UNITED NATIONS CONFERENCE ON TRADE AND DEVELOPMENT

Productive Capacities Index

2nd Generation

Enhanced Statistical and Methodological Approach with Results

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Executive Summary

The United Nations conference on Trade and Development (UNCTAD) launched the Productive Capacities Index (PCI) in 2021 (UNCTAD, 2021). The first version of the PCI (PCI 21) covered the period 2000-2018 and 193 economies. The PCI was developed in response to the request by member States at the UNCTAD XIV Conference in Nairobi (the Nairobi Maafikiano Paragraph 76k) and the United Nations Economic and Social Council (E/RES/2017/29) with the aim to guide policy formulation and implementation to foster productive capacities in developing countries.

Fostering productive capacities and structural transformation has been debated at major international conferences, such as the Fourth United Nations Conference on the Least Developed Countries, the Fifth United Nations Conference on the Least Developed Countries, the second United Nations Conference on Landlocked Developing Countries and the fourteenth and fifteenth sessions of the United Nations Conference on Trade and Development. Ministerial declarations, as well as the Programmes of Action, the Nairobi Azimio and Nairobi Maafikiano, and the Bridgetown Covenant adopted at UNCTAD XV, have all underlined that developing productive capacities is key for sustainable development in the least developed countries and landlocked developing countries.

The original methodology for the PCI is described in UNCTAD (2020). For the 2023 release of the PCI (PCI 23) the Index went through different iterations, including extensive testing, consultations and application of an improved and simplified data pipeline. This included an enhanced treatment of missing variables, and the application of new software that has been re-designed to comply with modern programming practices, which results in better flexibility, robustness and readability.

The first Statistical and Technical Advisory Group (STAG) met from 8 to 9 February 2023 at the Headquarters of the Technology Bank for LDCs in Istanbul (Gebze), Türkiye, and served as peer review to the statistical and methodological approach employed in the revised PCI. The STAG "expressed appreciation for the detailed, step-by-step statistical and methodological approaches employed in the construction and updating of the PCI. The Index was found to be a useful tool for evidence-based policy formulation and implementation at the national, sub-regional, regional, and global levels". The STAG also agreed that "the value of the Index lies in its capacity to reorient domestic policy formulation and implementation towards the fostering of economy-wide productive capacities. Its uniqueness as to its multidimensionality, should be maintained and enhanced. Also, the Index should remain simple to facilitate policy interpretation, and to ensure that it is statistically sound, and transparent. The STAG found the statistical tools and methods employed to be appropriate, considering the Index's aim for practical use and given the significant data constraints regarding some indicators and some countries".

Following the STAG meeting, data from the original sources was again updated and adjustments recommended by the STAG were implemented. PCI 23, which covers 194 economies for the period 2000-2022, incorporates newly collected data wherever possible. This edition of the index has been improved by enhancing its methodology through the use of the latest statistical programs and by modifying certain indicators that were used in the previous version of the PCI. This report elucidates the changes from PCI 21 to PCI 23.

PCI users are advised to consult the UNCTADStat Data Centre to download updated data and editable working files to ensure the most recent values are captured in their analysis. Statistics presented through the UNCTADStat Data Centre reflect the most up-to-date revision and should be considered the values of reference.

1. Introduction

This report details the methodological and technical changes made to PCI 23 released on UNCTADstat 20 June 2023. PCI users are advised to consult the UNCTADStat Data Centre to download updated data and editable working files to ensure the most recent values are captured in their analysis. Statistics presented through the UNCTADStat Data Centre reflect the most up-to-date revision and should be considered the values of reference.

The PCI is based on 42 indicators in 8 categories, which refer to variables directly collected or calculated as a combination of other collected variables (see Appendix 3.1.). The indicators were updated with the most recently available data and revisions based on the same sources as the original PCI version, before the update round described herein started. Only when the original source was no longer available was a new source sought.

It is important to highlight at the outset that one of the main challenges for the computation of the PCI is the paucity of data and the comprehensive nature of productive capacities itself. When data is available, it is not necessarily consistent for all the years and countries covered by the PCI, potentially leading to high levels of missing values in the data series used as inputs. Beyond the mere time update, the primary goal of the update was therefore, to improve, wherever possible, the original methodology in dealing with missing data, extrapolating data points. This update cycle also provides an opportunity to rethink the sequence of the building blocks of the PCI accordingly, as well as enhance, modernize and better document the computing programmes.

This report needs to be considered with the background note (UNCTAD, 2023a) prepared for the consideration of the STAG, as the latter does not engage in the *stricto sensus* economic interpretation of the new PCI values, nor does it discuss information on the overarching concept of productive capacities and the rationale for the principles of the PCI. These are also comprehensively discussed elsewhere (UNCTAD, 2020).

1.1 Terminology

In the present report, the following terminology was adopted:

- *"PCI 23"* refers to the updated PCI released on UNCTADstat on 20 June 2023 with data covering 2000-2022.
- *"PCI 21"* refers to the prior, original version of the PCI released on February 2021 with data covering 2000-2018.
- *"Indicator"* denotes a measurable economic indicator, for which data for all countries and all years are available or imputed.
- *"Category"* refers to one of the eight productive capacities that make up the PCI. They may have one or two components.
- *"Component"* refers to the variables extracted from a principal component analysis for a given category.
- *"Raw data"* refers to the untreated, uncleaned data that is collected for all indicators from various sources in various formats.
- *"Input data"* is the data input which consists of values for 194 economies over 23 years, ranging from 2000 to 2022.
- *"Data pipeline"* denotes the various data processing steps necessary to go from raw data to PCI scores. It involves obtaining indicators suitable for principal component analysis (PCA), the main statistical tool used to compute the PCI.
- *"Principal component analysis"* (PCA) is a dimension reduction technique that transforms a set of input variables into a smaller set of components.

2. The New Data Pipeline of PCI 23

PCI 23 not only has updated data, but benefits from an overhauled data pipeline, which is one of the main focuses of this report.

For PCI 21 the pipeline was organized according to the following five steps:

1. Read data;
2. Data interpolation;
3. Series imputation;
4. Series forecasting; and
5. Computing the PCI.

For PCI 23 the above five steps were restructured into the following six:

1. Read data;
2. Data interpolation;
3. Data extrapolation (with special extrapolation made for COVID years);
4. Series imputation;
5. Data transformation and computation of the final indicators; and
6. PCI computation (special steps taken to take into account COVID years).

In Step 1, the data is read and prepared, and the various settings are loaded. In Step 2, missing values for time series with sufficient data are interpolated. In Step 3, these series are extrapolated until the desired year. For PCI 23 data are extrapolated up until 2022. This involves a challenge of accounting for the COVID-19 pandemic. Indicators that were judged to be affected by the pandemic have a special extrapolation rule.

When interpolation is not sufficient, which occurs, for instance, when some indicators are fully missing for some countries, whole series imputations are performed using (nonlinear) multivariate techniques in Step 4. After Step 4, there are no longer missing data. In Step 5, the final indicators, as they are expected to be integrated into the PCI, are computed, considering transformations to meet the requirements for the principal component analysis (PCA). This involves, depending on the indicator, calculating per capita figures, winsorizing, transforming using logit, log or box-cox transformation, and/or inverting the direction of the indicator. In Step 6, the PCA is performed, and PCI scores estimated.

The sequence of the steps is important, as it affects the quality of the imputation, and hence, that of the final PCI estimates. Step 3 is performed prior to Step 4 because it benefits from the extrapolation carried out in Step 3. Step 5 is performed on fully imputed data, as some final indicators are computed using various series, in which a single missing value for a given year in one series will result in a loss of data in the corresponding year for the other series when they are combined to provide the final indicator. The transformations could also be performed before Step 2, but it was found that this had no significant effect on the computations (given the new imputation method applied in Step 4).

The following section provides further details on some of the steps and documents relevant changes compared to the methodology in PCI 21. Wherever relevant, some simulation studies to document the impact of the corresponding changes are included.

2.1 Step 1: Read Data

In this step, raw data from the original data sources on 45 indicators plus the auxiliary variables population and gross domestic product are read in their untransformed form. Some of these indicators are combined in step 5 resulting in the final 42 indicators (e.g., total domestic extraction of raw materials is divided by industry value added to arrive at Material intensity).

Six of the original nine indicators in the Private Sector category belong to the World Bank's Doing Business project. These indicators have been discontinued, with the World Bank discouraging the further use of the indicators. The World Bank is currently "formulating a new approach to assessing the business and investment climate in economies worldwide" through the Business Enabling Environment project (World Bank, 2022).

The indicators from the Doing Business project included in PCI 21 and removed for PCI 23 were:

- *Cost to export a container*
- *Time to export (days)*
- *Cost to import a container*
- *Time to import (days)*
- *Starting a business (time in days)*
- *Enforcing contracts (time in days)*

The indicators included in PCI 23 as replacements are:

- *Lending interest rate (%)*
- *Logistics performance index: Overall*

2.2 Steps 2-4: Dealing with Missing Data

Missing data is a major challenge, especially in low- and middle- income developing countries. The input data consists of 23 observations (one per year from 2000 to 2022) for 194 economies over 47 indicators, for a total of 209,714 data points. Of the latter, about 22% are missing values, most of which appear in either tails of the series or in the whole series (i.e., no observations were collected for this series).

Table 2.1 shows the percentage of missing observations per PCI component and development status of the respective economies. In general, data coverage is better for developing economies and the most missing data are found for LDCs.

Table 2.1

Percentage of missing observations per PCI component and development status.

	Development status		
PCI Component	Least Developed Countries	Other developing economies	Developed economies
Energy	41.0	22.5	13.3
Human Capital	36.3	29.9	14.7
ICT	22.2	18.7	16.2
Institutions	14.0	11.3	14.3
Natural Capital	11.1	10.9	9.6
Private Sector	54.6	42.0	35.3
Structural Change	12.7	10.5	8.1
Transport	60.2	40.2	23.2
Auxilliary	6.4	5.0	4.4

Note: The regional grouping refers to the UNCTAD classification, as specified in the UNCTAD classification, 2023 revision (UNCTAD, 2023b).

As the PCI is of particular interest for the Least Developed Countries (LDCs), special attention is warranted on the coverage of the data for these countries. This helps identify where the biggest gains can be made and where efforts should be concentrated in order to improve the assessment of productive capacities in LDCs. Examples of indicators where better coverage would benefit the Index are *"Research and development expenditure as share of GDP"* and *"Researchers in research and development per 100 people"* in the Human Capital category; *"Total km of rail lines"* in the Transport category; and *"Logistics index"*, "*Patent applications (per capita)"* and *"Trademark applications"* in the Private Sector category. For all these indicators, data are missing for more than 60 per cent of the possible observations among LDCs.

