

Cameron, Grant J.; Dang, Hai-Anh; Dinc, Mustafa; Foster, James; Lokshin, Michael

Working Paper

Measuring the Statistical Capacity of Nations

IZA Discussion Papers, No. 13895

Provided in Cooperation with:

IZA – Institute of Labor Economics

Suggested Citation: Cameron, Grant J.; Dang, Hai-Anh; Dinc, Mustafa; Foster, James; Lokshin, Michael (2020) : Measuring the Statistical Capacity of Nations, IZA Discussion Papers, No. 13895, Institute of Labor Economics (IZA), Bonn

This Version is available at:

<https://hdl.handle.net/10419/232647>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

DISCUSSION PAPER SERIES

IZA DP No. 13895

**Measuring the Statistical Capacity of
Nations**

Grant J. Cameron
Hai-Anh H. Dang
Mustafa Dinc
James Foster
Michael M. Lokshin

NOVEMBER 2020

DISCUSSION PAPER SERIES

IZA DP No. 13895

Measuring the Statistical Capacity of Nations

Grant J. Cameron
World Bank

Hai-Anh H. Dang
World Bank and IZA

Mustafa Dinc
World Bank

James Foster
George Washington University

Michael M. Lokshin
World Bank

NOVEMBER 2020

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Measuring the Statistical Capacity of Nations*

The international development community has used the World Bank's Statistical Capacity Index since its inception in 2004. The Sustainable Development Goals create new challenges for national statistical systems to produce high-quality and internationally comparable data. This paper reviews measurement methodologies, posits desired attributes, and presents theoretical and empirical frameworks to propose a new, improved index to monitor progress in the statistical capacity of nations. The paper illustrates the properties of the proposed index with global data from 2016.

JEL Classification: C8, H00, I00, O1

Keywords: statistical capacity, statistical indicators, statistical index, national statistical system, data, measurement

Corresponding author:

Hai-Anh H. Dang
Data Production & Methods Unit Development Data Group
World Bank
1818 H St. N.W.
Washington, D.C. 20433
USA
E-mail: hdang@worldbank.org

* We would like to thank the editor James Fenske, four anonymous reviewers, and participants at the World Congress of the International Statistical Institute (Kuala Lumpur) for useful feedback on earlier versions of the paper. We would like to thank Juderica Dias for helpful support with the data and Junhe Yang for capable research assistance. We are grateful to the UK Department of International Development for funding assistance through its Knowledge for Change (KCP) program and Strategic Research Program (SRP).

1. Introduction

The national statistical system, or NSS, plays a crucial role in modern economies. It provides stakeholders, ranging from policymakers to stock market analysts and the general public, with the latest data on the country's socio-economic developments. At the international level, monitoring progress on global undertakings such as the recently established Sustainable Development Goals (SDGs) requires high-quality data that must be produced consistently across different national statistical systems. Assessing and improving the capacity of a country's NSS has long been a part of the global agenda. The international Partnership in Statistics for Development in the 21st Century (PARIS21) Task Team was established in 2002 to help measure country statistical capacity. Over the subsequent years, a few capacity assessment tools have been developed to identify the weaknesses and strengths of national statistical systems.¹

The World Bank's Statistical Capacity Index (SCI) is one such tool that has been widely employed.² Several international and national agencies have adopted the SCI for measuring progress in statistical capacity building and related investments. The United Nations, for example, uses the SCI to measure trends in the development of national statistical capacity (United Nations, 2016). The SCI is used to evaluate the efficiency of statistical support provided to a country as well as the need to further develop its statistical capacity (PARIS21, 2002). Some regional organizations use the SCI to identify areas of improvement in their member countries (OIC, 2012), while researchers use the SCI as a benchmark to validate their new statistical indexes (Sanga et

¹ Statistical capacity is usually interpreted as the ability of an NSS to meet user needs for relevant and good quality statistics in a timely manner. An NSS often consists of a number of different data-producing agencies and departments (such as the national statistical office, the central bank, and statistical departments within other line ministries), which renders the task of directly measuring statistical capacity a difficult one.

² For brevity, we refer to both the Statistical Capacity Indicators and the Statistical Capacity Index as the SCI in the rest of the paper. We will make it clear where we refer to either the indicators or the index. We similarly refer to both the Statistical Performance Indicators and the Statistical Performance Index as the SPI. We also refer to the old SCI as the SCI, and the newly revised SCI presented here as the SPI.

al., 2011). The World Bank mainstreamed the SCI in its monitoring and assessment framework and has adopted it as a baseline indicator in various projects at the country level.³ The SCI is based on publicly available data, and this has various advantages over other indexes of statistical capacity. A key advantage of the SCI is that it can provide an assessment of a country's statistical capacity in an internationally comparable and cost-effective manner.

Existing efforts in building indexes to assess statistical capacity have focused on the practical aspects such as data collection, organization, and legal issues, paying little attention to the underlying theoretical principles that are indispensable for the construction of a reliable, transparent, and consistent statistical capacity index. For example, the UNECE, in a recent Global Assessment report, discusses only the legal basis, description of the statistical system, data source, and processing of the target country (UNECE, 2014). The FAO, in its guidelines for assessing country capacity in producing agricultural statistics, provides instructions on completing the questionnaires and on compiling the assessment indicator (FAO, 2014), but pays no attention to the axiomatic principles of these indicators. The U.S. Census Bureau developed and recently updated (2017) the Tool for Assessing Statistical Capacity (TASC) with a primary objective of measuring the overall capacity of an NSS by providing a breakdown of the areas of strength and weakness. However, the focus of this instrument is on measuring the capacity of an NSS to conduct household-based surveys and censuses.⁴ To our knowledge, only Sanga, Dosso, and Gui-Diby (2011) discuss the technical framework behind the African Statistical Development Index (ASDI).

³ For other recent examples that use the SCI, see: Beegle et al. (2016) for an analysis of the relationship between good governance and statistical capacity in African countries; Tapsoba, Noumon, and York (2017) for the impacts of statistical capacity on reducing procyclical fiscal policy; and UNICEF (2018) for the role of statistical capacity in tracking the SDG for child development.

⁴ We return to provide more discussion on the SCI and these other methods in Section 2 below.

In this paper, we aim at laying out the conceptual foundation behind statistical capacity indexes and construct a new index based on practical and theoretical considerations. We review existing measurement methodologies, posit desired attributes, and propose updated indicators, and an updated Statistical Capacity Index (hereafter referred to as the Statistical Performance Index, or SPI). On the empirical front, we expand the number of indicators in the old SCI by almost twice, and we extend the sample of covered countries by one-half to all countries in the world.

This paper consists of six sections. We provide a brief overview of the SCI in the next section before presenting the theory in Section 3. We offer in this section a detailed discussion on the proposed index ranging from the conceptual framework (including its policy relevance, its concept of statistical capacity, and desirable characteristics) to the technical framework (including its dimensions, aggregation methods, and axioms). We then describe the SPI and its new features before comparing it with the SCI in Section 4 and providing some empirical illustrations in Section 5. Section 6 concludes.

2. Background on the SCI

The SCI is a tool for assessing country-level statistical capacity, developed in 2004 to assess the effectiveness of the World Bank's lending projects related to improvements in countries' statistical capacity. Table 1 compares the SCI with the statistical capacity measurement indexes used by other organizations, including PARIS21, the Food and Agriculture Organization of the United Nations (FAO), the United Nations Economic Commission for Europe (UNECE), the United Nations Economic Commission for Africa (UNECA), and the U.S. Census Bureau. Table 1 shows that the SCI is the only tool that provides comparable data across different countries over time. Further, the SCI covers the largest number of countries—146 countries starting from 2004 and has by far the widest coverage of country-level indicators.

There is also a key methodological difference between the SCI and other assessment tools. The latter methods collect data directly from national statistical offices' staff or local experts. While this procedure may provide more in-depth analysis and uncover finer details in the organization of an NSS, it incurs high costs and is (far) more time-consuming. Furthermore, even the best evaluator can bring personal biases, non-uniform conceptions of capacity, or other subjective elements. Direct interviews of government officials might bias responses and complicate comparability across countries.⁵

The SCI follows a different approach by using publicly available data and focusing on a set of easily observable and verifiable indicators. It provides internationally comparable, objective, country-level assessments. The World Bank has mainstreamed these indicators in its monitoring and assessment frameworks such as the Corporate Score Card (CSC) and the IDA Results Measurement System (RMS). The SCI is also used in various World Bank projects as a baseline indicator.

Yet, there are several areas in which the existing SCI can be improved. First, it comprises of a limited number of indicators and includes no indicators of some important surveys such as the labor force surveys and establishment surveys. Second, it ignores the data dissemination practices of an NSS, which is one of the key features of data usage. Third, the SCI has been criticized for placing too much weight on statistical output and activities, while neglecting the infrastructure and resource components of statistical systems. It was also criticized for its weighting scheme (i.e., equal weighting of each dimension and individual indicator) and aggregation method (i.e., simple arithmetic average).

⁵ Government officials may have an incentive to overestimate their country's statistical capacity when there are concerns about their ability to deliver; the opposite can happen when they are requesting additional international aid or technical assistance.

Finally, since its launch in 2004, the SCI's methodology and coverage have remained the same, while the global data landscape has changed significantly. NSSs have made significant advancements in data collection and dissemination practices. At the same time, the adoption of the Sustainable Development Goals (SDGs) increased the demand for data and raised the bar for national statistical systems regarding their capacity to produce high-quality data. We thus propose to improve the current SCI to better suit the changing global data landscape.

We next present the theoretical framework that can be used to construct an index that measures statistical capacity.

3. Theory

3.1. Outline of Policy Relevant Measurement

In order to construct a measure that is policy relevant, it is helpful to follow a series of basic steps.⁶

The first step asks the question: what phenomenon is being measured? A clear conception helps orient the process by which the measure is assembled and will prove valuable in communicating its underlying meaning.

The second step asks: for what purpose or purposes is the index being sought? Knowing how the index will be used can greatly affect subsequent choices in its construction and its eventual suitability. In particular, it will help define the unit of analysis both for data gathering and reporting purposes.

⁶ This process is similar for many types of measurement exercises. See for example Alkire et al. (2015) in the context of multidimensional poverty measurement.

The third step identifies a list of essential characteristics, or desiderata, that the methodology should exhibit. This list of “pre-axioms” helps orient the construction process and define what success means.

A fourth step identifies the conceptual space in which measurement is to take place. If there are multiple conceptual dimensions, consideration must also be given to the relative importance of each.

The fifth step selects the form of the variables to be used and the aggregation method to be employed – how the variables are to be combined into an overall measure.

The sixth step identifies a set of axioms that the resulting index should satisfy to have the greatest practical utility. Axioms are not sterile mathematical requirements, but rather contain the salient nuggets of policy required of the index: which aspects of the data should be ignored, which should be reflected, and helpful consistency requirements over subsets of data. Together, these six steps comprise the core theoretical elements of our proposed measurement technology.

3.2. Process to Construct an Index of Statistical Capacity

We now turn to a detailed discussion of these six steps and the elements involved in the context of an index of statistical capacity. We will also consider the practical details of our implementation of the general measurement approach.

3.2.1. What Is Being Measured? The Concept of Statistical Capacity

Statistical capacity is the ability of a National Statistical System (NSS) to sustainably collect, compile, and disseminate data to inform national and international policy decisions. A system may have the capacity to produce quality data products but has not yet done so; or it may no longer

have the capacity to produce despite having succeeded in the past. As such, capacity may be largely, but not fully, revealed by observable characteristics of the NSS. Our approach is to focus on the observables for the NSS, and then to expand consideration to a broader range of other performance indicators, to better reflect its underlying capacity. The challenge then becomes how to identify the important dimensions of products and processes that should be covered by such a measure, as well as the specific variables within each dimension.

But before discussing dimensions and variables, it is essential to spell out the purpose of the index and its desirable characteristics.

3.2.2. The Purpose of the Index

The purpose of a statistical capacity index is to assess a country's statistical capacity to monitor the progress of reforms and projects in the area of statistical capacity building and identify the areas for improvements in the National Statistical Systems. An index can also facilitate inter-country comparisons and help interpretation of the trends both within a country over time and across countries.

3.2.3. Desiderata

The desiderata for an index (or more generally a measurement method) are the general characteristics or criteria that we would like it to have. Consider the following list that modifies a standard set found in the literature on measurement.⁷

- i. *Simple*. It must be understandable and easy to describe.

⁷ See, for example, Alkire et al. (2015).

- ii. *Coherent*. It must conform to a common-sense notion of what is being measured.
- iii. *Motivated*. It must fit the purpose for which it is being developed.
- iv. *Rigorous*. It must be technically solid.
- v. *Implementable*. It must be operationally viable.
- vi. *Replicable*. It must be easily replicable.
- vii. *Incentive Consistent*. It must respect country incentives.

The first characteristic speaks to the simplicity of a measurement approach and to the ease with which it might be communicated. Methods that measure an underlying concept in an unclear or unduly complicated fashion discourage participation by stakeholders in policy discussions. When there are significant barriers to understanding a measure, this by itself can lead stakeholders to question its authenticity as a policy relevant tool. In contrast, an index or method that is more easily understood allows stakeholders to evaluate for themselves its qualities. This desideratum also extends to the data upon which the measure is based by requiring a clear and understandable link between the indicators used in an index and the underlying data. If indicators are vaguely defined or sourced, then the interpretation of an index can be superficially clear, but actually obscure. This aspect of the requirement is facilitated by having online data sources and adequate documentation to offer a clear provenance for each indicator. Transparency of the measure and its components is a key characteristic of an index of statistical capacity, which will facilitate its take-up by stakeholders, promote independent confirmation of its findings, and support its credibility.

The second characteristic of coherence speaks to the measure's authenticity in capturing the phenomenon it aims to measure. Simply put, one should be able to describe in plain language the underlying concept of what is being measured by the index, and then argue that this concept is

indeed a credible version of what needs to be measured. In the present case, we will measure a nation's statistical capacity by examining its products and processes.

The third desideratum considers the extent to which the index fulfills the purpose for which it has been constructed. As noted above, the purpose of a statistical capacity index is to accurately and timely measure a country's statistical capacity. In creating the index, it is important to keep the motivating objectives in mind, and work towards their achievement.

