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# WORKING PAPER

# The Inclusive Sustainable Transformation Index

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**Abstract**

In this paper, we put forth an index of Inclusive Sustainable Transformation (IST) that captures the extent to which the country has developed a modern industry or services-based economy that at the same time protects the environment and is gender inclusive. This index distinguishes itself from other indicators of (industrial) development by accounting for the level of development when comparing the structural characteristics of countries, in line with New Structural Economics. In other words, it evaluates how well the country scores given its available means. In addition, by addressing availability problems using multiple imputation techniques, it is able to compare the performance on a wide range of topics for almost 200 countries over 25 years; including a large group of developing countries that are otherwise often left out. In addition to monitoring the progress made towards the establishment of an inclusive and environmental-friendly modern economy, the index can also serve as a useful tool for policy makers and analysts. By decomposing the score back into its components, the index can help identify which areas require additional attention, as well as identify the 'best practice' over all countries with similar level of development.

**Key words**: Structural transformation; Sustainability; Inclusiveness; New structural economics

## 1 Introduction

A century or two from now, when future historians analyze and chronicle the story of economic development and try to identify its defining and foundational moments (the conceptual points in time when the world decided to establish some baselines of commonality), it is very likely that they will pick 2015, the year of the adoption of the Sustainable Development Goals (SDGs) and of the Paris Agreement on climate change, as a major inflexion point. These global rendezvous were milestones in the long struggle for building global consensus on international priorities, and setting objectives that the human community of nations should strive for. Not surprisingly, even the most ambitious and transformational global objectives always generate a (healthy) dose of incredulity: why should anyone believe in the promises of a better world when such goals have often been stated in the past, to little results, and are predicated on the assumption that the global consensus that led to the signing of these two major international covenants will hold in countries at all levels of economic development?

There are indeed a few major puzzling issues about the SDGs and the Paris Accord: first, almost every single commitment made appears to be voluntary. Moreover, monitoring mechanisms are uncertain, which makes enforcement highly problematic. It is therefore important that the underlying mechanisms and dynamics that allow economies and societies to reach their noble goals be monitored carefully. It is necessary to measure how well each country and region in the world will address issues of economic production, employment generation, and the protection of the environment. Without steady and well-organized economic transformation that can occur only through responsible industrialization, the widely shared global goals of creating opportunities and improving human life will remain elusive.

Measurement of any global goal can be costly, hard, and frustrating.[1] In December 2014 UN Secretary-General Ban Ki-moon called for a *'comprehensive program of action on data.'* However, because the Open Working Group has recommended 169 targets for the proposed 17 SDGs, it would unrealistic to expect adequate funding to carry out all the necessary data collection exercise.[2] Under such circumstances it is best to adopt more focused approaches, which are still based on objective data analysis and monitoring, but cover only the factors and elements considered to be most important indicators of progress towards the SDGs. To that end, this paper focuses on one dimension that directly underlies as much as half of the SGDs: environmentally friendly and socially inclusive structural transformation.

Structural change is the foundation of sustained and inclusive growth and the condition for achieving the SDGs (Monga, 2013). Rarely has a country evolved from a low- to a high-income status without sustained structural transformation from agrarian or resource-based economy towards an industry- or services-based economy. Industrialization in particular is essential for lifting people out of poverty, creating jobs, advancing technology, and generating prosperity around the world. However, industry is also the largest single sector that emits greenhouse gas (GHG) with almost 30 percent of the global share. Fortunately, it is possible to transform conventional industrial development patterns to prevent dangerous anthropogenic interference with the atmosphere.[3] The global community needs monitoring tools that provide incentives to governments, the private sector, and other development stakeholders to promote climate resilient industrialization. As important as the environmental sustainability, we also track the extent to which these economic opportunities are open to all, regardless of gender.

This paper proposes the inclusive sustainable transformation (IST) index, which focuses on the critical elements of successful economic development strategies. In an era where there is no shortage of development indices, the IST index set itself apart by measuring while accounting for a country's development status. New Structural Economics tells us that that the feasible and desired characteristics of countries change with the level of development (Lin 2012a, 2012b). This idea is explicitly incorporated in the IST index, which shows in each year, the extent to which a country has a modern economy that is inclusive and sustainable relative to countries with a similar level of development. The relative nature of this index underscores the idea that sustainable development is a continuous process of improvement for all countries, rather than a fixed path with a clearly defined end goal.

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[1] Even for basic data on poverty, there is still much debate among experts and statisticians. Researcher Morten Jerven has pointed out that to estimate the number of poor in a country requires a household survey of consumption. Yet 6 out of the 49 countries in Sub-Saharan Africa have never had a household survey, and only 28 have had one in the past 7 years. Even a good-performing country such as Botswana whose poverty rate in 2008 was 12% according to the World Bank, based that number on just 1 household survey from 1993.

[2] A preliminary estimate by Morten Jerven suggests that even minimal data collection for all 169 targets would cost at least $254 billion—that is about twice last year's ODA aid flows--and this does not even include the cost of conducting all household surveys (Jerven, 2014).

[3] As noted in a recent UNIDO report, 'seizing the opportunity through mitigation potential, adaptation approaches and creating synergies between both measures can maximize the cost-effectiveness and benefits for industry. Implementing the development and transfer of sustainable energy solutions, capitalizing on positive spillovers and reducing trade-offs are key priorities for climate resilient development pathways.'

The remainder of this paper is organized as follows. The next section defines structural transformation, its importance for growth and convergence and how industrialization and services contribute. Section three surveys the theoretical challenges for building development indices, and presents the IST methodology. Finally, the fourth section discusses the indicators chosen and the resulting values of the IST index and its subcomponents.

# 2 Why the Need for an Index of Structural Transformation?

## *2.1 What is structural transformation?*

The importance of structural transformation as a process for generating prosperity and as the mechanics for improving the quality of life around the world cannot be underestimated. Rarely has a country evolved from a poor to a rich one without sustained structural transformation from agrarian or resource-based towards an industry or services-based economy. Ideally, that process involves improvements in the productivity of the agricultural sector in order to increase food provision, free up labor and even provide savings. These resources can in turn support the process of urbanization, industrialization and the development of a high-performing service sector that can absorb a growing fraction of the educated labor force. Sustained growth and economic prosperity require the shift of resources out of traditional agriculture and other low-productivity primary activities, into more productive sectors of manufacturing and services in both urban and rural areas. The ensuing expansion and upgrading of ‘modern’ sectors (including non-traditional agriculture) are at the core of the sustained productivity gains that characterize economic development. Indeed, there is ample consensus that rising productivity accounts for the bulk of long-term growth.

Structural transformation (or structural change) is therefore central focus of economic policy for countries at all levels of development. It involves five main features: *i*) a steadily declining share of agriculture in economic output and employment; *ii*) a rising share of urban economic activity in industry and modern services; *iii*) an increasingly sophisticated share of manufactured goods in production and exports; *iv*) migration of rural workers to urban settings; *v*) and a demographic transition that always leads to a spurt in population growth before a new equilibrium is reached. Sustaining high economic performance, improving living standards for the largest segments of society, and sharing prosperity widely to maintain social cohesiveness and peace, eventually require not only constant movement of resources to new, more productive industries, sectors, and firms, but also continuous infrastructure and institutional improvement, which becomes increasingly challenging as an economy approaches the technological frontier and can no longer rely on imitation to create value.

Structural differences between developed and developing countries reflect the differences in their endowment structure. A given economy’s structure of factor endowment –defined as the relative composition of natural resources, labor, human capital and physical capital– is innately different at each level of development. Because of this, for any given economy, its comparative advantage and optimal industrial structure will be different at different levels of development. To move from one level to another smoothly and quickly, the government needs to provide or coordinate the improvement in hard and soft infrastructure (Lin 2012a, 2012b).

What are the sectoral dynamics of structural change? The modernization of agriculture and sustainable industrialization are essential features of the structural transformation process. Prosperity is achieved only when a country’s resources (human, natural, and capital) are shifted from subsistence and informal activities into high-productivity activities. The economic development of today's industrialized countries was almost universally accompanied by an increase in agricultural productivity in the early stages of development. Sustained economic development typically requires that productivity increases in agriculture provide food, labor, and even savings to the process of urbanization and industrialization. *"A dynamic agriculture raises labor productivity in the rural economy, pulls up wages, and gradually eliminates the worst dimensions of absolute poverty"* (Timmer and Akkus, 2008, p. 3-4). Investments in agriculture aimed at promoting growth and generating an investable surplus are now widely viewed as necessary for industrial growth and for the benefits of development to reach the poor.

Agricultural growth stimulates growth in non-farm sectors, thus driving structural transformation and industrialization processes through various channels:

- Higher farm incomes generate more demand for non-food consumables (e.g. commercially manufactured goods), creating growth linkages into the rural non-farm economy and further afield.
- Increased demand in the agricultural sector for agricultural inputs, capital and services stimulates production of inputs such as fertilizer, machinery and tools.
- As farm productivity increases and marketable surplus grows, demand for commercial distribution and processing infrastructure and services increases.
- Increased productivity of agricultural labor means that labor can be released for employment in industrial and related sectors without damaging agricultural output.
- Increased profits from rising agricultural productivity generate capital that can be invested in other sectors of the economy.

The development of a competitive industrial sector yields an even higher payoff. Economists have established at least since the early1960s that manufacturing has always played a larger role in the total output of richer countries, and that countries with higher incomes are typically those with a substantially bigger economic contribution from the transport and machinery sectors. The countries that manage to pull out of poverty and get richer are those able to diversify away from agriculture and other traditional products. *"As labor and other resources move from agriculture into modern economic activities, overall productivity rises and incomes expand. The speed with which this structural transformation takes place is the key factor that differentiates successful countries from unsuccessful ones."* (McMillan and Rodrik 2011, p. 1). In fact, only in circumstances such as extraordinary abundance of land or resources have countries succeeded in developing without industrializing.

## *2.2 Industrialization as a source of growth*

Industrialization has always played a key role in growth acceleration processes that are sustained over time and eventually transform economies from 'poor' to 'rich'. In the early phases of modern economic growth, which started with the Industrial Revolution, manufacturing in particular played a larger role in the total output of successful countries and their higher incomes were associated with a substantially bigger role of transport and machinery sectors. Throughout the nineteenth and twentieth centuries, countries in North America, Western Europe and Asia were able to transform their economies from agrarian to industrial powers, which included a rapidly growing services sector fueled in large part by the multiplier effect of manufacturing. As a result, they built prosperous middle classes and raised their standards of living.

Besides the generally much higher levels of productivity in (manufacturing) industry than in traditional agriculture, the main reason for the growth in industrialization is the fact that its potential is virtually unlimited, especially in an increasingly globalized world. As agricultural or purely extractive activities expand, they usually face shortages of land, water or other resources. In contrast, manufacturing easily benefits from economies of scale. Industrial development has benefitted greatly from new inventions, technological development and changes in the global trade rules that have substantially decreased transport and unit costs of production over the past decades. Today, almost any small country can access the world market, find a particular niche, and establish itself as a global manufacturing place. For example, Qiaotou and Yiwu, two once small Chinese villages, have become powerhouses, producing more than two-thirds of the world's buttons and zippers, respectively.

Industrialization also promotes inclusive development by expanding the fiscal space for social investments. In such a context fiscal revenues are likely to increase due to: *i*) exports of higher value added, *ii*) rising profits of companies and *iii*) higher incomes earned by more productive and innovation labor force.[4] Figure 1 illustrates the positive relationship between the level of industrialization (horizontal axis) and a number of measures of social inclusiveness such as the non-poor ratio, the HDI and the inverse of the Gini coefficient.

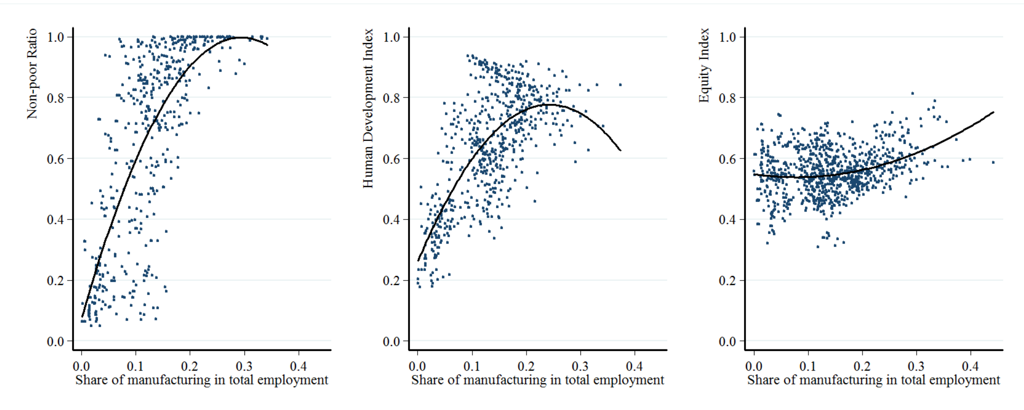



**Figure 1 - Inclusiveness indices by share of manufacturing in total employment, 1970-2010**

**Source**: UNIDO (2015)

**Note**: Sample of almost 100 countries. Each dot represents the average value of each country for a 5-year sub period. In all cases a quadratic trend is also included in the figures to indicate the general trend of inclusiveness.

