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Article

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Intellectual capital and total factor productivity

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ABSTRACT

This paper defines total factor productivity as a function of a nation's intellectual capital. By developing a simple model, it explored the long-run relationship between intellectual capital and total factor productivity. The value of total factor productivity for each country was computed from Penn World Tables 10 using the residual method, and an index of intellectual capital was constructed from several indicators taken from world development indicators. Using a common correlated effect approach, a panel of 29 countries over 31 years was estimated using various dynamic macro panel models. The result confirmed the existence of a positive and significant link between total factor productivity and intellectual capital index. This implies that a potential source of productivity difference lies with a nation's research and development, human capital, processing, and marketing capabilities in boosting the general innovation process. Thus, national and regional development policies need to consider ways to improve broader innovation. Future research on total factor productivity needs to consider things outside the box.

IMPACT STATEMENT

The essential causes of productivity has been a formidable question since enlightenment. In classical and pre-classical periods, the difference in productivity was attributed to differences in geographical and people's attitude to work and luxury. In neoclassical, productiveness was an effect of natural force inside material objects and hence, consider differences in material accumulation as cause of productivity difference. Following the failure of material accumulation, the difference was considered as residual or total factor productivity by exogenous growth models and later confined to technological ideas and its spillover effects by the new endogenous growth models. However, none of these could explain the twin productivity puzzles. In this paper, intellectual capital was hypothesized as an integral factor underlying the scatteredly presumed drivers of differences in productivity across countries. It also provided an empirical justification for an existence of consistent link between total factor productivity and intellectual capital across nations at all levels of development in all economic regions. This implies, the previously fragmented concepts and factors are now the characteristics of intellectual capital. The new insight could simplify the theoretical complexities and empirical inconsistencies in productivity literature. It could also be beneficial for national and regional policy makers to broaden their view beyond technological innovation in order to improve productivity and catch-up process.

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1. Introduction

The whole history of intellectual inquiry from early enlightenment to yet was all an effort to solve the so-called Dutch puzzle, the search for factors responsible for differences in productivity. Suppositions about sources of cross-country differences went from labor ethics in the 1660s to what Kendrick (1956) called total factor productivity (TFP) in the 1950s.

However, the question of factors contributing to TFP value has been an open endeavor since the 1950s. Following Fabricant (1954), some considered TFP as a measure of efficiency. In lines of

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Abramovitz (1956), it was crudely taken as a measure of our ignorance. The proponents of Schultz (1956) attributed it to skill and educational status. For Solow (1957), it was an effect of exogenous technical or technological shift factors. Following Griliches (1957), it was an effect of knowledge from R&D and its spillover effect.

Within and among these, there are inextricable conceptual and methodological complexities. After new endogenous growth theories, every study on determinants of TFP comes with its factor to extend the Benhabib and Spiegel (1994) human capital or the Coe and Helpman (1995) R&D-based model. However, the same factors appear with a nonlinear result across studies with different explanations. From this, the question of what drives TFP remains ambiguous.

Following the R&D-based models, the developing world managed to improve R&D investment, FDI attraction, and openness to global competition in expectation to enhance technological knowledge and narrow the productivity gap. However, except for some Asian countries, the relative TFP level fell from 55% in the 1960s to 6% in 2017 for SSA countries (Calderón, 2021). Moreover, the LDC's export-import gap rose from −5 to −80 billion dollars, and their demand and preferences were vitiated and diverted toward technological products (WTSR, 2019). All these imply, that most of the developing world are providing their burnt offerings for being late rather than leapfrogging to catch up as promised. Hence, the conviction of TFP as a measure of factors responsible for cross-country differences isn't likely with the conventional determinants of TFP and its accompanying policies.

Against these conceptual and empirical gaps, this paper defines TFP as an effect of intellectual capital—a composite index of broader national innovation capabilities. Thus, aimed to examine the effect of intellectual capital (IC) on TFP for a panel of 29 countries from 1990 to 2020.

This study, particularly from its contemplation into long theoretical perspectives and based on current empirical findings, found IC as an integral factor underlying the scattered presumed drivers of TFP. It contributes a new approach that integrates the previously fragmented concepts, models, and factors into the TFP literature. Unlike the previous studies, it doesn't narrow TFP to returns to scale, or R&D and spillover effects. It provided a new insight that could resolve the various empirical inconsistencies in productivity literature.

The rest of the paper is organized as follows: the second section presents the related theoretical and empirical literature. The third section explains the methods used. The fourth provided results and discussion, and the final section concluded.

2. Literature

2.1. Theoretical perspectives of productivity

2.1.1. The causes of productivity in mercantile and classical periods

In the traditional mercantile the accumulation of precious metals was a big challenge for the resourceful continental Europe relative to the resource-scarce Dutch. From this, William Petty and his adherents claimed people's attitude to luxury, effeminacy, and slothfulness, as a cause for the conundrum. In contrast, liberal mercantile contend that luxury stimulates demand by fostering emulation and thus rouses men from their indolence more effectively than the use of hunger pangs to prod men to work. They considered luxury as a spur to innovation. For those who import and export, it became a source of surplus; a means of imitation and diffusion of know-how (Stathakis & Vaggi, 2006).

However, Hutcheson stated luxury as a reward for toil and argued that every man prefers toil over sloth for further conveniences, except some few gentlemen pretended to be inured to sloth from their infancy, of weak bodies and weak minds (Spiegel, 1955). This spoiled the strong belief in luxury as a spur to sloth or toil and might be a reason for Smith to take the division of labor as a way out.

For Smith, the division of labor is a source of productivity for it, increases dexterity, saves time, and directs the minds toward new inventions. It is the effect of very slow and gradual consequence of a certain propensity in human nature, which may be the result of faculties of reason, common to all men (Smith, 1776). Contrarily, the Earl of Lauderdale, followed by Playfair (1805), argued that if Smith's division of labor holds: why doesn't everyone equally direct their mind and effort toward the invention of objects that increase the quantity and quality of production (Laudardale, 1819). Other than the social,

cultural, and geographical differences, they claimed the unequal distribution of wealth as a fatal problem for the ineffectiveness of liberal mechanics, as it kills attitudes and aspirations for innovation. Similarly, Mill listed natural advantages, labor talents, and protective institutions as conditions upon which the degree of productiveness depends. However, he argued that individuals differ so much in their capacity of present exertion for a distant object' (Mill, 1848).

Overall, the fundamental differential factor was intellect, the degree of foresight, capable of desiring and orienting the effort of a man in a way that sustains and preserves labor rather than that which prefers a repose. All the other conditions are either causes or consequences, of such human qualities. In the absence of anxiety and difficulty (a favorable climate and soil), there is nothing for the inhabitants to inspire but indulgence in repose. The absence of such human qualities in turn means poor capability to invent, improve, absorb, and diffuse technological products.

2.1.2. *The neo-classical accumulation mechanics*

Neo-classicalists had advanced the traditional mercantile perspective of progress, the accumulation of riches, to the liberal mechanics of saving and capital accumulation. They see saving as an ordinary act of behavior and attribute productiveness to a natural power inside objects. The view of capital reproducibility and skills as a source of surplus in the division of labor was diverted to the durability of capital goods and mere return to scale (Böhm-Bawerk, 1891; Young, 1928). Contrarily, Clark marked these views of productiveness as mechanics that had no place for human intellect (Clark, 1886). For Clark, the essential cause of productivity difference associated with the advancement of goods was neither time nor durable capital goods but mental effort imparted to objects. Strictly, Veblen (1908) argued that tangible goods owe their productivity and value to the immaterial equipment they embodied. For Veblen materials are useful only for men who have learned their use; they become museum exhibits with advanced knowledge. Vexed of capital productiveness, Schumpeter disintegrated capital as invested money and an investing entrepreneur(productive) (Schumpeter, 1911). Moreover, Hayek found depreciation, maintenance, technological knowledge, and social innovations as fatal problems of valuation in neo-classical mechanics (Hayek, 1935, 1937).

To analytically explain the causes of economic dissimilarities, Haavelom (1964) critically appraised all the theoretical perspectives from the classical assertions of differences in skills, habits, and geographical advantages to Schumpeter's innovation. After all, he suggested a need to understand the nature of the force behind human innovation as a way to find an answer to the causes of economic dissimilarities. From this, he might be the first to augment physical capital with education and technical know-how.

Similarly, Kaldor (1954) stated that the most plausible answer for the cause of dissimilarities has to do with human attitudes to risk-taking and money-making. In regards to Schumpeter's innovation, Kaldor stated that: Schumpeter's hero though, dismissed so summarily and contemptuously, is found to have a key role in explaining economic progress.

In the end, the theoretical plausibility of intangibles was also accompanied by strong empirical evidence. The traditional factors were found to explain only 1/8 of the total output growth, implying an apparent failure of neo-classical accumulation mechanics (Abramovitz, 1956; Fabricant, 1954; Solow, 1957).

2.2. *Empirical literature*

Following the progress of civilization, the notion of capital has been continuously changing with changes in the functioning of economies. From this, IC a newly emerged form of capital, is found to be a determining factor in today's knowledge economy. Its appearance in mainstream economics goes back to 1969 by J. Kenneth Galbraith (Sokół, 2017). But, it is still scarce in economics, particularly, in macroeconomic analysis. Almost all the literature linked to IC was dimensionally inclined to the organizational level (Pedro et al., 2018).

