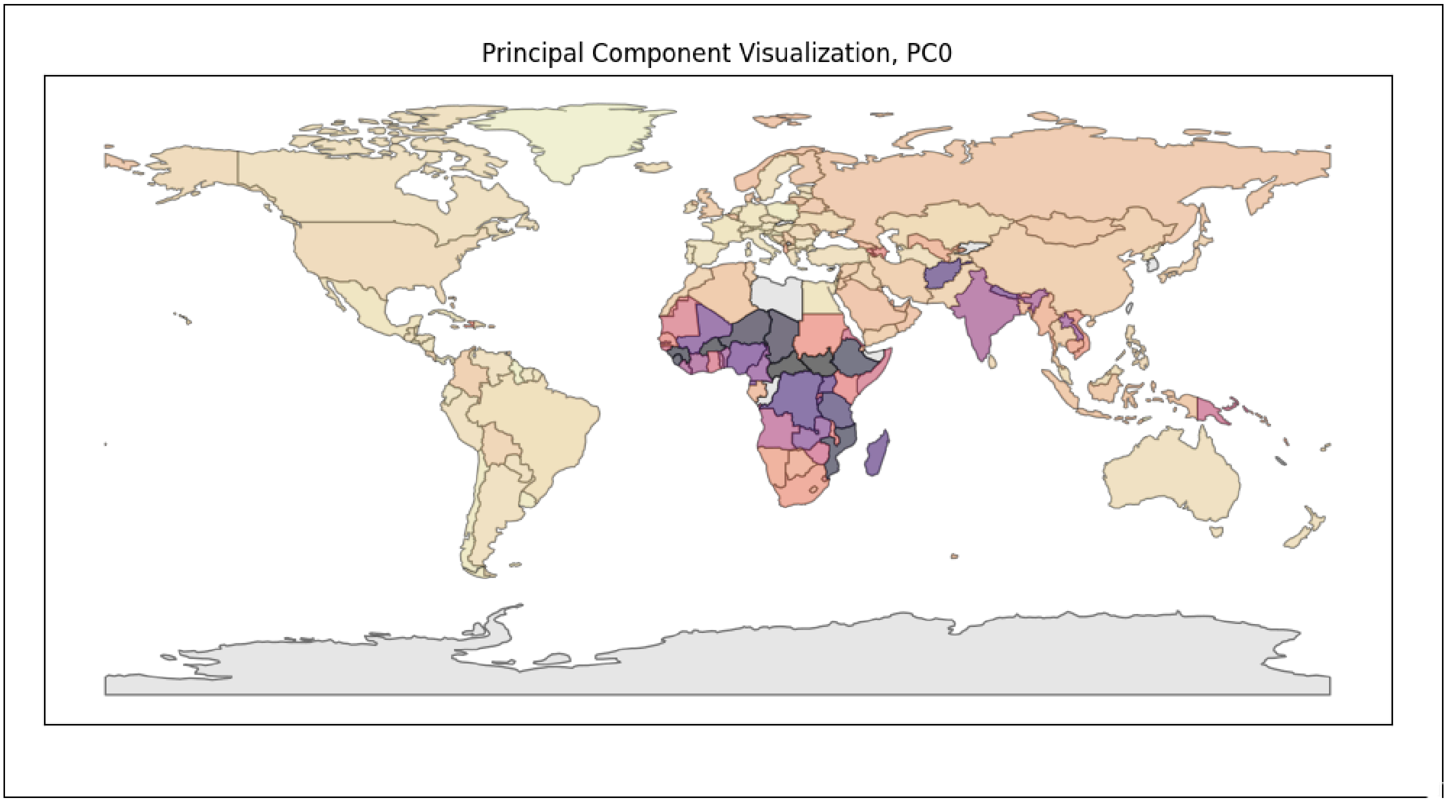



fig.7: plot of the principal component 0, with darker shades representing more poverty

- Not all countries in the dataset were displayed
- We used a Levenshtein Distance calculator to fuzzy match the country names from the dataset we were given to the names in the country geometry database from NACIS