Within the industrial sector, manufacturing has evolved and changed the dynamics of the world economy. The globalization of manufacturing is driven by many factors, including profound changes in geopolitical relations among world nations, the widespread growth of digital information, the decline of transportation costs, the development of physical and financial infrastructure, computerized manufacturing technologies, and the proliferation of bilateral and multilateral trade agreements. These developments have permitted the decentralization of supply chains into independent but coherent global networks that allow transnational firms to locate various parts of their businesses in different places around the world. The creative design of products, the sourcing of materials and components, and the manufacturing of products can now be done more cheaply and more efficiently from virtually any region of the planet while final goods and services are customized and packaged to satisfy the needs of customers in faraway markets.

[4] UNECA and AUC (2014)

The globalization of manufacturing has thus allowed developed economies to benefit from lower wages in developing countries such as China, India, Bangladesh, Costa Rica, Mexico, or Brazil while creating job and learning opportunities in these formally poor nations. The intensity of these exchanges has led to new forms of competition and co-dependency.

### *2.3 Achieving convergence*

Successful transformation is not necessarily a linear process. In fact, few developing economies have experienced successful structural transformation. Historical data on long-run growth compiled by Angus Maddison shows that since World War II, only two economies out of more than 200 have moved from low-income to high-income status: South Korea and Taiwan, China. Not many countries have been able to achieve economic convergence with the most advanced countries on a sustained basis. One approach to measuring progress is to look at per capita GDP relative to the United States, which has been the benchmark of advanced industrialized countries in the post-WWII era. Persistently, over 80 percent of the countries in the world have GDP per capita levels that are half or less than half of the level in the United States. There has also been some 'churning,' with countries not only converging up the ladder, but also diverging down the ladder. This is the case of some countries that have gone from being lower middle-income economies (MIC) at the time of their political independence to low-income in the 1980s. Since then, a few (mainly in Africa) have climbed back up to MIC status. Even some natural resource rich countries failed to diversify their economic base and as a result have experienced large declines in their relative income per capita. Some countries that used to be at the high-income end of the distribution have fallen back to MIC status – most notably Argentina. Others remained stuck in the so-called middle-income trap for a long period of time –Russia remained there for some 200 years. This explains why policymakers around the world and in particular those in the most dynamically growing emerging countries are concerned with the middle-income trap.

Figure 2 shows changes in income levels in African and Less Developed Countries (LDCs) relative to the United States between 1970 (horizontal axis) and 2014 (vertical axis). Nine areas are distinguished depending on the position of each country above or below two thresholds: a low-income threshold (defined as a relative income of 7 percent compared to the US), and a middle-income threshold (defined as a relative income of 45 percent compared to the US).

- **Catching-up economies** are those that have managed to move from low to middle-income ranges or from middle-income to high-income ranges between 1970 and 2014.
- **Falling-behind economies** are those that fell to a lower income range during the period. All of them are economies that in 1970 were considered middle-income but ended up in the low-income range in 2014.
- **The Poverty trap group** includes the economies that remained in the low-income range during the period.
- **The Middle-income trap group** includes those that remained in the middle-income range during the period.

The performance of most African and LDCs in Figure 2 reflects 50 years of missing opportunities. With only a few exceptions, they show a negative performance. For the 53 countries of this group for which data is available, 22 can be characterized as being in the poverty trap, 13 in the middle-income trap and 12 have actually lagged further behind during the period, moving from the middle- to the low-income range.[5] Six countries, however, have managed to move up one income category during the period: Bhutan, Botswana, Cabo Verde, Egypt, Equatorial Guinea and Lao PDR.

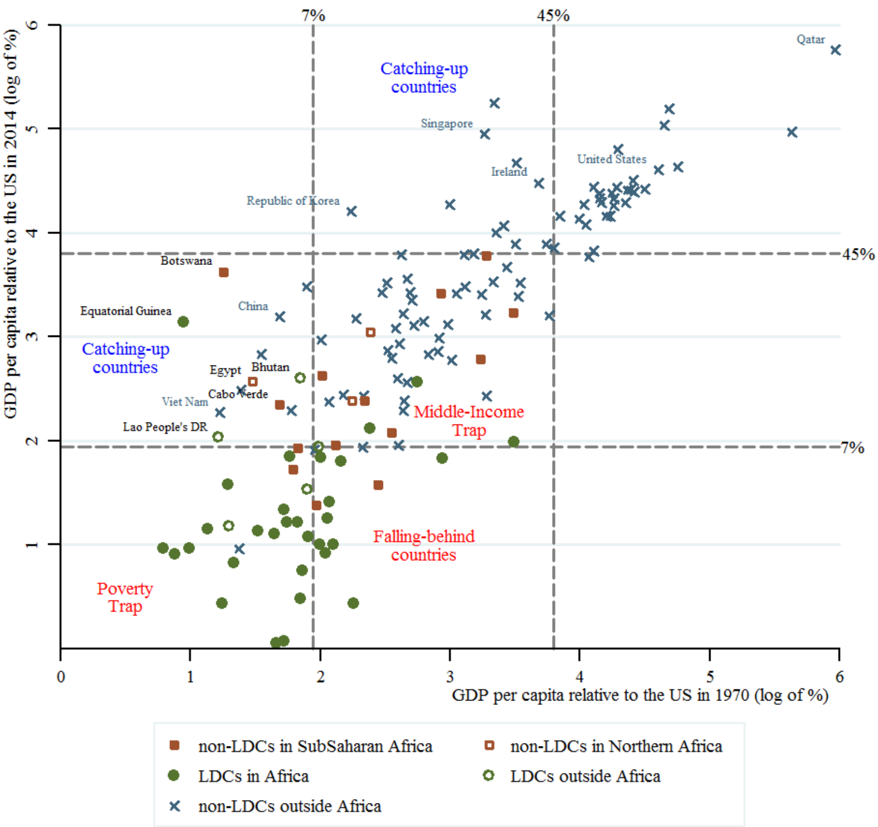



**Figure 2 - GDP per capita relative to the United States in 9 boxes, log of percent**

**Note**: Elaboration based on PWT 8.1 and United Nations Statistical Division.Thresholds based on Gill and Kharas (2015). 12 LDCs are not included because data for 1970 was not available.[6] The estimates are based on figures of per capita GDP at 2005 international dollars

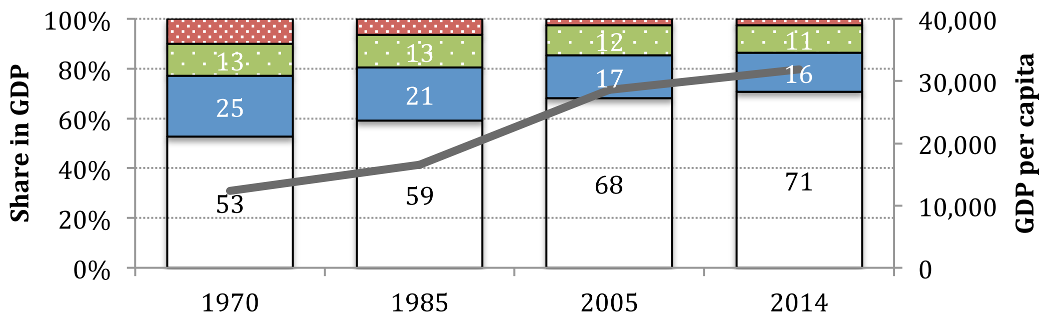
## *2.4 Does manufacturing still matter?*

In recent decades, innovation, technological developments and new sources of economic growth have led some economists to question whether 'manufacturing still matters.' Manufacturing's share of global value added has steadily declined over the past nearly 30 years as the global value added of services has grown. In 1985, manufacturing's share of global value added was 35 percent. By the late 2000s, it had declined to 27 percent. Services grew from 59 percent to 70 percent over the same period (UNIDO, 2009). However, these trends are mainly observed in high-income countries and can be explained by several factors. Firstly, productivity increases and rising standards of living in advanced economies have pushed up wages and forced many industries to delocalize their production in lower-costs nations. Secondly, increasing levels of efficiency in the world economy have reduced

[5] Countries in the poverty trap include: Bangladesh, Benin, Burkina Faso, Burundi, Cameroon, Central African Republic, Congo, D.R. of the Congo, Ethiopia, Lesotho, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Sierra Leone, Sudan, Togo, U.R. of Tanzania: Mainland and Uganda.
Those in the middle-income trap are: Angola, Djibouti, Gabon, Ghana, Mauritania, Mauritius, Morocco, Namibia, Nigeria, South Africa, Swaziland, Tunisia and Zimbabwe.
Those that moved from middle to low income are: Cambodia, Chad, Comoros, Côte d'Ivoire, Gambia, Guinea, Guinea-Bissau, Kenya, Liberia, Sao Tome and Principe, Senegal and Zambia
[6] These are: Afghanistan, Eritrea, Haiti, Kiribati, Myanmar, Solomon Islands, Somalia, South Sudan, Timor-Leste, Tuvalu, Vanuatu and Yemen

the relative prices of consumption goods while at the same time the demand for services such as healthcare, security, or transportation has increased. Finally, and perhaps even more important, manufacturing jobs have a multiplier effect on jobs in services as the development of industries everywhere automatically generates a wide variety of new economic activities, from transportation to housing, from restaurant to entertainment.[7]

Concerns about the future of manufacturing as a viable source of economic growth have been investigated empirically by Hausmann, et al. (2011) with a measure of the sophistication of an economy based on how many products a country exports successfully and how many other countries also export those products. The results are striking: over 70 percent of the income variations among nations can still be explained by differences in manufactured product export data alone (Hausman et al. 2011). The analysis of the composition and quantity of a nation's manufacturing revealed that sophisticated economies export a large variety of 'exclusive' goods that few other countries can produce. To do this, these economies have typically accumulated productive knowledge and developed manufacturing capabilities that others do not have. It therefore appears that national income and economic sophistication (economic complexity) tend to rise in tandem. Furthermore, the linkage between manufacturing, economic complexity and prosperity is highly predictive, with economic complexity being much better at explaining the variation in incomes across nations compared to any other leading indicators. This is exemplified in Figure 3 that contrasts the link between sectoral shares in GDP and income level of OECD countries with that of the least developed countries. In other words, even basic manufacturing expertise and capabilities can gradually breed new knowledge and capabilities and lead to new, more advanced products, provided that the right strategic and business decisions are made on industrial and technological upgrading. In the words of Hausmann and Hidalgo (2012, p. 13), economic development is *'a social learning process, but one that is rife with pitfalls and dangers. Countries accumulate productive knowledge by developing the capacity to make a larger variety of products of increasing complexity. This process involves trial and error. It is a risky journey in search of the possible. Entrepreneurs, investors and policy-makers play a fundamental role in this economic exploration. Manufacturing, however, provides a ladder in which the rungs are more conveniently placed, making progress potentially easier.'* In sum, manufacturing still generates economies of scale, sparks industrial and technological upgrading, fosters innovation, and has big multiplier effects.




a. OECD

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[7] A study by the U.S. Department of Commerce, Bureau of Economic Analysis, shows that manufacturing has a higher multiplier effect on the American economy than any other sector with US$ 1.40 in additional value added in other sectors for every US$ 1.00 in manufacturing value added. Source: World Economic Forum (2012).

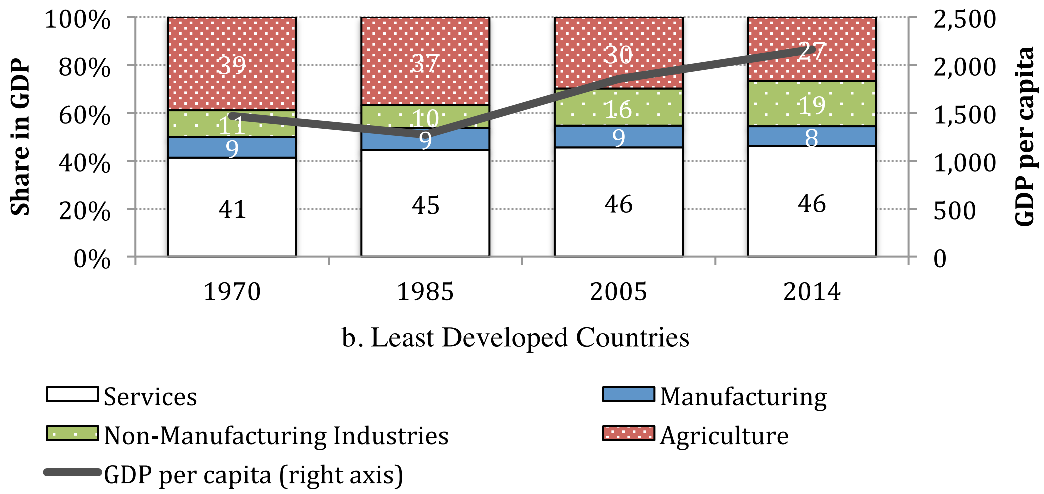


**Figure 3 - Sectoral shares in GDP and income level**

**Note:** Own elaboration based on PWT 8.1 and United Nations Statistical Division. Unweighted averages. GDP shares are based on data at current dollars. Income levels are based on data at 2005 international dollars.

## *2.5 Services and education as sources of growth*

Other researchers have wondered whether services should be considered the main engine of structural change as they contribute more to GDP growth, job creation, and poverty reduction than industry in many developing countries (Ghani and Kharas 2010). It is true that services now account for more than 75% of the global economy (45% in developing economies), and services are the fastest growing sector in global trade. As noted by Ghani et al. (2011), *"the average growth of service exports from poor countries has exceeded that of rich countries during the last two decades. Their service exports are growing faster than goods exports. In brief, the globalisation of services has enabled developing countries to tap into a new, dynamic source of growth."*

While productivity growth in poor countries in services is accelerating and appears to have outstripped productivity growth in industry, the expansion of sustainable services (IT, banking, insurance, etc.) is taking place mainly in upper middle-income countries. More important: the aggregation of very different types of low- and high-productivity activities under the label 'services' can be highly misleading. One should distinguish modern services from traditional services. The former are information communication technology (ICT) intensive and can be unbundled, disembodied, and splintered in a value chain just like manufacturing goods (Bhagwati 1984). The latter, however, are typically low-productivity activities, often in the informal sector. Modern services can be electronically transported internationally through satellite and telecom networks. Traditional services are often not ICT-intensive and lack the potential for generating the income levels that can lift large segments of populations out of poverty.