Thus, it is difficult to find an article relating IC and TFP in macroeconomic analysis. A few correlation studies on IC and economic growth, development, and welfare were found (Alfaro et al., 2014; Jednak et al., 2017; Kuzkin et al., 2019; Marciniak, 2013; Uziene, 2014).

However, several studies have found the positive and significant role of at least one component or indicator of IC on firms performance, efficiency and productivity (Costa, 2012; Do et al., 2022; Jola-Sanchez, 2022; Tiwari et al., 2023). However, micro-level studies are less favored here because of their particularistic concepts and measurement approaches.

The studies of Stähle et al. (2015) and Tian and Liu (2019) are the two opposite papers reflecting the two sides approaches of literature reviewed here. The former from its topic seems less related to IC and TFP. But actually, the paper developed a new national IC index and stated that a new index had explained over 72% of the residual for a sample of 48 countries. Though, it is quite different from the current paper in terms of purpose, conceptual, and methodological approach, it was a base for the current paper, particularly, in the construction of the national IC index.

On the contrary, an article by Tian and Liu (2019) was almost similar to the current paper in terms of topic. However, the employed concept and model were the same as Coe and Helpman (1995), an approach that fails to see beyond R&D and its spillovers. Tian and Liu took IC as synonymous with R&D knowledge, which is a too narrow view of IC. In this sense, it isn't different from the multitude of conventional literature reviewed hereunder.

Using factors like R&D, education, and institution with TFP as key terms for the search of literature a vast of literature was found. Following Benhabib and Spiegel (1994) many reaffirmed the positive contribution of human capital to TFP as an engine of invention and, or a facilitator of absorption (Benhabib & Spiegel, 2005; Cheng et al., 2013; Griffith et al., 2004). Contrarily, the contribution of education to TFP was insignificant for Miller and Upadhyay (2002), and Su and Nguyen (2022) and negative for Pritchett (2001).

Based on Coe and Helpman (1995) foundational work that explained a strong dependency of TFP on domestic and foreign R&D, Lichtenberg & van Pottelsberghe de la Potterie (1998) confirmed that the more open to trade a country is with research-intensive countries, the more likely it is to benefit from foreign R&D. Besides, Griffith et al. (2004) found that the foreign spillover effect depends on domestic R&D. Contrarily, Kao et al. (1999) re-estimated the Coe and Helpman model with a DOLS and confirmed the impact of domestic R&D but found no significant effect for the trade-related foreign R&D spillover.

The empirical ambiguity on foreign knowledge spillover led to a shift of approach from measuring spillovers to control of domestic channels, institutions, and social infrastructures assumed to facilitate foreign knowledge flow. Thus, a vast number of studies focused on FDI to account for the effect of foreign knowledge transfers and spillovers on TFP. However, the FDI productivity nexus was inconclusive. The result was found positive for (Uttama & Peridy, 2010; Woo, 2009), weak or insignificant for (Abdullah & Chowdhury, 2020), and negative for (Herzer & Donaubauer, 2017). For Pietrucha et al. (2018) the effect of spillover via FDI depends on the host country's market orientation, financial markets, human capital, and the way of doing business or institutions in general.

Madsen (2008), and Corrado et al. (2017) focused on control of openness and the import of ICT and high-tech goods and found positive contributions to TFP. While, some significantly explained the difference in TFP by controlling for effective institutions (Coe et al., 2009; Fadiran & Akanbi, 2017), social infrastructures (Hall & Jones, 1999), and resource miss allocation (Bellocchi et al., 2021; Comin & Mestieri, 2018).

Overall, the bewildering array of empirical results entails that the efforts to explain TFP as a function of human capital, R&D, and its spillover channels have made little contribution to explaining the TFP pattern across countries. This might be because, these lists are only a part of the many factors behind the general process of innovation, which are mostly complementary to each other. However, as per the review, such an all-inclusive trial was not observed. Meanwhile, this paper intends to use the meta concept of IC to resolve these inconsistencies and complexities. It takes its foundation back to the open theoretical framework of Griliches (1973) to account for contemporary arguments of new endogenous and evolutionary growth models.

2.3. Analytical models of TFP

The view of something intangible as a main source of growth was apparent in the early 1950's. The mysterious factor was often symbolized by 'A', but variously labeled as technical or technological change,

progress, innovation, or knowledge. And the unexplained output growth attributable to it was interpreted as a measure of our ignorance (Abramovitz, 1956), total factor productivity, (Kendrick, 1956), and residual (Domar, 1961). However, its essence, formation, and linkage to output growth remained a fascinating problem. Those who insisted on neoclassical mechanics explained it as the effect of scale, innovation, spillovers, quality labor, quality management, or everything other than capital and labor. In a Hicks neutral production function: $Y = A(t) F(K, L)$ Solow (1957) derived the residual as:

$$TFP = \dot{A}/A = \dot{Y}/Y - \alpha(\dot{K}/K) - (1-\alpha)\dot{L}/L \quad (1)$$

The relation in Equation (1) is not a model but an index that generates the value of an output growth contributed by exogenous factors.

However, for Schultz (1956) it was an effect of advanced techniques and labor (workers, entrepreneurs, and managers). For Griliches (1957), it was an effect of R&D knowledge adapted and diffused. Based on this, Griliches (1973) developed an open model relating knowledge to TFP and output:

$$Y = TFP * f(C, L) \text{ where, } TFP = G(K, O). \quad (2)$$

Here, Y is output, capital (C) and labor (L) are the usual inputs while total factor productivity (TFP) is a function of accumulated social and private research capital or productive knowledge (K) and other forces affecting research productivity (O). This became the first approach to explicitly model TFP as a function of knowledge.

Later, the new endogenous growth models regarded the elusive factor as an effect of endogenous innovation. That is an intentional investment in R&D generates ideas that could instantly developed to improve variety or quality intermediate inputs, thus enhancing productivity. Based on this, Coe and Helpman (1995) argued that the productiveness of input depends on the number of varieties or qualities of inputs resulting from domestic R&D and foreign R&D spillovers:

$$\log TFP = \alpha^0 + \alpha^d \log S^d + \alpha^f \log S^f. \quad (3)$$

Where S^d and S^f represent the domestic and foreign R&D capital stocks with constant and respective slope parameters (α). However, such models fail to account for the role of specialized skills working in complementarity with advanced technological products and as expertise in the absorption, adaption, and diffusion of productivity enhancing foreign knowledge, and social and technological innovations.

Meanwhile, Nelson (1956) stated that underdeveloped countries may escape the trap without crash investment and improvement in techniques. A decade later, Nelson and Phelps (1966) came up with another argument that: the differential role of human capital in output production is negligible in the absence of technological advancement. They developed a model where the rate at which the latest theoretical knowledge is practically realized as an improved productive technology (\dot{A}/A) depends on the level of education (h) and the gap between the level of theoretical knowledge (T_t) and the level technology in practice (A_t). The model assumes the generation of theoretical knowledge as exogenous and thus, hails the adaption role of human capital.

Benhabib and Spiegel (1994) adapted the Nelson and Phelps (1966) model simply by interpreting \dot{A}/A as TFP and T_t as technology level of the frontier country (A^f) and specified it as:

$$TFP = \dot{A}_t/A_t = g(h) + \Phi(h)[A_t^f - A_t]/A_t. \quad (4)$$

The model explains that the level of education (h) enhances TFP both in the development of its own technological innovations $g(h)$ and in the adaptation and implementation of foreign technologies.

In general, scholars interested in analyzing the effect of R&D on TFP prefer to employ models (2) and (3) with and without extensions while those emphasizing on role of human capital follow the Benhabib and Spiegel model. Some went eclectic by using their variable of interest without referring to either of these. Most researchers used to extend these models by adding the various characteristics of human capital, foreign inflows, infrastructures, organizational structures, social and marketing networks, and institutional.

Despite, all these efforts 'the residual was, after all, still the measure of our ignorance' Hulten (2001). Similarly, Mohnen (2019) concluded that 'whatever the innovation indicator is used, there will always be part of the variation of productivity that reflects miss-measured prices'. Griliches (1998), after four

decades of continued effort, came to conclude that the glass is still half-empty because the unknown keeps expanding as we learn. The measurement of knowledge stock and flows or input-output measures of R&D and its spillovers was a series problem. Besides, the intra and inter-inconsistencies of findings were a critical challenge for studies based on these models. Moreover, none of these extensions wouldn't be able to explain the twin puzzles of productivity for two reasons. One is the mere extension of these models may worsen the model fitness, because of the severity of endogeneity. Second, the residual remained unexplained not because learning reveals more causal factors, but because learning is itself a dynamic hallmark behind the incessant list of factors.

These, all imply a need for a new approach to define and model TFP, to account for its broader and dynamic features. There is no doubt in defining TFP as the residual, the portion of output growth unexplained by the conventional inputs. But, was it a function of R&D or education or social & organizational structures and institutions or errors? In the long run, it is the measure of how much more effectively a society can turn its available resources into valued goods and services (Coyle, 2019). Given this general understanding, TFP has to be defined as an integral of all these factors but, does not mean a function of an independent list of factors.