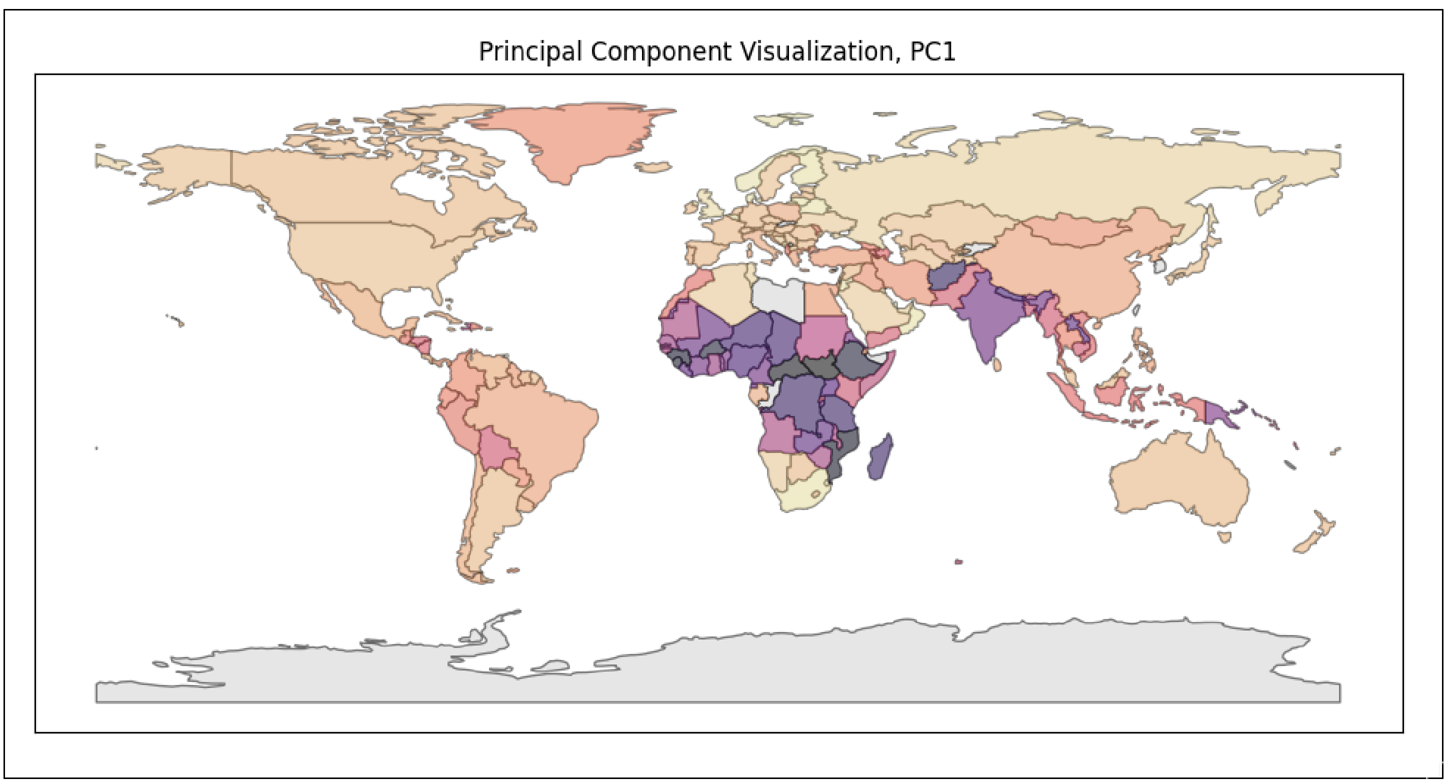



fig.8: plot of the principal component 1, with darker shades representing more poverty

| Indicator Name | Percent | Value |
|---|---|---|
| **Cause of death, by non-communicable diseases (% of total)** | 10.337021 | 110.070310 |
| **Wage and salaried workers, male (% of male employment) (modeled ILO estimate)** | 8.452371 | 90.002253 |
| **Wage and salaried workers, total (% of total employment) (modeled ILO estimate)** | 8.074317 | 85.976672 |
| **Wage and salaried workers, female (% of female employment) (modeled ILO estimate)** | 7.546476 | 80.356124 |
| **Women who were first married by age 18 (% of women ages 20-24)** | 3.698596 | 39.383261 |
| **Compensation of employees (current LCU)** | 1.544440 | 16.445456 |
| **Compensation of employees (current LCU), FIRST DERIVATIVE** | 1.342262 | 14.292630 |
| **Compulsory education, duration (years)** | 1.268850 | 13.510928 |
| **Adjusted savings: education expenditure (current US$)** | 1.250137 | 13.311663 |
| **Adjusted savings: education expenditure (current US$), FIRST DERIVATIVE** | 1.009790 | 10.752415 |

fig. 9: ten most impactful weights PC0, along with the percentage of the index it accounts for and the value multiplied by the Z-score of each indicator

| Indicator Name | Percent | Value |
|---|---|---|
| **Women who were first married by age 18 (% of women ages 20-24)** | 11.172679 | -36.154393 |
| **Wage and salaried workers, female (% of female employment) (modeled ILO estimate)** | 7.254800 | 23.476277 |
| **Wage and salaried workers, total (% of total employment) (modeled ILO estimate)** | 4.068380 | 13.165135 |
| **Compensation of employees (current LCU)** | 2.734822 | -8.849789 |
| **Women who were first married by age 15 (% of women ages 20-24)** | 2.733113 | -8.844256 |
| **Cause of death, by non-communicable diseases (% of total)** | 2.622606 | -8.486660 |
| **Compensation of employees (current LCU), FIRST DERIVATIVE** | 2.477356 | -8.016637 |
| **Births attended by skilled health staff (% of total), FIRST DERIVATIVE** | 2.322135 | -7.514347 |
| **Adjusted savings: education expenditure (current US$)** | 1.927543 | -6.237462 |
| **Compulsory education, duration (years)** | 1.688306 | -5.463300 |

fig. 10: the ten most impactful weights PC1, along with the percentage of the index it accounts for and the value multiplied by the Z-score of each indicator

```
[46]: pd.Series(scores[0], index=df2.index).sort_values(ascending=False)

[46]: Country Name
      Middle East & North Africa (excluding high income)      1.000000
      Latin America & Caribbean (excluding high income)       0.994477
      Latin America & the Caribbean (IDA & IBRD countries)    0.993827
      Latin America & Caribbean                               0.993013
      World                                                   0.989071
                                                                ...
      Niger                                                   0.058145
      Guinea                                                  0.036595
      Burkina Faso                                            0.031162
      South Sudan                                             0.000049
      Central African Republic                                0.000000
      Length: 221, dtype: float64

[35]: pd.Series(scores[1], index=df2.index).sort_values(ascending=False)

[35]: Country Name
      Singapore                   1.000000
      Qatar                       0.999416
      Norway                      0.983401
      Oman                        0.970688
      Lithuania                   0.970327
                                    ...
      Sierra Leone                0.074137
      Guinea                      0.057953
      Mozambique                  0.051877
      Central African Republic    0.021396
      South Sudan                 0.000000
      Length: 221, dtype: float64
```