It is modern services that are developing rapidly thanks to growing tradability, more sophisticated technology (including specialization, scale economies and off-shoring) and reduced transport costs (Ghani 2010). This raises serious questions on the viability of an economic development strategy that relies on services as the main sources of growth. First, blindly recommending the promotion of the services sector without making it explicit that only a fraction of it (modern services) can actually generate structural change can be deceptive. Second, the tradable services sector activities that are sustainable require years of training, which most developing countries cannot afford. And even when they do, they often end up training good people who then leave the country to pursue better employment opportunities elsewhere if the country's production structure cannot absorb their skills.

Building and retaining a sizeable workforce to support modern services takes time and is costly. Yet the payoff of that development strategy may not necessarily outweigh the costs, even when factoring in the expected benefits from the remittances sent home by well-trained migrants. A good example of this problem is the economic story of India, often considered the Mecca of the IT sector and by extension, a prime example of the promises and limitations of a development strategy relying primarily on modern services. India trains and exports quite a large number of highly educated people. India President Pranab Mukherjee recently made the following intriguing observation: *'With over 700 universities including 44 central universities and around 36,000 colleges, India at present has one of the largest higher education systems anywhere in the world. It is equally, however, a matter of concern that till very recently we did not have a single university figuring in the global top 200. It is only now, after concerted efforts and policy interventions that two of our institutions –Indian Institute of Science Bangalore and IIT Delhi– have broken into the top 200 globally in September [2015].'*[8] President Mukherjee concluded that the need of the hour, therefore, is to focus not only on education per se, but more importantly on the quality of education.

President Mukherjee could find some comfort in the fact that in 2015 India received $38 billion in foreign direct investment (FDI) inflows and nearly the double ($72 billion) in remittances. Remittances are obviously an excellent source of financing for the current account, and when they are stable they are also sources of growth. However, remittances do not have the transformative power of FDI (Drieffield and Jones 2013; de Mello 1997). India's excellent performance in gaining remittances has not yet translated into sustained, double-digit growth rates –the country still has a GDP per capita of only $1,600. A benefit-cost analysis of devoting the country's limited fiscal resources to building human capital for a modern services sector that is still too small for a workforce of about $600 million people highlights the importance of strategic choices for structural transformation. Unlike India, China has relied much less on remittances from migrants whose education was funded by taxpayers' money, and more on FDI, channeled into labor-intensive industries, and creating employment opportunities that can absorb its workforce. Learning lessons from past strategic mistakes, the Indian government has launched the Make in India Initiative that aims to stimulate industrialization and employment generation.[9]

## 3 Composing an index of inclusive and sustainable transformation

The adoption of the Sustainable Development Goals (SDGs) and the successful conclusion of the Climate Summit COP 21 in 2015 provide a good opportunity for researchers to bring new ideas on how best to implement policy agendas that are conducive to structural change. Both international covenants require all signatories (sovereign governments) to constantly assess and report on the progress made toward the ambitious objectives of eradicating extreme poverty and keeping global warming under control. However, the monitoring of progress will become the main challenge, especially given that economies around the world are at different levels of development and have

[8] Inauguration of the 98th Annual Conference of the Indian Economic Association (12/27/2015) http://pib.nic.in/newsite/mbErel.aspx?relid=133945

[9] 'Make in India' is a 'major national initiative designed to facilitate investment; foster innovation; enhance skill development; protect intellectual property, and build best-in-class manufacturing infrastructure' launched on September 25, 2014 by Prime Minister Narendra Modi. See http://www.makeinindia.com.

different production structures. As pointed out by Ahluwalia (2015, p. 5), the best one can expect is for economists to *"help to define a set of measurable indicators reflecting various aspects of inclusiveness and sustainability, taking into account availability of data on these indicators, and the scope for improving data availability over time. We could then set targets for each of these indicators and hope that they would be accepted by different stakeholders as representing significant improvement in each dimension."* The IST index proposed in this paper is a contribution towards these global objectives.

Each of the 17 SDGs requires a multidimensional policy framework for action, which justify their 169 targets. But this also makes the assessment of progress more challenging. Therefore, one should expect conflicting narratives (glasses half-full or half-empty) on whether progress is being made towards the goals. And each country involved may have legitimate arguments to back up their analyses of what has been done, or not done. Thus the need for synthetic indicators that can capture the essence of empirical analyses, and convey policy-relevant messages to development stakeholders who would be overwhelmed trying to make sense of the data generated about each indicator.

### *3.1 Measuring with Indexes: Beyond the Utopian Quest for Legitimate Indicators*

There is no shortage of composite indices to track economic development over time and across countries. In fact, there are so many of them out there that it has become almost impossible for policymakers to make sense of the stories that they tell, and to identify the specific, actionable policy levers that can yield clear economic and social gains. In his critical review of some popular composite indices of development Ravallion (2011) categorized them into two broad types: first, indices such as the gross domestic product (GDP), for which the choice of the component series and the aggregate function "*are informed and constrained by a body of theory and practice from the literature*." Second, indices such as the Human Development Index (HDI), which are based on '*a set of indicators that are assumed to reflect various dimensions of some unobserved (theoretical) concept*' (Ravallion 2014, p. 2-3). The former are discussed as more appropriate indices while the latter are viewed as lacking the necessary analytical legitimacy: "*neither the menu of the primary series nor the aggregation function is pre-determined from theory and practice, but are 'moving parts' of the index—key decision variables that the analysts is free to choose, largely unconstrained by economic or other theories intended to inform measurement practice."* (idem, p. 3). To illustrate his point, Ravallion contrasts an index whose variables and weights are instead based on a regression model calibrated to a survey dataset to an index whose variables and their weights are set by the analyst, who has some concept of economic welfare in mind, and aggregates sub-indicators based on his judgment. He refers to the latter as a 'mashup' index.

Such a distinction may seem like an elegant conceptualization of the problem at hand but it is actually an artificial one. The expectation that economists and other social scientists can elaborate development indicators that pass the test of 'pure theories' simply because such indicators would be 'based on a regression model calibrated to survey data' is utterly unrealistic. It is well known that any regression model is based on a host of assumptions; without them, legitimate inferences cannot be drawn from the model. While there are statistical procedures for testing some of these assumptions, the tests often cannot detect substantial failures. Furthermore, as pointed out by Freedman (2010), model testing may become circular; breakdowns in assumptions are detected, and the model is redefined to accommodate. In fine, ignoring the conceptual issues and hiding the problems is often an important goal of model building.

The contention that GDP should be <u>the</u> model index, one legitimated by some sort of 'pure' theoretical reasoning and rigorous analytical modeling, is invalidated by the strong body of academic research that has highlighted its many shortcomings—beyond being a randomly aggregated set of variables that form a series of accounting identities. GDP as an index is far from being beyond suspicion. Former Revolutionary President of Venezuela Hugo Chavez called it a 'capitalist conspiracy,' which may have been an extreme form of criticism. But as a model index, it carries many shortcomings and paradoxes –including the one pointed out by Coyle (2014): the widower who marries his housekeeper and thereby lowers GDP because he doesn't pay her wages anymore. While GDP measures output, it ignores central facts such as quality, costs, sustainability, or purpose (Stiglitz, et al. 2010).[10]

However appealing at face value, the dichotomy between 'credible' indices based on some theory or calibrated from regression analyses, and 'mashup' ones singled out as 'randomly elaborated' may not be a workable approach in practice as agreeing on what constitute an acceptable theoretical basis will always be a matter of debate. Such a distinction assumes the existence of a rationally-neutral analyst who can observe and monitor performance with distance, detachment, and balance. Philosophers have long provided good arguments about the impossibility of that type of rational actor. From Darwin to Marx, Nietzsche, Freud, Wittgenstein or Heidegger, there is an accumulated body of evidence that the so-called sovereign rational subject –the detached observer imagined by Kant– actually does not exists.[11] It follows that no development economist is intellectually autonomous and self-transparent and capable of identifying causal relationships and causal mechanisms in a rigorous manner. It is impossible to deny the role of the pre-conceptual and non-conceptual at the very core of the rational. The notion that subject and object can be set off from one another, which is the supreme dogma of empiricism, is simply an illusion.

Therefore, any economic theory or model –especially one built simply on regression analyses– should acknowledge the limits of its generated knowledge. Any index out there reflects an explicit or implicit theoretical analysis of the dynamics of economic development. The real criteria for assessing pertinence and effectiveness should be whether an index provides useful information to strengthen intellectual and policy arguments, and whether it helps focus the attention on social and economic goals deemed of importance to society.

### *3.2 Differentiating by level of development*

A central tenet from New Structural Economics thinking is that the structural characteristics of countries are not a one size fits all (Lin 2012a). Rather, the economic structure that best helps growth will change as the country develops, and with that change in development new characteristics become feasible. Simply put, it should not be expected of relatively poor countries such as India, Burundi or Ethiopia to have same environmental, institutional and economic characteristics as rich countries like Denmark or Japan. Rather than relying on people to take this into consideration when using the IST index, we want to embed this thinking directly into the index. In other words, it should indicate how high a country scores relative to countries with a similar level of development.

By way of illustration, panel *a* of Figure 4 shows the scatterplot of the indicator of the investment in R&D (in % of GDP), versus the level of development as measured by the log of GNI in 2012 (*dev).*

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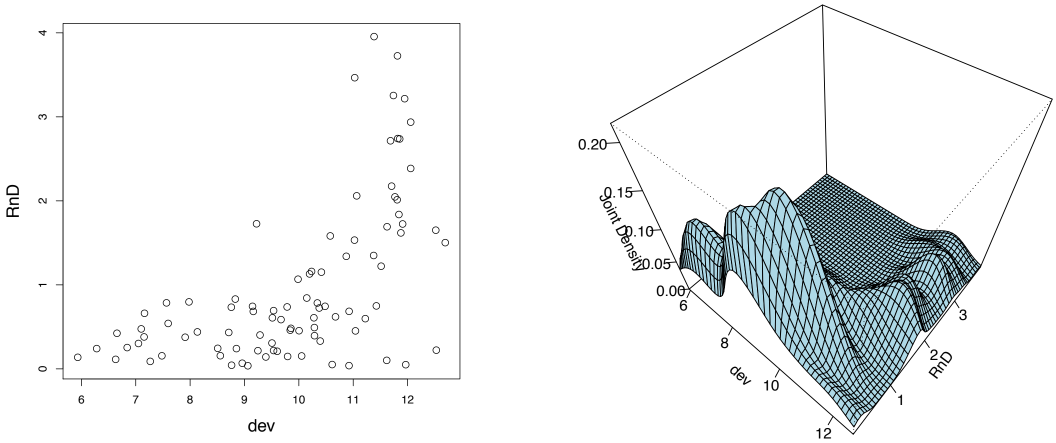
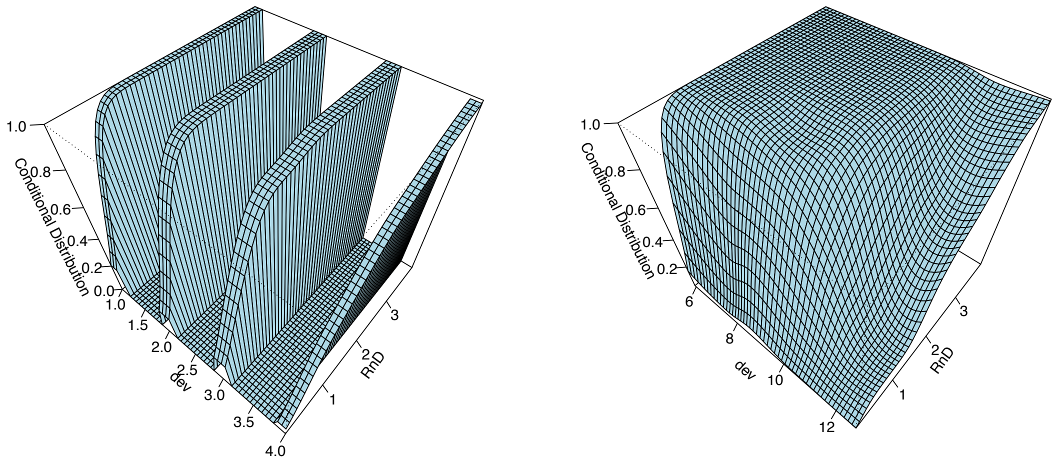
[10] GDP aims to measure the goods and services produced. But what's behind the official definition of totality of goods and services produced? "*Hidden below the overall intention, however, lurk choices and decisions invisible in our day-to-day lives. What are goods and services? How are they defined? Whose contributions count? What, in the end, are we growing? Definitions are based on a still-evolving, cumbersome system of criteria. What is counted as investment or income or expenditure, and how to define the difference between 'final' and 'intermediate' consumption follows a logic that often eludes even accountants*." (Philipsen 2015, p. 12)

[11] See Baynes et al. (1987) for an overview and useful discussion of debates about reason and lessons from post-philosophy.