This challenge must be addressed for the PCI to be computed. In PCI 23, similarly to the steps taken in the production of PCI 21, two strategies to deal with missing data are used, depending on whether the series have sufficient observations or not (or, indeed, if they have any observations at all). In the former case, the information provided by the observations in the series itself is used to impute the missing value by interpolation (Step 3) and extrapolation (Step 4); in the latter case, multivariate techniques are used to draw information from the observations and impute the whole series (Step 5).

2.2.1 Step 2: Data interpolation

In this interpolation step, for each country, series with sufficient observations (more than eight observations) and with gaps within the observations (with a maximum gap size of five) are linearly interpolated. Series which do not satisfy these conditions are imputed in Step 4, together with series with no observations at all.

Difference from PCI 21: After testing against other methodologies including "missForest" and "missPCA" (see Step 4), it was decided to keep the interpolation steps as long as the series had sufficient data, which is the same as was done in PCI 21. Other types of interpolation can be considered, but due to the approximate local linearity of the series, not many, if any improvements are expected to be gained with the application of other methods. The main difference from PCI 21 is that if there were trailing NAs in the latter (missing values at the end of the series), the last observed value was simply repeated as a form of crude forecasting. The steps taken in the present approach remain consistent when forecasting in the future and impute the trailing NA values in the next step, "Data Extrapolation".

2.2.2 Step 3: Data extrapolation

Data extrapolation (or forecasting) refers to the prediction of the future values of a series after the last observed data point, and until the last year for which predicted values are desired (hereafter *end year*). If the end year is the current year, this extrapolation would generally be referred to as "nowcasting". While the methodology and its software implementation allow for nowcasting (and indeed forecasting into the long-term future), it should be stressed that forecasting PCI values ahead of any available data merely reflects one possible development based on recent trends and is likely to change once the actual data is observed. Forecasting PCI values further than a few years ahead of available data is not recommended.

Difference from PCI 21: In this step, series are extrapolated using double-exponential smoothing, with the parameters estimated and the extrapolation performed using the function ets of the R package forecast (Hyndman and Khandakar, 2008; Hyndman et al., 2022). For PCI 21, the extrapolation was done in two steps: in the first step, the last observed value was repeated to complete the dataset: this was done because in the PCI 21, the extrapolation took place after the series imputation, for which a complete dataset was required. In the second step, those repeated values were treated as observed, and then two extra years were extrapolated. For the first extra year and for each series, an ARIMA (AutoRegressive Integrated Moving Average) model was fitted to the data with parameters automatically selected and estimated, and an extra year was predicted. Then, the observations corresponding to this extra year were treated as observed, and another ARIMA model was fitted to the data with parameters automatically selected and estimated, and the second extra year was predicted. The ARIMA model and this sequential approach was found to be unnecessarily complex and unreliable and therefore replaced for PCI 23.

Advantages of the new method: Since most series exhibit some trend, using double-exponential smoothing is likely to improve the extrapolations obtained over simply repeating the last observed value. Moreover, this method needs fewer parameters to be estimated than ARIMA. Double-exponential smoothing is known to perform well in a wide range of forecasting tasks including for time series with relatively few observations. In view of the above, it was found that the simplicity of the double-exponential smoothing and its better empirical performance were strong arguments for the change. For the reasons already discussed, it was also decided to perform extrapolation immediately following the interpolation step.

2.2.3 Step 3 bis: Accounting for the COVID-19 pandemic

Some indicators are thought to have been impacted by the Covid-19 pandemic (see Appendix 3.1 for which indicators were modelled to be affected). To extrapolate these indicators GDP was used as a predictor for the values of the corresponding series. For the series corresponding to these specific indicators, this is believed to be an improvement over the double-exponential smoothing, as this latter does not take into account the likely impact of the pandemic. However, it should be stressed that using GDP (or other auxiliary information) as a predictor for the indicator values should not be generalized for extrapolation, as it poses issues of endogeneity. GDP is an output measure of domestic productive capacities. It is only considered here as an exception to reflect the likely effect (in direction, if not in magnitude) of the pandemic on these indicators. For the sake of simplicity, linear regression was used for this extrapolation, in which the indicator series were first regressed on the GDP series in available years to estimate the model parameters, which were then used to predict the missing values until the end year.

Under the PCI methodological framework, which is discussed in Section 3, shocks are captured differently by the PCI depending on their nature. If the shock does not affect the underlying linkages between the different concepts and dimensions defining productive capacities, this will be reflected by a decline in the value of the PCI as long as the effects persist. This may occur, for instance, in the case of a climate disaster, which only has an ad-hoc or temporary effect on a large variety of components of productive capacities. Following the shock, however, the PCI will naturally return to its initial trajectory.

Alternatively, if the shock also has an impact on the linkages across various dimensions of productive capacities, it will also have repercussions on the assessment of productive capacities over the whole time period of the study. In this case, the general trajectory of the PCI will be affected, tending to shift downwards. For instance, a shock which profoundly limits the ability of the manufacturing sector to support exports may have this effect. This is because the loadings of the PCA, in the current methodology, are fixed over time and across countries.

Other specifications are possible for the “loadings”, but they come with major methodological challenges, identification issues and technical complications, against which their potential value added in factoring in structural shocks should be assessed. So far, quantitative analysis and policy recommendations have mostly been formulated based on the PCI factors, but some insights could be also drawn from the loadings, especially with respect to the evolution of the intrinsic definition of productive capacities over time. Beyond the issue of factoring in shocks, the PCA methodology requires a decision on the trade-off in distributing the information between the loadings and the factors.

Another challenge with regard to capturing shocks lies in the timeliness of data. Most data series used in the PCI are harmonized at the international level to ensure comparability, but are, in return, released with a one- or two-year lag at best. It is then difficult to deliver “real-time” estimates of the PCI to inform policy making during the onset of major crises, such as the COVID-19 pandemic or the war in Ukraine.

2.2.4 Step 4: Data imputation

Series which have too many missing values need to be imputed for the PCA to be run: the threshold for imputation (as opposed to interpolation and extrapolation) is set to gaps of 5 or more observations; this of course includes cases where series have no observation at all. That is, for such big gaps of missing values, instead of guessing the values of the series based on trend of previously observed values (in the cases where they exist), the missing values of the series, say, indicator j for country i, are imputed based on the values of the other indicators of the same country, as well as the relationship between the indicator j and the other indicators in countries which have sufficient data on indicator j.

We considered two methods for imputation that were not used for PCI 21:

- "missForest": a non-parametric method using random forests to make iteratively better predictions.
- "missPCA": an expectation-maximization (EM) approach based on iteratively predicting the missing values and computing the loadings of a PCA until convergence is reached.

In both cases, the imputations use information from all other original indicators used for the PCI, for the same country. This is in contrast to the imputation method in PCI 21, where only data for the same indicator but from other countries were used. Empirical results show a better performance of missForest, in particular due to its ability to represent non-linear relationships. These two methods are now presented in greater detail in the following section.

2.2.5 Step 4: Original imputation in PCI 21

In PCI 21, for each series that needed imputation, the imputing values were originally computed as the average of the 5 closest countries with available data corresponding to the indicator. This imputation technique is inspired by theories underlying the specification of "gravity models". If such models make sense when it comes to the trade-related indicators used, it was found that they were not so relevant for other indicators. For example, the original PCI values for DPRK, whose data is significantly affected by missing data, were largely biased by the productive capacities observed in very different neighbouring countries such as Republic of Korea, China and Japan.

2.2.6 Step 4: Imputation with the package missForest

missForest is a nonparametric imputation method that can accommodate almost any kind of data, and is provided in the package of the same name . It can cope with mixed-type variables, nonlinear relations, complex interactions and high dimensionality. It only requires the observations (i.e. the rows of the data frame supplied to the function) to be pairwise independent. The algorithm is based on random forests (Breiman, 2001), which are powerful predictive models which, for the sake of brevity, can be compared to very flexible nonlinear regression models.

Let the series X_j for indicator j be decomposed into an observed and missing part, which can be written as $X_j = (X_{j,obs}, X_{j,mis})$. Likewise, denote by $X_{-j} = \left(X_{-j,obs}, X_{-j,mis}\right)$ the observed and missing part of all the indicators except for indicator j. At every iteration of "missForest" and for each indicator j with missing values, missForest performs the following two steps:

1. Fits a random forest[1] on the observed part $X_{j,obs} \sim X_{-j,obs}$
2. Applies the trained random forest on $X_{-j,mis}$ to predict the missing part $X_{j,mis}$

Put simply, for each variable, "missForest" fits a random forest on the observed part and then predicts the missing part. The algorithm continues to repeat these two steps until a stopping criterion is met or the user specified maximum of iterations is reached.

[1] A random forest is, simply put, a group of decision trees generated using bootstrapped samples and considering only a subset of variables at each step.

2.2.7 Step 4: Imputation with PCA: missPCA

This method, which is referred to as “missPCA”, uses the iterative PCA “imputePCA” function of the package “missMDA” (Josse and Husson, 2016). It imputes the missing values of a dataset with the principal component analysis (PCA) model, by iteratively fitting the imputed model with the completed model and improving the imputed values. More details can be found in the official vignette of the function. It is noted that the iterative PCA algorithm is also known as the EM-PCA algorithm. This makes sense because it corresponds to an expectation-maximization (EM) algorithm for a PCA fixed-effects model (Besse et al., 1986).

This method is perhaps the most intuitive since it is based on PCA, which is later used to compute the PCI. However, through simulations it was found that in the PCI dataset, it does not perform as well as “missForest” (see Figure 2.1).