The fourth characteristic addresses the rigor of the methodology embodied in the measure. Much of this concerns the aggregation method employed and the axioms that might be satisfied by an index of statistical capacity. For example, one would not want to have a multidimensional index for which unambiguous improvements in individual components would be associated with a decrease in overall capacity as measured by the index. To give substance to this general characteristic, we outline several axioms that the index might fulfill. There are also other measurement problems that a technically solid index should avoid. For example, if the data used in the index are not cardinally relevant, then the index must respect this constraint when aggregating; or if there are several dimensions, but no meaningful basis has been established for comparisons, then the dimensions should not be combined. These latter two examples are closely linked to the broader concern of robustness, which requires results derived from the index to be robust to allowable changes in its components.

The fifth characteristic brings real world data collection and choice into the picture, requiring that the index can actually be implemented using available data. This carries with it restrictions on the qualities of the data to be used, such as the following considerations. Clearly the purpose and the coherence desiderata require the coverage of the data to be sufficient across countries and dimensions. Data should be homogenized across countries to ensure that the individual variables

are comparable and be suitable for evaluating countries at all levels of statistical capacity. This criterion also suggests that the index should be based on publicly verifiable data compiled, collected, and disseminated by the NSS. As such, the actual NSS products—such as the census, key SDG indicators, and other variables—could provide a reliable and cost-effective basis for an index designed to measure its statistical capacity.⁸ Implementability requires a verification that this is true.

The sixth characteristic also places constraints on data but focuses on the additional dimension of time. Not only should the index be able to be calculated and compared across countries at a given point in time but, consistent with its purpose, it should also be possible to construct the index across many points in time. Consequently, the data requirements should also be maintained through time to allow reasonably consistent estimates of progress and this should translate to a time path that is coherent and predictable. In contrast, if an index were to exhibit undue volatility through time this could suggest replicability problems stemming from the data, the aggregation method, or from both. It should be noted that replicability is also supported by the simplicity desideratum, which can lower the cost of replication by others and hence ensure that, through many eyes, there are fewer errors.

The seventh and final criterion concerns the interaction between actions by the NSS and the behavior of the index through time. In essence, a country should not see its index of statistical capacity fall when the only movement between time periods is an improvement in individual variables. Some global indices are constructed in such a way that the index value itself depends on

⁸ Again, other sources, such as expert opinions or intensive studies carry with them a number of problems, including high monetary cost and increased measurement error due to country-specific orientation and idiosyncratic or irregular collection. The choice of data will be further discussed below.

data from *other* countries. A given country can achieve absolute improvements in all facets of the measure and still have its index value drop.⁹ This possibility can disrupt the clear pathway between a country's policies and the index level, thereby diminishing the government accountability that the index is meant to support.¹⁰ Alternatively, suppose the index adopts a goal-oriented or targeted approach, by which targets are set and progress is measured as the extent of movement towards reaching them. A target may be fixed through time – like an absolute poverty line – when conditions change, or it might vary with the outside conditions – like a relative poverty line would. In the latter case, it can be unclear whether the progress (or lack thereof) is due to changes in the underlying variables of interest or changes in the target. Incentive consistency suggests using fixed or absolute targets that link the measure to actual progress.¹¹

In sum, constructing a measure of statistical capacity entails many distinct choices that can appear to be arbitrary and unrelated to one another if no context is provided. A set of desired characteristics, or desiderata, can provide the guiding principles that help organize these choices to obtain a relevant and useful measurement tool. The desiderata described above will be invoked several times in what follows.

⁹ This was a problem with the traditional Human Development Index, which relied on empirical goalposts (or its highest and lowest values for each dimension) to fix its minimum and maximum values. See Alkire and Foster (2010).

¹⁰ Undue volatility of an index, where the changes in index level appear to be spurious or unrelated to actual policies, can likewise disrupt the policy relevance of the index as an accountability tool. We return to more discussion in the next section.

¹¹ We would like to thank an anonymous reviewer for suggesting the additional criterion of non-manipulability for constructing the index. On one hand, the issue of manipulability is partially related to the desideratum of incentive consistency, where countries are accountable for improving their scores in a transparent way as discussed earlier. But on the other hand, it should be recognized that the index should accurately reflect the real progress with statistical capacity that countries make and should not be easily changed with only cosmetic alterations in the statistical processes. Put differently, the index should not be easily manipulable by the interested parties (for example, an NSO's management may artificially increase the index to demonstrate their good performance). Yet, while the importance of such an index property is well recognized, it is difficult to formalize in practice. One good way to achieve this might be to make the index as transparent as possible (as we have attempted to do here) and have civil society and the international statistical community scrutinize any changes in the index and hold NSOs accountable for such changes.

3.2.4. Dimensions

The concept adopted here views the statistical capacity of an NSS in terms of its range of products, and the processes it uses to produce and disseminate them. The production process for statistical outputs has certain similarities to the traditional production model from economics, and this analogy might be useful for identifying the salient dimensions of a statistical capacity measure. The production process begins with a technology that is used in generating statistical products, and the level of this technology is clearly a relevant component of statistical capacity. The resulting statistical outputs might be divided into two general categories. First are the intermediate products, which have direct use for specialists but require additional processing to create products suitable for general use. For example, a census can be helpful for policy analysts but must be processed to obtain useful statistics. Second are the final products, which are available in a form that can be understood by the public. The key macro statistics of a country would naturally be viewed as final products. Even after the products have been created, their existence does not imply that potential users will actually have access to them. Statistical products may be available to only a few users, or available to all. The final dimension then covers the extent to which statistical products are disseminated.

This simple framework helps to identify four coherent dimensions for a measure of statistical capacity, namely: (i) Methodology, Standards and Classifications (MSC), which provides information on the technology being used by the NSS; (ii) Census and Surveys (CS), which describes the intermediate products of the NSS; (iii) Availability of Key Indicators (AKI), which focuses on key final products needed for policy; and (iv) Dissemination Practices and Openness (DPO), which evaluates the extent to which products are publicly disseminated. It is easy to see

that each of these dimensions is centrally related to the statistical capacity of an NSS.¹² We return to more discussion on these four dimensions in Section 4.1.

As with any measurement exercise, there will likely be dimensions missing from the list. One dimension that could be particularly relevant for measuring statistical capacity is *flexibility*, or the ability of an NSS to adapt to changing circumstances.¹³ For example, in response to a change in national priorities, the NSS may need to alter the schedule or scope of data production. Alternatively, as new technologies for data gathering are being developed, international guidelines may change, requiring the NSS to alter its methods. However, to fully capture the missing dimension of flexibility, one needs data about circumstances that have not yet have happened, and this directly conflicts with the implementability desideratum.¹⁴ Likewise, the absence of such data in the present context leads to the use of more observable variables.¹⁵ A second missing dimension might be *statistical infrastructure*, as represented by the underlying array of inputs that the NSS has at its disposal for producing and disseminating data. This could include the physical plant, the quantity and quality of computing facilities, and the number and skill level of workers, among

¹² It may be useful to briefly discuss whether one dimension is inherently more important than another. For instance, since earlier dimensions are needed for the latter dimensions, they can be arguably viewed as being more important. Yet, from the point of view of stakeholders, the opposite could also be seen as true. Notice that both the first and last dimensions could be considered to be *process* dimensions, while the middle two are *product* dimensions. We could posit that process and product are equally important to evaluating statistical capacity, while making a judgment that the individual components are also of equal importance. If so, then the four dimensions would be consistent with Atkinson et al (2002) who observe that “the interpretation of a set of indicators is greatly eased where the individual components have degrees of importance that, while not necessarily exactly equal, are not grossly different.”

¹³ For fundamental discussions of flexibility in the context of production, see, for example, Kreps (1979).

¹⁴ Parts of this aspect might be captured in the technology or product dimensions: if the country is able to produce a best practice census, then it is plausible that it could produce comparably sophisticated products if and when needed. An analogy can be seen with Sen’s notion of capability, which evaluates a person’s well-being via sets of available options, or capability sets, which require information on alternatives that have not yet been chosen. The difficulty of obtaining counterfactual information has led many researchers to measure capability using actual achievements or functionings.

¹⁵ One related critique is that since the variables are based on past data, the resulting measure cannot be “forward looking” enough to convey the future possibilities for a given NSS. This inevitable consequence is analogous to the challenge of measuring “vulnerability to poverty” using household survey data. See Dang and Lanjouw (2017) for a recent study that addresses this challenge.

other inputs. All of these are clearly relevant information for gauging the capacity of an NSS. However, it is also clear that implementability would once again be a problem, since gathering accurate, homogenous data on inputs would be a costly and drawn out task.

3.2.5. Variables and Aggregation

Once the dimensions have been specified, attention turns to identifying the variables and selecting an appropriate aggregation method. The desiderata suggest that the variables in an index should be coherent with the concept being measured; they should be publicly available (i.e., drawn from NSSs, rather than from experts or other sources). The aggregation method should be selected with rigor in mind, including the axioms or properties that the method satisfies. At the same time, it should aim for simplicity to maximize general understanding and impact.

We turn next to discussing our proposed aggregation method. To help focus discussion on policy relevance and conceptual issues, we leave the more technical details to Appendix 1, Part A. We also offer a simple numerical example that further illustrates the ideas in this subsection in Appendix 1, Part B.

Basic Setup

In the domain of statistical capacity, a variable is typically derived from a simple “yes-no” question concerning a normative guideline that a country’s NSS should meet. For example, in the MSC dimension, a relevant question is whether a modern system of national accounts is being used. In the CS dimension, a question might ask whether there has been a population census within the last ten years. Such goals and targets can be found in discussions of standards and best practices

or international guidelines for an NSS.¹⁶ The resulting data on attainments are reported by the NSS to the World Bank, the IMF, the UN, the ILO, and other international organizations, or can be gathered directly from the NSS website.

Each of these “yes-no” questions generates a dichotomous variable having a 0-1 representation, where 1 means that the underlying test or target has been successfully achieved, while 0 indicates it has not. When there are $V \geq 2$ dichotomous variables a_v for $v = 1, \dots, V$, then, the basic data are given by an achievement vector or profile $\mathbf{a} = (a_1, a_2, \dots, a_V)$ summarizing the test or targets achieved by the NSS. As noted by Atkinson (2003), when variables are dichotomous (or can be dichotomized), a measurement approach called a “counting method” is applicable and, indeed, has become standard for many types of measurement exercises.¹⁷ We propose to apply this method here to construct our index.

A counting method begins with a vector $\mathbf{w} = (w_1, w_2, \dots, w_V)$ containing the values or weights $w_v > 0$ that will be used to assess the various achievements. The resulting counting C is the weighted mean $\mu(\mathbf{a}; \mathbf{w})$ where

$$\mu(\mathbf{a}; \mathbf{w}) = \frac{w_1}{w_1 + \dots + w_V} a_1 + \dots + \frac{w_V}{w_1 + \dots + w_V} a_V \quad (1)$$

¹⁶ Indeed, all the indicators under the dimension of “Availability of Key Indicators” are motivated by the SDGs and can be mapped to the SDG indicators.

¹⁷ See, for example, the adjusted headcount ratio of Alkire and Foster (2011), the social exclusion index of Chakravarty and D’Ambrosio (2006), the Women’s Empowerment in Agriculture Index (<http://ophi.org.uk/policy/national-policy/the-womens-empowerment-in-agriculture-index/>) and the Better Jobs Index (<https://mejorestrabajos.iadb.org/en/indice>).

so that the weight on each a_v is $w_v/(w_1 + \dots + w_V)$.¹⁸ Intuitively, the counting index calculates the sum of the values of the achievements in a as a share of the maximum total value that could be achieved. Clearly, C takes on values between 0 and 1.

A key challenge is how to discern the relative importance of the different attainments in order to aggregate up the counts. One overarching structure for doing so is found in the nested method of Alkire and Foster (2011), which extends Atkinson’s (2003) “equal importance” construction to subdimensions and variables. For example, in the case of statistical capacity, it could be argued that the CS dimension should be divided into two equally important subdimensions, one for censuses and a second for surveys. Likewise, variables that reside within a given subdimension (or dimension if it has no subdimensions) should be selected to have roughly equal contributions within the group. A nested approach helps to account for the relative values of variables, subdimensions and dimensions in a fashion that is coherent with the concept being measured.¹⁹

Useful Properties

Once \mathbf{w} has been set, and the counting index C has been defined, it offers four useful properties. We briefly discuss these properties below and offer more formal statements together with proofs

¹⁸ Although the entries of \mathbf{w} will typically sum to 1, this general definition allows the sum to exceed or fall short in line with different approaches to counting indices. This generality is also convenient in defining sub-indices that use only a subset of the values in \mathbf{w} .

¹⁹ Other empirical methods can be employed to infer the importance of individual variables, such as applying principal component techniques to obtain weights from the principal component combination that explains the most variation. This approach has the benefit of letting the data speak for themselves. However, estimation results are completely dependent on the timing and coverage of the data set used to calibrate the weights, which raises hard-to-answer questions: How far back in time should the data extend? What should be done when new data come online? Can an outside indicator of what is being measured actually be found? As such, empirical methods may yield data-oriented weights that totally ignore variables conceptually considered to be important. Decancq and Lugo (2013) offer a discussion of empirical methods for finding weights. They observe that equal weighting has often been defended by its simplicity or from the recognition that all indicators are equally important and that the implicit assumption about specific trade-offs between the dimensions should be made explicit, which we follow here with our discussion above.

in Appendix 1, Part A. First, C is additively decomposable by subsets of variables or dimensions.

For example, define the associated dimensional index $C^{(d)}$ as

$$C^{(d)} = \mu(\mathbf{a}^{(d)}; \mathbf{w}^{(d)}) = \frac{\mathbf{w}^{(d)} \cdot \mathbf{a}^{(d)}}{\mathbf{w}^{(d)} \cdot \mathbf{u}^{(d)}} \quad (2)$$

where $\mathbf{w}^{(d)}$, $\mathbf{a}^{(d)}$ and $\mathbf{u}^{(d)}$ contain only the data associated with variables in dimension d , for any $d = 1, 2, \dots, D$. We can then obtain the overall index C as the average of all the dimensional indices

$$C = \sum_{d=1}^D \frac{1}{D} C^{(d)} \quad (3)$$

Notably, in the process of defining weights for the index, we also need to define a tree structure of dimensions (and subdimensions) for the variables, where all the variables in the same dimension (or subdimension) have the same weight. This useful feature allows us to update the index over time by, say, adding variables and changing the composition of a relevant dimension while keeping the other dimensions fixed.²⁰

Second, C is additively decomposable by subsets of countries (or regions), which provides a way of monitoring regional or global progress that is based upon the progress in individual countries. This supplements the decomposition by dimension shown in Equation (2). Third, C can be constructed using either dichotomous or multi-valued variables. The nested counting index is well suited for dichotomous variables and its simple aggregation method – a weighted mean – is easy to interpret.²¹

²⁰ But note that the main decomposition axiom will be defined with respect to the basic groups.

