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Productive Capabilities Indicators for Industrial Policy Design

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Abstract

The debate around industrial policies is increasingly shifting from ‘why’ industrial policies to ‘what’, ‘when’ and ‘how’ these can be more effectively designed and implemented. Paradoxically, although industrial policies are by definition ‘selective policies’, we still lack an appropriate set of industrial diagnostic tools which support governments in the design and implementation of ‘selective measures’ aimed at the sectoral restructuring and technological upgrading of their country. The likelihood of governments achieving a specific set of macro-policy goals (i.e. structural change) depends on their capacity to understand, monitor and influence productive capabilities dynamics underlying structural change as well as on the technological upgrading of the overall economic system. Productive capabilities refer to personal and collective skills, productive knowledge and experiences embedded in physical agents and organizations that firms need to perform different productive tasks; they need to furthermore adapt and implement in-house improvements across different technological and organizational functions. This paper provides a theoretical framework for the analysis of productive capabilities and their role in structural change dynamics. On this basis, the paper critically reviews various synthetic indicators adopted by international organizations and researchers in cross-country comparisons of productive capabilities, industrial as well as of competitive performance. Finally, by identifying the methodological problems and informational limits of the various indicators that are currently available and the need to adopt multiple informational spaces, the paper introduces a new methodology for mapping the different drivers of structural change dynamics and for measuring productive capabilities at the national, industry and firm level.

Introduction

Over the last two decades, industrial policy has gradually re-entered both the policy debate in developed countries as well as that of development economists and policymakers in developing countries. The latter has been described by Dani Rodrik as a process of 'normalizing industrial policies' (Rodrik, 2008). If industrial policies are back on the government agendas of developed economies, especially as a result of their difficulties in finding new roads to sustained growth, developing economies, on the other side, are increasingly looking at the possibility of implementing industrial policies as a way of driving their structural change and catching up. Since the onset of the financial crisis, the increasing interest in industrial policies also derives from the resurfacing classical idea that the manufacturing sector has a prior role in driving productivity increases, while an 'over-servitization' (in particular, 'financialization') of an economic system might actually undermine its sustainability and prospects of technological upgrading (Pisano and Shy, 2009; for a review, see Andreoni and Lopez-Gomez, 2011).

If the debate throughout the 1990s focused on theoretical cases and historical evidence in favour of/opposition to industrial policies, academics as well as international actors such as the United Nations Industrial Development Organizations (UNIDO) are now focusing on the specific problems associated with the design, implementation and evaluation of context-specific policies for manufacturing development. In other words, the debate around industrial policies is increasingly moving from 'why' industrial policies to 'what', 'when' and 'how' to design and implement them more effectively. Paradoxically, although industrial policies are by definition 'selective policies' (Chang, 1994), we still lack an appropriate set of industrial diagnostic tools which support governments in the design and implementation of 'selective measures' aimed at the sectoral restructuring and technological upgrading of their country. The likelihood of governments achieving a specific set of macro-policy goals (i.e. structural change) depends on their capacity to understand, monitor and influence productive capabilities dynamics underlying structural change as well as on the technological upgrading of the overall economic system.

In fact, the transformation of the productive and technological structures of a given country, namely its structural change, is triggered and driven by industry-specific learning dynamics through which productive and technological capabilities are generated and accumulated. *Productive capabilities* refer to personal and collective skills, productive knowledge and experiences embedded in physical agents and organizations that firms need to perform different productive tasks; they need to furthermore adapt and implement in-house improvements across different technological and organizational functions.

Given the causational dynamics linking the development of productive capabilities with an economic system's process of structural change, the design and implementation of industrial policies should result from a fruitful combination of structural change analysis and the adoption of productive capabilities indicators at the country, industry and firm level. Being equipped with a set of tools suitable for different units and levels of analysis would allow governments to develop policies whose selectivity would result not only from the fact that specific sets of industries (and their firms as components) are selected, but also from the fact that different levels of policy intervention are taken into consideration. In other words, an enriched taxonomy of the relevant drivers of structural change operating at different levels of aggregation would lead to an innovative taxonomy of industrial policies for structural change.

The approach to and construction of productive capabilities indicators results from the analytical distinction of different classes of capabilities and from understanding the role that these entities play in production and structural change dynamics. The usual approach to production based on functional models does not contribute to opening up the black box of productive capabilities and, thus, to explaining and measuring their role as main drivers of production dynamics and structural change[1]. The significant costs and difficulties in collecting micro-level and sector-specific data on firms' productive, organizational and innovation activities have also discouraged the development of appropriate measurements. As a result, although research in economics, development, management and organizational studies has increasingly emphasized the central role productive capabilities play, both from a static and from a dynamic perspective, we still lack a comprehensive analytical framework, rigorous measurement tools and diagnostics.

The aim of this paper is to provide a theoretical framework for the analysis of productive capabilities and their role in structural change dynamics. Based on this, the paper critically reviews various synthetic indicators adopted by international organizations and researchers in cross-country comparisons of productive capabilities, industrial and competitive performances. Finally, by recognizing the methodological problems and informational limits of the various indicators available and the need to adopt multiple informational spaces, the paper introduces a new methodology for mapping the different drivers of structural change dynamics and for measuring productive capabilities at the national, industry and firm level.

[1] This point was raised in the classical work by Penrose (1959) and Richardson (1960 and 1972). See Georgescu-Roegen (1970), Landesmann and Scazzieri (1996) and Andreoni (2010) for a critical analysis of the limits of standard models of production.

The methodology proposed in this paper mainly relies on theoretically grounded quantitative indicators. However, given the complexity and intangibility of many of the aspects surrounding capabilities – e.g. the learning processes through which they develop; the level of analysis at which they can be observed; the sector specificity of 'task performance' profiles – our methodology suggests combining and integrating quantitative indicators with qualitative information derived from firm-level case studies and historical long-term analyses. The identification of causal structures and specific causational chains resides in the possibility of integrating multiple approaches through which different forms of 'evidence' can be collected[2].

The paper is structured as follows. The first section discusses the importance of linking structural change analysis with the study of productive capabilities dynamics. By combining different strands of research on capabilities, it also provides an operational definition of productive capabilities and a taxonomy for the development of productive capabilities indicators. The second section identifies the two main approaches that have been adopted at the national level to measure productive capabilities, industrial and competitive performances. By reviewing the different methodologies, theoretical premises and selected data, the third section assesses their validity and limits in a comparative perspective. The third section also outlines a new methodology for the study of productive capabilities at the national level and suggests two main strategies for measuring and benchmarking productive capabilities at a more disaggregated level of analysis.

1. Structural change and productive capabilities dynamics

Different historical times and contexts have witnessed the emergence of different ways of understanding development and, hence, the dominance of different theories, use of different empirical tools and implementation of different policies. Following a long period during which the production side of development was disregarded (Chang, 2010), the current debate in development economics is gradually rediscovering some of the issues that were central to 'classical development economists' like Prebisch, Hirschman, Myrdal and Kaldor as well as 'structuralists' such as Pasinetti, Syrquin, Leontief and Chenery. Recently, some attempts have been made to combine these structuralist theories of economic development with Schumpeterian evolutionary microeconomics (Nelson and Winter, 1981) and the capability theory of the firm (Penrose, 1959; Richardson, 1960). The integration and cross-fertilization among these traditions in economic analysis appears extremely promising given their respective focus on

[2] The use of empirical evidence in the identification of causal structures is discussed in Cartwright (1984).

demand-led structural change, supply-side technological efforts as well as institutional persistence and change (e.g. Cimoli and Porcile, 2009; Cimoli, Dosi and Stiglitz, 2009; McMillan and Rodrik, 2011)[3].

An analysis of these emerging contributions reveals that they all embrace the notion of development as '*a process that links micro learning dynamics, economy-wide accumulation of technological capabilities and industrial development*' (Cimoli, Dosi and Stiglitz, 2009:543). On the one hand, this definition entails the existence of a *causational chain* linking the productive capabilities dynamics at the micro- (firm and clusters of firms) and meso- (sub-sectors and sectors) levels with the structural change dynamics of the overall economic system (macro-level). On the other hand, this definition also leads to the analysis of another chain of causation which moves from the macro- to the meso/micro-levels – i.e. sectors (and firms/cluster of firms as their components). The latter 'top-bottom' causational chain refers to the possibility of influencing and even directing the process of productive capabilities building and accumulation at the micro-meso levels through the implementation of *selective industrial policies*. As defined by Chang (1994:60), industrial policies are policies 'aimed at particular industries (and firms as their components) to achieve the outcomes that are perceived by the state to be efficient for the economy as a whole'[4].

In order to understand how productive capabilities dynamics affect structural change dynamics and the design of selective industrial policies, the individual causational chains linking micro, meso and macro dynamics must be disentangled. In fact, it is becoming increasingly evident that new industrial diagnostics have to be developed and theories translated into both practice and specific recommendations if we seek to answer not only the question of 'why' industrial policies, but also the 'what', 'when' and 'how' related to the specific problems governments face in the implementation of effective industrial policies (Rodrik, 2004 and 2008; Chang and Lin, 2009; Chang, 2010; Lin, 2010; Lin and Monga, 2011; Haraguchi and Rezonja, 2011; Altenburg, 2011).

[3] It is far beyond the scope of this paper to review and discuss the main potentials and problems that such integration would imply from a theoretical and empirical perspective.
[4] Historically and across countries, selective industrial policies have been the main drivers of productive and technological capabilities building (Chang, 2002, 2009).

1.1 Structural change and manufacturing development

Structural change most commonly identifies the process of change of the sectoral composition of an economic system and thus the underlying transformation of its productive and technological structures as well as demand composition (Pasinetti, 1981; Chenery et al., 1986; Baranzini and Scazzieri, 1990; Andreoni and Scazzieri, 2011)[5]. Structural change dynamics entail both a process of *sectoral transition* – i.e. moving across sectors, from low to medium and high productivity sectors – and of *sectoral deepening* – i.e. moving within sectors, from low to high value added sub-sectors.

For a long time, the term *industrialization,* understood as the transition from the agricultural sector to the industrial sector (in particular, to manufacturing industries), was synonymous with development. Participation in the global industrialization race was considered a *conditio sine qua non* for achieving accelerated economic growth, increasing labour productivity and economic welfare. Historical evidence supported this pro manufacturing vision[6]. This notion that development mainly occurs within a process of structural change spearheaded by the expansion of the *industrial sector* found its first theoretical systematization in Albert Hirschman's and Nicholas Kaldor's seminal contributions.

In Hirschman's (1958) unbalanced growth model each sector is linked with the rest of the economic system by its direct and indirect intermediate purchase of productive inputs and sales of productive outputs – i.e. backward and forward linkages. Based on its system of linkages, each sector (as well as sub-sectors and firms as their components) exercises push and pull forces[7] on the rest of the economy. Unlike agriculture, the industrial sector (specifically, a set of manufacturing industries) is characterized by both strong backward and forward linkages and it consequently emerges as the main driver of development[8].

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[5] In this paper, the term sector is used to describe economic activities at the level of agriculture, industry and services. Manufacturing belongs to the industrial (secondary) sector. The latter is composed of many sub-sectors including a number of manufacturing industries. The use of this terminology is consistent with UNIDO's terminology (e.g. Haraguchi and Rezonya, 2011).

[6] As recently confirmed in Szirmai (2011), there is an *empirical correlation* between the dynamic growth of manufacturing output (and manufactured exports) and per capita income in the long run. See Szirmai and Verspagen (2010) for a review and test of the empirical evidence collected using growth accounting techniques and econometric analysis.

[7] See Park and Chan (1989) for an input-output analysis of intersectoral interdependencies and an empirical assessment of Hirschman's theoretical framework.

[8] The classical debate on agriculture vs manufacturing development is discussed in Andreoni (2011).

Table 1 Long-term patterns of structural change

	1950[a]				1960[b]				1980				2005[c]			
	AG	IND	MAN	SERV	AG	IND	MAN	SERV	AG	IND	MAN	SERV	AG	IND	MAN	SERV
Bangladesh[d]	61	7	7	32	57	7	5	36	32	21	14	48	20	27	17	53
China	51	21	14	29	39	32	27	29	30	49	40	21	13	48	34	40
India	55	14	10	31	43	20	14	38	36	25	17	40	18	28	16	54
Indonesia	58	9	7	33	51	15	9	33	24	42	13	34	13	47	28	40
Malaysia	40	19	11	41	35	20	8	46	23	41	22	36	8	50	30	42
Pakistan	61	7	7	32	46	16	12	38	30	25	16	46	21	27	19	51
Philippines	42	17	8	41	26	28	20	47	25	39	26	36	14	32	23	54
South Korea	47	13	9	41	35	16	10	48	16	37	24	47	3	40	28	56
Sri Lanka	46	12	4	42	32	20	15	48	28	30	18	43	17	27	15	56
Taiwan	34	22	15	45	29	27	19	44	8	46	36	46	2	26	22	72
Thailand	48	15	12	37	36	19	13	45	23	29	22	48	10	44	35	46
Turkey	49	16	11	35	42	22	13	36	27	20	17	54	11	27	22	63
Argentina	16	33	23	52	17	39	32	44	6	41	29	52	9	36	23	55
Brazil	24	24	19	52	21	37	30	42	11	44	33	45	6	30	18	64
Chile	15	26	17	59	12	41	25	47	7	37	22	55	4	42	16	53
Colombia	35	17	13	48	32	23	16	46	20	32	24	48	12	34	16	53
Mexico	20	21	17	59	16	21	15	64	9	34	22	57	4	26	18	70
Peru	37	28	15	35	21	32	20	47	12	43	20	45	7	35	16	58
Venezuela	8	48	11	45	7	43	11	50	6	46	16	49	4	55	18	40
Congo, Dem. Rep.	31	34	9	35					27	35	15	38	46	27	7	28
Cote d'Ivoire	48	13		39	48	13		39	26	20	13	54	23	26	19	51
Egypt	44	12	8	44	30	24	14	46	18	37	12	45	15	36	17	49
Ghana	41	10		49	41	10		49	58	12	8	30	37	25	9	37
Kenya	44	17	11	39	38	18	9	44	33	21	13	47	27	19	12	54
Morocco	37	30	15	33	32	26	13	42	18	31	17	50	13	29	17	58
Nigeria	68	10	2	22	64	8	4	28	21	46	8	34	23	57	4	20
South Africa	19	35	16	47	11	38	20	51	6	48	22	45	3	31	19	67
Tanzania	62	9	3	20	61	9	4	30			12		46	17	7	37
Zambia	9	71	3	19	12	67	4	21	15	42	19	43	23	30	11	47
Averages																
Asia	49	14	10	36	39	20	14	41	25	33	22	42	13	35	24	52
Latin America	22	28	16	50	18	34	21	48	10	40	24	50	7	37	18	56
Africa	44	19	9	36	37	24	10	39	25	32	14	43	26	30	12	45
Developing countries	41	19	11	40	33	25	15	42	21	35	20	44	16	34	18	51
16 advanced economies[e]	15	42	31	43	10	42	30	48	4	36	24	59	2	28	17	70

Sources: See detailed discussion of sources in Szirmai (2009). The primary sources used are: UN, *Yearbook of National Accounts Statistics, 1957, 1962 and 1967*; Groningen Growth and Development Centre, *10 Sector Database*, 2009, http://www.ggdc.net/index-dseries.html; World Bank, WDI online, accessed February 2009; World Bank, World Tables, 1980; Advanced economies, 1950, unless otherwise specified from OECD, *National Accounts*, microfiche edition, 1971, Japan 1953 from GGDC ten sector data base.

[a] Earliest year for which data are available: 1950, except for Morocco, Taiwan and Thailand, 1951; China and Tanzania, 1952; South Korea, 1953; Malaysia and Zambia, 1955; Ghana, Ivory Coast, 1960. Belgium, 1953, West Germany, Italy and Norway, 1951, Japan, 1952.

[b] China, 1962, proportions for 1960 not representative due to collapse of agriculture in great leap forward 58–60; Morocco, 1965, manufacturing share Tanzania, 1961.

[c] Canada 2003 instead of 2005; Venezuela 2004.

[d] Bangladesh 1950–1959, same data as Pakistan.

[e] Australia, Austria, Belgium, Canada, Denmark, Finland, France, (West) Germany, Italy, Japan, The Netherlands, Norway, Sweden, Switzerland, UK, USA.

Source: Szirmai (2011).

Building on the classical work on increasing returns by Allyn Young (1928), Kaldor (1966) developed the concept of *dynamic economies of scale* which captures the idea that the faster the growth of output in manufacturing industries, the faster the growth of manufacturing productivity[9]. In Kaldor's view, the rate of the overall economy's productivity growth depends on the expansion of the manufacturing sector as well as on the shrinkage of agriculture and other non-manufacturing industries such as services, which are characterized by decreasing

[9] The different sources of increasing returns identified in the classical line of Smith, Babbage, Young and Kaldor are discussed in Andreoni and Scazzieri (2011). See Toner (1999) for a review of Kaldor's laws and their contribution to Cumulative Causation Theory.

returns and contained productivity growth, respectively. Thus, specialization in manufacturing industries would imply a double productivity gain.

