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Reviewing Assessment Tools for Measuring Country Statistical Capacity

Hai-Anh H. Dang, John Pullinger, Umar Serajuddin, and Brian Stacy*

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Abstract

Country statistical capacity is increasingly recognized as crucial for development, but no academic study exists that reviews the available assessment tools. We offer the first review study that fills this gap, paying particular attention to data and practical measurement challenges. We compare the World Bank's recently developed Statistical Performance Indicators and Index (SPI) with other widely used indexes such as the Open Data Inventory index (ODIN), the Global Data Barometer index (GDB), and other regional and self-assessment tools. We find that the indexes bring their own advantages regarding their data sources, number of indicators, measurement focus, coverage of country and time periods, and correlation with common development indexes. Specifically, the ODIN covers most countries, the GDB collects data through its surveys, and the SPI offers clearer mathematical foundations and somewhat stronger correlation with Sustainable Development Goals indicators. We offer further thoughts on the potential mechanisms through which these tools can bring positive impacts on economic activities and some political economy concerns, as well as future directions of development.

Key words: statistical capacity, statistical performance, statistical indicators, statistical capacity index, national statistical system

JEL: C8, H00, I00, O1

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Introduction

A country's statistical capacity is increasingly recognized as crucial for its development, for richer and poorer countries alike. Stronger statistical capacity results in better measurement of economic and social activities and outputs, which facilitates timely decision by policy makers. Stronger statistical capacity can also contribute to better governance and accountability, where citizens are better informed about government activities and can be more engaged in the monitoring process. Indeed, the Sustainable Development Goals (SDGs) call for more capacity-building support to developing countries to help increase significantly the availability of high-quality, timely, and reliable data (United Nations, 2023; SDG number 17.18). In a recent global flagship report, the World Bank highlights the strong, positive relationships between a country's statistical capacity and the independence of its national statistical office (NSO) and its freedom of the press (World Bank, 2021).

Some practical examples can further illustrate the consequences of statistical capacity—stronger and weaker—in action. For the past decades, the U.S. Bureau of Labor Statistics closely keeps track of the latest (un)employment trends in the economy and publicly release these statistics every month. Data on employment trends keep all stakeholders well-informed, and typically feed into prompt actions by both the (interest-rate-setting) Federal Reserve Board and private investors in the stock market. Given the prominent role of the U.S. economy in the world, these actions typically reverberate overnight to other economies and stock markets around the world.

On the other hand, 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. Weak statistical capacity not only cause inefficiencies but could lead to corruption and consequential damages to the economy. A notable case occurred when three state-backed Mozambican firms borrowed US\$1.2 billion in government-guaranteed debt in 2013-2014—roughly 8 percent of the country's GDP—without the parliament and the public's knowledge. This lack of public debt transparency led to Mozambique facing severe restrictions to the international credit market when these loans were revealed in 2016 (Economist, 2019; IMF, 2019). More strikingly, a recent study estimates that, due to the incentive to overstate economic growth and a lack of checks and balances, autocratic regimes could overstate yearly GDP growth by 35 percent (Martinez, 2022).

These examples allude to the fact that statistical capacity varies by country characteristics, particularly by country income levels. Specifically, using the World Bank's poverty database, we plot the number of poverty estimates against a country's income (consumption) level (as measured in household surveys) over the past 40 years in Figure 1. The fitted line for the regression of these data points on country income is positive and strongly statistically significant, suggesting that countries with higher incomes more frequently implement household surveys. Indeed, a 10 percent increase in a country's average income is associated with almost two-thirds (i.e., 0.67) as many surveys. This gap of survey data is consistent with the observation that poorer countries, especially in Sub-Saharan Africa, tend to have weaker statistical capacity (Devarajan, 2013; Jerven, 2013; Sandefur and Glassman, 2015; Dargent *et al.*, 2018).

The international community has long placed much attention on assessing and improving country statistical capacity—particularly for (poorer) countries with weaker capacity—to better guide international support. The Statistical Capacity Index (SCI) was a tool developed by the World Bank in 2004 to assess global improvements in country statistical capacity (World Bank, 2020). Most recently, it was replaced by the Statistical Performance Indicators and Index (SPI), which offers a clearer conceptual framework and broader country coverage (Dang *et al.*, 2023). Other global assessment tools that have been employed for evaluating country statistical capacity include the Open Data Inventory index (ODIN) (Open Data Watch, 2022), the Global Data Barometer index (GDB) and its predecessor the Open Data Barometer index (ODB) (Global Data Barometer, 2022). Regional assessment tools (e.g., the Ibrahim Index of African Governance Statistical Capacity (IIAG)) and self-assessment tools were also employed by other international organizations for countries to self-report on their statistical capacity.

While these (assessment) tools offer policy makers different options to assess country statistical capacity, they typically follow different philosophical principles in generating their metrics as well as in collecting and processing data. It would be useful for various stake holders—policy makers, national statistical offices, international development organizations, researchers, private investors, and others—to have a clear understanding of these differences, and to appreciate the relative strengths and weaknesses of the tools, for their most effective use. We thus offer the first critical assessment of these tools.

Using the SPI framework as the reference point, we review the tools' guiding principles before discussing their coverage, groupings (dimensions), indicators, and data sources. To compare their

measurement power, we examine the relationship between these tools and representative development outcomes for each of the 17 SDGs, an overall SDG index, and several other common indexes. Finally, we offer some thoughts on other challenges, including potential mechanism for their impacts on the economy, political economy factors, and future development of these tools. For illustration, we offer new analysis based on their latest data updates, including new data for the SPI in 2021 and 2022 that were not analyzed before.

Results

We provide a brief overview of the various tools and highlight some key qualitative differences regarding their guiding principles, before offering a more detailed comparison over the dimensions, indicators, and countries covered by the tools. We subsequently examine the relationships of these tools with a number of key SDG outcomes and several other development indexes.

Overview of the tools and their guiding principles

Statistical Capacity Indicators and Index (SCI) and Statistical Performance Indicators and Index (SPI)

Following the guiding principles that the source data should be publicly available and meet certain quality standards (e.g., as provided by the curators of the international databases), the SCI collected data from publicly available, international databases and NSO websites, with the major share coming from the former source. The SCI has been employed by different international and national agencies since its inception in 2004 to measure progress with development trends (United Nations, 2016), or areas of statistical improvement in member countries (OIC, 2012), or tracking the SDGs for child development (UNICEF, 2018). The SCI was widely employed in academic research covering different disciplines, ranging from economics, international development, political science to statistics. We offer in Appendix A, Table S1 a brief overview of some selected academic studies in the past decade that employ the SCI.

The SCI, however, has several key limitations, including an outdated framework, a focus on poorer countries only, and a lack of underlying conceptual and mathematical principles. The SPI recently replaces and offers several advantages over the SCI on both the conceptual and empirical

fronts (Dang *et al.*, 2023). In particular, the SPI explicitly offers standard *desiderata* for a statistical index (i.e., simple, coherent, motivated, rigorous, implementable, replicable, incentive consistent). Conceptually, it consists of five pillars of data use, data services, data products, data sources, and data infrastructure, which can be further disaggregated into 22 dimensions. The SPI is also built on a clear mathematical foundation with three-level nested weighting structure that offers desirable properties for an index such as symmetry, monotonicity, and subgroup decomposability (Cameron *et al.*, 2021). Empirically, the SPI offers more than twice the number of indicators provided by the SCI. The SPI covers both low-income and high-income countries, while the SCI focuses on non-high-income countries alone. Finally, the SPI cover indicators related to the SDGs, while the SCI cover indicators related to the (older) MDGs.

Despite its infancy, to date the SPI has been adopted for measuring country statistical capacity in several high-profile policy reports such as *Sustainable Development Reports 2021, 2022, and 2023* (Sachs *et al.*, 2021, 2022, and 2023) and World Bank’s *World Development Report 2021* (World Bank, 2021). In particular, the index was used to help highlight various gaps in countries’ data dissemination and openness, with higher statistical capacity levels being positively correlated with more NSO independence (World Bank, 2021). The index has inspired further research on assessing data openness and accessibility in MENA, a traditionally data-scarce region (Ekhaton-Mobayode and Hoogeveen, 2022), or how best to construct measures for learning deficiency due to Covid-19-induced school closures (Azevedo, 2020), or to better understand how NSOs respond and adjust to the disruptions caused by the Covid-19 pandemic (Wollburg *et al.*, 2022). It also contributes to current thinking not only on improving the quality of NSSs, government use of data, and future official statistics (Radermacher, 2021; Asher *et al.*, 2022; Bersales, 2022), but also on other topics such as reducing GDP growth forecast errors (Gatti *et al.*, 2023), measuring public sector digital transformation (Dener *et al.*, 2021) and food and agriculture statistics (Bizier *et al.*, 2022), and selecting the appropriate context to measure student absenteeism and women’s empowerment (Yount *et al.*, 2022; Evans and Acosta, 2023).

We offer further discussion on the conceptual motivations and construction of the SPI in the Method section. We provide more details on the dimensions of the SPI, including ongoing data work, in Appendix A, Table S2 and a mapping of the SPI indicators to the SDG indicators in Table S3. We provide the latest update for the SPI country scores in 2022 in Appendix A, Table S4, with

further result breakdowns by income and region in Figures S1 and S2. Further comparison between the SPI and the SCI is provided in Dang *et al.* (2023).

Open Data Inventory (ODIN) index

The ODIN's objective is "to provide an objective and reproducible measure of the public availability of national statistics, and their adherence to open data standards" (Open Data Watch, 2023). The ODIN currently provides annual data starting from 2015 but offers comparable data starting only from 2016. In contrast with the SPI's data sources, the ODIN does not assess data published for countries on international organizations' websites. Consequently, the ODIN focuses on data that are available from the official website of the NSO and any official government website that is accessible from the NSO site. It assesses the coverage and openness of statistics, where coverage refers to the availability of important statistical indicators classified into three main groups of social statistics, economic and financial statistics, and environmental statistics (which are further broken down into 22 topical sub-groups or data categories).

Each data category is assessed on five elements of coverage (i.e., availability of indicators and disaggregations, availability of data in the last five and 10 years, and availability of data at the first and the second administrative geographic levels), and five elements of openness (i.e., availability of data in machine-readable format and non-proprietary format, availability of reference metadata, availability of download options that make the data more accessible, and availability of an open data license or open data terms of use). Aggregate scores are computed across categories and elements, resulting in the overall ODIN score being an index of how complete and open an NSO's data offerings are.

Open Data Barometer (ODB) and Global Data Barometer (GDB)

The ODB provides "a global measure of how governments are publishing and using open data for accountability, innovation and social impact". While first starting in 2013, the ODB has been further expanded to include other data aspects with its successor, the GDB, since 2017. Following a different approach from those of the SPI and the ODIN, the latest GDB collects primary data from an expert survey and supplements these primary data with other secondary data sources to generate its metrics (Global Data Barometer, 2022).

The GDB offers an overall country score, a pillar score, and a module score. The country scores are built on four pillar scores for governance, capability, availability, and use and impact. The module scores are available for the following thematic topics: (private) company information, land, political integrity, public finance, public procurement, climate action, health, and Covid-19. The GDB assigns different weights to each of its indicators, depending on whether it is a primary indicator (more weight) or secondary indicator (less weight) or which pillar it belongs to (i.e., governance, capability, availability pillars have more weight).

Other Tools

The Ibrahim Index of African Governance Statistical Capacity (IIAG) is a regional assessment tool aiming at “measuring African governance performance”, where governance is defined as “as the provision of the political, social, economic and environmental goods and services that every citizen has the right to expect from their state, and that a state has the responsibility to deliver to its citizens” (Mo Ibrahim Foundation, 2023). The IIAG consists of four main pillars of governance: Security and Rule of Law, Participation, Rights and Inclusion, Foundations for Economic Opportunity, and Human Development. These categories are comprised of 16 sub-categories and make up the Overall Governance score.

Besides the global and regional tools, there are several detailed self-assessment tools. These include the European Snapshot Tool, the UN NQAF (National Quality Assurance Framework) self-check tool, and the Paris21 NSDS (National Strategies for the Development of Statistics) self-assessment tool. Unlike the tools mentioned above these self-assessment tools do not offer explicit performance scores.

In summary, our brief review above suggests several key qualitative differences across the different tools. As their names suggest, the SPI (and SCI) aims to measure country statistical capacity, the other indexes focus more on aspects of statistical capacity such as data availability and open data standards (the ODIN and the ODB and GDB) or governance performance (the IIAG). The SPI, the ODIN, the GDB (and ODB), and the IIAG offer data points on country performance over time, while the self-assessment tools (including European Snapshot Tool, the UN NQAF self-check tool, and the Paris21 NSDS) are designed for self-assessment and do not offer such data.

The tools' methods of data collection differ, with the SPI obtaining most of the data from curated international databases, the ODIN exclusively from NSO websites, the GDB mostly from expert surveys, the IIAG from a mix of different sources, and the three self-assessment tools from expert self-assessment tools. These different methods come with their own strengths and weaknesses. Data that are provided by the curators of the international databases potentially ensure data quality and comparability, especially in countries with weak statistical capacity where data are not well-maintained or where data might at times be subject to weaker quality control or even manipulation (as discussed earlier). But such data are dependent on the curators' production cycles and hence at times can be a bit dated. On the other hand, collecting data directly from NSO websites or an expert survey could provide more in-depth analyses and uncover finer details, but it incurs high costs and could be far more time consuming. In addition, direct interviews of government officials might bias responses and complicate comparability across countries since government officials may have an incentive to overestimate their country's statistical capacity where concerns exist regarding their ability to deliver, or they may underestimate their country's statistical capacity where they are requesting additional international aid.

Notably, of the other assessment tools considered in this study (including the SCI), only the SPI offers an explicit discussion of its conceptual and mathematical foundations in peer-reviewed academic publications (Cameron *et al.*, 2021; Lokshin, 2022; Dang *et al.*, 2023). Consequently, we employ the SPI's five pillars as a reference point in the subsequent comparison of the different tools. We provide further discussion on the SPI framework in the Method section.

Further comparison of the tools

Country coverage, dimension, indicators, and data sources

We compare in Table 1 several other features of the tools (indexes), including their coverage of countries, dimensions, indicators and their data sources. For completeness, we show in this table both the current tools and their predecessors. In addition, we also broaden this comparison to include some self-assessment tools that have been employed by international organizations for countries to self-report on their statistical capacity. These include the EU Snapshot Tool, the UN NQAF self-check tool, and the Paris21 NSDS self-assessment tool. But there is no publicly available information on how many years or how many countries that these tools have been implemented for. The only available information includes the (number of) indicators each tool

employs, which we can compare against the SPI's five pillars. Table S5 in Appendix A provides the links to all the tools discussed above (as well as briefly review some other tools on related development topics such as open government data, governance, poverty and human capital).

Several remarks are useful. First, except for the IIAG that focuses on Africa, all the remaining tools are global and use a scale of 0-100, with a larger number indicating better capacity. Regarding the number of countries (and years) coverage, the ODIN comes first (192 countries during 2016-2022), followed by the SPI (186 countries during 2016-2022), the SCI (145 countries during 2004-2020), the ODB (116 countries during 2013-2016, and 30 countries for 2017), and the GDB (109 countries during 2021), and the IIAG (54 countries during 2010-2019). While the number of countries that an index covers can vary widely over the years, for comparison purposes, we show the number of countries covered by an index for its latest year available. All the indexes are generated annually, except for the GDB that is conducted biennially.

Second, except for the SCI and the IIAG that use simple weighting, all the indexes employ some form of nested weighting method to construct the overall score. The details of the nested structure differ significantly across indexes. The ODIN has a two-level nested structure with 65 indicators being categorized (under 22 smaller sub-groups) in three groups, and the ODIN overall score is an equal weighted average of these three group scores. The GDB also has a nested structure of pillars, indicators, sub-sections, and sub-questions, where the score at each level is a weighted average of its sub-components, which results in an overall weighted score. The SPI has a three-level nested weight structure. Yet, one feature setting apart the SPI from others is that its overall score is based on a mathematical framework, where desirable properties of the index are explicitly discussed such as symmetry, monotonicity, and subgroup decomposability (Cameron *et al.*, 2021).

Finally, regarding the number of indicators, the three self-assessment tools as a group have more indicators than the other indexes, with the Paris21 NSDS self-assessment tool leading this group (149), to be followed by the EU Snapshot Tool (131), and the UN NQAF self-check tool (87) (the numbers in parentheses are the number of indicators). For the other tools, the GDB ranks first (55), to be followed by the SPI (51), the ODB (46), the ODIN (44), the SCI (21), and the IIAG (3). Using the SPI's five pillars as a reference point, the other indexes seem to cover either too much or too little for certain pillars. For example, the ODIN splits its indicators over two pillars Data services and Data products, and have no indicators for the remaining three pillars. Only the

GDB and the three self-assessment tools cover all the five pillars, but with varying degrees for each pillar.

Yet, while the number of indicators provides a useful, quantifiable metric of statistical capacity for comparison, ultimately what this metric aims to capture is the different, quality aspects (dimensions) of statistical capacity. For this purpose, Table 1 also shows for each index the distribution of its indicators categorized by the five SPI pillars. Table 1 shows that all the three self-assessment tools focus much more on the data infrastructure pillar (with at least 60% of their indicators) than the other pillars.

Figure 2 offers an alternative visual presentation to Table 1, where we plot the percentage of coverage for each SPI pillars for all the tools. Since a balanced distribution would require a coverage rate of 20% for each of the five pillars, comparing each index's coverage against the light blue spider web in the background helps illustrate how much imbalance each index has. Again, this figure helps make clearer the patterns shown in Table 1. Compared to the SPI framework, the ODIN and the ODB focus more on data services and products, the IIAG and the SCI focus more on data products and infrastructure, and the GDB and all the three self-assessment tools focus more on data infrastructure.

Measuring country progress over time

The next question naturally arises: how do the tools keep track of country progress over time? We examine this question for the SPI and the ODIN for the recent period 2016-2022, since the GDB just offers data for one year and the ODB and the SCI cover earlier periods only. Similar to the slow evolution of state capacity (see, e.g., Glaeser et al. (2004) and Savoia and Sen (2019)), country statistical capacity typically takes time to build up and so would change gradually, rather than abruptly, under most normal circumstances (Ngaruko, 2008; Cameron *et al.*, 2021). Figure 3, the top left corner panel plots the scores in 2022 against those in 2016 for the two indexes. While the ODIN and the SPI has similar trends, the latter has somewhat stronger goodness-of-fit statistics (i.e., the R^2 equals 0.85 for the SPI and 0.58 for the ODIN). We further consider the standard deviation of the overall index for this period as another measure of index volatility. Overall, the ODIN overall scores are more volatile. It has a global average standard deviation of 6, which is about 20 percent larger than that of 5.1 for the SPI overall score.

For further illustration, we randomly select 15 countries and plot the trend of their overall ODIN and SPI scores over time. While the trends appear similar for both tools, the ODIN scores show slightly more volatility. In particular, certain countries show abrupt changes of more than 17 percentage points for the ODIN scores such as Romania during 2017-2018, Serbia during 2016-2017, and Ukraine 2019-2020. The changes for the SPI overall score is much less, averaging 5 percentage points only for these three countries.

Relationship with key development outcomes

Strong statistical capacity is well recognized as necessary for the functioning of the global sustainable development agenda, including creating and maintaining the infrastructure for monitoring SDG progress and generating the relevant data and indicators (Dang and Serajuddin, 2020; Barbier and Burgess, 2021; Bandon-Gill *et al.*, 2022). It would be useful to examine the relationship of the tools and the SDGs.

We plot in Figure 4 the bivariate correlation coefficients between the five tools (ODIN, ODB, GDB, SCI, and SPI) and a representative SDG indicator for each of the 17 SDGs and an SDG overall index generated as in Sachs *et al.* (2023), which reflects country progress in achieving SDG targets, with a higher score suggesting a stronger standing. We provide more detailed numbers in Appendix A, Table S6. The SPI shows the strongest correlation with most indicators (leading or tied in 10 out of 17 indicators), which is then followed by the GDB and the ODB (four indicators for each). The ODIN and the SCI each lead on one indicator only. For the overall SDG index, the SPI also shows the strongest correlation (0.82), to be followed by the GDB (0.74), the ODIN (0.72), the ODB (0.69), and the SCI (0.65). More careful tests of the correlations against each other is useful, and we show the t-tests to compare the correlations (i.e., the indexes shown in the smaller font in the right column under each index heading are not statistically significantly). For example, the SPI's correlation with the overall SDG index is statistically different from those of the other tools. This is further supported with similar multivariate regressions results shown in Appendix A, Tables S8 and S9.