fig. 12: top five and bottom five rated countries & country clusters in PC0 & PC1 respectively

```
[62]: pd.Series(scores[0], index=df2.index).sort_values(ascending=False).head(10)

[62]: Country Name
      Middle East & North Africa (excluding high income)      1.000000
      Latin America & Caribbean (excluding high income)       0.994477
      Latin America & the Caribbean (IDA & IBRD countries)    0.993827
      Latin America & Caribbean                               0.993013
      World                                                   0.989071
      Europe & Central Asia (excluding high income)           0.982790
      San Marino                                              0.981243
      Grenada                                                 0.979993
      Late-demographic dividend                               0.975158
      Guyana                                                  0.970538
      dtype: float64
```

fig. 11: top ten countries & country clusters in PC0

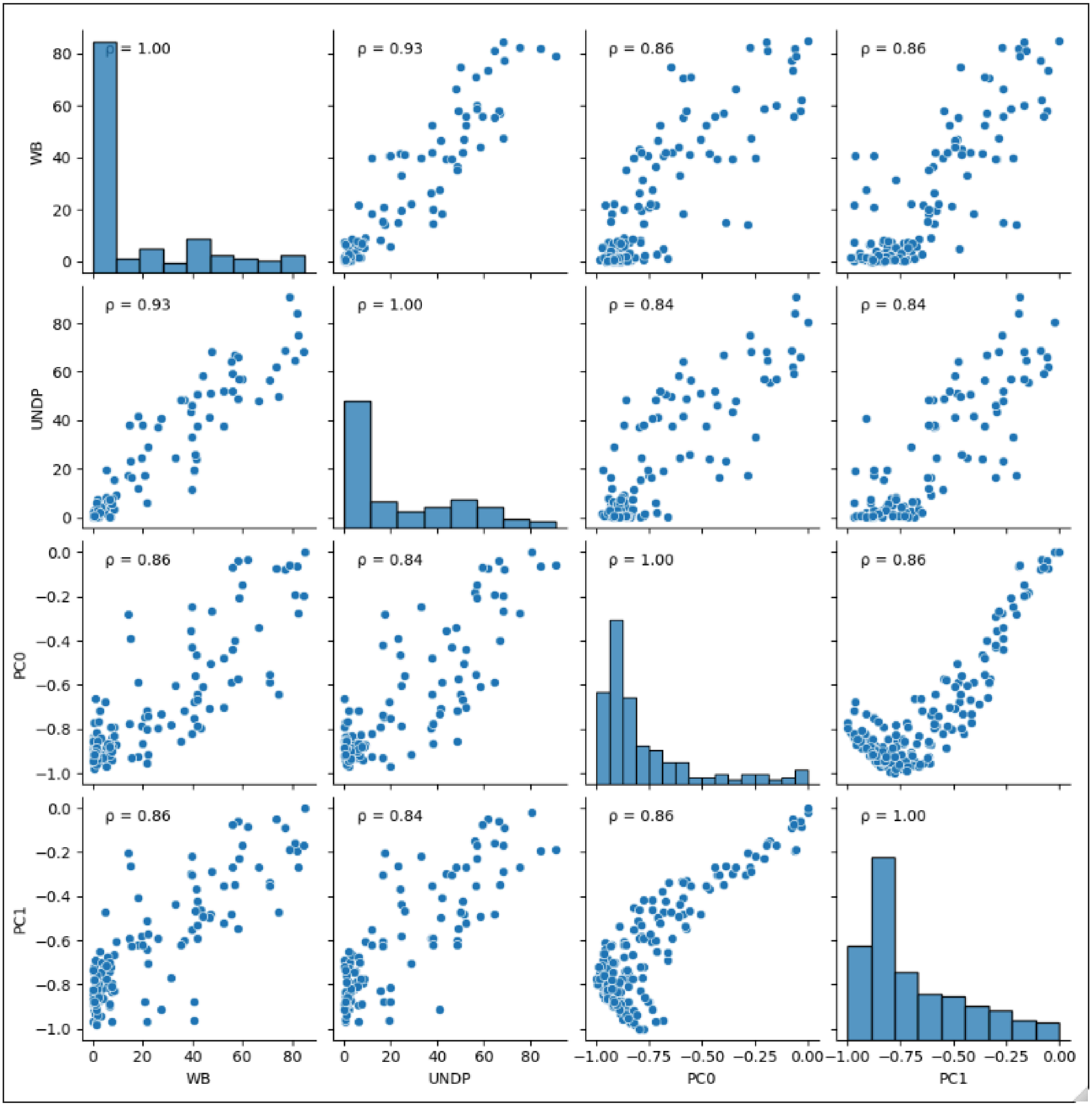



fig. 12: correlation between the principal components and the (non-logged) reference poverty indices