The pro-manufacturing vision was heavily criticized during the 1980s and was fully abandoned the following decade when the pro-services vision became dominant. Theoretical explanations for the rising share of services associated with economic growth primarily focused on final expenditure patterns and prices – i.e. demand side factors. The basic intuition is that as people's income increases, they begin to demand more services. The drop in demand for manufactured goods, so the argument goes, results in the shrinking of the manufacturing sector, which is declassed to a second rate activity, especially in countries in advanced stages of development. This new vision was supported by the fact that the services sector *prima facie* assumed the role of manufacturing in leading the process of economic growth in both advanced and in some developing countries. As a result of an accelerated process of de-industrialization, the most advanced economies have, since the 1960s, lost nearly half of their manufacturing sector as a percentage of GDP on average (see Figure 1). Moreover, it has been argued that several developing countries (India is often taken as a paradigmatic example) are in fact experiencing a historically unusual pattern of structural change which is determined by a new technological paradigm. According to this explanation, services such as ICTs, business services and finance are replacing and (more likely) complementing manufacturing in a pro-growth way.[10]

Although the pro-services vision continues to prevail worldwide, increased attention in the development economics debate has been paid to manufacturing over the last decade, as pressure on issues such as the loss of production jobs, loss of national level productive capabilities in advanced economies, loss of competitiveness vis-à-vis foreign competitors and trade imbalances has been rising. Indeed, an increasing number of analysts has begun raising the question 'Has de-industrialization gone too far?' and 'To what extent and in which direct and indirect ways does manufacturing contribute to the development of services (and *vice versa*)'?[11] In order to answer these questions, an increasing number of economists have recently refocused their attention on structural change dynamics and have complemented their research with, firstly, the

[10] Less emphasis has been given to the fact that developing countries may be running the risk of premature de-industrialization which would undermine their capacity to satisfy future changes in consumer demand or to accumulate/build those productive capabilities and institutions that characterize a manufacturing-led pattern of growth. See Palma (2005) and Andreoni and Lopez-Gomez (2011) for a critical review of this debate.

[11] See Andreoni and Lopez-Gomez (2011) for an analysis of the manufacturing versus services debate. The paper discusses how the bundle of interactions which connects manufacturing and services is becoming increasingly denser given the outsourcing of services activities from manufacturing firms to services providers in GVCs.

microeconomic analysis of firm-level learning processes through which productive capabilities develop and, secondly, with the study of a set of various institutional/organizational configurations (e.g. clusters, knowledge systems, national systems of innovation) that may trigger and/or enable processes of productive capabilities building. As for the latter issue, that is, enabling institutional/organizational configurations, an excellent theoretical assessment is provided by Bell and Albu (1999), while O'Sullivan (2011) offers a comprehensive review of international approaches to manufacturing research.

1.2 The economics of capabilities: A critical review and taxonomy

The concept of capability 'floats in the literature like an iceberg in a foggy arctic sea, one iceberg among many, not easily recognized as different from several icebergs nearby' (Dosi et al., 2000: 5-6). The main reason why the economics of capabilities lacks a comprehensive analytical framework is that capabilities – generally defined as capacities to act in an intentional way – have been described by very different actors (and their different actions and functions, see section 1.2.2): from *individual agents* such as entrepreneurs, workers and bureaucrats, to *collective entities*, organizations and institutions, such as firms or clusters of firms. For example, Moses Abramovitz (1986) introduced the concept of social capabilities at the country level to capture those 'tenacious societal characteristics' that influence the responses of given societies to economic opportunities. In developing the catching up hypothesis, Abramovitz equates social capabilities with managerial and technical competences, but more crucially with a set of political, commercial, industrial and financial institutions owned by countries[12]. This systemic concept of capabilities has also been re-proposed in various contributions on regional/national technological capabilities or innovation systems (Lall, 1992), as well as in recent literature on business environment and industrial commons (Pisano and Shy, 2009)[13].

The present paper focuses on the analytical assessment and measurement of productive capabilities at different levels of aggregation, namely the 'national level', the 'sector and sub-sectors level' (in particular, manufacturing industries) and the 'firm level'. The following sections introduce the so-called 'capability theory of the firm' in which the concept of

[12] See also the recent contribution by Pritchett et al. in which a similar concept is adopted in the analysis of 'state capability traps' (Pritchett et al., 2010).
[13] Although it is far beyond the scope of this paper, a concept of consumer capabilities can be identified by combining Sen's (1985) seminal work on commodities and capabilities and Pasinetti's (1981) work on consumer learning and the qualitative and quantitative expansion of demand.

productive capabilities is rooted and, secondly, propose an operational definition and taxonomy for the analysis of productive capabilities.

1.2.1 The capability theory of the firm

In the Coasian theory of the firm (Coase, 1937), 'production costs determine the technical substitution choices [while] transaction costs determine which stages of the productive process are assigned to the institution of the price system and which to the institution of the firm' (Langlois, 1998: 186). Thus, the firm emerges as the more convenient way of realizing the production process which is the lowest cost option for obtaining control over the relevant cluster of capabilities needed. On the other hand, as theorized by Edith Penrose (1959), creating a firm may not simply be a way of reducing transaction costs, but may denote the highest value option for the creation and development of capabilities. Penrose's (1959:149) definition of the firm as 'a pool of resources the utilization of which is organized in an administrative framework' constitutes the original foundation of the capability theory of the firm.

The firm is a collection of physical and human *resources* which can be deployed in a variety of ways to provide a variety of productive *services*. In fact, 'the services yielded by resources are a function of the way in which they are used – exactly the same resource when used for different purposes or in different ways and in combination with different types or amounts of other resources provides a different service or set of services' (Penrose 1959: 25). The growth process, in the Penrosian framework, is realized through the firm's recognition and exploitation of productive *opportunities*, specifically of 'all of the productive possibilities that its entrepreneurs see and can take advantage of' (Penrose, 1959:31). As Best (1999:108) points out, 'productive opportunities link the firm to the customer in an interactive relationship in which new product concepts are developed. The advances in productive services can extend the firm's productive opportunities by enlarging the members' capacity to recognize and respond to new product concept possibilities in the environment'.

By developing the Penrosian theory of the firm and building on his classical contribution *Information and Investment* (1960), George B. Richardson was the first to introduce the term capabilities to economics. Maintaining the analytical distinction between productive resources and productive services, Richardson (1972:888) describes industries and their firms as entities in which a large number of activities are carried out through the adoption of an appropriate cluster of productive capabilities.

> 'It is convenient to think of industry as carrying out an indefinitely large number of activities, activities related to the discovery and estimation of future wants, to research, development, and design, to the execution and co-ordination of processes of physical transformation, the marketing of goods, and so on. And we have to recognize that these activities have to be carried out by organizations with appropriate *capabilities*, or, in other words, with appropriate knowledge, experience, and skills.'

Richardson's definition stresses how the concept of capabilities refers to a form of *know-how*, namely 'appropriate knowledge, experience and skills' that cannot be reduced to *know-that*. The reason is that productive capabilities imply the *capacity to apply the know-that* needed to obtain a given intended result (Loasby, 1999)[14]. This know-how evidently emerges and accumulates through a continuous process of trial and error, interpretations and falsifications on the basis of an experimental and pragmatic approach to the solutions of technological and organizational problems in production – i.e. *learning processes* (Arrow, 1962; Rosenberg, 1976, 1982 and 1994; Andreoni, 2010). The learning processes through which capabilities develop are cumulative in the sense that 'the acquisition of certain kinds of know-how facilitates the acquisition of further knowledge of the same kind, and impedes the acquisition of knowledge of incompatible kinds' (Loasby, 1999:58).

The specific way in which capabilities are built and accumulated has two main implications. First, firms tend to specialize in the execution of a certain set of interrelated productive tasks (i.e. *similar activities*) that require the availability of a limited set of capabilities. Secondly, firms need to not only know how to perform certain productive tasks, but also how to get others to perform productive tasks for them. Firms can indirectly acquire capabilities through two major means: either by gaining *control* of other capabilities (e.g. through the institution of the firm or through inter-firm cooperation) or by obtaining *access* to them (e.g. through the institution of the market)[15]. Thus, as shown by Richardson (1972), capabilities dynamics are at work at the very basis of the *organization of industry*.

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[14] The need to identify the set of feasible operations in production processes given a set of existing 'work capacities' or capabilities has also been stressed in Scazzieri (1993); Landesmann and Scazzieri (1996); Andreoni (2010).

[15] As Marshall (1920) notes, evolution through the division of labour tends to favour both greater specialization (increasing capabilities) and closer integration (an increasing number of institutional devices to coordinate capabilities and activities). This idea was complemented by the famous aphorism by A. Young (1928) according to which 'the division of labour depends upon the extent of the market, but the extent of the market depends upon the division of labour'. This means that 'an increase in the market triggers further specialization which is a process that simultaneously increases the size of the market for specialist skills and activities' (Best 1999:107). Thus, the division of labour is the fundamental premise for a process of specialization and to more effectively increase capabilities.

1.2.2 Productive capabilities: An operational definition and taxonomy

The execution of different technological and organizational *functions* and productive *activities* by a given firm requires a set of relevant capabilities. Specifically, each function entails the execution of a certain number of activities (and *tasks* as their components). These functions and activities are, of course, industry-specific as well as process and product-specific. The reason why a multitude of concepts of capabilities has been proposed is that each theoretical and empirical contribution has formulated a new set of concepts according to (i) the specific functions or activities focused on; or (ii) the static versus dynamic role played by the capabilities under consideration. For example, for the first criterion, the technological capability matrix proposed by Sanjaya Lall (1992:167; see Table 2) systematizes firm-level capabilities according to different functional areas (e.g. process and product engineering) and the degree of complexity of different activities (from simple routines to innovative activities)[16]. Based on this, three main sets of capabilities have been identified by Lall:

(1) *Investment capabilities*: those capabilities needed to identify, prepare, obtain technology for, design, construct, equip, staff and commission a new facility (or expansion);

(2) *Productive capabilities*: the skills involved in both process and product engineering as well as the monitoring and control functions included under industrial engineering;

(3) *Linkage capabilities*: the skills needed to transmit information, skills and technology to, and receive them from, component or raw material suppliers, subcontractors, consultants, service firms and technology institutions.

Applying the second criterion, Bell and Pavitt (1993) distinguish capabilities used to produce industrial goods at a given level of efficiency and given input combinations (static perspective) from those needed to discover, absorb, adapt and change productive and organizational techniques (dynamic perspective)[17].

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[16] The work by Dosi, Nelson and Winter (2000) focuses on the non-reducible and collective nature of some of these productive capabilities. Thus, they highlight the fact that productive capabilities are owned more by organizations than by their individual members. The concept of organizational capabilities they propose seeks to capture the different dynamics responsible for: firstly, the spontaneous emergence of routines *vis à vis* the intentional development of organizational capabilities; and secondly, the process through which a certain productive capability becomes routinized and, *vice versa*, a routine emerges as a distinctive organizational capability.

[17] The same focus on a specific subset of productive capabilities, namely those required to manage technological change, can be found in the operation management and business studies literature. The concept of capabilities introduced therein is that of *dynamic capabilities*, that is, 'firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments' (Teece et al., 1997: 516). This set of capabilities is crucial in explaining differences in firms' competitive advantages, as it refers to the specific capacity of the firm to balance continuity – i.e.

Table 2 Lall's matrix of technological capabilities

		FUNCTIONAL					
		INVESTMENT		PRODUCTION			
DEGREE OF COMPLEXITY		PRE INVESTMENT	PROJECT EXECUTION	PROCESS ENGINEERING	PRODUCT ENGINEERING	INDUSTRIAL ENGINEERING	LINKAGES WITHIN ECONOMY
BASIC	SIMPLE, ROUTINE (Experience based)	Prefeasibility and feasibility studies, site selection, scheduling of investment	Civil construction, ancillary services, equipment erection, commissioning	Debugging, balancing, quality control preventive maintenance, assimilation of process technology	Assimilation of product design, minor adaptation to market needs	Work flow, scheduling, time-motion studies. Inventory control	Local procurement of goods and services, information exchange with suppliers
INTERMED	ADAPTIVE DUPLICATIVE (Search based)	Search for technology source. Negotiation of contracts. Bargaining suitable terms. Info. systems	Equipment procurement, detailed engineering, training and recruitment of skilled personnel	Equipment stretching, process adaptation and cost saving, licensing new technology	Product quality improvement, licensing and assimilating new imported product technology	Monitoring productivity, improved coordination	Technology transfer of local suppliers, coordinated design, S&T links
ADVANCED	INNOVATIVE RISKY (Research based)		Basic process design. Equipment design and supply	In-house process innovation, basic research	In-house product innovation, basic research		Turnkey capability, cooperative R&D, licensing own technology to others

Source: Lall (1992:167).

Building on a critical analysis of the main theoretical and empirical contributions in the capabilities field[18], the present paper proposes the following operational definition of productive capabilities.

Productive capabilities are personal and collective skills, productive knowledge and experiences embedded in physical agents and organizations needed for firms to perform different productive tasks as well as to adapt and undertake in-house improvements across different technological and organizational functions.

From a 'static efficiency' point of view, productive capabilities are skills, experiences and productive knowledge that agents require to choose, install and maintain capital goods; operate technical and organizational functions; and perform and monitor the execution of a set of interdependent productive tasks given certain time and scale constraints. In fact, performing a set of interdependent productive tasks does not only require capable agents, that is, agents endowed with productive knowledge and relevant skills, but the establishment of a certain *production capacity* as well, that is, of *a scale-appropriate assortment of equipment, machinery and other capital goods*. In fact, the consideration of productive capabilities independently of a

execution of invariant processes – with change – i.e. transformation of capabilities, given a certain exogenous shock.

[18] The main roots of the literature on which the proposed definition of productive capabilities is based can be found in the empirical research conducted in Latin America in the 1970s – i.e. the so called 'Katz Programme' – and in the research work of Sanjaya Lall in India. See also Stewart and James (1982); Katz (1987); Dahlman et al. (1987); Lall, (1987 and 1992); Bell and Pavitt (1993); Romijn (1999); Iammarino et al. (2008).

firm's production capacity would undermine the fact that, according to the production capacity installed, different combinatorics of 'productive capabilities – functions/activities/tasks' are actually feasible (Andreoni, 2010)[19]. Clearly, the expansion of the productive capacity of a given firm results from strategic investments in capital goods such as machines, equipment, hardware and software.

From a 'dynamic efficiency' perspective, the absorption, adaptation and improvement of given productive techniques, as well as innovations across different organizational and technological functions, mainly depend on the availability of a specific subset of productive capabilities called *technological capabilities*. Capabilities needed to generate, absorb and manage technological and organizational change may differ substantially from those needed to perform in existing production systems. Although this distinction may be useful as a focusing device, it tends to underestimate the fact that technical change, especially in the form of small improvements, takes place throughout the entire production process and in all functional areas and thus requires the activation of all kinds of productive capabilities. This implies that although some productive capabilities – i.e. what we call technological capabilities – represent the main drivers in the process of technological and organizational change, they are not the only set of capabilities these processes require. In other words, it would be misleading to believe that 'labs' and 'R&D departments' where technological capabilities are presumably concentrated are the unique *loci* of technological and organizational change. In fact, as economic historians (Schumpeter, 1934; Rosenberg, 1976, 1982 and 1994; Kline and Rosenberg, 1986) have shown, the accumulation of productive capabilities (and, in particular, of technological capabilities) results from deliberate in-house efforts as well as cumulative processes of *learning by doing*, *by using* and *by interacting*, realizing the first investment and product design phase all the way up to the organizational and production phases[20].

To visualize the different classes of productive capabilities which allow firms to operate across different functional areas and to perform productive and technical change activities, we develop a detailed taxonomy (see Table 3). The taxonomy is structured on two main axes. The vertical axis identifies different *functional areas*, while the horizontal axis distinguishes between a list of *productive activities* (static perspective) and a list of specific *technical change activities* (dynamic perspective) for each functional area. As discussed, technical change activities require

[19] Andreoni (2010) develops a 'capability theory of production' in which capabilities concepts are embedded in a structural analysis of production processes.
[20] See also Andreoni (2010) on the concept of '*structural learning*', that is, the process of reconfiguring the analytical map of production relationships triggered by complementarities discovery in historical time.

a specific subset of productive capabilities, namely those technological capabilities that are necessary (albeit not sufficient) to change the way in which productive activities are performed in each functional area. The proposed taxonomy also sheds some light on the fact that few productive capabilities are function-specific and activity-specific, but more importantly, it suggests that even performing the simplest productive activities very often requires the activation and matching of interdependent clusters of productive capabilities. In other words, taxonomies should not fix specific sets of productive capabilities in one exclusive functional area.

Table 3 A taxonomy of productive capabilities

	Functional areas				
	1.Investment	**2.Product design**	**3.Process organization**	**4.Production process**	**5.Linkage and cooperation**
Productive activities:	Feasibility studies	Replication of fixed specifications and designs	Production planning and control	Work flow scheduling and monitoring	Exchange with suppliers
	Negotiations and bargaining suitable terms and conditions	Standard design for manufacturing	International certification (ISO 9000)	Manufacture of components	Horizontal cooperation across firms
	Equipment and machinery procurement	Development of prototypes	Automation of processes	Sub-assembly and assembly of components and final goods	Distribution and marketing
	Recruitment of skilled personnel		Adoption of modern organizational techniques (e.g. just in time and total quality control)	Stretching, control and maintenance of machinery and equipment	After sale services
			Flexible and multi-skilled production	Inventory control	
			Architectural services	Productivity and quality control	
Technical change activities:	Search for technology sources	Adaptations to product technology driven by market needs and requests	Selection of technology and organizational formats	Efficiency improvement in tasks execution	Technological transfer and S&T linkages development
	Equipment design and adaptation	Improvement of product standards and quality	Minor changes to process technology to adapt it to local conditions	Improvement and cost savings in machinery and equipment	Coordinated R&D and joint ventures
	Engineering training	Development of complementary products (e.g. embedded software) or components	Improvement and development of new organizational techniques	Inverse engineering and development of machinery	Licensing own technologies to others
	Joint ventures	R&D into new product generation	Improvement to layout		
		R&D (basic) into new materials and new specifications	Process oriented R&D (basic) for radical innovation		

Source: Author.