²¹ Notably, other options exist for aggregating dichotomous variables, but these have limitations. For example, one option is the class of general means (or means of order α), which includes the geometric mean as a special case. Since variables here have 0 values, only general means with positive parameter α are applicable (the geometric mean is also problematic in that it takes on a value of 0 whenever any variable is 0 and thus violates monotonicity). Furthermore,

Finally, C allows for different emphasis on progress for countries at different outcome levels. Since the constructed single variable has a linear scale (i.e., with equal increments between adjacent levels), the resulting index is neutral in gauging improvements at different starting values. In certain circumstances, though, it might be helpful to have a range of indices that emphasizes improvements at different outcome levels (i.e., the incentive consistent desideratum). For example, for high-performing nations that have covered all the basics, it could be useful to have an index that emphasizes improvements at the upper level. Likewise, for low-performing nations that have not yet achieved basic levels, an index that emphasizes improvements at lower levels might have merit. Our index can be modified to accommodate these cases, following the intuition found in the poverty measurement literature.²²

Alternatively, we can identify a cut-off point, above which C will be given the same value (e.g., the maximal score). In other words, if there are small imperfections left for high-performing nations, the measure does not take into account changes with these small imperfections. There can be several justifications for that, including the fact that beyond a certain point the task of achieving the perfect statistical capacity can be daunting. On the other hand, we can also use an absolute or relative cut-off point to identify low-performing countries, say the 40th percentile of the statistical performance index such that countries falling under this threshold will need more assistance. A similar example to this idea is the concept of shared prosperity supported by the SDGs, where we focus on the economic growth of the bottom 40 percent of a country's income distribution.²³

a general means would rank countries the same way but lose the useful decompositions and simple interpretation of the index value. Another option is a dashboard approach, where disaggregated variables are presented in their natural state. Yet, this approach does not offer easy interpretation, especially in our case where the number of variables is large.

²² Another interpretation of the case where the index emphasizes improvements at lower levels for nations is that we place less weights on improvements for higher capacity nations. See for example Foster, Greer, and Thorbecke (1984).

²³ We would like to thank an anonymous reviewer for suggesting this point. See also the discussion of the incentive consistency desideratum above.

3.2.6. Axiomatics

Axioms are rigorous properties for an index to satisfy, and they are more formalized and generalized than the properties discussed earlier in Subsection 3.2.5. Axioms help in understanding what an index is actually measuring and in deciding which index to use. Knowing which properties an index satisfies can help in interpreting the empirical results obtained using that index; certain forms of policy analysis become possible only when the index satisfies a given property. Some axioms can be interpreted as “nuggets of policy” that specify the kinds of changes that should leave the index value unchanged and those that should alter it. Others break down the index value to help understand how dimensions contribute to that value. Our proposed index satisfies three axioms, which include symmetry, monotonicity, and subgroup decomposability.

As noted in Foster et al. (2013), axioms can be usefully grouped into three categories: invariance axioms, which indicate what not to measure; dominance axioms, which indicate what the index should measure; and subgroup axioms, which break down or build up indices by variables or units of analysis. The three axioms our proposed index of statistical capacity satisfies are closely related to these three groups of axioms. In what follows, a generic index of statistical capacity over profiles $\mathbf{a} = (a_1, \dots, a_V)$ will be denoted by C .

Symmetry: in other measurement environments where the number of people, dimensions, or other factors may differ across comparisons, invariance axioms are often used to ensure consistency. In the present context, the index C is being applied to one country’s data with a fixed number of dimensions and dichotomous variables, so properties of this sort are not needed. A second common form of invariance axiom is anonymity or symmetry, whereby the index value is unaffected when variable levels are switched. In the present context, where the variables have a

structure as represented by hierarchical tree T and partition W , universal symmetry is not appropriate. Motivated by Basu and Foster (1998), one might consider a weaker form of symmetry that is contingent on variables being “similarly placed” in the variable structure. We say that profile \mathbf{b} is obtained from profile \mathbf{a} by a *basic switch* if $\mathbf{b}_v = \mathbf{a}_{v'}$ and $\mathbf{b}_{v'} = \mathbf{a}_v$ for some $v \neq v'$ in the same basic group (dimension), while $\mathbf{b}_{v''} = \mathbf{a}_{v''}$ for all other v'' . In other words, the only difference between \mathbf{b} and \mathbf{a} is that two variable values in the same basic group have been switched. A statistical capacity measure C satisfies *basic symmetry* if $C(\mathbf{a}) = C(\mathbf{b})$ whenever \mathbf{b} is obtained from \mathbf{a} by a basic switch. Notice that any nested counting index C satisfies basic symmetry because it has the same weight on every variable in the same dimension.

Monotonicity: the main axiom for C is an intuitive dominance axiom requiring the index value to reflect improvements in variables. We say that profile \mathbf{b} is obtained from profile \mathbf{a} by an *improvement* if $\mathbf{a}_v \geq \mathbf{b}_v$ for all v , and $\mathbf{a} \neq \mathbf{b}$ or, in other words, if profile \mathbf{a} vector dominates profile \mathbf{b} . A statistical capacity index C satisfies *monotonicity* if $C(\mathbf{a}) > C(\mathbf{b})$ whenever \mathbf{a} is obtained from \mathbf{b} by an improvement. This simple but significant requirement ensures that the index value rises whenever one variable rises from 0 to 1 and the rest of the variables do not fall in value. The index $C(\mathbf{a}; \mathbf{w})$ satisfies this property since each w_v is strictly positive. Notice that monotonicity supports the incentive consistency criterion, since it ensures that a country is not penalized when it successfully raises its profile.

Subgroup decomposability: subgroup axioms allow the index to be divided into salient sub-indices and linked back to the original index for policy analysis. In the present case, the main decomposition is over the basic groups given in partition $\mathbf{W} = (w_1, \dots, w_K)$. A statistical capacity index C satisfies *basic decomposability* if there exist weights $w_k \geq 0$ summing to 1 and sub-indices $c_k(w_k)$ such that

$$\mathcal{C}(\mathbf{a}) = \sum_{k=1}^K w_k c_k(w_k) \quad (4)$$

In other words, there is a collection of indices, one for each basic group of variables, such that \mathcal{C} can be expressed as a weighted average of these basic indices. This is clearly the case for the nested counting index $\mathcal{C}(\mathbf{a}; \mathbf{w})$, as it is based on a weighted mean. Likewise, Equation (3) follows from Equation (4) by aggregating across basic groups within each dimension, so that the overall index value is just the average of the dimensional index values. These decompositions can help inform why one country is doing better than another or help describe how a single country is progressing over time.

Notably, the single country index $\mathcal{C}(\mathbf{a}; \mathbf{w})$ can be expanded into an index $\mathcal{C}(\mathbf{A}; \mathbf{w})$ that covers all countries in a region or even the universe of covered countries. The formula used to do this (shown in Proposition 2 in Appendix 1) doubles as another form of decomposition that expresses the aggregate index and an average of the country indices. This allows users to have a better understanding of regional levels and trends in statistical capacity.

4. Description of the SPI

We apply the theoretical framework discussed above to develop a new Statistical Performance Indicator (and Index, or SPI). In this section, we discuss the features of the SPI, and compare it with the SCI. We also briefly discuss some data challenges with the construction of the SPI.

4.1. SPI and Its New Features

The SPI is built around four main dimensions: i) Methodology, Standards, and Classifications, ii) Censuses and Surveys, iii) Availability of Key Indicators, and iv) Dissemination Practices and Openness. These four dimensions are closely linked and capture the production cycle of NSSs in

collecting, producing, and disseminating high-quality statistics. By following internationally recommended standards and classifications, an NSS can produce data of good quality that are both comparable within the country over time and across different countries. By combining administrative sources and timely censuses and surveys, an NSS can collect, process, and generate data products covering different aspects of households and establishments. Finally, an NSS can disseminate these data products through its official websites, regular publications, and by submitting them to relevant international organizations, which further strengthen data transparency and quality. We briefly discuss these dimensions in this section and provide more details on each indicator, its score, and its data sources in Appendix 2.

The first dimension (Methodology, Standards, and Classifications) assesses whether NSSs have the necessary capacity to adopt and comply with international statistical standards. Twelve indicators are proposed for the first dimension to ensure that data from different sources can be compared, and to inform data users that the data are reliable and meet established technical standards. The setting and applying standards are usually regulated by law and typically the responsibility of the main national statistical agency.

The second dimension (Censuses and Surveys) reflects the availability and frequency of major censuses and surveys, which are designed to collect information mandated by the National Statistical Acts. This dimension comprises of eight indicators on population and housing census, agricultural census, business census, income and expenditure surveys, and other surveys on agriculture, health, labor force, and establishments.

The third dimension (Availability of Key Indicators) evaluates NSSs by reviewing the availability of the country data for the most recent year in international databases. The 12 indicators included in this category range from the headcount poverty rate to the under-five mortality rate,

the primary school completion rate, the manufacturing value added in GDP, and net trade in goods and services. These indicators overlap to a large extent with the Tier 1 SDGs, and also include other standard macro-economic indicators.

The last dimension (Dissemination Practices and Openness) is built on the principle that an NSS should deliver quality statistics to the public in a timely, easily accessible manner and free of charge. It includes 10 indicators grouped under two sub-sections: Dissemination Capacity of NSO and Openness of Data.

Table 2 provides a summary of the data sources of the different indicators that comprise the SPI. Since we use data from more than one source to construct an indicator, the numbers shown in this table are the maximum numbers of indicators each data source contributes to. Table 2 shows that the indicators produced by the World Bank account for more than half of all the indicators, followed by the indicators produced by the IMF and the NSOs; other UN agencies contribute the remaining indicators.

4.2. Comparing the SPI and the SCI

The SPI has several advantages over the SCI, particularly in terms of data coverage. Table 3 shows that SPI has:

- i) Richer and more comprehensive dimensions covering different data aspects ranging from data generation, curation, and dissemination to data analysis.

- ii) More indicators: the SPI has 42 indicators (of which 39 are used for scoring), versus 25 indicators in the SCIs.

- iii) More countries: the SPI covers more than 200 countries, especially including high-income countries, while the SCI covers fewer than 150 countries and includes no high-income countries.

More importantly, the SPI is built on the conceptual and theoretical framework laid out above (Section 3), while the theoretical principles of the SCI are not clearly formulated. The SPI satisfies all the desiderata of a statistical capacity index: simple, coherent, motivated, rigorous, implementable, replicable, and incentive consistent. Furthermore, from an institutional viewpoint, the SPI is designed to be better aligned with other capacity assessment tools. For example, it is consistent with the Systematic Country Diagnostics (SCD), a new assessment tool that the World Bank recently developed to identify a country's priority development areas.

On the other hand, the increased numbers of indicators and countries covered for the SPI require more data compared to the SCI. The data for the SPI come from different sources, ranging from established databases with international organizations to national statistical agencies' websites. Given this heterogeneity of data sources, some data inconsistency may be expected. The complexities with the former are not just simply linearly related to the increase in quantities, but also concern data quality challenges such as missing data. Missing indicators for less-developed countries can represent a quite different data situation from missing indicators for richer countries. While the former may suggest weak statistical capacity, the latter might be explained by the little need to track certain indicators. A specific example is child stunting. In the SPI database, we assign maximum scores to richer countries (including the OECD and the EU) for this indicator assuming that richer countries have achieved the desired target of reducing child stunting and provide the benchmark against which progress for developing countries can be measured.

5. Some Empirical Illustrations

5.1. Data

We have constructed the database for the SPI for 2016. Efforts are underway to construct indicators for the SPI after 2016, as well as going backward several years for better comparison.²⁴ We provide below some empirical illustrations using the available SPI data and various other data sources, including the World Bank's World Development Indicators database (World Bank, 2018b), MIT's Economic Complexity Index (see, e.g., Hidalgo and Hausmann (2009)), and UNICEF's SDG indicators for child welfare (UNICEF, 2018).

5.2. Empirical Illustrations

We discuss in this subsection the relationship between the SPI scores and some major characteristics of a country such as its GDP, population size, and economic complexity. We subsequently offer a decomposition of the SPI by region, before providing some further empirical comparison between the SPI and the SCI.

SPI and Country Characteristics

We start first by examining the relationship between the SPI and a country's log GDP per capita (Figure 1). We expect richer countries to have better statistical systems because they have more resources to allocate for statistical activities, and also because they tend to have more complex and diversified economies that require more data. Indeed, there is a statistically significant and positive correlation between a country's SPI and its income level. Figure 1 suggests that a 10 percent increase in a country's GDP per capita is associated with approximately a 0.7 percentage point increase in its SPI score (see the box inside the figure).²⁵

²⁴ The 2016 SPI data (and future updates) can be downloaded from the weblink <https://sites.google.com/site/haianhhdang/publications>.

²⁵ Alternatively, moving up an income category (as defined by the World Bank (2018a)) can see a country improve its SPI score by 4.9 percentage points (Figure 1.2, Appendix 1).

As discussed earlier, a country's statistical system produces statistics that reflect the socio-economic conditions of the nation. As such, the more complex (advanced) a country's economic level is, the more likely that its NSS is more developed. Indeed, besides an inherently stronger demand for the NSS to keep track of its various economic activities, a richer country likely has more resources to invest in its NSS. To examine this hypothesis, we plot in Figure 2 a country's SPI against its Economic Complexity Index (ECI). This figure indicates a strong positive relationship between the two indexes, with a 0.1 increase in a country's ECI being associated with a 1.5 percentage point increase in its SPI score.²⁶

A Regional Decomposition of SPI Scores

We turn next to decomposing the SPI score by region in Figure 3. We apply both an unweighted average of region scores and an average with population weights to better take into account the different population size for each region. The unweighted graph (Figure 3, Panel A) demonstrates that among the six regions, Europe and Central Asia (ECA) and South Asia (SAS) perform above the global average, with the remaining four regions falling behind in the following decreasing order: Middle East and North Africa (MENA), East Asia and Pacific (EAP), Latin American (LAC), and Sub-Saharan Africa (SSA). Notably, ECA stands out from the other regions, which have a more similar score: the difference between its score and that of the second-strongest region SAS is 15 percentage points, which is more than the difference between the latter region's score and that of the weakest-performing region SSA. We subsequently apply population weights to better take into account the different population size for each region. Figure 3, Panel B shows a qualitatively similar order for the different regions, except that the MENA region now falls from

²⁶ For comparison, the US and the UK both have an ECI of 1.6, while the corresponding figure for China and Mexico is 0.9.

number 3 to number 5 in terms of ranking, possibly because of the large population in countries such as China or India in the EAP and SAS regions.