- The greek letter Rho is used to represent the pearson correlation coefficient (usually r is used)
- Our indicators explain $R^2 = 74\%$ and $R^2 = 70\%$ of the variance in the world bank and UNDP datasets respectively

```
[57]: from scipy import stats
def ttest(x_col, y_col):
    df_ttest = df_pov[[x_col, y_col]].dropna()
    print(stats.linregress(x=df_ttest[x_col], y=df_ttest[y_col]))
ttest("PC0", "WB")
ttest("PC0", "UNDP")
ttest("PC1", "WB")
ttest("PC1", "UNDP")
```

```
LinregressResult(slope=np.float64(83.87354651474037), intercept=np.float64(81.8730077379106), rvalue=n
p.float64(0.8554413553163873), pvalue=np.float64(1.4297426052991338e-45), stderr=np.float64(4.105203588
49499), intercept_stderr=np.float64(3.2539726574087084))
LinregressResult(slope=np.float64(77.22232723025391), intercept=np.float64(76.93249353175506), rvalue=n
p.float64(0.8374026124291323), pvalue=np.float64(1.4304737937893528e-29), stderr=np.float64(4.895697644
719876), intercept_stderr=np.float64(3.6255517087606988))
LinregressResult(slope=np.float64(83.58112495150233), intercept=np.float64(75.78652537462534), rvalue=n
p.float64(0.8563292038734827), pvalue=np.float64(9.247580835060741e-46), stderr=np.float64(4.0750551364
41435), intercept_stderr=np.float64(2.9617974908352402))
LinregressResult(slope=np.float64(79.73201337767269), intercept=np.float64(73.04517354918342), rvalue=n
p.float64(0.8399408284828312), pvalue=np.float64(6.665388617076401e-30), stderr=np.float64(5.0034932313
49854), intercept_stderr=np.float64(3.3648518173817163))
```

fig. 13: the statistics generated from the regression analysis of each principal component against each reference poverty index

- The p-value displayed represents the p-value generated by a t-test with the null hypothesis asserting a true slope of zero
- The probability (p-value) that a correlation of this magnitude (r = 0.84 ~ 0.86) between the principal components and the indices occurs by random chance ranges from $10^{-29}$ to $10^{-46}$, well below the de-facto standard of scientific rigor: p-value = 0.05
- From this we can conclude that the principle components accurately measures poverty

# 5. Discussion

- Disclaimer: my knowledge of economics and geopolitics is mostly limited to Asian, European, and North American countries. Further analysis is strongly encouraged
  - I know about the Rwandan genocide, Wagner coups, and the M23 situation right now but not much more than that
- Even though our principal components correlate strongly with the reference poverty indices, we have not yet fully understood what each component means
  - All ~200 indicators have a slight effect on each principal component
    - The most significant indicator accounts for 24% and 11.3% of the indices respectively when its sub-categories are summed together (see fig. 9 & 10)
  - As previously stated, the relative poverty of African countries is not my field of expertise
  - On the poor end of the index, the only thing I can say is that their scores correlate strongly with the reference indices
  - Most of this analysis will be based on extrapolations from the parabolic divergence between the rich end of PC0 and PC1 as shown in fig. 6
- PC0 seems to identify small, often tropical countries that attract western upper-middle-class tourists

        - They tend to attract disproportionately rich people despite their size, but that wealth may not be equally distributed among locals
        - This includes countries like San Marino, Grenada, San Marino, Kiribati, Seychelles, Dominican Republic, and Panama
            - Basically anywhere you can imagine luxury villas
        - Although there are some exceptions to this
            - Guyana is currently the world's fastest growing economy due to recent oil discoveries, with its GDP growing by 44% last year ([IMF, 2024](IMF, 2024))
                - With this in mind, its placement near the top of PC0 is slightly less surprising
            - Countries that shouldn't be high in the index but is:
                - Honduras is high in poverty but also high on PC0
                - Poland: I don't know anyone who would go there for vacation but it ranks higher than almost every other European country
    - PC1 seems to identify incredibly rich but incredibly unequal countries, and countries where a subset of the population has immense personal wealth
        - Countries such as Singapore, Qatar, Oman, Bahrain, Kuwait, UAE, Macao, United Kingdom, Saudi Arabia, and Russia rank the highest in the PC1 index
        - Many of these countries are petrodollar states, home to the world's richest oligarchs, and have poignant class divisions
            - Not sure if any of the exploited migrant workers being actively concealed by the Arab governments were counted in the dataset we were given
        - Eswatini, one of the poorest countries in the world, also ranks highly on PC1
            - At first glance, this feels like a nonsensical outlier that should be ignored
            - However, Nathan Kirsh is a billionaire in Eswatini with a net worth of 7.4 billion (Forbes, 2025), which is 50% greater than the country's annual GDP of 4.4 billion (WB, 2023).
            - If this is indicative of a larger trend, this finding will support the interpretation of PC1 as a measure of economic inequality
            - Either the point above is true or this is an artifact of replacing all NaN values with the mean
    - Other outliers:
        - Warzones like Syria, Yemen, and Gaza are ranked highly
            - Most census bureaus would not walk head first into a war zone, so it is likely that the many NaNs were replaced with means
            - Since the PCA is only linear, it may have mistakenly identified them as petrodollar welfare states when referencing outdated statistics
        - Countries like Venezuela, Sri Lanka, and Lebanon are still ranked highly despite intense economic setbacks
            - Taking the mean during data processing may have smoothed out these recent economic upsets
    - Looking at the weight distribution of both indices, it seems to be taken up by these categories:
        - Percent of employees that receive a regular wage and salary
            - As previously stated, this index accounts for 24% and 11.3% of the indices when its