Figure 5 similarly plots the correlations for the tools and six other commonly used development indexes, which include the the Economics Complexity Index (Hartmann *et al.*, 2017), the Environmental Performance Index (Wolf *et al.*, 2022), the OECD Better Life Index (Durand, 2015), the United Nations Human Development Index (UN, 2022), the World Bank Human

Capital Index (Kraay, 2019), and the World Press Freedom Index (Reporters without Borders, 2023). The SPI has strongest correlation with three out of the six indexes, followed by the ODB (two indexes), and the ODB (one index). However, most of these correlation coefficients are not statistically significant from each other as shown by statistical tests and further multivariate regression results (Appendix A, Table S7 and Tables S10 to S21), suggesting the tools having rather similar relationships with these six development indexes.

Discussion

We offer the first rigorous assessment of the various tools that are commonly used to assess country statistical capacity. These include the Global Data Barometer index (GDB), the Open Data Inventory index (ODIN), the Statistical Performance Indicators and Index (SPI), their predecessors (the ODB and the SCI), and some regional and self-assessment tools (including the IIAG). Each tool follows its own guiding principles in collecting data and generating its metrics. Compared to the SPI framework, the ODIN and the ODB focus more on data services and products, the IIAG and the SCI focus more on data products and infrastructure, and the GDB and all the three self-assessment tools focus more on data infrastructure. While the SPI (and SCI) obtaining most of the data from curated international databases, the ODIN exclusively from NSO websites, the GDB (and ODB) mostly from expert surveys, the IIAG from a mix of different sources, and the three self-assessment tools from expert self-assessment tools. These different methods could offer their own strengths and weaknesses.

Except for the IIAG that focuses on Africa, all the remaining tools are global. The ODIN covers most countries, to be followed by the SPI (and the SCI), the GDB (and the ODB), and the IIAG (54 countries during 2010-2019). Regarding measuring recent country progress over time, the ODIN and SPI are the two available choices, with the SPI showing somewhat less volatility. Since strong statistical capacity is crucial for monitoring SDG progress and other key development outcomes, we examine their relationships with the tools. For the overall SDG index, the SPI also shows the strongest correlation, to be followed by the GDB, and the ODIN. The SPI and the ODB have stronger correlations with other popular development indexes such as the Economics Complexity Index, the OECD Better Life Index, the United Nations Human Development Index, the World Bank Human Capital Index, the World Press Freedom Index, and Yale University's Environmental Performance Index.

Potential mechanisms

While the different components of each tool form an integral whole, the self-reinforcing five SPI pillars help showcase a virtuous data cycle (Figure A.1 in Dang *et al.* (2023)). For specific illustration, Figure 6 suggests a theory of change, where the five SPI pillars together result in greater data production transparency that enables more data investment and analysis capability and facilitates data flows to key users. The key users—which consist of the government, international organizations, civil society, academia, and the private sector—ensure greater data accountability, provide better policy making and service delivery, and obtain more business efficiency. A better functioning economy, in turns, can contribute more resources to strengthen the country’s statistical capacity. This whole process leads to better development outcomes. Conceptually, this process applies not just to the SPI, but other assessment tools as well. More generally, this theory of change is consistent with the economic theory of asymmetric information (information economics), whereby better information flows among different stakeholders in the economy (including firms, workers, investors, and traders) produce more economic benefits and enable the economy to operate more smoothly (Stiglitz, 2002).

This process is broadly consistent with the cumulating evidence from a growing literature in economics that investigates related data topics. These include the studies that analyze the SCI (Appendix A, Table S1). Other recent studies suggest that increased data transparency is found to have beneficial effects on GDP and economic growth (Arezki *et al.*, 2020; Islam and Lederman, 2020), external borrowing costs (Kubota and Zeufack, 2020) as well as a positive relationship with more democracy (Janus, 2022). More data dissemination, as measured by the amount of data that countries reported to the World Development Indicators (WDI) database maintained by the World Bank, could also help raise economic growth (Hodelin, 2022). The beneficial impacts of improved data transparency are also well-documented in other disciplines such as political science (e.g., Kelly and Simmons (2014)) and natural sciences (e.g., Nagaraj *et al.* (2020)). As a recent example, Canergie *et al.* (2021) observe that populist governments report less data to the WDI compared to non-populist governments.

Political economy concerns

However, a note of caution can be useful. Better statistics may work (more effectively) under certain conditions. Improving a country's statistical capacity equips this country with a better tool, but perhaps what is more important is how these tools are used for the public good and ensuring that these tools are not misused. Put differently, improving a country's statistical capacity should not be considered separately as an end by itself, but should be examined together with other political economy factors such as governance (including government incentives) to maximize its beneficial impacts. Indeed, some recent theoretical evidence suggests that improved economic statistics may even inhibit government reform attempts, since with better statistics, politicians no longer can hide if their reform efforts are failing and thus face a higher risk of electoral losses (Binswanger and Oechslin, 2020).

Alternatively, policymakers and politicians may fear public or timely data dissemination for a variety of reasons, such as more accountability, increased public scrutiny (e.g., the data may present a simplistic perspective that does not do full credit to the complex policy-making process) or potential loss of immediate public support (e.g., policies may take more time than expected to work) (Taylor, 2016; Dargent *et al.*, 2018; Agrawal and Kumar, 2020) or not being able to secure more loans (Coyle, 2015). Similarly, for sustainable solutions, improving statistical capacity may not just include setting things right in the short term, but may also require more nuanced thinking about the varying degrees that official economic indicators can be manipulated in specific contexts, and how solutions can be tailor-made to address these challenges on a long-term basis. This process is appropriately named “many shades of wrong” by Aragao and Linsi (2022).

Future directions

More optimistically, the world is expected to be moving toward an integrated national data system (INDS) framework, which enables the production of data relevant to development, and fosters the equitable and safe flow of data between government, individuals, civil society, academia, and the private sector (World Bank, 2021). In this process, countries at different levels of data (or resources) development can formulate their own best strategy to improve their statistical capacity. Specifically, at the basic level, countries can prioritize establishing the fundamentals of a national data system. Once the fundamentals are in place, countries can seek to initiate better data flows among different stakeholders. At advanced levels of data maturity, the goal is to optimize the system for the best possible outcomes.

Kitzmüller *et al.* (2021) offer a discussion of the data systems and efforts to improve them using three real-life country examples—Ghana, Mexico, and Estonia that correspond to the three levels of data development—and well illustrate each country’s current position regarding statistical capacity with their SPI score. Jolliffe *et al.* (2023) argue that data produced by the public sector can have transformational impacts on development outcomes through better targeting of resources, improved service delivery, cost savings, increased accountability, and more. Carpenter *et al.* (2022) and Reddy *et al.* (2023) describe various South-South and North-South initiatives to improve local statistical capacity (in medical statistics), ranging from setting up joint graduate study programs and research projects to consulting consortiums for rapid response to the COVID-19 pandemic. Using volunteer data collected by other stakeholders, including citizen scientists, private sector companies, and other organizations, could encourage the public to further participate in building up statistical capacity, filling SDG data gaps, and enhancing government ability to monitor public service delivery and better protect the environment (Conrad and Hilchey, 2011; Meijer and Potjer, 2018; Fritz *et al.*, 2019).

Yet, while the amount of data produced by the public sector is increasing rapidly, the full potential of data to improve development outcomes has not been realized yet because of challenges of suboptimal data quality or lack of data on vulnerable groups. This limitation is most highlighted during times of crises. For example, recent studies on the COVID-19 pandemic suggest that vulnerable groups, including poorer households, women, children, and refugees, were most affected (Dang and Nguyen, 2021; Sumner *et al.*, 2022; Li *et al.*, 2023). In this regard, the importance of measurement of statistical capacity has been recognized in the SDG indicator framework with the recent formal population of SDG indicator 17.18.1 with the SPI pillars 4 and 5 indicators and the ODIN data availability indicators is a step in the right direction. Since better statistical capacity could help collect more data, such as on gender-disaggregated data and climate change, assessment tools such as the SPI can be regarded both as a tool for monitoring development and as a development goal itself (Tichenor, 2022).

Besides the approaches to improving country statistical capacity discussed above, a promising direction to address these challenges is to operationalize the SPI using a bottom-up approach. There have been ongoing efforts at the World Bank to include SPI indicators at the project level as specific metrics for monitoring statistical capacity, especially for low-income countries in Sub-Saharan Africa. This setting is similar to the other metrics that have been employed to measure

project performance in other development projects. The SPI framework is flexible enough to allow either direct application of all its indicators, some of its indicators, or even some re-weighted version of its indicators to better suit the specific country context. Another direction is to “collect more data about data”, that is, implementing institutional surveys to directly collect data from NSOs to measure progress with their statistical capacity. These surveys can offer supplementary information to enrich the current indicators and, if designed appropriately, may help shed more light on the country-specific political economy environment regarding statistical capacity.

Materials and Method

Conceptual motivations and construction of the SPI

Conceptual motivations

The SPI is built on a framework that is forward looking, measures less mature statistical systems as well as advanced systems, covers a country’s entire NSS (rather than just the NSO as with some previous index), and provides countries with incentives to build a modern statistical system. In particular, by helping countries and development partners identify the strengths and weaknesses of NSSs, the SPI can support policy advice to improve or benchmark NSSs, offer advocacy for national statistics, and facilitate investment decisions for governments and (bilateral and multilateral) donors. The SPI is also built on standard *desiderata* for a statistical index (i.e., simple, coherent, motivated, rigorous, implementable, replicable, incentive consistent), as well as clear conceptual and mathematical foundations. Importantly, the SPI is also open-data and open-code where users can freely access data and experiment with different adjustments to the index on the World Bank’s website. (We return to more discussion on data access in the next section).

It is useful to note that while measuring a country’s statistical *capacity* is our ultimate goal, this task is difficult, if not impossible to implement at scale for all countries, given the typically unobserved inherent characteristics with an NSS. It is, however, relatively more straightforward to measure a country’s statistical *performance* through objective and comparable indicators. (This challenge is highlighted by a large number of indicators with missing data that we discuss later. Also see Cameron *et al.* (2021) for further discussion on this and the *desiderata*).

We identify five key pillars of a country’s statistical performance, as shown in Figure 7. These are data use, data services, data products, data sources, and data infrastructure, which can be further disaggregated into 22 dimensions. This figure shows these pillars and dimensions in the form of a

dashboard, which can help countries identify areas for development in their statistical system. We briefly describe these pillars below and provide more details on the dimensions of the SPI, including ongoing data work, in Appendix A, Table S1.

Since statistics have no value unless they are used, the first pillar of the SPI is data use. In order to meet user needs, the statistical system must develop a range of services that connect data users and producers and facilitate dialogue between them. The second pillar of the SPI is therefore data services that are trusted by users. The dialogue between users and suppliers in turn drives the design of statistical products that are to be created including the quality of product needed for the country requirement. This will incorporate accuracy, timeliness, frequency, comparability, and levels of disaggregation. The third pillar of the SPI is therefore data products. In order to create the products required, the statistical system needs to make use of a variety of sources from both inside and outside the government. This includes making use of typical data collection methods like censuses and surveys, but also administrative data, geospatial data, and data generated from the private sector and from citizens. The fourth pillar of the SPI is therefore data sources. For the cycle to be complete, capability needs continuously to be reviewed to ensure that it is enough to deliver the products, services and ultimately data use required. The fifth pillar of the SPI is therefore data infrastructure.

In summary, a successful statistical system offers highly valued and well-used statistical services, generates high quality statistical indicators that can also track progress for the SDGs, draws on all types of data sources relevant to the indicators that are to be produced, develops both hard infrastructure (including legislation, governance, standards) and soft infrastructure (including skills, partnerships), and has the financial resources to deliver. Figure A.1 (Dang *et al.*, 2023) offers an alternative visual description of the beneficial interactions of the different data pillars, which reinforce each other through stakeholders' partnership, joint accountability, better capacity, and meeting user needs. Improvements in performance can be represented as a virtuous data cycle that can become self-sustaining.

Further description of SPI pillars and dimension

A quick primer on names. We refer to the 5 rows in the framework in Figure 7 as pillars. We refer to the 22 cells in the framework in Figure 7 as dimensions. Finally, each dimension may be composed of multiple indicators. For instance, the dimension on censuses and surveys is made up

of indicators on whether population censuses have been conducted, agriculture censuses, labor force surveys, etc.

3.1 Data use

The data use pillar is segmented by user type. The tiles on the Dashboard provide an indicator of use of statistics respectively by the legislature, executive, civil society (including sub-national actors), academia and international bodies. A mature system would score well across the tiles. Areas for development would be highlighted by weaker scores in that domain enabling questions to be asked about prioritization among user groups and why existing services are not resulting in higher use of national statistics in that segment.

3.2 Data services

The data services pillar is segmented by service type. The tiles on the Dashboard provide an indicator of the quality of data releases, the richness and openness of online access, the effectiveness of advisory and analytical services related to statistics and the availability and use of data access services such as secure microdata access. Advisory and analytical services might incorporate elements related to data stewardship services including ethical consideration of proposals and calling out misuse of data in accordance with the Fundamental Principles of Official Statistics.

3.3 Data products

The data products pillar is segmented by topic and organized into social, economic, environmental and institutional domains using the typology of the Sustainable Development Goals. This approach enables comparisons across countries and anchors the system in the 2030 agenda so that a global view can be generated while enabling different emphasis to be applied in different countries to reflect the user needs of that country.

3.4 Data sources

The data sources pillar is segmented between sources generated by the statistical office (censuses and surveys) and sources accessed from elsewhere (administrative data, geospatial data, private sector data and citizen generated data). The appropriate balance between these types of sources will vary depending on the institutional setting and maturity of the statistical system in each country. High scores should reflect the extent to which the sources being utilized enable the necessary statistical indicators to be generated. For example, a low score on environment statistics

may reflect a lack of use of (and low score for) geospatial data. This linkage, which is inherent in the data cycle approach, should help highlight areas for investment if country needs are to be met.

3.5 Data infrastructure

The data infrastructure pillar is segmented into hard and soft infrastructure segments itemizing essential cross-cutting requirements for an effective statistical system. The segments are:

1. Legislation and governance covering the existence of laws and a functioning institutional framework for the statistical system
 2. Standards and methods addressing compliance with recognized frameworks and concepts
 3. Skills including level of skills within the statistical system and among users (statistical literacy)
 4. Partnerships reflecting the need for the statistical system to be inclusive and coherent
- Finance, both domestically and from donors

Construction of the SPI

We employ Cameron *et al.*'s (2021) nested weighting structure to construct the SPI overall score. Compared to other weighting schemes, this weighting structure offers properties such as symmetry, monotonicity, and subgroup decomposability. It is based on Atkinson's (2003) counting method, which was employed to construct a social exclusion index (Chakravarty and D'Ambrosio, 2006) and to measure adjusted multi-dimensional poverty (Alkire and Foster, 2011). Our statistical performance indicators have a three-level structure, and the SPI overall score is formed by sequentially aggregating the indicators at each level.

To begin we produce a score for each dimension within a given pillar, which, unless otherwise stated, is an unweighted average of the indicators within that dimension

$$SPI.DIM_{ctpd} = \sum_{i=1}^{N_I} \frac{SPI.IND_{ctpdi}}{N_I} \quad (1)$$

where $SPI.IND_{ctpdi}$ is an indicator i in dimension d , pillar p , time period t , and country c , and N_I is the number of indicators in dimension d . For instance, the score for the Standards and Methods dimension is obtained by taking the unweighted average of all indicators in this dimension, including the indicators for the system of national accounts in use, national accounts base year, classification of national industry, CPI base year, and classification of household consumption (Appendix A, Table S1).

A score for each pillar is subsequently computed as the average score of the dimensions in that pillar. For pillars 1, 2, 4, and 5, the unweighted average of the dimensions within each pillar is

taken. For pillar 3 on data products, we take a weighted average of the dimensions, where the weights are based on the number of SDGs in each dimension (6 SDGs in dimension 3.1 on social statistics, 6 SDGs in dimension 3.2 on economic statistics, 2 in dimension 3.3 on environmental statistics, and 2 in dimension 3.4 on institutional statistics. SDG 14 - Life Below Water - is omitted because land-locked countries do not report on these indicators.). This reflects a perspective that all SDGs are of equal importance, and therefore the dimensions are weighted accordingly. Additionally, for Pillar 4 on data sources, censuses and surveys are given separate weights, so that censuses, surveys, administrative data, and geospatial data each receives a weight of 1/4. While censuses and surveys are in the same pillar in the framework, and therefore each would typically only receive a weight of 1/6 in this dimension, because of their importance in producing many indicators, they are given extra weight such that each gets a weight of 1/4. (Using a weight of 1/6 for censuses and surveys provides very similar results. In particular, the correlation between the SPI overall score under the preferred approach and the alternative approach is 0.998). The score for each pillar ($SPI.PIL_{ctp}$) is calculated as follows

$$SPI.PIL_{ctp} = \sum_{d=1}^{N_d} \frac{\omega_{pd} \times SPI.DIM_{ctpd}}{N_d} \quad (2)$$

ω_{dp} is the weight for dimension d in pillar p , and N_d is the number of dimensions in pillar p .

Finally, the SPI overall score for country c in time t is derived by taking the average across the 5 pillars. The SPI overall score has a maximum score of 100 and a minimum of 0. A score of 100 would indicate that a country has every single element that we measure in place. A score of 0 indicates that none is in place. The SPI overall score ($SPI.INDEX_{ct}$) is calculated as follows

$$SPI.INDEX_{ct} = \sum_{p=1}^{N_p} \frac{SPI.PIL_{ctp}}{N_p} \quad (3)$$

where $SPI.PIL_{ctp}$ is the SPI pillar scores for country c in time t for the five pillars discussed above, and N_p is the number of pillars.

For illustration, Figure S1 shows the correlation between the SPI pillars, which ranges from 0.47 (Data use and Data products) to 0.73 (Data infrastructure and Data sources). All pillars are positively correlated with one another. On the other hand, no pillar is perfectly correlated with any of the other pillars, which indicate that each pillar provides additional information on a country's statistical performance.

We can further decompose the SPI into the contributions from each pillar, in both absolute and relative terms, by country income level (Appendix A, Figure S2). For example, in low income

countries, adequate data sources (Pillar 4) and data infrastructure (Pillar 5) represent severe capacity limitation. For a hypothetical country that scores perfectly in each pillar, the figure would show 20 points for each pillar. In low-income countries, adequate data sources (Pillar 4) contributes only 4.9 points out of the maximum 20 points to the SPI overall score. Data infrastructure (Pillar 5) is another area of concern, with low-income countries receiving only 8.7 points, compared to 16.5 points for high income countries. In relative terms, as shown in Figure S2, Panel B (Appendix A), low-income countries are doing comparatively well in terms of the data use pillar, with 26.6 percent of low income countries scores coming from this pillar, and relatively poor on data sources with only 9 percent of the overall score coming from this pillar. High-income countries are doing relatively poorly in terms of data products with 19 percent of the overall score coming from Pillar 3.

Figures S3 and S4 (Appendix A) show much heterogeneity for countries in different geographical regions or at different income levels, as well as significant variation in the SPI overall score within regions. Countries with a higher income level have a higher SPI score. Overall, the correlation in 2022 between (logged) GDP per capita and the SPI overall score is 0.62. We examine a related ranking of the SPI by World Bank’s country lending status, which shows a similar positive correlation between country income level and its SPI score. In particular, the SPI scores are lowest for IDA (poorest) countries and highest for unclassified (high-income) countries. Similarly, dividing countries into FCS (Fragile and Conflict) status versus non-FCS status respectively yields the scores of 73 and 51 for the former and latter groups of countries (results are available upon request).

Some evidence suggests that lower-capacity countries improve more between 2016 and 2022. Figure S5 (Appendix A) plots the growth of countries classified into ten deciles based on their SPI score in 2016 and shows that countries in the bottom three deciles grow fastest in 2022. In particular, these countries average a change of more than 15.5 points on the 0-100 scale, which is higher than the global average growth of 12.1 points. We provide detailed discussion on the data collection process for the SPI indicators and other related challenges (e.g., potential issues with missing data) in Dang *et al.* (2023). The SPI is publicly available at www.worldbank.org/spi. The associated code and underlying raw data are available at our project site <https://github.com/worldbank/SPI>.