It can be useful to further examine whether the patterns seen in Figure 3 apply to scores in all four dimensions. Disaggregating the regional scores further by the four dimensions can help us disentangle which dimensions drive these differences and can be improved. Estimation results (without population weights) are shown in Figure 1.3 (Appendix 1), which offers several interesting observations. First, a country's score on a certain dimension can be quite different from that of its overall SPI score. In particular, all dimensions—except for the DPO dimension—have a ranking order for country performance that is different from that with the overall score. An interesting example is the ECA region, which is consistently the best performer on all dimensions but AKI, where the SAS region is now the best performer. On the other hand, SSA performs slightly better than the global average on the AKI dimension, but is the weakest performer on the rest. Second, countries generally perform best in the AKI dimension, where their average dimension score is 77 percent, which is almost the corresponding figure for the other dimensions.

Further Comparison of the SPI versus the SCI

We turn next to comparing the SPI and the SCI for 2016, when data for both indexes are available. We restrict our comparison sample to the 146 countries covered by both indexes. Estimation results suggest that richer countries, or countries with a more complex economy tend to have higher SPI scores. Indeed, for this sample of countries, a 10 percent increase in a country's GDP per capita is associated with approximately a 0.6 percentage point increase in its SPI score, twice the corresponding increase for the SCI. Similarly, a 0.1 increase in a country's ECI being associated with a 1.5 percentage point increase in its SPI score but only a 1.1 percentage point

increase in its SCI score. For further visual illustration, we plot in Figure 4 the SPI and SCI scores against log of GDP per capita (Panel A) and economic complexity index (Panel B). While we leave out the regression results shown in previous figures for lack of space, the slopes of the fitted lines for the SPI scores are clearly steeper than those for the SCI scores in both these graphs. Furthermore, when the standardized distributions of both indexes are plotted on the same graph (Figure 5), the SCI has a shorter tail on the right, suggesting that it has a less full range than the SPI.²⁷

The SPI also does a better job of distinguishing country statistical capacity. Table 1.1 shows that it offers a unique score for 131 countries and a tied score for 14 countries. In contrast, the SCI has a unique score for only 44 countries, with the remaining countries having (multiple) tied scores. Unsurprisingly, the rankings of countries are also different for the two indexes. A particularly interesting case is El Salvador, a lower-middle-income country in Latin America.²⁸ This country ranks as number 5 of 145 countries based on the SCI scores. This would place this country in a surprisingly higher position than many richer countries, including its regional upper-middle-income neighbor—Colombia—which is ranked at number 10. Yet, according to a recent evaluation for 44 indicators concerning children in the 2030 SDG agenda by UNICEF, El Salvador has inadequate data for tracking progress on more than half (i.e., 27) of these indicators. The same figure for Colombia is much lower at just 14 indicators (UNICEF, 2018). The SPI ranks El Salvador as 47, while the ranking of Colombia changes to 12.

²⁷ Since the two indexes have different scales, we standardize the two indexes so that they both have mean 0 and standard deviation 1 for better comparison in Figure 1.3. In addition, this figure also indicates that the SPI appears more similar to the normal distribution than the SCI, which is confirmed by formal statistical tests. One possible reason is that, since the SPI is the average of a larger number of indicators than the SCI, it is more likely to have a normal distribution by the central limit theorem (see, e.g., Casella and Berger (2002)).

²⁸ Unless otherwise noted, we use the World Bank's (2018) income classification for all countries.

Another example is Botswana, an upper-middle-income country in Africa. This country has an SCI rank of 129, near the bottom of the SCI scores. This places Botswana lower than Madagascar (number 88) and Zimbabwe (number 105), both low-income countries in Sub-Saharan Africa. Indeed, Botswana's GDP per capita was \$15,807 in 2011 PPP, which was respectively 11 times and 8 times higher than that of Madagascar and Zimbabwe (World Bank, 2018b). Furthermore, a recent study suggests that Botswana has accomplished both upward consumption mobility and pro-poor growth in the past decade, which reduced its headcount poverty rate to 18 percent (using the international poverty line of \$1.90/day in 2011 PPP dollars). The opposite story held Madagascar, where the country has undergone much downward mobility, which drove its poverty rate up to as high as 82 percent (Dang and Dabalen, 2019). Zimbabwe, on the other hand, has a higher income level than Madagascar, but is observed to have implemented at most one household consumption survey during the period 1990-2012; the corresponding figure for Botswana is two comparable surveys (Beegle et al., 2016). Perhaps these studies can provide supportive evidence to help understand why Botswana sees its SPI ranking go up significantly to number 52, while the corresponding figure for Madagascar falls to number 133, and that of Zimbabwe slightly changed to number 106.

6. Discussion and Conclusion

In this paper, we offer a systematic discussion of the construction of the Statistical Performance Index. Our theoretical and empirical methodology builds on the existing strengths of the widely-used Statistical Capacity Indicator of the World Bank. We present the conceptual and mathematical foundation behind this index, and significantly expand the number of indicators and

countries covered by this index. We also provide some brief empirical illustrations of the updated index with global data in 2016.

We acknowledge that our proposed index has certain limitations. In particular, since it relies on easily accessible and publicly available information, it does not include aspects of an NSO's capacity that are harder both to observe and to quantify on a comparable basis across countries. For example, it does not cover the resources available to the NSO—either financial or human, its quality of management, human resources systems, and infrastructure (including hardware and software), or the regulatory framework under which the NSO operates, or the level of data integration. All these features would likely be included in an ideal index but are omitted for the reasons mentioned above. It neither covers new sources of data, such as administrative data and big data, nor addresses the emerging topic of data confidentiality and disclosure risk.

Yet, our framework promises of new directions for policy-relevant research. Its potential contributions for addressing various topics have been highlighted in several recent studies. For example, Dang and Serajuddin (2020) propose that it can be used to construct an index to monitor country progress on the SDG. Visser *et al.* (2020) suggest that the SPI can be employed to gauge the reliability of statistical information from individual countries, say in judging the uncertainty in these countries' human security indicator, including peace or governance. This practical use of the SPI for evidence-based policy making cannot be overemphasized. Indeed, Roseth *et al.* (2019) observe that inaccuracies in the measurement of the municipal population resulted in approximately US\$92 million in mis-targeted government budget transfer in El Salvador between

2000 and 2007, which equals 700 percent of the cost of the latest census and more than 27 times the annual budget of the statistical office.²⁹

More generally, our proposed framework can be regarded as an attempt to respond to recent calls to rigorously examine the quality of data and statistics in tracking economic growth and poverty reduction, particularly in poorer countries. In particular, Devarajan (2013) highlights the notion of “Africa’s statistical tragedy”, or the challenges of weak capacity, inadequate funding, and a lack of coordination of statistical activities facing African economies. Similarly, Jerven (2013, 2019) emphasizes the importance of a strategy for improving statistical capacity for sub-Saharan Africa economies. He concludes that reliable statistics, including estimates of economic growth rates and per-capita income, are basic to government operations in poorer countries and vital to nongovernmental organizations and aid agencies that support these countries.

This new index could be seen as the first step before more resource-intensive country-specific assessments to inform multi-year improvement plans. Our proposed framework is also flexible enough to allow for future revisions as the global data landscape evolves. For example, we can incorporate new indicators such as whether an NSO uses cloud computing to store their data or implements household panel surveys in the relevant dimensions without creating major changes to the total scores. Since the SPI is currently available only for 2016, another promising direction is to collect time series data for the new index, both going forward and for several years past, and expand the current framework to allow for dynamic changes over time.

²⁹ Another promising direction is to examine in more detail the relationship between a country’s level of economic activities, as measured by its economic complexity index as discussed earlier, and the SPI. Furthermore, the SPI can also be employed for updated analysis in previous studies that employ the SCI to investigate different topics such as the relationship between good governance and statistical capacity (Beegle *et al.*, 2016), the impacts of statistical capacity on reducing procyclical fiscal policy (Tapsoba *et al.*, 2017), or to identify countries where investments in statistical capacity can be most fruitful (Hoogeveen and Nguyen, 2019).

References

- Alkire, Sabina and James Foster. (2011). "Counting and multidimensional poverty measurement." *Journal of Public Economics*, 95(7): 476-487.
- Alkire, Sabina, José Manuel Roche, Paola Ballon, James Foster, Maria Emma Santos, and Suman Seth. (2015). *Multidimensional Poverty Measurement and Analysis*. United Kingdom: Oxford University Press.
- Atkinson, Tony, Bea Cantillon, Eric Marlier, and Brian Nolan. (2002). *Social Indicators: The EU and Social Inclusion*. New York: Oxford University Press.
- Atkinson, Anthony B. (2003). "Multidimensional deprivation: contrasting social welfare and counting approaches." *Journal of Economic Inequality*, 1(1): 51-65.
- Beegle, K., Christiaensen, L., Dabalen, A., & Gaddis, I. (2016). *Poverty in a Rising Africa*. Washington DC: The World Bank.
- Casella, George and Roger L. Berger. (2002). *Statistical Inference*, 2nd Edition. California: Duxbury Press.
- Chakravarty, Satya R. and Conchita D'Ambrosio. (2006). "The Measurement of Social Exclusion". *Review of Income and wealth*, 52(3): 377-398.
- Dang, Hai-Anh and Andrew L. Dabalen. (2019). "Is Poverty in Africa Mostly Chronic or Transient? Evidence from Synthetic Panel Data". *Journal of Development Studies*, 55(7): 1527-1547.
- Dang, Hai-Anh and Peter Lanjouw. (2017). "Welfare Dynamics Measurement: Two Definitions of a Vulnerability Line and Their Empirical Application". *Review of Income and Wealth*, 63(4): 633-660.
- Dang, Hai-Anh and Umar Serajuddin. (2020). "Tracking the sustainable development goals: Emerging measurement challenges and further reflections." *World Development*, 127: 104570.
- Decancq, Koen and María Ana Lugo. (2013). "Weights in multidimensional indices of wellbeing: An overview." *Econometric Reviews*, 32(1): 7-34.
- Devarajan, Shantayanan. (2013). "Africa's statistical tragedy." *Review of Income and Wealth*, 59: S9-S15.
- Fantom, N. and N. Watanabe (2008). "Improving the World Bank's Database of Statistical Capacity". *African Statistical Newsletter*, 2(2): 21-22.
- Food and Agriculture Organization of the United Nations, Asia and Pacific Commission on Agricultural Statistics (2012). *Report on Initial Country Assessments*.

http://www.fao.org/fileadmin/templates/ess/ess_test_folder/Workshops_Events/APCAS_24/Paper_after/APCAS-12-7-Report_Country_Assessment.pdf.

- Food and Agriculture Organization of the United Nations (2014). *Guidelines for Assessing Country Capacity to Produce Agricultural and Rural Statistics*. June. http://gsars.org/wp-content/uploads/2014/09/Guidelines_Country-Assessment_FINAL.pdf.
- Foster, James, Joel Greer, and Erik Thorbecke. (1984). "A Class of Decomposable Poverty Measures." *Econometrica*, 52(3): 761-766.
- Foster, James, Suman Seth, Michael Lokshin, and Zurab Sajaia. (2013). *A Unified Approach to Measuring Poverty and Inequality: Theory and Practice*. Washington DC: World Bank.
- Hidalgo, César A. and Ricardo Hausmann. (2009). "The Building Blocks of Economic Complexity." *Proceedings of the National Academy of Sciences*, 106(26): 10570-10575.
- Hoogeveen, Johannes, and Nga Thi Viet Nguyen. (2019). "Statistics Reform in Africa: Aligning Incentives with Results." *Journal of Development Studies*, 55(4): 702-719.
- Jerven, Morten. (2013). *Poor numbers: how we are misled by African development statistics and what to do about it*. Cornell University Press.
- . (2019). "The Problems of Economic Data in Africa." In *Oxford Research Encyclopedia of Politics*.
- Kreps, David M. (1979). "A Representation Theorem for 'Preference for Flexibility'." *Econometrica*, 47(3): 565-577.
- Ngaruko, Floribett. (2008). "The World Bank's Framework for Statistical Capacity Measurement: Strengths, Weaknesses, and Options for Improvement". *The African Statistical Journal*, Volume 7. November.
- Organisation of Islamic Cooperation (2012). *Current State of Statistical Capacity in the OIC Member Countries*. February.
- Partnership in Statistics for Development in the 21st Century (PARIS21) (2002). *Statistical Capacity Building Indicators Final Report*. <https://www.paris21.org/sites/default/files/scbi-final-en.pdf>.
- Roseth, Benjamin, Angela Reyes, and Karla Yee Amezaga. (2019). "The Value of Official Statistics: Lessons from Intergovernmental Transfers." *Technical Note IDB-TN-1682*. Washington DC: Inter-American Development Bank.
- Sanga, D., Dosso, B., and Gui-Diby, S. (2011). "Tracking Progress towards Statistical Capacity Building Efforts: The African Statistical Development Index". *International Statistical Review*, 79(3): 303-329.

Stamp, Josiah. (1929). *Some Economic Factors in Modern Life*. London: P.S. King and Sons.

Tapsoba, Sampawende J-A., Codjo Neree Noumon, and Robert C. York. (2017). "Can Statistical Capacity Building Help Reduce Procyclical Fiscal Policy?" *Journal of International Development*, 29(4): 407-430.

UNICEF. (2018). *Progress for Every Child in the SDG Era*. New York: UNICEF.

United Nations (2016). *Evaluation of the Contribution of the United Nations Development System to Strengthening National Capacities for Statistical Analysis and Data Collection to Support the Achievement of the Millennium Development Goals (MDGs) and other Internationally-agreed Development Goals*. Technical report.

United Nations Economic Commission for Europe. (UNECE). (2014). Global Assessment Report: National Statistical System of Mongolia. https://www.unece.org/fileadmin/DAM/stats/documents/technical_coop/GA_Mongolia_EN.pdf.