It clearly shows that the distribution of investment in R&D is highly dependent on the level of development. The higher *dev*, the more the distribution shifts towards higher values of R&D. In what follows we will discuss the level of development in terms of GDP per capita. Alternative measures of development are discussed in the robustness section.




a. Scatterplot of R&D and *dev*　　　　b. Joint density of *R&D* and *dev*




c. CDF of R&D for each level of development　　　　d. Conditional CDF of R&D|*dev*

**Figure 4 - Conditional kernel density estimator**

Panel a shows the scatterplot of the investment in R&D as percentage of GDP and the level of development *dev* as measured by the log of GNI; panel b the estimated joint probability function of R&D*y* and *dev*; panel c the CDF of R&D computed for each level of development from low income (1) to high income countries (4); and panel d the conditional cumulative density function of *R&D* given *dev*.

An intuitive way to solve this is by grouping countries in terms of their level of development and only comparing their characteristics within these groups. In line with NSE theory, PPP converted per capita income can be used as an indicator of the level of development and capacity of an economy. For example, the income classification employed by The World Bank identifies three (or four) groups: low-income, (lower- and upper-) middle-income and high-income countries.[12]

The distribution of values of an indicator can be quite diverse over different groups, within groups and especially between different indicators. Some indicators might be scattered over their entire

[12] As of 1 July 2015, these groups are defined using the Gross National Income per capita in the following way: LIC ≤ 1,045; 1,045 < LMIC ≤ 4,125; 4,125 < UMIC ≤ 12,746; and HIC >14,746. See:
`http://data.worldbank.org/news/2015-country-classifications`

domain, while others might be clustered around one or multiple modes. The empirical cumulative density function allows us to compare the different indicators over different groups without imposing any ex ante assumptions on distribution of the data. The value of the cumulative density function indicates the fraction of countries that score worse than the country in question: $\mathrm{F_y(a)} = \mathrm{p(y \leq a)} = \int_{-\infty}^{a} f_y\,(\mathrm{x})\mathrm{dx}$, where $f_y(x)$ is the density function of *y* evaluated at point *x*. In other words, a CDF of 0 means that the country scores worse than all other countries with as similar level of development; and vice versa for a score of 1. This non-parametric transformation can capture whatever pattern is present in the data, whether it is linear, inverted-U, multi-modal or otherwise. Moreover, it can do this regardless of whether the characteristic in question is a binary, discrete or continuous variable (Henderson and Parmeter, 2015). Panels $b$ and *c* show the joint distribution of *y* and $dev$ and how this translates into the conditional CDF for the four income-levels. In general, countries with a high investment in R&D will get a higher score. However, for a given percentage of investment in R&D, a low-income country will receive a higher score than a middle or high-income country.

While intuitively very clear, using discrete income groups to differentiate between different levels of development has one important drawback: it creates discontinuities for countries lying on the border. A small change in the level of development can change the group a country belongs to, which can have significant consequences for those variables that are strongly dependent on the level of development. This can lead to a situation where a small improvement nevertheless leads to a decrease in the index value, simply because the country is now compared to a completely different set of countries 'with a similar level of development.' It also biases the comparison between countries that lie on either side of the cut-off point. This problem can be avoided by using a continuous way of controlling for the level of development like the *conditional* cumulative density function: $F_{y|dev}(a) = p(y \leq a|dev)$. As illustrated in panel $d$, the transformed values using the conditional CDF are very similar to those using fixed thresholds, but without the discontinuity problems for countries whose level of development is close to the thresholds.

Finally, the data are transformed such that a higher score is always something to strive for. If an indicator $y_i$ measures something positive (e.g. the share of renewable energy) for country $i$, its transformation ($\widehat{y_i}$) indicates the probability of finding countries with a similar level of development ($dev_i$) that score lower:

$$\widehat{y_i} = F_{y|dev}(y_i|dev_i)$$

Vice versa, for indicators that measure something negative (e.g. $CO_2$ emissions) the transformed indicator ($\widehat{y_i}$) shows the probability of finding a country that scores higher:

$$\widehat{y_i} = 1 - F_{y|dev}(y_i|dev_i)$$

The conditional cumulative density $F_{y|dev}$ is estimated using a multivariate kernel density estimator. An essential feature of this type of estimator is that it assigns a higher weight to information in the vicinity of the point of interest; both in terms of the variable *y* but most importantly in terms of the level of development *dev*. What exactly constitutes the vicinity of a point is determined by the bandwidth of estimator: the larger the bandwidth, the more dissimilar countries' performance is taken into account. In this case, the size of the bandwidth was estimated using the least squares cross validation method (using Gaussian kernel).[13] Using an estimated bandwidth rather than a rule of thumb allows us to differentiate between different indicators. If an indicator is strongly dependent on the level of development, only the information of countries with a very similar level of development is used. However, if the level of development were to have no effect on $y$, the larger bandwidth ensures that more information is used, reducing uncertainty of the estimated CDF.

The estimation of the CDF is done year-by-year, using only the information on the distribution of the indicator $y$ available at that point in time. This ignores the older patterns in the distribution of the indicators, $y$, allowing the frame of reference to change over time. As a result, the transformed scores $\hat{y}$ will always represent a country's position relative to its peers at that point in time. The CDF will not change if all countries improve (or deteriorate) at the same rate. Similarly, a country's score will decrease if it remains unchanged but its peers improve. In this way, the index underlines the idea that inclusive and sustainable industrial development is a continuous process of improvement for all countries, rather than a fixed path with a clearly defined end goal. An additional benefit of this relative approach is that it undermines what Ravallion (2011) termed rank seeking behavior: the improvement of score until it just exceeds a benchmark. Unless a government is willing to deliberately start decreasing its level of development, each aspect of the index will need continuous improvement in order to keep with its peers.

### *3.3 Weighing and aggregation*

After transformation, the indicators are combined into the IST outcome index using a simple average. This means that each component receives equal weight in the final index. Moreover, it assumes perfect substitutability between all goals: e.g. a high score on manufacturing compensates 1:1 for lower environmental scores. However, in the robustness section we abandon the assumption of perfect substitutability and use a geometric average instead. For example, while the couples {0.5, 0.5} and {0.7, 0.3} both have the same average, their geometric means are .5 and .46, respectively, meaning that the latter is penalized for the imbalance in its score.

As the weights used sum up to one, the IST index has the same range as the transformed indicators: i.e. between zero and one. An overall score of one means that the country is outperforms all of its peers and vice versa for zero, while score in between can be interpreted as the average fraction of countries that preform worse.

### *3.4 Addressing missing values*

The final issue that needs to be addressed before the index can be computed is how to deal with missing values. The IST index is comprised of a large number of indicators and as we will see in Table 1, the coverage of those indicators can be markedly different. Figure 5 illustrates the severity of this problem using the first 16 indicators. Each row shows the availability of a variable using black and white rectangles, where the latter indicate that the data is missing. The columns show the different combinations in which the various indicators are available, where the width of the column indicates the prevalence of each combination. As the different combinations are listed decreasing order of prevalence, it shows that the most prevalent combination (9% of all observations) is the lack of information on any of the variables. A completely black column never occurs, meaning that there is always at least one variable missing.

[13] An important advantage of this method when estimating a conditional probability is that it ignores the influence of irrelevant variables. The estimation was done using the non-parametric np package in R (Hall, et al., 2004; R Core Team, 2015).

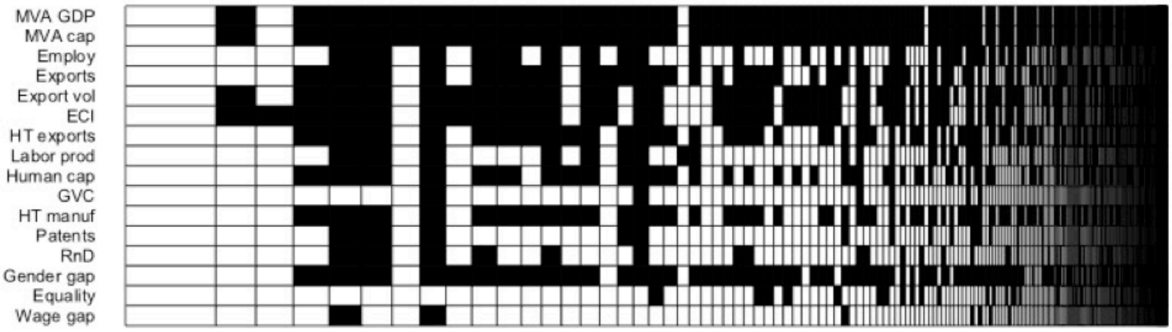



Figure 5 - Availability of the indicators in the IST index.

**Note:** Available data is represented by a black rectangle, missing values by white rectangle. The width of the columns indicates the prevalence of the different combinations, which are listed in decreasing order.

A first solution is to limit the number of countries and years for which the index is computed, which we follow to some extent. That is, we excluded those countries whose data availability that is less than 25%.[14] In a similar vein, you can leave out the variables that have the lowest availability. For example, excluding the participation in global value chain, the gender wage gap, gender equality, patents applied and labor productivity would already decrease the number of missing values by half. However, changing the variables also affect the meaning of the index, as it quintessentially the same as imposing a zero weight on those variables. Moreover, all but the most restrictive of reductions in the scope and span of the index would still leave differences in the availability of the indicators, making it hard to rule out that changes in the index are not due to differences in availability of the underlying indicators.

Instead, we opted to solve the missing data problem using multiple imputation, which means that we try to fill in the gaps in the dataset with the most likely values. Unlike simple imputation (e.g. linear interpolation), multiple imputation will draw many different possible values for each missing observation. The index computed for each these imputed samples and the final result is computed as the average over all imputations. The variance over the different imputations indicates its reliability: the more data is missing and the worse the available data is at filling in the gaps, the greater the variance and lower the reliability. The net results is that the IST index can be computed in spite of the significant data availability problems without having to reduce the scope of the index or omit certain variables ex ante. At the same time, it produces confidence intervals that express the reliability of the index values and the transformed indicators.

To estimate the most likely value of the missing observations, we started from the Multivariate Imputation by Chained Equations (MICE) method of Buuren and Groothuis-Oudshoorn (2011). This technique uses the values of the other indicators to predict what the missing value could have been. For example, it will use the information on the number of patents applied to estimate what the level of investment in research and development could have been. While this works well in cross-section analysis of countries, MICE does not use any of the time-patterns present in the dataset. As we have a panel dataset and many of the many of the indicators in our dataset depend strongly on their previous values, we expanded the MICE method to also take the time-dependence of the indicators into account. The resulting model (dubbed Multivariate Imputation by State-Space model) was able to vastly improve the imputation of the missing data, decreasing the size of the confidence intervals.

[14] For the most part, this removed a number of smaller island nations and city-states, like Gibraltar, Nauru, Reunion and Lichtenstein.

Technical details on the imputation and a comparison of the two techniques can be found in appendix 6.2.

To test the robustness of the imputation algorithm, we also ran the model on a reduced dataset where the availability of each country was at least 50%. This reduced the total number of countries by half relative to our baseline model (which only imposed 25% availability). However, the imputation of the missing values remained virtually unaffected. For all but one variable, the correlation between the mean imputed values was in excess of 99%. What the change in sample did affect was the size of the confidence intervals, but not all in the same way. A third of the sample had confidence intervals that were at least 10% smaller in the reduced sample; a third had larger confidence intervals, while the rest had confidence intervals that were more or less the same.[15]

# 4 The Inclusive Sustainable Transformation Index

## *4.1 Indicators of inclusive sustainable transformation*

The IST outcome index can be subdivided into eight categories that each contain between two and five indicators, which are listed in Table 1. In addition to a short description of each indicator, it also shows the availability of each indicator over time, how many countries it covers and the source of the data.

As quickly becomes clear when looking at the list of indicators, there is often a significant overlap in what the indicators are measuring within the different subcategories. For example, the export subcomponent (*O2)* contains both the value of exports of goods and services (*O2.1*) as well as the total volume of exports (*O2.2).* It could be argued that it would be better to reduce the number of indicators, as the marginal contribution of this second indicator to the measurement of export performance is relatively low. However, there are a number reasons for allowing this plenitude of indicators. First, while one indicator can proxy the overall state, including different indicators enables us to build a more replete image of the current situation. Secondly, the overall contribution of some variables might be relatively limited, but their inclusion can be much more important for specific groups of countries. For example, the national electrification rate (*O7.2*) matters much more developing countries. Finally, including multiple indicators allows us to exploit differences in availability and enhances the performance of the multiple imputation algorithm. For instance, while the number of patents per capita (*O3.2*) is available for a longer period, it covers fewer countries than the expenditure on research and development (*O3.1*). In general, even if the selection is disputed, we show in the robustness section that the index results remain virtually unaffected by the exclusion of any one of the indicators.