In a way to define or construct a new model the relationship in (2) needs to be extended to account for all the various arguments. Following the arguments of Blackburn et al. (2000) and Frantzen (2000) all three models from Equations (2)–(4) have to be put in a single framework. Let's introduce human capital with its two roles in Equation (4) into Equation (3) and then substitute it back into Equation (2) as:

$$TFP = G(H_A^d, R^d, H^f, R^f, O). \quad (5)$$

Where Equation (5) implies TFP as a function of domestic human capital in the R&D sector (H^d), the domestic managers facilitating adaption and experts in knowledge sharing programs (H^f), other domestic R&D spending (R^d), and foreign R&D via FDI, import of high-tech goods (R^f).

However, Prescott (1998) argued that usable knowledge may explain inter-temporal productivity differences but not TFP differences among nations. Hence, suggests the inclusion of institutional innovations (marketing, financing, and networking policies) and organizational innovations (leadership, systems, processes, and structures). Similarly, Corrado et al. (2005) argued that Griliche's sources of growth framework have to be expanded to include intangible spending on product design, marketing, and organizational development as essential inputs for innovation along with spending on R&D. Moreover, Corrado et al. (2010) argued that spending on R&D to generate new ideas may define the possibilities but not the outcome because new products don't sell themselves. That is the final output production or value also depends on the qualities of social institutions and organizations. Consideration of all these factors, institutions, procedures, management, and marketing capabilities, as organizational capital (O_c) gives Equation (6) as:

$$TFP = G(H_A^d, R^d, H^f, R^f, O_c, O). \quad (6)$$

The neoclassical arguments of TFP as a measure of our ignorance or other exogenous factors and errors were accounted for by 'O'.

From intellectual capital literature, Edvinsson and Malone (1997) defined intellectual capital (IC) as the possession of knowledge, experience, organizational technology, customer relationships, and professional skills that provide a competitive edge in the market. For Bontis (2004), it denotes intangible assets inherent in people, companies, institutions, communities, and regions that constitute both the present and future potential sources of wealth. The literature divides IC at the national level into four components. The renewal capital (R_c) refers to the capacity to generate and utilize new ideas and knowledge; the human capital (H_c) is related to skills and education; relational or marketing capital (M_c) refers to social and marketing networks and finally, the organizational systems, processes, and institutions as process capital (P_c) (Michalczyk & Fiedorczyk, 2017). Given these definitions, it is worth noting that IC is a function of R&D, human, marketing, and process capabilities that facilitate the creation of valuable products and services. This implies, that IC is a meta-concept that could effectively comprise and give a definite view for scattered factors in Equation (6) as:

$$TFP = G(R_c, H_c, P_c, M_c, O). \quad (7)$$

Where; $R_c = R^d + R^f$; $H_c = H^d + H^f$; $O_c = P_c + M_c$ and $O = ve^{ut}$. Assuming relation Equation (7) to take a Cobb-Douglas functional form gives as:

$$TFP = H_c^{\gamma_1} R_c^{\gamma_2} M_c^{\gamma_3} P_c^{\gamma_4} v_i e^{ut}. \quad (8)$$

After taking a natural log on both sides of Equation (8):

$$tfp = \gamma_1 h_c + \gamma_2 r_c + \gamma_3 m_c + \gamma_4 p_c + v_i + e_t. \quad (9)$$

By definition of $IC = H_c + P_c + M_c + R_c$ or $ic = h_c + r_c + m_c + p_c$; therefore, Equation (9) could be simplified as:

$$tfp = \beta ic + v_i + u_t. \quad (10)$$

Where, v_i and u_t are unobservable varying across units and time.

In the end, Equation (10) becomes a new model of TFP. The model defines TFP as a function of a nation's integral capability to undertake technological, social, organizational, and marketing innovations.

3. Methods

3.1. Data sources and description

To estimate Equation (10) a panel of 29 countries was drawn from a Groningen growth and development center sample frame as given in Table A1 (in the Appendix). The sample frame was preferred for its sound classification and data availability. The time dimension was limited to 1990–2020 due to the prevalence of missing data before 1990. Moreover, countries like China (Hong Kong and Taiwan), India, and Costa Rica, were dropped for population size and administrative factors. Missing data within the period were linearly interpolated and the total missing labor share for some SSA countries was filled by taking the regional average.

The TFP growth values are generated using Solow's growth accounting:

$$\Delta A/A = \Delta Y/Y - \alpha(\Delta K/K) - (1 - \alpha)\Delta L/L. \quad (11)$$

While the level values of TFP are computed as:

$$A = Y/K^\alpha L^{1-\alpha}. \quad (12)$$

The detail of variable and parameter definitions and sources are provided in Table 1.

Solow's residual approach was preferred for the study and follows a non-frontier non-parametric approach as there is no dominant country in terms of every IC indicator. Besides, the non-frontier parametric approaches face the critical problem of endogeneity. Particularly, holding the assumption of independence of errors from capital or labor implies assuming technological knowledge as exogenous. Finally, relative to Tornqvist and Divisa indexes, the modified Solow residual, allowed for varying factor shares, is simple and more relevant to the current emphasis of TFP as a measure of intangibles than mere distortion of prices or measurement errors.

For the construction of the IC index, various indicators were adapted from Stähle et al. (2015) as summarized in Table A2 (in the appendix). All the necessary data were sourced from the World Development Indicators (WDI) database. As shown in Table A2 at least five various quantitative and qualitative indicators are selected to form a single component of national IC. To integrate these indicators as the national IC index of a given nation the simple additive or weighted linear combination method was adapted from Uziene (2014) and Thakkar (2021). Accordingly, each indicator noted as a positive contributor to national IC was first normalized by dividing each indicator's series of values by its respective overall maximum value across all nations and overtime (j_{\max}). That is: $r_{j,t}^i = x_{j,t}/x_{j,\max}$. For indicators assumed to possess a dragging-out effect or whose higher value implies conditions of poor IC, the overall minimum (j_{\min}) was dividend for the series of entries. That is $r_{j,t}^i = x_{j,\min}/x_{j,t}$. Where, $i = 1, 2, 3, \& 4$ _referring to the sub-components of IC; $j = 1, 2, \dots, 5$ or 6 refers to the various indicators and t = period from 1990 to 2020. In this way, each indicator was normalized to a ratio between 0 and 1 to

Table 1. Variable definitions and data sources.

Variable	Definition	Data Source
Y	Output-side real GDP at chained PPPs (in mil. 2017US\$)	PWT 10.0
K	Capital stock at current PPPs (in mil. 2017US\$)	PWT 10.0
L	Number of persons engaged (in millions)	PWT 10.0
(1- α)	Share of labor varying across units and time	PWT 10.0
top	Total factor productivity level (dependent variable)	Derived
tfp_g	Total factor productivity growth (dependent variable)	>>
ic	National intellectual capital level (independent var.)	>>
ic_g	National intellectual capital growth (independent var.)	>>

Source: Feenstra *et al.*, 2015.**Table 2.** Descriptive statistics of variables.

Variable	Mean	Std. dev	Min	Max
tfpl	238.8091	257.9822	8.086	1282.04
Intfpl	4.811024	1.224316	2.090	7.15621
tfp_g	0.0035538	0.0486834	-0.2897	0.233879
ic	1.428746	0.5453389	0.4367	2.77262
Inic	0.2795242	0.4027394	-0.8284	1.01979
ic_g	0.0152826	0.0482072	-0.6579	0.2532

Source: Current Data.

Table 3. Mean TFP and IC (level and growth) by income level and region.

Income Category	Obs	tfpl	ic	tfp_g	ic-g
Low-Income Countries (LIC)	62	28.18	0.68	0.0019	0.024
Lower Middle-Income Countries (LMIC)	186	63.79	0.93	0.0003	0.008
Upper Middle-Income Countries (UMIC)	248	129.13	1.28	0.0022	0.018
High-Income Countries (HIC)	403	419.48	1.87	0.0061	0.016
AEC (Singapore, Thailand & S. Korea)	93	214	1.80	0.0086	0.021

Source: Current Data.

avoid the unnecessary effects of variations coming from differences in measurement units across indicators. Second, the simple average of the normalized indicators of a given component is taken as an index of that particular component of a nation at that particular year. Finally, the simple summation of the four indices makes up a national IC index in a given year. While, taking average and summation each indicator or sub-index was given an equal weight, to allow Solow's (1963) argument for equal role of embodied technological and disembodied technical progress or this time social innovation and technological innovation capabilities.

Table 2 presents the descriptive statistics of variables, TFP, and IC at level, growth, and natural log form for the 899 full observations. The mean TFP growth is about 0.35 percent with a standard deviation of 0.049 which is comparable to 0.4 percent of USA TFP growth from 2019 to 2022 (BLS, 2023). The mean IC index is 1.4 for the full sample while a minimum of 0.4 and a maximum of 2.8 levels of IC index are recorded for Ethiopia (in 1990) and Singapore (in 2020) respectively.

