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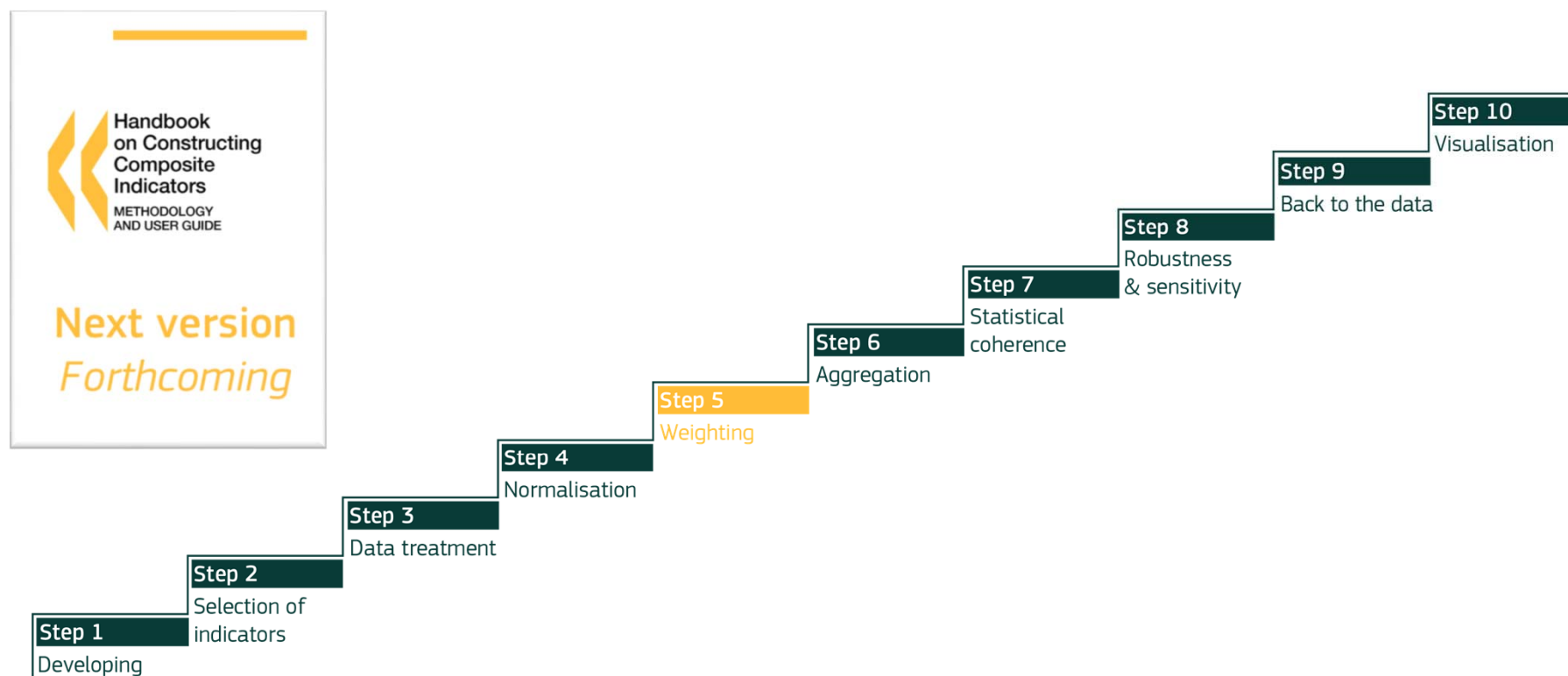
Joint Research Centre

Step 5: Weighting methods (I)

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COIN 2019 - 17th JRC Annual Training on Composite Indicators & Scoreboards
5/11/2019, Ispra (IT)

Ten steps



Weighting

Selecting a weighting scheme for a composite indicator is a delicate task!