United States Census Bureau. Tool for Assessing Statistical Capacity (TASC)—Version 2.0. <https://www2.census.gov/software/tasc/tasc-booklet.pdf>

Visser, H., S. de Bruin, A. Martens, J. Knoop, and W. Ligtoet. (2020). "What users of global risk indicators should know." *Global Environmental Change*, 62: 102068.

World Bank. (2018a). *Country Income Classification*. <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups>

---. (2018b). *World Development Indicators Online*.

Table 1: Comparing SCIs with other statistical capacity measurement tools

Tools ³⁰ Criteria	PARIS21	UNECE	FAO	UNECA	US Census Bureau	WB
Country-level data	No	Yes	No ³¹	Yes	No	Yes
Countries covered	NA.	10 (ECA countries)	NA.	43	NA.	146 (old); 218+ (new)
Time covered	NA.	One year	NA.	NA.	NA.	2004-2016 (old SCT); 2016- (new SPI)
Designed data collection method	Primary data collection	Primary data collection	Primary data collection	Primary data collection	Primary data collection	Secondary data collection
Selected indicators						
Number of indicators	16 (quantitative); 18 (qualitative)	5 broad categories, 40-50 specific aspects ³²	24 sub-categories	42 variables	110	25 (old); 42 (new)
Dimensions covered	System-wide indicators; agency-related indicators; data-related indicators.	Legal Basis; National Statistical System; Statistics Authority; Data Sources and Processing Statistical Domains.	Institutional infrastructure; Resources; Statistical methods and practices; Availability of statistical information; Critical constraints	Functioning of the National Statistical Systems; Statistical infrastructure; Data dissemination; Human capital development; Funding	Institutional capacity; Planning and management; Mapping; Sampling; Questionnaire content and testing	Revised SCIs: Methodology, standards and classification; Censuses and Surveys; Dissemination Practices and Openness; Availability of Key Indicators
Operational relevance	<ul style="list-style-type: none"> Useful both for national management and international comparison; More useful to countries that are “statistically challenged”. Facilitate coordination among the organizations involved in technical assistance. 	<ul style="list-style-type: none"> Recommendations from the reports could be incorporated into statistical capacity-building programs and strategies; These strategies are then made operational through annual statistical programs of work and implemented by the beneficiary countries. 	<ul style="list-style-type: none"> CAQ can be used to create country profiles and group countries into quartiles or to identify priority interventions that could be implemented at the regional level. The in-depth assessment will further provide insights on agricultural and rural statistics. 	<ul style="list-style-type: none"> Support the monitoring and evaluation of RRSF identify for each African country weaknesses and strengths in order to support interventions; Provide a general idea of the performance of African countries’ statistical systems. 	<ul style="list-style-type: none"> Aid NSOs in identifying areas of improvement; Assist NSOs and donors to justify the need for funding for training; Provide a measure of the impact of capacity building activities by being administered at two points in time, before and after. 	<ul style="list-style-type: none"> Provide an assessment of country statistical capacity over time in a cost-effective, sustainable way; Provide guidance to the WB teams in assessing the progress and sustainability of the Bank supported projects; Inform Systematic Country Diagnostics; Provide a monitoring tool for countries’ SDGs data production capacity.

³⁰ Partnership in Statistics for Development in the 21st Century (PARIS21): Statistical Capacity Building Indicators; United Nations Economic Commission for Europe: Global Assessment; Food and Agriculture Organization of the United Nations: Country Capacity Indicators; United Nations Economic Commission for Africa: African Statistical Development Index; US Census Bureau: Tool for Assessing Statistical Capacity, World Bank: Statistical Capacity Indicator.

³¹ The pilot study was conducted in Asia Pacific countries in 2012. In-depth country assessment will be carried out, following the established guidelines.

³² Referred to the most recent GA report on National Statistical System of Mongolia. No specific indicators were referred to, but the report focused on assessing different specific areas of the Mongolian statistical system.

Table 2: Number of Indicators by Data Sources

No	Data Sources	Number of Indicators	
		Total	Percent.
Category A: International Organization			
1	IMF		
	Dissemination Standards Bulletin Board (DSBB)	3	6
	Government Finance Statistics (GFS)	1	2
	International Financial Statistics (IFS)	2	4
	World Economic Outlook (WEO)	3	6
	Subtotal	9	19
2	Other United Nations Agency		
	UN Economic Commission for Europe (UNECE)	1	2
	UN Industrial Development Organization (UNIDO)	1	2
	UN Statistical Division (UNSD)	2	4
	Food and Agriculture Organization of the United Nations	1	2
	International Labour Organization (ILO)	2	4
	Subtotal	6	13
3	World Bank		
	Interational Household Survey Network Catalogu (IHSN)	9	19
	PovCalNet	4	9
	Microdata Library	4	9
	World Development Indicators (WDI)	15	32
	Demographic and Health Surveys (DHS)	1	2
	Subtotal	24	51
Category B: National Statistical Agency			
	National Statistics Office (NSO)	8	17
Total		47	100

Note: One indicator can be constructed based on data from more than one source.

Table 3: Comparing the SPI and the SCI

	SCIs	SPI
<i>Coverage</i>		
Country coverage	146	218+
Time covered	2004-2016	2016 onwards
<i>Selected indicators</i>		
Number of indicators	25	42
Dimensions covered	Methodology; Source Data; Periodicity and Timeliness	Methodology, Standards and Classifications; Censuses and Surveys; Dissemination Practices and Openness; Availability of Key Indicators
<i>Aggregation method</i>	Simple arithmetic average	Revised weighted average
<i>Operational relevance</i>	<ol style="list-style-type: none"> 1) Track the strengths and weaknesses of country statistical capacity overtime in a cost-effective manner; 2) Track the progress and sustainability of Bank-financed projects in statistical capacity building; 3) With a focus on MDGs in Periodicity section, the old SCIs provided a monitoring tool for country MDGs data production capacity. 	<ol style="list-style-type: none"> 1) Provide an objective, justifiable assessment of country statistical capacity over time with comprehensive, up-to-date information; 2) Provide guidance to the WB teams in assessing the progress and sustainability of the Bank supported projects; 3) Inform Systematic Country Diagnostics; 4) Provide a monitoring tool for countries' SDGs data production capacity.
<i>Limitations/Identified weaknesses</i>	<ol style="list-style-type: none"> 1) Output focused, failing to address the infrastructure/resource part of the NSOs; 2) Relative narrow scope of dimensions and indicators; 3) Unable to reflect the change of data landscape and new data requirements brought up by the SDGs. 	<ol style="list-style-type: none"> 1) Selection of indicators, especially under the Availability of Key Indicators section, is constrained by the development stage of SDGs indicators. This leaves room for future development of the SCIs structure.

Figure 1: SPI Scores versus Country Income, 2016

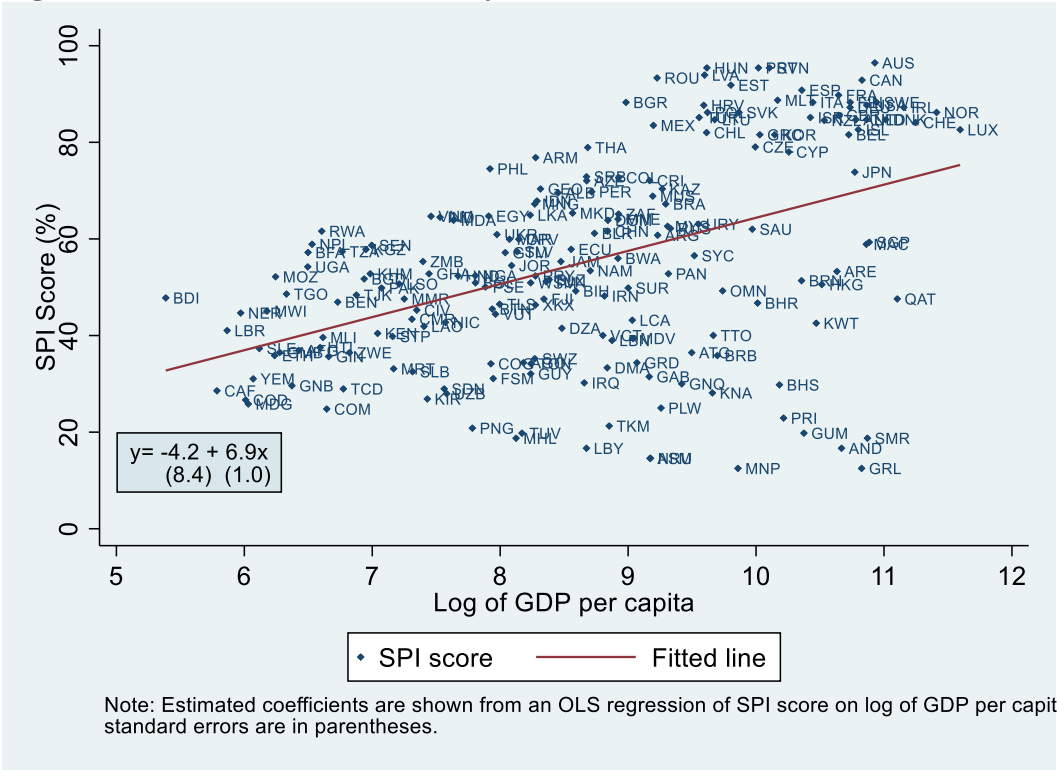


Figure 2: SPI Scores versus Country Economic Complexity, 2016

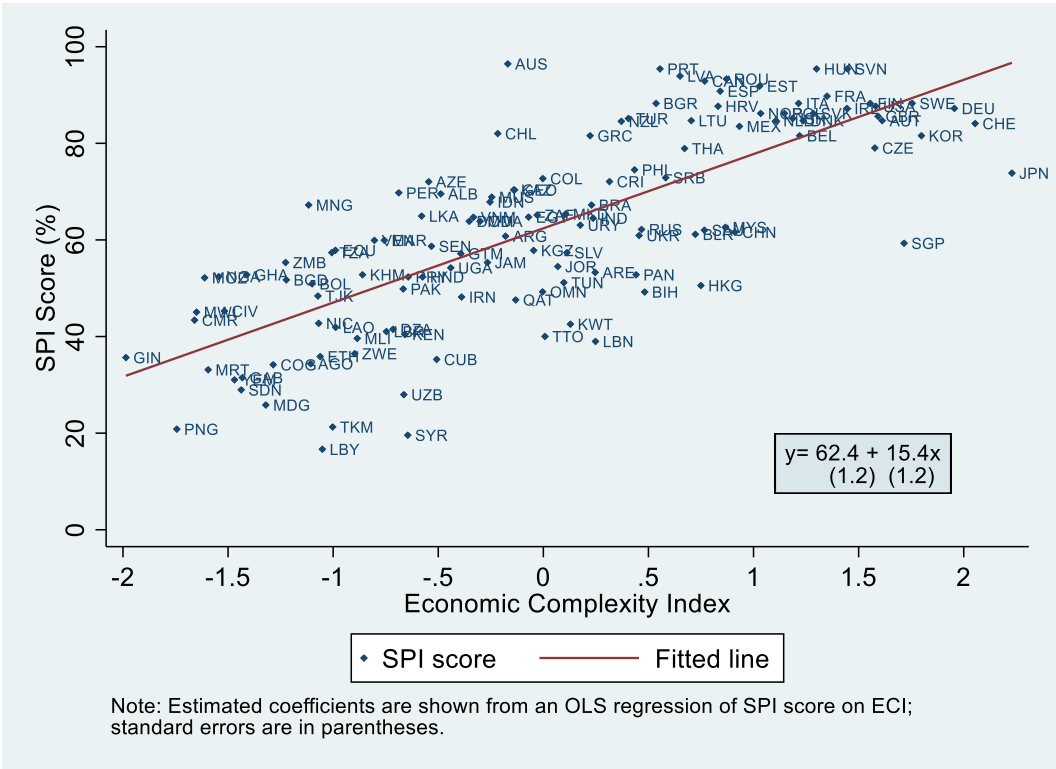


Figure 3: SPI Scores by Region, 2016

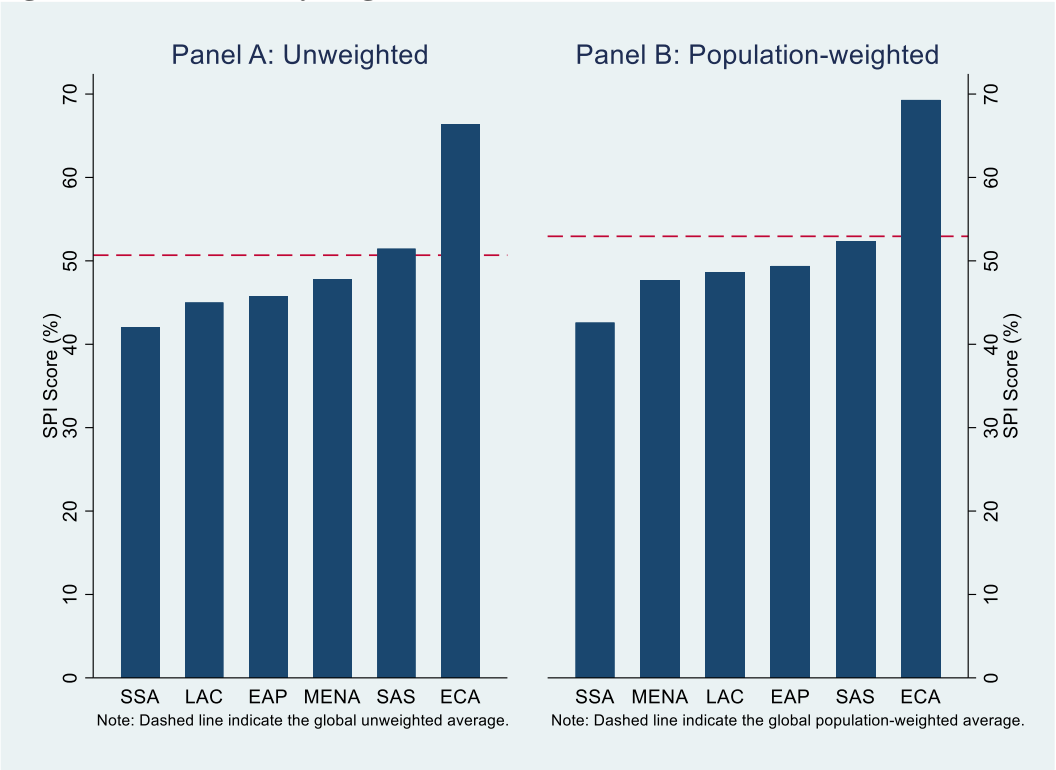


Figure 4: SPI and SCI Scores versus Country Income and Country Economic Complexity, 2016