The selection of indicators measuring IST is based to a large extent on the literature on the measurement of progress on the Sustainable Development Goals. Almost half of the development goals are directly linked to the idea of inclusive structural transformation, including goal five which is ‘to achieve gender equality and empower all women and girls’; goal number eight promoting ‘sustained inclusive and sustainable economic growth, full and productive employment and decent work for all’; goal nine which is to ‘build resilient infrastructure, promote inclusive and sustainable

[15] The effect on the final index could not be determined as the index compares all countries to each other and the set of countries in the robustness check is only half that of the baseline model.`

industrialization and foster development'; and goal number twelve which aims to 'ensure sustainable consumption and production patterns.'[16]

**Table 1 – IST indicators**

| Name | Description | Countries | Years | Source[c] |
|---|---|---|---|---|
| **O1** | **Manufacturing** | | | |
| O1.1 | Manufacturing value added (% GDP) | 206 | 1990-2015 | UNIDO: MVA |
| O1.2 | Manufacturing value added per capita (log) | 206 | 1990-2015 | UNIDO: MVA |
| O1.3 | Share of medium and high tech industry (% value added) | 143 | 1990-2013 | UNIDO: CIP |
| **O2** | **Trade** | | | |
| O2.1 | Exports of manufactured goods and commercial services per capita (log) | 189 | 1980-2013 | WTO |
| O2.2 | Export volume in tons per capita (log) | 212 | 1995-2014 | CEPII: BACI |
| O2.3 | Participation in global value chains | 61 | 1995-2011 | WTO: TiVA |
| O2.4 | Share of medium and high tech exports | 143 | 1990-2013 | UNIDO:CIP |
| **O3** | **Innovation** | | | |
| O3.1 | Research and development expenditure (% GDP) | 127 | 1996-2014 | WB: WDI |
| O3.2 | PCT Patents per capita (log) | 45 | 1970-2014 | OECD |
| O3.3 | Economic Complexity Indicator | 212 | 1995-2014 | BACI // ECI |
| **O4** | **Employment** | | | |
| O4.1 | Manufacturing employment (% total employment) | 118 | 1980-2014 | WB: WDI |
| O4.2 | Labor productivity per hour worked in 2014 USD | 70 | 1950-2015 | CB: TED |
| O4.3 | Human capital | 134 | 1950-2011 | PWT8.1 |
| **O5** | **Gender Inclusiveness** | | | |
| O5.1 | Gender gap in employment[a] (% Male - Female) | 175 | 1991-2014 | WB: WDI |
| O5.2 | Gender equality rating | 81 | 2005-2014 | WB: CPIA |
| O5.3 | Gender Wage Gap (% male median wage) | 34 | 1970-2014 | OECD |
| **O6** | **Pollution** | | | |
| O6.1 | CO2 emissions[a] (kg per 2011 PPP of GDP) | 188 | 1990-2011 | WB: WDI |
| O6.2 | PM2.5 air pollution[a], mean annual exposure | 187 | 1990-2013 | WB: WDI |
| O6.3 | Consumption of ozone depleting substances[a] per capita (log) | 42 | 1986-2014 | UNEP |
| O6.4 | Municipal waste[a] per capita | 38 | 1975-2014 | OECD |
| O6.5 | Municipal waste recovery (% of total) | 38 | 1975-2014 | OECD |
| **O7** | **Energy** | | | |
| O7.1 | Renewable energy share of TFEC (%) | 201 | 1990-2012 | WB: SE4A |
| O7.2 | National electrification rate (% population) | 212 | 1990-2013 | WB/IEA: SE4A |
| **O8** | **Resource management** | | | |
| O8.1 | Access to improved water source (% of population) | 201 | 1990-2015 | WB:WDI |
| O8.2 | Ocean Health Index | 175 | 2012-2015 | Halpern 2015 |
| O8.3 | Change in forest area (% land area) | 205 | 1991-2013 | WB: WDI |
| O8.4 | Terrestrial and marine protected areas (% territorial area) | 204 | 1990-2012 | WB: WDI |

[a] Indicators for which higher values indicate a deterioration of the country's outcome
[c] The list of abbreviations can be found in appendix 7.1.

As primary sources of indicators, we looked at two UN reports on the monitoring of the SGDS: Indicators and a Monitoring Framework for the SDGs (SDSN, 2015) and the report of the Inter-Agency and Expert Group on SDG Indicators (ECOSOC, 2016). This list of indicators was supplemented with those discussed in the paper by Kroll (2015) on the readiness of developed countries for the SDGs, the WEF and IMD's reports on (sustainability adjusted) global competitiveness and the Human Development Index.[17] We retained the indicators from these reports that were available for a large group of countries over the past decade. Since the focus lies on structural transformation rather than economic growth and development in general, there are differences between the indicators listed in these sources and those selected in the IST index.

[16] Other SDGs that pertain to Inclusive and Sustainable Structural Transformation are goals (6) ensure availability and sustainable management of water and sanitation for all ; (7) ensure access to affordable, reliable, sustainable and modern energy for all; and (11) make cities and human settlements inclusive, save, resilient and sustainable.
[17] The first three sources are also used in a 2016 preliminary paper by Sachs, Schmidt-Traub and Durand-Delacre that aims to compose an index and dashboard monitoring the SDGs.

Appendix 6.3 maps our selection of indicators on the different sources, highlighting certain variables like participation in global value chains or the economic complexity index which are unique to IST index. Nevertheless, three quarters of the indicators are used in one or more of these reports, and many are described in great detail in the ECOSOC and SDSN reports.

The first two components look at the strength of the manufacturing and export sectors. Specifically, it looks at the value added by the manufacturing sector per capita, as well as its share in GDP. When studying trade, we consider both the exports of manufactured goods and commercial services and include the volume of exports to compensate for sudden shifts in the terms of trade. To capture the transition to a modern economy, we also consider the contribution of medium and high tech firms to the value added of exports and the manufacturing sector. Finally, because of their increasing importance to the worldwide trade, we also track the country's participation in global value chains.

The third component measures the technological expertise embedded in the economy. To that end, we track the overall investment in research and development, the number of patents applied and the complexity of a country's export basket. The latter is measured using the economic complexity index of Hausman, et al (2011), which combines information on the diversity of goods a country produces with the ubiquity of those goods (i.e. the number of countries that is capable of producing those goods).

Component four and five deal with the strength and inclusiveness of the labor market. To capture the former we include indicators of the number of people working in manufacturing, their labor productivity and level of education. Gender equality is measured in terms of the fraction of male vs. female employment, the difference in their wages as well as the existence and strength of institutional policies promoting equal access to men and women.

The final three subcomponents consider the environmental performance, starting with the lack of pollution. Air pollution is captured by $CO_2$ emissions, the abundance of fine particle matter in the air and the consumption of ozone depleting substances. We also consider the total municipal waste that is generated, but counterbalance this with the percentage of this waste that is recycled or composted. The second environmental component looks at the structure of the energy market, in particular the percentage of the population that has access to modern energy (i.e. electricity) and the share of renewable energy in the total final energy consumption. The last component evaluates the way in which environmental resources are managed. This includes the percentage of the population that has access to drinkable water, the annual change in forest area (as a percentage of land area) and the percentage of terrestrial and marine area that is environmentally protected. Also included is an indicator capturing the health of the ocean, but only if the country has access to the sea. The IST index for landlocked countries does not include variable *O8.2*.

As is the case for all components of the index, the environmental variables are also judged conditional on the level of development. This relative approach might seem incongruous with certain variables, most noticeably $CO_2$ emissions as it has worldwide environmental consequences. However, the goal of the index is not to measure environmental impact, for which there already exist numerous qualitative indicators that also take consumption and offshoring of polluting activities into account (e.g. ecological footprint). Instead, this section of the index measures how well the environment is protected, given the available means. For a country's overall impact on the environment, we refer instead to these other indexes. Similarly, as the index is focused on structural transformation, it does not include a measure of the sustainability of agriculture. That being said, a number of the indicators suggested to that purpose are included separately in the index.[18]

Finally, while our index only conditions on the level of development, it is true that for a number of indicators the capability of countries to score well depends on more than the level of development. E.g. the location of a country determines access to certain sources of renewable energy, while the lack of access to the sea significantly increases the cost of trade. However, many of these problems can be overcome with the right investments, and continued technological progress is likely to continue to increase the predominance of the level of development as a constraint.

### *4.2 The Inclusive Sustainable Transformation index*

Using this dataset and the methodology described above, we can compute the IST index from 1990 to 2014 for 195 countries. As the number of indicators drops with 50% in 2014, we will focus the discussion of the index mainly on the year before. However, except for an increase in the confidence bands in this final year, this does not really affect the overall picture.

When using the index to make comparisons between countries or over time, it is important to keep in mind that they always reflects a country's position relative to countries with a similar level of development in that year. As a result, a decrease in the index does not necessarily mean that a country’s absolute position deteriorated, but could also mean that its peers made (more) progress. Figure 6 shows the worldwide distribution of the IST outcome index in 2013. Countries that score above average are colored blue and those that score below average are colored red, with the darker colors corresponding to respectively higher or lower values. While theoretically the values of the IST index can lie between zero and one, we find that the actual values of the index lie between 0.29 and 0.72. As the values of the individual transformed indicators lie much closer to the theoretical extremes, this means that counties that score very high on one component always compensate this with lower scores in others components and vice versa. Overall, the values of the outcome index tend to be slightly negatively skewed, with the below average scores centered on 0.45 and the above average scores having a fatter tail. In other words, most countries that score below average tend to do so only slightly and there are more countries that have a very high score than those have a very low score.

By taking the level of development into account when comparing the structural characteristics of countries, the IST index can identify countries that are performing well in spite of their lower level of development. For example, Malaysia’s IST score is higher than all (other) countries on the Asian, American and African continent. At the same time, the overall picture drawn mostly conforms to our expectations. Except for Greece, European countries score highly and while Central and North America also score above average, South America scores below average. In general Southeast Asian countries also score above average. Africa on the other hand has more mixed results, but most South-East African countries tend to perform well. The high scores for some of the richer European countries are due to the fact that they outperform other high-income countries like Macao (0.33), Kuweit (0.33) and Bermuda (0.37). However, some of the best scores on the European continent are accrued by lower and upper-middle income Eastern European countries Belarus (0.65), Romania (0.63) and Moldova (0.58).

[18] See e.g. http://www.wri.org/publication/indicators-sustainable-agriculture-scoping-analysis

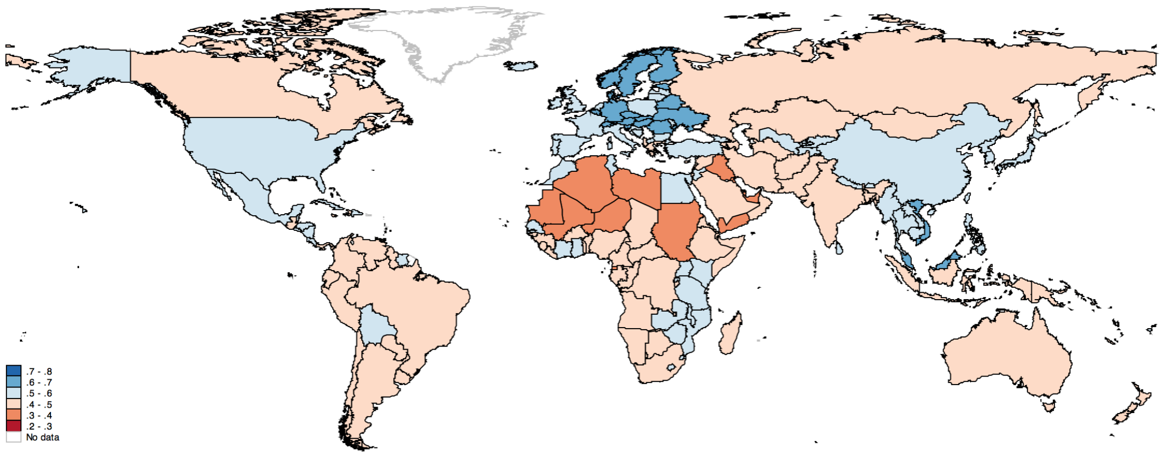
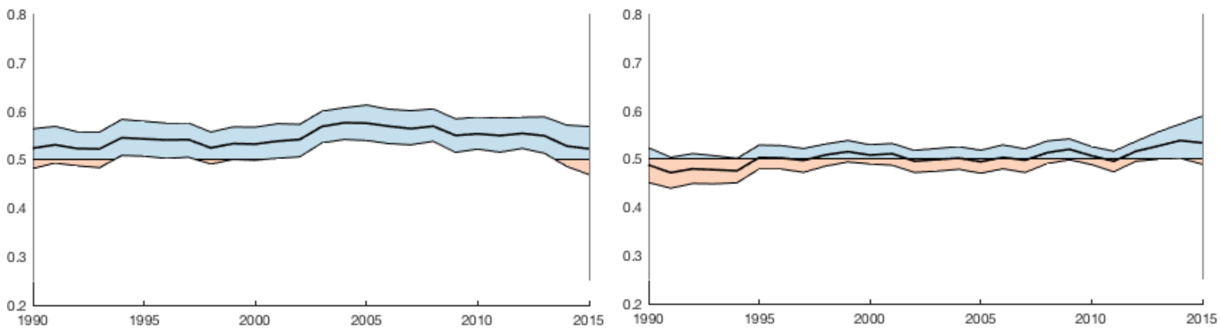



**Figure 6 - Map of the IST index in 2013**

**Note:** Countries that perform better than average are in blue; those that perform worse than average are shaded and red.

As you would expect, the IST index is relatively stable over time: the cross-country variation is almost twice as large as the variation over time. This is illustrated in Figure 7 where IST index of China and Mexico is plotted over time. For both countries the index changes only gradually, especially given the size of the (95%) confidence intervals. Nevertheless, there are 53 countries where changes in the outcome index are big enough that the 95% confidence intervals no longer overlap. For example, this is the case for the increase in Mexico's IST values between the early 1990s and early 2000s.




A. China B. Mexico

**Figure 7 - The IST index over time**

**Note**: IST index of China and the Mexico from 1990 to 2015. The colored band represents the 95% confidence interval, where below average values are colored red and above average values are colored blue.

As expected, the correlation between IST and per capita GDP is low, but positive (0.11). This is a stark contrast with other similar indicators, like Kroll (2015) whose index is strongly positively correlated with the level of development even as it is restricted to developed countries (0.81). The correlation between IST and the Human Development Index is higher (0.32), which happens to be identical to the correlation between Kroll's index and IST. However once we control for GDP per capita we find a much higher partial correlation coefficient of 0.63 between the latter two.