- No established methodology on how to choose the best method
- Different stakeholders have different opinions on choosing weighting scheme
- Weights have a strong impact on the final composite indicator score and on the resulting ranking

✓ Take into account the theoretical framework ✓ Be explicit and transparent

Weighting methods

- **Equal weights**
- **Weights based on statistical methods**
 - Principal component analysis
 - Factor analysis
 - Data envelopment analysis
 - Regression approach
- **Weights based on expert/public opinion**
 - Budget allocation process
 - Analytic hierarchy process
 - Conjoint analysis

Equal Weights

Straightforward method

Easy to communicate

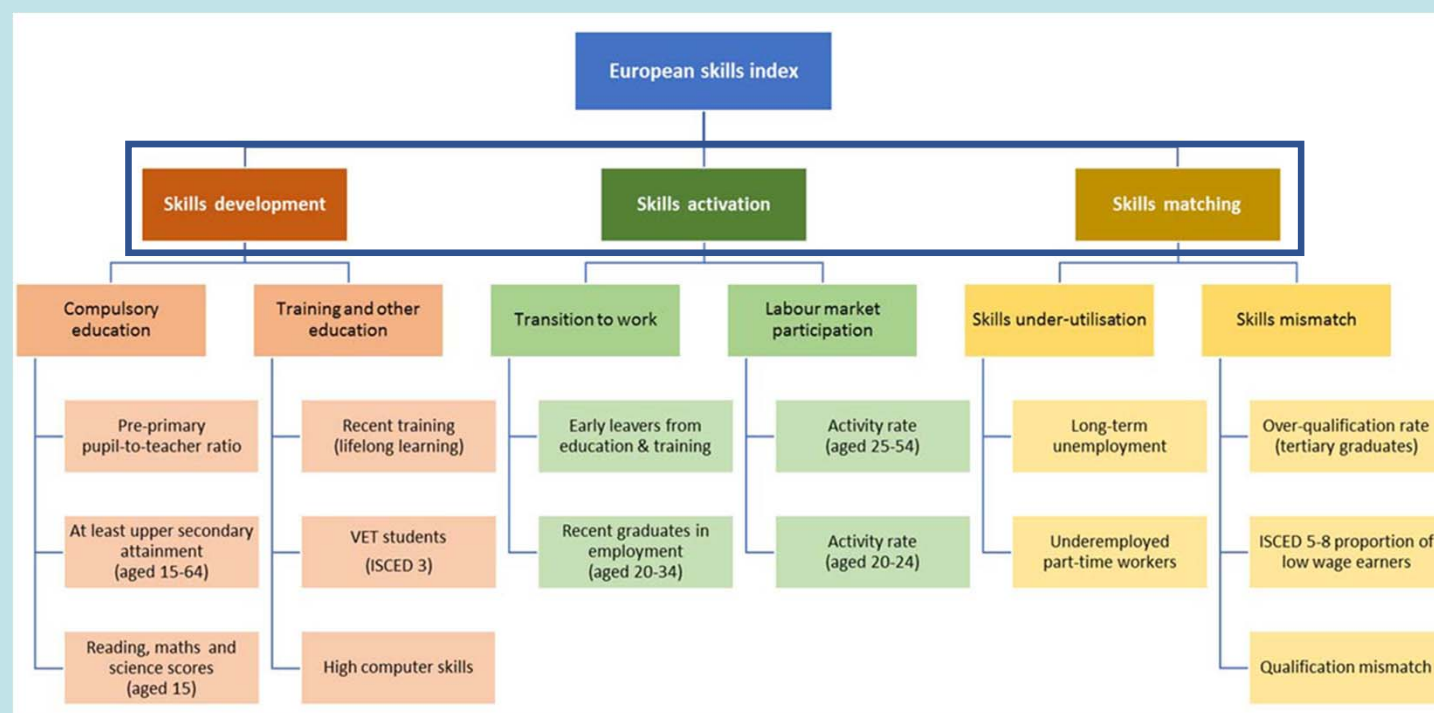
There is no clear reference in the literature about the importance of the elements of the composite indicator

However:

Equal weighing does not guarantee equal importance and equal contribution of the indicators to the composite indicator!