        - sub-categories are summed together
        - This makes it the most significant indicator in both indices
        - Humans are incredibly fragile on the economically speaking
            - It doesn't matter how much money the farm makes on a good year if a single drought will kill the family
        - Welfare is something humans invented to hedge the risk of absolute poverty, and in countries where the state is too fragile to provide it, the employer provides it in the form of a consistent paycheck
        - In many poor countries, most people work self-employed in rural areas as there is a lack of stable, high-quality jobs caused by unstable institutions, exclusionary economic policies, and foreign extractivism (as described in *Why Nations Fail*)
            - Even when those are available, most do not have the education to take advantage of them
    - Percent of deaths caused by non-communicable diseases
        - This was the second most significant indicator in PC0 and the fifth in PC1
        - On one hand, diabetes and heart disease is more prevalent in wealthy countries as they can be triggered by an excess ability to access high-caloric low-nutrient foods
        - On the other hand, a high percentage of deaths in non-communicable disease means a relatively low percentage of death in viral infections such as tuberculosis and malaria
        - According to the WHO, "8 of the top 10 causes of death in 2021 in low-income countries were communicable diseases"
        - Effect of communicable diseases on an economy
            - Work-related gatherings may become superspreader events
            - More resources will be used to care and grieve for the diseased (by loved ones or professionals), which hinders their potential to generate economic value
    - Percent of women first married at 15 or 18 (among 20-24 year old women)
        - This was the second most significant indicator in PC1 and the third in PC0, and it had a strong negative weight
        - On the rich end, women in wealthier countries tend to marry much older than 18 (in Canada it is around 30)
        - On the poor end, countries with a culture of teenage female wedlock tend to have strict gender roles and stark gender inequality
            - Many of those countries give women less rights than men, and women are often passed over for opportunities that are afforded to men
            - Marital duties, state-enforced discrimination, and a lack of a quality education may hinder the ability for 50% of the population to meaningfully contribute to the economy
            - This causes some economies to be up to 50% smaller than what they could have been
- Why did we not do independent component analysis? (ICA)
    - The ICA algorithm is non-deterministic, incredibly unstable, and we do not yet have the programming or mathematical knowledge to control what indicator it converges to
    - We tried running the ICA algorithm on the result of the PCA and it generated components with

correlation to the reference indices ranging from r = 0.84 to r = 0.04

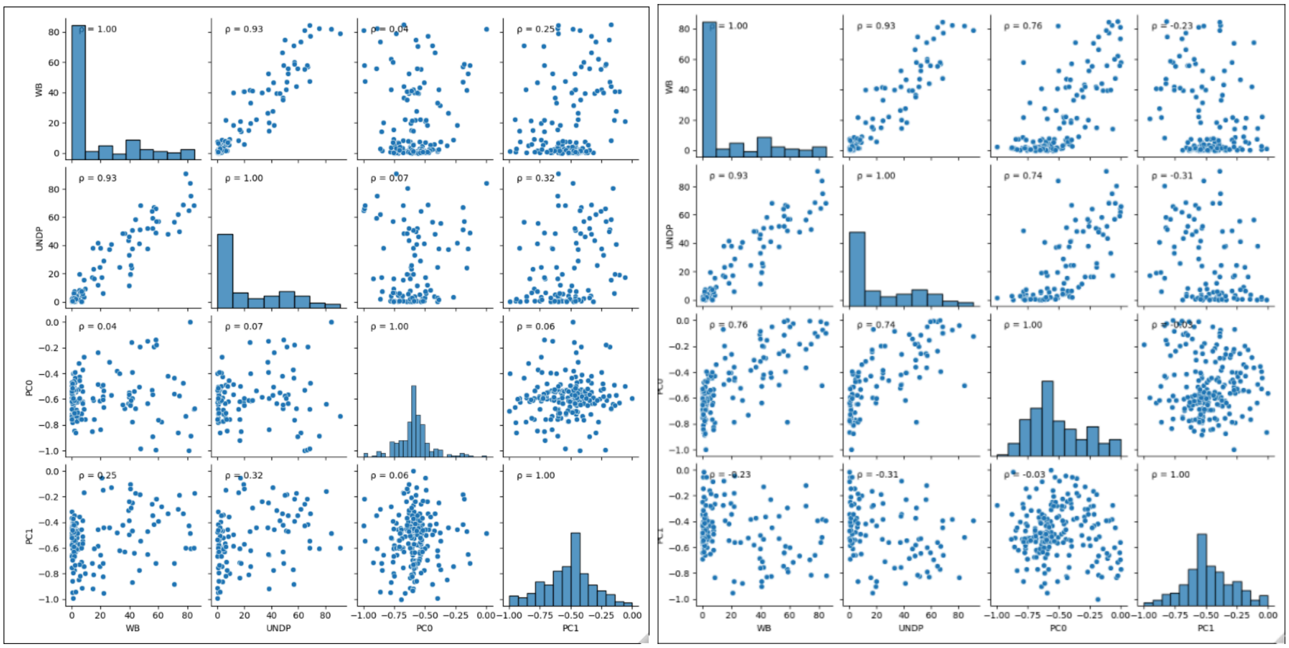


fig. 14: two runs of the ICA algorithm on the same dataset and the same code

# 6. Policy Recommendations

## 1. Boosting Formal Employment in the 20 Poorest Nations

In countries like the Central African Republic, Chad, South Sudan, & much of the bottom 20 of our index, over 70% of workers rely on unstable, informal jobs. These often offer extremely low pay & massive volatility, leaving workers in a constant sense of poverty & uncertainty. Governments should encourage businesses to create formal employment with higher pay & social benefits. Aligned with SAP's sustainability goals, this empowers citizens to run at their best, accelerating local business, & building future skills. SAP can directly support this through digital workforce management tools that help small businesses grow, free educational content to teach valuable skills, & supplying people & businesses alike with key technological infrastructure.