2.2.8 Step 4: Comparison of imputation methods

A simulation was performed in which, for each indicator, 10% of the series with observations were randomly removed (i.e., replaced by missing values), and the three imputation methods were used to impute these missing values. This provided a way to compare the performance of the methods since the true values of the series that were artificially removed were actually known. For each method and each indicator j, the imputed values $X_{j,imp}$ were then compared to the true values $X_{j,true}$, and the normalized root mean squared error was calculated, defined as

$$\sum_{j} \sqrt{\frac{mean\left(\left(X_{j,true} - X_{j,imp}\right)^{2}\right)}{var\left(X_{j,true}\right)}}$$

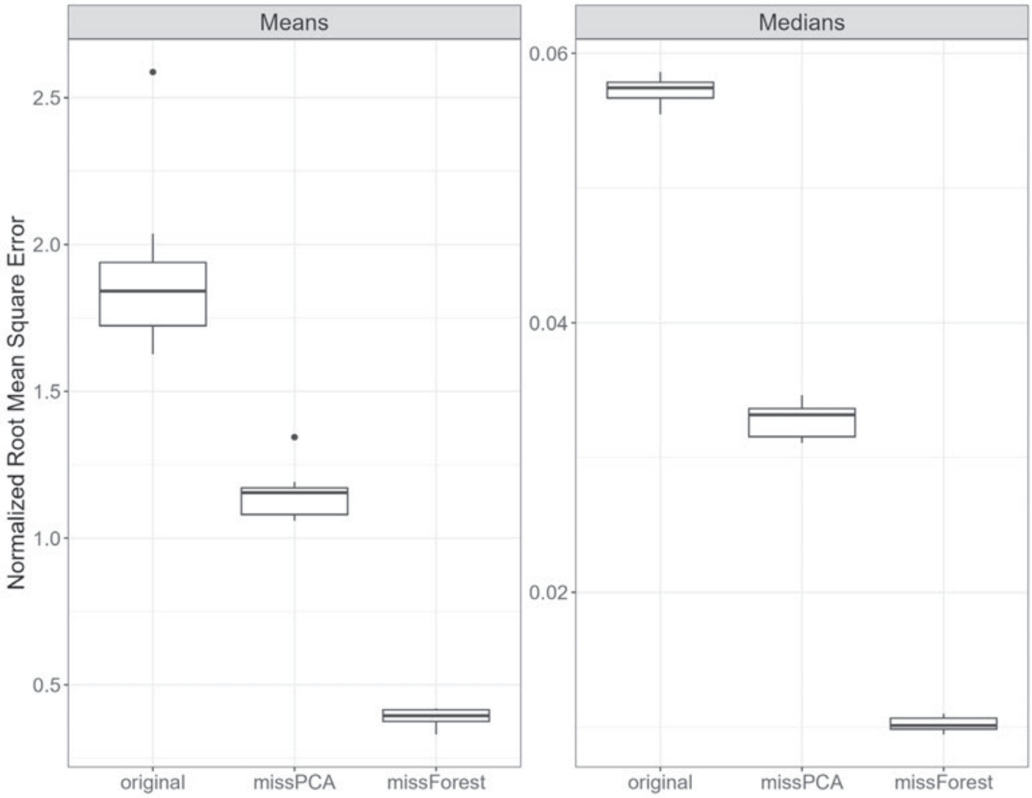
as well as the normalized root median squared error, defined as

$$\sum_{j} \sqrt{\frac{median\left(\left(X_{j,true} - X_{j,imp}\right)^{2}\right)}{var\left(X_{j,true}\right)}}$$

The experiment was repeated 50 times and the distribution of these errors are displayed in Figure 2.1.

Figure 2.1

Summary of normalized root mean (median) squared error for the different imputation methods.



It can be seen that both “missPCA” and “missForest” perform better than the original methodology used in PCI 21, with “missForest” performing the best of all. In view of these results, “missForest” was used for this step.

2.3. Step 5: Data Transformation

After the data have been imputed, they need to be transformed in such a way that they represent the measure of interest and meet the statistical requirements for principal component analysis (PCA). For each indicator separately, the appropriate data processing steps were performed. The data processing steps are indicated per indicator in Appendix 3.1.

Data processing steps were introduced for several indicators in PCI 23 that were not in PCI 21. This gives more robust results from the PCA and results in final scores with more normal distribution and more centralized scores.

2.3.1 Computing special final indicators

To obtain the final indicators used for PCA, two indicators were computed in this stage by combining initial indicators: *Industrial ratio and Material intensity. (Electric power transmission and distribution losses* were calculated before reading data.) The formulas for these and the sources for the initial indicators can be found in Appendix 3.1.
Similarly, another six initial indicators were divided by population to arrive at a per capita form of those indicators.

2.3.2 Transformation

For each year, the distribution of the indicators across countries should, indeed, be approximately normally distributed. This prevents a few countries with abnormally low (or high) values from having a disproportionately large impact in computing the factor.

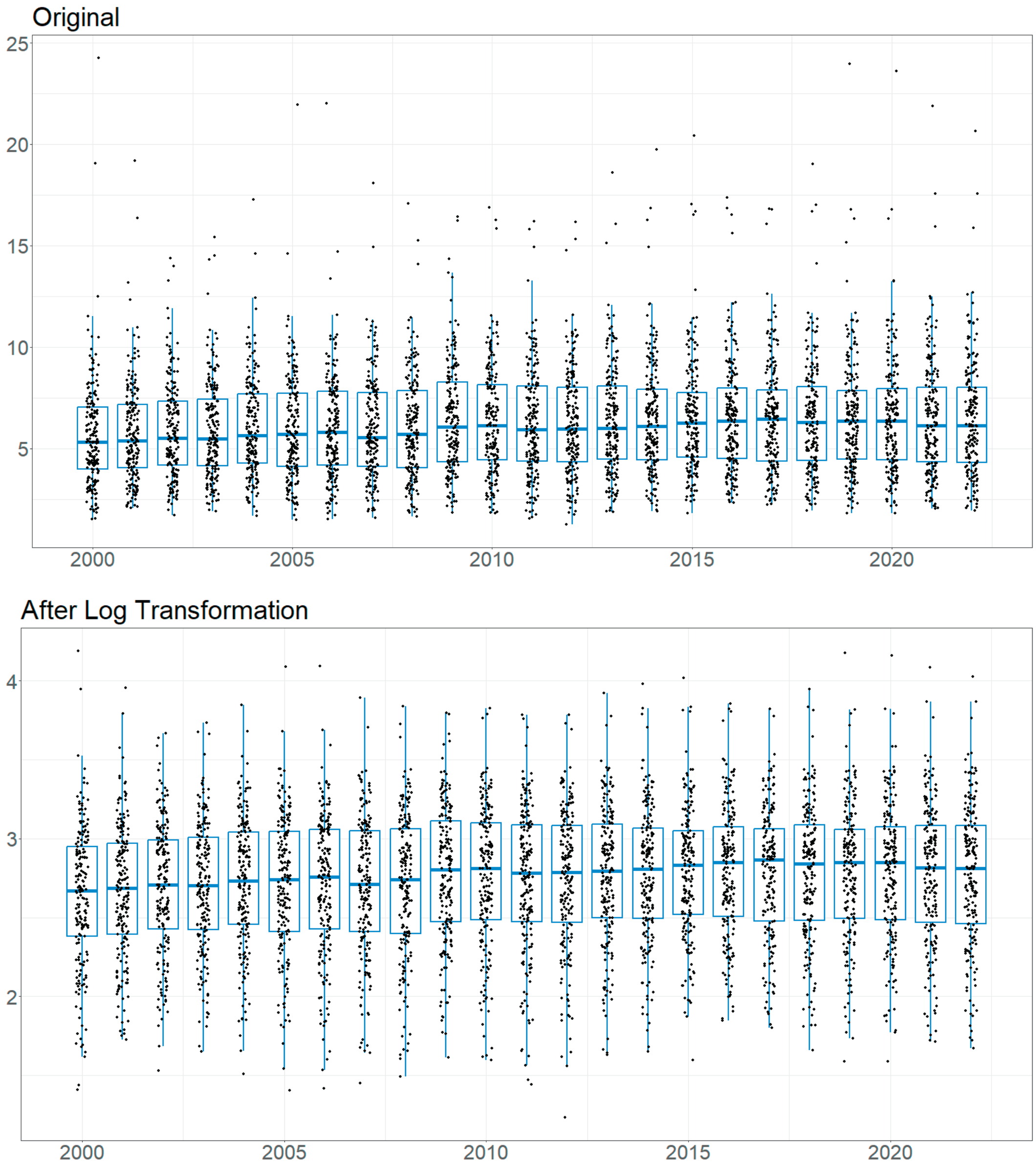
These transformations have implications on the "elasticities" between the PCI values and the indicators. For instance, in its original scale, increasing the health expenditure as a share of GDP from 2% to 3% has the same effect as increasing it from 15% to 16%. It can be argued, especially in view of the empirical distributions and cross tabulations of the series, that the increase from a lower level, say from 2% to 3%, may go along with a greater increase in productive capacities than an increase from 15% to 16%.

It is equally important to stress that, from the policy point of view, the PCI should not be viewed through the behaviour of a single indicator or a component. Instead, it should be seen from an integrated and holistic perspective. It is an improvement in all the components and indicators that will have substantial and irreversible development gains as opposed to generating lags or progress in one or a few categories or indicators. After all, the PCI is designed to guide domestic policy formulation and implementation by reorienting interventions away from traditional, short term and project-based interventions towards holistic and economy-wide approaches to development.

In light of all these considerations, some indicators were transformed using log, logit or box-cox transformations. Figure 2.2 illustrates the effect of log transformation of the indicator *health expenditures as a share of GDP*.

Figure 2.2

Distributions of health expenditures as a share of GDP by year, before and after log transformation.



Source: UNCTAD Statistics' calculations based on variable health expenditure (WHO, 2022).

Most of the indicators requiring transformation are either right-skewed or are compositional data, i.e., they represent a share of some quantity. In the former case, a log transformation is often appropriate (and determined to be sufficient for the construction of the PCI); in the latter case, a logit transformation was considered, which is one of the standard options for compositional data (Aitchison, 1983). In two cases, neither of these transformation methods were judged to be sufficient and were thus treated with a box-cox transformation (Box and Cox, 1964).

2.3.3 Accounting for outliers: Winsorizing

Even after the above transformations, there may be some outliers present in the data. To prevent some outliers from having too much weight in the computation of the PCI, the top and bottom two and a half percent of the data are winsorized prior to performing the PCA (in the case of *Gross fixed capital formation per capita* only the top and bottom one per cent were winsorized). This process moves extreme values from their original point to the value of the specified percentile and adds robustness to abnormal values for the indicators.

2.3.4 Inverting the direction of an indicator

Four initial indicators: *Electric power transmission and distribution losses, Fertility rate, Lending rates, and Export concentration index* are indicators were the lower values (rather than higher) are desirable from the perspective of productive capacities. For the PCA loadings and their interpretation to be consistent, the direction of these indicators was inverted by taking the maximum of the indicator and subtracting the initial indicators value. Thus, hereafter, for example, a positive correlation between the *Human Capital* score and the indicator *Fertility rate* should be seen as a positive correlation between human capital and a low fertility rate.