In Table 3 the mean statistics of all the variables are compared across various income categories. When collapsing the whole sample by the mean TFP and IC level or growth the LIC overwhelmingly occupies the bottom 5 while, HIC dominates the top 10. The mean value for both level and growth variables shows a direct proportionality with income level, except the lowest growth of TFP and IC recorded for LMIC and the highest IC growth rate recorded for LIC. The 2.4 percent mean IC growth recorded for LIC is plausible given their previous lower IC level. Uniquely, the three Asian emerging countries (AEC) possessed the highest mean IC and TFP growth. The previous studies linked the miracle growth with human capital but here the data shows a direct proportionality with IC growth.

Moreover, the trend of IC and TFP for various economies is described over time. Accordingly, Figure 1 shows a continued but very sluggish rise in the mean index of IC level for HIC countries and the USA. Meanwhile, the mean IC index was moderately improving for the other groups. As a result, the mean index of IC for AEC exceeded the mean of HIC excluding the USA. The variation in the trend of mean IC across income groups in Figure 1 reflects that developing countries are improving their quality of human capital, and social and technological innovations relative to the previous lower status. Declining progress for advanced countries could be attributed to the deteriorating relational or marketing and

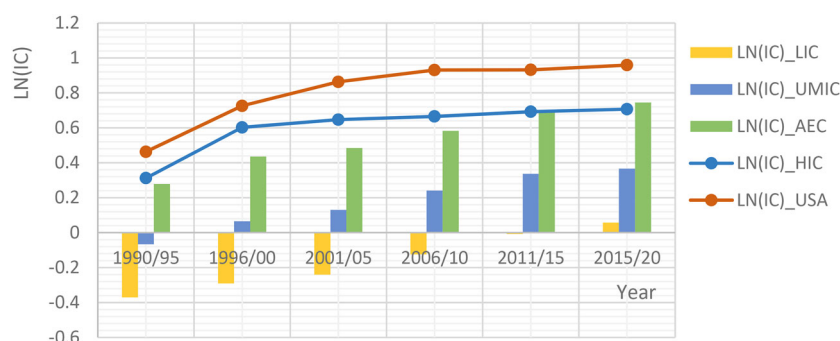


Figure 1. The level of IC index across income level and time.

Table 4. The CD and slope homogeneity test.

Model	Variable	Definition	CD statistic	α	Delta
1	Intfpl	natural log of TFP level	4.54**	0.64	5.42**
	lnic	natural log of IC level	86.96**	0.99	adj. 6.10**
2	tfp_g	TFP growth	23.34**	0.77	3.97**
	lc_g	IC growth	10.54**	0.75	adj. 4.47**

**refers to a 1% level of sig. $0.5 \leq \alpha < 1 \rightarrow$ strong cross-sectional dependence.

Table 5. Sequential test for multiple breaks (Ditzen *et al.*, 2021).

	Test Statistic		Bai & Perron Critical Values		
	Model1	Model2	1%	5%	10%
F(1/0)	0.19	1.29	12.29	8.58	7.04
F(2/1)	7.30	4.69	13.89	10.13	8.51
F(3/2)	4.89	0.31	14.80	11.14	9.41
F(4/3)	0.55	7.61	15.28	11.83	10.04
F(5/4)	0.53	2.52	15.76	12.25	10.58

Detected number of breaks: No breaks found.

social capital indicators. Particularly, it implies that the knowledge inflow from the rest world to advanced economies is weakening relative to the outflow as indicated by FDI. For instance, the USA is still at the frontier of technological knowledge or the IC index in general, but its innovation level may be falling because of incumbents' rivalry and restrictive policies.

3.2. Data diagnostic tests

The choice of a proper estimation method depends on certain cross-sectional and time-series properties of the data. For this, the data were diagnosed for cross-sectional dependence (CSD), slope homogeneity, structural breaks, panel unit root, and co-integration properties before estimation. Table 4 presents the Pesaran (2015) cross-sectional dependence test. The null hypothesis of weak CSD for both variables is rejected at 1% and the estimated exponent of dependence (α) is greater than 0.5. This implies the existence of strong CSD among cross-sectional units, suggesting a need to look for estimation and test methods that address CD.

Accordingly, the Blomquist and Westerlund (2013) test of slope heterogeneity was used as it accounts for CSD. Following, Bersvendsen and Ditzen (2021) argument, the test was allowed to be a heteroskedastic autocorrelation (HAC) robust estimator. As shown in Table 4 the delta values are significant at 1% for both models, implying that the null hypothesis of homogeneous slope is rejected.

Expecting the possibility for unknown structural breaks the Ditzen *et al.* (2021) sequential test for multiple breaks at unknown break points was employed. Moreover, to control for the observed CD, the csd option is allowed. Without any prior knowledge of the number of breaks or their exact dates, the result for the maximum number of breaks is reported in Table 5. However, the result shows the null hypothesis of 0 breaks is not rejected implying the absence of structural breaks.

Table 6. Panel Unit Root Tests.

Model	Var	CIPS		Karavias and Tzavalis (2014)		
		no trend	trend	break	no trend	trend
1 (level)	Intfpl	−0.1	−0.4	1	−3.16**	−2.20
	L.Intfpl	−1.3	−2.4**	2	−3.15**	−2.51
	Inic	−2.5**	−5.0**	1	−35.39**	−5.88**
	L.Inic	−1.2	−1.9*	2	−33.87**	−7.26**
1 st diff	d.Intfpl	−15.0**	−12.8**	1	−42.56**	−24.74**
	d.Intfpl	−10.0**	−7.5**	2	−41.58**	−23.34**
2 (level)	tfp_g	−13.6**	−12.5**	1	−43.77**	−25.96**
	L.tfp_g	−6.0**	−4.7**	2	−42.83**	−24.21**
	ic_g	−20.7**	−18.5**	1	−47.51**	−27.41**
	L.ic_g	−13.3**	−10.1**	2	−45.74**	−25.32**

* & ** refers to 1% 5% level of sig.

Table 7. Co-integration tests.

Statistic	Gt	Ga	Pt	Pa
M1	−2.1*	−8.9*	−9.4	−5.9*
M2	−3.8**	−21.2**	−21.0**	−22.0**

H0: no co-integration. * & ** refers to 5% and 1% level of sig.

Given evidence for CSD and slope heterogeneity, a second-generation panel unit root test is used to investigate the integration levels of the variables. As shown in Table 6 the growth of TFP and IC indexes are stationary in level, both with and without trend. The level value of TFP isn't stationary at level but at the first difference, while the level value of IC is stationary at level both with and without trend. Furthermore, Karavias and Tzavalis (2014) panel unit root test advanced by Chen et al. (2022) to control for known and unknown structural breaks was used. The result from the new command shows that all the variables except the natural log of TFP level(Intfpl) are stationary at the level both with and without linear trend while considering single and double unknown structural breaks.

Finally, the Persyn and Westerlund (2008) error-correction-based test was employed to check for the existence of co-integration. In Table 7 three of the four statistics for the first model and all the four for the second model turn significant at 5% and 1% respectively. The result rejected the null hypothesis of no co-integration.

3.3. Estimation method

Following the dimensional specification of the data and nature of the variables, the equation in (10) could be better stated as a dynamic macro panel:

$$tfp_{i,t} = \lambda tfp_{i,t-p} + \beta ic_{i,t-p} + v_i + u_{i,t}. \quad (13)$$

In the pre-estimation tests carried out above, the rejection of CSD and slope homogeneity assumptions was a practical challenge to get an estimator that could reconcile these with stationarity properties in dynamic macro panels. The PMG, panel dynamic OLS, and panel FMOLS approaches are useful for slope heterogeneity but don't allow for error CSD. The strong CSD implies that common factors may correlate with regressors and lead to biased and inconsistent estimation if uncontrolled.

This paper followed Chudik and Pesaran (2015) more recent and profound common correlated effect approach to CSD in the context of dynamic macro panels. The approach treats CSD as part of an error term as follows: $u_{i,t} = \sum_{l=1}^m \gamma_{i,l} f_{t,l} + e_{i,t}$. Accordingly, Equation (13) becomes:

$$tfp_{i,t} = \lambda tfp_{i,t-p} + \beta ic_{i,t-p} + v_i + \sum_{l=1}^m \gamma_{i,l} f_{t,l} + e_{i,t}. \quad (14)$$

Where, $f_t = (f_{i,1}, \dots, f_{i,m})$ are the unobserved common factors, while p implies the maximum number of lags. Following Pesaran (2006) and Chudik and Pesaran (2015) in their successive works, they approximated the common factors by taking cross-sectional averages of the contemporaneous dependent and independent variables (\bar{z}_t) with a floor of $PT = T^{1/3}$ lags. That is,

Table 8. Dynamic CCE estimation result (Intfpl as dependent).