The next step is to look at the underlying indicators to better understand how certain scores came about. To that end, Figure 8 shows the transformed scores of the indicators in the IST index for two low, middle and high-income countries in 2013 using a radar chart. The countries in the left column have one of the lowest scores in their development group, while the countries on the right have of the highest scores.  These graphs once again make clear that the IST index expresses a country's outcome relative to its level of development. Take for example the national electrification rate (*O7.2*). Mali has a much higher score than Macau (0.42 versus 0.06), even though in Mali only 26% of the population has access to electricity while this is the case for 91% of the population in Macau. Nevertheless, because it is a low-income country Mali's electrification rate compares more favorably to its peers than that of Macau given that the vast majority of high-income countries have an electrification rate of 100%.

The radar charts can be an useful tool for economic and development policy as they clearly highlight the policy areas that require more attention as well as specific issues that need to be addressed. The IST index can subsequently help guide countries towards policies to address these issues, since they also identify those countries with similar levels of development that score highly. For example, panel a shows that Mali's low score is rooted in its poor performance on the manufacturing component. Rather than try to emulate the economic structure of high-income countries, Mali could look at the economic policies of Swaziland which scores highly on both indicators (over 0.94). In contrast, Germany scores highly on almost all components and as a result ends up with the highest score in 2013. Nevertheless, Germany's score could rise even further if it managed to decrease the total amount of municipal waste that is created. For help on achieving the first goal, Germany could take a closer look at Korea, Japan or Iceland. All three countries have similar levels of development but score exceptionally well on this component: respectively 0.92, 0.94 and 0.95 versus Germany's 0.09.

### *4.3 Robustness Checks*

In this final section we determine the index sensitivity to some of the modeling choices that were made. First, we look at how the results change when an alternative measure of the level of development is used. To that end, we use the UN's Human Development Index, a composite index that combines GDP per capita with life expectancy and education level. With the HDI as our measure of development, the individual indicators from Table 1 were transformed using the kernel density estimators and the results were combined into a second index: $IST^{HDI}$. While there are some differences, the correlation between this index and our baseline estimates is high (83%). The development category where the biggest changes take place is in the lower-middle income group. While the holistic nature of the HDI might make it a more appealing choice as measure of development, there are several reasons why GDP per capita is a better choice. To start, there is the overlap between HDI and the indicator of human capital (*O4.3*). However, the most important reason is that from 1990 to 2010, HDI is only available every 5 years.[19]

Second, we use a geometric average to combine the indicators. While a simple average imposes perfect substitutability on all categories, the geometric mean penalizes countries with asymmetric component scores. The effect on the index is very small, as the correlation between $IST^{GEO}$ and the baseline IST is 94%. Nevertheless, a number of countries with asymmetric scores find their scores significantly decreased, like Macao that sees a 42% decrease (from 0.33 to 0.19). While the distribution of IST was negatively skewed, $IST^{GEO}$ has a much more symmetric distribution. On the other hand, the size of the confidence intervals is also much larger for the latter index.

[19] The values for the intervening years are typically linearly interpolated, although we used the MISS algorithm.

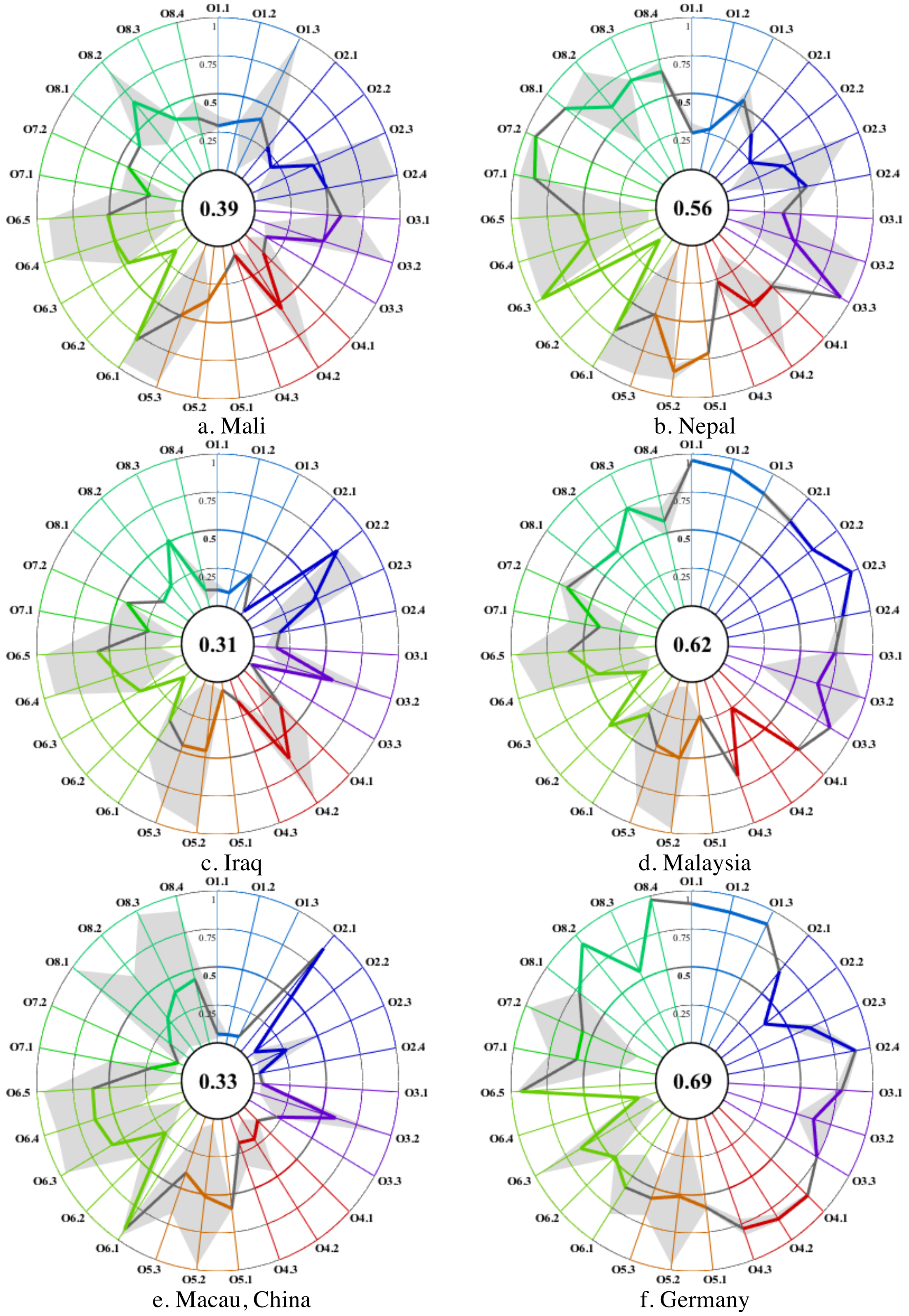



**Figure 8 - IST indicators in 2013 for low, middle and high-income countries**

**Note**: Radar plot of the transformed IST indicators in 2013. The 90% confidence intervals are indicated by the gray marked area. The indicators are grouped into: O1: Manufacturing; O2: Trade; O3: Innovation; O4: Employment; O5: Gender Inclusiveness; O6: Pollution; O7: Energy; O8: Resource Management. The full description of each indicator can be found in Table 1.

We also checked to what extent the index changes when certain variables are omitted. To that end, the index was recomputed 26 times using all but one of the indicators. However, regardless of which variable was left out, the index results are almost identical both in terms of the mean index value as well as its standard deviations: the correlation of both exceeds 0.97 each time. Finally, as some categories contain more variables than the others, we also checked how the results change when each category, rather than each indicator, receives equal weight in the final index. However, similar to the leave-one-out estimations, the results are practically identical.

# 5 Conclusion

The universal adoption of the Sustainable Development Goals and the successful conclusion of the Climate Summit were seen as turning points in the pursuit of shared global prosperity. However, the monitoring of these goals has become a significant challenge, especially since economies around the world are at different levels of development and have different production structures. This paper proposed the Inclusive Sustainable Transformation (IST) index as contribution to the monitoring of these global objectives.

The IST index measures the extent to which a country has developed a modern industry or services-based economy that protects the environment and is gender inclusive. In contrast with other development indicators, the level of development is taken into account when the structural characteristics of countries are compared. This is line with New Structural Economics thinking, which posits that a country's most optimal development strategy depends on its level of development. To make this conditional comparison, we employ a continuous method of transformation (a kernel density estimator) that unlike discrete methods does not bring about structural breaks in the index. Our results show that taking the level of development into account can reveal patterns that are otherwise hidden, with some countries performing much better/worse than otherwise expected.

Given the ambitious scope of the index, both in terms of countries covered and indicators included, missing data is a big concern. However, we are able to address this problem using multiple imputation. This allows us to estimate the relative performance of close to 200 countries and provides us with an estimate of how the reliability of the index is affected by the missing data.

Rather than simply measuring a country's overall progress, our focus lies on how the different components of the index contribute to the overall score. To that end, radar graphs provide are intuitive method of disaggregating the results and allow us to quickly identify which policy areas are leading and which are lagging. This should increase the usefulness of this index to policy makers and analysts, who can use it to for example identify 'best practice' among countries with similar level of development in a wide range of policies.

# Acknowledgements

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# 6 Appendix

## 6.1 List of abbreviations

| | |
|---|---|
| BACI | Base pour l'Analyse du Commerce International |
| CB | The Conference Board |
| CEPII | Centre d'Études Prospectives et d'Informations Internationales |
| CIP | Competitive Industrial Performance index |
| CPIA | Country Policy and Institutional Assessment |
| ECOSOC | United Nations Economic and Social Council |
| GFD | Global Financial Development |
| i-Tip | Integrated Trade Intelligence Portal |
| IEA | International Energy Agency |
| IFC | International Finance Corporation |
| ILO | International Labour Organization |
| IMD | Institute for Management Development |
| IMF | International Monetary Fund |
| MVA | Manufacturing Value Added |
| OECD | Organization for Economic Co-operation and and Development |
| PWT | Penn World Tables |
| SDSN | Sustainable Development Solutions Network |
| SE4A | Sustainable Energy for All |
| TED | Total Economy Database |
| TiVA | Trade in Value-Added |
| UNEP | United Nations Environment Programme |
| UNIDO | United Nations Industrial Development Organization |
| WB | The World DataBank |
| WDI | World Development Indicators |
| WEF | World Economic Forum |
| WITS | World Integrated Trade Solution |
| WTO | World Trade Organization |

## 6.2 Multiple Imputation using State-Space model (MISS)

Multiple imputation using chained equations (MICE) uses both the available and imputed data of the other variables to estimate possible values for the missing data. This means that to impute the values of the first variable, the imputed values of the second variable are used and to compute those you need the imputed values of the first variable. This self-referential problem is solved by repeatedly running through the estimation algorithm.

Say that $\boldsymbol{X}_t$ is a vector of containing the original variables at time *t*, and that $\widehat{\boldsymbol{X}}_t$ is the vector containing the imputed values.[20] Using the superscript we will select certain variables from these vectors: $X_t^i$ is the *i*th variable from $X_t$, while $\widehat{\boldsymbol{X}}_t^{-i}$ contains the entire $\widehat{\boldsymbol{X}}_t$ vector except for the *i*th variable (with vectors are indicated in bold). The MICE algorithm works in the following way:[21]

1. Initialize the model by replacing the missing data with the average value
2. Estimate a linear model that captures the dependence between the first variable and the rest of the dataset: $X_t^1 = a + \widehat{\boldsymbol{X}}_{\boldsymbol{t}}^{-1}\,\boldsymbol{b} + e_t$
3. Use the estimated parameters $a$ and $\boldsymbol{b}$ to predict a new value for $\hat{X}_t^1$.

[20] For convenience's sake, we are writing down the model for a time-series model, but these techniques can be equally applied to a panel dataset.
[21] As all variables are continuous, we can estimate the dependencies between the variables using a linear regression model. However, both MICE and MISS techniques can be adapted to deal with binary or categorical data.

4. Repeat step 2 and 3 for all other variables in the dataset.
5. Repeat steps 2 through 4 until the model have converged.

While MICE uses all available information from the other variables, it ignores information is available in the past and future values of the indicators. In contrasts, methods like (linear) interpolation use only the past and future values of a variable to fill in likely values for the missing data points. This implies that MICE is preferable over interpolation only when the other variables are better predictors of the missing data than its own past and future values.

The Multiple Imputation by State Space models (MISS) combines both techniques by adding this interpolation component to the MICE model. Specifically, it uses the information contained in the (imputed) data of the other variables, as well as the past and future (imputed) values of the variable itself to determine the most likely value for each missing data point. To combine the information from the other variables with the own past and future values, we rewrite this problem as a state-space model. As was the case for the MICE estimator, the self-referential nature of MISS is solved by imputing the values for each indicator separately and repeatedly running through the algorithm.

As there are entire books devoted to state-space models and how to estimate them (e.g. Kim and Nelson 1999, Durbin and Koopman 2012) we will keep the explanation short and refer the interested reader to these sources. A state-space model is a dynamic model that contains unobserved variables. It typically consists of two equations. The *measurement equation* describes how the observed variables are related to the unobserved, to-be-estimated state variable. The *state equation* on the other hand describes how the unobserved variable depends on its previous values. When estimating the state-space model, the most likely values of the unobserved variable are determined as a weighted average of the information in the observed variables and that in the past and future values of the state variable. The weights are determined by how reliable the observed data is versus how strongly the variable depends on its past values.