Statistical analysis: Country fixed-effects regressions

As a start, we estimate the following pooled OLS model

$$Y_{c,t} = \alpha_0 + \alpha_1 SPI_{c,t} + \eta_{c,t} \quad (4)$$

where $Y_{c,t}$ represents the outcome variable for country c in year t , which can be either GDP per capita (in logarithmic form based on 2015 constant US dollars) or the WGI. $\eta_{c,t}$ is an idiosyncratic error term. $SPI_{c,t}$ is the value of the country overall SPI score in year t . Furthermore, we also examine another model specification where we replace the overall SPI score with the five SPI pillar scores (on data use, data services, data products, data sources, and data infrastructure). This disaggregation allows us to probe more deeply into the relationship of the outcome variable and the different SPI components.

While Equation (4) offers a useful exploratory analysis, it does not control for country-specific or year-specific characteristics that can affect the outcome variables. These can include, for example, country income or education levels or the structure of its economy, or global macro-economic time trends. Consequently, we further estimate a panel data model with country and year fixed effects (FE)

$$Y_{c,t} = \beta_0 + \beta_1 SPI_{c,t} + \pi_c + \tau_t + \epsilon_{c,t} \quad (5)$$

where π_c is the country fixed effects, τ_t is a year dummy variable. We also estimate the following country and year FE panel data model where we explicitly control for several country characteristics

$$Y_{c,t} = \gamma_0 + \gamma_1 SPI_{c,t} + \gamma' X_{c,t} + \theta_c + \sigma_t + \epsilon_{c,t} \quad (6)$$

Equation (6) adds to Equation (5) a vector of control variables $X_{c,t}$, which includes the added values in manufacturing, agriculture, forestry, and fishing, and trade values (all as shares of country GDP), which are measures of the sectoral composition of the economy. All these three variables are measured as a percentage of the country GDP. $X_{c,t}$ also includes the gross primary school enrollment rate. $X_{c,t}$ further includes either an index of political institutions as measured by WGI (when the outcome variable is log of GDP per capita) or country income levels as measured by log of GDP per capita (when the outcome variable is WGI).

Since we do not have all the country-year observations for these control variables (except for the WGI), we impute for the missing observations with the nearest available values. The percentage of missing values ranges from 1 percent (agriculture, forestry, and fishing added values as a share of GDP) to more than 25 percent (gross primary school enrolment). We focus on the resulting balanced panel data for 159 countries with data for the SPI, WGI, and other control variables between 2016 and 2022. The main reason that most countries do not have an overall SPI score in 2016 is due to data unavailability from Open Data Watch's Open Data Inventory (ODIN), which was used for the SPI measures of data openness and geospatial information. The other reasons are missing human capital index scores or trade data. As such, Equation (5) is our preferred model for analysis but Equation (6) can offer useful robustness checks.

It is important to emphasize that these econometric models are unlikely to allow us to identify the causal impacts of the SPI on GDP growth or governance (which is beyond the scope of analysis in this paper). Yet, these models can help shed exploratory, useful insights on the correlational relationship between a country's statistical performance and its economic growth and governance.

References

- Agrawal, A., & Kumar, V. (2020). Delays in the release of India's census data. *Statistical Journal of the IAOS*, 36(1), 217–230.
- Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, 95(7), 476–487.
- Anderson, D. M., & Whitford, A. B. (2017). Developing knowledge states: Technology and the enhancement of national statistical capacity. *Review of Policy Research*, 34(3), 400–420.
- Angrist, N., Goldberg, P. K., & Jolliffe, D. (2021). Why is growth in developing countries so hard to measure? *Journal of Economic Perspectives*, 35(3), 215–242.
- Aragão, R., & Linsi, L. (2022). Many shades of wrong: What governments do when they manipulate statistics. *Review of International Political Economy*, 29(1), 88–113.
- Arezki, R., Lederman, D., El-Mallakh, N., Islam, A. M., Abou Harb, A., Fan, R. Y., Nguyen, H. M., & Zouaidi, M. (2020). *Where missing data hurts the most: Low growth, macroeconomic vulnerability, and labor market outcomes in Middle East and North Africa*. World Bank Publications. <https://doi.org/10.1596/978-1-4648-1561-4>
- Asher, S., Bhowmick, A., Campion, A., Lunt, T., & Novosad, P. (2022). Big, Open Data for Development: A Vision for India. In Gupta, P., Bosworth, B., & Muralidharan, K. (Eds.). *India Policy Forum 2021: Volume 18*. SAGE Publishing India.
- Atkinson, A. B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality*, 1(1), 51–65.
- Azevedo, J. P. (2020). Learning poverty: Measures and simulations. *Policy Research Working Paper*, 9446. <http://hdl.handle.net/10986/34654>
- Bandola-Gill, J., Grek, S., & Tichenor, M. (2022). *Governing the sustainable development goals: Quantification in global public policy*. Springer Nature.
- Barbier, E. B., & Burgess, J. C. (2021). *Economics of the SDGs*. Springer International Publishing.
- Bersales, L. G. S. (2022). Standards in social statistics: The capacity of national statistical systems to adapt to the international standards, problems, challenges. *Statistical Journal of the IAOS*, 38, 533–543.
- Binswanger, J., & Oechslin, M. (2020). Better statistics, better economic policies? *European Economic Review*, 130, 103588.
- Bizier, V., Gennari, P., & Navarro, D. K. (2022). Role of international, regional and country organizations in adapting to statistical standards and regional differences: The case of food and agriculture statistics. *Statistical Journal of the IAOS*, 38, 511–532.
- Cameron, G., Dang, H.-A., Dinc, M., Foster, J., & Lokshin, M. (2021). Measuring the statistical capacity of nations. *Oxford Bulletin of Economics and Statistics*, 83(4), 870–896.

- Carnegie, A., Clark, R., & Zucker, N. (2021). Global governance under populism: The challenge of information suppression. *Manuscript, Columbia University and Princeton University*.
- Carpenter, J. R., Todd, J., Baisley, K., Bradley, J., Tumwesigye, N. M., Musonda, P., & Chirwa, T. (2022). Training and capacity building in medical statistics in Sub-Saharan Africa: Impact of the London School of Hygiene & Tropical Medicine MSc in Medical Statistics, 1969 to 2021. *Statistics in Medicine*, 41(5), 838-844.
- Chakravarty, S. R., & D'Ambrosio, C. (2006). The measurement of social exclusion. *Review of Income and Wealth*, 52(3), 377–398.
- Conrad, C. C., & Hilchey, K. G. (2011). A review of citizen science and community-based environmental monitoring: issues and opportunities. *Environmental monitoring and assessment*, 176, 273-291.
- Coyle, D. (2015). *GDP: a brief but affectionate history*. Revised and expanded edition. Princeton University Press.
- Dang, H.-A., & Serajuddin, U. (2020). Tracking the sustainable development goals: Emerging measurement challenges and further reflections. *World Development*, 127, 104570.
- Dang, H. A. H., & Nguyen, C. V. (2021). Gender inequality during the COVID-19 pandemic: Income, expenditure, savings, and job loss. *World Development*, 140, 105296.
- Dang, H.-A. H., Pullinger, J., Serajuddin, U., & Stacy, B. (2023). Statistical performance indicators and index: A new tool to measure country statistical capacity. *Scientific Data*, 10, 146.
- Dargent, E., Lotta, G., Mejía-Guerra, J. A., & Moncada, G. (2018). *The political economy of statistical capacity in Latin America: Who wants to know?* Inter-American Development Bank. <https://publications.iadb.org/en/who-wants-know-political-economy-statistical-capacity-latin-america>
- Dener, C., Nii-Aponsah, H., Ghunney, L. E., & Johns, K. D. (2021). *GovTech maturity index: The state of public sector digital transformation*. World Bank. <http://hdl.handle.net/10986/36233>
- Devarajan, S. (2013). Africa's statistical tragedy. *Review of Income and Wealth*, 59, 9–15.
- Diedenhofen, B., & Musch, J. (2015). cocor: A comprehensive solution for the statistical comparison of correlations. *PloS ONE*, 10(4), e0121945.
- Durand, M. (2015). The OECD better life initiative: How's life? and the measurement of well-being. *Review of Income and Wealth*, 61(1), 4-17.
- Economist. (2019, August 22). The net tightens: A \$2bn loan scandal sank Mozambique's economy. *The Economist*. <https://www.economist.com/middle-east-and-africa/2019/08/22/a-2bn-loan-scandal-sank-mozambiques-economy>
- Ekhatior-Mobayode, U. E., & Hoogeveen, J. (2022). Microdata collection and openness in the Middle East and North Africa. *Data & Policy*, 4, e31.

- Evans, D. K., & Acosta, A. M. (2023). How to measure student absenteeism in low-and middle-income countries. *Economics of Education Review*, 96, 102454.
- Fritz, S., See, L., Carlson, T., Haklay, M., Oliver, J. L., Fraisl, D., ... & West, S. (2019). Citizen science and the United Nations sustainable development goals. *Nature Sustainability*, 2(10), 922-930.
- Gatti, R., Lederman, D., Islam, A., Fan, R. Y., Wood, C., Lotfi, R., ... & Mousa, M. (2022). *Reality Check: Forecasting Growth in the Middle East and North Africa in Times of Uncertainty*. World Bank Policy Research Working Paper No. 10406. <https://documents1.worldbank.org/curated/en/099410204122333916/pdf/IDU059a788530925704a0b08f7e0c3e8b9e9d753.pdf>
- Glaeser, E. L., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2004). Do institutions cause growth? *Journal of Economic Growth*, 9, 271-303.
- Global Data Barometer (2022). *First Edition Report – Global Data Barometer*. ILDA. DOI: <https://doi.org/10.5281/zenodo.6488349>.
- Hanson, J. K., & Sigman, R. (2021). Leviathan's latent dimensions: Measuring state capacity for comparative political research. *Journal of Politics*, 83(4), 1495–1510.
- Hartmann, D., Guevara, M. R., Jara-Figueroa, C., Aristarán, M., & Hidalgo, C. A. (2017). Linking economic complexity, institutions, and income inequality. *World development*, 93, 75-93.
- Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2), 994–1028.
- Hodelin, R. S. (2022). Statistical disclosure and economic growth: What is the nexus? *World Development*, 160, 106036.
- Hu, Y., & Yao, J. (2022). Illuminating economic growth. *Journal of Econometrics*, 228(2), 359–378.
- IMF. (2019). *Republic of Mozambique: Diagnostic report on transparency, governance, and corruption* [IMF Country Report 19/276,]. IMF. <https://www.imf.org/en/Publications/CR/Issues/2019/08/23/Republic-of-Mozambique-Diagnostic-Report-on-Transparency-Governance-and-Corruption-48613>
- Islam, A. M., & Lederman, D. (2020). Data transparency and long-run growth. *World Bank Policy Research Working Paper No. 9493*. <http://hdl.handle.net/10986/34915>
- Jacob, A. (2017). Mind the gap: Analyzing the impact of data gap in millennium development goals'(MDGs) indicators on the progress toward MDGs. *World Development*, 93, 260–278.
- Janus, T. (2022). Democracy and statistical capacity. *Applied Economics Letters*, 1–5.
- Jerven, M. (2013). *Poor numbers: How we are misled by African development statistics and what to do about it*. Cornell University Press.

- Jolliffe, D., Mahler, D. G., Veerappan, M., Kilic, T., & Wollburg, P. (2023). What Makes Public Sector Data Valuable for Development? *World Bank Research Observer*, 38(2): 325–346.
- Kelley, J. G., & Simmons, B. A. (2015). Politics by number: Indicators as social pressure in international relations. *American Journal of Political Science*, 59(1), 55–70.
- Kitzmueller, L., Mahler, D. G., Wollburg, P. R., Jolliffe, D. M., Veerappan, M. (2021). *Creating an Integrated National Data System - Lessons from Estonia, Ghana, and Mexico*. World Bank Data Blog. <https://blogs.worldbank.org/opendata/creating-integrated-national-data-system-lessons-estonia-ghana-and-mexico>
- Kraay, A. (2019). The World Bank human capital index: a guide. *The World Bank Research Observer*, 34(1), 1-33.
- Kubota, M., & Zeufack, A. (2020). *Assessing the returns on investment in data openness and transparency*. Policy Research Working Paper, 9139. <http://hdl.handle.net/10986/33295>
- Li, L., Taeihagh, A., & Tan, S. Y. (2023). A scoping review of the impacts of COVID-19 physical distancing measures on vulnerable population groups. *Nature communications*, 14(1), 599.
- Lokshin, M. (2022). The highways and side roads of statistical capacity building. *Statistical Journal of the IAOS*, 38, 753–768.
- Martinez, L. R. (2022). How much should we trust the dictator’s GDP growth estimates? *Journal of Political Economy*. <https://doi.org/10.1086/720458>
- Meijer, A., & Potjer, S. (2018). Citizen-generated open data: An explorative analysis of 25 cases. *Government Information Quarterly*, 35(4), 613-621.
- Mo Ibrahim Foundation. (2023). *2022 Ibrahim Index of African Governance Index Report*. <https://mo.ibrahim.foundation/sites/default/files/2023-01/2022-index-report.pdf>.
- Nagaraj, A., Shears, E., & Vaan, M. de. (2020). Improving data access democratizes and diversifies science. *Proceedings of the National Academy of Sciences*, 117(38), 23490–23498.
- Ngaruko, F. (2008). The World Bank’s framework for statistical capacity measurement: Strengths, weaknesses, and options for improvement. *African Statistical Journal*, 7.
- Oechslin, M., & Steiner, E. (2022). Statistical capacity and corrupt bureaucracies. *Review of International Organizations*, 17(1), 143–174.
- Open Data Watch. (2023). *Open Data Inventory 2022/23 Methodology Guide*. <https://opendatawatch.com/reference/odin-2022-23-methodology-guide/>
- Radermacher, W. J. (2021). Governing-by-the numbers–résumé after one and a half years. *Statistical Journal of the IAOS*, 37, 701–711.
- Reddy, T., Nsubuga, R. N., Chirwa, T., Shkedy, Z., Mwangi, A., Awoke, A. T., ... & Janssen, P. (2023). Sustainable Statistical Capacity-Building for Africa: The Biostatistics Case. *Annual Review of Statistics and Its Application*, 10, 97-117.

- Reporters without Borders. (2023). World Press Freedom Index. Available at https://rsf.org/en/methodology-used-compiling-world-press-freedom-index-2023?year=2023&data_type=general
- Roseth, B., Reyes, A., & Amezaga, K. Y. (2019). The value of official statistics: Lessons from intergovernmental transfers. In *IDB Technical Note 1682*. Inter-American Development Bank Washington, DC. <http://dx.doi.org/10.18235/0001883>
- Sachs, J., Kroll, C., Lafortune, G., Fuller, G., & Woelm, F. (2021). *Sustainable development report 2021*. Cambridge University Press. <https://doi.org/10.1017/9781009106559>
- Sachs, J., Kroll, C., Lafortune, G., Fuller, G., & Drumm, E. (2023). *Sustainable development report 2023*. Cambridge University Press. <https://doi.org/10.25546/102924>
- Sandefur, J., & Glassman, A. (2015). The political economy of bad data: Evidence from African survey and administrative statistics. *Journal of Development Studies*, 51(2), 116–132.
- Sanga, D., Dosso, B., & Gui-Diby, S. (2011). Tracking progress towards statistical capacity building efforts: The African statistical development index. *International Statistical Review*, 79(3), 303–329.
- Savoia, A., & Sen, K. (2015). Measurement, evolution, determinants, and consequences of state capacity: A review of recent research. *Journal of Economic Surveys*, 29(3), 441–458.
- Sumner, Andy, Eduardo Ortiz-Juarez, and Christopher Hoy. (2022). "Measuring global poverty before and during the pandemic: a political economy of overoptimism." *Third World Quarterly* 43, 1: 1-17.
- Tapsoba, S. J. -A., Noumon, C. N., & York, R. C. (2017). Can statistical capacity building help reduce procyclical fiscal policy? *Journal of International Development*, 29(4), 407–430.
- Taylor, M. (2016). The political economy of statistical capacity: A theoretical approach. Washington, DC: BID. <https://publications.iadb.org/en/political-economy-statistical-capacity-theoretical-approach>
- UNICEF. (2018). *Progress for every child in the SDG era*. UNICEF New York. <https://www.unicef.org/reports/progress-every-child-sdg-era>
- 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]. <https://digitallibrary.un.org/record/840707?ln=en>
- . (2022). Human Development Report 2021-22. *Human Development Reports*.
- . (2023). Sustainable Development Goals no. 17. Strengthen the means of implementation and revitalize the Global Partnership for Sustainable Development. <https://sdgs.un.org/goals/goal17>
- Visser, H., Bruin, S., Martens, A., Knoop, J., & Ligtoet, W. (2020). What users of global risk indicators should know. *Global Environmental Change*, 62, 102068.

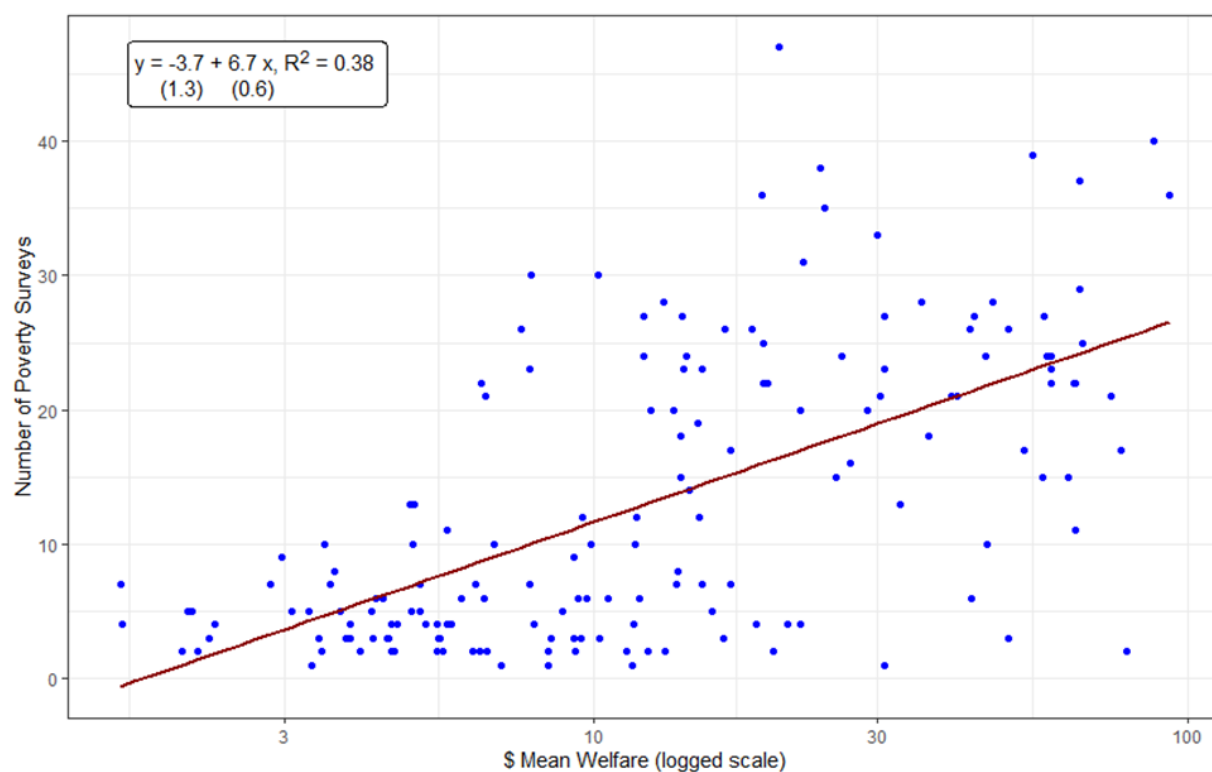
- Wolf, M. J., Emerson, J. W., Esty, D. C., de Sherbinin, A., Wendling, Z. A., *et al.* (2022). *2022 Environmental Performance Index*. New Haven, CT: Yale Center for Environmental Law & Policy.
- Wollburg, P., Contreras, I., Carletto, C., Morales, L. G., Perucci, F., & Zezza, A. (2022). The uneven effects of the COVID-19 pandemic on national statistical offices. *Statistical Journal of the IAOS*, 38(3), 785–803.
- World Bank. (2020). *Statistical capacity indicators*. <https://datatopics.worldbank.org/statisticalcapacity/>
- . (2021). *World development report 2021: Data for better lives*. World Bank. <https://wdr2021.worldbank.org/>
- Yount, K. M., Johnson, E., Sharma, K., Meinzen-Dick, R. S., & Sinharoy, S. (2022). *Conceptualizing and measuring women's empowerment: Insights from country stakeholders in Asia*. <https://doi.org/10.2139/ssrn.4088823>.