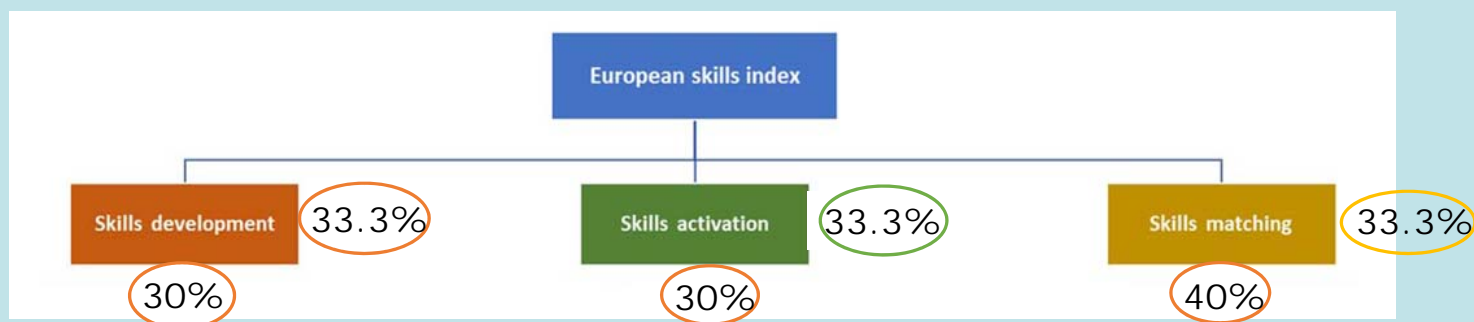


Example 1: European Skills Index



Source: European Skills Index (2018), Cedefop.

Example: European Skills Index



Equal Weights

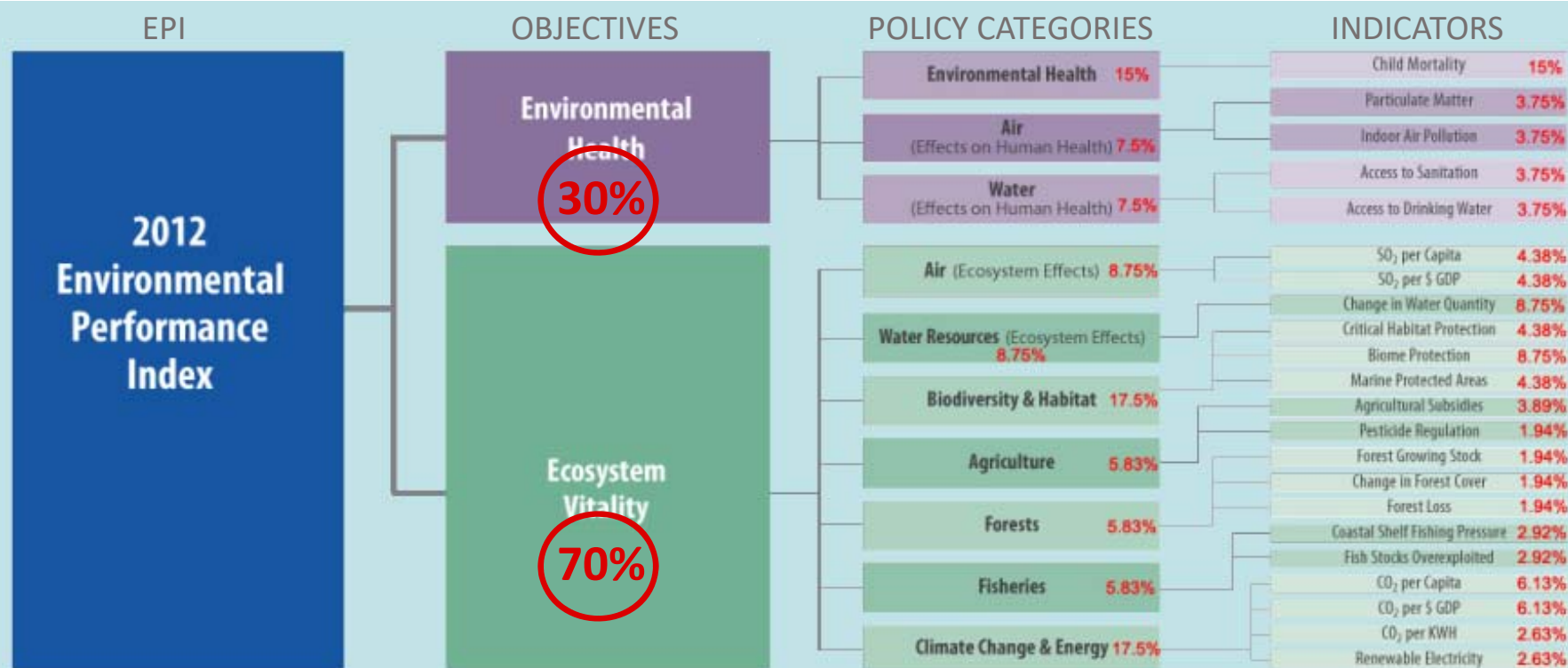
Pillars	Pearson Correlation Coefficient	R ²
Skills Development	0.80	0.64
Skills Activation	0.81	0.66
Skills Matching	0.64	0.41