2.4 Step 6: Principal Component Analysis and Computing the PCI

2.4.1 Raw category scores from principal component scores

Scores are calculated independently for each of the eight categories. For each category a principal components analysis (PCA) was performed. The number of components extracted equals the number of components with both eigenvalues over 1.0 and variance explained over 10%. If more than one component were extracted, these were rotated using *varimax* rotation.

For four PCI components (Human Capital, ICT, Institutions and Transport) a single component was extracted. For the other four (Energy, Natural Capital, Private Sector and Structural Change) the extraction rule results in two extracted components. Multiple extracted components imply that these PCI categories have more than one dimension and since *varimax* is used as the rotation method, the extracted component scores are uncorrelated.

For example, the loadings of the PCA in the Private Sector category imply that the indicators *Patent applications (per capita)* and *Trademark applications (per capita)* are closely related to a second component that is distinct from a component that is more strongly related to the remaining three indicators.

A raw category score is calculated by first calculating component scores for each extracted component. When only one component is extracted, the score on this component is also the raw category score. When two components are extracted the category score is the average of the two component scores weighted by the variance explained of the two components in the PCA.

2.4.1 Scaling and calculating overall PCI score

The raw category scores are scales so that the lowest value of any country in any year gets the score 1. The highest observed score in the time series for the category is given the score 100.

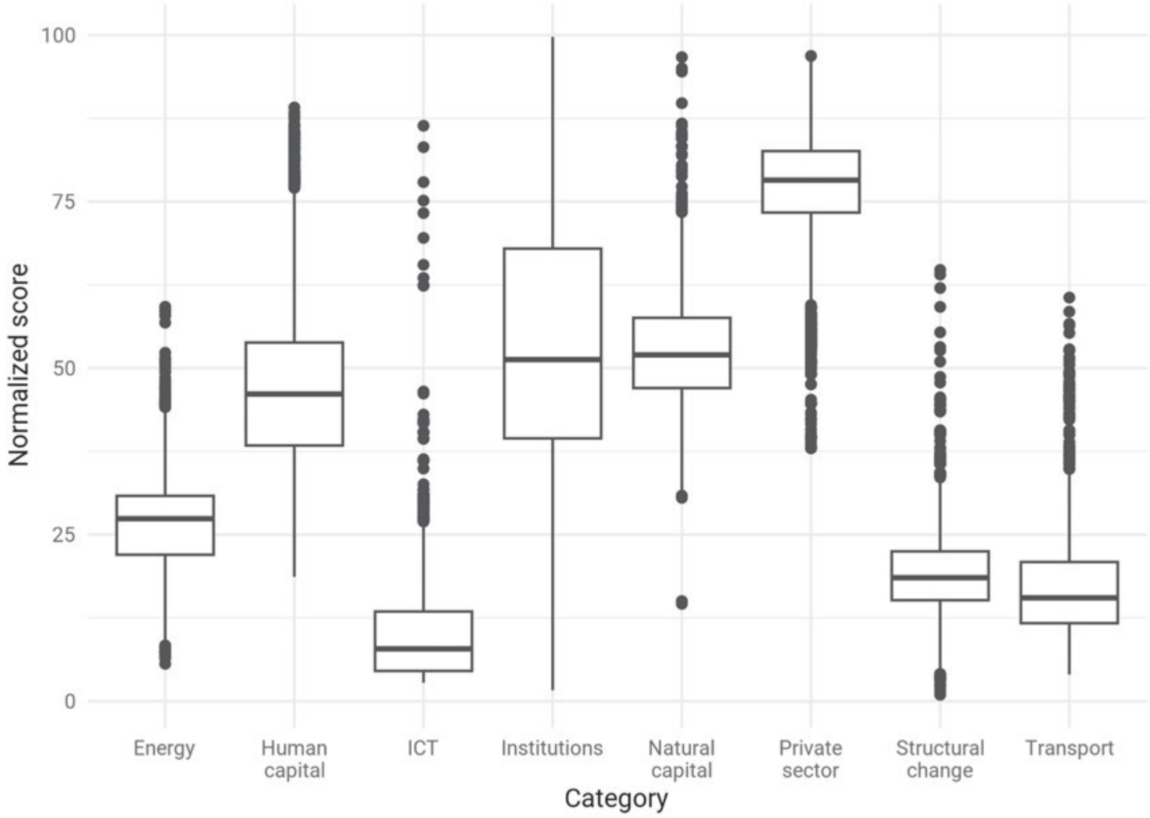
With all categories given a score between 1 and 100, these scaled scores are used to calculate the overall PCI score as the geometric mean of the category scores.

2.4.2 Comparison to PCI 21

In PCI 21 component scores were scaled using *min-max normalization* in a manner that constricted the effective scale of components with more than one PCA component. This came from a method of finding theoretical minima and maxima constructed from minima and maxima on all extracted components. Since all categories except Institutions had more than one component in PCI 21, this affected most category scores. As can be seen in Figure 2.3, only Institutions had scores on the full range between 0 and 100. However, the other categories had values with a more constricted and arbitrary range.

Figure 2.3

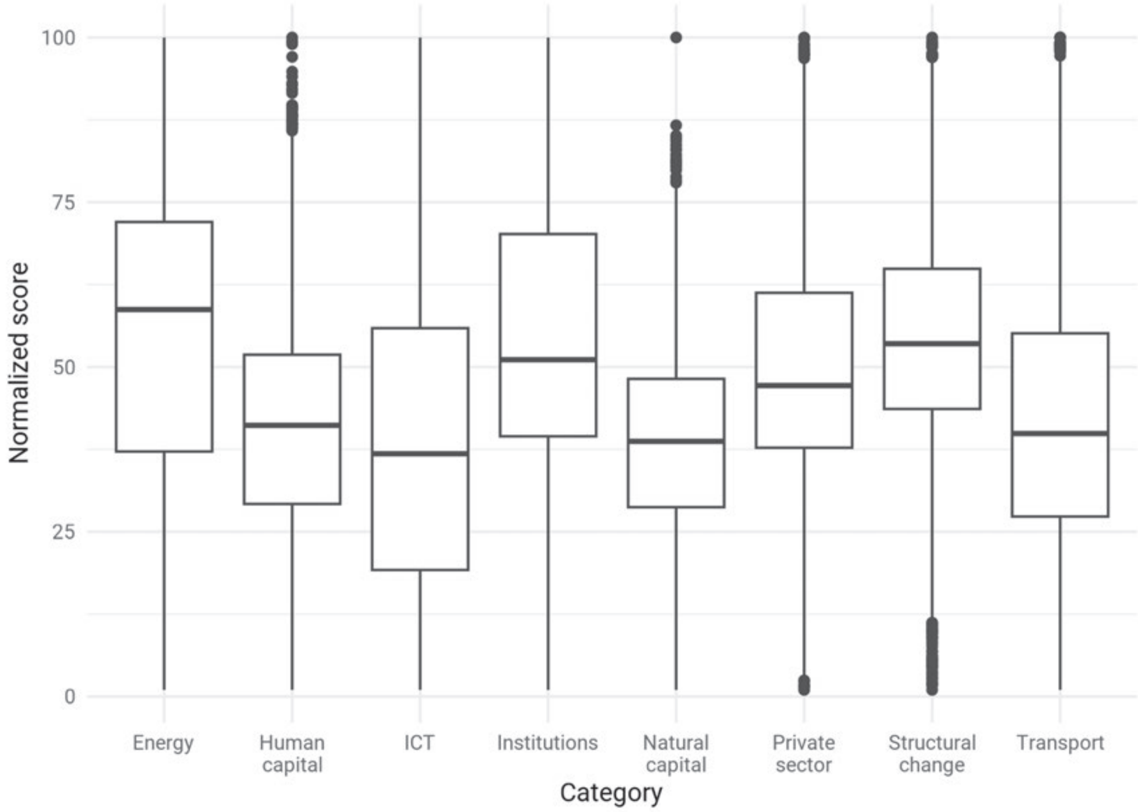
Box plots of normalized category scores in PCI 21 per category 2000 to 2018.



The method of finding theoretical maxima and minima was found to lack value for interpretation and was abandoned for PCI 23. As can be seen in Figure 2.4, though the category scores do not have identical distributions, they all use the full scale between 1 and 100.

Figure 2.4

Box plots of normalized PCI component scores in PCI 23, 2000 to 2022



3. Appendices

3.1 Metadata for Input Variables

Indicator	Source / Formula	Data processing steps	Modelled Covid-19
Energy			
• Access to electricity (% of population)	IEA, IRENA, UNSD, World Bank, WHO. 2023. *Tracking SDG 7: The Energy Progress Report.**		
• GDP per total energy supply (thousand 2015 USD PPP per toe)	IEA World Energy Statistics and Balances. *World Indicators.*		✓
• Renewable energy consumption (% of total final energy consumption)	IEA, IRENA, UNSD, World Bank, WHO. 2023. *Tracking SDG 7: The Energy Progress Report.**	3	
• Total primary energy supply per capita	IEA. *World Indicators*	4	✓
• Total energy consumption (per capita)	IEA. *World Energy Balances.*	1, 2, 4	
• Electric power transmission and distribution losses (% of output)	a/b * 100	4, 6	
a: Losses of electricity output (ktoe)	IEA. *World Energy Balances.*		
b: Electricity output (ktoe)	IEA. *World Energy Balances.*		
Human capital			
• Health expenditure, total (% of GDP)	World Health Organization. Global Health Expenditure database.	4	✓
• Research and development expenditure (% of GDP)	UNESCO Institute for Statistics		✓
• Fertility rate, total (births per woman)	UN Population Division. *World Population Prospects: 2022* National statistical offices Eurostat UNSD. *Population and Vital Statistics Report* U.S. Census Bureau: *International Database* Secretariat of the Pacific Community*	6	
• Health adjusted life expectancy (years)	The Institute for Health Metrics and Evaluation		
• Researchers in R&D (per million people)	UNESCO Institute for Statistics		
• Expected years of schooling	UNDP. Human Development Reports.		
Information and Communication Technology			
• Fixed broadband subscriptions (per 100 people)	ITU *World Telecommunication/ICT Indicators Database**	3	✓
• Fixed telephone subscriptions (per 100 people)	ITU *World Telecommunication/ICT Indicators Database**	3	
• Individuals using the Internet (% of population)	ITU *World Telecommunication/ICT Indicators Database**	3	✓
• Mobile cellular subscriptions (per 100 people)	ITU *World Telecommunication/ICT Indicators Database**		✓
• Secure Internet servers (per 1 million people)	Netcraft (netcraft.com) and World Bank population estimates.*	4	✓
Institutions			
• Control of corruption	Worldwide Governance Indicators		
• Government effectiveness	Worldwide Governance Indicators		
• Political stability and absence of violence/ terrorism	Worldwide Governance Indicators		
• Regulatory quality	Worldwide Governance Indicators		
• Rule of law	Worldwide Governance Indicators		
• Voice and accountability	Worldwide Governance Indicators		✓