1.3 Causational chains: A synthesis

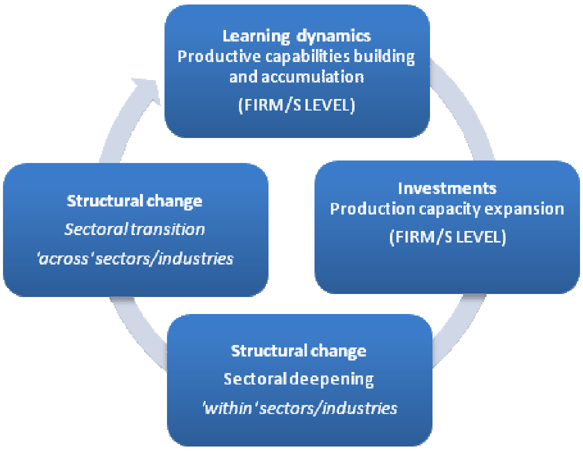
The analysis developed in the previous sections starts from the recognition that a specific *causal structure* exists which links productive capabilities dynamics at the micro-meso levels with the structural change of the overall economic system. Productive capabilities dynamics are clearly not only responsible for sectoral transition (from agriculture to manufacturing and services), but also for sectoral deepening, that is, for technological upgrading and the subsequent increase of productivity within each sector (as well as within the subsectors, in particular, in the manufacturing industries). The difficulties in identifying the broader causal structure as well as disentangling the complex causational chains linking micro-meso and macro-level processes are attributable to two main facts.

Firstly, causational chains are not linear. At the micro- (firm) and meso- (sector and sub-sectors) levels, productive capabilities interact in a circular and cumulative process of mutual reinforcement in which the introduction of new productive techniques leads to new productive activities and opportunities of consumption that, in turn, spur new technological innovations and eventually trigger processes of sectoral deepening and sectoral transition (see Figure 1).

Secondly, the process of productive capabilities building and accumulation has to be complemented by a congruent expansion of the production capacity. For example, if a firm in a given economic system undergoes a process of productive capabilities building and accumulation, and intends to fully realize it, it will have to make strategic investments for the expansion of its production capacity. The reason why the increasing availability of productive capabilities has to be matched with an expansion of the production capacity is that if the production capacity is not adjusted accordingly, the firm will be constrained by the material structures of production (such as a given assortment of machines, equipment, hardware and software), the emergence of organizational and technological bottlenecks and the changing inter-firm vertical and horizontal relationships. Clearly, the lack of coordination among different but interdependent investments in production capacity expansion and productive capabilities building may prevent processes of sectoral deepening and/or sectoral transition, especially in the context of catching up economies.

To realize each specific dynamic process presented in the boxes in Figure 1, as well as each causational chain linking them, specific industrial diagnostics have to be developed. The set of methodologies presented in this paper (part III) are first attempts in this direction.

Figure 1 Causational chains



Source: Author.

2. Measuring productive capabilities at the national level: A menu for choice

The first national science and technology (S&T) indicators were developed in the United States in 1973. Early indicators were mainly focused on input-based variables, while they were weaker on the output and impact sides (Grupp and Mogee, 2004). In the same period, from the 1970s to the 1980s, national reports were produced by UK, Germany, France, Japan, Austria, Italy, the Netherlands and Scandinavian countries, and later followed by Eastern European countries. Among them, the Japanese NISTEP (National Institute of Science and Technology Policy) developed 'cascade models' to integrate S&T indicators as well as experimental factor analysis (Kodama, 1987). Among international organizations, OECD made an important contribution by making statistics and indicators comparable among member states, with the celebrated *Frascati Manual* and, later, with the *Oslo* and *Bogota Manuals* (OECD, 1992, 2002 and 2006).

Many of these *national level indicators* have been developed for different goals, from S&T assessment to innovation and competitiveness analysis[21]. The menu of indicators reviewed here is constructed by selecting those indicators which appear to be more suitable for capturing the level of productive and technological capabilities of a given country as well as those indicators that refer to a broad sample of low, middle and high income countries. Two main approaches exist to measure and/or proxy national-level productive capabilities:

[21] Other reviews of these indicators are proposed in Archibugi and Coco (2005) and in Archibugi et al. (2009a).

(1) The first group of indicators (detailed in section 2.1 and subsections) consists of country-level indicators which combine information primarily extracted from input-based variables, as well as in some cases from a few output-based variables. Apart from a few exceptions, these indicators tend to be methodologically homogenous and recur in similar data sources. A comparative analysis across indicators (e.g. data sources, countries and time coverage) is presented in section 2.2.

(2) The second group of indicators (detailed in section 2.3) comprises what we call 'trade-based indicators'. These indicators were recently developed as indirect measures of country-level productive capabilities. They infer country-level productive capabilities on the basis of the degree of complexity/sophistication of the products exported by countries in global trade.

2.1 Country-level productive capabilities indicators, competitiveness assessment and cross-country comparisons

2.1.1 The Global Innovation Scoreboard (EU Commission)

- ***Summary Innovation Index (SII)***

  (Synthetic index - European Innovation Scoreboard)

  The SII was developed and has been computed since 2000 as part of the European Innovation Scoreboard. It is estimated as an arithmetic mean of the 25 normalized values obtained from 25 sub-indicators. All 25 indicators have been assigned the same weight. These indicators include variables which account for innovation inputs (innovation driver, knowledge creation, innovation & entrepreneurship) and innovation output (application and intellectual property). Data are collected for 34 countries and integrated by the Community Innovation Survey (CIS).

- ***Global Summary Innovation Index (GSII)***

  (Synthetic index - Global Innovation Scoreboard)

  In 2006, the GSII was introduced to compare the 34 countries included in SII with other major international competitors (other 14 major R&D performing countries in the world). The GSII includes five composite sub-indicators covering the five dimensions applied in SII: innovation inputs (innovation driver, knowledge creation, innovation &

entrepreneurship) and innovation output (application and intellectual property). See section 2.2 for a detailed analysis of variables included and data sources.

- ***New Global Summary Innovation Index (newGSII) - 2008***
  (Synthetic index – New Global Innovation Scoreboard, GIS 2008)
  The new Global Innovation Scoreboard 2008 (GIS, 2008) explores the innovation performance of the EU-27 and other major R&D spenders in the world: Argentina, Australia, Brazil, Canada, China, Hong Kong (SAR), India, Israel, Japan, New Zealand, Republic of Korea, Mexico, Russian Federation, Singapore, South Africa and the United States. The GIS 2008 methodology includes nine indicators of innovation and technological capabilities, grouped in three main dimensions (pillars) and weighted as shown in Table 4. For each pillar a composite indicator is obtained as the simple average of the sub-indicators. The GIS 2008 has been calculated relative to 1995 and 2005.

Table 4 The Global Summary Innovation Index, 2008

Pillar	Indicator	Contribution to the total GIS value
Firm Activities and Outputs (40%)	Triadic patents per population (3 years average)	20%
	Business R&D - BERD - (%GDP)	20%
Human Resources (30%)	S&T tertiary enrolment ratio	7,5%
	Labour force with tertiary education (% total labour force)	7,5%
	R&D personnel per population	7,5%
	Scientific articles per population	7,5%
Infrastructures and Absorptive Capacity (30%)	ICT expenditures per population	10%
	Broadband penetration per population	10%
	Public R&D - (HERD + GOVERD) - (%GDP)	10%

Source: Archibugi et al. (2009b); European Commission (2010 and 2011).

All indicators in the GIS are indicators of intensity: all values are weighted to account for the different size of nations. All variables are normalized on a scale from 0 to 1, and countries are ranked on an ordinary scale.

2.1.2 Science, Technology and Industry Scoreboard (OECD)

The Science, Technology and Industry Scoreboard (STI) has been published every other year since 1981. The last STI scorecard published in 2009 (OECD, 2009) includes 35 countries

(OECD countries and major non-OECD countries, notably Brazil, Russia, India, China and South Africa). The scorecard provides detailed country-level measures in the areas of R&D and innovation, human resources in science and technology (knowledge and skills), patents and other IPRs, ICT infrastructures, knowledge flows embedded in trade and investment and the impact of knowledge in productive activities.

2.1.3 Knowledge Assessment Methodology (World Bank)

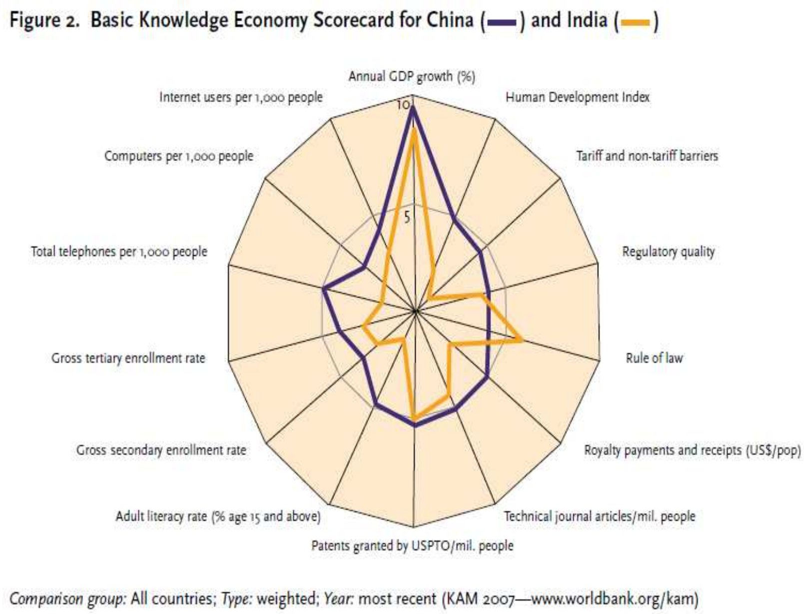
The Knowledge Assessment Methodology (KAM) is the statistical package developed by the World Bank for cross-country comparisons on various aspects of the knowledge economy. The most recent version (KAM, 2008) provides comparisons for around 140 countries based on 83 structural and qualitative variables grouped in four main dimensions (pillars). All variables are normalized on a scale from 0 (weakest) to 10 (strongest), and all countries are ranked on an ordinal scale. The four pillars are presented in Table 5. Measures of individual indicators are summarized through radar graphs for cross-country comparisons (see Figure 2 for an example).

Table 5 The KAM basic scorecard

Pillar	*Indicator*
Economic and institutional regime	• Tariff and non-tariff barriers • Regulatory quality • Rule of law
Education and skill of population	• Adult literacy rate • Gross secondary enrollment rate • Gross tertiary enrollment rate
Information infrastructure	• Telephones per 1,000 people • Computers per 1,000 people • Internet users per 1.000 people
Innovation system	• Royalty payments and receipts, US$ per person • Technical journal articles per million people • Patents granted to nationals by the U.S. Patent and Trademark Office per million people

Source: World Bank (2009:3).

Figure 2 A radar graph comparison, KAM (2007)



Source: World Bank (2009:3).

- ***Knowledge Economy Index (KEI)***

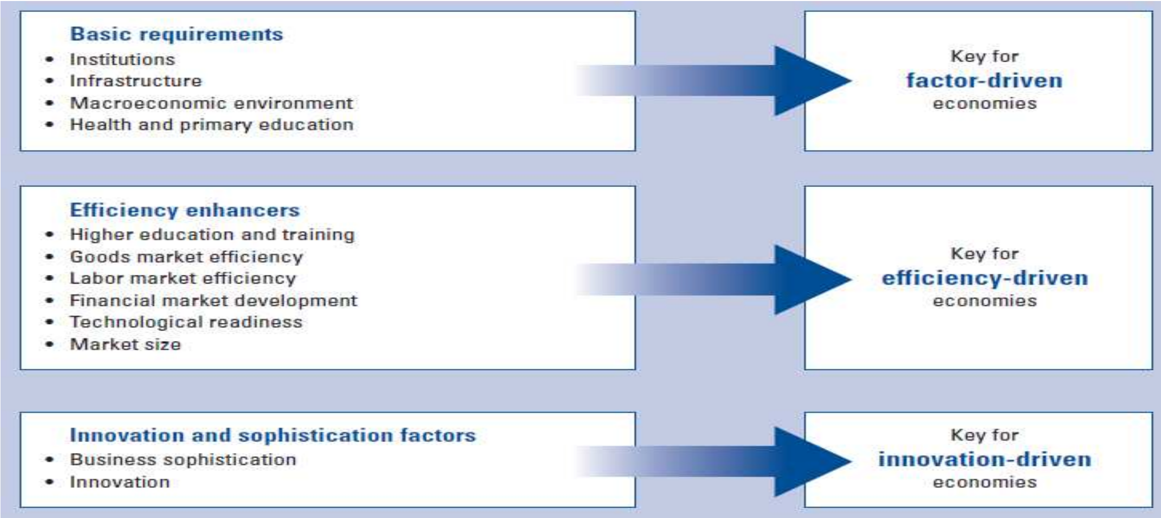
  (Synthetic index – Knowledge Assessment Methodology)

  The most known composite indicator included in the KAM is the Knowledge Economy Index (KEI). This index is obtained as the simple average of the normalized values of the 12 indicators listed in Table 4. The closer the KEI score is to 10, the higher the amount of good 'knowledge pillars' in the respective economy. Over time, comparisons are possible for two points in time: 1995 and the most recent year covered.

2.1.4 Competitiveness indexes (World Economic Forum)

The competitiveness indexes promoted by the World Economic Forum have been widely publicized by mass media, although in-depth analysis has revealed the existence of flaws and inconsistencies (Lall, 2001; Godin, 2004). The WEF defines competitiveness as 'the set of institutions, policies, and factors that determine the level of productivity of a country' (WEF, 2008:3). The determinants/components of competitiveness are grouped in the '12 pillars' scheme (Table 6).

Table 6 The '12 pillars' of competitiveness (WEF, 2008)



Source: WEF, 2008.

It is beyond the scope of this paper to review all indexes used and the different methodologies adopted for each pillar since the first Global Competitiveness Report was published. This section focuses on a selection of indexes developed to capture productive and technological capabilities at the country level and on outlining the methodology developed for the New Global Competitiveness Index (WEF, 2008).

- ***GroCI – Growth Competitiveness Index (WEF)***

  Sub-indicator: Technology Index (Tech)

  GroCI was introduced in 2001/2002 to capture growth potentials of countries in the medium term. It was based on three macroeconomic pillars: quality of the macroeconomic setting, robustness of public institutions and technological innovation capabilities. The last dimension is captured by the sub-indicator *Technology Index (Tech)* which consists of three technological variables: innovative capabilities, diffusion of new ICTs and technology transfer. The latter variable, captured by non-primary exports, is only considered for non-core economies, namely those with less than 15 US patents per million population. The Tech Index has been calculated for 125 countries based on both hard and soft data (Global Competitiveness Report, GCR 2006-2007 edition). See section 2.2 for a detailed description of variables included and data sources.

- ***GloCI – Global Competitiveness Index (WEF)***

  Sub-indicator: Technological Readiness Index (TechRead)

  Sub-indicator: Technological Innovation Index (TechInnov)

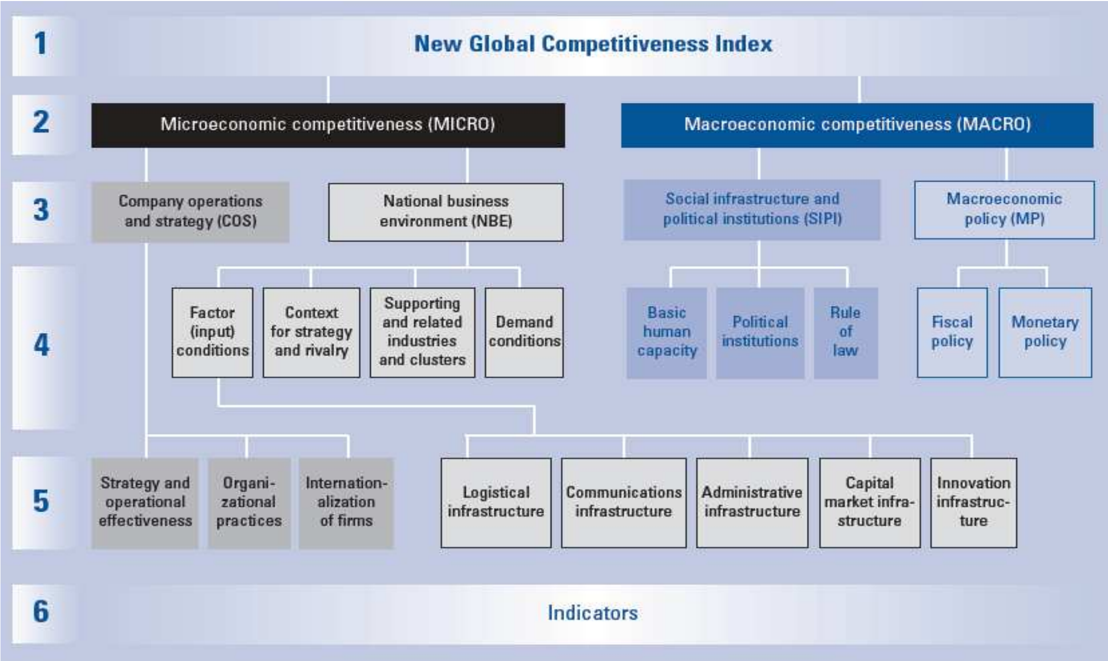
  The second composite indicator, GloCI, was firstly introduced in the GCR 2004/05 edition. It is composed of approximately 89 indicators, subdivided in three sub-groups: a) basic requirements; b) efficiency enhancers; and c) innovation and sophistication factors. Different aggregation methods are adopted for these sub-groups and in accordance with the given country's developmental stage. Countries at the initial stage of development assigned the following normalized weight to the sub-groups: 0,5 – 0,4 – 0,1; countries at the intermediate stage: 0,4 – 0,5 – 0,1; and countries at an advanced stage: 0,3 – 0,4 – 0,3. Per capita GDP defines different countries' stage of development. Data are drawn from both secondary sources as well as the WEF Executive Opinion Survey. The GloCI index is based on 9 pillars: institutions, infrastructure, macroeconomy, health and primary education, higher education and training, market efficiency, technological readiness, business sophistication and innovation. The seventh and ninth pillars, namely those which strictly refer to technological capabilities, are captured by the TechRead and the TechInnov indexes. See section 2.2 for a detailed description of the variables included in these two indexes[22].