## 2. Strengthening Healthcare in the 15 Most Vulnerable Countries

Nations like Mozambique, Niger, & Burundi see nearly half of their deaths caused by preventable diseases, crippling economic progress & destroying families. Expanding healthcare funding by improving vaccine access, medical infrastructure, & ensuring universal primary care can mitigate this. SAP's data-driven healthcare solutions can help governments allocate resources effectively & software tools can help track disease outbreaks in real time. Furthermore, doing this hits SAP's sustainability goals by clearly providing empathy & care whilst also prioritizing mental health & ensuring well-being.

## 3. Closing the Gender Gap in the 12-Worst Affected Regions

Countries such as Mali, Afghanistan, & Yemen have some of the highest rates of adolescent marriages, limiting women's access to education & economic participation. Strengthening legal protections and expanding healthcare programs for girls can drive long-term prosperity. By doing so, we can fulfill SAP's goals of helping people reach their full potential and driving innovation through diversity extremely effectively. In particular, SAP’s digital education tools can provide remote learning access & career training to help close this gap. SAP offices and/or partners can also host events to provide support for women in this regions & offer insights into work opportunities.

## 4. Expanding Sustainable Infrastructure in the 10-Least Connected Countries

Nations such as the Democratic Republic of the Congo (DRC), South Sudan, & Malawi frequently struggle with unreliable electricity and poor transportation networks, limiting economic opportunities. Expanding renewable energy projects, improving digital connectivity, & upgrading transport systems are crucial. SAP’s sustainability solutions can support these efforts by helping governments & businesses transition to net-zero emissions while ensuring equitable infrastructure development. Furthermore, through digital learning resources citizens can be educated on sustainability & gain insights into new fields which will help their nations & environment prosper for the long-term future. This also strongly aligns with SAP’s sustainability goals of leading by example, collaborating for sustainability, & building future skills.

## Overall Recommendations & Insights

Policies must prioritize the promotion of gender equality, consolidation of healthcare systems, and an increase in formal employment to attain transformative change. Governments must tighten worker protections and offer incentives to companies to create stable, wage-paying jobs. The healthcare system has to be upgraded, particularly in nations where a large number of deaths still result from preventable diseases. Here, digital technologies can be of great help in tracking public health outcomes and resource distribution as efficiently as possible. Furthermore, reducing adolescent marriages and increasing women's labor force participation by education and legislative reforms could improve economic productivity and long-run growth. By enabling data-driven insights for informed policymaking and sustainable development programs, SAP's technology may facilitate these efforts.

It is not just morally obligatory but also possible to eliminate poverty if we act positively and backed by evidence. With the help of technology, community development, and enforcement of laws that ensure social justice and economic stability, it is possible to help millions of people overcome the poverty cycle. SAP's vision for sustainability and innovation places it at the forefront of this battle, towards a future with zero waste, zero emissions, and zero inequalities. If we possess the right rules, resources, and collective determination, we can make sure that no one will be left behind. We hold the future in our hands.

# 7. Appendix (Raw index values)

| Country Name | PC0 | PC1 |
|---|---|---|
| Afghanistan | 0.182240 | 0.147421 |
| Africa Western and Central | 0.656990 | 0.338725 |
| Albania | 0.772654 | 0.721076 |
| Algeria | 0.833691 | 0.910245 |
| Angola | 0.505145 | 0.482538 |
| Argentina | 0.914223 | 0.878541 |
| Armenia | 0.663614 | 0.687013 |
| Australia | 0.922654 | 0.868096 |
| Austria | 0.937082 | 0.864289 |
| Azerbaijan | 0.661500 | 0.654140 |
| Bahamas, The | 0.870207 | 0.902003 |
| Bahrain | 0.868606 | 0.912336 |
| Bangladesh | 0.787281 | 0.581854 |
| Barbados | 0.936222 | 0.859276 |
| Belarus | 0.841466 | 0.968818 |
| Belgium | 0.837844 | 0.963340 |
| Belize | 0.918576 | 0.802431 |
| Benin | 0.398979 | 0.345818 |
| Bhutan | 0.679726 | 0.471395 |
| Bolivia | 0.869523 | 0.604988 |
| Bosnia and Herzegovina | 0.890972 | 0.911109 |
| Botswana | 0.748221 | 0.877289 |
| Brazil | 0.910188 | 0.808545 |
| Brunei Darussalam | 0.892684 | 0.903061 |
| Bulgaria | 0.935823 | 0.873089 |
| Burkina Faso | 0.031162 | 0.082711 |
| Burundi | 0.275209 | 0.270010 |
| Cabo Verde | 0.882898 | 0.834175 |
| Cambodia | 0.738821 | 0.605328 |
| Cameroon | 0.355036 | 0.298269 |
| Canada | 0.922995 | 0.870602 |