Natural capital			
• Agricultural land (% of land area)	Food and Agriculture Organization*		
• Extraction flows (% of GDP)	United Nations Environment Programme, International Resource Panel. *Global Material Flows Database.*	4	✓
• Forest area (% of land area)	Food and Agriculture Organization*	4	
• Material intensity	c / d		
c: Total domestic extraction of raw materials (t)	United Nations Environment Programme, International Resource Panel. Global Material *Flows Database.*		
d: Industry (including construction), value added (constant 2015 US$)	World Bank and OECD national accounts data*		
• Total natural resources rents (% of GDP)	World Bank staff estimates based on sources and methods described in the World Bank's *The Changing Wealth of Nations.**	4	
Private sector			
• Domestic credit to private sector (% of GDP)	IMF, *International Financial Statistics* and data files, and World Bank and OECD GDP estimates.*	4	✓
• Patent applications (per capita)	WIPO statistics database	1, 2, 4	
• Trademark applications (per capita)	WIPO statistics database	1, 2, 4	✓
• Lending interest rate (%)	IMF, *International Financial Statistics* and data files.*	2, 4, 6	
• Logistics performance index: Overall	World Bank: *Logistics Performance Index**		
Structural change			
• Export concentration index	UNCTADstat	4, 6	✓
• Economic complexity index	UNCTAD secreteriat calculations based on UN COMTRADE.		
• Industrial ratio (Industry and Services VA over total GDP)	(d + e) / (d + e + f) * 100		✓
d: Industry (including construction), value added (constant 2015 US$)	World Bank and OECD national accounts data*		
e: Services, value added (constant 2015 US$)	World Bank and OECD national accounts data*		
f: Agriculture, forestry, and fishing, value added (constant 2015 US$)	World Bank and OECD national accounts data*		
• Gross fixed capital formation (% of GDP)	UNSD. National Accounts Main Aggregates Database	2	
Transport			
• Air transport, freight (million ton-km per capita)	International Civil Aviation Organization (ICAO), *Civil Aviation Statistics of the World* and ICAO staff estimates.*	1, 2, 5	✓
• Km of roads (100km2 land)	International Road Federation	2, 4	
• Air passengers (per capita)	ICAO, *Civil Aviation Statistics of the World* and ICAO estimates*	1, 2, 4	
• Km of rail lines (per capita)	International Union of Railways (UIC)*	1, 2, 5	
• Air transport, registered carrier departures worldwide (per capita)	ICAO, *Civil Aviation Statistics of the World* and ICAO estimates*	1, 2, 4	

Notes: *Sourced via World Bank Open Data. Data preprocessing steps: 1. Raw data divided by population, 2. Winsorization, 3 Logit transformation, 4 Log tranformation, 5 Box-Cox transformation, 6. Inverting indicating lower scores as more desirable

3.2. PCA Loadings

The loadings of the indicators grouped by PCI component are presented below. PC stands here for a single principal component. Rotation is not relevant for single components. RC stands for a principal component rotated with varimax rotation. Absolute loadings over .4 are underlined and bolded. For each PCI component, the number of loadings reflects the number of components retained in the formulation of the PCI score.

Table 3.2.1

Loadings for the Energy category.

Indicator	RC 1	RC 2
Access to electricity (% of population)	**.78**	.42
Electric power transmission and distribution losses (% of output)*	**.52**	.48
Renewable energy consumption (% of total final energy consumption)	**-.80**	-.28
GDP per total energy supply (thousand 2015 USD PPP per toe)	-.06	**.89**
Total primary energy supply (per capita)	**.96**	-.05
Total energy consumption (per capita)	**.85**	-.15

Notes: Variance explained: RC1 53%, RC2 22%. *Values for Electric power losses inverted so that higher values indicate more efficient transmission and distribution.

Table 3.2.2

Loadings for the Human Capital category.

	PC
Expected years of schooling	**.89**
Research and development expenditure (% of GDP)	**.78**
Health adjusted life expectancy (years)	**.84**
Health expenditure, total (% of GDP)	**.55**
Fertility rate, total (births per woman)*	**.81**
Researchers in R&D (per million people)	**.86**

Notes: Variance explained: 63%. *Values for Fertility rate inverted so that higher values indicate lower fertility

Table 3.2.3

Loadings for ICT category.

	PC
Fixed broadband subscriptions (per 100 people)	**.93**
Mobile cellular subscriptions (per 100 people)	**.82**
Fixed telephone subscriptions (per 100 people)	**.77**
Individuals using the Internet (% of population)	**.92**
Secure Internet servers (per 1 million people)	**.91**

Note: Variance explained: 77%

Table 3.2.4

Loadings for the Institutions category.

	PC
Control of corruption	**.95**
Government effectiveness	**.95**
Political stability and absence of violence/terrorism	**.83**
Regulatory quality	**.94**
Rule of law	**.98**
Voice and accountability	**.86**

Note: Variance explained: 85%

Table 3.2.5

Loadings for the Natural Capital category.

	RC1	RC2
Agricultural land (% of land area)	.14	**.66**
Forest area (% of land area)	.05	**-.81**
Extraction flows (% of GDP)	**.91**	.11
Material intensity	**.76**	-.05
Total natural resources rents (% of GDP)	**.79**	.10

Note: Variance explained: RC1 41%, RC2 22%

Table 3.2.6

Loadings for the Private Sector component.

	RC 1	RC 2
Domestic credit to private sector (% of GDP)	**.62**	**.47**
Lending interest rate (%)*	**.87**	.10
Logistics performance index: Overall	**.88**	.16
Trademark applications (per capita)	.24	**.85**
Patent applications (per capita)	.12	**.88**

Notes: Variance explained: RC1 41%, RC2 22%. *Values for Lending rates inverted so that higher values indicate lower and more favorable lending rates.

Table 3.2.7

Loadings for the Structural Change component.

	RC 1	RC 2
Export concentration index*	**.85**	**-.09**
Economic complexity index	**.87**	**-.02**
Gross fixed capital formation (% of GDP)	**-.02**	**.95**
Industrial ratio (Industry and Services VA over total GDP)	**.62**	**.38**

Notes: Variance explained: RC1 47%, RC2 26%. *Values for Export concentration index inverted so that higher values represent more export diversification.

Table 3.2.8

Loadings for the Transport component.

	PC
Air transport, registered carrier departures worldwide (per capita)	**.96**
Air transport, freight (million ton-km per capita)	.81
Air passengers (per capita)	**.93**
Km of roads (100km2 land)	**.43**
Km of rail lines (per capita)	**.80**

Note: Variance explained: 66%

3.3. The Productive Capacities Index

The rankings of the countries according to the composite Index of productive capacities computed in the present study are presented below.

PCI users are advised to consult the UNCTADstat Data Centre to download updated data and editable working files to ensure the most recent values are captured in their analysis. Statistics presented through the UNCTADstat Data Centre reflect the most up-to-date revision and should be considered the values of reference.

Table 3.3.1. Productive Capacities Index, 2022 shows the final results of PCI 23, with values released on UNCTADstat on 20 June 2023.

Table 3.3.2. shows the results of the overall index in PCI 23 release on 20 June 2023. Data are presented for the years 2019, 2020, 2021 and 2022. Countries/economies were ranked according to 2022 PCI.

Table 3.3.1

Productive Capacities Index, 2022
(PCI 23 released on UNCTADStat on 20 June 2023)

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
1	Denmark	75.2	90.3	82.2	96.0	29.6	72.0	82.8	63.1	70.3
2	Australia	78.2	83.0	70.4	90.1	44.8	82.8	68.1	54.2	69.8
3	United States of America	78.1	81.6	79.2	79.6	26.7	90.7	94.9	57.3	69.2
4	Kingdom of the Netherlands	79.9	82.4	84.6	92.8	26.2	79.2	85.9	54.6	68.8
5	New Zealand	68.7	79.7	73.8	94.4	30.8	89.4	65.1	58.8	66.9
6	Canada	73.9	73.4	76.4	89.4	30.3	84.7	77.6	53.3	66.8
7	Norway	68.7	81.8	74.0	95.4	27.4	76.8	72.3	62.2	66.4
8	Germany	75.6	83.7	87.3	88.2	20.6	77.7	93.6	48.2	65.8
9	United Kingdom of Great Britain and Northern Ireland	71.8	73.8	83.5	84.7	30.1	76.0	88.2	46.2	65.8
10	Sweden	69.4	93.4	77.7	93.4	18.5	74.9	85.5	58.1	65.2
11	Iceland	72.5	82.4	81.3	91.5	24.0	74.1	51.2	70.8	64.1
12	Austria	73.6	84.5	78.9	87.6	17.8	71.7	90.4	56.9	64.0
13	Switzerland, Liechtenstein	79.5	85.9	85.8	94.6	12.4	84.1	88.4	55.0	64.0
14	Luxembourg	78.7	64.7	87.0	94.2	15.8	94.4	65.3	66.9	63.7
15	Qatar	86.8	43.3	61.5	69.2	51.7	69.8	67.8	68.1	63.6
16	United Arab Emirates	82.7	55.9	79.2	70.9	37.3	72.6	65.4	57.2	63.5
17	Republic of Korea	81.9	100.0	81.8	78.4	12.8	96.6	82.1	46.9	63.0
18	Ireland	91.1	72.5	82.4	88.4	19.2	58.3	70.3	65.1	62.9
19	Belgium	77.9	87.8	77.5	83.1	19.7	73.1	85.3	45.2	62.9
20	France	71.3	76.6	78.4	81.0	20.8	75.7	92.2	48.3	62.8
21	Israel	80.6	85.9	81.6	70.8	27.7	76.4	68.7	41.5	62.8
22	Finland	72.1	90.3	74.2	96.5	18.8	71.3	73.7	51.7	62.7
23	China, Hong Kong SAR	93.3	70.3	99.2	81.4	19.0	100.0	62.8	34.1	61.9