Table 1. Comparing the SPI and Other Data and Statistics Indexes

No	Index	Assessment Type/ Frequency	Country Coverage	Time Coverage	Index Methodology	No. of Indicators	Share of indicators in each pillar					
							Data Use	Data Services	Data Products	Data Sources	Data Infra.	Data Sources (Share)
1	Open Data Inventory Indicators & Index (ODIN)	Global/ Annual	192	2016-2022	Nested weight	44	0%	50%	50%	0%	0%	NSO Websites
2	Open Data Barometer (ODB)	Global/ Annual	116	2013-2017	Nested weight	46	15%	30%	37%	0%	15%	Expert Survey
3	Global Data Barometer (GDB)	Global/ Biennial	109	2019-2021	Nested weight	55	9%	4%	20%	16%	45%	Expert Survey
4	Statistical Performance Indicators & Index (SPI)	Global/ Annual	186	2016-2022	Nested weight	51	10%	16%	31%	20%	24%	Public International Databases (86%), NSO Websites (14%)
5	Statistical Capacity Indicators & Index (SCI)	Global/ Annual	145	2004-2020	Simple arithmetic average	25	0%	0%	40%	20%	40%	Public International Databases (80%), NSO Websites (20%)
6	Ibrahim Index of African Governance Statistical Capacity (IIAG)	Regional/ Annual	54	2010-2022	Simple weight	3 statistical capacity indicators	0%	4%	37%	19%	41%	Expert Survey (33%), ODIN (33%), SCI databases (33%)
7	EU Snapshot tool	Self-assessment/ N.A.	N.A.	N.A.	N.A.	131	6%	12%	10%	8%	64%	Expert self-assessment
8	UN NQAF self-checklist	Self-assessment/ N.A.	N.A.	N.A.	N.A.	87	10%	16%	2%	7%	64%	Expert self-assessment
9	Paris21 NSDS self-assessment	Self-assessment/ N.A.	N.A.	N.A.	N.A.	149	14%	23%	1%	1%	61%	Expert self-assessment

Note: N.A. stands for not available. The number of countries shown under the column “Country coverage” are for the latest year for all the indexes. The SPI covers between 167 and 186 countries for 2016-2022. The SCI covers between 115 and 145 countries for 2004-2020. The ODIN covers between 125 and 192 countries for 2015-2022 but offers comparable data starting from 2016. The ODB covers between 30 and 115 countries for 2013-2017. The ODB only covers 30 countries in 2017 and is replaced by the GDB after this year. The GDB covers 109 countries for 2019-2021. The IIAG covers 54 countries for all the years for 2010-2019. All the indexes provide annual data, except for the GDB that provides a single data point for each country for 2019-2021.

Figure 1. Number of Household Surveys vs. Country Income, 1981- 2022



Note: Estimated coefficients are shown from an OLS regression of the number of surveys on log of mean consumption (income); robust standard errors are in parentheses.

Note: This figure employs data from the World Bank's poverty database.

Figure 2. Mapping Other Data Tools to SPI Framework

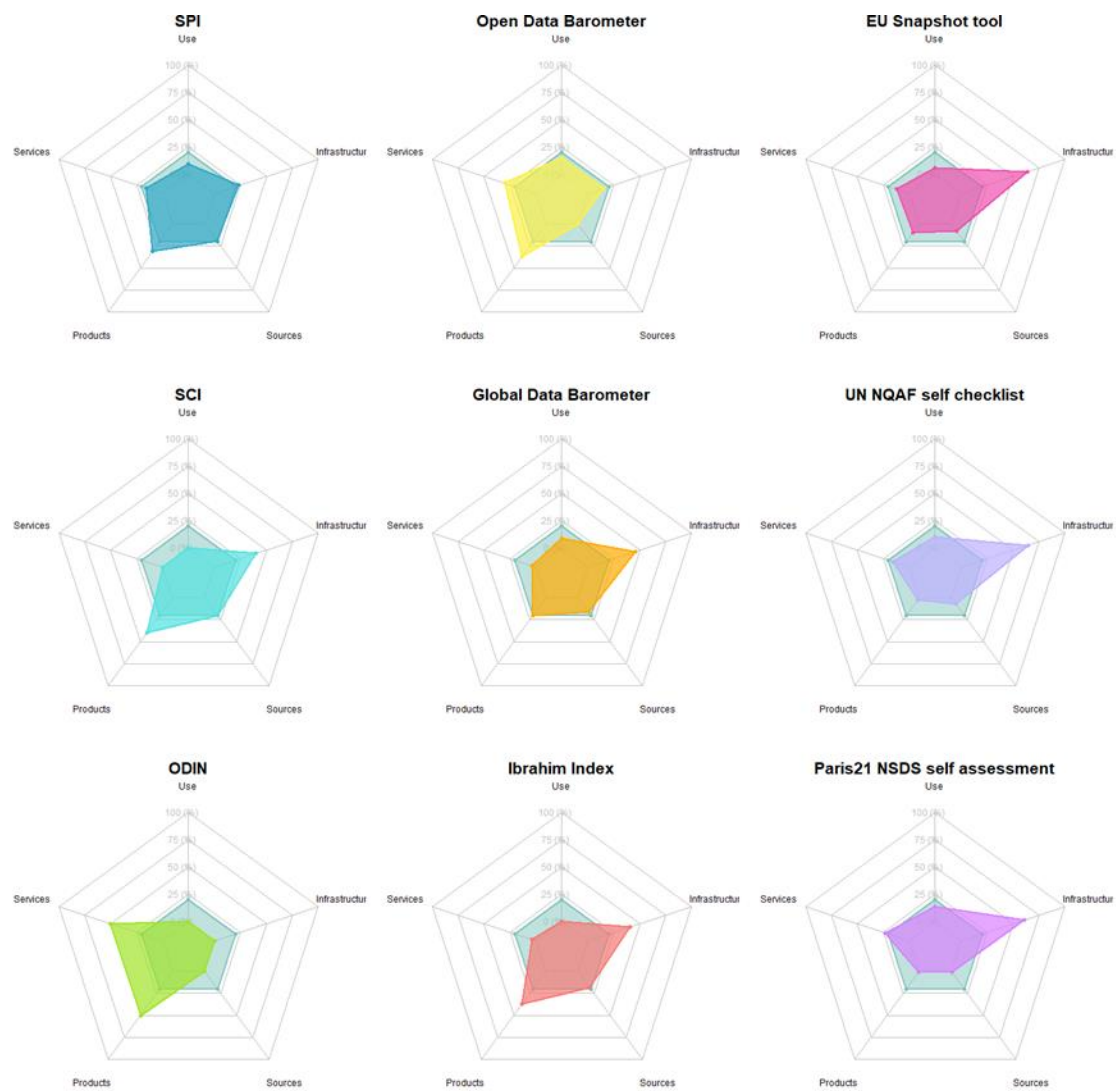


Figure 3. Scatter plot and Trends of ODIN and SPI Overall Scores for 2016 and 2022

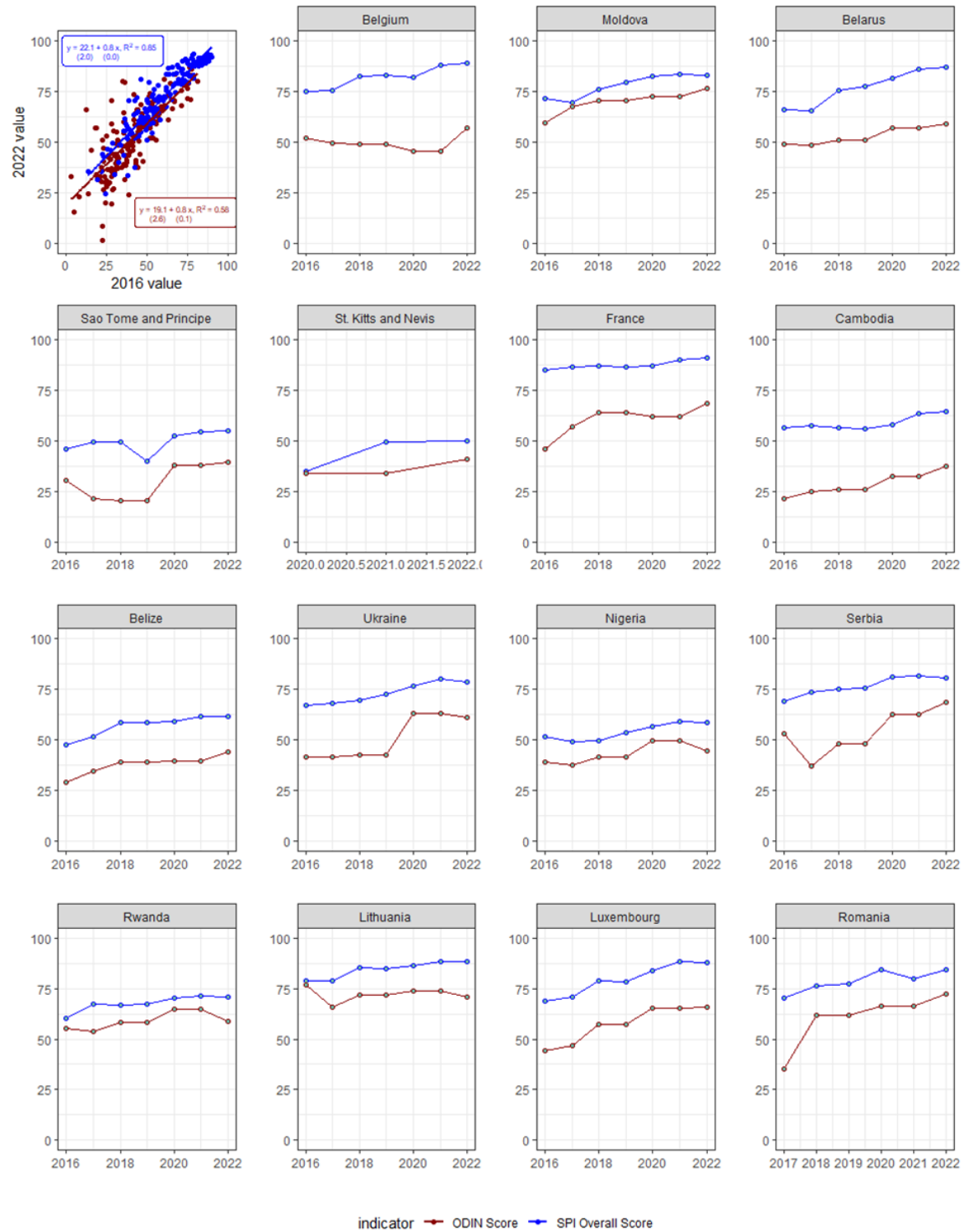
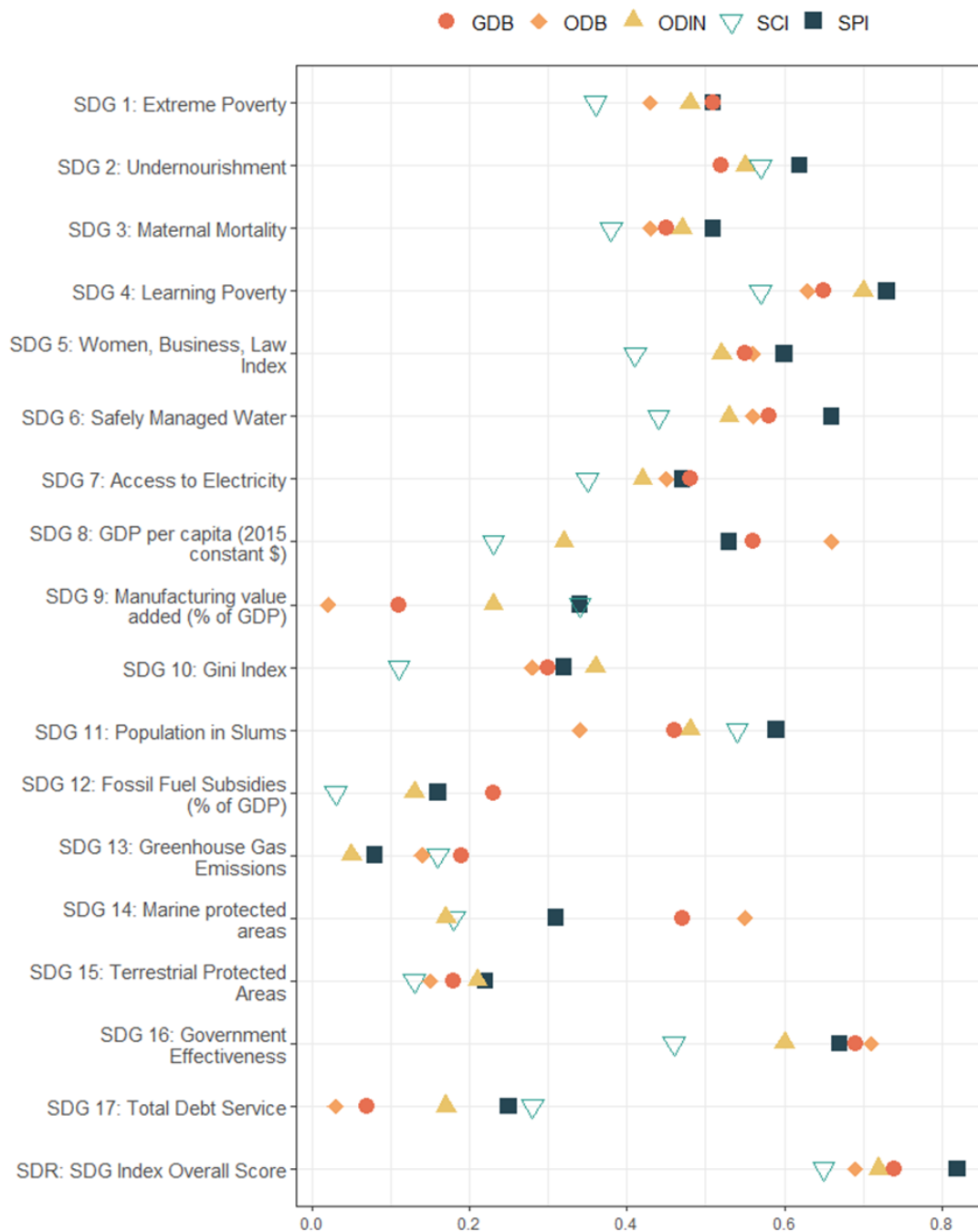
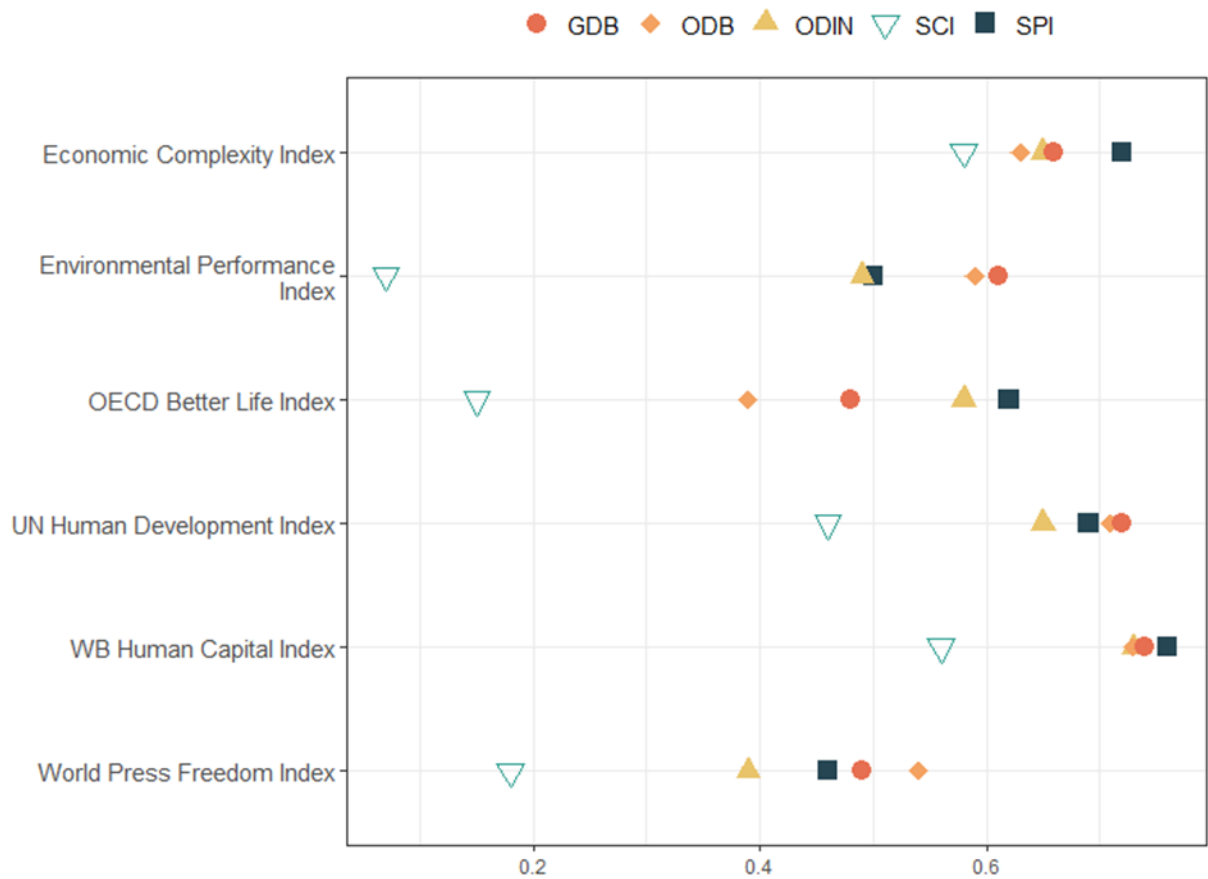


Figure 4. Absolute Value of Correlation between Key SDGs and Indexes



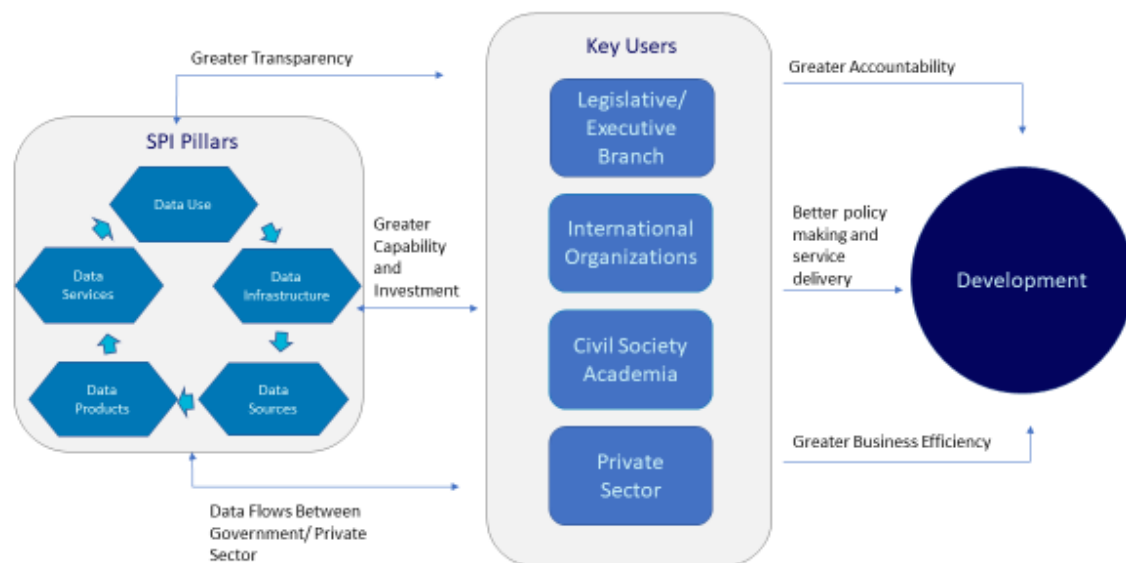
Note: The correlation coefficients are fully shown with the statistically significant levels in Table S6. SDR: SDG Index Overall Score comes from Sachs et al. (2023).