Adjusted Weights

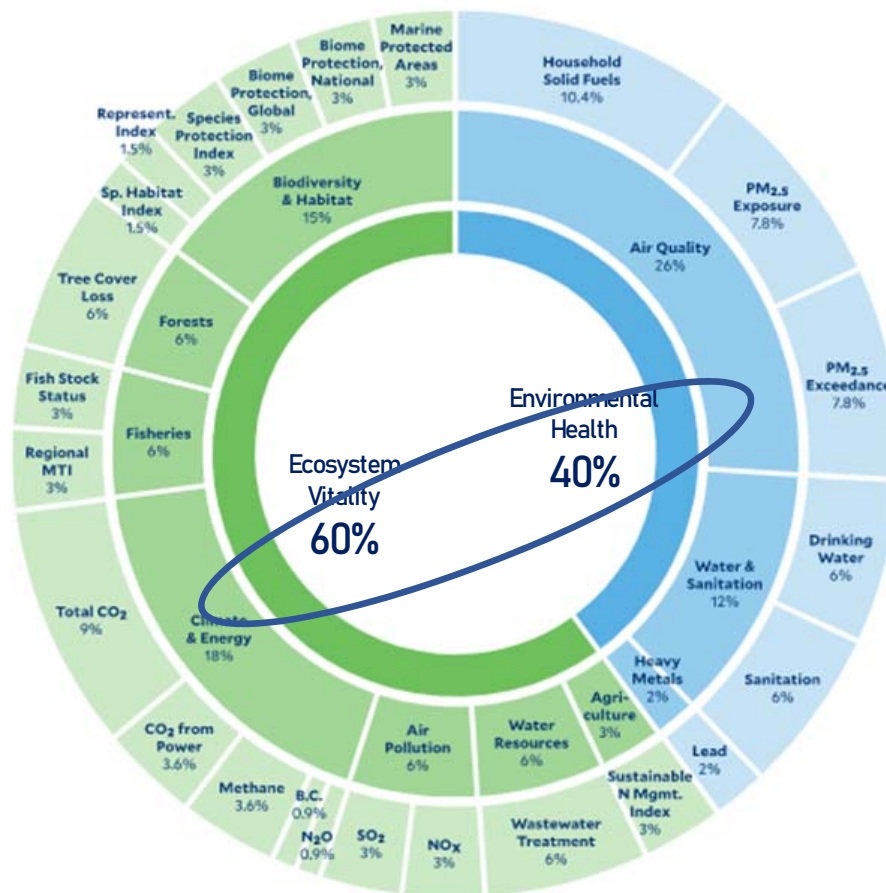
Pillars	Pearson Correlation Coefficient	R ²
Skills Development	0.77	0.59
Skills Activation	0.76	0.58
Skills Matching	0.71	0.50