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
24	Malta	78.3	65.7	84.0	74.9	27.2	64.5	57.7	56.8	60.8
25	Bahrain	82.9	47.4	71.1	55.3	42.3	71.7	61.6	64.0	60.7
26	China	69.7	63.9	66.2	50.8	39.8	81.2	99.0	38.2	60.7
27	Portugal	66.4	74.5	71.8	77.7	25.2	70.4	77.4	46.7	60.4
28	Spain	67.8	70.6	68.5	74.6	22.3	74.4	81.2	48.8	59.7
29	Czechia	72.4	70.6	75.4	78.6	28.5	60.8	79.4	37.3	59.4
30	Latvia	66.5	57.1	74.6	75.5	30.0	58.7	75.6	51.0	58.9
31	Poland	71.1	64.9	73.6	68.3	33.8	61.6	79.1	37.5	58.8
32	Chile	69.3	55.8	68.4	73.2	44.4	66.2	56.7	42.2	58.4
33	Guam	81.6	49.5	56.4	77.5	19.7	82.7	55.6	81.3	58.1
34	Hungary	68.5	66.6	77.8	66.5	32.9	50.2	77.1	42.9	58.0
35	San Marino	82.3	52.6	64.2	78.6	11.3	98.2	53.6	95.8	57.8
36	Andorra	75.5	53.3	69.7	77.0	16.3	67.0	58.0	89.7	57.7
37	Japan	75.9	82.6	67.1	86.2	8.6	92.5	88.2	46.2	57.4
38	Estonia	68.1	69.6	85.7	85.2	32.2	63.6	79.0	20.7	57.3
39	Aruba	77.0	53.6	73.6	83.0	14.9	73.1	51.8	78.0	57.0
40	Saudi Arabia	79.0	49.1	67.1	52.3	62.2	57.3	53.2	42.4	56.9
41	Oman	76.2	42.0	55.6	56.7	55.0	64.0	56.2	48.8	56.0
42	Curaçao	71.0	49.5	62.1	72.2	20.0	64.2	55.3	84.9	55.9
43	Tonga	75.2	43.9	40.6	61.5	49.7	54.5	45.0	91.9	55.7
44	Barbados	72.7	53.4	66.2	73.9	18.7	59.9	56.5	76.7	55.7
45	China, Macao SAR	79.9	60.9	68.6	76.3	14.1	72.2	57.5	60.7	55.5
46	Italy	71.7	66.6	66.7	67.7	19.5	69.9	92.0	31.7	55.2
47	Greece	67.5	72.5	61.2	65.0	25.0	64.6	56.8	46.3	54.9
48	Serbia	60.2	58.5	71.3	54.5	40.8	56.1	69.5	38.0	54.9
49	Kuwait	79.0	45.2	45.6	56.0	48.7	68.2	51.7	49.8	54.5
50	Uruguay	60.2	55.5	67.7	78.6	47.4	50.5	53.1	34.4	54.5
51	Cyprus	73.8	58.7	73.8	71.2	23.5	65.1	56.3	38.7	54.3
52	Lithuania	61.9	64.5	80.9	78.4	29.7	57.3	71.1	24.5	54.2
53	Tuvalu	74.6	41.2	44.9	65.6	26.2	58.7	55.0	95.4	54.1
54	Türkiye	68.2	58.3	53.5	46.4	35.9	56.0	81.7	44.5	54.0
55	Croatia	61.7	58.6	68.1	65.7	27.1	59.7	70.4	38.4	53.9
56	Panama	69.1	45.9	61.4	57.2	27.8	61.6	63.7	51.5	53.0
57	Singapore	100.0	81.5	80.3	93.8	3.1	98.4	70.6	43.4	52.5
58	Romania	65.4	49.2	70.1	51.6	37.3	52.0	74.3	33.7	52.4
59	Bermuda	88.2	55.6	81.0	80.5	4.5	95.6	42.4	96.5	52.3
60	Dominica	70.6	45.8	62.1	69.2	18.7	56.7	47.6	78.5	52.2
61	South Africa	57.6	43.6	48.9	55.5	53.4	61.4	63.7	38.7	52.2
62	Malaysia	71.1	46.2	67.1	64.7	35.7	71.0	62.2	24.3	52.1
63	Bulgaria	66.7	55.6	73.2	58.5	39.1	61.0	66.4	21.1	52.0
64	Trinidad and Tobago	82.9	46.0	55.7	56.9	32.6	48.4	49.0	56.7	51.9
65	Seychelles	77.9	43.9	70.1	70.4	14.3	52.8	54.8	71.4	51.6
66	Thailand	63.0	58.7	60.8	49.9	36.7	69.5	74.8	23.3	51.6

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
67	Russian Federation	71.8	57.7	63.0	40.1	36.4	44.5	61.3	46.1	51.3
68	Kazakhstan	74.6	38.9	59.7	48.6	63.3	43.0	51.1	40.6	51.3
69	Saint Vincent and the Grenadines	71.7	45.0	56.3	70.0	15.2	53.8	54.7	81.4	51.1
70	Brunei Darussalam	78.5	41.5	58.6	74.8	30.8	54.4	58.3	32.9	51.0
71	Costa Rica	61.6	54.7	61.4	68.9	27.8	58.5	51.3	38.0	50.9
72	Republic of Moldova	59.8	48.8	68.0	50.1	46.6	46.6	58.5	35.3	50.8
73	Slovakia	71.4	59.4	71.2	70.3	24.7	58.2	63.3	22.5	50.7
74	Cabo Verde	58.3	39.9	42.9	69.0	40.5	48.6	70.3	41.0	50.0
75	State of Palestine	59.3	44.9	51.1	52.7	43.1	51.2	58.1	42.3	50.0
76	Mauritius	72.2	48.4	59.3	74.7	26.0	54.7	56.5	29.2	49.6
77	Mexico	62.0	47.3	53.0	44.0	37.8	51.7	69.8	38.1	49.4
78	Saint Lucia	67.9	44.4	53.2	68.4	14.8	57.2	50.6	75.1	49.4
79	Maldives	71.3	50.5	58.4	53.2	19.2	52.9	61.1	49.2	49.2
80	Cayman Islands	87.5	54.8	86.2	76.9	2.8	94.1	42.7	93.9	49.0
81	Ukraine	61.5	50.5	57.5	44.0	58.6	43.8	52.1	31.5	49.0
82	Belize	57.6	44.1	51.7	51.0	29.8	53.2	48.6	64.2	49.0
83	Mongolia	61.3	38.9	55.9	53.3	74.3	45.2	47.4	29.1	49.0
84	Slovenia	71.2	77.1	76.1	76.4	20.7	60.4	65.2	12.2	48.7
85	Brazil	52.2	57.0	47.7	50.3	39.8	43.9	66.8	37.1	48.6
86	Belarus	69.0	51.7	67.0	36.7	38.0	45.2	60.1	33.4	48.4
87	Armenia	63.7	50.4	57.6	51.3	50.7	49.8	48.5	25.6	48.3
88	Argentina	61.2	58.0	57.7	50.6	38.9	37.7	56.6	32.7	48.0
89	Peru	57.3	48.5	50.2	50.1	39.6	49.8	56.7	34.8	47.8
90	Tunisia	55.3	53.5	49.1	50.5	48.0	47.3	53.7	30.0	47.7
91	El Salvador	52.7	45.1	56.0	47.3	35.5	51.7	56.8	40.3	47.6
92	Timor-Leste	55.2	42.9	39.4	49.6	44.5	40.3	63.4	49.9	47.6
93	Bahamas	75.9	46.4	55.0	68.7	8.8	61.2	55.2	66.2	47.6
94	Colombia	59.8	50.1	50.9	50.1	37.9	44.4	51.0	39.8	47.5
95	Marshall Islands	71.1	40.3	41.3	52.5	23.5	70.2	36.0	69.3	47.4
96	Grenada	70.3	52.0	57.6	66.5	6.0	56.8	61.2	86.3	47.4
97	Viet Nam	62.5	45.2	61.7	48.4	40.6	59.1	70.1	16.5	46.9
98	North Macedonia	56.0	47.8	64.6	56.4	30.3	62.4	65.1	18.9	46.7
99	Indonesia	60.1	40.2	48.8	54.7	37.6	49.4	68.7	27.5	46.7
100	Bhutan	49.2	43.7	43.1	69.1	43.2	48.6	54.9	30.5	46.7
101	Palau	82.4	55.5	43.4	60.1	4.0	82.1	56.3	100.0	46.6
102	Morocco	53.8	48.5	54.5	48.3	41.8	44.3	61.7	28.1	46.5
103	Fiji	61.4	39.3	39.4	62.6	30.3	55.9	50.1	39.5	46.0
104	Suriname	60.3	41.6	48.6	51.0	38.6	40.4	59.4	34.1	45.9
105	Georgia	61.3	50.9	62.5	64.9	36.1	49.3	53.7	15.9	45.8