MG effect	Variables	DCC-MG	CS-ARDL	CS-DL	CS-ECM
Short Run Est.	A. Intfpl	0.434**	0.434**		
	(Std. Errors)	(0.0608)	(0.0608)		
	Inic	0.521**	0.521** (0.1704)		
	(Std. Errors)	(0.17043)			
	L.Inic (Std. Errors)	0.165	0.165	−0.334	−0.165
		(0.2011)	(0.2011)	(0.24889)	(0.2011)
Adjust.Term	lr_Intfpl (Std. Errors)		−0.566**		−0.566**
			(0.0608)		(0.0608)
Long Run Est.	lr_Inic(Std. Errors)		3.085**	0.998**	3.085**
			(0.9016)	(0.29891)	(0.9016)
	CD Statistic	−1.55	−1.55	−1.53	−1.55
	R ² (MG)	0.91	0.91	0.86	0.51
Observations		783	783	783	783

* & ** refers to a 5% and 1% level of significance, respectively.

$$tfp_{i,t} = v_i + \lambda tfp_{i,t-p} + \beta ic_{i,t-p} + \sum_{l=0}^{PT} \gamma_{i,l} \bar{z}_{t-l} + e_{i,t}. \quad (15)$$

Where T refers to the time dimension of the panel data and v_i is a unit-specific fixed effect. The λ , β , and γ are the heterogeneous slopes and factor loadings across units, and e_i is white noise.

Chudik and Pesaran (2015) proposed a mean group estimation by a cross-sectionally augmented autoregressive distributed lag CS-ARDL(py, px) for a dynamic macro panel. While Chudik et al. (2016) added CS-DL to estimate long-run coefficients based on a distributed lag representation that does not include lags of the dependent variable. They suggested it as complementary and not as superior to CS-ARDL. Moreover, Ditzen (2021) provided a cross-sectionally augmented error correction approach (CS-ECM) as a third option to estimate long-run effects in macro panels with CSD and heterogeneous slopes. Here, we employ all these 3 approaches to estimate Equation (15) using the xtdcce2 version 3.01 Stata command with maximum lags of (1,1). The command directly estimates long-run relationships and provides a comparable result for all three models.

The CCE estimator is preferred because it adds the averages of the independent and dependent variables to approximate the common factors without prior information. ARDL was preferable given the high possibility of a mixed order of integration for both observable and unobservable common factors. Particularly, the CS-DL approach is more robust to small sample bias and possible breaks in residuals.

4. Result and discussion

Table 8 reports the estimation result from all possible estimators for the first model where the natural logarithm of TFP level (Intfpl) is taken as a dependent factor.

A post-estimation CD-test statistic is very small and statistically insignificant. This implies the strong CSD results observed in the pre-estimation diagnostics were effectively taken out of the model by the common correlated effect approach. As Chudik et al. (2016) and Ditzen (2018, 2021) suggested, all the alternative estimators provided the same result, except for the lower coefficients for CS-DL. The mean group estimate coefficients of all important explanatory variables and adjustment terms are significant and carry the expected signs at the one percent level of significance. Moreover, for all estimators, the scored values of standard errors are lower with a higher mean group residual square. All these imply the model is efficient and well-fitted with data and the chosen estimators.

The coefficients for the adjustment term from the CS-ARDL and CS-ECM, which are also indicators of the existence of long-run co-integration, imply that 56.6 percent of the long-run disequilibrium is adjusted every period. A 1 percent rise in the level of the intellectual capital index contributes to a 0.52% rise in the TFP level in the short run and over 3 percent in the long run. Uniquely, the result from CS-DL shows an exact one-to-one long-run relationship between levels of the intellectual capital index and TFP. The dynamic effect of the previous year's TFP level also contributed up to 0.43 percent.

Table 9. Dynamic CCE estimation result for 2nd model (tfp_g as dependent).

Mean group effect	Variables	DCC-MG	CS-ARDL	CS-DL	CS-ECM
Short Run	L.tfp_g	0.022 (0.0571)	0.022 (0.0571)		
	ic_g	0.083** (0.0351)	0.083** (0.0351)		
	L.ic_g	0.059* (0.0340)	0.059* (0.0340)	−0.045 (0.0378)	−0.059* (0.0340)
	Adjust.Term		−0.978*** (0.0571)		−0.978*** (0.0571)
Long Run Est	lr_ic_g		0.171*** (0.0641)	0.143*** (0.0542)	0.171*** (0.0641)
CSD	CD Statistic	−1.05	−1.05	−1.55	−1.05
R-squared (MG)		0.73/0.34	0.83/0.33	0.82/0.32	0.34/0.66
Total Observations		812	812	812	812

*, ** & *** refers to 10%, 5% & 1% significance level and the values in (.) indicate Std. Errors.

Altogether, the result for the first model indicates that the level of the intellectual capital index of a given nation has a significant and positive contribution to its TFP value both in the short run and the long run.

Table 9 presents the mean group estimates of the second model where the growth of TFP is a dependent variable. The result shows that the problem of cross-sectional dependence was effectively controlled, as indicated by statistically insignificant lower coefficients. Except for the lags, all the important variables, including the adjustment term, carry the expected sign and are statistically significant.

The mean group estimate coefficients from DCC-MG and CS-ARDL show a one percent growth in the intellectual capital index contributing about 0.1% growth of TFP in the short run. Meanwhile, the results from the CS-ARDL, CS-DL, and CS-ECM show that a 100 percent growth in the national intellectual capital index brings about 14–17% of the nation's TFP growth in the long run. This implies that the growth of the intellectual capital index has made a significant and positive contribution to the national TFP both in the short and long runs. The negative 0.978 coefficient of the adjustment term implies that 98% of the disequilibrium is adjusted every period. Unlike in the first model, the dynamic effect is found to be insignificant for TFP growth.

The estimation results from both models altogether reflect that neither the conventional exogenous views nor the contemporary endogenous growth theories that attune TFP with technological progress and accompanying spillover effects are correct. Unlike the previous studies, the observed result justifies that TFP in a given nation was not a mere function of its: nurture of trade or FDI linkage, economic development, regional dummies, R&D, and its spillover effects as in the case of many conventional studies. R&D and its spillovers measured in whatever way form only one component of the whole (intellectual capital).

The result strongly explains TFP as an effect of intellectual capital or an integral effect of human innovation, the composite function of education and health status, R&D, and institutional and organizational processing capabilities. The fact is, the expected synergy of human, organizational, and institutional capabilities of a given society determines the level of understanding, adapting, or adopting and utilizing technological innovations developed elsewhere. In this sense, The use IC index resolves the inconsistent explanations across countries and time. The strong and positive relationship between IC and TFP in turn confirms Rosenberg's (1982) view that attributes the differences in countries' productivity to the functioning of complex social systems, institutions, values, and incentive structures.

Importantly, the result from econometric estimation is consistent with the real data description in Section 3.1. The observed positive result shows the existence of a direct relationship between IC and TFP, both in the short run and long run. The result is generally consistent with studies on the complementarity effect of R&D and human capital with non-R&D (Ma et al., 2022), organizational innovation (Brynjolfsson et al., 2018; Mohnen et al., 2018), quality management (Bloom & Van Reenen, 2007). The result also confirms the conceptual arguments of low productive digital entertainment (Gordon, 2018) and the capabilities of processing existing ideas (James et al., 2022). In other words, it isn't in support of R&D studies pushing TFP paradoxes to measurement errors or the dearth of ideas. Here, the observed upward, constant, and downward trending of TFP growth across income levels closely follows the IC growth path as shown by Figures 2–4 for sample countries.

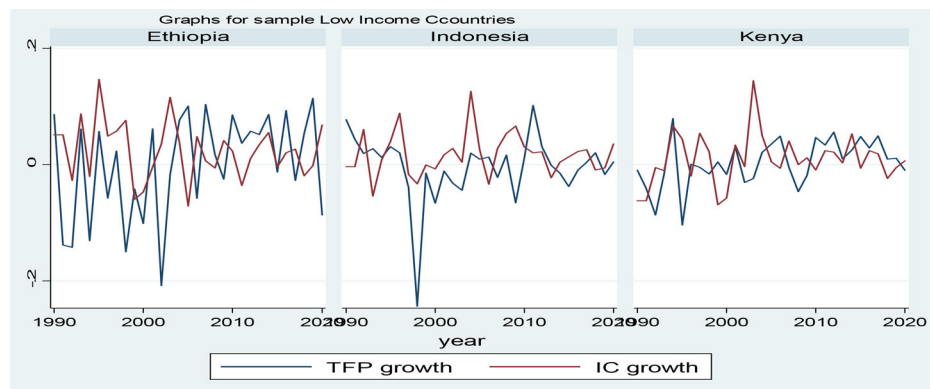


Figure 2. Graphs for sample low income countries.

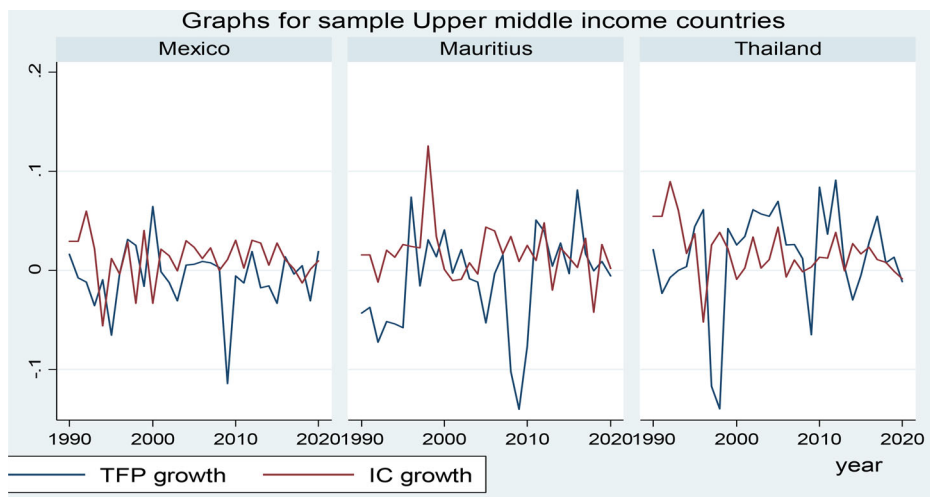


Figure 3. Graphs for sample upper middle income countries.