In this case, the unknown state variable is the to-be-imputed variable ($\hat{X}_t^i$). As was the case in the MICE model, we use the (imputed) values of the other variables ($\hat{\boldsymbol{X}}_t^{-i}$) as observed variables, assuming a linear relation: $\hat{X}_t^j = \alpha^j + \beta^j \hat{X}_t^i + \epsilon_t^j$ with $j = \{1, \dots, k\}$ and $i \neq j$. The variance of the error term of $\epsilon^j$ captures the extent to which the imputed variable $\hat{X}^j$ is a good predictor. Naturally, if the data is not missing the imputed data has to be identical to the observed data ($\hat{X}_t^i = X_t^i$). Using matrix notation, these equations can be summarized into the following measurement equation:

$$\begin{bmatrix} \hat{\boldsymbol{X}}_t^{-i} \\ X_t^i \end{bmatrix} = \begin{bmatrix} \boldsymbol{\alpha}^{-i} \\ 0 \end{bmatrix} + \begin{bmatrix} \boldsymbol{\beta}^{-i} \\ 1 \end{bmatrix} \hat{X}_t^i + \begin{bmatrix} \boldsymbol{\epsilon}_t^{-i} \\ 0 \end{bmatrix}$$

As the number of years in the dataset is relatively limited, the autocorrelation of each variable is simply modeled as an autoregressive process with one lag. This gives us the following state equation.

$$\hat{X}_t^i = A^i \hat{X}_{t-1}^i + \mu_t^i$$

More details on how to estimate this model can be found in Kim and Nelson (1999).

The MISS algorithm then runs through the following steps:

1. Initialize the model by replacing the missing data with the average value
2. Estimate the k-1 equations describing the relation between the first variable and the other variables in the dataset: $X_t^j = \alpha^j + \beta^j \hat{X}_t^i + \epsilon_t$.
3. Estimate the parameters of the state-equation using the actual values of $X^1$:
   $X_t^i = A^i X_{t-1}^i + \mu_t^i;\ \forall\, i \neq j$.

4. Stack the estimated parameters of the state and measurement equation and use state-space model techniques (i.e., a Kalman filter and simulation smoother) to draw new values for $\hat{X}_t^1$.
5. Repeat step 2 and 3 for all other variables in the dataset.
6. Repeat steps 2 through 5 until the imputed values have converged.

### A. Comparison with MICE

As Figure 9 illustrates, the effect of MISS on the imputation of missing values can be substantial. Especially for variables that are available every 5 years (panel a) or that depend strongly on their previous values (panel b), the range of imputed values is drastically reduced when using the state-space technique. This decrease in the variance of the imputed values in turn leads to a smaller variance in the transformed indicators and the IST index.

### A. Monte Carlo simulation

In order to get a better understanding of how the model performs when the number of missing values increases, we ran a Monte Carlo simulation on a generated dataset whose characteristics mimic the dataset of the IST index. Specifically, we first generated nine variables (1000 observations each) that have both an autoregressive part and are moderately correlated to two other variables:

$$X_t = 0.9 * X_{t-1} + \mu_t \quad \text{with } \mu_t \sim N(0, \Sigma)$$

where $\Sigma = (\delta\delta')^{-1}$ and $\delta$ is an upper triangular matrix with filled with 0.5.

After normalizing the data, we subsequently randomly deleted 10% of the observations of the first variable, 20% of the second, and so on until the last variable only has 10% of his original observations left. The MISS algorithm was then used to try to fill in the gaps in the dataset. The MISS estimator ran for a 1100 iterations of which the first 1000 were discarded as burn-in and the entire Monte Carlo simulation was repeated a hundred times.

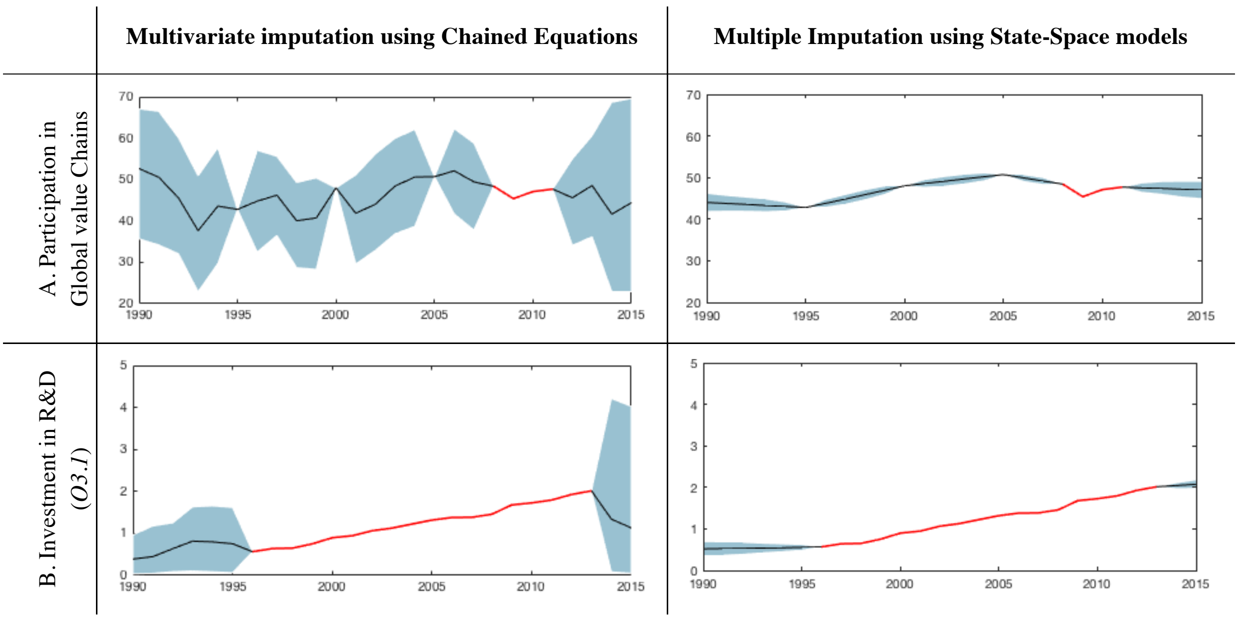


**Figure 9 - MISS vs MICE**

**Note:** Plot of the actual (red) and imputed (black) data on global value chains and investment in R&D of China. The values in the graphs on the left were imputed using MICE, while those on the right using MISS. 95% confidence intervals of the imputed values are indicated by the blue shaded area.

The results are shown in Table 2, whose he first row compares the actual values with the imputed values of the MISS algorithm. Even when the 90% of the data is missing, the algorithm shows no bias, although the second row indicates that the standard deviation of the bias does increase. In line with expectations, row three reveals that the size of the confidence bounds gradually increases as the number of missing values increases. Nevertheless, they remain well below 1.4, which is what you would get if these values were filled using iid normal random draws.

Overall, the Monte Carlo simulations support the earlier finding that when the dataset is reduced to only those countries with more than 50% availability, the results of the MISS algorithm remain the same.

**Table 2 - Monte Carlo simulation on the reliability of MISS**

| | **Percentage of missing variables** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% |
| **Average bias** | -0.0062 | 0.0011 | 0.0004 | -0.0026 | -0.0022 | -0.0031 | -0.0218 | 0.0266 | -0.012 |
| **St. dev. Bias** | 0.0367 | 0.0251 | 0.0312 | 0.0366 | 0.0454 | 0.0701 | 0.1327 | 0.195 | 0.1865 |
| **Average st. dev.** | 0.3189 | 0.3222 | 0.3482 | 0.3611 | 0.3749 | 0.3968 | 0.4251 | 0.4796 | 0.5675 |

## *6.3 Comparison of the indicators included in the IST index with other indicators of sustainable development*

| | | | | | **Sustainable Development Goals: Are the Rich Countries Ready?**<br>*Kroll, 2015* | **Indicators and a monitoring framework for the sustainable development goals**<br>*SDSN* | **Report on inter-agency and expert group on Sustainable Development Goal Indicators**<br>*ECOSOC* | **World Development yearbook**<br>*IMD* | **Global Competitiveness Report (Sustainability adjusted)**<br>*WEF* | **Human Development Index**<br>*UN* |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | GNI/cap (used to differentiate level of development) | 5 | Included | Included | | Included | market size index | Included |
| O1 | Manuf. | O1.1 | Manufacturing value added (% GDP) | 2 | | Included | Included | | | |
| | | O1.2 | Manufacturing value added per capita | 0 | | | | | | |
| | | O1.3 | Share of medium and high tech industry (% value added) | 1 | | | Included | | | |
| O2 | Trade | O2.1 | Exports of manufactured goods and commercial services per capita | 2 | | | | Included | Included | |
| | | O2.2 | Export volume in tons per capita | 0 | | | | | | |
| | | O2.3 | Participation in global value chains | 0 | | | | | | |
| | | O2.4 | Share of medium and high tech exports | 1 | | | | Included | | |
| O3 | Innovat. | O3.1 | Research and development expenditure (% GDP) | 4 | Included | Included | Included | Included | | |
| | | O3.2 | PCT. Patents per capita | 3 | | | Green patents | Included | Included | |
| | | O3.3 | Economic Complexity Indicator | 0 | | | | | | |
| O4 | Employ. | O4.1 | Manufacturing employment (% total employment) | 4 | Unemployment (% population) | Included | Included | Included | | |
| | | O4.2 | Labor productivity per hour worked in 2014 USD | 0 | | | | | | |
| | | O4.3 | Human capital | 4 | | | Various indicators on schooling | Secondary school enrollment | Various education levels | Education index |
| O5 | Gender | O5.1 | Gender gap in employment (% Male - Female) | 1 | | | | Included | | |
| | | O5.2 | Gender equality rating | 0 | | | | | | |
| | | O5.3 | Gender Wage Gap (% male median wage) | 2 | Included | Included | | | | |
| O6 | Pollution | O6.1 | CO2 emissions (kg per 2011 PPP of GDP) | 4 | Production based CO2 emissions | | Included | Included | Included | |
| | | O6.2 | PM2.5 air pollution, mean annual exposure | 4 | Included | Included | Included | | Included | |
| | | O6.3 | Consumption of ozone depleting substances per capita | 1 | | Included | | | | |
| | | O6.4 | Municipal waste per capita | 1 | Included | | | | | |
| | | O6.5 | Municipal waste recovery (% of total) | 2 | | Included | Included | | | |
| O7 | En. | O7.1 | Renewable energy share of TEC (%) | 4 | Included | Included | Included | Included | | |
| | | O7.2 | National electrification rate (% population) | 3 | | Included | Included | | Included | |
| O8 | Resource management | O8.1 | Access to improved water source (% of population) | 2 | | Included | Included | | Included | |
| | | O8.2 | Ocean Health Index | 0 | | | | | | |
| | | O8.3 | Change in forest area (% land area) | 3 | | Included | Net permanent forest loss | Included | | |
| | | O8.4 | Terrestrial and marine protected areas (% territorial area) | 3 | Terrestrial only | Terrestrial and marine separate | Terrestrial and marine separate | | | |