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
106	Jordan	58.5	44.6	45.7	54.1	30.2	51.8	56.2	34.0	45.8
107	Azerbaijan	67.5	44.2	50.7	42.4	50.3	39.0	39.1	36.2	45.3
108	India	48.3	37.8	37.5	53.6	44.7	54.6	76.1	25.9	45.3
109	Vanuatu	48.9	29.5	36.6	59.2	36.7	53.7	53.6	49.8	44.9
110	Botswana	47.2	35.5	48.5	68.7	39.0	54.5	51.9	26.5	44.8
111	Ecuador	55.8	51.3	50.2	47.4	33.5	49.2	47.6	29.7	44.7
112	Samoa	60.8	36.1	32.1	69.0	26.8	52.5	57.6	39.0	44.5
113	Egypt	59.4	44.1	48.3	39.8	49.7	45.6	52.9	23.7	44.1
114	Kiribati	55.6	35.2	23.7	65.9	50.0	51.7	35.2	51.1	44.0
115	Bolivia (Plurinational State of)	55.6	43.2	44.3	38.6	47.3	48.4	40.9	36.5	44.0
116	Iran (Islamic Republic of)	68.1	52.9	46.3	27.2	47.3	39.5	50.1	32.2	43.8
117	Philippines	53.9	39.7	47.1	48.4	39.6	54.4	57.2	22.6	43.8
118	Algeria	65.3	46.5	38.9	36.5	49.8	42.1	56.0	26.8	43.8
119	Albania	52.6	51.1	58.8	54.3	38.5	51.1	50.7	15.7	43.8
120	Turkmenistan	69.8	41.4	38.4	24.0	52.2	43.1	65.7	33.1	43.6
121	Montenegro	55.5	51.7	68.8	57.2	32.2	63.2	54.0	10.1	43.4
122	Sri Lanka	59.3	42.6	47.8	50.6	26.4	45.7	61.9	26.9	43.3
123	Sao Tome and Principe	54.1	35.2	34.5	50.3	34.5	46.9	46.2	48.1	43.1
124	Djibouti	47.1	24.7	34.3	34.4	52.8	39.9	67.3	61.2	43.1
125	Paraguay	54.1	42.7	45.8	46.6	41.5	51.6	47.6	22.0	42.7
126	Cuba	68.7	56.0	39.8	43.9	34.4	38.5	46.3	25.8	42.5
127	Bosnia and Herzegovina	59.6	50.5	64.2	45.0	37.8	62.7	65.7	7.7	42.4
128	Jamaica	51.3	47.4	50.0	59.9	32.3	45.3	47.5	20.1	42.2
129	Uzbekistan	58.7	36.9	46.9	38.4	53.5	34.9	53.0	25.0	42.0
130	Guyana	59.0	38.3	57.2	50.2	36.2	43.2	45.3	20.8	41.9
131	Nicaragua	38.3	44.0	41.1	33.7	46.1	48.0	48.8	34.6	41.4
132	Dominican Republic	64.2	44.6	52.1	54.4	34.0	44.8	66.1	10.5	41.4
133	Namibia	41.5	37.1	36.7	61.9	49.8	54.8	46.8	18.4	41.1
134	Lesotho	31.0	30.5	27.3	45.2	66.3	38.6	57.0	47.3	41.1
135	Lebanon	62.9	45.0	28.8	31.4	33.9	48.5	48.2	39.6	41.0
136	Bangladesh	52.2	39.5	42.4	37.5	40.3	47.7	57.6	20.8	40.7
137	Nepal	33.8	41.0	43.2	44.2	43.1	46.3	52.5	25.4	40.4
138	Senegal	37.1	31.0	38.0	53.1	43.3	45.9	58.5	18.7	38.7
139	Solomon Islands	37.4	24.9	28.1	49.7	45.2	53.4	31.2	46.1	38.2
140	Honduras	37.2	38.4	40.5	38.4	34.5	48.3	52.7	22.9	38.1
141	Kenya	30.6	35.2	35.9	43.4	44.1	44.2	49.0	25.9	37.8
142	Ghana	52.8	33.7	37.7	56.0	50.9	36.8	36.0	16.3	37.8
143	Libya	57.3	40.9	36.6	14.0	53.5	41.6	41.2	37.1	37.7
144	Eswatini	39.5	36.1	34.6	41.2	48.9	45.0	46.7	19.3	37.6
145	Côte d'Ivoire	35.7	24.7	40.1	44.4	50.6	51.5	47.9	19.3	37.3

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
146	Kyrgyzstan	47.8	41.3	48.2	39.6	57.6	36.0	49.1	9.5	37.2
147	Rwanda	25.4	37.3	28.1	57.1	51.4	40.3	45.4	25.3	37.1
148	Comoros	44.6	32.9	25.0	31.3	49.9	46.9	23.3	56.4	37.0
149	Mauritania	39.1	26.4	35.6	37.4	68.1	35.4	63.6	15.1	36.6
150	Togo	26.1	34.8	30.0	41.1	57.3	48.2	37.8	26.2	36.4
151	Lao People's Democratic Republic	52.6	30.1	37.4	39.4	39.3	33.5	61.3	15.1	36.0
152	Cambodia	44.5	38.1	41.0	38.2	38.3	46.0	47.7	12.4	35.9
153	Guatemala	48.7	36.8	49.1	39.8	37.7	44.6	53.3	6.4	34.5
154	Gabon	41.4	34.0	41.0	38.9	32.0	36.0	42.7	16.0	34.0
155	Gambia	31.0	22.0	32.8	45.0	48.5	29.5	52.5	23.1	33.9
156	Pakistan	40.0	25.5	29.8	37.1	45.9	39.6	42.1	19.8	33.8
157	Tajikistan	44.4	37.3	34.4	31.1	51.1	32.0	48.6	11.5	33.6
158	Papua New Guinea	35.4	25.2	24.9	41.3	35.4	44.2	32.8	33.5	33.5
159	Venezuela (Bolivarian Republic of)	49.6	40.8	47.0	14.2	38.1	35.7	39.3	20.0	33.1
160	Iraq	50.2	33.4	36.7	22.1	47.5	34.2	30.5	19.3	32.7
161	Zambia	26.5	28.1	21.6	44.1	50.6	39.9	52.2	15.6	32.2
162	Nigeria	31.7	23.7	26.6	31.8	49.2	38.4	45.5	19.8	31.9
163	United Republic of Tanzania	22.1	27.8	29.9	43.9	43.5	39.8	43.2	17.5	31.9
164	Myanmar	37.6	35.3	25.9	24.5	41.6	36.0	46.6	18.0	31.8
165	Guinea	25.6	23.8	28.8	33.7	58.4	33.3	34.6	26.0	31.8
166	Liberia	12.9	32.7	20.3	38.4	49.7	36.5	40.9	38.2	31.3
167	Syrian Arab Republic	44.6	30.5	35.2	11.3	59.2	33.5	32.7	23.5	30.9
168	Equatorial Guinea	63.9	24.0	18.4	26.2	31.9	33.8	34.2	29.5	30.8
169	Ethiopia	21.7	27.2	21.1	35.4	46.4	37.7	38.7	25.4	30.5
170	Zimbabwe	24.8	30.3	32.4	27.8	45.3	27.8	39.6	20.7	30.2
171	Mozambique	18.4	26.8	20.0	36.6	52.3	38.0	47.5	16.7	29.5
172	Angola	36.5	24.0	17.8	36.6	45.2	31.9	37.5	17.4	29.2
173	Madagascar	23.4	27.0	18.9	37.3	57.5	28.2	38.5	17.9	29.0
174	Congo	22.5	26.8	19.3	27.6	44.3	32.2	36.1	26.1	28.5
175	Benin	23.7	23.7	29.5	48.8	43.2	47.9	43.8	4.6	27.6
176	Cameroon	27.5	29.6	32.2	31.3	38.6	33.2	42.5	5.9	26.8
177	Sudan	27.0	26.1	15.6	21.0	44.9	31.2	24.7	24.4	25.8
178	Afghanistan	46.4	31.9	18.0	18.6	46.0	25.8	28.1	11.8	25.8
179	Haiti	16.1	26.7	26.5	25.1	42.5	31.5	41.1	10.4	25.2
180	Guinea-Bissau	15.4	30.8	24.0	30.4	48.0	45.8	4.5	41.9	24.8
181	Burundi	8.8	28.7	14.9	25.3	69.8	35.8	22.7	26.6	24.8
182	Central African Republic	13.3	16.6	11.9	19.9	50.4	34.3	44.7	31.7	24.5
183	Eritrea	23.8	23.2	15.0	18.3	52.9	33.3	32.5	12.6	24.0

Rank	Economy	Energy	Human Capital	ICT	Institutions	Natural capital	Private Sector	Structural Change	Transport	PCI
184	Burkina Faso	13.8	25.8	25.5	43.1	54.5	44.5	33.6	3.3	23.9
185	Yemen	45.0	28.0	17.1	11.3	48.6	26.4	24.7	12.5	23.6
186	South Sudan	31.6	22.6	9.5	10.3	51.3	20.5	32.8	36.0	23.3
187	Somalia	19.3	19.1	19.3	8.6	62.3	28.0	33.6	14.6	21.9
188	Democratic Republic of the Congo	6.3	22.3	19.0	38.6	44.7	29.7	44.5	8.4	21.8
189	Mali	19.2	17.4	31.9	31.2	58.7	48.2	23.0	2.2	21.7
190	Uganda	15.9	27.2	22.0	41.1	54.5	34.3	45.7	1.3	21.4
191	Sierra Leone	14.5	32.4	19.0	41.0	73.8	4.8	9.7	21.4	20.1
192	Chad	12.3	17.8	11.9	25.2	83.1	31.3	10.4	10.2	19.2
193	Malawi	10.0	34.4	20.9	45.9	63.0	29.4	24.2	1.0	18.7
194	Niger	4.4	17.7	17.5	38.9	65.3	40.2	37.8	1.2	16.9

Source: UNCTADstat
Note: With regard to PCI values and ranking, small island developing States (SIDS) appear to perform better than other developing countries. However, this performance must be interpred with caution and understood in the context of their unique geographical and structural characteristics. Due to their demographic features (small population) and smaller size and/or surface area, SIDS perform better statistically when measured using indicators that utilize population or geographical ratios as units of measurements. And additional substantive reason for the better-than-expected PCI performance of SIDS compared with other developing countries is their relative shift of their economic activities towards the services sector and particular financial intermediation, tourism and other intangible services.

Table 3.3.2

Productive Capacities Index (Overall), 2019, 2020, 2021 and 2022
(PCI 23 released on UNCTADStat on 20 June 2023)

Rank	Economy	2019	2020	2021	2022
1	Denmark	69.7	69.2	70.5	70.3
2	Australia	70.5	68.7	69.7	69.8
3	United States of America	68.5	67.6	69.7	69.2
4	Netherlands	68.4	66.7	68.8	68.8
5	New Zealand	67.4	66.3	67.2	66.9
6	Canada	66.7	64.8	66.6	66.8
7	Norway	66.5	64.8	66.0	66.4
8	Germany	66.5	64.7	65.5	65.8
9	United Kingdom	67.5	64.4	65.7	65.8
10	Sweden	64.3	62.8	65.4	65.2
11	Iceland	64.3	63.5	64.5	64.1
12	Austria	63.7	62.6	63.8	64.0
13	Switzerland, Liechtenstein	63.5	63.1	63.7	64.0
14	Luxembourg	62.6	62.4	63.6	63.7
15	Qatar	64.1	62.3	63.6	63.6
16	United Arab Emirates	64.0	61.1	62.9	63.5
17	Korea, Republic of	63.8	62.9	62.3	63.0
18	Ireland	66.1	65.3	62.5	62.9
19	Belgium	63.4	61.6	62.6	62.9
20	France	63.4	61.7	62.7	62.8
21	Israel	61.7	59.9	62.7	62.8
22	Finland	62.5	61.5	62.5	62.7
23	China, Hong Kong SAR	65.6	64.2	63.8	61.9
24	Malta	60.8	60.4	60.6	60.8
25	Bahrain	59.6	59.0	60.7	60.7
26	China	59.0	58.7	60.3	60.7
27	Portugal	60.6	59.3	60.3	60.4
28	Spain	59.9	58.6	60.2	59.7
29	Czechia	60.8	58.9	59.7	59.4
30	Latvia	57.5	57.1	58.3	58.9
31	Poland	58.9	57.1	58.4	58.8
32	Chile	58.4	56.8	58.3	58.4
33	Guam	58.1	57.7	57.9	58.1
34	Hungary	58.8	59.1	59.1	58.0
35	San Marino	59.3	57.6	57.7	57.8
36	Andorra	61.1	57.0	57.5	57.7
37	Japan	60.0	58.6	57.2	57.4
38	Estonia	52.1	56.3	57.2	57.3
39	Aruba	56.1	53.6	55.7	57.0
40	Saudi Arabia	55.4	54.1	56.5	56.9
41	Oman	58.4	55.6	55.8	56.0