Figure 5. Absolute Value of Correlations between Key Development Indices



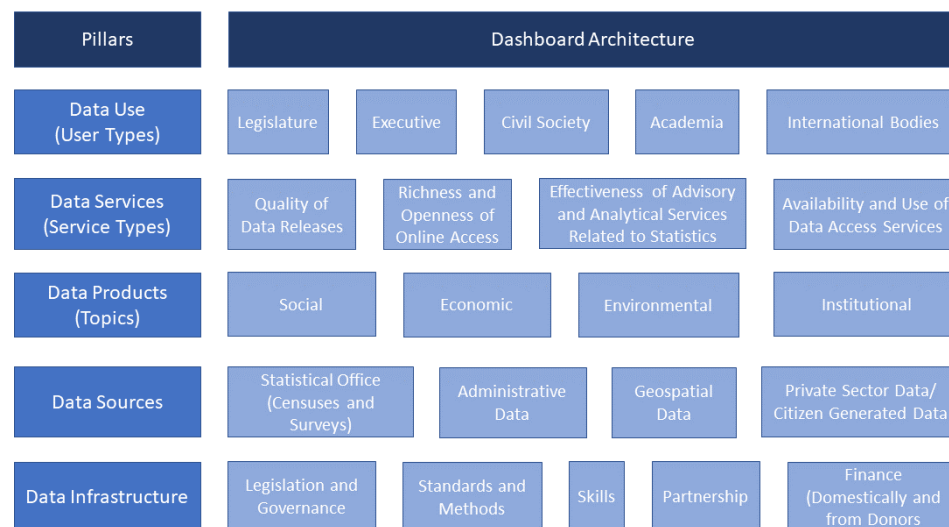
Note: The correlation coefficients are fully shown with the statistically significant levels in Table S7.

Figure 6. Theory of Change



Note: Modified from Figure O.1 in the WDR 2021 on Data for Better Lives (World Bank, 2021)

Figure 7. The Pillars and Dimensions that Construct the New SPI



Source: Dang *et al.* (2023).

Appendix A. Additional Tables and Figures

Table S1. An Overview of the World Bank's Statistical Capacity Index (SCI) in Selected Recent Studies

1	Angrist, Goldberg & Jolliffe (2021)	<i>Journal of Economic Perspective</i>	Global analysis	Measuring economic growth in developing countries	Poorer countries have lower statistical capacity, which can severely bias their reported measurements of economic growth.
2	Anderson & Whitford (2017)	<i>Review of Policy Research</i>	100 countries	Technological attainment and statistical capacity	Countries with greater levels of technological attainment have greater national statistical capacity.
3	Goren & Winkler (2022)	<i>Journal of African Economies</i>	57 African countries	Low-quality statistics, slave trades and development	Replacing mismeasured GDP per capita by nighttime light intensity per capita significantly reduces the impact of the slave trade on economic development by a factor of 2 to 4.
4	Hanson & Sigman (2021)	<i>Journal of Politics</i>	139 countries	Measuring state capacity in political science research	The SCI is most strongly correlated with state capacity compared to other indicators in bureaucratic quality, public administration, law and order ratings, or state fiscal capacity.
5	Henderson, Storeygard & Weil (2012)	<i>American Economic Review</i>	113 countries	Better measuring income growth with night lights data	SCI can help provide more accurate estimates of country income growth.
6	Hu & Yao (2022)	<i>Journal of Econometrics</i>	162 countries	Estimating the relationship between nighttime light growth and GDP growth	SCI can help provide more accurate estimates of country GDP growth.
7	Jacob (2017)	<i>World Development</i>	145 countries	Impact of data gaps on Millennium Development Goals achievement (MDG)	Stronger country statistical capacity increases the probability of MDG success.

8	Martinez (2022)	<i>Journal of Political Economy</i>	137 countries	Autocracies overstate yearly GDP growth	Limitations in country statistical capacity do not significantly affect autocracies' exaggeration of GDP growth.
9	Oechslin & Steiner (2022)	<i>Review of International Organization</i>	146 countries	Statistical capacity and corrupt bureaucracies	A positive relationship between the growth rate of real GDP per capita and statistical capacity exists for countries with low corruption, but not for countries with high corruption.
10	Sanderfur & Glassman (2015)	<i>Journal of Development Studies</i>	Sub-Saharan African countries	Political economy of bad data	Sub-Saharan African countries as a whole have a lower SCI score (i.e., 58) than the global average (i.e., 64), but much heterogeneity exists with country scores ranging from the bottom to more than the 75th global percentile.
11	Sanga et al. (2011)	<i>International Statistical Review</i>	43 African countries	Proposing an index to measure statistical capacity for African countries	The SCI does not cover certain aspects of an NSO such as organization, human development, and funding. There is a weak correlation between the SCI and the proposed index.
12	Tapsoba et al. (2017)	<i>Journal of International Development</i>	62 developing countries	Statistical capacity building impacts on reducing procyclical fiscal policy	IMF-supported technical analysis to countries improves their statistical capacity during 1990-2012.

Note: SCI stands for statistical capacity index.

Table S2. Description of SPI Dimensions

Dimension	Brief Description
Dimension 1.1: Data use by national legislature	Not included because of lack of established methodology. In principle it may be possible to utilize websites of national legislatures but this will require further work and assessment.
Dimension 1.2: Data use by national executive branch	Not included because of lack of established methodology. There are some usable data sources (as used by (PARIS21 2019)) but gaps in data across countries have prevented full adoption.
Dimension 1.3: Data use by civil society	Not included because of lack of established methodology. There are some usable data sources with good coverage, for example from social media but more data is required to help assess and allow for likely biases between and within countries.
Dimension 1.4: Data use by academia	Not included because of lack of established methodology. We have not been able to find usable data sources with global coverage on which a new methodology could be developed.
Dimension 1.5: Data use by international organizations	Five measures usefulness or reliability of country produced measures for international organizations have been included. First, on comparability of poverty estimates for the World Bank reporting on international poverty using the Poverty and Inequality Portal (PIP) . Second on usable surveys for statistics on child mortality for the UN Inter-agency Group for Child Mortality Estimation . Third on accuracy of debt reporting as classified by the World Bank (Source: World Bank WDI metadata). Fourth, on availability of safely managed drinking water data for use by WHO/UNICEF Joint Monitoring Programme . Fifth, on labor force participation data for use by ILO. While these data sources provide only a partial coverage of data used by international organizations, they do provide an indication of the performance of the national statistical system.
Dimension 2.1: Data releases	SDDS/e-GDDS subscription. This indicator is based on whether the country subscribes to IMF SDDS+, SDDS, or e-GDDS standards. The source is the IMF Dissemination Standards Bulletin Board. This is a reliable data source but we recognize that it is a proxy for the concept we are seeking to capture rather than a direct measurement.
Dimension 2.2: Online access	ODIN Open Data Openness score (Jamison Crowell et al. n.d.). This is a well-established data source with good country coverage, which scores countries based on whether indicators are available online in a format that is machine readable, in a non-proprietary format, downloadable, with metadata available and terms of use. Scores range from 0-1. For more details, consult the ODIN technical documentation
Dimension 2.3: Advisory/ Analytical Services	Not included because of lack of established methodology. This could be a new indicator of the number of non-recurring products on NSO website (ad hoc/experimental rather than regular releases). The indicator is the number of products found. No established source exists for this indicator.
Dimension 2.4: Data access services	NADA metadata. This indicator checks whether NADA microdata cataloging is available for surveys produced by NSO. NADA is an open source microdata cataloging system, compliant with the Data Documentation Initiative (DDI) and Dublin Cores RDF metadata standards. Source: NSO websites.

Dimension	Brief Description
Dimension 3.1: social statistics	Availability of Goal 1-6 indicators, measured by an average score. The primary data source is the UN SDG database. While this is a database with comprehensive coverage that all countries have signed up to, many countries are not yet submitting all their available national data. Scores for some countries thus may not capture their performance in calculating the indicators. For OECD countries, we supplement the UN SDG database with comparable data submitted to the OECD following the methodology in Measuring Distance to the SDG Targets 2019: An Assessment of Where OECD Countries Stand .
Dimension 3.2: economic statistics	Availability of Goal 7-12 indicators, measured by an average score. See 3.1.
Dimension 3.3: environmental statistics	Availability of Goal 13 & 15 indicators, measured by an average score. Goal 14 - Life on Water - is not included because land-locked countries do not report on these indicators. See 3.1.
Dimension 3.4: institutional statistics	Availability of Goal 16-17 indicators measured by an average score. See 3.1.
Dimension 4.1: censuses and surveys	Availability of recent censuses and surveys covering broad areas. The following censuses and surveys are considered: Population & Housing census, Agriculture census, Business/establishment census, Household Survey on income/ consumption/ expenditure/ budget/ Integrated Survey, Agriculture survey, Labor Force Survey, Health/Demographic survey, Business/establishment survey. Source: NSO websites, World Bank microdata library, ILO microdata library, IHSN microdata library
Dimension 4.2: administrative data	Availability of Civil Registration and Vital Statistics (CRVS) indicator. An ideal indicator would include a score based on the density of administrative data available in sectors of social protection, education, labor, and health. However, social protection, education, health, and labor admin data indicators not included because of lack of established methodology. While several promising sources for administrative data from the World Bank's ASPIRE team, WHO, UNESCO, and ILO have been identified, the were not included due to incomplete coverage across countries. Further research and data collection effort would be needed to fill in this information, so that a more comprehensive picture of administrative data availability can be produced.
Dimension 4.3: geospatial data	Geospatial data available at 1st Admin Level. This data source from Open Data Watch focusing on data availability at the sub-national level provides a partial understanding of a country's ability to produce geospatial data. A research and data collection effort is needed to develop an more comprehensive global database of the availability of key geospatial indicators.
Dimension 4.4: Private/citizen generated data	Not included because of lack of established methodology. Currently no comprehensive source exists to measure the use of private and citizen generated data in national statistical systems, and this should be another area where more data collection is needed by the international community.
Dimension 5.1: Legislation and governance	This indicator is based on PARIS21 indicators on SDG 17.18.2 (national statistical legislation compliance with UN Fundamental Principles of Official Statistics), existence of National Statistical Council, national statistical strategy generation, national statistical plan. Limited country coverage makes cross country comparison limited. So this is included in the dashboard, but not in the overall SPI score or index.

Dimension	Brief Description
Dimension 5.2: Standards and Methods	This set of indicators is based on countries' use of internationally accepted and recommended methodologies, classifications and standards regarding data integration. These indicators help facilitate data exchange and provide the foundation for the preparation of relevant statistical indicators. The following methods and standards are considered: System of national accounts in use, National Accounts base year, Classification of national industry, CPI base year, Classification of household consumption, Classification of status of employment, Central government accounting status, Compilation of government finance statistics, Compilation of monetary and financial statistics, Business process. Further work could improve the validity of this indicator and reduce the risk that countries may be incentivized to adopt only traditional standards and methods and neglect innovative solutions that may be more valid in the current context.
Dimension 5.3: Skills	Not included because of lack of established methodology or suitable data sources. A new indicator drawing on PARIS21 indicators such as statistical society presence and data literacy could be developed and is an area of future work.
Dimension 5.4: Partnerships	Not included because of lack of established methodology or suitable data sources. A new indicator based on textual analysis of NSS reports/websites for references to partner organizations could be developed. This is an area of future work.
Dimension 5.5: Finance	The indicator is based on PARIS21 SDG indicators (SDG 17.18.3 (national statistical plan that is fully funded and under implementation). It is included in dashboard, but not in the overall SPI score or index because of insufficient country coverage.

Table S3. Mapping of SPI Indicators to SDG Indicators

	SPI Indicator	SPI Dimension	SDG	Data Source
1	Availability of Comparable Poverty headcount ratio at \$1.90 a day (5 year moving average of availability)	Dimension 1.5: Data use by international organizations	SDG 1.1.1	World Bank's PIP
2	Availability of Mortality rate, under-5 (per 1,000 live births) data meeting quality standards according to UN IGME (5 year moving average of availability)	Dimension 1.5: Data use by international organizations	SDG 3.2.1	Child Mortality Metadata from UN IGME
3	Quality of Debt service data according to World Bank	Dimension 1.5: Data use by international organizations	SDG 17.4.1	Debt Reporting Metadata from World Bank
4	Safely Managed Drinking Water	Dimension 1.5: Data use by international organizations	SDG 6.1.1	Availability of Safely Managed Drinking Water data for use by JMP
5	GOAL 1: No Poverty (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 1	UN Global SDG Indicators Database

6	GOAL 2: Zero Hunger (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 2	UN Global SDG Indicators Database
7	GOAL 3: Good Health and Well-being (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 3	UN Global SDG Indicators Database
8	GOAL 4: Quality Education (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 4	UN Global SDG Indicators Database
9	GOAL 5: Gender Equality (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 5	UN Global SDG Indicators Database
10	GOAL 6: Clean Water and Sanitation (5 year moving average of availability)	Dimension 3.1: Social (SDG 1-6)	SDG 6	UN Global SDG Indicators Database
11	GOAL 7: Affordable and Clean Energy (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 7	UN Global SDG Indicators Database
12	GOAL 8: Decent Work and Economic Growth (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 8	UN Global SDG Indicators Database
13	GOAL 9: Industry, Innovation and Infrastructure (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 9	UN Global SDG Indicators Database
14	GOAL 10: Reduced Inequality (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 10	UN Global SDG Indicators Database
15	GOAL 11: Sustainable Cities and Communities (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 11	UN Global SDG Indicators Database
16	GOAL 12: Responsible Consumption and Production (5 year moving average of availability)	Dimension 3.2: Economic (SDG 7-12)	SDG 12	UN Global SDG Indicators Database
17	GOAL 13: Climate Action (5 year moving average of availability)	Dimension 3.3: Environmental (SDG 13,15)	SDG 13	UN Global SDG Indicators Database
18	GOAL 15: Life on Land (5 year moving average of availability)	Dimension 3.3: Environmental (SDG 13,15)	SDG 15	UN Global SDG Indicators Database
19	GOAL 16: Peace and Justice Strong Institutions (5 year moving average of availability)	Dimension 3.4: Institutional (SDG 16-17)	SDG 16	UN Global SDG Indicators Database
20	GOAL 17: Partnerships to achieve the Goal (5 year moving average of availability)	Dimension 3.4: Institutional (SDG 16-17)	SDG 17	UN Global SDG Indicators Database
21	Legislation and governance	Dimension 5.1: Legislation and governance	SDG 17.18.2	UN Global SDG Indicators Database

22	Finance	Dimension 5.5: Finance	SDG indicators 17.18.3 and 17.19.1	UN Global SDG Indicators Database
		Notes: SDG 14 not included due to inapplicability to landlocked countries		

Table S4. SPI overall score and Pillar Scores in 2022

Below, the full list of countries by their SPI overall score in 2022 is presented. The first column is the country name and the following columns are the overall SPI overall score, and then the sub-scores for pillars 1, 2, 3, 4, and 5.

The purpose of the SPI is to help countries assess and improve the performance of their statistical systems. The presentation of SPI overall scores is designed to reflect that aim. Small differences between countries should not be stressed since they can reflect imprecision arising from the currently available indicators rather than meaningful differences in performance. Instead, the presentation of overall SPI scores focuses on larger groupings of countries reflecting broad categories of performance as measured by the indicator framework. In total there are 186 countries with sufficient data to compute an index value. This set of countries covers 99.3 percent of the world population.

Countries shaded in dark orange are the lowest performing, countries in dark green are the highest performing. Countries are grouped into five groups:

1. **Top Quintile:** Countries in the top 20% are classified in this group. Shading in dark green.
2. **4th Quintile:** Countries in the 4th quantile, or those above the 60th percentile but below the 80th percentile are in this group. Shading in light green.
3. **3rd Quintile:** Countries in the 3rd quantile, or those between the 40th and 60th percentile, are classified in this group. Shading in yellow.
4. **2nd Quintile:** Countries in the 2nd quantile, or those above the 20th percentile but below the 40th percentile, are in this group. Shading in light orange.
5. **Bottom 20%:** Countries in the bottom 20% are classified in this group. Shading in dark orange.

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Finland	93.6	100.0	96.4	88.5	83.3	100
Norway	93.5	100.0	97.1	87.2	83.1	100
Canada	92.9	100.0	92.6	83.7	88.3	100
Netherlands	92.8	100.0	96.9	87.8	79.5	100
United States	92.8	100.0	93.6	86.0	84.4	100
Slovenia	92.5	100.0	97.5	87.1	78.1	100
Sweden	92.2	100.0	96.0	86.4	78.7	100
Italy	91.9	100.0	93.0	88.7	77.8	100
Denmark	91.6	90.0	98.7	86.5	82.9	100
Poland	91.6	90.0	97.1	86.8	84.0	100
Spain	91.4	100.0	91.1	82.9	83.1	100

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Ireland	91.3	100.0	96.4	87.2	72.9	100
Germany	91.0	100.0	94.9	85.0	80.1	95
Czechia	90.9	100.0	88.8	84.4	81.2	100
France	90.8	100.0	92.1	86.2	75.6	100
Georgia	90.7	100.0	92.0	91.5	79.9	90
Austria	90.0	100.0	89.5	88.6	76.8	95
Australia	89.9	90.0	92.9	83.0	83.9	100
Costa Rica	89.9	100.0	86.3	93.1	80.2	90
Japan	89.9	100.0	90.3	84.9	79.2	95
Estonia	89.6	90.0	96.9	83.9	77.0	100
Portugal	89.3	90.0	93.1	87.4	76.1	100
Slovak Republic	89.1	90.0	94.5	85.3	76.0	100
Belgium	88.9	100.0	86.9	81.3	76.4	100
Latvia	88.8	100.0	97.1	76.1	70.9	100
Switzerland	88.8	100.0	88.4	85.6	80.0	90
Greece	88.7	100.0	88.1	78.6	77.0	100
New Zealand	88.7	100.0	92.4	82.9	78.4	90
Mexico	88.6	100.0	93.4	93.0	81.5	75
Lithuania	88.1	90.0	91.1	82.3	77.2	100
Hungary	87.9	100.0	89.0	88.2	72.3	90
Korea, Rep.	87.8	100.0	92.1	83.0	79.2	85
Luxembourg	87.8	100.0	93.4	81.7	64.1	100
Turkiye	87.7	100.0	86.8	94.2	57.6	100
Chile	87.4	100.0	85.6	87.2	69.4	95
United Kingdom	87.1	100.0	88.0	85.2	72.6	90
Iceland	86.9	100.0	86.3	76.3	71.8	100
Belarus	86.7	100.0	85.4	87.5	65.4	95
Singapore	86.6	100.0	99.7	64.1	88.9	80
Colombia	85.9	100.0	82.9	92.3	74.2	80
Cyprus	85.1	100.0	88.8	70.5	71.0	95

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Romania	84.3	90.0	94.2	76.5	75.9	85
Russian Federation	84.1	93.4	87.6	76.5	72.8	90
Mongolia	84.0	100.0	97.2	89.7	73.4	60
Bulgaria	83.9	90.0	91.3	75.7	72.4	90
North Macedonia	83.5	100.0	87.5	74.6	75.3	80
Albania	83.4	90.0	69.8	87.2	70.1	100
Philippines	83.4	100.0	90.6	89.8	81.4	55
West Bank and Gaza	83.4	100.0	92.1	73.1	66.7	85
Israel	83.3	100.0	91.1	70.9	59.3	95
Croatia	83.1	90.0	87.5	72.3	71.0	95
Armenia	82.8	90.0	85.4	86.6	61.9	90
Moldova	82.8	90.0	95.4	75.5	68.0	85
Thailand	82.5	100.0	81.3	91.5	54.8	85
South Africa	82.4	80.0	86.0	87.6	73.4	85
Kyrgyz Republic	81.5	100.0	81.0	91.8	54.4	80
Serbia	80.8	100.0	74.5	86.1	73.6	70
Saudi Arabia	80.8	100.0	88.2	71.6	79.1	65
Brazil	80.5	90.0	87.2	80.2	75.3	70
Malta	80.3	100.0	86.1	65.6	74.6	75
Egypt, Arab Rep.	79.6	100.0	77.1	83.9	67.0	70
United Arab Emirates	79.5	100.0	79.6	71.2	67.0	80
Ecuador	79.2	100.0	89.1	89.8	56.9	60
Sri Lanka	79.1	100.0	81.8	78.0	80.4	55
Indonesia	79.0	100.0	91.1	90.2	53.5	60
Ukraine	78.9	100.0	53.8	87.1	58.5	95
Kazakhstan	78.2	90.0	89.3	89.4	62.3	60
Jordan	78.2	80.0	90.4	87.6	62.9	70
Montenegro	78.1	100.0	69.9	83.2	57.2	80
Uruguay	77.7	100.0	87.9	89.1	56.7	55