- ***New Global Competitiveness Index (NGCI)***

  The New Global Competitiveness Index was introduced in the WEF Report 2008-9 with the explicit aim of replacing the two main indexes discussed above with a single fully integrated index. The majority of individual indicators used in the previous indexes have been incorporated into the new index. However, the way in which they are combined has changed drastically on account of the adoption of a new 'hierarchical model' for the assessment of competitiveness (see Table 7) and more rigorous statistical methodologies (see Table 8). The data used for the development of the NGCI cover 130 countries for up to 7 years (2001–07).

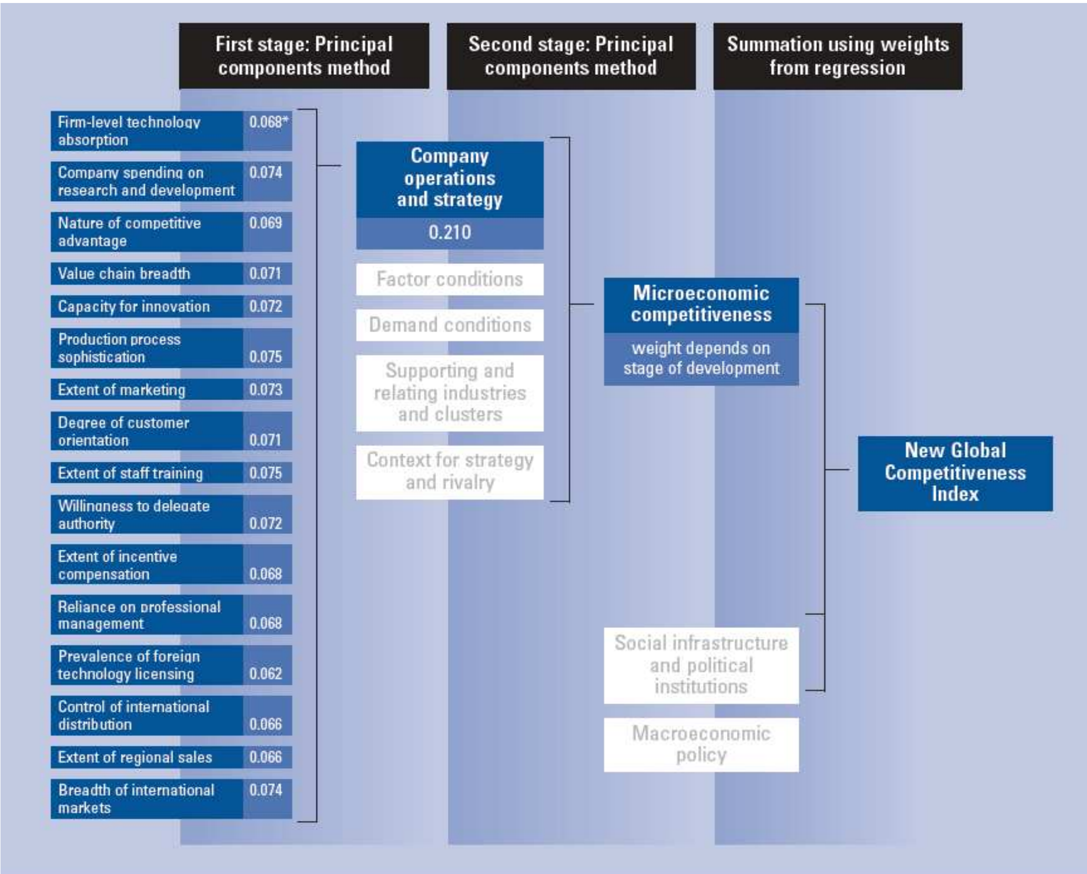
[22] See also the WEF (2011) Appendix A: Computation and structure of the Global Competitiveness Index.

Table 7 The New Global Competitiveness Model



Source: WEF (2008:55).

Table 8 The New Global Competitiveness Methodology



* Numbers shown are weights.

Source: WEF (2008:57).

2.1.5 Technology Achievement Index (UNDP)

The TAI has been developed by Desai et al. (2002:101) and reported in the *Human Development Report 2001* only. The index focuses on four dimensions of technological capacity:

1. *Technology creation*: measured by the number of patents granted to residents per capita and by receipts of royalties and license fees from abroad per capita.
2. *Diffusion of recent innovations*: measured by the number of Internet hosts per capita and the share of high-technology and medium-technology exports in total goods exports.
3. *Diffusion of old innovations*: measured by telephones (mainline and cellular) per capita and electricity consumption per capita.
4. *Human skills*: measured by the mean years of schooling in the population aged 15 and older, and the gross tertiary science enrolment ratio.

Thus, each dimension is captured by two sub-indicators which, in turn, are aggregated (simple average and standard normalization) in the synthetic indicator TAI for 84 countries. See section 2.2 for a detailed analysis of variables and data sources.

2.1.6 Innovation Capability Index (UNCTAD)

The UNCTAD Innovation Capability Index (UNICI) was developed by UNCTAD (World Investment Report 2005) and calculated for 117 countries for the years 1995 and 2001. This index is based entirely on quantitative variables which are direct measures of technological activity and technical human capital. It is composed of two sub-indicators: the Technology Activity Index (TAct) and the Human Capital Index (HCI) which, respectively, capture the innovative activity and the skills availability for such activity. As detailed in Table 9, UNICI sub-indicators and their variables are assigned the same weights (the only exception being the HCI).

Table 9 The Innovation Capability Index (UNICI)

Indices	Components	Weights attached
Technological Activity Index	R&D personnel per million population United States patents granted per million population Scientific publications per million population	All 3 components have equal weights
Human Capital Index	Literacy rate as % of population Secondary school enrolment as % age group Tertiary enrolment as % of age group	Weight of 1 Weight of 2 Weight of 3
UNCTAD Innovation Capability Index	Technological Activity Index Human Capital Index	Both indices have equal weights

Source: UNCTAD (2005:113).

2.1.7 The Industrial Development Scoreboard (UNIDO)

UNIDO has a longstanding tradition in the analysis of industrial competitive performances at the country level as well as in the assessment of countries' industrial capabilities, that is, of those specific capabilities that drive production in manufacturing industries[23]. This section reviews the two main sets of indicators developed over the last decade as part of UNIDO's Industrial Development Scoreboard (IDS)[24]:

- Industrial capability indicators (UNIDO, 2002);
- Indicators of *industrial performance,* namely the Competitive Industrial Performance Index (UNIDO, 2002; UNIDO, 2007; UNIDO, 2009; UNIDO, 2010)[25] and the Industrial cum Technological Advance Index (UNIDO, 2005).

All indicators included in the IDS focus on manufacturing industries and rely on a small number of structural variables only for which hard data are available. The combined use of these country-level indicators allows us to conduct cross-country comparisons and, consequently, to 'benchmark' industrial development.

2.1.7.1 Industrial capability indicators: The drivers of industrial performance

Industrial capability indicators result from the identification and measurement of five drivers of industrial performance – i.e. skills, technological effort, inward FDI, royalty and technical payments abroad, modern infrastructure – and are based on two fundamental methodological premises. The first premise is that 'mapping the structural influences on industrial performance – termed *drivers* – calls for selectivity and simplification' (UNIDO, 2002:34); the second one is that as countries combine the drivers in different ways, it is convenient to construct sub-indicators (see Table 10) and to group countries by conducting a cluster analysis (as an example, see Figure 3) to conflate all the drivers into one overly composite indicator.

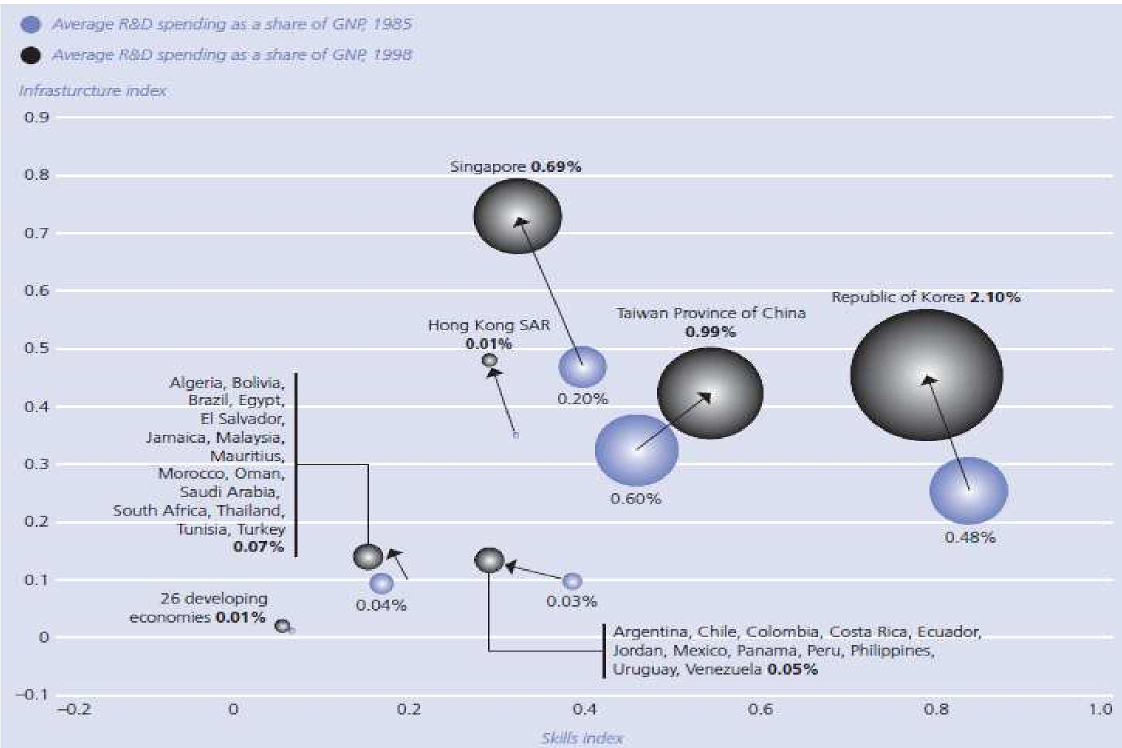
[23] Many of them were first introduced in the *Industrial Development Report 2002-3.* See also the series of *Industry and Development Global Reports*, in particular, The UNIDO 1989/90 and 1990/91 *Industry and Development Global Reports* discussed in section 3.5.
[24] See also Lall and Albaladejo, QEH WP 2002 (published as Lall, 2003).
[25] The Industrial Development Report, 2009: Chapter 11 offers the last updated version of the CIP index. The UNIDO Working paper 05/2009 applies CIP's sub-indicators to trace 'changing patterns in industrial performance'.

Table 10 The UNIDO Industrial Capability Indicators

Drivers[27]	Proxy	Cluster analysis/Composite indicators
Skills[28]	Tertiary enrolments (total and technical subjects)	Cluster analysis (see figure 3) <u>SKILLS, R&D, INFRASTRUCTURES</u> (skills and infrastructures are measured by composite indices while R&D is normalized by GPN)
Technological effort	R&D spending per capita by Productive Enterprises (or as a % of GNP)	Cluster analysis RELIANCE ON <u>DOMESTIC R&D EFFORTS versus FDI</u>
Inward FDI (foreign direct investment)	FDI per capita (or as a % of GNP) (averaged over three years and not disaggregated for mfg)	Cluster analysis RELIANCE ON <u>DOMESTIC R&D EFFORTS versus FDI</u> *AND* <u>HIGH TECH EXPORTS</u>
Royalty and Technical payments abroad	Royalties and technical payments abroad (e.g. purchases of know-how, patents, licenses and blue prints)	**<u>INDEX OF TECHNOLOGICAL EFFORT AND INVENTIVENESS</u>** average of two standardized variables and equal weights: R&D (input) and patents taken out internationally (output)
Modern infrastructure	**Infrastructure index**: (telephone mainlines and mobiles, personal computer and internet hosts)	+ Capital goods imports per capita = **Technology Import Index** (Lall, 2003); Lall (2003:1674) combines this index of 'technological effort' and the one of 'industrial performance' (CIP) in one composite index

Source: Author. Coloured lines identify the various combined uses of drivers in cluster analysis and composite indicators.

Figure 3 Cluster analysis of skills, infrastructures and R&D in developing economies



Source: UNIDO (2002:61).

2.1.7.2 The Competitive Industrial Performance index (CIP)

The Competitive Industrial Performance index benchmarks countries' ability to produce and export manufactures competitively. A combination of four sub-indicators of industrial performance is used to capture different dimensions of countries' competitiveness in production. The four sub-indicators[26] are obtained from basic indicators about the productive and technological structures of countries:

- Manufacturing value added per capita (**MVA**)
- Manufactured exports per capita (**MEXP**)
- Technological structure of MVA and MEXP according to the classification:
  - *Resource-based* manufactures: processed food, refined petroleum, organics
  - *Low-tech* manufactures: textiles/garments, simple metal/plastics, furniture
  - *Medium-tech* manufactures (**MTM**): heavy industry products such as automobiles, industrial chemicals, machinery and relatively standard electrical and electronics product
  - *High-tech* manufactures (**HTM**): complex electrical and electronic (including telecommunications) products, aerospace, precision instruments, fine chemicals and pharmaceuticals.

The four sub-indicators are combined as illustrated in the following Table 11.

Table 11 The CIP index formula

Sub-indicator I_i with i = 1,…,4
I_1: **MVA per capita** (captures a country's level of industrialization)
I_2: **MEXP per capita** (captures a country's ability to produce goods competitively)
I_3: **Industrial intensity: IInt=** (share of MVA in GDP **+** share of MTM and HTM in MVA) / 2
I_4: **Export quality: MXq=** (share of MEXP in total EXP **+** share of MTM and HTM in MEXP) / 2
(Standardization formula: $I_i = (X_i - minX_i) / (maxX_i - minX_i)$)
CIP index = $\frac{1}{4} \Sigma_{i=4} I_i$

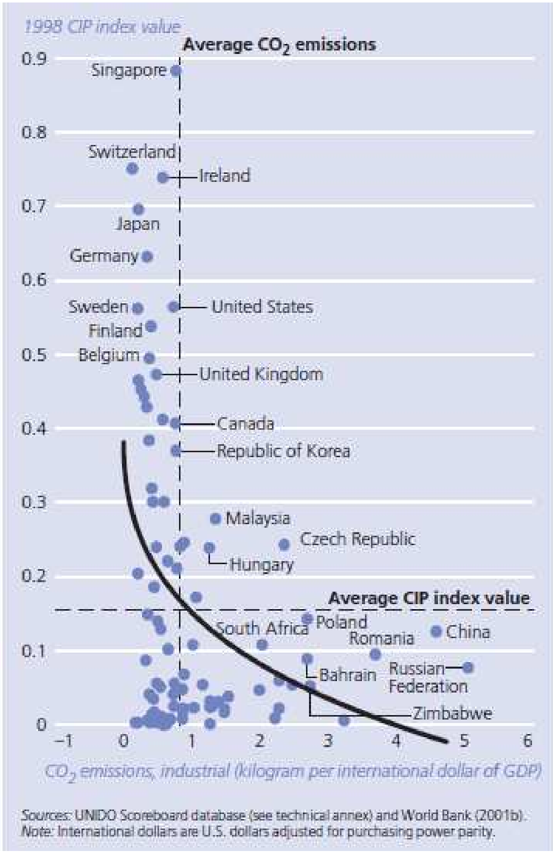
Source: Author.

As the analyses based on the CIP index have shown (in particular, see UNIDO, 2002; Lall, 2003; UNIDO, 2009), this output-based indicator of productive capabilities can be adopted in different contexts, from assessing industrial performance over time or explaining export performances up to more innovative analyses such as of 'industrial sustainability'. UNIDO

[26] The four components of the CIP are highly correlated, especially MVA and industrial intensity.

(2002), for example, analyses the relationship between industrial performance (CIP index) and environmental performance (CO_2 emissions). The regression analysis has shown that industrialization can raise the propensity to pollute, but that this relationship follows an inverted U pattern (see Figure 4)[27].

Figure 4 Regression of CIP on CO_2



Source: UNIDO (2002:54).