The unequal weights result in equal importance

Example 2: Environmental Performance Index

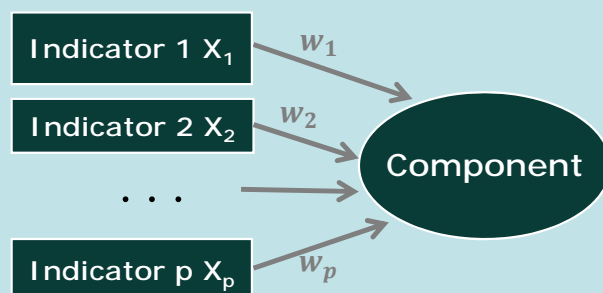


Environmental Performance Index 2018



Principal Component Analysis

PCA



Observed indicators are reduced into components

Identify a small number of “averages” (PCs) that explain most of the variance observed.

PCA summarizes information of all indicators and reduces it into a fewer number of components

Each principal component PC_i is a new variable computed as a linear combination of the original (standardized) variables

$$PC_1 = w_1x_1 + w_2x_2 + \cdots w_px_p$$

But...which is the magic number?

How many components do we keep in PCA?

Several methods exist. The 3 most common are:

1) Kaiser–Guttman 'Eigenvalues greater than one' criterion

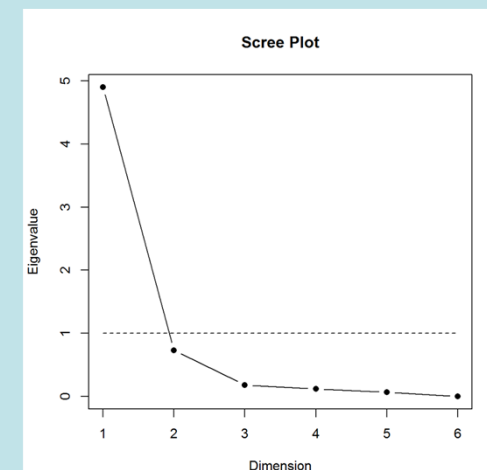
(Guttman (1954), Kaiser (1960)). Select all components with eigenvalues over 1 (or 0.9)

2) Cattell's scree test

(Cattell (1966)) "Above the elbow" approach

3) Certain percentage of explained variance

e.g., $>2/3$, 75%, 80%,...



Weights based on Principal Component Analysis

- This method applies only when we have just one Principal Component (one-dim solution)
- The coefficients (standardised) of the first principal component are used as weights