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Mauritius	77.3	90.0	85.5	80.9	60.1	70
Malaysia	76.6	80.0	87.6	85.1	75.4	55
Paraguay	75.8	90.0	69.4	87.7	57.1	75
Tunisia	75.1	90.0	89.5	82.8	58.4	55
India	74.2	80.0	87.7	86.3	62.0	55
El Salvador	73.8	90.0	78.8	78.3	51.7	70
Azerbaijan	73.5	80.0	68.8	82.5	66.1	70
Peru	73.3	90.0	87.3	90.9	53.1	45
Dominican Republic	72.4	100.0	68.0	77.1	42.0	75
Morocco	72.3	80.0	89.6	85.9	60.8	45
Senegal	72.2	80.0	82.0	78.5	45.6	75
Viet Nam	72.2	100.0	69.3	77.2	74.2	40
Guatemala	72.0	80.0	62.0	85.9	62.1	70
Myanmar	72.0	100.0	67.4	85.3	42.1	65
Argentina	71.8	70.0	78.9	90.2	59.8	60
Bolivia	71.2	100.0	66.9	82.0	62.0	45
Pakistan	71.1	100.0	61.9	86.8	46.9	60
Uganda	70.7	100.0	65.4	81.6	36.8	70
Qatar	70.6	100.0	62.1	67.4	58.8	65
Bosnia and Herzegovina	70.6	70.0	63.8	77.5	61.8	80
Rwanda	70.6	90.0	70.6	79.5	52.8	60
Uzbekistan	70.6	80.0	74.7	78.7	44.4	75
Panama	70.5	80.0	66.0	87.4	64.1	55
Zimbabwe	70.2	100.0	67.0	88.0	36.1	60
Bangladesh	69.7	90.0	61.9	85.8	51.0	60
Kuwait	69.2	100.0	63.2	66.2	61.5	55
Tanzania	67.3	90.0	70.7	76.6	44.4	55
Togo	66.7	90.0	63.7	87.0	32.7	60
Kenya	66.3	90.0	60.1	76.6	34.9	70

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Oman	66.1	100.0	46.6	61.2	67.8	55
St. Lucia	66.0	70.0	69.6	68.6	66.8	55
Seychelles	66.0	90.0	44.2	68.4	57.3	70
Cabo Verde	65.7	80.0	64.4	76.1	63.0	45
Niger	65.3	90.0	60.8	84.8	30.8	60
Liberia	64.9	90.0	65.7	82.3	26.5	60
Burkina Faso	64.8	80.0	68.9	81.5	33.8	60
Malawi	64.8	90.0	62.0	80.6	46.5	45
Barbados	64.6	100.0	57.6	62.2	48.3	55
Gambia, The	64.4	80.0	65.5	89.4	32.3	55
Brunei Darussalam	64.4	90.0	71.0	57.7	53.2	50
Cambodia	64.3	80.0	63.6	81.0	42.0	55
Ghana	64.2	66.6	61.8	88.8	44.0	60
Fiji	63.2	80.0	63.1	75.4	37.3	60
Algeria	63.2	80.0	57.8	82.0	46.0	50
Benin	62.6	80.0	69.7	83.6	29.5	50
Samoa	62.4	70.0	63.0	78.8	40.5	60
Cote d'Ivoire	62.2	80.0	57.7	79.1	29.4	65
Zambia	62.1	90.0	60.4	86.7	28.5	45
Nepal	62.0	80.0	62.8	85.5	36.6	45
Belize	61.9	70.0	64.6	67.2	62.5	45
Maldives	61.8	70.0	63.9	82.5	57.7	35
Jamaica	61.6	60.0	72.6	77.8	57.9	40
Suriname	61.5	50.0	69.2	69.6	58.9	60
Botswana	61.2	50.0	68.8	77.8	64.4	45
Ethiopia	61.1	90.0	64.5	81.5	29.5	40
Honduras	61.0	90.0	62.1	84.1	38.5	30
Lao PDR	60.4	76.6	65.5	79.2	40.7	40
Tonga	59.9	70.0	63.2	75.9	45.4	45
Timor-Leste	59.9	80.0	61.0	64.5	28.8	65

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
China	59.6	83.4	43.8	77.5	43.3	50
Bhutan	59.6	80.0	63.9	75.2	38.8	40
Bahrain	59.4	80.0	72.8	52.3	61.7	30
Sierra Leone	59.2	80.0	65.3	79.0	31.7	40
Mali	59.1	80.0	60.7	82.6	27.4	45
Mauritania	58.9	80.0	63.2	66.6	24.5	60
Iran, Islamic Rep.	58.7	80.0	29.3	70.7	68.6	45
Mozambique	58.7	70.0	59.7	76.5	32.2	55
Nigeria	58.6	80.0	63.8	77.8	31.5	40
Lebanon	58.5	60.0	61.6	79.6	51.3	40
Afghanistan	58.0	80.0	59.4	78.6	17.0	55
Guinea	57.9	80.0	62.8	76.6	20.2	50
Lesotho	57.5	80.0	29.4	76.3	41.7	60
Guyana	56.5	70.0	62.7	71.5	33.0	45
Iraq	56.3	60.0	64.5	78.3	33.8	45
Namibia	55.8	60.0	62.7	77.6	23.6	55
Trinidad and Tobago	55.4	60.0	61.2	64.2	36.9	55
St. Vincent and the Grenadines	55.3	60.0	67.4	60.9	48.1	40
Sao Tome and Principe	54.8	60.0	60.9	69.2	49.0	35
Cameroon	54.5	60.0	64.2	82.1	21.2	45
Bahamas, The	54.1	80.0	27.7	49.5	38.5	75
Madagascar	53.7	60.0	60.6	78.2	25.0	45
Angola	53.5	60.0	60.8	71.3	35.2	40
Tajikistan	53.4	80.0	29.2	81.7	46.2	30
Nicaragua	52.7	60.0	61.1	64.2	23.3	55
Venezuela, RB	52.3	80.0	59.9	62.2	34.1	25
Eswatini	51.7	80.0	22.3	71.7	24.3	60
Vanuatu	51.2	56.6	59.1	72.2	33.2	35

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Congo, Dem. Rep.	51.1	70.0	62.4	67.5	15.5	40
Burundi	50.7	60.0	62.9	79.7	15.8	35
St. Kitts and Nevis	50.0	60.0	66.7	44.8	43.6	35
Chad	49.2	63.4	59.2	75.8	17.8	30
Somalia	48.4	80.0	47.9	69.7	4.4	40
Palau	48.3	40.0	59.6	56.4	45.7	40
Solomon Islands	48.2	50.0	59.3	65.8	15.9	50
Antigua and Barbuda	48.2	60.0	26.9	64.6	49.3	40
Djibouti	46.6	50.0	59.5	63.8	14.5	45
Papua New Guinea	46.0	60.0	59.2	70.6	10.1	30
Dominica	44.2	60.0	28.3	59.3	43.4	30
Kiribati	43.8	40.0	59.5	75.4	18.9	25
Sudan	43.6	53.4	57.9	67.8	18.8	20
Gabon	42.8	60.0	29.8	66.1	13.2	45
Central African Republic	42.6	50.0	58.6	68.8	10.7	25
Grenada	41.1	40.0	22.1	68.7	45.0	30
Guinea-Bissau	40.0	70.0	23.7	71.7	14.6	20
Haiti	39.6	50.0	18.0	71.6	13.3	45
Equatorial Guinea	39.0	30.0	59.6	58.7	21.8	25
Tuvalu	38.1	40.0	59.4	60.8	15.5	15
Congo, Rep.	37.5	50.0	29.4	62.6	20.2	25
Marshall Islands	35.5	10.0	58.3	64.0	25.3	20
Micronesia, Fed. Sts.	35.3	20.0	59.1	58.6	13.7	25
South Sudan	33.8	40.0	37.8	53.9	7.5	30
Yemen, Rep.	33.2	46.6	28.0	55.6	16.0	20
Nauru	32.6	30.0	37.6	55.4	35.0	5
Syrian Arab Republic	31.9	36.6	23.1	55.0	15.0	30
Turkmenistan	31.4	60.0	0.5	69.6	11.7	15

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
Libya	24.4	20.0	25.6	53.6	7.6	15
American Samoa		40.0		22.6		
Andorra		80.0		38.6		15
Aruba		60.0		28.5		
Bermuda		60.0		27.1		
British Virgin Islands		60.0		27.2		
Cayman Islands		50.0		28.6		
Channel Islands		60.0				
Comoros		50.0		68.2		40
Cuba		60.0		69.7		
Curacao		80.0		28.5		
Eritrea		36.6		51.7		10
Faroe Islands		60.0		14.7		
French Polynesia		60.0		24.0		
Gibraltar		60.0		18.1		
Greenland		50.0		21.0		
Guam		60.0		22.1		
Hong Kong SAR, China		80.0		43.8		
Isle of Man		70.0		12.3		
Korea, Dem. People's Rep.		30.0		51.6		
Kosovo		40.0	66.5		50.3	80
Liechtenstein		70.0		38.3		
Macao SAR, China		80.0		37.7		
Monaco		90.0		41.6		
New Caledonia		80.0		31.6		
Northern Mariana Islands		60.0		16.0		
Puerto Rico		60.0		35.4		

Country	SPI overall score	Pillar 1: Data Use	Pillar 2: Data Services	Pillar 3: Data Products	Pillar 4: Data Sources	Pillar 5: Data Infrastructure
San Marino		90.0	60.7	38.1		55
Sint Maarten (Dutch part)		50.0		19.7		
St. Martin (French part)		40.0		13.6		
Turks and Caicos Islands		60.0		31.5		
Virgin Islands (U.S.)		60.0		19.0		

Table S5. Comparison of SPI to Other Statistical and Development Indices

Index	Assessment Type	Country Coverage	Time Coverage	Aggregation Methodology	Number of Indicators	Data Sources	Methodology Link
1 SPI	Global	186	2016-2022	Nested Weight Structure	51	Public International Databases (86%), NSO Websites (14%)	https://openknowledge.worldbank.org/handle/10986/35301
2 SCI	Global	145	2004-2020	Simple arithmetic average	25	Public International Databases (80%), NSO Websites (20%)	https://datatopics.worldbank.org/statisticalcapacity/SCIdas_hboard.aspx
3 ODIN	Global	192	2015-2022	Nested Weight Structure	44	NSO Websites	https://odin.opendatawatch.com/
4 Open Data Barometer	Global	116	2013-2017	Nested Weight Structure	46	Expert Survey	https://opendatabarometer.org/leadersedition/methodology/
5 Global Data Barometer	Global	109	2021	Nested Weight Structure	55	Expert Survey	https://globaldatabarometer.org/research/methodology/
6 Ibrahim Index of African Governance Statistical Capacity Measure	Regional	54	2010-2022	Simple arithmetic average	3	Expert Survey (33%), ODIN (33%), SCI databases (33%)	https://mo.ibrahim.foundation/iag/methodology
7 EU Snapshot tool	Self Assessment	--	--	--	131	Expert Self Assessment	https://ec.europa.eu/eurostat/web/international-statistical-cooperation-tools/capacity-building-tools/the-snapshot
8 UN NQAF self checklist	Self Assessment	--	--	--	87	Expert Self Assessment	https://unstats.un.org/unsd/methodology/dataquality/tools/
9 Paris21 NSDS self assessment	Self-Assessment	--	--	--	149	Expert Self-Assessment	https://www.paris21.org/nsds-self-assessment-evaluation-tool
10 World Governance Indicators	Global	214	1996-2022	Unobserved components model	6	Public International Databases	https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1682130
11 OPHI Global Multidimensional Poverty Index	Global	109	2010-2021	Nested Weight Structure	10	Public International Databases	https://ophi.org.uk/gmpi-2018/

12	World Bank Multidimensional Poverty Measure	Global	150	2009-2022	Nested Weight Structure	6	Public International Databases	https://www.worldbank.org/en/topic/poverty/brief/multidimensional-poverty-measure
13	World Bank Human Capital Index	Global	174	2018, 2020	Weighted multiplication	3	Public International Databases	https://openknowledge.worldbank.org/handle/10986/34432?cid=GGH_e_hcpexternal_ext
14	UN Human Development Index	Global	191	1990-2021	Geometric Average	3	Public International Databases	https://hdr.undp.org/content/human-development-report-2021-22
15	IHME Human Capital Index	Global	195	1990-2016	Life expectancy adjusted by educational attainment, learning, and functional health status	5	Public International Databases, imputation	https://www.thelancet.com/pdfs/journals/lancet/PIIS0140-6736(18)31941-X.pdf
16	World Bank Women, Business and the Law	Global	190	1971-2022	Nested Weight Structure	35	Expert Survey	https://wbl.worldbank.org/en/methodology
17	European Data Portal Open Data Maturity Assessment	Regional	35	2015-2021	Nested Weight Structure	16	NSO Questionnaire	https://data.europa.eu/sites/default/files/edp_landscaping_insight_report_n6_2020.pdf

Table S6. Bivariate Correlation between Statistical Indexes and Key Development Outcomes

SDG	GDB	ODB	ODIN	SCI	SPI
SDG 1: Extreme Poverty	-0.51*** ODB, ODIN, SCI, SPI	-0.43*** GDB, ODIN, SCI, SPI	-0.48*** GDB, ODB, SCI, SPI	-0.36*** GDB, ODB, ODIN	-0.51*** GDB, ODB, ODIN,
SDG 2: Undernourishment	-0.52*** ODB, ODIN, SCI, SPI	-0.52*** GDB, ODIN, SCI, SPI	-0.55*** GDB, ODB, SCI,	-0.57*** GDB, ODB, ODIN, SPI	-0.62*** GDB, ODB SCI
SDG 3: Maternal Mortality	-0.45*** ODB, ODIN, SCI, SPI	-0.43*** GDB, ODIN, SCI, SPI	-0.47*** GDB, ODB, SCI, SPI	-0.38*** GDB, ODB, ODIN	-0.51*** GDB, ODB, ODIN
SDG 4: Learning Poverty	-0.65*** ODB, ODIN, SCI, SPI	-0.63*** GDB, ODIN, SCI, SPI	-0.7*** GDB, ODB, SCI, SPI	-0.57*** GDB, ODB, ODIN	-0.73*** GDB, ODB, ODIN
SDG 5: Women, Business, Law Index	0.55*** ODB, ODIN, SCI, SPI	0.56*** GDB, ODIN, SCI, SPI	0.52*** GDB, ODB, SCI,	0.41*** GDB, ODB, ODIN	0.6*** GDB, ODB
SDG 6: Safely Managed Water	0.58*** ODB, ODIN, SCI, SPI	0.56*** GDB, ODIN, SCI, SPI	0.53*** GDB, ODB, SCI,	0.44*** GDB, ODB, ODIN	0.66*** GDB, ODB
SDG 7: Access to Electricity	0.48*** ODB, ODIN, SCI, SPI	0.45*** GDB, ODIN, SCI, SPI	0.42*** GDB, ODB, SCI, SPI	0.35*** GDB, ODB, ODIN	0.47*** GDB, ODB, ODIN
SDG 8: GDP per capita (2015 constant \$)	0.56*** SPI	0.66***	0.32*** SCI,	0.23*** ODIN	0.53*** GDB
SDG 9: Manufacturing value added (% of GDP)	0.11** ODIN	-0.02	0.23*** GDB SCI	0.34*** ODIN, SPI	0.34*** SCI
SDG 10: Gini Index	-0.3*** ODB, ODIN SPI	-0.28*** GDB, ODIN, SCI, SPI	-0.36*** GDB, ODB SPI	-0.11** , ODB	-0.32*** GDB, ODB, ODIN,
SDG 11: Population in Slums	-0.46*** ODIN, SCI, SPI	-0.34*** ODIN, SCI,	-0.48*** GDB, ODB, SCI,	-0.54*** GDB, ODB, ODIN, SPI	-0.59*** GDB , SCI
SDG 12: Fossil Fuel Subsidies (% of GDP)	-0.23** ODB, ODIN SPI	-0.23** GDB, ODIN SPI	-0.13* GDB, ODB, SCI, SPI	-0.03 ODIN,	-0.16** GDB, ODB, ODIN,
SDG 13: Greenhouse Gas Emissions	0.19** ODB, ODIN, SCI, SPI	0.14** GDB, ODIN, SCI, SPI	0.05 GDB, ODB, SCI, SPI	0.16* GDB, ODB, ODIN,	0.08** GDB, ODB, ODIN,
SDG 14: Marine protected areas	0.47*** ODB	0.55*** GDB	0.17** SCI	0.18* ODIN	0.31***
SDG 15: Terrestrial Protected Areas	0.18* ODB, ODIN, SCI, SPI	0.15** GDB, ODIN, SCI, SPI	0.21*** GDB, ODB, SCI, SPI	0.13** GDB, ODB, ODIN,	0.22*** GDB, ODB, ODIN,
SDG 16: Government Effectiveness	0.69*** ODB, ODIN SPI	0.71*** GDB, ODIN SPI	0.6*** GDB, ODB	0.46***	0.67*** GDB, ODB
SDG 17: Total Debt Service	0.07 ODB, ODIN, SCI,	0.03 GDB, ODIN	0.17* GDB, ODB, SCI, SPI	0.28*** GDB ODIN, SPI	0.25*** ODIN, SCI
SDR: SDG Index Overall Score	0.74*** ODB, ODIN, SCI,	0.69*** GDB, ODIN, SCI,	0.72*** GDB, ODB, SCI,	0.65*** GDB, ODB, ODIN	0.82***

Note: The correlations are shown for the listed indices and the averaged value of the SDG over the past two years (to reduce volatility). The indices listed in the right column under each heading do not have a statistically distinguishable correlation coefficient with the index in the heading and the specific SDG in the row. For instance, for SDG1: Extreme Poverty (the first row), the GDB index does not have a statically significantly different correlation from those of the ODB, ODIN, and SPI. We use the R package “cocor” (Diedenhofen and Much, 2015) to test for the correlations with overlapping samples.

Table S7. Bivariate Correlation between Statistical Indexes and Key Development Indices

Index	GDB		ODB		ODIN		SCI		SPI	
Economic Complexity Index	0.66***	ODB, ODIN, SCI, SPI	0.63***	GDB, ODIN, SCI, SPI	0.65***	GDB, ODB, SCI,	0.58***	GDB, ODB, ODIN,	0.72***	GDB, ODB
Environmental Performance Index	0.61***	ODB, ODIN	0.59***	GDB, ODIN SPI	0.49***	GDB, ODB SPI	0.07**		0.5***	ODB, ODIN
OECD Better Life Index	0.48***	ODB, ODIN, SCI, SPI	0.39**	GDB, ODIN, SCI,	0.58***	GDB, ODB, SCI, SPI	0.15	GDB, ODB, ODIN	0.62***	GDB ODIN
UN Human Development Index	0.72***	ODB, ODIN SPI	0.71***	GDB, ODIN SPI	0.65***	GDB, ODB SPI	0.46***		0.69***	GDB, ODB, ODIN
WB Human Capital Index	0.74***	ODB, ODIN SPI	0.73***	GDB, ODIN SPI	0.73***	GDB, ODB SPI	0.56***		0.76***	GDB, ODB, ODIN
World Press Freedom Index	0.49***	ODB, ODIN SPI	0.54***	GDB , SPI	0.39***	GDB , SPI	0.18**		0.46***	GDB, ODB, ODIN

Note: The correlations are shown for the listed indices and the averaged value of the SDG over the past two years (to reduce volatility). The years used for the indicators are: Economic Complexity Index (2021,2020), Environmental Performance Index (2022), OECD Better Life Index (2018,2017), UN HDI (2021,2020), WB HCI (2020), World Press Freedom Index (2023,2022). The indices listed in the right column under each heading do not have a statistically distinguishable correlation coefficient with the index in the heading and the specific SDG in the row. For instance, for SDG1: Extreme Poverty (the first row), the GDB index does not have a statically significantly different correlation from those of the ODB, ODIN, SPI, and SCI. We use the R package “cocor” (Diedenhofen and Much, 2015) to test for the correlations with overlapping samples.