2.1.7.3 Industrial cum Technological Advance Index (ITA)

Sub-indicator: Technology Advance Index (TechAd)

Sub-indicator: Industrial Advance Index (IndAd)

The ITA was presented in UNIDO's *Industrial Development Report* 2005 and was calculated for 161 countries for 1990 and 2002. It is composed of two sub-indicators, namely the TechAd and the IndAd, which, respectively, capture the technology and industrial advance axes of the

[27] Luetkenhorst (2010: 18) highlights that 'industrial policy today cannot be relevant, cannot be effective, and cannot be credible, unless it is explicitly framed in the context of natural resource scarcity'. The design of 'sustainable industrial policies' calls for the development of new indicators which facilitate the identification of different patterns of sustainable industrialization.

six performance indicators model. The industrial advance index is defined as the arithmetic mean of the share of manufacturing in GDP and the share of manufactures in total exports. In analogy, the Technology Advance Index is obtained as the arithmetic mean of the share of medium- or high-technology activities in MVA and the corresponding share in exports. The values of both indicators, which are obtained as averages of shares, lie between zero and one. See Table 12 below for a detailed reference of included variables.

2.2 A comparative analysis of country level indicators

By comparing the set of indicators presented in section 2.1, Table 12 shows how the statistical sources used are often similar, while their coverage (in terms of countries and years of observation) may differ significantly. This last issue may represent a serious problem of comparability across indicators.

Table 12 A menu for choice

Typology	*Variable*	*Data source*	*Coverage countries (years)*	*Included in*
INPUT-RELATED VARIABLES	Public R&D exp (% GDP)	EUROSTAT+CIS	48 (2006)	GSII
	Business R&D exp (% GDP)	EUROSTAT+CIS WEF opinion survey	48 (2006) 125 (2004-06)	GSII TechInnov
	R&D expenditure (% GDP)	WEF opinion survey	125 (2004-06)	Tech
	Firms' capabilities in adopting new technologies	WEF opinion survey	125 (2004-06)	TechRead
	Electricity consumption	UNDP ArCo (2004)	72 (1995 – 2000) 162 (1990 & 2000)	TAI ArCo
	ICT expenditures (% GDP)	EUROSTAT+CIS	48 (2006)	GSII
	Land lines per 100 population Land lines per 100 population Telephone mainlines Land lines per 1000 pop	K4D WEF hard data UNDP ArCo (2004)	132 (2006) 125 (2004-06) 72 (1995 – 2000) 162 (1990 & 2000)	KEI Tech TAI ArCo
	Mobile phones per 100 pop Mobile phones per 1000 pop	WEF hard data WEF hard data ArCo (2004)	125 (2004-06) 125 (2004-06) 162 (1990 & 2000)	Tech TechRead ArCo
	PC per 1000 population PC users per 100 population	K4D WEF hard data WEF hard data	132 (2006) 125 (2004-06) 125 (2004-06)	KEI Tech TechRead
	Internet users per 1000 pop Internet hosts per 10000 pop Internet hosts per 10000 pop Internet users per 10000 pop	K4D WEF hard data UNDP WEF hard data WEF hard data ArCo (2004)	132 (2006) 125 (2004-06) 72 (1995 – 2000) 125 (2004-06) 125 (2004-06) 162 (1990 & 2000)	KEI Tech TAI Tech TechRead ArCo
	Capacity of the institutions to create a propitious environment for the diffusion and efficient use of ICTs	WEF opinion survey	125 (2004-06)	Tech
	ICT laws	WEF opinion survey	125 (2004-06)	TechRead
	IPRs	WEF opinion survey	125 (2004-06)	TechInnov
	Receipts of royalty and license fees	UNDP	72 (1995 – 2000)	TAI

	Secondary school enrolment	K4D UNCTAD	132 (2006) 117 (1995 & 2001)	KEI UNICI
	University enrolment Tertiary enrolment rate	K4D WEF hard data	132 (2006) 125 (2004-06)	KEI Tech
	Literacy rate as % pop	UNCTAD ArCo (2004)	117 (1995 & 2001) 162 (1990 & 2000)	UNICI ArCo
	Years of schooling	UNDP ArCo (2004)	72 (1995 – 2000) 162 (1990 & 2000)	TAI ArCo
	Tertiary science enrolment	UNDP UNCTAD ArCo (2004)	72 (1995 – 2000) 117 (1995 & 2001) 162 (1990 & 2000)	TAI UNICI ArCo
	Scientific & engineering graduates (% labour force)	EUROSTAT+CIS	48 (2006)	GSII
	Researcher per million population	EUROSTAT+CIS K4D UNCTAD	48 (2006) 132 (2006) 117 (1995 & 2001)	GSII KEI UNICI
	Scientists and engineers availability	WEF opinion survey	125 (2004-06)	TechInnov
	Public demand for high-tech products	WEF opinion survey	125 (2004-06)	TechInnov
	Research cooperation activities between universities and firms	WEF opinion survey WEF opinion survey	125 (2004-06) 125 (2004-06)	Tech TechInnov
	Quality of research institutions	WEF opinion survey	125 (2004-06)	TechInnov
	FDI	WEF opinion survey	125 (2004-06)	TechRead
OUTPUT-RELATED VARIABLES	Patents per million pop. (USTPO) (EPO for GSII) National patents	EUROSTAT+CIS K4D WEF hard data WEF hard data UNCTAD ArCo (2004) UNDP	48 (2006) 132 (2006) 125 (2004-06) 125 (2004-06) 117 (1995 & 2001) 162 (1990 & 2000) 72 (1995 – 2000)	GSII KEI Tech TechInnov UNICI ArCo TAI
	Medium- and high-tech exports	UNDP	72 (1995 – 2000)	TAI
	Scientific articles per million population	EUROSTAT+CIS K4D UNCTAD ArCo (2004)	48 (2006) 132 (2006) 117 (1995 & 2001) 162 (1990 & 2000)	GSII KEI UNICI ArCo
	Share of exports in high-tech industries (% total exports)	EUROSTAT+CIS	48 (2006)	GSII
	Share of VA in high-tech industries (% TVA)	EUROSTAT+CIS	48 (2006)	GSII
	Manufacturing value added (Industrial Capacity-MVApc)	UNIDO	122 (2000 & 2005)	CIP
	Manufactured exports per capita (Mfg Export Capacity-MXpc)	UNIDO	122 (2000 & 2005)	CIP
	Share of MHT in MVA (Industrialization Intensity-MVAsh)	UNIDO	161 (1990 & 2002) 122 (2000 & 2005)	ITA (TechAd) CIP
	Share of MHT exports in total manufactured exports (Export Quality-MHXsh)	UNIDO	161 (1990 & 2002) 122 (2000 & 2005)	ITA (TechAd) CIP
	Share of MVA in GDP (Industrialization Intensity-MHVAsh)	UNIDO	161 (1990 & 2002) 122 (2000 & 2005)	ITA (IndAd) CIP
	Share of mfg exports in total exports (Export Quality-MXsh)	UNIDO	161 (1990 & 2002) 122 (2000 & 2005)	ITA (IndAd) CIP

Note 1: SII and STI are not reported as the available databases include less than 40 countries.

Note 2: the ArCo Index is included in the menu as it is developed by re-elaborating the TAI and the IDS indexes. The variables selected allow for coverage of 162 countries for the years 1990 and 2000. See Archibugi and Coco (2004).

Source: Author.

However, if we focus on the 45 countries (G45) for which a number of indicators are available (last year available), we discover that the position of countries is relatively stable with only few exceptions. Given a selected set of productive capabilities indicators (Archibugi et al., 2009b), Table 13 shows the position, mean and standard deviation for the cluster of G45 countries.

Table 13 Ranking of the G45 countries based on a selection of synthetic indicators

Country	Tech *WEF*	TechRead *WEF*	TechInnov *WEF*	GSII *EUComm*	KI *WB*	ArCo	TAI *UNCTAD*	TechAdv *UNIDO*	Media *Rank*	St. Dev. *Rank*
Sweden	2	1	6	2	1	1	1	8	2.75	2.71
United States	1	8	3	7	6	5	4	3	4.63	2.33
Switzerlan	8	5	2	3	12	3	3	9	5.63	3.62
Finland	3	12	4	1	3	2	2	18	5.63	6.07
Japan	4	17	1	4	13	8	5	2	6.75	5.60
Denmark	6	9	8	9	2	9	6	20	8.63	5.18
Netherland	10	10	10	11	8	11	12	12	10.50	1.31
United Kingdom	16	6	11	12	9	13	15	4	10.75	4.20
Germany	17	18	5	8	14	12	9	5	11.00	5.07
Singapore	15	2	9	5	25	20	11	1	11.00	8.57
Canada	14	15	12	10	11	6	7	14	11.13	3.31
Israel	9	3	7	6	22	4	17	22	11.25	7.89
Iceland	7	4	18	15	4	14	8	33	12.88	9.66
Korea, Rep.	5	16	14	13	20	18	19	6	13.88	5.69
Norway	11	13	17	17	7	7	10	29	13.88	7.24
Australia	12	7	21	18	5	10	13	30	14.50	8.19
France	27	22	13	14	17	19	16	11	17.38	5.21
Austria	18	19	16	19	16	17	18	17	17.50	1.20
Belgium	28	24	15	16	15	16	14	19	18.38	5.04
Ireland	29	21	19	20	19	22	21	7	19.75	6.07
New Zealand	23	20	22	21	10	15	20	41	21.50	8.96
Honk Kong	22	11	20	22	28	21	32	28	23.00	6.44
Slovenia	24	25	29	24	18	25	22	23	23.75	3.11
Spain	21	28	30	26	23	24	24	15	23.88	4.58
Estonia	13	14	26	28	21	30	25	34	23.88	7.43
Czech Republic	20	23	24	27	26	29	29	16	24.25	4.53
Hungary	25	30	27	29	29	31	27	10	26.00	6.74
Italy	34	27	33	25	24	23	26	25	27.13	4.12
Slovak Republic	26	26	32	33	34	27	37	21	29.50	5.32
Portugal	19	29	28	34	32	33	30	38	30.38	5.58
Greece	30	36	36	31	33	26	28	42	32.75	5.15
Lithuania	31	32	37	30	27	38	31	40	33.25	4.53
Russian Federation	44	44	41	23	35	28	23	31	33.63	8.75
South Africa	35	34	25	35	42	40	33	27	33.88	5.77
Poland	41	38	34	42	31	32	36	32	35.75	4.23
Brazil	32	33	42	39	30	36	38	44	36.75	4.92
Latvia	36	41	31	38	40	43	41	24	36.75	6.36
Mexico	39	40	40	40	41	41	42	13	37.00	9.74
Cyprus	33	31	39	44	36	35	39	45	37.75	4.98
Bulgaria	43	42	45	36	37	34	35	36	38.50	4.17
Argentina	42	43	44	41	38	37	34	35	39.25	3.77
China	45	45	35	32	44	44	44	26	39.38	7.37
India	38	39	23	43	45	45	45	37	39.38	7.41
Turkey	40	37	38	37	43	42	43	39	39.88	2.53
Romania	37	35	43	45	39	39	40	43	40.13	3.36

Source: Archibugi et. al. (2009b:19).

Finally, for the same cluster of countries (G45), the following Table 14 presents the correlation matrix among the productive capabilities indicators selected. Clearly, the correlation coefficients are very high for homogenous groups of productive capabilities indicators.

Table 14 The correlation matrix among the main productive capabilities indicators

G45	Tech *WEF*	TechRead *WEF*	TechInnov *WEF*	GSII *EUComm*	KI *WB*	ArCo	TAI *UNCTAD*	TechAdv *UNIDO*
Tech *WEF*	1							
TechRead *WEF*	0.9112	1						
TechInnov *WEF*	0.8515	0.8436	1					
GSII *EUComm*	0.8352	0.8474	0.9059	1				
KI *WB*	0.8519	0.8474	0.7769	0.8451	1			
ArCo	0.8567	0.8648	0.8435	0.9219	0.9174	1		
TAI *UNCTAD*	0.8519	0.8304	0.8538	0.9424	0.9245	0.9441	1	
TechAdv *UNIDO*	0.5415	0.5278	0.7221	0.7057	0.4788	0.5561	0.6075	1

Source: Archibugi et. al. (2009b:20).

2.3. Trade-based indicators: Product complexity rankings and cross-country comparisons

Given the extensive and disaggregated information on products that enter international markets, only few scholars have recently proposed a set of indirect measures of countries' productive capabilities. As we have seen, traditional indicators are based on factor input data (extracted from input-output tables or industrial censuses typically available at the 2-digit level) and technological intensity (mainly based on R&D expenditure). In contrast, trade-based indicators only require information on the exports of each product and per capita incomes of exporting countries. Trade-based indicators seek to classify exports and to consequently rank countries according to their export basket. The different methodologies proposed share a common analytical starting point[28], namely:

- The complexity/sophistication of a product is a function of the productive capabilities it requires;
- The higher the average income of an exporter, the more sophisticated the export (assumption);
- By looking at countries' export baskets, we can infer the degree of complexity/sophistication of a country's technological and productive structure.

[28] The indicators developed by the Harvard research group on economic complexity are also applied to define the so-called 'product space'. The theoretical building blocks of this approach are detailed in the following sections.

This section reviews the three best known methodologies[29]: the first one is that introduced by Lall et al. (Lall et al., 2005; see also UNIDO, 2009); the last two have been recently developed by the Harvard research group on economic complexity. The method of reflections has been proposed by the Harvard group to resolve the fundamental problem of 'circularity', that is, 'rich countries export rich-countries product' (Hidalgo and Hausmann, 2009). This problem is attributable to the fact that the degree of complexity/sophistication of a given product is extrapolated from an 'income content' measure, rather than from an 'engineering content' measure (Felipe et al., 2010).

2.3.1 The 'Sophistication' index

The Sophistication index has been designed to calculate sophistication at different levels of disaggregation and for different purposes. At the *product level*, the 'soph score' is calculated by taking the weighted average of exporters' income (the weights being each country's shares of world export). Lall et al. (2006) ran this exercise for products at the 3-digit and 4-digit level (SITC Rev 2) for 1990 and 2000. To obtain the average value for exporters' income, countries are divided into 10 income groups for each year (allowing for changes in the groups' composition). Finally, they 'multiply the share in world exports of each product for each income group by the group's average income to get a dollar value for each product' (for an example, see Lall et al., 2006:224). Interestingly, by matching the indicator of sophistication with that of technology intensity (measured as R&D/sales ratio) they are also able to identify: (i) situations in which high sophistication does not equate with technological depth; (ii) patterns of fragmentation in production processes when we observe a combination of high technology with low sophistication (see Table 15).

[29] Previous research and methodologies have relied on trade-based data. See, for example, the classical work by Michaely (1984). See also Alcorta and Peres (1995: 5). The latter proposes a Technology Specialization Index which depicts 'how much any particular country or region adapts its trade structure to changing patterns of world trade in high and low technology products'.

Table 15 Export sophistication and technology intensity

Technology level	Sophistication level	
	Low	High
Low	Technologically simple products whose export production has shifted to low wage areas	Technologically simple products whose export production remains in high wage areas because of trade distortions, resource availability, logistical needs to be near the main markets
High	Technologically advanced products with fragmentable processes located in low wage areas	Technologically advanced products without fragmentable processes where high wage countries retain strong comparative advantage

Source: Lall et al. (2006:226).

At the *country level*, as part of a competitiveness assessment, the 'soph index' can complement the analysis of changes in world market shares (WMS). In particular, a country's export basket can be differentiated by level of sophistication of the products contained in the basket. At an aggregate level, the index can also be adapted as a measure of export similarity among countries. Finally, the 'soph index' can be used as a benchmark tool. An example is provided by Lall et al. (2006:234) who point out how 'the direction of deviation [of a given country] from the predicted relation within a particular industry or category may be revealing of underlying trends'. For example, a country's upgrading is apparent when the difference between a country's actual soph score and the one predicted by its income level increases.

2.3.2 The PRODY index and the method of reflections

The indicators developed by Hausmann et al. (2007:2) are rooted in the idea that 'countries become what they produce'. This means that economic development is primarily a process of learning how to produce (and export) increasingly complex/sophisticated products. In other words, it is a process of productive capabilities building and accumulation.

In such a setting, the PRODY is developed as a quantitative index that ranks traded goods according to the income levels of the countries that export them. For each product *k,* the $PRODY_k$ is calculated as a weighted average of the income per capita of the countries exporting the product.

The country *j* has a GDP per capita equal to Y_j, while its total export is equal to the sum of products *l* in the overall export basket, $X_j = \Sigma_j x_{jl}$. In the PRODY, the weight is the index of revealed comparative advantage (RCA) and is calculated as the ratio of the value share of the product in a country's overall export basket (x_{jk} / X_j) to the sum of all value shares across all countries exporting that product Σ_j (x_{jk} / X_j). The PRODY is measured in 2005 PPP $.

$$\text{PRODY}_k = \sum_j \underbrace{\frac{(x_{jk}/X_j)}{\sum_j (x_{jk}/X_j)}}_{\text{RCA}} Y_j. \qquad \text{EXPY}_i =_l \left(\frac{x_{il}}{X_i}\right) \text{PRODY}_l.$$

At the country level, the EXPY index is simply calculated as a weighted average of the complexity of products exported by the country (measured by the PRODY index). The weight is the share of the product in the country's export basket.