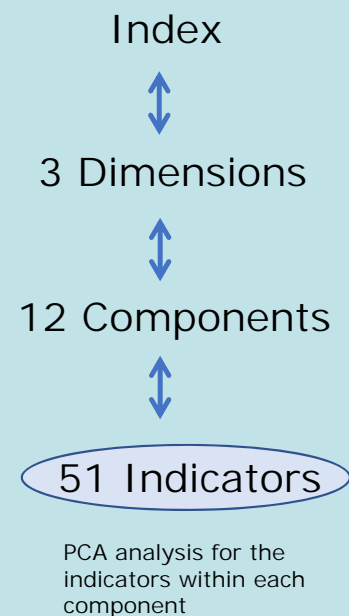
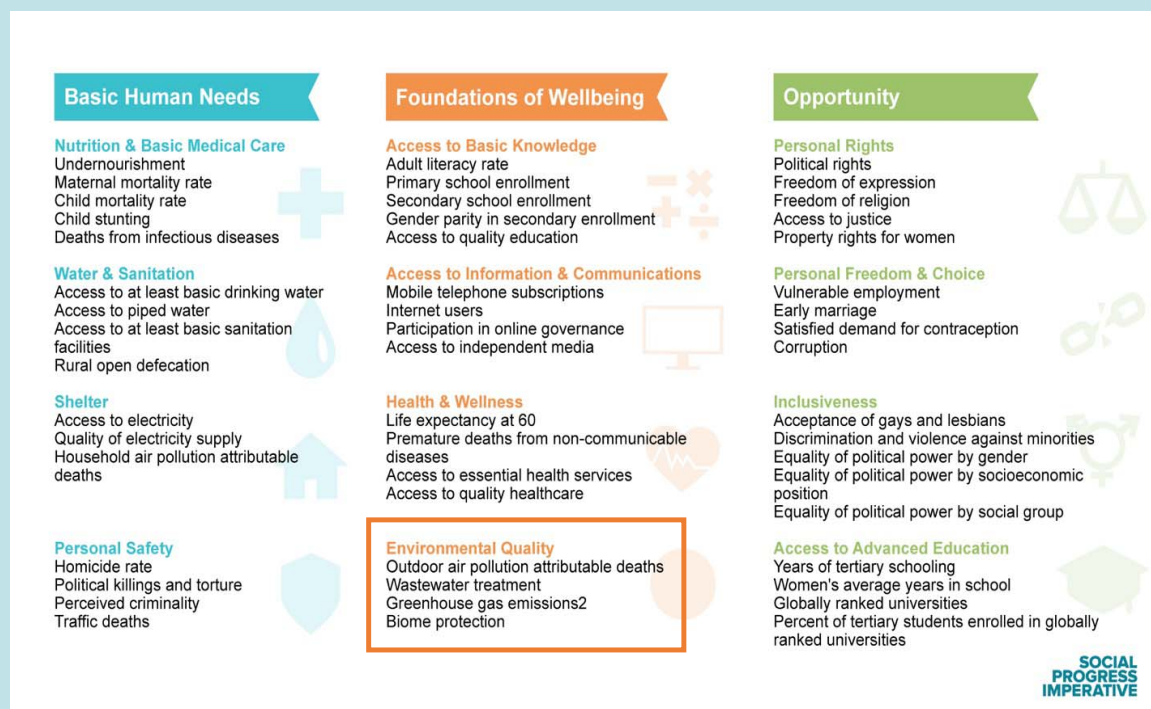
$$PC_1 = w_1X_1 + w_2X_2 + \dots + w_nX_n$$

Weights

Empirical and objective option for weight selection

Good mathematical properties, determining the set of weights which explains the largest variation in the original indicators

PCA weights example: Social Progress Index



Source: Social Progress Index(2018)

PCA weights example: Social Progress Index

Total variance explained			
Component	Eigenvalue	Variance (%)	Cumulative variance (%)
PC1	2.28	57.11	57.11
PC2	0.87	21.81	78.92
PC3	0.51	12.80	91.71
PC4	0.33	8.29	100

*Stopping criterion Eigenvalue > 1.0
(or cumulative variance over 0,70)*

Environmental quality component

Pearson correlation coefficient between indicators and principal components				
Indicators	PC1	PC2	PC3	PC4
Outdoor air pollution attributable deaths	0.88	-0.12	-0.11	-0.45
Wastewater treatment	0.83	-0.13	-0.44	0.32
Greenhouse gas emissions	0.78	-0.26	0.55	0.16
Biome protection	0.47	0.88	0.08	0.03