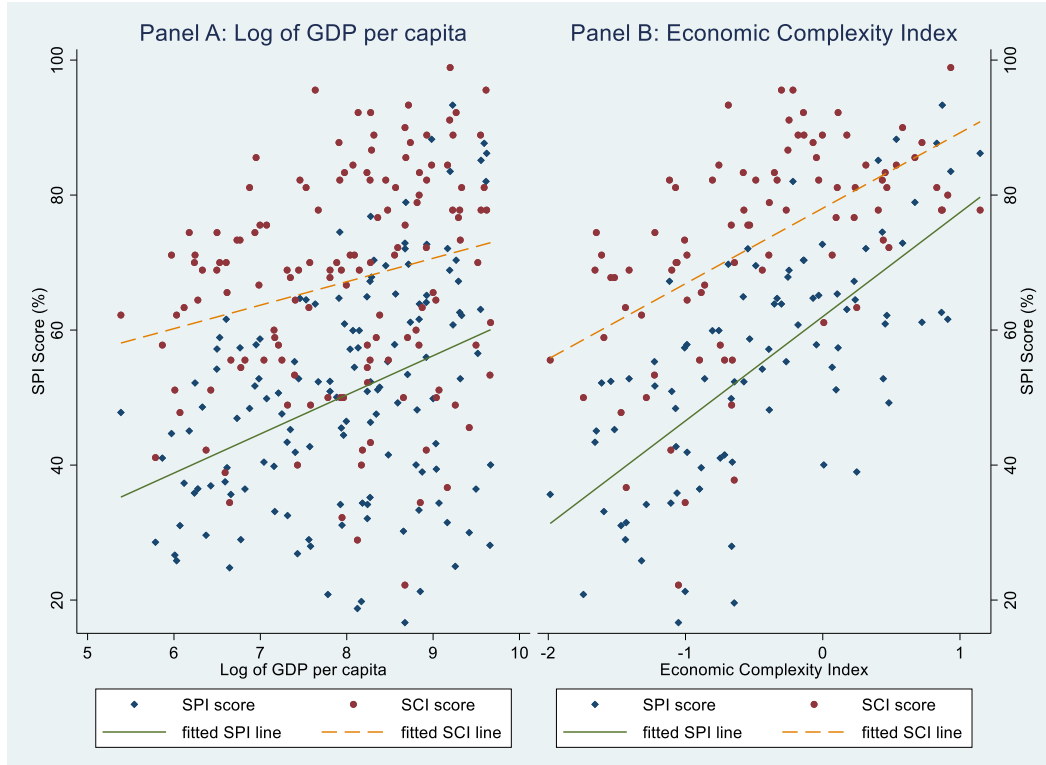
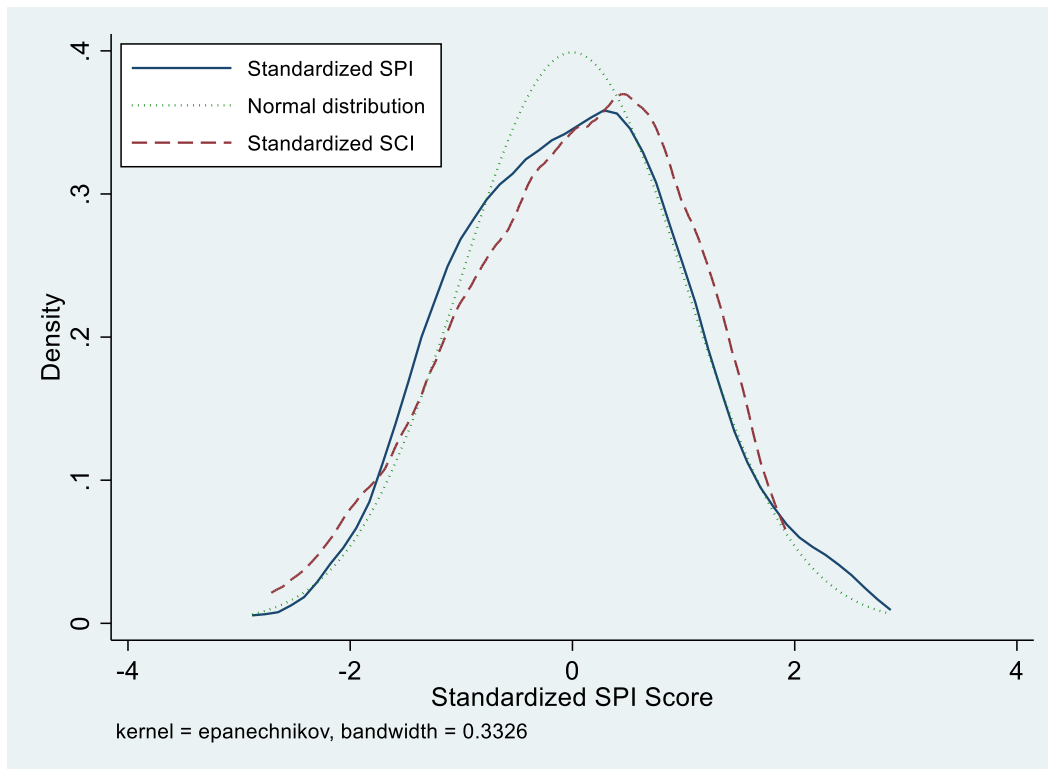


Figure 5: The Standardized Distribution of the SPI vs. the Standardized Distribution of the SCIs for the Same Countries, 2016



Appendix 1: Proofs, Axiomatics, and a Numerical Example (for online publication)

Part A: Proofs

Proposition 1. Decomposability into Subsets of Variables

Let S and S' be two nonempty sets of variables with empty intersection whose union is $\{a_1, \dots, a_V\}$.

Define the two associated sub-indices of C as

$$C^S = \mu(\mathbf{a}^S; \mathbf{w}^S) = \frac{\mathbf{w}^S \cdot \mathbf{a}^S}{\mathbf{w}^S \cdot \mathbf{u}^S}; \quad C^{S'} = \mu(\mathbf{a}^{S'}; \mathbf{w}^{S'}) = \frac{\mathbf{w}^{S'} \cdot \mathbf{a}^{S'}}{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}$$

where \mathbf{w}^S , \mathbf{a}^S and \mathbf{u}^S (or $\mathbf{w}^{S'}$, $\mathbf{a}^{S'}$ and $\mathbf{u}^{S'}$) are obtained from \mathbf{w} , \mathbf{a} and \mathbf{u} by removing the variables outside of S (respectively, S').

The index C can be decomposed into these two sub-indices as follows

$$C = \frac{\mathbf{w}^S \cdot \mathbf{u}^S}{\mathbf{w} \cdot \mathbf{u}} C^S + \frac{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}{\mathbf{w} \cdot \mathbf{u}} C^{S'}$$

Proof

Since S and S' are two nonempty and exclusive sets of variables whose union is $\{a_1, \dots, a_V\}$, we have

$$\mathbf{w} \cdot \mathbf{a} = \mathbf{w}^S \cdot \mathbf{a}^S + \mathbf{w}^{S'} \cdot \mathbf{a}^{S'} \quad (1.1)$$

Divide both sides of Equation (1.1) by $\mathbf{w} \cdot \mathbf{u}$, we have

$$\frac{\mathbf{w} \cdot \mathbf{a}}{\mathbf{w} \cdot \mathbf{u}} = \frac{\mathbf{w}^S \cdot \mathbf{a}^S}{\mathbf{w}^S \cdot \mathbf{u}^S} + \frac{\mathbf{w}^{S'} \cdot \mathbf{a}^{S'}}{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}} \quad (1.2)$$

or equivalently

$$C = \frac{\mathbf{w}^S \cdot \mathbf{u}^S}{\mathbf{w} \cdot \mathbf{u}} C^S + \frac{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}{\mathbf{w} \cdot \mathbf{u}} C^{S'} \quad (1.3)$$

Indeed, for Equation (1.3), the term on the left hand side follows from Equation (1.2) using the definition of C . The two terms on the right hand side for the same equation are obtained by multiplying the term on the right hand side of Equation (1.2) respectively with $\frac{\mathbf{w}^S \cdot \mathbf{u}^S}{\mathbf{w}^S \cdot \mathbf{u}^S}$ and $\frac{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}$ and then rewriting using the definitions of C^S as $\frac{\mathbf{w}^S \cdot \mathbf{a}^S}{\mathbf{w}^S \cdot \mathbf{u}^S}$, and $C^{S'}$ as $\frac{\mathbf{w}^{S'} \cdot \mathbf{a}^{S'}}{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}$.

A similar proof applies where we partition the set $\{a_1, \dots, a_V\}$ into D subsets, such that C can be decomposed into D associated dimensional indices $C^{(d)}$.

Notice that $\mathbf{w}^S \cdot \mathbf{u}^S$ gives the sum of values for variables in S , while $\mathbf{w} \cdot \mathbf{u}$ is the sum of all values, and hence the coefficient on C^S is the share of the total value from variables in S ; an analogous interpretation holds for S' . As such, the relative contribution of each group of variables to the overall index can be obtained by dividing the two terms on the right-hand side of Equation (1.3) by the overall index value C .

Proposition 2. Decomposability into Subsets of Countries

Let N be the number of countries considered and let \mathbf{A} denote the $N \times V$ achievement matrix whose n^{th} row \mathbf{a}^n is the achievement vector for country $n = 1, \dots, N$.

Define the index applied to the collection $\{1, \dots, N\}$ of countries as

$C = C(\mathbf{A}; \mathbf{w}) = \mu(\mathbf{A}; \mathbf{w})$, where the weighted mean $\mu(\mathbf{A}; \mathbf{w})$ of matrix \mathbf{A} is given by

$$\mu(\mathbf{A}; \mathbf{w}) = \sum_{n=1}^N \sum_{v=1}^V \left(\frac{1}{N} \frac{w_v}{w_1 + \dots + w_V} \right) a_v = \sum_{n=1}^N \frac{1}{N} \mu(\mathbf{a}^n; \mathbf{w}) \quad (6)$$

The index C can be decomposed into the country-level (or region-level) sub-indices as follows

$$C(\mathbf{A}; \mathbf{w}) = \frac{1}{N} \sum_{n=1}^N C(\mathbf{a}^n; \mathbf{w}) \quad (7)$$

Proof

Let N be the number of countries considered and let A denote the $N \times V$ achievement matrix whose n^{th} row a^n is the achievement vector for country $n = 1, \dots, N$. Then the index applied to the collection $\{1, \dots, N\}$ of countries is defined by $C = C(A; \mathbf{w}) = \mu(A; \mathbf{w})$. Since the weighted mean $\mu(A; \mathbf{w})$ of matrix A is given by an arithmetic mean of $N \times V$ elements

$$\mu(A; \mathbf{w}) = \sum_{n=1}^N \sum_{v=1}^V \left(\frac{1}{N} \frac{w_v}{w_1 + \dots + w_V} \right) a_v = \sum_{n=1}^N \frac{1}{N} \mu(a^n; \mathbf{w}) \quad (1.4)$$

there are two ways to obtain C . The first way is to average across the dimension as with Proposition 1. The second way is to calculate the index for each country n first as $C(a^n; \mathbf{w})$, and then obtain the average for the whole world (or region). This can be formally stated as follows

$$C(A; \mathbf{w}) = \frac{1}{N} \sum_{n=1}^N C(a^n; \mathbf{w}) \quad (1.5)$$

Note that the domain for the global (regional) index $C(A; \mathbf{w})$ includes the country or the region indexes, while that for $C(a; \mathbf{w})$ includes the dimension indexes or the indicators.

Proposition 3. Equivalence between Dichotomous and Multi-Valued Indicators

Suppose that there are T many related dichotomous variables providing information on ascending levels of a component (dimension) of a statistical capacity index. Let S' be the set of subscripts for these T variables so that $\mathbf{a}^{S'}$ denotes the relevant vector of achievements. Let $C(\mathbf{a}^{S'}; \mathbf{w}^{S'})$ be the counting index for this subset of variables; it assigns for $\mathbf{a}^{S'}$ the $T+1$ options of the numerical values of $0, 1/T, \dots, (T-1)/T$, and 1 , respectively. Now replace the T dichotomous variables with the single variable x having one of these $T+1$ values and assign it the total weight inherited from the original T variables. The weighted mean across x and the remaining dichotomous variables generates identical index values as the original counting measure.

Proof

Let $S = \{a_1, \dots, a_v\}$ and $S' = \{a_{v+1}, a_{v+2}, \dots, a_T\}$. The T dichotomous variables in S' can be replaced with one variable x having the values $0, 1/T, \dots, (T-1)/T$, and 1 , where x inherits a total weight of w_T from the original T variables. That is,

$$x = C^{S'} \quad (1.6)$$

and

$$\mathbf{w}_x = \sum_{k=v+1}^T w_k = \frac{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}{\mathbf{w} \cdot \mathbf{u}} \quad (1.7)$$

Let $C(\mathbf{a}^{S'}; \mathbf{w}^{S'})$ be the counting index for the subset of variable S' . We then have

$$C(\mathbf{a}; \mathbf{w}) = \frac{\mathbf{w}^S \cdot \mathbf{u}^S}{\mathbf{w} \cdot \mathbf{u}} C^S + \frac{\mathbf{w}^{S'} \cdot \mathbf{u}^{S'}}{\mathbf{w} \cdot \mathbf{u}} C^{S'} \quad (1.8)$$

or

$$C(\mathbf{a}; \mathbf{w}) = \frac{\mathbf{w}^S \cdot \mathbf{u}^S}{\mathbf{w} \cdot \mathbf{u}} C^S + w_x x \quad (1.9)$$

where Equation (1.8) follows from the decomposition of the two indices by sets of variables (from Proposition (1)), and Equation (1.9) follows from replacing the second term on the right-hand side of Equation (1.8) with the corresponding terms in Equations (1.6) and (1.7).

Part B: Numerical Example

Figure 1.1 graphically illustrates the nested counting method for an example having nine variables and three dimensions. The first two dimensions have two variables apiece; the third dimension has two subdimensions. The first of these subdimensions has two variables while the second subdimension has three. The example has been constructed according to the nested approach, with the width of each dimension, subdimension or variable indicating its relative importance. The implied weight for each variable – which is the width for the variable divided by the overall width – is listed for each at the base of the figure. Now suppose that the nine achievements from right to left take on the values $\mathbf{a} = (1,0,1,1,1,0,1,0,0)$, where each “1” variable is shaded in the figure, and each “0” is indicated by a lack of shading. The counting approach essentially adds up the associated weights, or equivalently the shaded widths divided by the total width (as with Equation (1)), resulting in

$$C = 1/6 + 1/6 + 1/6 + 1/12 + 1/18 = 23/36 \quad (1.10)$$

or about 0.639.