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| Central African Republic | 0.000000 | 0.021396 |
| Central Europe and the Baltics | 0.961484 | 0.851632 |
| Chad | 0.060887 | 0.191078 |
| Chile | 0.951455 | 0.818807 |
| China | 0.847382 | 0.808510 |
| Colombia | 0.863952 | 0.738135 |
| Comoros | 0.795709 | 0.591334 |
| Congo, Dem. Rep. | 0.193255 | 0.158182 |
| Congo, Rep. | 0.466559 | 0.366587 |
| Costa Rica | 0.877443 | 0.871935 |
| Cote d'Ivoire | 0.430989 | 0.299986 |
| Croatia | 0.945921 | 0.856877 |
| Cuba | 0.941189 | 0.846287 |
| Cyprus | 0.933836 | 0.870281 |
| Czechia | 0.911429 | 0.874534 |
| Denmark | 0.839611 | 0.969992 |
| Djibouti | 0.780325 | 0.770649 |
| Dominican Republic | 0.907729 | 0.701475 |
| Early-demographic dividend | 0.956311 | 0.610192 |
| East Asia & Pacific | 0.964643 | 0.710658 |
| East Asia & Pacific (IDA & IBRD countries) | 0.945298 | 0.689273 |
| East Asia & Pacific (excluding high income) | 0.943413 | 0.686056 |
| Ecuador | 0.943493 | 0.725220 |
| Egypt, Arab Rep. | 0.929262 | 0.787141 |
| El Salvador | 0.939325 | 0.791769 |
| Equatorial Guinea | 0.292636 | 0.302181 |
| Eritrea | 0.572867 | 0.329081 |
| Estonia | 0.917479 | 0.891072 |
| Eswatini | 0.679745 | 0.962658 |
| Ethiopia | 0.077900 | 0.088798 |
| Europe & Central Asia | 0.954003 | 0.861806 |
| Europe & Central Asia (IDA & IBRD countries) | 0.968270 | 0.844969 |
| Europe & Central Asia (excluding high income) | 0.982790 | 0.792920 |
| Fiji | 0.897740 | 0.885668 |
| Finland | 0.839690 | 0.965445 |

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| France | 0.926567 | 0.871690 |
| Gabon | 0.789541 | 0.828172 |
| Gambia, The | 0.588047 | 0.406154 |
| Georgia | 0.789628 | 0.716896 |
| Germany | 0.929797 | 0.870863 |
| Ghana | 0.604060 | 0.437729 |
| Greece | 0.926180 | 0.811260 |
| Grenada | 0.979993 | 0.749010 |
| Guatemala | 0.916530 | 0.702364 |
| Guinea | 0.036595 | 0.057953 |
| Guinea-Bissau | 0.588608 | 0.479211 |
| Guyana | 0.970538 | 0.785915 |
| Haiti | 0.707837 | 0.494386 |
| Heavily indebted poor countries (HIPC) | 0.593602 | 0.333044 |
| High income | 0.933943 | 0.874291 |
| Honduras | 0.925261 | 0.619136 |
| Hungary | 0.928105 | 0.863953 |
| IBRD only | 0.964344 | 0.690728 |
| IDA & IBRD total | 0.968124 | 0.661689 |
| IDA blend | 0.887435 | 0.533443 |
| IDA only | 0.820252 | 0.451197 |
| IDA total | 0.794410 | 0.463488 |
| Iceland | 0.910358 | 0.881482 |
| India | 0.417699 | 0.302412 |
| Indonesia | 0.829015 | 0.666543 |
| Iran, Islamic Rep. | 0.854035 | 0.768979 |
| Iraq | 0.878633 | 0.774246 |
| Ireland | 0.913719 | 0.877478 |
| Israel | 0.920377 | 0.878963 |
| Italy | 0.939939 | 0.837370 |
| Jamaica | 0.884833 | 0.873731 |
| Japan | 0.867958 | 0.892850 |
| Jordan | 0.835257 | 0.967709 |
| Kazakhstan | 0.886351 | 0.883257 |
| Kenya | 0.640426 | 0.587881 |

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| Kiribati | 0.968058 | 0.812055 |
| Korea, Rep. | 0.910047 | 0.822866 |
| Kuwait | 0.822610 | 0.933359 |
| Kyrgyz Republic | 0.911352 | 0.833498 |
| Lao PDR | 0.387758 | 0.263744 |
| Late-demographic dividend | 0.975158 | 0.731010 |
| Latin America & Caribbean | 0.993013 | 0.799133 |
| Latin America & Caribbean (excluding high income) | 0.994477 | 0.795578 |
| Latin America & the Caribbean (IDA & IBRD countries) | 0.993827 | 0.796539 |
| Latvia | 0.925097 | 0.880238 |
| Least developed countries: UN classification | 0.773067 | 0.418118 |
| Lebanon | 0.834196 | 0.917196 |
| Lesotho | 0.752783 | 0.876293 |
| Liberia | 0.440596 | 0.266570 |
| Lithuania | 0.835736 | 0.970327 |
| Low & middle income | 0.955926 | 0.640777 |
| Low income | 0.589986 | 0.335576 |
| Lower middle income | 0.801172 | 0.509299 |
| Luxembourg | 0.919137 | 0.887287 |
| Macao SAR, China | 0.824877 | 0.925485 |
| Madagascar | 0.197990 | 0.169164 |
| Malawi | 0.645125 | 0.468747 |
| Malaysia | 0.910588 | 0.860481 |
| Maldives | 0.896092 | 0.889053 |
| Mali | 0.267642 | 0.285843 |
| Malta | 0.915484 | 0.890803 |
| Marshall Islands | 0.938725 | 0.770612 |
| Mauritania | 0.608602 | 0.490862 |
| Mauritius | 0.929112 | 0.862647 |
| Mexico | 0.926540 | 0.819366 |
| Middle East & North Africa (excluding high income) | 1.000000 | 0.775883 |
| Middle income | 0.961651 | 0.657248 |
| Moldova | 0.845544 | 0.741688 |
| Mongolia | 0.825481 | 0.775113 |
| Montenegro | 0.885823 | 0.933663 |