As anticipated above, to respond to the criticism that the PRODY index is afflicted by a fundamental problem of 'logical circularity', Hidalgo and Hausmann (2009) recently developed a new methodology called 'method of reflections'. This method aims to separate the information derived from income levels and that drawn from the network structure of countries and the products exported. The authors present the idea behind their new method using the *Lego* models as an analogy. Each productive capability in a country is seen as a Lego piece in the country 'Lego box'. Accordingly, countries will only be able to manufacture those products for which they have the necessary productive capabilities (Lego pieces). Thus, countries' diversification in production (and export) depends on the limited set of activities their productive capabilities allow them to perform. Moreover, as certain commodities require special and exclusive productive capabilities, we can expect that some products are exported by fewer (less ubiquitous) countries. This observation has been empirically tested by representing the network of relatedness between products – i.e. product space (Hidalgo et. al, 2007; Hidalgo and Hausmann, 2009). Network analysis has shown that 'countries tend to move to goods close to those they are currently specialized in, allowing nations in more connected parts of the product space to upgrade their exports basket more quickly' (Hidalgo et. al, 2007:1).This approach builds on the same intuition we find in Richardson (1972), who determined that there are products whose embedded productive capabilities can be easily redeployed for *similar* productive activities, while other productive capabilities (which are quite exclusive) can only be used in a limited range of productive processes. Given this framework, Hidalgo and Hausmann (2009:10573) develop two complexity measures for both countries and products:

- Diversification: number of products that a country exports with RCA

$$k_{c,0} = \sum_{p} M_{cp},$$

- Ubiquity: number of countries that export the product with RCA

$$k_{p,0} = \sum_{c} M_{cp}.$$

where c denotes the country, p the product and $M_{cp} = 1$, if country c exports product p with RCA or $M_{cp} = 0$ otherwise. By calculating these two measures jointly and iteratively, the two measures of complexity are refined step by step as they take into account the information from the previous iterations, for $N \geq 1$

$$k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} k_{p,N-1}, \qquad k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} k_{c,N-1},$$

The results obtained by adopting this methodology are explained by the theoretical framework developed by Hausmann and Hidalgo (2010). Their model not only shows that countries with a limited set of capabilities will be able to manufacture few products, but also that the process of accumulation of additional capabilities is characterized by increasing returns dynamics. Clearly, the explanation has to be found in the fact that 'the likelihood that a new capability will be able to synergize with existing capabilities and become useful for the production of a new product is low in the absence of the other requisite capabilities' (Hausmann and Hidalgo, 2010:25). On the contrary, countries with a broader set of available capabilities would greatly benefit from the acquisition of an additional capability, which has the greatest potential for as many combinations with the other capabilities they possess[30].

2.4 A comparative analysis of trade-based indicators

Some of the results obtained by adopting the set of indicators discussed in section 2.3 are reported below.

[30] A similar approach is developed in Andreoni (2010) and Andreoni and Scazzieri (2011). However, the former focuses on the development of a capability theory of production while the latter focuses on the identification of the triggers of increasing and decreasing returns.

Table 16 Regional sophistication scores (ranked by 2000 scores)

Region	1990	2000
N America	84.06	74.47
W Europe	80.86	71.88
LAC 1 (including Mexico)	69.14	64.91
E Asia 2 (excluding China)	69.95	64.83
E Asia 1 (including China)	69.18	62.78
LAC 2 (excluding Mexico)	65.87	61.28
SSA 1 (including South Africa)	NA *	59.55
SSA 2 (excluding South Africa)	59.17*	55.93
MENA	62.60	55.72
S Asia 1 (including India)	58.53	50.68**
S Asia 2 (excluding India)	53.51	39.73**

Notes: * There are no export data for South Africa for 1990; this is why the SSA 1 and SSA 2 scores are identical.
** South Asian data for 2000 includes export data for 2001 for Bangladesh and Sri Lanka, which are missing 2000 data.

Source: Lall et al. (2005:13).

Table 17 Top and bottom world exports in sophistication at the 4-digit level, 2000

SITC code	Product	1990		2000	
		Rank	Score	Rank	Score
Most sophisticated 20 products					
5843	Cellulose acetates	50	90.73	1	100.00
7223	Track-laying tractors	2	99.52	2	97.78
9510	Armored fighting vehicles, arms, and ammunition	17	93.65	3	96.43
6812	Platinum and other metals	264	80.71	4	95.56
7126	Steam and other vapor power units	7	96.13	5	94.57
8748	Electrical measuring, checking, analyzing instruments	24	93.09	6	94.12
2120	Fur skins, raw	14	93.95	7	93.79
7133	Int. combustion piston engines for marine propulsion	9	95.73	8	93.57
7239	Parts of civil engineering/contractors plant	46	90.89	9	93.30
2512	Mechanical wood pulp	236	81.94	10	93.03
8744	Instruments for physical or chemical analysis	37	91.71	11	92.44
7741	Electro-medical apparatus	5	98.05	12	92.20
0459	Buckwheat, millet, canary seed, grain	168	84.87	13	91.37
2511	Waste paper, paperboard for use in papermaking	35	91.93	14	89.93
8933	Ornamental objects of resin, plastics, cellulose	524	64.13	15	89.87
7149	Parts of non-electrical engines and motors	68	89.30	16	89.21
5155	Other organo-inorganic compounds	60	89.68	17	89.08
7268	Bookbinding machinery and parts	12	94.34	18	89.03
6880	Uranium depleted, thorium and their alloys	539	62.98	19	89.01
7144	Reaction engines	347	76.87	20	88.85
Least sophisticated 10 products					
4245	Castor oil	746	16.31	757	9.22
0611	Sugars, beet, and cane (raw, solid)	733	25.46	758	8.27
2613	Raw silk	759	8.55	759	6.69
2713	Fertilizers of natural calcium/alum. phosphate	761	6.65	760	5.66
2232	Palm nuts and palm kernels	737	21.73	761	5.54
2640	Jute and other textile bast fibers n.e.s.	764	4.25	762	5.43
2655	Manila hemp, raw or processed	765	2.01	763	4.68
4244	Palm kernel oil	750	13.76	764	4.35
2714	Potassium salts, natural or crude	763	5.07	765	4.19
2235	Castor oil seeds	766	0.00	766	0.00

Source: Lall et al. (2006:228).

Table 18 Share in country's total exports, by product complexity

Country	Rank	Product Complexity Level (1 -highest; 6- lowest)						
		1	Top 100	2	3	4	5	6
Japan	1	39.7	10.0	19.0	21.9	11.4	6.6	1.5
Germany	2	39.6	7.9	24.5	16.0	10.9	5.6	3.4
USA	6	28.1	7.2	21.5	22.8	12.9	9.4	5.2
France	10	26.2	3.2	22.3	22.0	16.1	7.5	5.9
Singapore	19	14.3	1.5	14.0	39.2	11.1	4.2	17.2
Rep. of Korea	21	17.7	2.2	18.9	32.5	14.6	8.3	8.0
Malaysia	38	4.7	0.5	14.3	38.6	15.6	7.4	19.4
India	49	8.1	0.7	9.2	8.3	9.4	30.4	34.7
China	50	5.7	0.5	13.9	20.7	19.5	15.6	24.5
Thailand	59	6.8	0.5	9.1	31.3	16.2	11.5	25.1
Philippines	74	3.3	0.3	7.3	49.2	20.5	6.4	13.4
Indonesia	76	3.1	0.4	5.3	12.9	15.2	14.4	49.1
Viet Nam	98	1.8	0.2	3.0	4.2	7.3	14.2	69.6
Pakistan	101	0.7	0.1	2.2	2.2	3.5	11.9	79.6

Note: 1 is the most complex and 6 the least. Top 100 refers to the top most complex products. Rank is the ranking of the country (in a total of 124 countries) according to the measure of country complexity (as

Source: Felipe et al. (forthcoming:23).

Table 19 List of 10 most complex products

Rank	HS 6-digit level description	HS 2-digit level description
1	Other cyclic hydrocarbons: Cumene	Organic ch emicals
2	Metalworking machine-tools/ultrasonic machine-tools: For dry-etching patterns on semiconductor materials	Nuclear reactors, boilers, machinery, etc.
3	Particle accelerators, and parts thereof, nes: Ion implanters for doping semiconductor materials	Electrical, electronic equipment
4	Methacrylic acid, salts	Organic chemicals
5	Carbide tool tips, etc.: Tool plates/tips/etc., sintered metal carbide & cermets	Tools, implements, cutlery, etc. of base metal
6	Photo, cine laboratories equipment, nes; screens for projectors: Direct write-on-wafer apparatus	Optical, photo, technical, medical, etc. apparatus
7	Other inorganic esters: Hexamethylenediamine, its salts	Organic chemicals
8	Other electronic measuring, controlling, etc., apparatus: Instruments nes using optical radiations (UV, visible, IR)	Optical, photo, technical, medical, etc. apparatus
9	Other machinery, mechanical appliances having individual functions: Laser, light, and photon beam process machine tools	Nuclear reactors, boilers, machinery, etc.
10	Sheet, plates, rolled of thickness 4.75mm plus, of iron or steel or other alloy steel: Cold rolled alloy-steel nes nfw, <600mm wide	Iron and steel

Source: adjusted from Felipe et al. (forthcoming:23).

3. Towards new industrial diagnostics for policy design

3.1 Measurement with or without theory: Methodological problems and informative limits

For capability indicators to be meaningful, the assumptions made for their construction as well as their informative limits need to be known. Actually, the more synthetic indicators are grounded in a thorough analytical framework, the more informative and testable they are. Moreover, by comparing/integrating the information they provide with other pieces of quantitative and qualitative evidence (e.g. disaggregated data on sector-specific and/or firm-specific productive capabilities), a stylized representation of productive capabilities dynamics and the resulting competitiveness performances is possible. Building indicators without theory has various shortcomings[31]. For example, variables tend to be selected more on the basis of data availability rather than their informative content. Secondly, overly composite indicators are generated under the assumption that more ingredients will provide the cake with a better taste (Lall, 2001; UNIDO, 2002). Thirdly, indicators tend to be adopted by practitioners and policymakers in an uncritical way – i.e. *list disease* without realizing that these measures are mainly proxies of extremely complex and multilayered processes (Archibugi, 1988). Therefore, some key methodological considerations have to be made. Being aware of the theoretical assumptions and methodological problems is extremely helpful for the refinement of current indicators and the identification of new industrial diagnostics for policy design.

Productive capabilities: 'Determinants' and 'enablers'

Firms are socially-structured production units characterized by certain technological and organizational knowledge bases. As discussed in section 1.2.1, the same knowledge resources can provide different services. This implies that firms with the same technological and organizational knowledge basis can actually manifest and develop different capabilities in production. Thus, widely used variables such as expenditure in R&D, investments in capital goods and licenses and various indicators of worker quality (e.g. literacy rates) appear to be 'proxies of *determinants* of capability rather than indicators of capability itself' (Romijn, 1999:3). The reason is that productive capabilities are not simply prepackaged stocks of codified knowledge. Instead, given a certain amount of knowledge resources, capabilities continuously develop in a circular and cumulative manner through micro-learning processes

[31] For a detailed discussion of methodological problems and informative limitations, see also Archibugi and Coco (2005); Archibugi et al. (2009a), while Godin (2007) discusses the link between input and output measures and the functional model of production.

(Kline and Rosenberg, 1986; Andreoni, 2010). This also implies that productive capabilities indicators should not simply attempt to capture the knowledge basis of firms – i.e. *determinants* of capabilities, but also those factors external to the firm that affect learning processes – i.e. *enablers* of productive capabilities building.

This approach would allow us to better capture those disembodied capabilities, forms of tacit knowledge and conscious decisions by the agents involved in technological learning which are responsible for the heterogeneity we observe among firms and, ultimately, for their different degrees of competitiveness. Moreover, the recognition that the same determinants, that is, the same stock of technological and organizational knowledge, may drive different patterns of productive capabilities building/accumulation suggests that the information provided by these indicators is interpreted in a non-deterministic way. As stressed by Katz (2006: 897) 'Unlike some physical processes social activities are never completely deterministic nor are they completely random'. It is therefore extremely important to identify causal structures and the set of causational chains that regulate development processes.

Learning processes in historical time: Time lags and time scales

Learning proceeds in historical time and is technological/sector-specific (Rosenberg, 1994; Bell, 2006; Andreoni, 2010). This means that indicators which fail to consider the existence of time lags and technological/sector-specific characteristics will provide a very misleading picture of the capabilities owned by countries' productive/technological structures (and by firms as their components). For example, let's consider a firm like Nokia in its first years of high-tech production. A capability indicator based on output variables would only convince us that Nokia's story is an incontrovertible one of continued business failure, as it did not make any profit in high-tech production for nearly two decades[32]. Productive capabilities development takes time and is cumulative, and hence, relying solely on output variables does not allow us to capture the ongoing learning process, the result of which will eventually be registered by our output-based indicator in the future. In other words, 'there may be intensive processes of knowledge acquisition under way that are not yet reflected in economic outcomes, for example, in trade patterns' (OECD, 2006:201). However, relying on input-based measures only does not resolve the time lag problem, either. Without registering the tremendous success of Nokia in the output (e.g. competitiveness performances), we would not have had any way of determining whether Nokia had a *learning-rich* or *learning-poor* experience.

[32] Interestingly, the learning trajectory from industry entry point to the initiation of significant innovation was around 20 years, e.g. in the case of Samsung (Bell, 2006:29).

Even if we recognize the existence of time lags and thus of qualitative transformations and discontinuities, truncations and reverses, we are still quite far from an explicit treatment of the time/stages firms require to build productive capabilities and to consequently move from low- to medium- and high-tech industries – i.e. *time scales*[33]. From a managerial as well as a policy design perspective, it becomes crucial to find stylized answers to questions such as ‘over what time period must the investments in specific kinds of productive capabilities be made?’ or ‘when will the returns be realized?’, and finally ‘what factors might affect those time scales (e.g. learning faster/slower)?’. Possible answers can be drawn from detailed long-term longitudinal studies and/or in tracking changes over time. This, of course, calls for the collection of time-series data. In this respect, synthetic indicators should be developed to capture the rate of change of key variables more than their level at any particular moment.

Factors aggregation: Weights, complementarities and correlations

Many factors are included in the development of productive capabilities as determinants or enablers. Thus, capabilities indicators very often tend to aggregate multiple variables which proxy these factors. As we will see, capability indicators frequently conflate input-based variables with output-based variables, a choice which exacerbates aggregation problems (Lall, 2001; Grupp and Mogee, 2004; OECD, 2008). Composite indicators are characterized by two fundamental aggregation problems (Kaplan, 2004). On the one hand, when the importance of each component – i.e. its weight – is the result of an *ex ante* subjective evaluation, the same data set can provide entirely different information. On the other hand, the choice of aggregating different components (especially mixing input-based and output-based variables) derives from the assumption that they are substitutable.

Even when avoiding overly composite indicators, productive capabilities indicators which aggregate only ‘proxies of determinants of capabilities’ – i.e. input-based variables – are equally subject to aggregation problems. The various factors should be available according to a certain *degree of proportionality* in order to obtain the intended productive outcomes and achieve certain levels of competitiveness. For example, increasing R&D investment for the building of new labs without proportionately raising the amount of engineers universities can graduate will not have the expected impact on technological capabilities development.

[33] See Katz (1987) for a collection of initial attempts to identify technological learning stages and respective time scales. Bell (2006) provides a retrospective critique of the technological capability literature which focuses excessively on cross-sectional differences instead of on an explicit treatment of time scales.

As a result of existing complementarities among given factors (which reveal underlying structural relationships), variables in composite indicators are very often highly correlated. For example, 'countries with a high share of graduates have at the same time a high rate of scientific publications, patents and so on' (Archibugi et al., 2009a:3). These correlations suggest that capabilities determinants and enablers complement each other, although their interdependencies cannot be read as causal links or as a set of deterministic relationships (UNIDO, 2002:59-60). In this respect, cross-correlation tables may be compiled with the different proxies, which enter indicators of capabilities determinants and capabilities enablers or output-based indicators. In fact, when looking at the resulting correlation matrixes, we might, for example, discover that correlations between various factors such as R&D and output differ substantially at different stages of development. This result would suggest that R&D activities play a distinctive role in determining the competitiveness performance of countries at different stages of development. In fact, the distinct histories of countries' industrialization demonstrate how capabilities determinants and enablers (as well as the resulting productive capabilities) can be combined in various ways in line with different development strategies and paths.

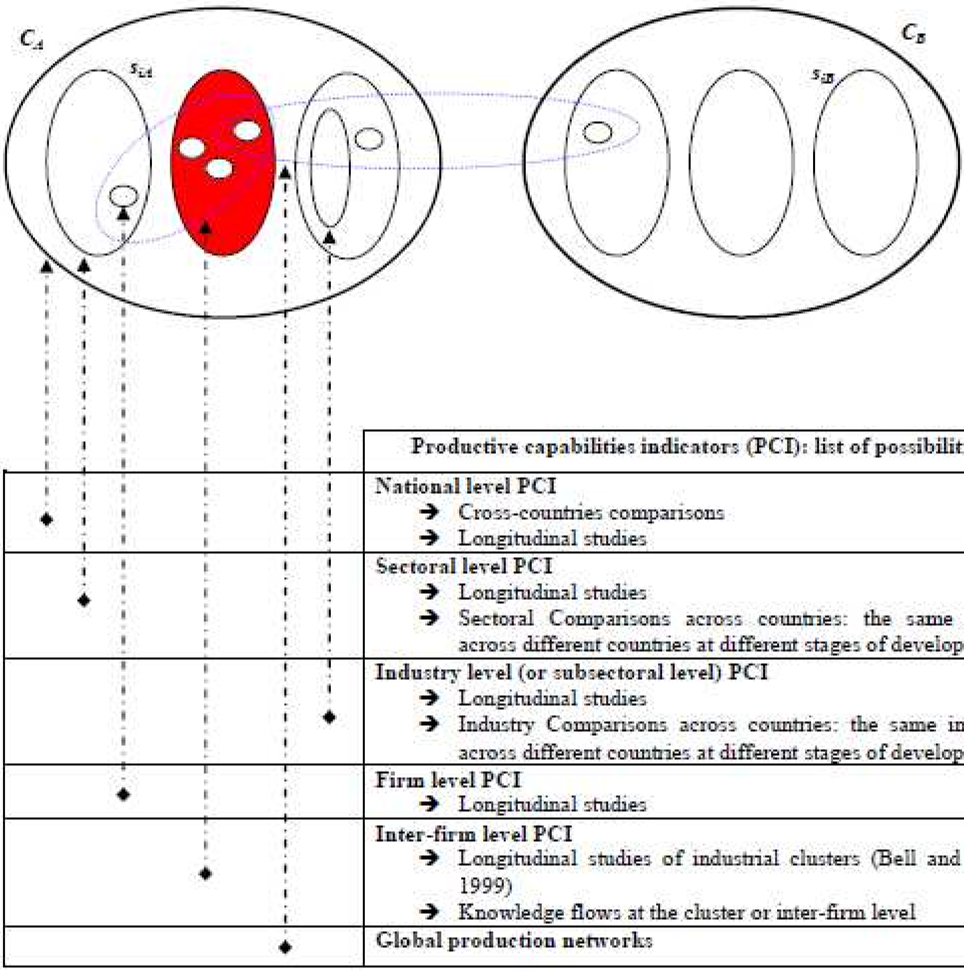
Levels of aggregation and disaggregation

Productive capabilities are embedded in physical agents – i.e. machines and workers – as well as in organizational configurations and institutional arrangements. According to the *loci* where they reside as well as the degree of aggregation considered – i.e. individual agent, collective agent (e.g. organizations) or systemic (e.g. regional, national level) – different capabilities indicators should be developed. The reason behind this is that productive capabilities indicators at different levels of aggregation – i.e. firm, sectoral, regional, country level – provide distinct information for benchmarking and industrial policy design. As a matter of fact, national level indicators tend to conceal important sectoral and regional differences while sectoral indicators conceal important firm differences (see Figure 5).