Equivalently, the aggregate value for the counting measure is obtained by taking the inner product of the weighting vector $\mathbf{w} = (w_1, \dots, w_9) = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{12}, \frac{1}{12}, \frac{1}{18}, \frac{1}{18}, \frac{1}{18})$ and the profile $\mathbf{a} = (1,0,1,1,1,0,1,0,0)$ (as with Equation (2)), yielding

$$C = (w_1 + w_3 + w_4 + w_5 + w_7)/1 = 23/36 \quad (1.11)$$

as before. Notice that $M = 1 - C = 13/36$ is a complementary measure of the extent to which targets have yet to be met, as indicated by the share of the figure that is left unshaded.³³

Returning to the example with profile $\mathbf{a} = (1,0,1,1,1,0,1,0,0)$, weighting vector $\mathbf{w} = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{12}, \frac{1}{12}, \frac{1}{18}, \frac{1}{18}, \frac{1}{18})$ and three dimensions, it follows that

$$C = \frac{1}{3}C^{(1)} + \frac{1}{3}C^{(2)} + \frac{1}{3}C^{(3)} \quad (1.12)$$

where $C^{(1)} = 1/2$, $C^{(2)} = 1$, and $C^{(3)} = 5/12$. Summing the right side of Equation (1.12) yields 23/36 as before, which illustrates Equation (4). Dividing each term in this equation by the value of C , the relative contribution of each dimension is approximately 26%, 52%, and 22%, respectively.

It is likewise possible to define indices for subdimensions. In the example there are two subdimensions for dimension 3, the first of which includes variables 5 and 6 and the second of which includes variables 7, 8 and 9. Where $C^{(31)}$ and $C^{(32)}$ denote the associated indices, it follows that $C^{(31)} = 1/2$ and $C^{(32)} = 1/3$, and that

$$C^{(3)} = \frac{1}{2}C^{(31)} + \frac{1}{2}C^{(32)} = 5/12 \quad (1.13)$$

where the contribution of the first subdimension to the dimensional index is 60% and the contribution of the second subdimension is 40%. Overall, the decomposition formula over these basic groups of variables – namely the dimensional and sub-dimensional variables – is given by

$$C = \frac{1}{3}C^{(1)} + \frac{1}{3}C^{(2)} + \frac{1}{6}C^{(31)} + \frac{1}{6}C^{(32)} \quad (1.14)$$

³³ M is analogous to the individual poverty measure underlying the adjusted headcount ratio M_0 of Alkire and Foster (2011) with a “union” identification step.

Notice that in the process of defining weights for the index, a tree structure T of dimensions and subdimensions has been spelled out for the variables. For instance, the above example has the structure $T = (\mathbf{a}^{(1)}, \mathbf{a}^{(2)}, (\mathbf{a}^{(31)}, \mathbf{a}^{(32)}))$, where $\mathbf{a}^{(1)} = (a_1, a_2)$, $\mathbf{a}^{(2)} = (a_3, a_4)$, $\mathbf{a}^{(31)} = (a_5, a_6, a_7)$, and $\mathbf{a}^{(32)} = (a_8, a_9)$ are the basic groups at the end of the tree structure. The extra parentheses around $\mathbf{a}^{(31)}$ and $\mathbf{a}^{(32)}$ indicate that they are both part of the same dimension. The basic groups, in turn, together form a partition \mathbf{P} of variables into, say, K many basic groups of variables p_k for $k = 1, \dots, K$ having the property that if one variable in p_k is in a given dimension, then all variables in the p_k are in that dimension; and if one variable in p_k is in a given subdimension, all variables in p_k are in that subdimension. For instance, in the above example there are $K = 4$ basic groups and the partition is given by $\mathbf{P} = (\mathbf{p}_1, \mathbf{p}_2, \mathbf{p}_3, \mathbf{p}_4) = (\mathbf{a}^{(1)}, \mathbf{a}^{(2)}, \mathbf{a}^{(31)}, \mathbf{a}^{(32)})$.³⁴

Proposition 3 can be illustrated with the help of the example in Figure 1.1. Let $S = \{a_1, \dots, a_6\}$ and $S' = \{a_7, a_8, a_9\}$, where the latter three variables comprise subdimension 2 of dimension 3. Suppose that these three variables are related as described above, and thus yield the four options (0,0,0), (1,0,0), (1,1,0), and (1,1,1). The three dichotomous variables in S' can be replaced with one variable x having the values 0, 1/3, 2/3, and 1, where x inherits a total weight of 1/6 from the subdimension. The resulting seven variables and weights are denoted by $\mathbf{a}' = (a_1, \dots, a_6, x)$ and $\mathbf{w}' = (w_1, \dots, w_6, \frac{1}{6})$. For example, for $\mathbf{a} = (1,0,1,1,1,0,0)$, the original counting index is

$$C(\mathbf{a}; \mathbf{w}) = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} + \frac{1}{12} + \frac{1}{18} = 23/36 \quad (1.15)$$

while for the analogous $\mathbf{a}' = (1,0,1,1,1,0, \frac{1}{3})$, the alternative index is

$$C(\mathbf{a}'; \mathbf{w}') = \frac{1}{6} + \frac{1}{6} + \frac{1}{6} + \frac{1}{12} + \frac{1}{6} \cdot \frac{1}{3} = 23/36 \quad (1.16)$$

Consequently, the user can choose either approach without altering the results.

Finally, Equation (9) can be illustrated with the help of the example in Figure 1.1 where the initial six variables in \mathbf{a}' have values (1,0,1,1,1,0). How does $C_\alpha(\mathbf{a}'; \mathbf{w}')$ change as the final variable rises from 0 to 1/3 to 2/3 to 1? Note that the index takes on the value 0.58 when the final variable is 0 and the value 0.75 when the final variable is 1, regardless of α . What is different for different α is how the two intermediate levels line up. For the original index with $\alpha = 1$, each increment in the variable leads to the same increase in the index value along the way from 0.58 to 0.75. For $\alpha = 1/2$ the index values are 0.58, 0.68, 0.72, and 0.75 as the final variable increases. Countries that move from 0 to the first rung of the variable generate the largest increase in $C_{1/2}$. Likewise, for $\alpha = 2$ the respective index values are 0.58, 0.60, 0.66, and 0.75. It is now the movement from the penultimate to the highest rung that generates the greatest improvement in index C_2 . This suggests that the class C_α of indices might be helpful as a diagnostic tool in support of the main index C .

³⁴ The main decomposition axiom is defined with respect to the basic groups, analogous to equation (5).

Figure 1.1: Illustration for the Dimensions and Weights

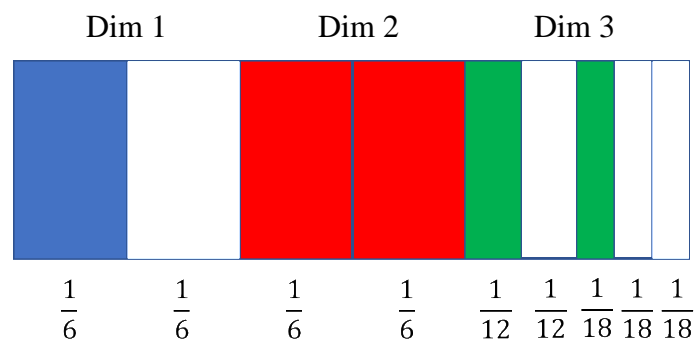


Figure 1.2: SPI Scores versus Country Income Level, 2016

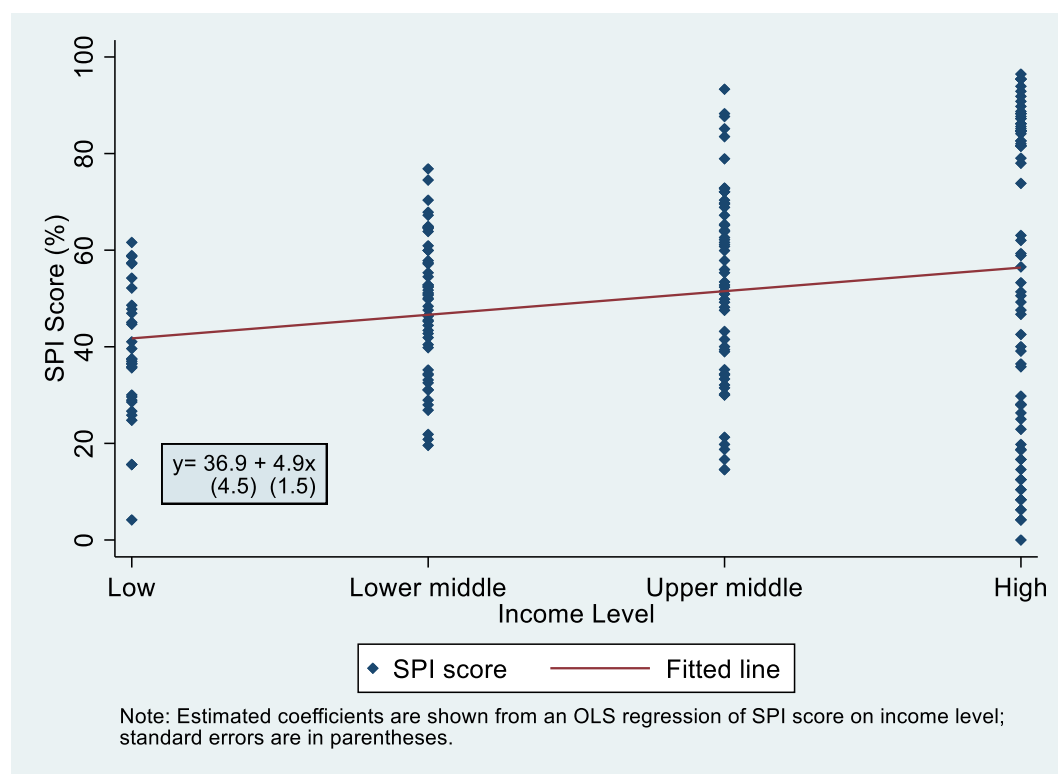


Figure 1.3: Dimension SPI Scores by Region, 2016

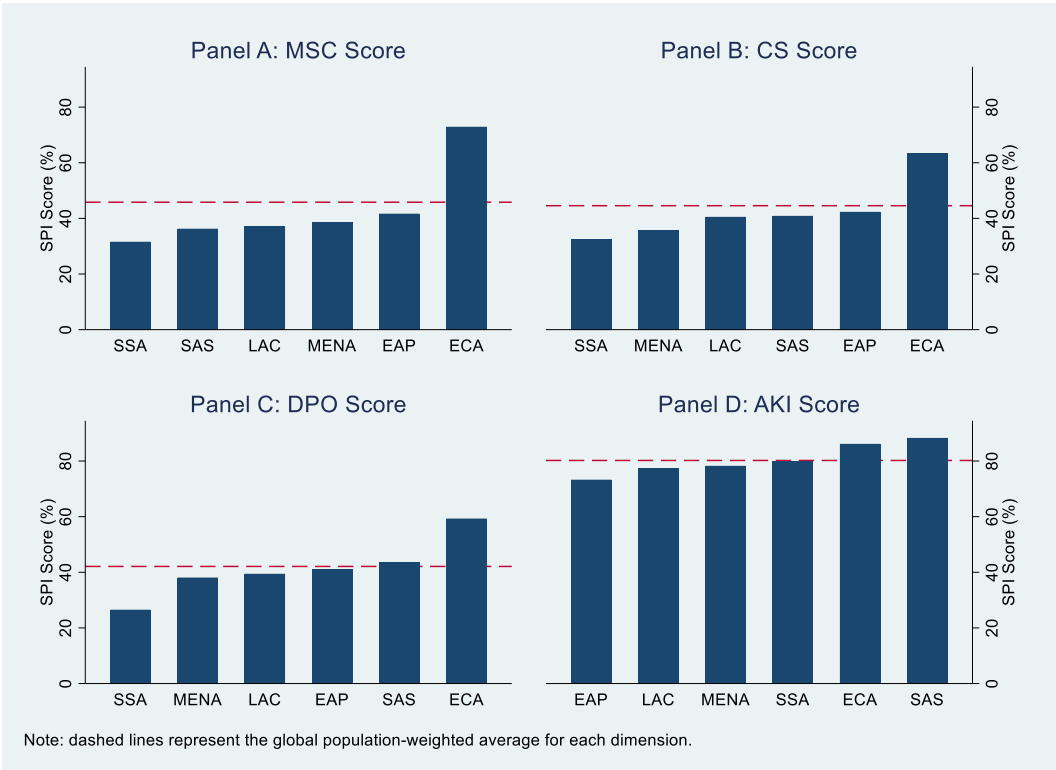


Table 1.1: Country SPI and SCI Scores, 2016

No	Country	SPI	SCI
1	Afghanistan	36.9	51.1
2	Albania	69.6	82.2
3	Algeria	41.5	55.6
4	Angola	34.4	42.2
5	Antigua and Barbuda	36.5	57.8
6	Argentina	60.8	88.9
7	Armenia	76.8	92.2
8	Azerbaijan	72.1	75.6
9	Bangladesh	51.7	74.4
10	Belarus	61.2	87.8
11	Belize	51.5	62.2
12	Benin	46.9	73.3
13	Bhutan	45.5	68.9
14	Bolivia	50.9	68.9
15	Bosnia and Herzegovina	49.2	72.2
16	Botswana	56.0	42.2
17	Brazil	67.2	76.7
18	Bulgaria	88.3	84.4
19	Burkina Faso	57.2	74.4
20	Burundi	47.8	62.2
21	Cabo Verde	59.9	68.9
22	Cambodia	52.8	66.7
23	Cameroon	43.4	68.9
24	Central African Republic	28.6	41.1
25	Chad	29.0	54.4
26	Chile	82.0	95.6
27	China	61.6	80.0
28	Colombia	72.7	88.9
29	Comoros	24.8	34.4
30	Congo, Dem. Rep.	26.7	51.1
31	Congo, Rep.	34.2	50.0
32	Costa Rica	72.1	84.4
33	Cote d'Ivoire	45.3	67.8
34	Croatia	87.7	81.1
35	Djibouti	21.9	53.3
36	Dominica	33.3	57.8
37	Dominican Republic	63.9	83.3
38	Ecuador	57.9	71.1
39	Egypt, Arab Rep.	64.7	87.8
40	El Salvador	57.4	92.2
41	Equatorial Guinea	30.0	45.6
42	Eritrea	15.6	28.9
43	Ethiopia	35.9	70.0
44	Fiji	47.6	58.9