Table S8. Relationship between the SDG Index Overall Score from the 2023 Sustainable Development Report and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.539*** (0.03)	0.024* (0.01)	0.027** (0.01)			
SPI Pillar 1 Score (Data use)				0.061 (0.04)	0.002 (0.00)	0.002 (0.00)
SPI Pillar 2 Score (Data services)				0.015 (0.02)	-0.001 (0.00)	0.002 (0.00)
SPI Pillar 3 Score (Data products)				-0.061** (0.03)	0.009 (0.01)	0.007 (0.01)
SPI Pillar 4 Score (Data sources)				0.277*** (0.03)	0.004 (0.01)	0.000 (0.01)
SPI Pillar 5 Score (Data infrastructure)				0.133*** (0.02)	0.013*** (0.00)	0.013*** (0.00)
Log GDP per capita (constant 2015 US\$)			3.002*** (0.85)			3.050*** (0.85)
Trade (% of GDP)			-0.008* (0.00)			-0.007 (0.00)
Agriculture, forestry, fishing value added (% of GDP)			-0.004 (0.04)			-0.011 (0.04)
Manufacturing value added (% of GDP)			-0.038 (0.03)			-0.035 (0.02)
School Enrollment, Primary (% gross)			0.024** (0.01)			0.024** (0.01)
Year 2017		0.590*** (0.05)	0.537*** (0.05)		0.612*** (0.07)	0.537*** (0.06)
Year 2018		0.869*** (0.08)	0.772*** (0.08)		0.946*** (0.10)	0.804*** (0.09)
Year 2019		1.255*** (0.09)	1.102*** (0.09)		1.308*** (0.10)	1.107*** (0.10)
Year 2020		1.427*** (0.11)	1.381*** (0.09)		1.451*** (0.14)	1.396*** (0.13)
Year 2021		1.679*** (0.14)	1.565*** (0.12)		1.607*** (0.24)	1.504*** (0.20)
Year 2022		1.791*** (0.15)	1.663*** (0.15)		1.717*** (0.25)	1.585*** (0.22)
Constant	31.128*** (2.60)			42.807*** (4.03)		
Sigma_u		5.67	4.78		4.98	4.64
Sigma_e		0.73	0.68		0.7	0.66
R2	0.645	0.997	0.997	0.747	0.997	0.997
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	146	146	146	146	146	146
No of observations	1016	1016	1016	1016	1016	1016

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S9. Relationship between the SDG Index Overall Score from the 2023 Sustainable Development Report and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.424*** (0.03)	0.005 (0.01)	0.008 (0.01)				
Open Data Barometer Score				0.327*** (0.03)	0.011** (0.00)	0.011** (0.00)	
Global Data Barometer Score							0.375*** (0.04)
Trade (% of GDP)			-0.009* (0.00)			-0.016* (0.01)	
Agriculture, forestry, fishing value added (% of GDP)			-0.006 (0.05)			0.014 (0.06)	
Manufacturing value added (% of GDP)			-0.030 (0.03)			-0.058 (0.04)	
School Enrollment, Primary (% gross)			0.025** (0.01)			-0.003 (0.02)	
Year 2014					0.468*** (0.07)	0.405*** (0.07)	
Year 2015					0.896*** (0.10)	0.779*** (0.10)	
Year 2016					1.133*** (0.11)	0.929*** (0.13)	
Year 2017		0.638*** (0.05)	0.596*** (0.05)		1.522*** (0.19)	1.294*** (0.18)	
Year 2018		0.962*** (0.07)	0.873*** (0.08)				
Year 2019		1.372*** (0.09)	1.227*** (0.11)				
Year 2020		1.563*** (0.10)	1.514*** (0.10)				
Year 2021		1.913*** (0.11)	1.810*** (0.12)				
Year 2022		2.010*** (0.13)	1.898*** (0.16)				
Constant	47.294*** (1.86)			57.430*** (1.25)			57.382* ** (1.63)
Sigma_u		6.51	5.22		5.89	4.78	
Sigma_e		0.84	0.76		0.71	0.57	
R2	0.503	0.997	0.997	0.560	0.998	0.998	0.523
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	144	144	144	100	100	100	94
No of observations	1007	1007	1007	373	373	373	93

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S10. Relationship between the Economic Complexity Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.048*** (0.00)	0.005 (0.00)	0.004 (0.00)			
SPI Pillar 1 Score (Data use)				0.004 (0.00)	0.001 (0.00)	0.001 (0.00)
SPI Pillar 2 Score (Data services)				0.002 (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 3 Score (Data products)				-0.012*** (0.00)	0.005** (0.00)	0.004** (0.00)
SPI Pillar 4 Score (Data sources)				0.022*** (0.00)	0.004** (0.00)	0.004** (0.00)
SPI Pillar 5 Score (Data infrastructure)				0.015*** (0.00)	-0.001 (0.00)	-0.001 (0.00)
Log GDP per capita (constant 2015 US\$)			0.165 (0.22)			0.086 (0.22)
Trade (% of GDP)			0.001 (0.00)			0.000 (0.00)
Agriculture, forestry, fishing value added (% of GDP)			-0.015 (0.02)			-0.015 (0.02)
Manufacturing value added (% of GDP)			0.019*** (0.01)			0.019*** (0.01)
School Enrollment, Primary (% gross)			0.000 (0.00)			0.000 (0.00)
Year 2017		-0.015 (0.01)	-0.019 (0.02)		-0.013 (0.01)	-0.012 (0.02)
Year 2018		-0.022 (0.03)	-0.033 (0.03)		-0.015 (0.02)	-0.017 (0.03)
Year 2019		-0.025 (0.02)	-0.036 (0.03)		-0.007 (0.02)	-0.010 (0.03)
Year 2020		-0.034 (0.03)	-0.024 (0.03)		-0.045 (0.03)	-0.030 (0.03)
Year 2021		-0.062 (0.04)	-0.069 (0.04)		-0.106** (0.04)	-0.099** (0.05)
Year 2022		-0.063 (0.04)	-0.085 (0.05)		-0.103** (0.04)	-0.108** (0.05)
Constant	-3.268*** (0.24)			-1.763*** (0.35)		
Sigma_u		0.64	0.47		0.59	0.47
Sigma_e		0.14	0.14		0.14	0.14
R2	0.494	0.982	0.983	0.601	0.983	0.983
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	121	121	121	121	121	121
No of observations	841	841	841	841	841	841

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S11. Relationship between the Environmental Performance Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.497*** (0.05)	-0.030 (0.07)	-0.035 (0.07)			
SPI Pillar 1 Score (Data use)				0.007 (0.04)	0.042 (0.03)	0.046 (0.03)
SPI Pillar 2 Score (Data services)				0.073** (0.03)	0.013 (0.02)	0.011 (0.02)
SPI Pillar 3 Score (Data products)				-0.537*** (0.04)	-0.004 (0.05)	0.004 (0.06)
SPI Pillar 4 Score (Data sources)				0.300*** (0.05)	-0.083 (0.06)	-0.093* (0.06)
SPI Pillar 5 Score (Data infrastructure)				0.234*** (0.03)	-0.036 (0.03)	-0.035 (0.03)
Log GDP per capita (constant 2015 US\$)			3.455 (4.42)			4.744 (4.42)
Trade (% of GDP)			0.029 (0.03)			0.028 (0.03)
Agriculture, forestry, fishing value added (% of GDP)			0.051 (0.15)			0.069 (0.16)
Manufacturing value added (% of GDP)			-0.026 (0.21)			-0.028 (0.23)
School Enrollment, Primary (% gross)			-0.019 (0.07)			-0.018 (0.06)
Year 2017		0.072 (0.17)	-0.064 (0.21)		-0.158 (0.28)	-0.347 (0.32)
Year 2018		0.147 (0.35)	-0.089 (0.42)		-0.216 (0.47)	-0.506 (0.55)
Year 2019		0.155 (0.37)	-0.144 (0.49)		-0.081 (0.46)	-0.450 (0.60)
Year 2020		-8.912*** (0.70)	-8.844*** (0.70)		-8.993*** (0.81)	-8.983*** (0.80)
Year 2021		-8.761*** (0.91)	-9.000*** (0.93)		-8.446*** (1.26)	-8.877*** (1.28)
Year 2022		-12.418*** (0.98)	-12.974*** (1.10)		-12.159*** (1.25)	-12.944*** (1.37)
Constant	19.224*** (3.03)			54.355*** (3.09)		
Sigma_u		8.91	5.25		6.8	5.11
Sigma_e		5.88	5.88		5.26	5.24
R2	0.298	0.925	0.926	0.574	0.926	0.927
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	158	158	158	158	158	158
No of observations	1100	1100	1100	1100	1100	1100

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S12. Relationship between the OECD Better Life Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.090*** (0.03)	0.004 (0.01)	0.002 (0.01)			
SPI Pillar 1 Score (Data use)				0.014 (0.03)	-0.004 (0.00)	0.001 (0.00)
SPI Pillar 2 Score (Data services)				0.009 (0.01)	0.004 (0.00)	0.002 (0.00)
SPI Pillar 3 Score (Data products)				-0.045*** (0.01)	0.011* (0.01)	0.006 (0.01)
SPI Pillar 4 Score (Data sources)				0.045** (0.02)	0.002 (0.01)	-0.002 (0.01)
SPI Pillar 5 Score (Data infrastructure)				0.048*** (0.01)	-0.009* (0.00)	-0.004 (0.01)
Log GDP per capita (constant 2015 US\$)			2.339*** (0.82)			2.156** (0.90)
Trade (% of GDP)			-0.002 (0.00)			-0.002 (0.00)
Agriculture, forestry, fishing value added (% of GDP)			0.080 (0.05)			0.097* (0.05)
Manufacturing value added (% of GDP)			-0.064** (0.03)			-0.048 (0.03)
School Enrollment, Primary (% gross)			0.028* (0.02)			0.023 (0.02)
Year 2017		-0.130*** (0.04)	-0.181*** (0.04)		-0.166*** (0.05)	-0.203*** (0.05)
Year 2018		-0.228** (0.09)	-0.310*** (0.08)		-0.293*** (0.08)	-0.339*** (0.08)
Year 2019		-0.229** (0.09)	-0.358*** (0.08)		-0.256*** (0.09)	-0.360*** (0.08)
Year 2020		-0.232** (0.10)	-0.273*** (0.08)		-0.291*** (0.09)	-0.311*** (0.08)
Year 2021		-0.248* (0.13)	-0.379*** (0.11)		-0.419*** (0.13)	-0.447*** (0.11)
Year 2022		-0.248* (0.13)	-0.425*** (0.13)		-0.421*** (0.13)	-0.489*** (0.12)
Constant	-0.922 (2.67)			0.389 (2.80)		
Sigma_u		1.18	0.62		0.97	0.55
Sigma_e		0.23	0.22		0.23	0.22
R2	0.123	0.977	0.981	0.441	0.979	0.982
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	43	43	43	43	43	43
No of observations	297	297	297	297	297	297

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S13. Relationship between the UN Human Development Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.007*** (0.00)	0.000 (0.00)	0.000 (0.00)			
SPI Pillar 1 Score (Data use)				0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 2 Score (Data services)				0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 3 Score (Data products)				-0.003*** (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 4 Score (Data sources)				0.005*** (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 5 Score (Data infrastructure)				0.002*** (0.00)	0.000 (0.00)	0.000 (0.00)
Log GDP per capita (constant 2015 US\$)			0.038*** (0.01)			0.039*** (0.01)
Trade (% of GDP)			0.000 (0.00)			0.000 (0.00)
Agriculture, forestry, fishing value added (% of GDP)			0.000 (0.00)			0.000 (0.00)
Manufacturing value added (% of GDP)			0.000 (0.00)			0.000 (0.00)
School Enrollment, Primary (% gross)			0.000*** (0.00)			0.000*** (0.00)
Year 2017		0.004*** (0.00)	0.003*** (0.00)		0.004*** (0.00)	0.003*** (0.00)
Year 2018		0.008*** (0.00)	0.006*** (0.00)		0.007*** (0.00)	0.006*** (0.00)
Year 2019		0.012*** (0.00)	0.010*** (0.00)		0.012*** (0.00)	0.009*** (0.00)
Year 2020		0.006*** (0.00)	0.006*** (0.00)		0.006*** (0.00)	0.006*** (0.00)
Year 2021		0.005*** (0.00)	0.004*** (0.00)		0.005** (0.00)	0.004** (0.00)
Year 2022		0.005*** (0.00)	0.003*** (0.00)		0.005** (0.00)	0.003 (0.00)
Constant	0.295*** (0.04)			0.581*** (0.04)		
Sigma_u		0.1	0.04		0.07	0.04
Sigma_e		0.01	0.01		0.01	0.01
R2	0.518	0.999	0.999	0.757	0.999	0.999
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	160	160	160	160	160	160
No of observations	1114	1114	1114	1114	1114	1114

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S14. Relationship between the WB Human Capital Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.007*** (0.00)	0.001*** (0.00)	0.001*** (0.00)			
SPI Pillar 1 Score (Data use)				0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 2 Score (Data services)				0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 3 Score (Data products)				-0.003*** (0.00)	0.000** (0.00)	0.000** (0.00)
SPI Pillar 4 Score (Data sources)				0.004*** (0.00)	0.000 (0.00)	0.000 (0.00)
SPI Pillar 5 Score (Data infrastructure)				0.003*** (0.00)	0.000*** (0.00)	0.000*** (0.00)
Log GDP per capita (constant 2015 US\$)			-0.015 (0.01)			-0.015 (0.01)
Trade (% of GDP)			0.000 (0.00)			0.000 (0.00)
Agriculture, forestry, fishing value added (% of GDP)			-0.001 (0.00)			-0.001 (0.00)
Manufacturing value added (% of GDP)			0.000 (0.00)			0.000 (0.00)
School Enrollment, Primary (% gross)			0.000 (0.00)			0.000 (0.00)
Year 2017		0.019*** (0.00)	0.019*** (0.00)		0.018*** (0.00)	0.018*** (0.00)
Year 2018		0.018*** (0.00)	0.018*** (0.00)		0.019*** (0.00)	0.019*** (0.00)
Year 2019		0.018*** (0.00)	0.018*** (0.00)		0.018*** (0.00)	0.019*** (0.00)
Year 2020		0.013*** (0.00)	0.013*** (0.00)		0.011*** (0.00)	0.011*** (0.00)
Year 2021		0.010*** (0.00)	0.010*** (0.00)		0.004 (0.00)	0.004 (0.00)
Year 2022		0.010*** (0.00)	0.011*** (0.00)		0.004 (0.00)	0.004 (0.00)
Constant	0.127*** (0.03)			0.411*** (0.03)		
Sigma_u		0.09	0.06		0.06	0.05
Sigma_e		0.02	0.02		0.02	0.02
R2	0.562	0.991	0.991	0.769	0.992	0.992
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	151	151	151	151	151	151
No of observations	1051	1051	1051	1051	1051	1051

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S15. Relationship between the World Press Freedom Index and SPI scores, 2016-2022

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Overall SPI Score	0.367*** (0.06)	-0.023 (0.06)	-0.009 (0.06)			
SPI Pillar 1 Score (Data use)				-0.064 (0.08)	0.035 (0.04)	0.031 (0.03)
SPI Pillar 2 Score (Data services)				0.102** (0.05)	0.002 (0.01)	0.005 (0.01)
SPI Pillar 3 Score (Data products)				-0.088 (0.09)	-0.022 (0.05)	-0.006 (0.05)
SPI Pillar 4 Score (Data sources)				0.045 (0.09)	0.000 (0.03)	-0.005 (0.03)
SPI Pillar 5 Score (Data infrastructure)				0.190*** (0.06)	-0.044** (0.02)	-0.039* (0.02)
Log GDP per capita (constant 2015 US\$)			2.520 (3.96)			2.886 (3.93)
Trade (% of GDP)			0.047** (0.02)			0.045* (0.02)
Agriculture, forestry, fishing value added (% of GDP)			-0.064 (0.15)			-0.050 (0.15)
Manufacturing value added (% of GDP)			-0.351** (0.14)			-0.341** (0.13)
School Enrollment, Primary (% gross)			0.049 (0.04)			0.048 (0.04)
Year 2017		0.052 (0.13)	-0.137 (0.18)		0.124 (0.19)	-0.119 (0.24)
Year 2018		0.109 (0.28)	-0.237 (0.35)		0.121 (0.32)	-0.277 (0.40)
Year 2019		-0.232 (0.38)	-0.659 (0.45)		-0.115 (0.38)	-0.588 (0.45)
Year 2020		-0.066 (0.51)	-0.071 (0.49)		0.187 (0.63)	0.054 (0.60)
Year 2021		-0.378 (0.74)	-0.731 (0.76)		0.354 (1.09)	-0.255 (1.12)
Year 2022		-6.908*** (0.91)	-7.654*** (1.00)		-6.175*** (1.27)	-7.166*** (1.36)
Constant	40.807*** (4.52)			56.578*** (7.71)		
Sigma_u		12.98	11.91		12.55	11.26
Sigma_e		3.99	3.92		3.86	3.8
R2	0.145	0.959	0.960	0.187	0.959	0.961
Country FE	No	Yes	Yes	No	Yes	Yes
No of countries	151	151	151	151	151	151
No of observations	1051	1051	1051	1051	1051	1051

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data are from the World Bank's World Development Indicators (WDI) and SPI. In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value.

Table S16. Relationship between the Economic Complexity Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.036*** (0.00)	0.002* (0.00)	0.002 (0.00)				
Open Data Barometer Score				0.028*** (0.00)	-0.001 (0.00)	0.000 (0.00)	
Global Data Barometer Score							0.035*** (0.00)
Trade (% of GDP)			0.000 (0.00)			-0.001 (0.00)	
Agriculture, forestry, fishing value added (% of GDP)			-0.013 (0.02)			0.007 (0.02)	
Manufacturing value added (% of GDP)			0.020*** (0.00)			0.003 (0.01)	
School Enrollment, Primary (% gross)			-0.001 (0.00)			0.008** (0.00)	
Year 2014					0.008 (0.01)	0.004 (0.01)	
Year 2015					0.015 (0.02)	0.008 (0.02)	
Year 2016					-0.018 (0.02)	-0.028 (0.03)	
Year 2017		-0.009 (0.01)	-0.016 (0.02)		-0.018 (0.02)	-0.022 (0.03)	
Year 2018		-0.017 (0.02)	-0.030 (0.03)				
Year 2019		-0.015 (0.02)	-0.030 (0.03)				
Year 2020		-0.029 (0.03)	-0.023 (0.03)				
Year 2021		-0.037 (0.03)	-0.054 (0.04)				
Year 2022		-0.038 (0.03)	-0.069 (0.05)				
Constant	-1.755*** (0.18)			-0.642*** (0.12)			-1.153*** (0.17)
Sigma_u		0.72	0.52		0.7	0.45	
Sigma_e		0.14	0.14		0.1	0.1	
R2	0.380	0.982	0.983	0.408	0.992	0.992	0.405
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	119	119	119	94	94	94	85
No of observations	848	848	848	352	352	352	85

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S17. Relationship between the Environmental Performance Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.468*** (0.04)	-0.032 (0.04)	-0.027 (0.04)				
Open Data Barometer Score				0.467*** (0.04)	0.000 (0.00)	0.000 (0.00)	
Global Data Barometer Score							0.747*** (0.06)
Trade (% of GDP)			0.025 (0.03)			0.000 (0.00)	
Agriculture, forestry, fishing value added (% of GDP)			0.006 (0.15)			0.000 (0.00)	
Manufacturing value added (% of GDP)			-0.317 (0.21)			0.000 (0.00)	
School Enrollment, Primary (% gross)			-0.047 (0.07)			0.000 (0.00)	
Year 2014					0.000* (0.00)	0.000 (0.00)	
Year 2015					0.000* (0.00)	0.000 (0.00)	
Year 2016					0.000 (0.00)	0.000 (0.00)	
Year 2017		0.019 (0.04)	-0.084 (0.12)		0.000 (0.00)	0.000 (0.00)	
Year 2018		0.162 (0.20)	-0.053 (0.31)				
Year 2019		0.162 (0.20)	-0.126 (0.38)				
Year 2020		-8.778*** (0.68)	-8.835*** (0.68)				
Year 2021		-8.822*** (0.67)	-9.030*** (0.69)				
Year 2022		-12.604*** (0.76)	-13.011*** (0.85)				
Constant	29.617*** (1.91)			43.581*** (1.64)			22.852*** (2.03)
Sigma_u		8.79	5.46		8.81	6.37	
Sigma_e		6.37	6.31		0	0	
R2	0.277	0.926	0.927	0.539	1.000	1.000	0.579
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	156	156	156	102	102	102	93
No of observations	1074	1074	1074	373	373	373	93