The multilevel analysis we envisage here is further complicated by the fact that productive capabilities at different levels – i.e. firm, sectoral, regional, country level – are interrelated with each other in different ways in accordance with specific country characteristics. In this respect, the concept of social capabilities introduced above seems to capture the country-specific way through which linkages among different capable entities work, develop and cluster. One particular subset of these linkages is that which connects firms embedded in the same regional innovation system or firms which are part of global production networks (GPNs). The spread of

GPNs poses serious challenges in terms of the usefulness of country level indicators. This notwithstanding, as governments' policies operate at the national level, we should integrate national level productive capability indicators with other appropriate diagnostics.

Figure 5 **Productive capabilities indicators in a 3 sectors, 2 countries model**



Productive capabilities indicators (PCI): list of possibilities
National level PCI ➔ Cross-countries comparisons ➔ Longitudinal studies
Sectoral level PCI ➔ Longitudinal studies ➔ Sectoral Comparisons across countries: the same sector across different countries at different stages of development
Industry level (or subsectoral level) PCI ➔ Longitudinal studies ➔ Industry Comparisons across countries: the same industry across different countries at different stages of development
Firm level PCI ➔ Longitudinal studies
Inter-firm level PCI ➔ Longitudinal studies of industrial clusters (Bell and Albu, 1999) ➔ Knowledge flows at the cluster or inter-firm level
Global production networks

Source: Author.

Cross-countries comparability and scale adjustments

International comparisons are particularly difficult when countries involved are at different stages of development. Not only are countries at different stages of development endowed with various degrees of productive and technological capabilities, but their capabilities most probably vary as the technologies employed in production differ. This implies that cross-country comparisons can be more useful if conducted among groups of countries which are at the same stage of development, that is, countries with similar production/technological structures. The selection of various groups of countries may either result from the application of cluster analysis techniques or from selecting groups of countries on the basis of development level indicators. For example, highly reliable and more detailed databases are available for OECD countries.

According to these different clusters of countries, various group-specific sets of productive capability indicators can be developed. By following this strategy, more refined measurements can be elaborated and, hence, more detailed cross-country comparative and convergence analyses performed – e.g. the European integration process. However, comparisons need to be normalized. Recent research denotes that ‘a performance indicator derived from a ratio that exhibits a scaling correlation between the numerator and denominator must be scale-adjusted before it is used in comparisons’ (Katz, 2006:895). Thus, all time indicators rely on ratios such as GERD/GDP, GDP/population or citations/paper, and although the denominator is a measure of size, we cannot simply assume that the indicator is normalized by the denominator.

3.2 A new set of indicators for the assessment of country-level productive capabilities

The analysis provided above reveals the numerous limits of today’s available country-level synthetic indicators, but also proposes possible solutions and areas of improvement. In fact, some of the shortcomings highlighted, such as the fact of using overly composite indicators or measures which do not incorporate time lags and time scales, might be avoided. Building on the theoretical and empirical analysis provided so far, this section suggests a new set of indicators and methodologies to assess and compare country-level productive capabilities. The research carried out to date on productive and technological capabilities has not been able to develop a comprehensive and consistent analytical framework and a set of suitable indicators. On the contrary, many ideas and concepts have been attached to the word capabilities in an attempt to capture all possible capability dimensions at different levels of aggregation (see section 1.2). However, there is wide acceptance of the fact that *productive capabilities result from learning processes in production.* Although it is practically impossible to quantify all the complex and multilayered learning processes through which a given country’s productive capabilities develop, the second best strategy would be to identify, distinguish and group the most important factors that *enter, interact with* and *exit from* these learning processes (provided that the necessary data is available).

Productive Capabilities Indicators (PCI)

The new of set of productive capabilities indicators proposed here builds on four factors, namely capability determinants, capability enablers, capability outcomes and production outputs. The analytical framework describing how these factors relate to each other is illustrated in Figure 6.

- ***Capability determinants***

  A set of 'input factors', such as technical education and R&D spending, represent 'knowledge ingredients' in learning processes. These knowledge ingredients are primarily human capital and investments in the acquisition of codified knowledge (e.g. design and engineering specifications for machineries). Before turning into productive and technological capabilities, these knowledge ingredients have to first be processed, transformed and adapted by those actors engaged in production in firms. A broad range of machines, equipment and firm infrastructures, all of which are elements that define the production capacity of a given firm, complement these actors. In fact, as discussed in section 1.2.2, the transformation of knowledge ingredients in productive capabilities would not be possible without a series of strategic investments aiming at the expansion of production capacity. Thus, the set of input factors entering the learning processes in production must be proxied by a series of information which captures the presence of 'knowledge ingredients' and the 'production capacity' at the country level. Taken together, 'knowledge ingredients' and 'production capacity' constitute what we call the *capability determinants* (see Figure 6).

- ***Capability enablers***

  The firm-level process of productive capabilities development, its speed, effectiveness and multi-directionality are affected by the presence (absence) of a series of 'mediating factors' which are country-specific. These mediating factors, mainly infrastructures such as roads, railways, port network systems, public research infrastructures and ICTs, act as facilitating factors rather than directly entering the firm-level process of productive capabilities building. In other words, by reducing *transaction costs* (e.g. transportation costs of machinery or technicians exchange) and *learning costs* (e.g. increasing absorption capacities with ICTs, faster diffusion of productive best practices) these factors enable processes of productive capabilities building and accumulation at firm level. They are referred to here as *capability enablers*.

To recap, processes of productive capabilities building and accumulation are triggered by two groups of input factors which we refer to here as '*capability determinants*' and '*capability enablers'*, respectively. The main reason for distinguishing between these two groups of input factors is that they play different roles in productive capabilities building. Another reason behind this is that input factors, being determinants or enablers, are linked more by a relationship of complementarity than one of substitutability (see also sections 1.2.2 and 3.1). In fact, by developing sub-indicators for investments in production capacity on the one hand, and sub-indicators for knowledge ingredients (mainly investments in human capital), on the other, it is also possible to analyse the relationships of complementarity that exist among the input factors grouped into capabilities determinants. Clearly, at the country level, investments in production capacity and investments aimed at increasing the amount of knowledge ingredients available to firms (typically, human capital) call for different forms of policy intervention.

- ***Production outputs and capability outcomes***

  According to the amount and quality of capabilities determinants and capability enablers available in a certain country, and given the ability of its entrepreneurs to identify and capture productive opportunities, individual firms (or groups of firms):

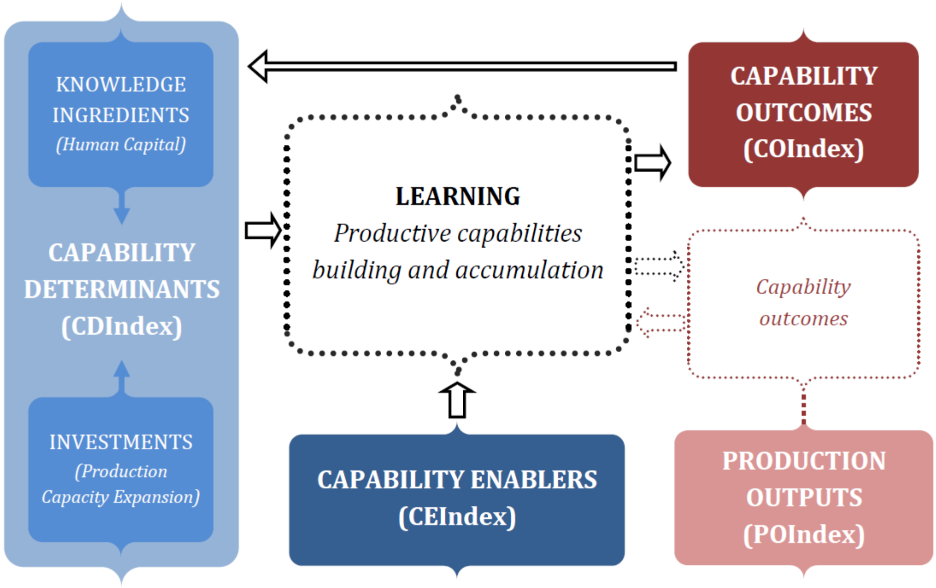
  - Will be able to undertake production processes in a certain combination of sectors and industries;
  - Will experience cumulative processes of learning and productive capabilities building triggered by 'internal compulsions' in production (Rosenberg, 1969 and 1972);
  - Will be continually reshaped by processes of 'creative destruction' (Schumpeter, 1932).

As a result of these dynamics, a certain amount of productive capabilities develop and accumulate, while others are simply transformed or even lost. In turn, the new developed and accumulated productive capabilities, referred to here as *capability outcomes,* are continuously reinserted in production and affect the same learning processes from which they have been derived – i.e. feedback mechanisms. Given the fact that the firm-level dynamics generating capability outcomes are extremely complex and interconnected, measuring the amount of capability outcomes generated in a certain country and time period turns out to be particularly difficult. Two strategies are proposed here.

Firstly, as shown by trade-based indicators (see section 2.3), the development and accumulation of productive capabilities at the country level is 'reflected' in its *productive outputs*, that is, in the basket of commodities produced and internationally traded. The latter can be proxied by considering the specialization of a given country in the production of certain commodities with a certain degree of complexity or by looking at output indexes such as MVA, also disaggregated for low-, medium- and high-tech sectors[34]. Thus, these productive outputs are indirect measures of the productive capabilities developed and employed in production by the set of firms producing in a certain country.

However, there are few capability outcomes such as new products, new machineries or new blueprints that can be directly measured. The reason is that these kinds of capabilities outcomes tend to be codified and, when possible, patented. In fact, capability outcomes such as patents become part of the stock of knowledge ingredients which triggers the initial process of learning in production – i.e. the feedback mechanisms. Thus, there are a set of directly measurable capability outcomes that re-enter the learning in production process as new capability determinants.

Figure 6 A new analytical framework for country-level productive capabilities indicators



Source: Author.

[34] For any given country, the patterns of specialization and diversification followed by its firms will determine their technological and productive structure.

To recap, the new methodology suggested here focuses on three direct measures of productive capabilities – i.e. capability determinants (CD), capability enablers (CE) and capability outcomes (CO) – and one indirect measure of country-level capability outcomes – i.e. production outputs (PO). The possible variables and data sources that are included in the construction of each composite indicator are synthesized in the following Table 20.

Table 20 Composite indicators for capability determinants, capability enablers, capability outcomes and production outputs

<table>
<tr><th colspan="5">PRODUCTIVE CAPABILITIES INDICATORS (PCI)</th></tr>
<tr><td colspan="4">DIRECT MEASURES</td><td>INDIRECT MEASURES</td></tr>
<tr><td colspan="2">Capability Determinants CDIndex</td><td>Capability Enablers CEIndex</td><td>Capability Outcomes COIndex</td><td>Production Outputs POIndex</td></tr>
<tr><td rowspan="6">ENDOGENOUS EFFORT</td><td>R&D expenditure by productive enterprises (per capita and as a % of GNP)</td><td>R&D public expenditure (per capita and as a % of GDP)</td><td>Patents taken out in the US (per 1000 people)</td><td>Industrial intensity (as calculated for the CIP)</td></tr>
<tr><td>Secondary and tertiary education</td><td>Traditional infrastructure (e.g. commercial energy use)</td><td>ISO certificates (per 1000 people)</td><td>Export quality (as calculated for the CIP)</td></tr>
<tr><td>Vocational students (as a % of population)</td><td>Personal computers (per 1000 people)</td><td>Product complexity and diversification (e.g. export baskets)</td><td></td></tr>
<tr><td>Tertiary technical enrolments (as a % of population)</td><td>Internet hosts (per 1000 people)</td><td></td><td></td></tr>
<tr><td>Graduates in science and engineering (as a % of population)</td><td>Mobile phones (per 1000 people)</td><td></td><td></td></tr>
<tr><td></td><td>Telephone mainlines (per 1000 people)</td><td></td><td></td></tr>
<tr><td rowspan="3">IMPORTED</td><td>Royalty and licences payments (per capita and as a % of GDP)</td><td></td><td></td><td></td></tr>
<tr><td>FDI inward per capita</td><td></td><td></td><td></td></tr>
<tr><td>Capital goods import per capita</td><td></td><td></td><td></td></tr>
<tr><td colspan="5">Note: The list of variables for each composite indicator is not definitive as various tests (e.g. correlations among variables) have to be performed to confirm that these variables can be used as a proxy for each of the dimensions selected: CD, CE, CO and PO.</td></tr>
</table>

Source: Author.

Benchmarking, ranking, cross-country comparisons and the analysis of trajectories

Given the fact that the four productive capabilities indicators proposed here are modular, it is possible:

(i) To add variables into homogenous groups of factors, namely capability 'determinants', 'enablers', 'outcomes' and production 'outputs';

(ii) To consider the interaction among different sets of variables inside each group. For example, the CDIndex might be disaggregated to separately analyse (and in an interacting way) the 'knowledge ingredients' component from the 'investment in production capacity' component. This makes it possible to determine the existence of mismatches between the two sets of complementary input factors as well as whether the industrial policies have been oriented mostly towards one component or the other. Another possibility is to aggregate input factors according to their origin, in particular by distinguishing capability determinants that are endogenously generated from those which are imported from other countries (the latter typically being technology acquisitions of codified knowledge measured by royalty payments or production equipment measured by capital goods imports).

(iii) To integrate the set of indicators developed with other available sets. For its theoretical and methodological premises, the most immediate integration is the one with UNIDO's *Industrial Development Scoreboard* (see section 2.1.7.2). Specifically, if we substitute the Production Output Index (POI) with the index of Competitive Industrial Performance (CIP), we obtain an updated version of the IDS which combines the CIP as an output measure with the three composite indexes for capabilities determinants (CDI), capabilities enablers (CEI) and capabilities outcomes (COI).

The set of possibilities listed above mainly refers to *benchmarking* and *ranking* countries as well as performing *cross-countries comparisons* at each point in time. However, the Productive Capabilities Indicators (PCI) can also be adopted with time-series data for performing different longitudinal analyses (see section 3.1 on the importance of considering time lags and time scales) and cluster analyses[35]. As illustrative cases of the many possibilities offered by these indicators, the paper stylizes the following possible analytical exercises:

[35] Cluster analysis is a statistical technique for identifying relatively homogenous groups of cases (e.g. countries) according to their quantitative features (e.g. a certain level of capability determinants).