Weights scaled to unity

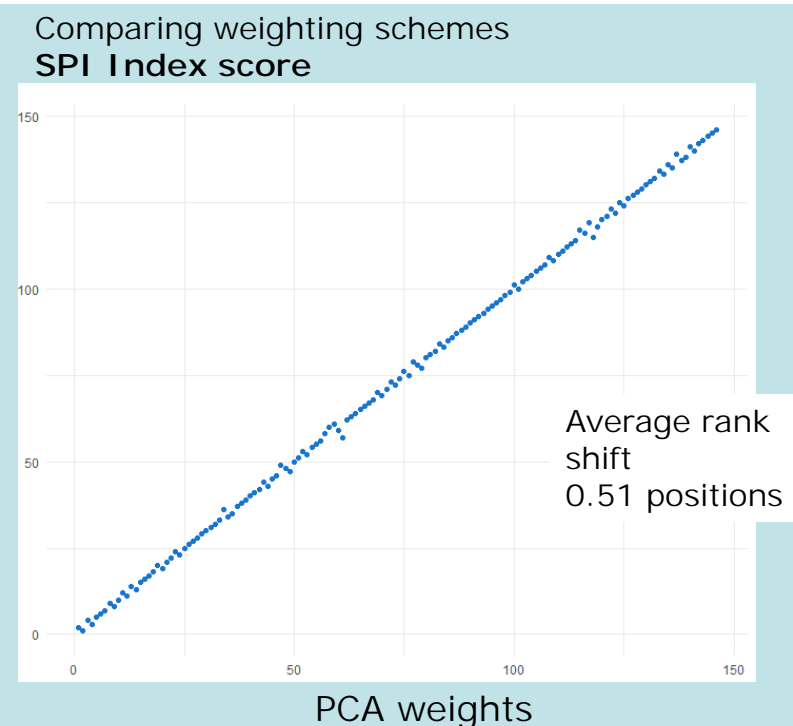
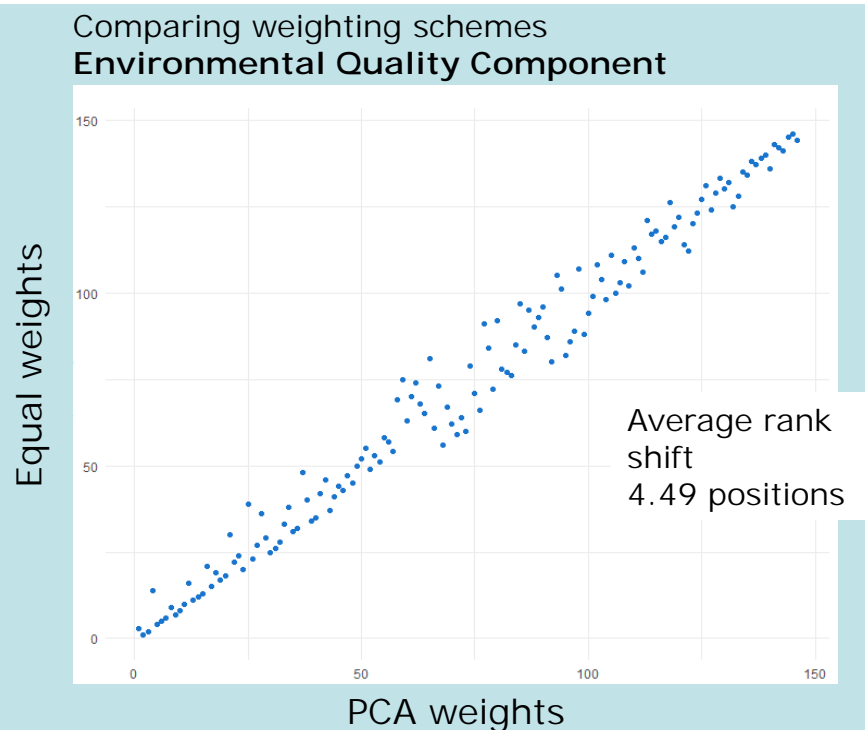
PC1 _{norm}
0.30
0.28
0.26
0.16

Equal Weights
0.25
0.25
0.25
0.25

$$PC1 = 0.88 X1 + 0.83 X2 + 0.78 X3 + 0.47 X4$$

$$PC1_{norm} = 0.30 X1 + 0.28 X2 + 0.26 X3 + 0.16 X4$$

PCA weights example: Social Progress Index



Similar rankings: choose the most simple!