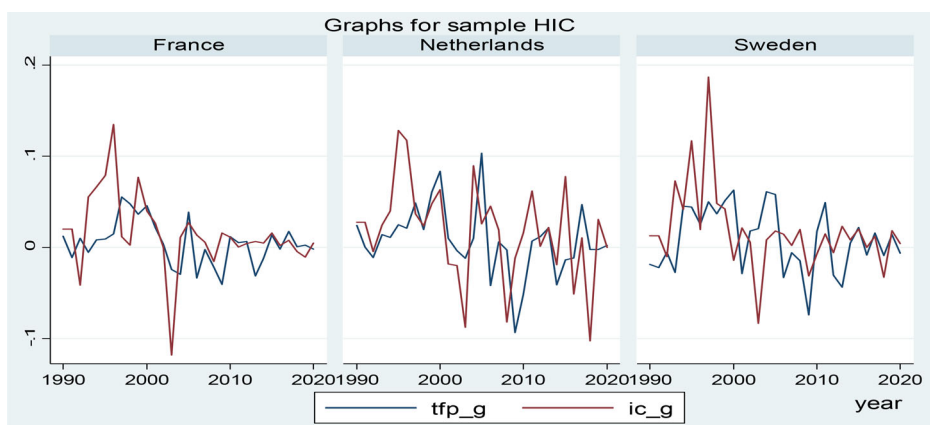


Figure 4. Graphs for sample HIC.

To this end, the current result is also checked for robustness to change of estimator, variable measurement, and the sample size. In the first case, the specified models are estimated using four alternative estimation methods as already presented in [Tables 8 and 9](#). The result is consistent, except for the lower coefficients observed for CS-DL, implying the current model is robust for various estimation methods. Second, both the growth and level values of TFP are allowed to change from the previous by changing factor share to every two years average of the values provided in PWT 10. This approach is taken as one means of robustness check because the approach provides values comparable with the tornqvist index.

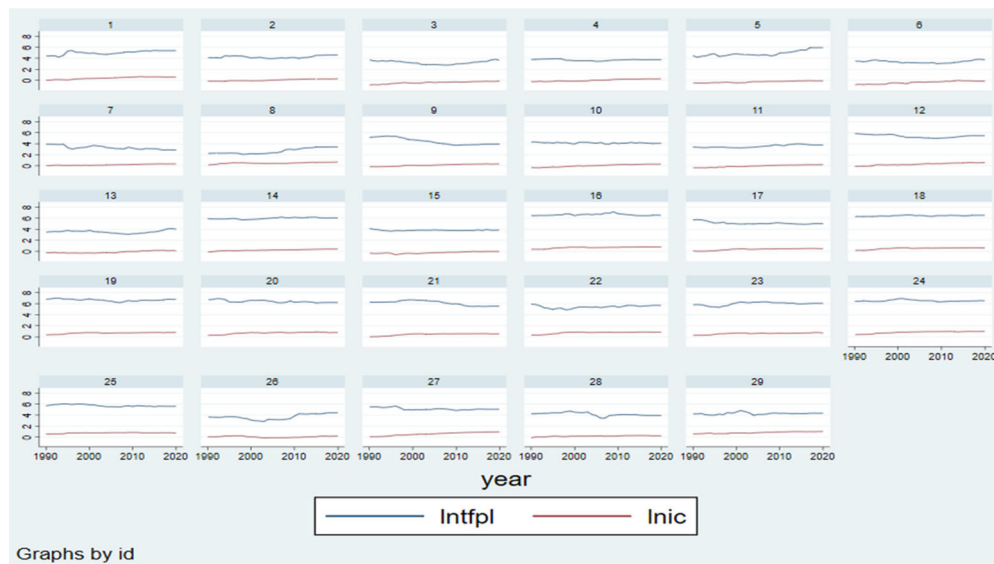


Figure 5. Shows the relationship between IC and TFP is linear after the natural log.

Table 10. CS-ARDL results for 10 advanced countries.

Mean Group Effect	Ln (TFP level) as dependent		TFP growth as the dependent variable		
	Coef	Std. Err	Var	Coef	Std. Err
L.Intfpl	0.86***	0.033	L.tfp_g	0.44**	0.179
Inic	0.61***	0.139	lc_g	−0.006	0.134
Adj. Term	−0.14***	0.033	Adj. term	−0.56***	0.179
lr_inic	4.26***	0.566	lr_ic_g	0.43**	0.211
Total obs.	250			250	
R2-(MG)	84			81	

** & *** refers to 5% and 1% level of significance.

Following this, there is no change in the sign or size of the parameters. Thus, this implies the results are robust to changes in the measurement of variables used.

In the third, the above-estimated models are now estimated for 10 advanced countries (the 8 OECD countries plus Japan and the USA) as presented in Table 10. Compared to the main result there are minor differences. For both models, the coefficients are found higher for the new result, which is expected because advanced countries have a higher share of their output level and growth of TFP compared to LDCs. A little exception is, that the short-run coefficient of IC growth is insignificant and shows unexpected signs. Besides, the lag of TFP growth is now found significant in contrast to the general sample. Nonetheless, the result is generally robust to changes in estimation methods, valuation techniques, and sample size.

5. Conclusion and policy implication

This paper understands TFP as an effect of IC, the composite indicator of a nation's capability to invent, absorb, and utilize tangible and intangible resources. It developed an IC index from various indicators of human capital, social, marketing, R&D, and organizational innovations. From this, the paper derived a new empirical model that defines TFP as an explicit function of IC. The new model is estimated by various dynamic common correlated effect estimators for a panel of 29 countries from 1990 to 2020. The result shows the existence of significant and positive short-run and long-run relationships between TFP and IC. This implies a need to understand TFP as an effect of IC, an integral factor behind the broader innovation process. Hence, for developing countries to narrow their productivity, national policymakers need to consider improvements in technological and social innovations, either scientific or non-scientific, in the production, processing, and marketing of products and services. Moreover, this study incites a new direction in the analysis of source differences in total factor productivity across countries. However, the lack of

adequate and rigorous data for some key indicators was a challenge for the construction of the national intellectual capital index in developing countries.

Thus, studies in the future should take into account additional tests of robustness and various scenario analyses to ensure that a level of national intellectual capital is accurately measured.

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Data availability statement

The data that support the findings of this study are openly available in figshare at 10.6084/m9.figshare.25048061.

References

- Abdullah, M., & Chowdhury, M. (2020). FDI and TFP: Any nexus? *Margin: The Journal of Applied Economic Research*, 14(2), 164–190. <https://doi.org/10.1177/0973801020904473>
- Abramovitz, M. (1956). Resource and output trends in the United States since 1870. *The American Economic Review*, 46(2), 5–23.
- Alfaro, J. L., Lopez, V. R., & Nevado, D. (2014). Economic growth and intangible capitals: Europe versus Asia. *Panoeconomicus*, 61, 261–274.
- Bellocci, A., Sanchez, C. E., & Travaglini, G. (2021). What drives TFP long-run dynamics in five large European economies? *Economia Politica*, 38(2), 569–595. <https://doi.org/10.1007/s40888-021-00215-x>
- Benhabib, J., & Spiegel, M. M. (1994). The Role of human capital in economic development evidence from aggregate cross-country data. *Journal of Monetary Economics*, 34(2), 143–173. [https://doi.org/10.1016/0304-3932\(94\)90047-7](https://doi.org/10.1016/0304-3932(94)90047-7)
- Benhabib, J., & Spiegel, M. M. (2005). Human capital and technology diffusion. In P. Aghion, and S. Durlauf (Eds.), *Handbook of economic growth* (vol. 1, pp. 936–965). North Holland. [https://doi.org/10.1016/S1574-0684\(05\)01013-0](https://doi.org/10.1016/S1574-0684(05)01013-0)
- Bersvendsen, T., & Ditzen, J. (2021). Testing for slope heterogeneity in Stata. *The Stata Journal*, 21(1), 51–80. <https://doi.org/10.1177/1536867X211000004>
- Blackburn, K., Hung, V. T. Y., & Pozzolo, A. F. (2000). Research, development and human capital accumulation. *Journal of Macroeconomics*, 22(2), 189–206. [https://doi.org/10.1016/S0164-0704\(00\)00128-2](https://doi.org/10.1016/S0164-0704(00)00128-2)
- Blomquist, J., & Westerlund, J. (2013). Testing slope homogeneity in large panels with serial correlation. *Economics Letters*, 121(3), 374–378. <https://doi.org/10.1016/j.econlet.2013.09.012>

- Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, 122(4), 1351–1408. <https://doi.org/10.1162/qjec.2007.122.4.1351>
- BLS. (2023). Historical total factor productivity measures. <https://www.bls.gov/productivity/tables/home.htm>.
- Böhm-Bawerk, E. (1891). *The positive theory of capital*. Macmillan.
- Bontis, N. (2004). National intellectual capital index: A UN initiative for the Arab region. *Journal of Intellectual Capital*, 5(1), 13–39. <https://doi.org/10.1108/14691930410512905>
- Brynjolfsson, E., Rock, D., & Syverson, C. (2018). The productivity J-curve: How intangibles complement general purpose technologies. NBER WP 25148.
- Calderón, C. (2021). *Boosting productivity in Sub-Saharan Africa: Policies and institutions to promote efficiency*. World Bank. <https://doi.org/10.1596/978-1-4648-1550-8>
- Chen, P., Karavias, Y., & Tzavalis, E. (2022). Panel unit-root tests with structural breaks. *The Stata Journal*, 22(3), 664–678. <https://doi.org/10.1177/1536867X221124541>
- Cheng, C. S., Razak, A. A., & Abdullah, H. (2013). Human capital and technological catch-up in the Asian Developing Countries. *Proceedings of Malaysia Handbook on the Economic, Finance, and Management Outlooks*.
- Chudik, A., Mohaddes, K., Pesaran, M. H. and Raissi, M. (2016). Long-Run Effects in Large Heterogeneous Panel Data Models with Cross-Sectionally Correlated Errors. In *Essays in Honor of Aman Ullah (Advances in Econometrics, Volumn 36)*, ed. R. C. Hill, G. Gonzalez-Rivera, and T.-H. Lee, 85(135). Emerald Group Publishing Limited.
- Chudik, A., & Pesaran, M. H. (2015). Common Correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420. <https://doi.org/10.1016/j.jeconom.2015.03.007>
- Clark, J. (1886). *The philosophy of wealth: Economic principles newly formulated*. GINN & Company.
- Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review*, 39(5), 859–887. [https://doi.org/10.1016/0014-2921\(94\)00100-E](https://doi.org/10.1016/0014-2921(94)00100-E)
- Coe, D. T., Helpman, E., & Hoffmaister, A. (2009). International R&D spillovers and institutions. *European Economic Review*, 53(7), 723–741. <https://doi.org/10.1016/j.euroecorev.2009.02.005>
- Comin, D., & Mestieri, M. (2018). If technology has arrived everywhere, why has income diverged? *American Economic Journal*, 10(3), 137–178. <https://doi.org/10.1257/mac.20150175>
- Corrado, C., Haskel, J., & Lasinio, C. J. (2017). Knowledge spillovers, ICT and productivity. *Oxford Bulletin of Economics and Statistics*, 79(4), 592–618. <https://doi.org/10.1111/obes.12171>
- Corrado, C., Hulten, C., & Sichel, D. (2005). Measuring capital and technology: an expanded framework. In C. Corrado, J. Haltiwanger, and D. Sichel, (Eds.), *Measuring capital in the new economy* (pp. 11–45). The University of Chicago Press.
- Corrado, C., Hulten, C., & Sichel, D. (2010). Measuring intangible capital: how do you measure a “technological revolution”? *American Economic Review*, 100(2), 99–104. <https://doi.org/10.1257/aer.100.2.99>
- Costa, R. (2012). assessing intellectual capital efficiency and productivity: An application to the Italian yacht manufacturing sector. *Expert Systems with Applications*, 39(8), 7255–7261. <https://doi.org/10.1016/j.eswa.2012.01.099>
- Coyle, D. (2019). Measuring productivity in the context of technological change. In *Work in the Age of Data*. By Turner, BBVA.: Madrid.
- Ditzen, J. (2018). Estimating dynamic common-correlated effects in stata. *The Stata Journal*, 18(3), 585–617. <https://doi.org/10.1177/1536867X1801800306>
- Ditzen, J. (2021). Estimating long-run effects and the exponent of cross-sectional dependence: An update to xtdcce2. *The Stata Journal*, 21(3), 687–707. <https://doi.org/10.1177/1536867X211045560>
- Ditzen, J., Karavias, Y., & Westerlund, J. (2021). Testing and Estimating Structural Breaks in Time Series and Panel Data in Stata. *arXiv:2110.14550v2*.
- Do, M., Tam, H., & Kim-Duc, N. (2022). Investigating intellectual capital: The role of intellectual property rights reform. *Cogent Economics & Finance*, 10(1), 2106630.
- Domar, E. D. (1961). On the measurement of technological change. *The Economic Journal*, 71(284), 709–729. <https://doi.org/10.2307/2228246>
- Edvinsson, L., & Malone, M. S. (1997). *Intellectual capital: Realizing your company's true value by finding its hidden brainpower*. Harper Business.
- Fabricant, S. (1954). Economic progress and economic change. *34th Annual Report of NBER*.
- Fadiran, D., & Akanbi, O. (2017). Institutions and other determinants of total factor productivity in Sub-Saharan Africa. *Research Papers in Economics*.
- Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. *American Economic Review*, 105(10), 3150–3182. <https://doi.org/10.1257/aer.20130954>
- Frantzen, D. (2000). R&D, human capital, and international technology spillovers: A cross-country analysis. *The Scandinavian Journal of Economics*, 102(1), 57–75. <https://doi.org/10.1111/1467-9442.00184>
- Gordon, R. J. (2018). Why has economic growth slowed when innovation appears to be accelerating? NBER WP 24554.
- Griffith, R., Redding, S., & Van Reenen, J. (2004). Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. *Review of Economics and Statistics*, 86(4), 883–895. <https://doi.org/10.1162/0034653043125194>

- Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, 25(4), 501–522. <https://doi.org/10.2307/1905380>
- Griliches, Z. (1973). Research expenditures and growth accounting. In B. R. Williams (Ed.), *Science and Technology in Economic Growth*. IEA.
- Griliches, Z. (1998). Productivity, R&D, and the data constraint. In Z. Griliches (Ed.), *R&D and Productivity: The Econometric Evidence*. (pp. 347–374). University of Chicago Press.
- Haavelom, T. (1964). *A study in the theory of economic evolution*. North-Holland Publishing Company.
- Hall, R. E., & Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, 114(1), 83–116. <https://doi.org/10.1162/003355399555954>
- Hayek, F. A. (1935). The maintenance of capital. *Economica*, 2(7), 241–276.
- Hayek, F. A. (1937). Economics and knowledge. *Economica*, 4(13), 33–54.
- Herzer, D., & Donaubauer, J. (2017). The long-run effect of foreign direct investment on total factor productivity in developing countries: a panel cointegration analysis. *Empirical Economics*, 54(2), 309–342. <https://doi.org/10.1007/s00181-016-1206-1>
- Hulten, C. R. (2001). Total factor productivity: a short biography. In Charles R. Hulten, Edwin R. Dean, and Michael Harper (Eds.), *New developments in productivity analysis*. University of Chicago Press. <https://doi.org/10.7208/chicago/9780226360645.003.0001>.
- James, K., Kotak, A., & Tsomocos, D. (2022). Ideas, idea processing, and TFP growth in the US: 1899 to 2019. The LSE Discussion Paper. <https://doi.org/10.2139/ssrn.4161964>
- Jednak, S., Dmitrovic, V., & Damjanovic, V. (2017). Intellectual capital as a driver of economic development. *Journal of Economics and Business*, 15(2), 71–84.
- Jola-Sanchez, A. F. (2022). How does warfare affect firms' productivity? *Production and Operations Management*, 31(5), 1940–1962. <https://doi.org/10.1111/poms.13658>
- Kaldor, N. (1954). "The Relation of Economic Growth and Cyclical Fluctuations." *The Economic Journal* 64(253), 53–71.
- Kao, C., Chiang, M., & Chen, B. (1999). International R&D spillovers: An application of estimation and inference in panel cointegration. *SSRN Electronic Journal*, <https://doi.org/10.2139/ssrn.1807962>
- Karavias, Y., & Tzavalis, E. (2014). Testing for unit roots in short panels allowing for a structural break. *Computational Statistics & Data Analysis*, 76(c), 391–407. <https://doi.org/10.1016/j.csda.2012.10.014>
- Kendrick, W. (1956). Productivity trends: Capital & labor. *Review of Economics & Statistics*, 38(3), 248–257.
- Kuzkin, Y., Cherkashyna, T., Nebaba, N., & Kuchmacz, B. (2019). Economic growth of the country and NIC. *Problems and Perspectives in Management*, 17(1), 348–359. [https://doi.org/10.21511/ppm.17\(1\).2019.30](https://doi.org/10.21511/ppm.17(1).2019.30)
- Laudardale, E. (1819). *An Inquiry into the nature and origin of public wealth and the means and cause of its increase*.
- Lichtenberg, F. R., & van Pottelsberghe de la Potterie, B. (1998). International R&D Spillovers: A Comment. *European Economic Review*, 42(8), 1483–1491. [https://doi.org/10.1016/S0014-2921\(97\)00089-5](https://doi.org/10.1016/S0014-2921(97)00089-5)
- Ma, X., Jia, F., Jiang, H., & Xu, X. (2022). The impact of Non-R&D intangible capital on TFP growth. *Journal of the Knowledge Economy*, 13(4), 2890–2910. <https://doi.org/10.1007/s13132-021-00848-0>
- Madsen, J. B. (2008). Economic growth, TFP convergence and the world export of ideas: A century of evidence. *Scandinavian Journal of Economics*, 110(1), 145–167.
- Marcin, K. (2013). Intellectual capital as a key factor of socio-economic development of regions and countries. *Procedia Economics and Finance*, 6, 288–295. [https://doi.org/10.1016/S2212-5671\(13\)00142-1](https://doi.org/10.1016/S2212-5671(13)00142-1)
- Michalczyk, G., & Fiedorczyk, J. (2017). Macroeconomic Perspective of Intellectual Capital. *Optimum. Studia Ekonomiczne*, 5(89), 117–133. <https://doi.org/10.15290/ose.2017.05.89.08>
- Mill, J. S. (1848). *Principles of political economy with some of their application to social philosophy* (7th ed.). Longmans.
- Miller, S. M., & Upadhyay, M. P. (2002). Total factor productivity and the convergence hypothesis. *Journal of Macroeconomics*, 24(2), 267–286. [https://doi.org/10.1016/S0164-0704\(02\)00022-8](https://doi.org/10.1016/S0164-0704(02)00022-8)
- Mohnen, P. (2019). R&D, innovation, and productivity. In T. ten Raa, & W. Greene (Eds.), *The Palgrave Handbook of Economic Performance Analysis*. Cham: Palgrave Macmillan. https://doi.org/10.1007/978-3-030-23727-1_4
- Mohnen, P., Polder, M., & van Leeuwen, G. (2018). ICT, R&D, and organizational innovation: exploring complementarities in investment and production. WP 25044.
- Nelson, R. R. (1956). A theory of the low-level equilibrium trap in underdeveloped economies. *The American Economic Review*, 46(5), 894–908.
- Nelson, R. R., & Phelps, E. (1966). Investment in humans, technological diffusion, and economic growth. *The American Economic Review*, 56, 69–75.
- Pedro, E., Leitão, J., & Alves, H. (2018). Back to the future of intellectual capital research: a systematic literature review. *Management Decision*, 56(11), 2502–2583. <https://doi.org/10.1108/MD-08-2017-0807>
- Persyn, D., & Westerlund, J. (2008). Error-correction-based cointegration tests for panel data. *The Stata Journal*, 8(2), 232–241. <https://doi.org/10.1177/1536867X0800800205>
- Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74(4), 967–1012. <https://doi.org/10.1111/j.1468-0262.2006.00692.x>
- Pesaran, M. H. (2015). *Time series and panel data econometrics*. OUP.