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| Morocco | 0.866982 | 0.674975 |
| Mozambique | 0.074093 | 0.051877 |
| Myanmar | 0.776052 | 0.589627 |
| Namibia | 0.734125 | 0.910497 |
| Nepal | 0.282299 | 0.204307 |
| Netherlands | 0.934461 | 0.865349 |
| New Zealand | 0.920415 | 0.864963 |
| Nicaragua | 0.932587 | 0.625046 |
| Niger | 0.058145 | 0.186120 |
| Nigeria | 0.247218 | 0.220525 |
| North America | 0.922078 | 0.895700 |
| North Macedonia | 0.896567 | 0.899106 |
| Norway | 0.817172 | 0.983401 |
| OECD members | 0.947453 | 0.868856 |
| Oman | 0.822203 | 0.970688 |
| Other small states | 0.956613 | 0.834977 |
| Pakistan | 0.868218 | 0.619182 |
| Panama | 0.948101 | 0.797792 |
| Papua New Guinea | 0.552911 | 0.351761 |
| Paraguay | 0.917708 | 0.744956 |
| Peru | 0.919612 | 0.697358 |
| Philippines | 0.898433 | 0.809330 |
| Poland | 0.951054 | 0.831426 |
| Portugal | 0.931590 | 0.854041 |
| Pre-demographic dividend | 0.685571 | 0.378389 |
| Puerto Rico | 0.856485 | 0.904021 |
| Qatar | 0.772638 | 0.999416 |
| Romania | 0.897164 | 0.871816 |
| Russian Federation | 0.842040 | 0.943842 |
| Rwanda | 0.572126 | 0.545426 |
| Samoa | 0.889139 | 0.892959 |
| San Marino | 0.981243 | 0.772003 |
| Sao Tome and Principe | 0.820132 | 0.551722 |
| Saudi Arabia | 0.820821 | 0.916693 |
| Senegal | 0.669582 | 0.422610 |

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| Serbia | 0.857426 | 0.889619 |
| Seychelles | 0.960259 | 0.758454 |
| Sierra Leone | 0.066777 | 0.074137 |
| Singapore | 0.795241 | 1.000000 |
| Slovak Republic | 0.906110 | 0.887253 |
| Slovenia | 0.918795 | 0.878680 |
| Solomon Islands | 0.784252 | 0.528284 |
| Somalia | 0.576303 | 0.535056 |
| South Africa | 0.719434 | 0.968178 |
| South Asia | 0.733491 | 0.458807 |
| South Asia (IDA & IBRD) | 0.733483 | 0.458798 |
| South Sudan | 0.000049 | 0.000000 |
| Spain | 0.932687 | 0.864020 |
| Sri Lanka | 0.899703 | 0.832117 |
| St. Lucia | 0.944308 | 0.844570 |
| St. Vincent and the Grenadines | 0.947149 | 0.862801 |
| Sub-Saharan Africa | 0.733179 | 0.414289 |
| Sub-Saharan Africa (IDA & IBRD countries) | 0.733301 | 0.414345 |
| Sub-Saharan Africa (excluding high income) | 0.733335 | 0.414412 |
| Sudan | 0.700014 | 0.518642 |
| Suriname | 0.935805 | 0.818282 |
| Sweden | 0.915572 | 0.882368 |
| Switzerland | 0.920615 | 0.868174 |
| Syrian Arab Republic | 0.847227 | 0.878927 |
| Tajikistan | 0.882567 | 0.889278 |
| Tanzania | 0.148564 | 0.168527 |
| Thailand | 0.854230 | 0.732245 |
| Timor-Leste | 0.716381 | 0.598716 |
| Togo | 0.479951 | 0.352023 |
| Tonga | 0.887203 | 0.786072 |
| Trinidad and Tobago | 0.871317 | 0.956317 |
| Tunisia | 0.856848 | 0.936171 |
| Turkiye | 0.924152 | 0.779363 |
| Turkmenistan | 0.919363 | 0.888409 |
| Uganda | 0.208329 | 0.227435 |

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| Ukraine | 0.887239 | 0.909900 |
| United Arab Emirates | 0.803999 | 0.934783 |
| United Kingdom | 0.847168 | 0.953614 |
| United States | 0.904618 | 0.887530 |
| Upper middle income | 0.969644 | 0.715987 |
| Uruguay | 0.947236 | 0.825047 |
| Uzbekistan | 0.768668 | 0.856873 |
| Vanuatu | 0.743378 | 0.572331 |
| Venezuela, RB | 0.925009 | 0.819907 |
| Viet Nam | 0.715098 | 0.648590 |
| West Bank and Gaza | 0.915213 | 0.879644 |
| World | 0.989071 | 0.719815 |
| Yemen, Rep. | 0.855936 | 0.618203 |
| Zambia | 0.338903 | 0.267378 |
| Zimbabwe | 0.556323 | 0.463804 |