Example: European Skills Index



Total variance explained

Component	Eigenvalue	Variance	Cumulative variance
PC1	1.75	58	58
PC2	0.88	29	88
PC3	0.37	12	100

Stopping criterion Eigenvalue > 1.0 (or cumulative variance over 0,70)

Pearson correlation coefficient

Pillars	PC1	PC2	PC3
Skills Development	0.88	-0.16	-0.44
Skills Activation	0.84	-0.36	0.41
Skills Matching	0.51	0.85	0.09

PC1 _{norm}
0.40
0.38
0.23

$$ESI = 0.40 P1 + 0.38 P2 + 0.23 P3$$

Example: European Skills Index



Equal Weights

Pillars	Pearson Correlation	
	Coefficient	R ²
Skills Development	0.80	0.64
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PCA Weights

Pillars	Pearson Correlation	
	Coefficient	R ²
Skills Development	0.84	0.70
Skills Activation	0.87	0.75
Skills Matching	0.52	0.27

The Index becomes even more unbalanced!

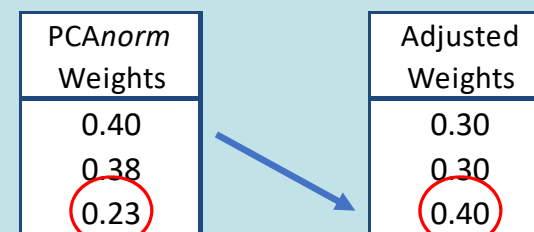
Con: small weights are assigned to indicators which are poorly correlated with others, irrespective of their possible related contextual importance (“Elitist index”)

Example: European Skills Index - Calibrated PCA weights



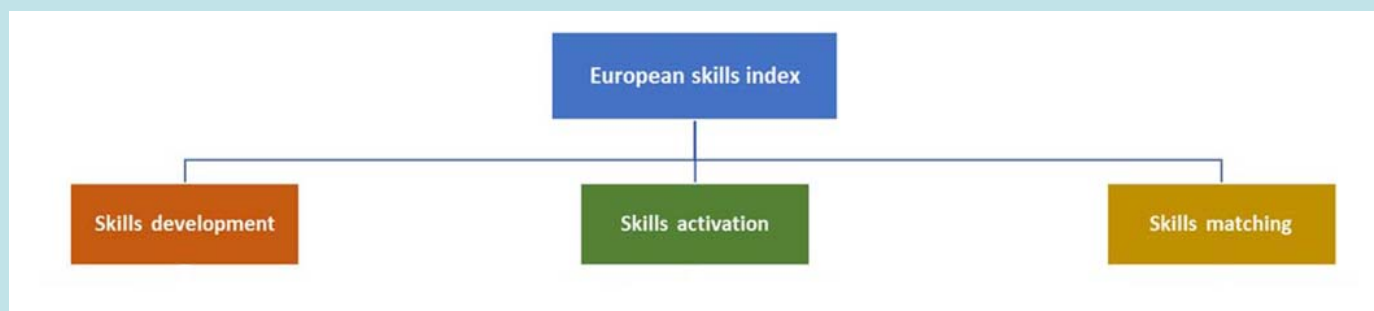
Pearson correlation coefficient

Pillars	PC1	PC2	PC3
Skills Development	0.88	-0.16	-0.44
Skills Activation	0.84	-0.36	0.41
Skills Matching	0.51	0.85	0.09



$$ESI = 0.30 P_1 + 0.30 P_2 + 0.40 P_3$$

Example: European Skills Index - Calibrated PCA weights



Equal Weights

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	Coefficient	R ²
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PCA Weights

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All Pillars are equally important!

Conclusions

Transparency is a key!

Weights have a strong impact on the final composite indicator score and on the resulting ranking. They should be explicit and transparent.

Opt for the simple!

Complicate approaches – more difficult to be communicated.

Test your selection!

The weighting method should always be tested using uncertainty and sensitivity analysis.

References

Becker W., Saisana M., Paruolo P., Vandecasteele I. "Weights and importance in composite indicators: Closing the gap". Ecological Indicators 80:12-22, 2017

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Paruolo P., Saisana M. and Saltelli A., "Ratings and rankings: voodoo or science?." Journal of the Royal Statistical Society: Series A (Statistics in Society) 176.3: 609-634, 2013



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