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S18. Relationship between the OECD Better Life Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.058*** (0.01)	-0.001 (0.01)	0.000 (0.00)				
Open Data Barometer Score				0.051*** (0.01)	-0.008** (0.00)	-0.007* (0.00)	
Global Data Barometer Score							0.064*** (0.02)
Trade (% of GDP)			-0.002 (0.00)			-0.001 (0.01)	
Agriculture, forestry, fishing value added (% of GDP)			0.084 (0.05)			0.017 (0.05)	
Manufacturing value added (% of GDP)			-0.072*** (0.02)			-0.032 (0.02)	
School Enrollment, Primary (% gross)			0.029* (0.02)			0.009 (0.01)	
Year 2014					0.019 (0.04)	-0.014 (0.04)	
Year 2015					0.097* (0.05)	0.055 (0.05)	
Year 2016					-0.219*** (0.05)	-0.278*** (0.06)	
Year 2017		-0.124*** (0.03)	-0.177*** (0.04)		-0.310*** (0.07)	-0.394*** (0.08)	
Year 2018		-0.208** (0.09)	-0.299*** (0.08)				
Year 2019		-0.208** (0.09)	-0.348*** (0.08)				
Year 2020		-0.206** (0.10)	-0.264*** (0.08)				
Year 2021		-0.207** (0.09)	-0.359*** (0.09)				
Year 2022		-0.206** (0.10)	-0.402*** (0.11)				
Constant	3.015*** (0.94)			4.310*** (0.47)			3.295*** (1.07)
Sigma_u		1.13	0.5		0.97	0.37	
Sigma_e		0.23	0.22		0.24	0.22	
R2	0.255	0.977	0.981	0.419	0.986	0.987	0.230
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	41	41	41	38	38	38	30
No of observations	297	297	297	172	172	172	30

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S19. Relationship between the UN Human Development Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.006*** (0.00)	0.000 (0.00)	0.000 (0.00)				
Open Data Barometer Score				0.005*** (0.00)	0.000 (0.00)	0.000 (0.00)	
Global Data Barometer Score							0.006*** (0.00)
Trade (% of GDP)			0.000 (0.00)			0.000* (0.00)	
Agriculture, forestry, fishing value added (% of GDP)			0.000 (0.00)			-0.001 (0.00)	
Manufacturing value added (% of GDP)			0.000 (0.00)			0.001 (0.00)	
School Enrollment, Primary (% gross)			0.000*** (0.00)			0.000 (0.00)	
Year 2014					0.005*** (0.00)	0.004*** (0.00)	
Year 2015					0.009*** (0.00)	0.007*** (0.00)	
Year 2016					0.014*** (0.00)	0.010*** (0.00)	
Year 2017		0.004*** (0.00)	0.003*** (0.00)		0.016*** (0.00)	0.012*** (0.00)	
Year 2018		0.007*** (0.00)	0.006*** (0.00)				
Year 2019		0.011*** (0.00)	0.009*** (0.00)				
Year 2020		0.006*** (0.00)	0.005*** (0.00)				
Year 2021		0.005*** (0.00)	0.003*** (0.00)				
Year 2022		0.005*** (0.00)	0.002** (0.00)				
Constant	0.440*** (0.02)			0.581*** (0.02)			0.550*** (0.02)
Sigma_u		0.1	0.04		0.09	0.04	
Sigma_e		0.01	0.01		0.01	0	
R2	0.472	0.999	0.999	0.567	0.999	1.000	0.519
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	160	160	160	101	101	101	95
No of observations	1098	1098	1098	374	374	374	95

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S20. Relationship between the WB Human Capital Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.006*** (0.00)	0.000 (0.00)	0.000 (0.00)				
Open Data Barometer Score				0.005*** (0.00)	0.000 (0.00)	0.000 (0.00)	
Global Data Barometer Score							0.006*** (0.00)
Trade (% of GDP)			0.000 (0.00)			0.000 (0.00)	
Agriculture, forestry, fishing value added (% of GDP)			-0.001 (0.00)			-0.001 (0.00)	
Manufacturing value added (% of GDP)			0.000 (0.00)			0.001 (0.00)	
School Enrollment, Primary (% gross)			0.000 (0.00)			0.001 (0.00)	
Year 2014					0.001 (0.00)	0.001** (0.00)	
Year 2015					0.000 (0.00)	0.002** (0.00)	
Year 2016					0.000 (0.00)	0.002** (0.00)	
Year 2017		0.021*** (0.00)	0.021*** (0.00)		0.022*** (0.01)	0.026*** (0.01)	
Year 2018		0.021*** (0.00)	0.022*** (0.00)				
Year 2019		0.022*** (0.00)	0.022*** (0.00)				
Year 2020		0.017*** (0.00)	0.018*** (0.00)				
Year 2021		0.017*** (0.00)	0.018*** (0.00)				
Year 2022		0.017*** (0.00)	0.018*** (0.00)				
Constant	0.273*** (0.02)			0.413*** (0.02)			0.389*** (0.02)
Sigma_u		0.09	0.06		0.09	0.06	
Sigma_e		0.02	0.02		0.01	0.01	
R2	0.529	0.991	0.991	0.585	0.998	0.998	0.531
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	149	149	149	100	100	100	92
No of observations	1035	1035	1035	373	373	373	92

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Table S21. Relationship between the World Press Freedom Index and ODIN, Open Data Barometer, and Global Data Barometer scores, 2013-2022

	ODIN - Model 1	ODIN - Model 2	ODIN - Model 3	ODB - Model 1	ODB - Model 2	ODB - Model 3	GDB - Model 1
ODIN Score	0.315*** (0.06)	-0.029 (0.03)	-0.026 (0.03)				
Open Data Barometer Score				0.353*** (0.06)	0.000 (0.00)	0.000 (0.00)	
Global Data Barometer Score							0.393*** (0.07)
Trade (% of GDP)			0.042** (0.02)			0.000 (0.00)	
Agriculture, forestry, fishing value added (% of GDP)			-0.107 (0.15)			0.000 (0.00)	
Manufacturing value added (% of GDP)			-0.183 (0.13)			0.000 (0.00)	
School Enrollment, Primary (% gross)			0.059 (0.04)			0.000 (0.00)	
Year 2014					0.000 (0.00)	0.000 (0.00)	
Year 2015					0.000 (0.00)	0.000 (0.00)	
Year 2016					0.000 (0.00)	0.000 (0.00)	
Year 2017		-0.005 (0.05)	-0.227** (0.10)		0.000 (0.00)	0.000 (0.00)	
Year 2018		0.133 (0.19)	-0.300 (0.28)				
Year 2019		-0.167 (0.27)	-0.693** (0.35)				
Year 2020		0.026 (0.43)	0.085 (0.42)				
Year 2021		-0.309 (0.45)	-0.746 (0.49)				
Year 2022		-7.024*** (0.76)	-7.908*** (0.85)				
Constant	50.162*** (3.12)			56.116*** (2.85)			53.384*** (2.81)
Sigma_u		13.2	12.3		13.25	12.42	
Sigma_e		4.16	4.06		0	0	
R2	0.123	0.959	0.960	0.242	1.000	1.000	0.186
Country FE	No	Yes	Yes	No	Yes	Yes	No
No of countries	150	150	150	104	104	104	94
No of observations	1046	1046	1046	374	374	374	94

Note: * p<0.10, ** p<0.05, *** p<0.01. Standard errors are clustered at the country level. Data from the World Bank's World Development Indicators (WDI), Open Data Watch (ODIN), Global Data Barometer (GDB), and Open Data Barometer (ODB). In cases where data are missing for a particular covariate, the data are imputed forward using the nearest available value. Estimates with country fixed effects not available for the Global Data Barometer, because the indicator contains only one time period.

Figure S1. Correlation between the SPI Pillars

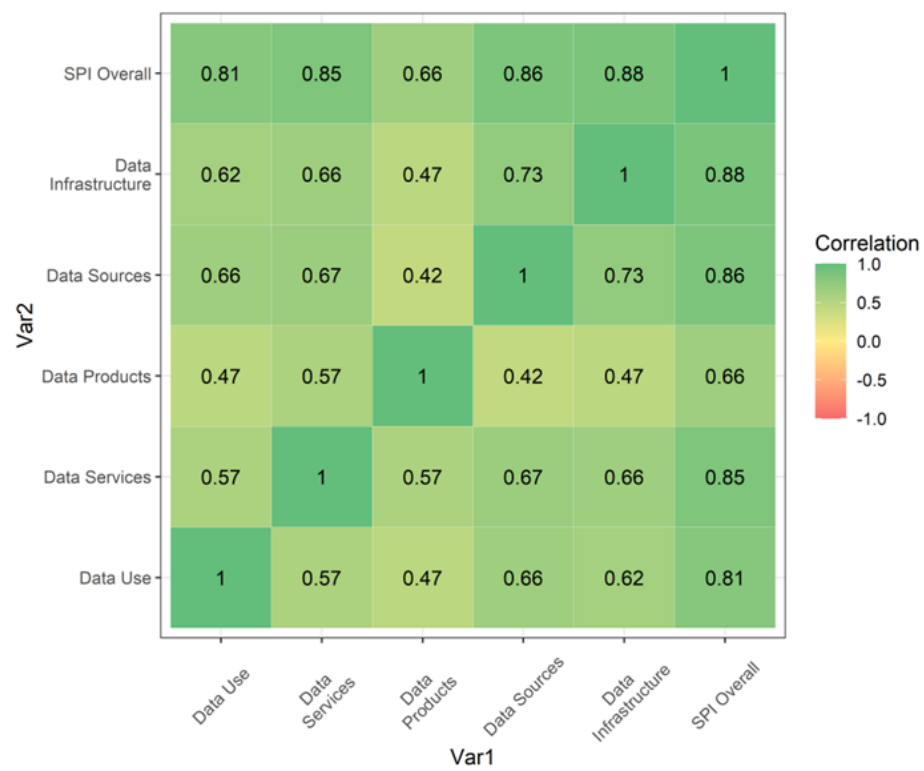
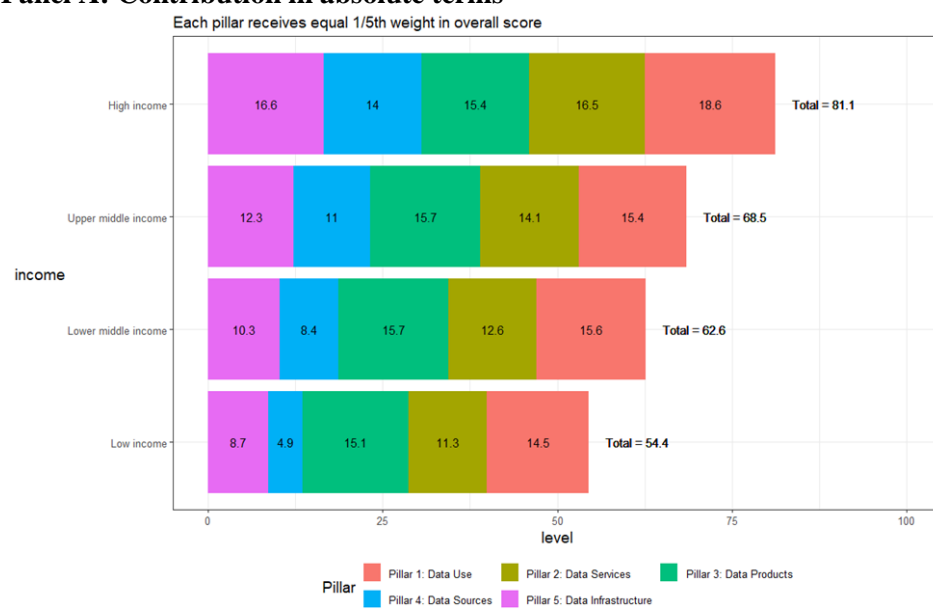


Figure S2. Contribution of Each Pillar to SPI Score, by Country Income Level

Panel A: Contribution in absolute terms



Panel B: Contribution in relative terms

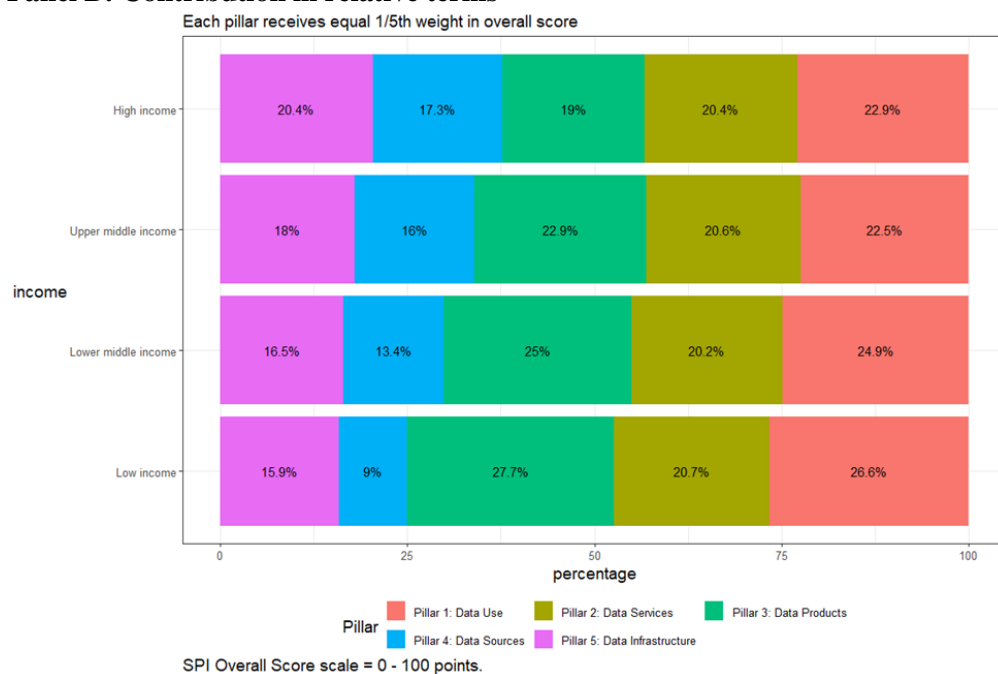
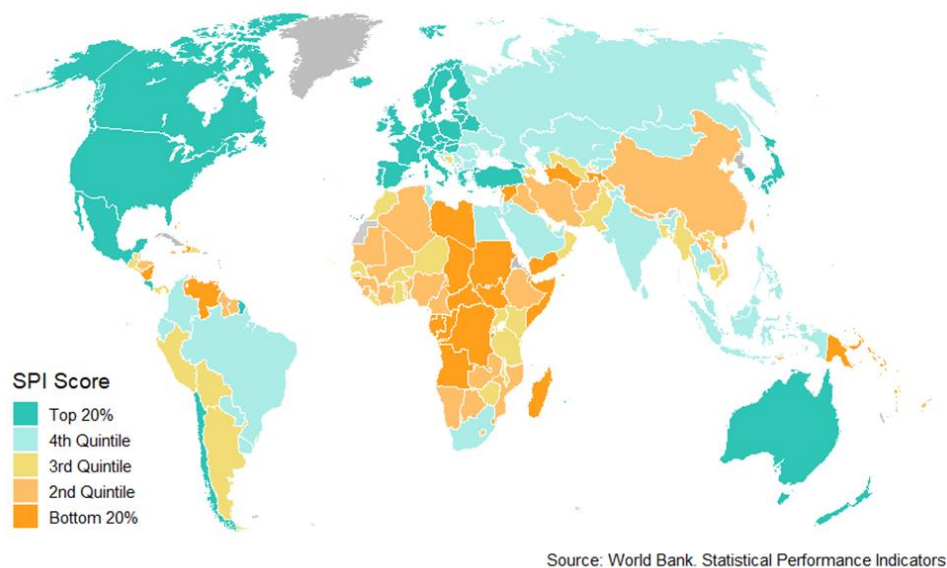
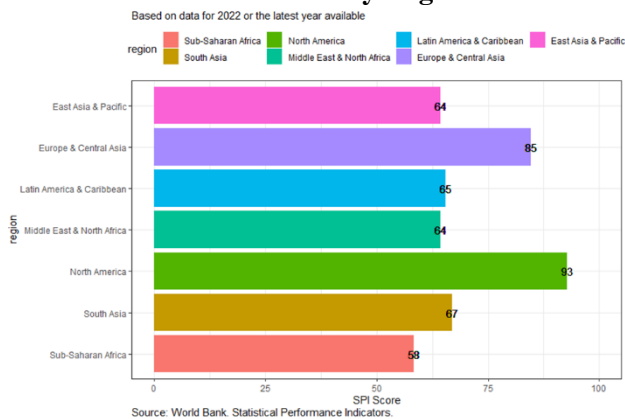


Figure S3. SPI Score, by Region and Income

Panel A. SPI Overall Score



Panel B. SPI Overall Score by Region



Panel C. SPI Overall Score by Income Levels

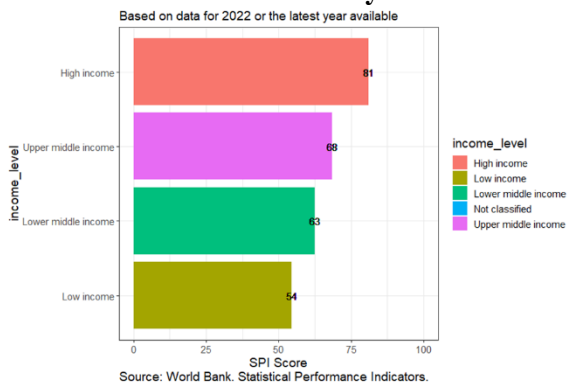


Figure S4. SPI Overall Score by Country within Each Region

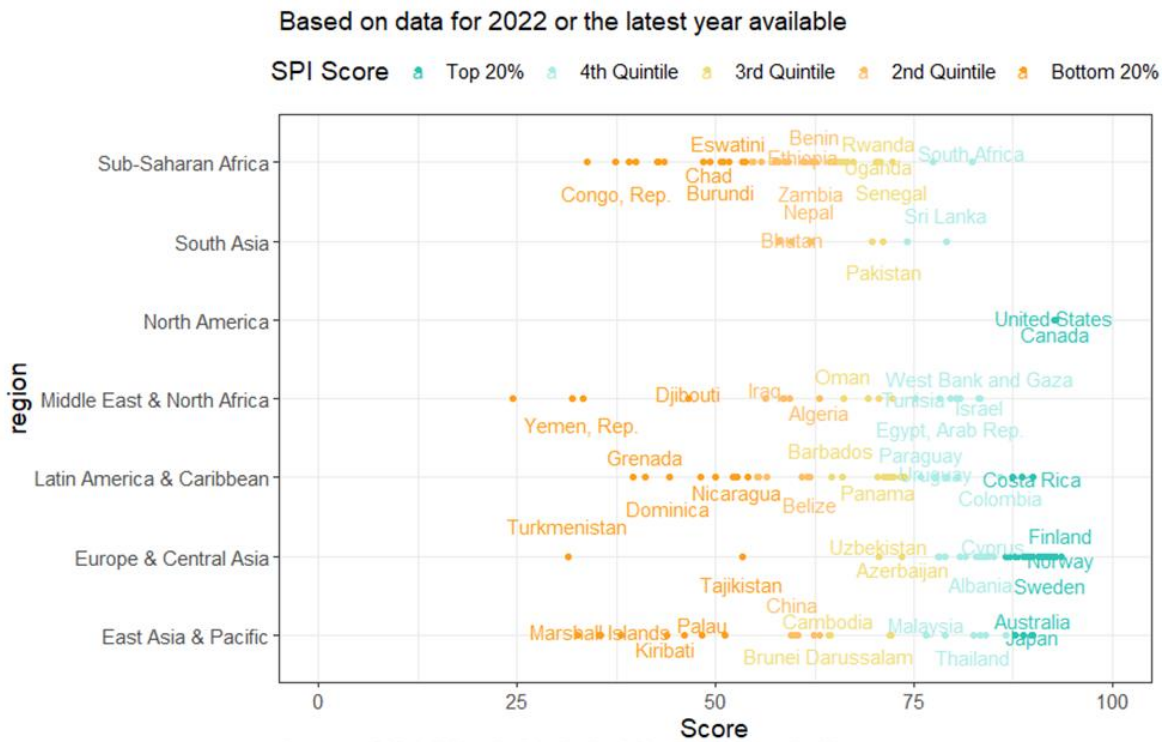


Figure S5. Changes with the SPI Overall Score between 2016 and 2022