45	Gabon	31.5	36.7
46	Gambia, The	36.5	64.4
47	Georgia	70.4	88.9
48	Ghana	52.8	68.9
49	Grenada	34.4	51.1
50	Guatemala	57.2	71.1
51	Guinea	35.7	55.6
52	Guinea-Bissau	29.6	42.2
53	Guyana	32.1	57.8
54	Haiti	37.5	38.9
55	Honduras	52.4	77.8
56	India	64.5	81.1
57	Indonesia	67.9	86.7
58	Iran, Islamic Rep.	48.2	78.9
59	Iraq	30.2	50.0
60	Jamaica	55.3	77.8
61	Jordan	54.5	71.1
62	Kazakhstan	70.4	92.2
63	Kenya	40.4	55.6
64	Kiribati	26.9	40.0
65	Kosovo	46.3	43.3
66	Kyrgyz Republic	57.8	85.6
67	Lao PDR	41.9	64.4
68	Lebanon	39.0	63.3
69	Lesotho	50.7	57.8
70	Liberia	41.0	57.8
71	Libya	16.7	22.2
72	Macedonia, FYR	65.4	81.1
73	Madagascar	25.8	62.2
74	Malawi	45.1	74.4
75	Malaysia	62.6	77.8
76	Maldives	39.4	50.0
77	Mali	39.6	65.6
78	Marshall Islands	18.8	28.9
79	Mauritania	33.1	58.9
80	Mauritius	68.9	91.1
81	Mexico	83.5	98.9
82	Micronesia, Fed. Sts.	31.1	32.2
83	Moldova	63.9	95.6
84	Mongolia	67.2	82.2
85	Montenegro	64.1	72.2
86	Morocco	59.9	84.4
87	Mozambique	52.2	71.1
88	Myanmar	47.6	55.6
89	Namibia	53.4	58.9
90	Nauru	14.6	n.a.

91	Nepal	58.9	70.0
92	Nicaragua	42.7	70.0
93	Niger	44.7	71.1
94	Nigeria	52.4	67.8
95	Pakistan	49.9	75.6
96	Palau	25.0	48.9
97	Panama	52.8	73.3
98	Papua New Guinea	20.8	50.0
99	Paraguay	52.4	70.0
100	Peru	69.8	93.3
101	Philippines	74.5	82.2
102	Poland	86.2	77.8
103	Romania	93.3	77.8
104	Russian Federation	62.2	81.1
105	Rwanda	61.6	70.0
106	Samoa	50.9	54.4
107	Sao Tome and Principe	39.8	60.0
108	Senegal	58.7	75.6
109	Serbia	72.9	90.0
110	Seychelles	56.5	70.0
111	Sierra Leone	37.3	63.3
112	Solomon Islands	32.5	48.9
113	Somalia	4.2	20.0
114	South Africa	65.1	82.2
115	South Sudan	30.0	37.8
116	Sri Lanka	64.9	83.3
117	St. Kitts and Nevis	28.1	53.3
118	St. Lucia	43.2	64.4
119	St. Vincent and the Grenadines	40.0	60.0
120	Sudan	29.0	63.3
121	Suriname	49.9	65.6
122	Swaziland	35.2	55.6
123	Syrian Arab Republic	19.6	37.8
124	Tajikistan	48.4	81.1
125	Tanzania	57.4	73.3
126	Thailand	78.9	85.6
127	Timor-Leste	46.5	66.7
128	Togo	48.6	68.9
129	Tonga	34.2	52.2
130	Trinidad and Tobago	40.0	61.1
131	Tunisia	51.2	76.7
132	Turkey	85.1	77.8
133	Turkmenistan	21.3	34.4
134	Tuvalu	19.8	40.0
135	Uganda	54.2	68.9
136	Ukraine	60.9	83.3

137	Uruguay	63.1	88.9
138	Uzbekistan	28.0	48.9
139	Vanuatu	44.4	50.0
140	Venezuela, RB	59.9	82.2
141	Vietnam	64.7	82.2
142	West Bank and Gaza	50.1	70.0
143	Yemen, Rep.	31.0	47.8
144	Zambia	55.3	53.3
145	Zimbabwe	36.5	55.6

Note: "n.a." stands for missing data.

Appendix 2: SPI Scoring Methodology Matrix (for online publication)

Methodology, Standards & Classifications							
#	Indicator	Score 1	Score 0.5	Score 0	Weight	Sources	Link
1	System of National Accounts in use	SNA2008/ESA 2010	SNA1993/ ESA 1995	Otherwise	1	World Development Indicators Primary Data Documentation (WDI/PDD); International Monetary Fund's (IMF) World Economic Outlook (WEO), Table G of Statistical Appendix	http://data.worldbank.org/products/wdi http://www.imf.org/en/publications/weo
2	National Accounts base year	Annual chain linking	Within past 10 years	Otherwise	1	World Development Indicators Primary Data Documentation (WDI/PDD); International Monetary Fund's (IMF) World Economic Outlook (WEO), Table G of Statistical Appendix	http://data.worldbank.org/products/wdi http://www.imf.org/en/publications/weo
3	Classification of national industry	Latest version is adopted (ISIC Rev 4, NACE Rev 2 or a compatible classification)	Previous version is used (ISIC Rev 3, NACE Rev 1 or a compatible classification)	Otherwise	1	United Nations Monthly Bulletin of Statistics Database, Index of Industrial Production	https://unstats.un.org/UNSD/mbs/app/DataSearchTable.aspx
4	CPI base year	Annual chain linking	Within past 10 years	Otherwise	1	IMF: International Financial Statistics (IFS) / Country notes	http://www.elibrary.imf.org/browse?freeFilter=false&pageSize=10&sort=datedescending&t_7=urn%3ASeries%2F041
5	Classification of household consumption	Follow Classification of Individual Consumption by Purpose (COICOP)	NA.	Otherwise	1	IMF: Dissemination Standards Bulletin Board (DSBB)	http://dsbb.imf.org/Default.aspx

6	Classification of status of employment	Follow International Labour Organization, International Classification of Status in Employment (ICSE-93)	NA.	Otherwise	1	IMF: Dissemination Standards Bulletin Board (DSBB)	http://dsbb.imf.org/Default.aspx
7	Central government accounting status	Consolidated central government accounting follows noncash recording basis	Consolidated central government accounting follows cash recording basis	Otherwise	1	IMF: Government Finance Statistics (GFS) Yearbook/Guide to country tables	http://www.elibrary.imf.org/browse?freeFilter=false&pageSize=10&sort=datedescending&t_7=urn%3ASeries%2F043
8	Compilation of government finance statistics	Follow the latest Government Finance Statistical Manual (2014)/ ESA2010 or GFSM 2001	NA.	Otherwise	1	IMF: WEO, Table G of Statistical Appendix	http://www.imf.org/en/publications/weo
9	Compilation of monetary and financial statistics	Follow the latest Monetary and Finance Statistics Manual (2000) or Monetary and Finance Statistics: Compilation Guide (2008)	NA.	Otherwise	1	IMF: IFS / Country notes	http://www.elibrary.imf.org/browse?freeFilter=false&pageSize=10&sort=datedescending&t_7=urn%3ASeries%2F041
10	SDDS/e-GDDS subscription	Subscribing to IMF SDDS standards	Subscribing to IMF e-GDDS standards	Otherwise	1	IMF: SDDS/e-GDDS website	http://dsbb.imf.org/Pages/GDDS/Home.aspx

11	CRVS	Vital registration complete	NA	Otherwise	1	WDI book: Primary Data Documentation	http://data.worldbank.org/products/wdi
12	Business process	GSBPM is in use	NA	Otherwise	1	United Nations Industrial Development Organization (UNIDO) United Nations Economic Commission for Europe (UNECE)	https://statswiki.unece.org/display/GSBPM/United+Nations+Industrial+Development+Organization+(UNIDO)+use+of+GSBPM https://statswiki.unece.org/display/GSBPM/Case+Studies+of+Metadata+use+with+GSBPM+and+GSIM

Censuses and Surveys								
Censuses								
#	Indicator	Score 1	Score 0.5	Score 0	Weight	Sources		Link
1	Population & Housing census	Population census done within last 10 years	Population census done within last 20 years	Otherwise	1	United Nations Statistical Division (UNSD): 2020 World Population and Housing Census Programme		https://unstats.un.org/unsd/demographic/sources/census/censusdates.htm#ASIA
2	Agriculture census	Agriculture census done within last 10 years; OECD and/or EU member	Agriculture census done within last 20 years	Otherwise	1	Food and Agriculture Organization (FAO): World Programme for the Census of Agriculture		http://www.fao.org/world-census-agriculture/countries/en/
3	Business/establishment census	Business/establishment census done within last 10 years; OECD and/or EU member	Business/establishment census done within last 20 years	Otherwise	1	NSO websites		https://unstats.un.org/home/nso_sites/
Surveys								
#	Indicator	Score 1	Score 0.6	Score 0.3	Score 0	Weight	Sources	Link

4	Household Survey on income/consumption /expenditure/budget/ Integrated Survey	3 or more household surveys done within past 10 years; OECD and/or EU member	2 household surveys done within past 10 years;	1 household survey done within past 10 years;	None within past 10 years	1	Microdata library / World Bank, Development Research Group PovcalNet International Household Survey Network Catalog (IHSN) IHSN Gender Data Navigator	http://microdata.worldbank.org/index.php/home http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx http://catalog.ihsn.org/index.php/catalog http://datanavigator.ihsn.org/
5	Agriculture survey	3 or more agriculture surveys done within past 10 years; OECD and/or EU member	2 agriculture surveys done within past 10 years;	1 agriculture survey done within past 10 years;	None within past 10 years	1	Microdata library / World Bank, Development Research Group PovcalNet International Household Survey Network Catalog (IHSN)	http://microdata.worldbank.org/index.php/home http://catalog.ihsn.org/index.php/catalog http://datanavigator.ihsn.org/ http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx

							IHSN Gender Data Navigator	
6	Labor Force Survey	3 or more labor force surveys done within past 10 years; OECD and/or EU member	2 labor force surveys done within past 10 years;	1 labor force survey done within past 10 years;	None within past 10 years	1	International Labour Organisation (ILO) Microdata Repository	http://www.ilo.org/surveydata/index.php/catalog/central#r=&collection=&country=94,140&dtype=&from=2006&page=1&ps=&sid=&sk=&sort_by=nation&sort_order=&to=2016&topic=&view=s&vk= http://www.ilo.org/dyn/lfsurvey/lfsurvey.list?p_lang=en http://microdata.worldbank.org/index.php/home http://catalog.ihsn.org/index.php/catalog http://datanavigator.ihsn.org/ http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx
7	Health/Demographic survey	3 or more health surveys done within past 10 years; OECD and/or EU member	2 health surveys done within past 10 years;	1 health survey done within past 10 years;	None within past 10 years	1	Demographic and Health Surveys	https://dhsprogram.com/What-We-Do/survey-search.cfm?pgType=main&SrvyTp=type
8	Business/establishment survey	3 or more business/establishment surveys done within	2 business/establishment surveys	1 business/establishment	None within	1	Microdata library / World Bank, Development	http://microdata.worldbank.org/index.php/home

		past 10 years; OECD and/or EU member	done within past 10 years;	nt survey done within past 10 years;	past 10 years		Research Group PovcalNet International Household Survey Network Catalog (IHSN) IHSN Gender Data Navigator	http://catalog.ihsn.org/index.php/catalog http://datanavigator.ihsn.org/ http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx
--	--	--	----------------------------------	---	------------------	--	--	---

Availability of Key Indicators						
#	Indicator	Score 1 - Data is available once in three years, prior to reference year	Score 0	Weight	Source	Link
1	Poverty headcount ratio at national poverty lines/ availability of similar key indicators	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
2	Mortality rate, under-5 (per 1,000 live births)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

3	Child immunization (proportion of one-year-old children immunized against measles)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
4	Primary completion rate, both sexes (%)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
5	Adult literacy rate, population 15+ years, both sexes (%)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
6	Proportion of population using safely managed drinking water services	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
7	Unemployment, total (% of total labor force)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
8	Manufacturing value added as a proportion of GDP	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
9	Gross capital formation (% of GDP)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
10	GDP implicit price deflator (annual % growth)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

11	Net trade in goods and services (BoP, current US\$)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
12	Prevalence of undernourishment (% of population)	Yes	No	1	WDI database	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

Dissemination Practices & Openness						
1) Dissemination capacity of NSO						
#	Indicator	Score 1	Score 0	Weight	Source	Link
1	NSO has an Advance Release Calendar and it is published	Yes	No	1	UNSD Partners National Statistics Office (NSO) websites	https://unstats.un.org/home/nso_sites/
2	NSO has a listing of surveys and microdata sets (or NADA)	Yes	No	1	NSO websites / Accelerated Data Program of IHSN	https://unstats.un.org/home/nso_sites/ http://www.adp.ihsn.org/country_activities
3	NSO has a data portal	Yes	No	1	NSO websites	https://unstats.un.org/home/nso_sites/
4	Timeseries indicators are available for download in reusable format for free	Yes	No	1	NSO websites	https://unstats.un.org/home/nso_sites/

5	Metadata is available providing definition, methodology, standards or classifications for existing data series	Yes	No	1	NSO websites	https://unstats.un.org/home/nso_sites/
6	NSO has conducted a user satisfaction survey	Yes	No	1	NSO websites	https://unstats.un.org/home/nso_sites/
7	Geospatial data available on relevant agency website	Yes	No	1	NSO / Relevant agency websites	https://unstats.un.org/home/nso_sites/
2) Openness of data						
#	Indicator	Score		Weight	Source	Link
8	Open Data Inventory	ODIN score		0	Open Data Watch	http://odin.opendatawatch.com/
9	Open Data Barometer	ODB score		0	The Open Data Barometer	http://opendatabarometer.org/
10	Open Data Index	ODI score		0	Global Open Data Index	https://index.okfn.org/
Maximum score for sub-category “Openness of data”: 0						