Rank	Economy	2019	2020	2021	2022
42	Curaçao	56.0	56.7	55.8	55.9
43	Tonga	55.8	55.7	55.7	55.7
44	Barbados	53.8	54.6	55.7	55.7
45	China, Macao SAR	58.6	55.4	55.9	55.5
46	Italy	57.5	55.6	55.4	55.2
47	Greece	54.6	53.5	54.8	54.9
48	Serbia	54.3	52.8	54.6	54.9
49	Kuwait	57.3	54.2	54.4	54.5
50	Uruguay	53.4	53.9	54.8	54.5
51	Cyprus	54.4	54.0	54.2	54.3
52	Lithuania	51.0	54.0	53.8	54.2
53	Tuvalu	55.1	54.7	55.8	54.1
54	Türkiye	54.4	52.2	53.9	54.0
55	Croatia	53.8	52.4	53.6	53.9
56	Panama	52.6	50.4	52.8	53.0
57	Singapore	54.4	53.4	54.0	52.5
58	Romania	51.8	51.0	52.5	52.4
59	Bermuda	51.8	51.5	52.1	52.3
60	Dominica	51.3	52.1	52.6	52.2
61	South Africa	53.6	51.0	52.3	52.2
62	Malaysia	56.6	55.1	54.6	52.1
63	Bulgaria	53.6	53.0	51.6	52.0
64	Trinidad and Tobago	53.7	51.6	51.6	51.9
65	Seychelles	51.9	50.2	50.5	51.6
66	Thailand	55.3	54.2	54.0	51.6
67	Russian Federation	53.0	51.2	52.0	51.3
68	Kazakhstan	51.2	50.6	51.3	51.3
69	Saint Vincent and the Grenadines	50.3	51.0	51.3	51.1
70	Brunei Darussalam	57.1	55.2	53.5	51.0
71	Costa Rica	51.6	50.4	51.1	50.9
72	Moldova, Republic of	50.5	49.9	51.1	50.8
73	Slovakia	46.5	50.1	50.5	50.7
74	Cabo Verde	50.4	50.4	50.0	50.0
75	State of Palestine	49.2	48.4	49.7	50.0
76	Mauritius	53.8	52.3	52.0	49.6
77	Mexico	50.0	47.8	49.8	49.4
78	Saint Lucia	48.2	49.1	49.2	49.4
79	Maldives	48.2	47.9	49.3	49.2
80	Cayman Islands	49.2	48.8	49.1	49.0
81	Ukraine	49.7	47.8	49.4	49.0
82	Belize	48.1	48.7	49.3	49.0
83	Mongolia	50.3	47.7	47.9	49.0
84	Slovenia	57.0	55.0	53.1	48.7
85	Brazil	49.7	47.6	48.7	48.6
86	Belarus	52.0	48.6	48.4	48.4

Rank	Economy	2019	2020	2021	2022
87	Armenia	47.9	46.7	48.2	48.3
88	Argentina	49.6	46.5	48.0	48.0
89	Peru	47.4	45.9	47.5	47.8
90	Tunisia	49.8	46.6	47.5	47.7
91	El Salvador	47.3	46.3	47.6	47.6
92	Timor-Leste	42.6	42.0	46.6	47.6
93	Bahamas	47.2	46.1	47.6	47.6
94	Colombia	49.8	46.8	48.2	47.5
95	Marshall Islands	49.7	46.3	47.7	47.4
96	Grenada	49.6	49.8	49.0	47.4
97	Viet Nam	50.5	50.5	50.4	46.9
98	North Macedonia	46.0	45.5	46.6	46.7
99	Indonesia	46.8	45.6	46.4	46.7
100	Bhutan	49.0	46.9	46.8	46.7
101	Palau	52.6	51.8	49.5	46.6
102	Morocco	46.9	45.3	46.7	46.5
103	Fiji	48.9	47.6	47.2	46.0
104	Suriname	48.8	47.1	45.8	45.9
105	Georgia	50.2	47.2	47.7	45.8
106	Jordan	45.4	44.5	45.8	45.8
107	Azerbaijan	46.9	44.1	45.3	45.3
108	India	44.7	43.9	45.1	45.3
109	Vanuatu	42.8	43.1	44.6	44.9
110	Botswana	45.7	44.2	44.8	44.8
111	Ecuador	46.1	43.3	44.5	44.7
112	Samoa	46.5	45.9	45.3	44.5
113	Egypt	44.0	43.0	44.1	44.1
114	Kiribati	44.7	43.3	44.0	44.0
115	Bolivia (Plurinational State of)	44.1	43.0	44.0	44.0
116	Iran (Islamic Republic of)	47.2	43.4	43.8	43.8
117	Philippines	45.3	43.1	43.5	43.8
118	Algeria	46.3	42.9	43.6	43.8
119	Albania	43.9	43.9	43.5	43.8
120	Turkmenistan	44.4	43.7	43.3	43.6
121	Montenegro	52.7	51.3	44.2	43.4
122	Sri Lanka	44.6	43.0	43.1	43.3
123	Sao Tome and Principe	41.9	41.6	43.3	43.1
124	Djibouti	43.0	42.8	42.7	43.1
125	Paraguay	44.7	42.5	42.9	42.7
126	Cuba	43.8	42.8	42.1	42.5
127	Bosnia and Herzegovina	42.1	41.4	42.1	42.4
128	Jamaica	42.8	43.5	44.1	42.2
129	Uzbekistan	43.4	40.4	42.0	42.0
130	Guyana	43.5	42.7	41.4	41.9
131	Nicaragua	39.6	39.9	41.2	41.4

Rank	Economy	2019	2020	2021	2022
132	Dominican Republic	40.9	39.0	41.6	41.4
133	Namibia	44.1	42.5	41.3	41.1
134	Lesotho	41.0	40.4	40.9	41.1
135	Lebanon	45.4	43.0	42.0	41.0
136	Bangladesh	39.3	39.3	40.1	40.7
137	Nepal	39.7	39.8	40.2	40.4
138	Senegal	37.8	37.2	38.5	38.7
139	Solomon Islands	36.9	37.4	38.0	38.2
140	Honduras	37.5	37.2	37.9	38.1
141	Kenya	37.8	36.7	37.6	37.8
142	Ghana	36.4	36.8	37.6	37.8
143	Libya	38.5	36.8	37.8	37.7
144	Eswatini	38.8	36.5	37.6	37.6
145	Cote d'Ivoire	36.6	36.0	37.4	37.3
146	Kyrgyzstan	42.2	39.6	37.0	37.2
147	Rwanda	34.0	35.3	36.3	37.1
148	Comoros	36.6	36.5	36.6	37.0
149	Mauritania	35.3	33.1	36.1	36.6
150	Togo	34.0	34.6	36.1	36.4
151	Lao People's Dem. Rep.	39.3	38.4	37.8	36.0
152	Cambodia	38.3	37.6	36.4	35.9
153	Guatemala	36.9	36.7	34.3	34.5
154	Gabon	34.4	35.3	34.0	34.0
155	Gambia	31.1	33.1	33.8	33.9
156	Pakistan	32.8	32.7	33.7	33.8
157	Tajikistan	36.0	35.2	35.1	33.6
158	Papua New Guinea	33.1	32.8	33.3	33.5
159	Venezuela (Bolivarian Rep. of)	33.5	33.5	33.2	33.1
160	Iraq	34.5	31.4	32.5	32.7
161	Zambia	34.1	30.7	32.4	32.2
162	Nigeria	31.0	30.8	31.9	31.9
163	Tanzania, United Republic of	31.5	30.9	31.8	31.9
164	Myanmar	35.6	33.5	31.5	31.8
165	Guinea	30.8	31.0	31.6	31.8
166	Liberia	30.6	29.9	30.9	31.3
167	Syrian Arab Republic	28.8	30.3	31.0	30.9
168	Equatorial Guinea	33.9	31.6	30.8	30.8
169	Ethiopia	30.4	30.3	30.1	30.5
170	Zimbabwe	28.9	30.5	29.6	30.2
171	Mozambique	30.7	28.5	29.1	29.5
172	Angola	30.4	28.8	29.2	29.2
173	Madagascar	29.8	28.7	28.8	29.0
174	Congo	30.3	27.3	28.4	28.5
175	Benin	28.0	26.9	27.5	27.6
176	Cameroon	28.4	24.2	27.2	26.8

Rank	Economy	2019	2020	2021	2022
177	Sudan	26.7	25.2	25.9	25.8
178	Afghanistan	29.4	27.6	27.0	25.8
179	Haiti	24.9	24.2	24.9	25.2
180	Guinea-Bissau	24.9	24.5	25.3	24.8
181	Burundi	24.6	24.1	24.4	24.8
182	Central African Republic	24.1	23.5	24.0	24.5
183	Eritrea	24.4	23.8	23.7	24.0
184	Burkina Faso	26.2	22.1	24.1	23.9
185	Yemen, Arab Republic	22.7	24.0	23.7	23.6
186	South Sudan	22.9	23.0	23.5	23.3
187	Somalia	19.8	21.2	21.6	21.9
188	Congo, Dem. Rep. of the	22.5	20.6	21.7	21.8
189	Mali	23.4	25.3	21.4	21.7
190	Uganda	26.3	21.2	21.3	21.4
191	Sierra Leone	19.9	20.2	19.8	20.1
192	Chad	19.9	19.1	19.1	19.2
193	Malawi	22.4	19.1	19.0	18.7
194	Niger	21.0	16.4	16.5	16.9

Source: UNCTADstat

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