(i) PCI can be used to evaluate *industrial development precursors*, that is, the 'starting point conditions' in terms of productive capabilities shown by a given country at a certain stage of development. Interestingly, the latter can be proxied by levels of income per capita, but also by more production-based measures such as the composition of the export basket as well as the stage of industrial development measured by MVA;

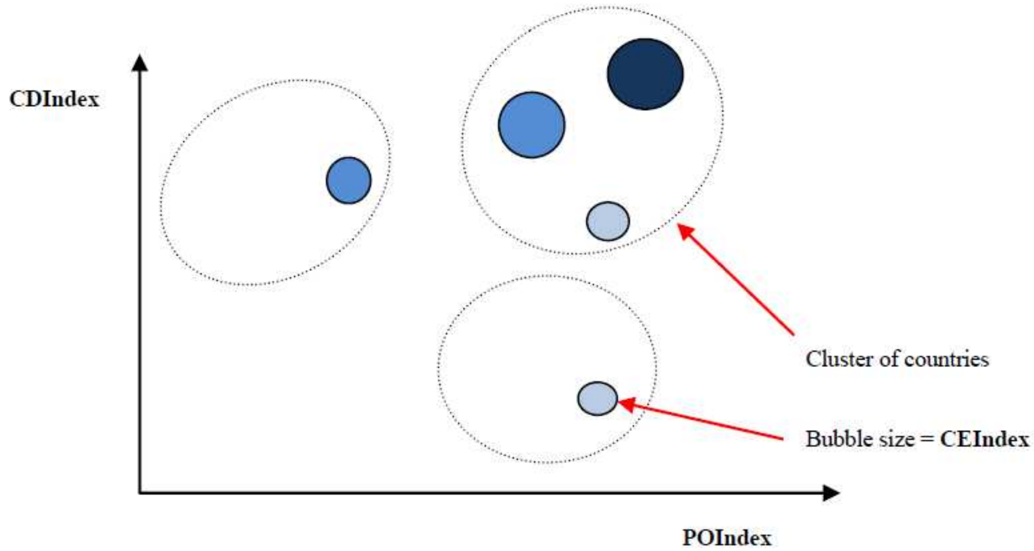
(ii) Given certain initial conditions, PCI can be used as a focusing device for the identification of those clusters of countries that experience 'learning-rich' vs. 'learning-poor' experiences (e.g. fast growth of POI with a relatively slow growth of CDI);

(iii) PCI can be used for tracking the process of productive capabilities accumulation followed by a given country over time (as illustrated in Figure 7). In other words, it is possible to track how the relationships between CD, CE, CO, PO change over time;

(iv) PCI can be used as a focusing device for the identification of those clusters of countries that experience unbalanced patterns of productive capabilities accumulation (e.g. high-sustained CEI and low/discontinuous CDI);

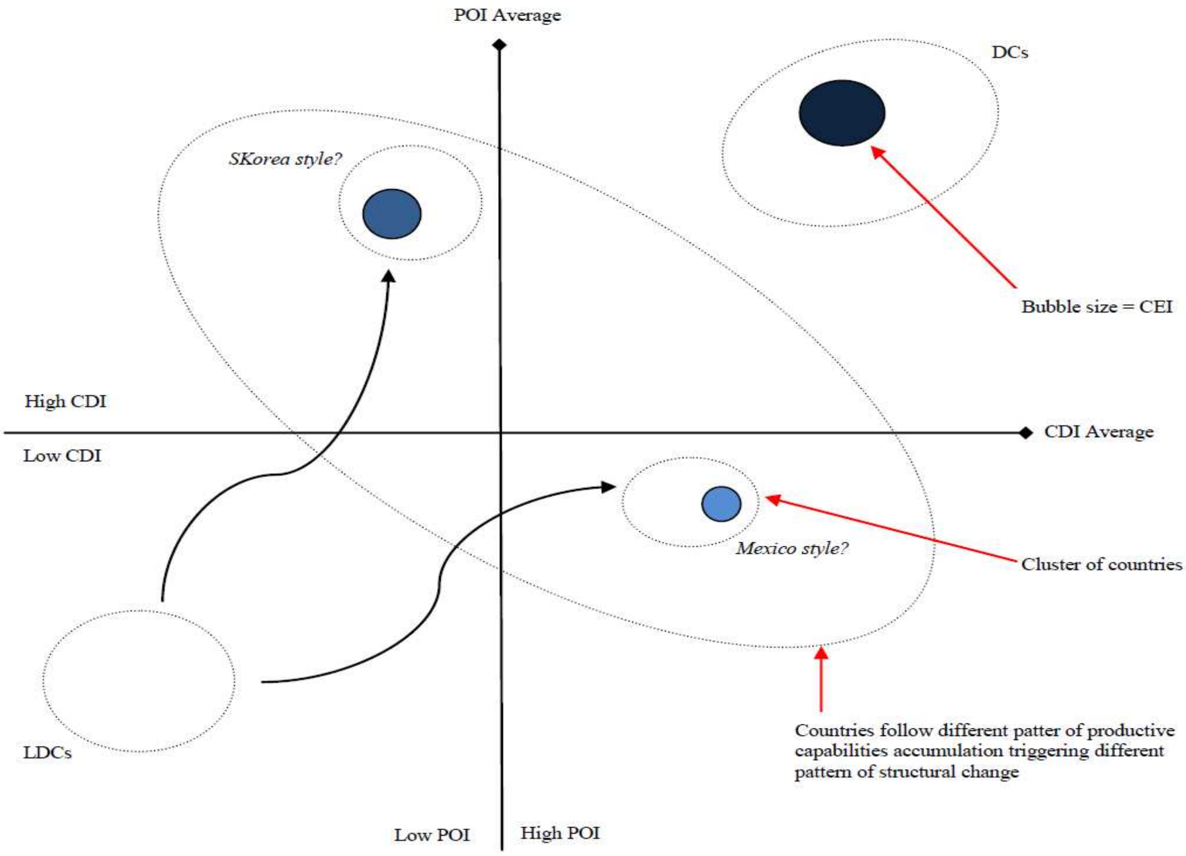
(v) PCI can complement structural change analysis by displaying the different patterns of productive capabilities accumulation underlying the transformation of the productive/technological structure of a given country over time (see Figure 8).

Figure 7 Tracking the relationships among different factors over time



Source: Author.

Figure 8 Patterns of structural change and productive capabilities accumulation



Source: Author.

Further research needs to be carried out to test these new methodologies and compare the results obtained with other similar direct and indirect indicators of productive capabilities.

3.3 Disaggregated diagnostics: Industry-specific and firm-level productive capabilities

Productive capabilities development in some industries (e.g. manufacturing/capital goods production) is more complex than in others (e.g. process industries). For example, the fact that firms in manufacturing industries have the necessary tools to self-construct machinery for their own use or upgrade and recondition second hand machinery opens a broad range of opportunities for in-house technical change as well as productive capabilities building and accumulation (Rosenberg, 1969, 1976, 1982; Romijn, 1999)[36]. Thus, capability indicators have to be constructed taking into account the specificities of different industries determined by each industry's productive capabilities requirements, knowledge base, divisibility of tasks and modularity, scale and time constraints, materials in use, etc. (Pavitt, 1984). These differences remain obscured by the typical 2-digit level analysis. Unfortunately, data sets at the 3 and 4-digit levels that cover a broad range of countries are extremely rare for all sectors, even for more advanced economies[37]. Interestingly, recent innovation indexes have begun introducing sectoral and sub-sectoral differentiations on the basis of detailed national surveys. The NESTA (2009) research work for the UK productive/technological structure exemplifies this tendency.

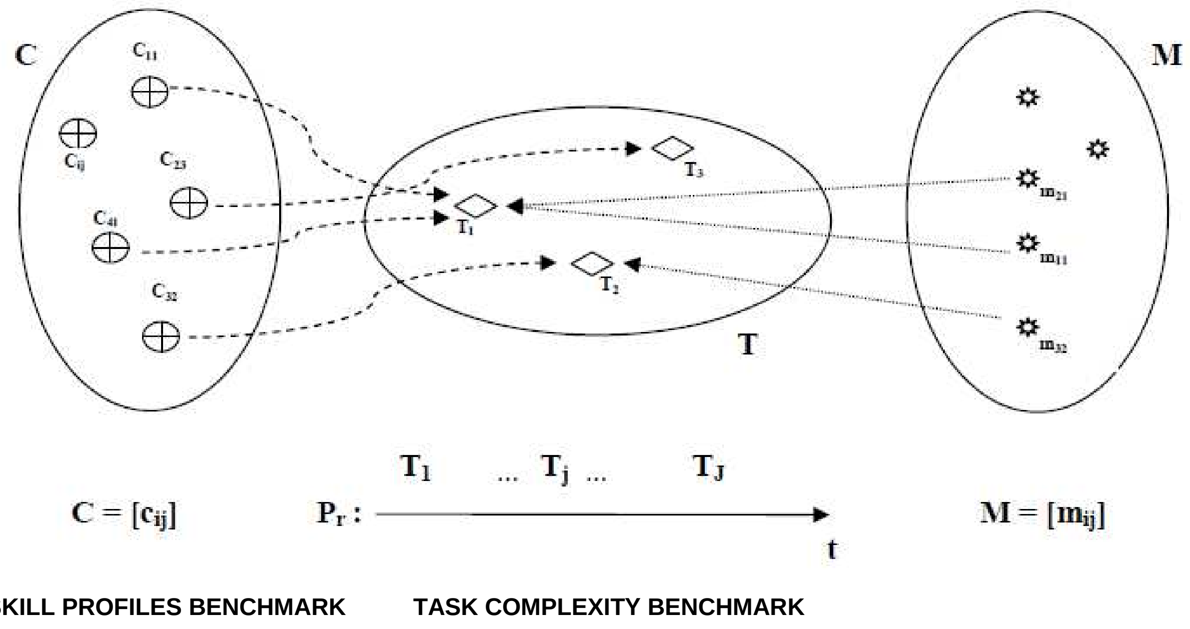
This paper suggests two possible strategies to analyse industry-specific productive capabilities and, thus, the construction of indicators with meaningful technological contents. Both strategies are based on a common analytical framework which is consistent with structuralist analyses of production processes (Scazzieri, 1993; Landesmann and Scazzieri, 1996; Andreoni, 2010). These approaches open the black box of production by describing it as a specific network of interrelated tasks through which transformations of materials are performed according to different patterns of capabilities coordination and are subject to certain scale and time conditions. Thus, three analytical focuses are identified, namely the set of tasks performed in a process (space of tasks **T**), the set of materials transformed (space of materials **M**) and, finally, the set of productive capabilities (capabilities space **C**) necessary for performing that specific production process. These three spaces are visualized in Figure 9.

The first approach for measuring industry-specific capabilities is based on the idea that focusing on the set of tasks that have to be performed to produce a certain commodity allows us to infer on the specific capabilities owned by a generic firm in the given industry – i.e. a *task complexity benchmark*. A refined methodology based on the task complexity benchmark approach is developed by Romijn (1999). This study is a best practice example of a firm-level in-depth survey on productive capabilities. Here, an adjusted indicator is developed based on a survey of small metal working firms in developing countries. The measurements are obtained as a combination of inputs variables (e.g. machines, personnel) and output variables (e.g. degree of manufacturing complexity). The reason why input-related variables are not sufficient and, consequently, have to be complemented by output variables – i.e. product range and complexity

[36] This is another reason why 'manufacturing development' is particularly relevant in the process of economic catching-up.
[37] In this respect, the *UNIDO Industrial Statistics series* is an exception, as it allows capturing main indicators for the manufacturing sector at 2- and 3-digit levels.

– is that a given set of machines and equipment can be used to produce a wide range of products of varying degrees of manufacturing complexity. In fact, the manufacture of some products requires technically more advanced tasks to be carried out using certain machines and equipment than others. Moreover, as each product is made up of different components produced by different firms, the output indicator (product range and complexity) has to be adjusted with input indicators which take indirect productive capabilities into consideration (e.g. those obtained by buying components produced by others and sold in the market). A set of variables used in Romijn's (1999) firm-level study are synthesized in the following Table 21.

Figure 9 The analytical map of production



Source: Andreoni (2010:22).

Table 21 A first review of variables for firm-level capability survey design

i1. Complexity of products
i2. Quality of products (indirect measures: use of measuring equipment, testing methods, etc)
i3. Degree of product diversification
i4. Level of internal design skills (indirect measures: mastery of technical drawings, no. of designers, etc.)
i5. Incidence of self-construction/improvement/adjustment of machines and equipments
i6. Complexity of the organization of production (indirect measures: no. of supervisors, functional division of tasks, etc.)
i7. Adoption of scientific production methods
i8. Expenses for R&D and training
i9. *Range and complexity of engineering products* (UNIDO, 1989)

Source: Author.

An increasing number of innovation surveys, like the one conducted by Romjin, have been undertaken in the last decade, although many of them lack the analytical grounding necessary for making the research process effective and, thus, informative. The OECD's recent publication, *Innovation in firms: a microeconomic perspective*, together with the Oslo Manual (OECD, 1991) are useful tools for designing consistent and comparable innovation surveys. Although the subjective nature of many of the responses obtained through innovation surveys have been criticized, they make it possible for us to grasp important 'process information'. For example, they can allow for the consideration and development of process indicators about firms' objectives, barriers, informal linkages, intangibles, etc.

The second approach, labelled here as the *skill profiles benchmark*, is based on the direct observation of skills requirements in each industry and thus on the idea that it is possible to extrapolate a stylized representation of the skills profiles that a generic firm in a specific sector has to be equipped with to conduct certain productive activities. Skills profiles provide a stylized representation (proxy) of an important subset of the productive capabilities a generic firm in a specific industry has to be equipped with to perform a certain set of tasks. This approach has been rarely followed, especially with regard to our specific goal of assessing sector-specific productive capabilities. Few exceptions can be found in ad hoc national, regional and firm-level surveys or in studies about demand for skills and skills change (Wolff, 1996 and 2002) or skill-relatedness (Neffke and Henning, 2009). Defining specific skills profiles benchmarks for each industry should not let us forget that the same production process can actually be performed by different combinations of productive capabilities and that they have to be complemented by investments in the appropriate expansion of firms' production capacity .

However, this exercise can be useful for countries that aim to design selective industrial policies. As a matter of fact, an assessment of the productive capabilities of a given country can only tell us half the story. Being informed about a certain country's capabilities endowment does not allow us to predict the country's likelihood of entering a certain new productive activity. To do so, we need to know what productive capabilities are required in that specific new industry. By interfacing this information with our country-level capability assessment, we can evaluate which capabilities are and which are not (or not sufficiently) available in the country. Lacking capabilities for entering a specific industry should not, of course, lead a country to abandon legitimate aspirations to structural change as such capabilities may be deliberately created. Instead, a lack of specific capabilities has to be read as an explicit call for selective industrial policies.

The TCI – Technology Complexity Index

Industry and Development Global Reports - UNIDO (1989/90: 123-128) and (1990/91:34)

The TCI is, to our knowledge, among the first detailed indicators which takes account of sector-specific characteristics starting from a refined combination of the two approaches detailed above. This methodology termed 'technology complexity analysis' has been conducted by a team of experts, mainly engineers, since 1979. This methodology was applied to the 145 most commonly produced capital goods in the machinery and equipment industry, ranging from simple metal drums to commercial airplanes. Capital goods were used because their manufacture requires those working skills and productive knowledge essential for industrialization. Each 'capital good' is produced by assembling a series of 'constituent parts'. Based on a detailed list of 'parts' and 'components' as well as technical information about the assembling process, a team of engineers defined the skill score (S) for each assembling process and for the production of each part and component. This evaluation considered 45 distinct technology elements including organizing, managing and executing factory operations in addition to various machine operating skills. Based on this information, the TCI_i results for each capital good *i* are derived from the sum of the skills score of the assembling activity S_i and the sum of the *TCI* of each part and component *j*

$$TCI_i = S_i + \Sigma_j \, TCI_j * P_j$$

where P_j is equal to 1 if the *j* part is domestically produced, and otherwise equal to 0. Next, an overall technological complexity index (OTCI) for each developing country was calculated by adding the net technology complexity index of each sub-product domestically produced[38].

Concluding remarks

The need for productive capabilities indicators becomes evident when we face the problem of designing selective industrial policies for structural change. In order to be contextually viable, time-effective and structurally feasible, these policies have to be informed by appropriate productive capabilities indicators. Although many of today's industrialized countries have implemented successful industrial policies by relying mainly on the 'rule of thumbs' provided by classical development economics (List 1844; Prebisch, 1950; Hirschman, 1958; Kaldor,

[38] See also Hobday (1998) and Hobday, et al. (2004) on the qualitative and quantitative assessment of CoPS: Complex Products and Systems.

1966; Chang, 1994)[39], this paper suggests that in today's global division of labour, catching-up economies can also benefit from adopting other heuristics and benchmarks, including productive capabilities indicators.

Productive capabilities have been defined as personal and collective skills, productive knowledge and experiences embedded in physical agents and organizations needed for firms to perform different productive tasks as well as to adapt and conduct in-house improvements across different technological and organizational functions. The paper has developed an analytical framework for the study of productive capabilities and has highlighted the need to link the analysis of structural change with productive capabilities dynamics. Various synthetic indicators adopted by international organizations and independent researchers in cross-country comparisons of productive capabilities, industrial and competitive performances have been reviewed and compared. By subsequently identifying the methodological problems and informational limits of the various indicators available, the paper has developed a new set of industrial diagnostics to map the different drivers of structural change dynamics and to measure productive capabilities at the national, industry and firm levels.

The methodology offered here is based on the distinction of three sets of factors which, respectively, enter, interact and result from processes of learning in production. For each of them, the paper proposes three direct measures of productive capabilities – i.e. capability determinants (CD), capability enablers (CE) and capability outcomes (CO) – and one indirect measure of country-level capability outcomes – i.e. production outputs (PO). The paper highlights that reliance on multiple informational spaces and the analysis of the relationships among input, output and mediating factors into a consistent causal structure is a fundamental starting point for the design of industrial policies.

In fact, country-level indicators of productive capabilities can function as focusing devices and tools for benchmarking and ranking countries according to the process of productive capabilities building and accumulation experienced. In particular, productive capabilities indicators are extremely useful tools for assessing and comparing the productive and technological structures of different countries. Moreover, by relying on time-series data they can be employed as diagnostics for identifying the presence of *industrial development precursors* (that is, the 'starting point conditions' in terms of productive capabilities demonstrated by a given country at a certain stage of development); the different trajectories of productive capabilities

[39] See Chang (2002) for an analysis of industrial policies in a historical perspective.

accumulation at the country level and, finally, their impact on productive performances and structural change dynamics.

Finally, the paper also underscores how the design of selective industrial policies depends on the availability of industrial diagnostics at different levels of aggregation. Moreover, the latter should allow policymakers to capture the specific productive capabilities requirements of different industries. Therefore, the analysis of country-level indicators has been complemented by the elaboration of new methodologies to analyse industry-specific learning dynamics based, respectively, on skills profiles benchmarks and task complexity benchmarks. Further work will need to be conducted to test and integrate these new methodologies and to compare the results obtained with other similar direct and indirect indicators of productive capabilities.

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