## 6.4 IST index from 2011 to 2014

| | 2011 | 2012 | 2013 | 2014 | | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| **Aruba** | 0.432 | 0.424 | 0.411 | 0.414 | **Liberia** | 0.465 | 0.428 | 0.439 | 0.451 |
| **Afghanistan** | 0.460 | 0.459 | 0.458 | 0.459 | **Libya** | 0.329 | 0.325 | 0.333 | 0.354 |
| **Angola** | 0.452 | 0.444 | 0.442 | 0.451 | **St. Lucia** | 0.401 | 0.408 | 0.397 | 0.425 |
| **Albania** | 0.499 | 0.498 | 0.498 | 0.509 | **Sri Lanka** | 0.513 | 0.508 | 0.508 | 0.517 |
| **United Arab Emirates** | 0.383 | 0.381 | 0.396 | 0.401 | **Lesotho** | 0.509 | 0.513 | 0.526 | 0.528 |
| **Argentina** | 0.451 | 0.448 | 0.442 | 0.464 | **Lithuania** | 0.581 | 0.592 | 0.587 | 0.573 |
| **Armenia** | 0.496 | 0.509 | 0.498 | 0.497 | **Luxembourg** | 0.441 | 0.451 | 0.449 | 0.469 |
| **Antigua and Barbuda** | 0.482 | 0.487 | 0.463 | 0.455 | **Latvia** | 0.600 | 0.599 | 0.580 | 0.582 |
| **Australia** | 0.473 | 0.475 | 0.479 | 0.477 | **Macao (China)** | 0.330 | 0.334 | 0.331 | 0.348 |
| **Austria** | 0.640 | 0.644 | 0.635 | 0.620 | **Morocco** | 0.511 | 0.528 | 0.523 | 0.526 |
| **Azerbaijan** | 0.445 | 0.456 | 0.458 | 0.451 | **Moldova** | 0.576 | 0.608 | 0.583 | 0.578 |
| **Burundi** | 0.517 | 0.487 | 0.471 | 0.467 | **Madagascar** | 0.496 | 0.491 | 0.491 | 0.497 |
| **Belgium** | 0.610 | 0.620 | 0.615 | 0.606 | **Maldives** | 0.463 | 0.467 | 0.481 | 0.472 |
| **Benin** | 0.433 | 0.456 | 0.452 | 0.464 | **Mexico** | 0.495 | 0.515 | 0.526 | 0.538 |
| **Burkina Faso** | 0.431 | 0.417 | 0.435 | 0.448 | **Marshall Islands** | 0.476 | 0.467 | 0.466 | 0.471 |
| **Bangladesh** | 0.467 | 0.488 | 0.496 | 0.491 | **Macedonia, FYR** | 0.560 | 0.566 | 0.566 | 0.563 |
| **Bulgaria** | 0.618 | 0.630 | 0.590 | 0.578 | **Mali** | 0.412 | 0.389 | 0.375 | 0.379 |
| **Bahrain** | 0.403 | 0.414 | 0.429 | 0.425 | **Malta** | 0.510 | 0.530 | 0.521 | 0.514 |
| **Bahamas** | 0.508 | 0.505 | 0.515 | 0.520 | **Myanmar** | 0.495 | 0.496 | 0.500 | 0.502 |
| **Bosnia & Herzegovina** | 0.512 | 0.519 | 0.521 | 0.523 | **Montenegro** | 0.511 | 0.497 | 0.494 | 0.498 |
| **Belarus** | 0.672 | 0.673 | 0.658 | 0.645 | **Mongolia** | 0.448 | 0.442 | 0.448 | 0.466 |
| **Belize** | 0.568 | 0.524 | 0.517 | 0.526 | **Mozambique** | 0.514 | 0.521 | 0.552 | 0.562 |
| **Bermuda** | 0.357 | 0.366 | 0.368 | 0.364 | **Mauritania** | 0.372 | 0.371 | 0.378 | 0.383 |
| **Bolivia** | 0.497 | 0.502 | 0.504 | 0.51 | **Mauritius** | 0.514 | 0.506 | 0.512 | 0.502 |
| **Brazil** | 0.442 | 0.438 | 0.449 | 0.456 | **Malawi** | 0.524 | 0.512 | 0.530 | 0.532 |
| **Barbados** | 0.425 | 0.416 | 0.411 | 0.420 | **Malaysia** | 0.629 | 0.626 | 0.620 | 0.606 |
| **Brunei Darussalam** | 0.397 | 0.415 | 0.431 | 0.434 | **Namibia** | 0.494 | 0.493 | 0.498 | 0.520 |
| **Bhutan** | 0.600 | 0.571 | 0.551 | 0.549 | **New Caledonia** | 0.448 | 0.447 | 0.442 | 0.452 |
| **Botswana** | 0.493 | 0.489 | 0.493 | 0.496 | **Niger** | 0.389 | 0.385 | 0.39 | 0.382 |
| **Central African Rep.** | 0.494 | 0.498 | 0.480 | 0.474 | **Nigeria** | 0.409 | 0.404 | 0.411 | 0.416 |
| **Canada** | 0.488 | 0.488 | 0.479 | 0.491 | **Nicaragua** | 0.532 | 0.539 | 0.555 | 0.546 |
| **Switzerland** | 0.664 | 0.660 | 0.653 | 0.633 | **Netherlands** | 0.594 | 0.598 | 0.600 | 0.585 |
| **Chile** | 0.494 | 0.486 | 0.489 | 0.496 | **Norway** | 0.616 | 0.617 | 0.606 | 0.608 |
| **China** | 0.549 | 0.553 | 0.549 | 0.527 | **Nepal** | 0.547 | 0.557 | 0.559 | 0.553 |
| **Cote d'Ivoire** | 0.494 | 0.500 | 0.504 | 0.499 | **New Zealand** | 0.473 | 0.476 | 0.457 | 0.451 |
| **Cameroon** | 0.485 | 0.476 | 0.464 | 0.473 | **Oman** | 0.412 | 0.406 | 0.419 | 0.431 |
| **Congo, DR** | 0.489 | 0.490 | 0.494 | 0.493 | **Pakistan** | 0.467 | 0.471 | 0.463 | 0.456 |
| **Congo, Rep.** | 0.476 | 0.482 | 0.482 | 0.511 | **Panama** | 0.492 | 0.450 | 0.447 | 0.459 |
| **Colombia** | 0.451 | 0.440 | 0.457 | 0.460 | **Peru** | 0.471 | 0.470 | 0.467 | 0.480 |
| **Comoros** | 0.502 | 0.506 | 0.505 | 0.505 | **Philippines** | 0.583 | 0.584 | 0.578 | 0.571 |
| **Cape Verde** | 0.479 | 0.467 | 0.461 | 0.462 | **Palau** | 0.396 | 0.391 | 0.401 | 0.399 |
| **Costa Rica** | 0.560 | 0.550 | 0.564 | 0.556 | **Papua New Guinea** | 0.447 | 0.418 | 0.415 | 0.421 |
| **Cuba** | 0.515 | 0.525 | 0.517 | 0.503 | **Poland** | 0.574 | 0.590 | 0.592 | 0.574 |
| **Cyprus** | 0.424 | 0.433 | 0.424 | 0.428 | **Korea, DR** | 0.543 | 0.555 | 0.551 | 0.545 |
| **Czech Rep.** | 0.674 | 0.686 | 0.684 | 0.672 | **Portugal** | 0.526 | 0.558 | 0.558 | 0.562 |
| **Germany** | 0.706 | 0.702 | 0.692 | 0.676 | **Paraguay** | 0.473 | 0.466 | 0.485 | 0.491 |
| **Djibouti** | 0.451 | 0.454 | 0.453 | 0.445 | **West Bank & Gaza** | 0.497 | 0.498 | 0.499 | 0.503 |
| **Dominica** | 0.454 | 0.440 | 0.444 | 0.448 | **French Polynesia** | 0.404 | 0.397 | 0.399 | 0.405 |
| **Denmark** | 0.608 | 0.606 | 0.604 | 0.582 | **Qatar** | 0.364 | 0.372 | 0.399 | 0.411 |
| **Dominican Rep.** | 0.527 | 0.525 | 0.522 | 0.528 | **Romania** | 0.624 | 0.630 | 0.626 | 0.610 |
| **Algeria** | 0.399 | 0.400 | 0.392 | 0.385 | **Russian Fed.** | 0.497 | 0.493 | 0.490 | 0.513 |
| **Ecuador** | 0.447 | 0.447 | 0.456 | 0.469 | **Rwanda** | 0.514 | 0.501 | 0.501 | 0.495 |
| **Egypt, Arab Rep.** | 0.519 | 0.520 | 0.525 | 0.520 | **Saudi Arabia** | 0.403 | 0.407 | 0.411 | 0.413 |
| **Eritrea** | 0.465 | 0.480 | 0.472 | 0.481 | **Sudan** | 0.374 | 0.385 | 0.384 | 0.391 |
| **Spain** | 0.548 | 0.562 | 0.558 | 0.545 | **Senegal** | 0.482 | 0.496 | 0.508 | 0.500 |
| **Estonia** | 0.678 | 0.670 | 0.659 | 0.657 | **Singapore** | 0.564 | 0.560 | 0.548 | 0.575 |
| **Ethiopia** | 0.505 | 0.502 | 0.483 | 0.473 | **Solomon Isl.** | 0.484 | 0.470 | 0.483 | 0.482 |
| **Finland** | 0.640 | 0.626 | 0.626 | 0.620 | **Sierra Leone** | 0.461 | 0.446 | 0.443 | 0.442 |
| **Fiji** | 0.539 | 0.521 | 0.533 | 0.530 | **El Salvador** | 0.501 | 0.504 | 0.506 | 0.509 |
| **France** | 0.600 | 0.602 | 0.594 | 0.570 | **Somalia** | 0.465 | 0.472 | 0.471 | 0.463 |
| **Gabon** | 0.454 | 0.459 | 0.459 | 0.463 | **Serbia** | 0.555 | 0.571 | 0.581 | 0.568 |
| **United Kingdom** | 0.561 | 0.557 | 0.541 | 0.518 | **Sao Tome & Pr.** | 0.517 | 0.504 | 0.494 | 0.490 |

| | 2011 | 2012 | 2013 | 2014 | | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|---|---|
| **Georgia** | 0.539 | 0.535 | 0.550 | 0.561 | **Suriname** | 0.539 | 0.522 | 0.515 | 0.508 |
| **Ghana** | 0.501 | 0.510 | 0.518 | 0.527 | **Slovak Republic** | 0.685 | 0.691 | 0.688 | 0.674 |
| **Guinea** | 0.429 | 0.427 | 0.444 | 0.504 | **Slovenia** | 0.683 | 0.704 | 0.688 | 0.673 |
| **Gambia** | 0.492 | 0.493 | 0.509 | 0.512 | **Sweden** | 0.679 | 0.704 | 0.671 | 0.663 |
| **Guinea-Bissau** | 0.494 | 0.473 | 0.456 | 0.456 | **Swaziland** | 0.544 | 0.516 | 0.529 | 0.522 |
| **Equatorial Guinea** | 0.410 | 0.384 | 0.387 | 0.405 | **Seychelles** | 0.458 | 0.469 | 0.474 | 0.482 |
| **Greece** | 0.424 | 0.439 | 0.451 | 0.444 | **Syrian Arab Rep.** | 0.430 | 0.459 | 0.483 | 0.462 |
| **Grenada** | 0.446 | 0.427 | 0.425 | 0.417 | **Turks and Caicos Isl.** | 0.379 | 0.387 | 0.386 | 0.411 |
| **Guatemala** | 0.494 | 0.495 | 0.496 | 0.500 | **Chad** | 0.447 | 0.413 | 0.417 | 0.423 |
| **Guyana** | 0.468 | 0.447 | 0.446 | 0.458 | **Togo** | 0.474 | 0.491 | 0.489 | 0.488 |
| **Hong Kong (China)** | 0.459 | 0.453 | 0.445 | 0.442 | **Thailand** | 0.609 | 0.610 | 0.597 | 0.591 |
| **Honduras** | 0.512 | 0.522 | 0.524 | 0.536 | **Tajikistan** | 0.540 | 0.543 | 0.534 | 0.530 |
| **Croatia** | 0.568 | 0.578 | 0.577 | 0.575 | **Turkmenistan** | 0.444 | 0.446 | 0.445 | 0.448 |
| **Haiti** | 0.458 | 0.475 | 0.494 | 0.495 | **Timor-Leste** | 0.420 | 0.411 | 0.433 | 0.429 |
| **Hungary** | 0.679 | 0.700 | 0.688 | 0.663 | **Tonga** | 0.497 | 0.515 | 0.527 | 0.537 |
| **Indonesia** | 0.500 | 0.503 | 0.497 | 0.503 | **Trinidad & Tobago** | 0.519 | 0.512 | 0.513 | 0.500 |
| **India** | 0.491 | 0.499 | 0.498 | 0.477 | **Tunisia** | 0.589 | 0.596 | 0.591 | 0.570 |
| **Ireland** | 0.591 | 0.584 | 0.581 | 0.556 | **Turkey** | 0.495 | 0.498 | 0.506 | 0.501 |
| **Iran** | 0.459 | 0.455 | 0.459 | 0.474 | **Tuvalu** | 0.448 | 0.442 | 0.439 | 0.432 |
| **Iraq** | 0.313 | 0.324 | 0.311 | 0.326 | **Taiwan (China)** | 0.595 | 0.587 | 0.581 | 0.570 |
| **Iceland** | 0.565 | 0.563 | 0.563 | 0.551 | **Tanzania** | 0.529 | 0.534 | 0.530 | 0.528 |
| **Israel** | 0.514 | 0.508 | 0.499 | 0.487 | **Uganda** | 0.559 | 0.533 | 0.520 | 0.512 |
| **Italy** | 0.546 | 0.559 | 0.553 | 0.543 | **Ukraine** | 0.611 | 0.617 | 0.611 | 0.602 |
| **Jamaica** | 0.429 | 0.436 | 0.438 | 0.444 | **Uruguay** | 0.488 | 0.467 | 0.471 | 0.465 |
| **Jordan** | 0.500 | 0.496 | 0.506 | 0.501 | **United States** | 0.524 | 0.527 | 0.518 | 0.500 |
| **Japan** | 0.544 | 0.575 | 0.589 | 0.594 | **Uzbekistan** | 0.521 | 0.521 | 0.512 | 0.505 |
| **Kazakhstan** | 0.446 | 0.465 | 0.437 | 0.456 | **St. Vincent & Gr.** | 0.431 | 0.404 | 0.402 | 0.408 |
| **Kenya** | 0.541 | 0.541 | 0.533 | 0.514 | **Venezuela, RB** | 0.468 | 0.427 | 0.441 | 0.416 |
| **Kyrgyz Rep.** | 0.571 | 0.560 | 0.564 | 0.547 | **Vietnam** | 0.595 | 0.601 | 0.604 | 0.591 |
| **Cambodia** | 0.513 | 0.523 | 0.538 | 0.543 | **Vanuatu** | 0.489 | 0.469 | 0.489 | 0.489 |
| **Kiribati** | 0.471 | 0.456 | 0.474 | 0.481 | **Samoa** | 0.520 | 0.518 | 0.542 | 0.542 |
| **St. Kitts & Nevis** | 0.437 | 0.438 | 0.445 | 0.443 | **Yemen, Rep.** | 0.349 | 0.351 | 0.357 | 0.357 |
| **Korea, Rep.** | 0.590 | 0.592 | 0.587 | 0.594 | **South Africa** | 0.473 | 0.477 | 0.490 | 0.493 |
| **Kuwait** | 0.304 | 0.316 | 0.332 | 0.337 | **Zambia** | 0.515 | 0.516 | .525 | .535 |
| **Lao PDR** | 0.554 | 0.510 | 0.524 | 0.529 | **Zimbabwe** | 0.505 | 0.508 | .502 | .529 |
| **Lebanon** | 0.445 | 0.441 | 0.445 | 0.455 | | | | | |