- Pietrucha, J., Żelazny, R., Kozłowska, M., & Sojka, O. (2018). Import and FDI as channels of international TFP spillovers. *Equilibrium*, 13(1), 55–72. <https://doi.org/10.24136/eq.2018.003>
- Playfair, W. (1805). *An inquiry into the permanent causes of the decline and fall of powerful and wealthy nations*. Greville-Street.
- Prescott, E. C. (1998). Needed: A theory of total factor productivity. *International Economic Review*, 39(3), 525–551. <https://doi.org/10.2307/2527389>
- Pritchett, L. (2001). Where has all the education gone? *The World Bank Economic Review*, 15(3), 367–391. <https://doi.org/10.1093/wber/15.3.367>
- Schultz, T. W. (1956). Reflections on agricultural production, output and supply. *Journal of Farm Economics*, 38(3), 748. <https://doi.org/10.2307/1234459>
- Schumpeter, J. A. (1911). *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*. HU Press.
- Smith, A. (1776). *An Inquiry Into the Nature and Causes of the Wealth of Nations* E. Cannan (Ed.). Elec Book Classics.
- Sokoł, A. (2017). Diagnosis of IC in macroeconomic terms on the example of Szczecin and opportunities for development of creative sector. *HRM & Ergonomics*, 11(2), 59–75.
- Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 39(3), 312–320. <https://doi.org/10.2307/1926047>
- Solow, R. M. (1963). *Capital Theory and the Rate of Return*. Amsterdam: North-Holland.
- Spiegel, H. W. (1955). Theories of economic development: History and classification. *Journal of the History of Ideas*, 16(4), 518–539. <https://doi.org/10.2307/2707508>
- Stähle, P., Stähle, S., & Lin, C. (2015). Intangibles and national economic wealth – a new perspective on how they are linked. *Journal of Intellectual Capital*, 16(1), 20–57. <https://doi.org/10.1108/JIC-02-2014-0017>
- Stathakis, G., & Vaggi, G. (2006). *Economic development & social change: Historical roots & modern perspectives*. Taylor & Francis e-Library.
- Su, T. D., & Nguyen, C. P. (2022). Productive contribution of public spending and human capital in developing countries revisited: The role of trade openness. *Foreign Trade Review*, 57(1), 66–84. <https://doi.org/10.1177/00157325211045471>
- Thakkar, J. J. (2021). *Multi-criteria decision making: Studies in systems, decision and control*. Springer.
- Tian, F., & Liu, L. (2019). The impact of intellectual capital spillover on total factor productivity: an empirical study in coastal regions of China. *Journal of Coastal Research*, 94(1), 920–925. <https://doi.org/10.2112/SI94-181.1>
- Tiwari, R., Vidyarthi, H., & Kumar, A. (2023). Nexus between intellectual capital and bank productivity in India. *Journal of Risk and Financial Management*, 16(1), 54. <https://doi.org/10.3390/jrfm16010054>
- Uttama, N. P., & Peridy, N. J. (2010). Foreign direct investment and productivity spillovers: the experience of ASEAN countries. *Journal of Economic Integration*, 25(2), 298–323. <https://doi.org/10.11130/jei.2010.25.2.298>
- Uziene, L. (2014). National intellectual capital as an indicator of the wealth of nations: the case of the Baltic States. *Social and Behavioral Sciences*, 156, 376–381.
- Veblen, T. (1908). On the nature of capital. *The Quarterly Journal of Economics*, 22(4), 517–542. <https://doi.org/10.2307/1884915>
- Woo, J. (2009). Productivity growth and technological diffusion through FDI. *Economic Inquiry*, 47(2), 226–248. <https://doi.org/10.1111/j.1465-7295.2008.00166.x>
- WTSR. (2019). World trade statistical review.
- Young, A. A. (1928). Increasing returns and economic progress. *Economic Journal*, 38(152), 527–542.

Appendix A

Table A1. Sample countries by income group and region.

Income group	SSA	MENA	LA	Asia	Europe	NA
LIC ($\leq \$1085$)	Ethiopia 3 Malawi 6					
LMIC (\$1086–\$4255)	Ghana 13 Kenya 5 Senegal 15	Morocco 10		Indonesia 4 Philippines 26		
UMIC (\$4256–13,205)	Mauritius 9 S.Africa 12		Brazil 1 Mexico 7 Colombia 2 Peru 11	Malaysia 8 Thailand 14		
HIC ($> \$13,205$)			Chile 28	Japan 25 S. Korea 27 Singapore 29	Germany 19 France 18 UK 23 Netherlands 20 Sweden 22 Denmark 16 Italy 17 Spain 21	USA 24

Source: Income level according to 2023 WB classification.

Table A2. Compositions of intellectual capital index.

Code		Indicators and or proxies	relation	Measures
Renewal capital (RC)	1	Payments + receipts for the use of intellectual property + technical cooperation grants	Positive	BoP, current US\$
	2	Design applications (resident + non resident)	Positive	count
	3	Patent applications (resident + non resident)	Positive	count
	4	Research and development expenditure	Positive	% of GDP
	5	Scientific and technical journal articles	Positive	counts
Process Capital (PC)	1	Communications, computer, etc.	Positive	% serv export & import
	2	Cost of business start-up procedures	Negative	% of GNI per capita
	3	Internet + tele subscribers	Positive	per 100 people
	4	Procedures to build, register business & property	Negative	Number
	5	Time to register business & property	Negative	Days
Marketing Capital (MC)	6	Corruption perception index	Negative	Number
	1	Trade to GDP ratio	Positive	% of GDP
	2	Domestic credit to the private sector	Positive	% of GDP
	3	Market capitalization	Positive	% of GDP
	4	Foreign direct investment, net inflows	Positive	% of GDP
Human Capital (HC)	5	ICT goods & service exports	Positive	% service exports
	6	Medium and high-tech exports	Positive	% manufacturing exports
	1	Population ages 15–64	Positive	% of the total population
	2	Mortality rate, infant	Negative	per 1,000 live births
	3	Pupil-teacher ratio, 1 ^o , 2 ^{ry} & tertiary	Negative	Number
	4	School enrollment, 1 ^o , 2 ^{ry} & tertiary	Positive	% gross
	5	Researchers & Technicians in R&D	Positive	per million people

Source: Adapted from Stähle *et al.* (2015) and Global competitiveness index.