Green Total Factor Productivity for India: Some Recent Estimates and Policy Directions[1]

Shruti Joshi (Corresponding Author)
Research Officer
sjoshi@rbi.org.in
Reserve Bank of India
Shaheed Bhagat Singh Road, Fort, Mumbai 400001

Siddhartha Nath
Assistant Adviser
siddharthanath@rbi.org.in
Reserve Bank of India
Shaheed Bhagat Singh Road, Fort, Mumbai 400001

Abhishek Ranjan
Manager (research)
abhishekranjan@rbi.org.in
Reserve Bank of India
Shaheed Bhagat Singh Road, Fort, Mumbai 400001

[1] Authors belong to Reserve Bank of India, Mumbai. The views expressed in this paper are those of the authors and do not necessarily represent that of the Reserve Bank of India.

Abstract

The conventional estimate of aggregate productivity growth of a nation, the total factor productivity, or TFP, can be upwardly biased if environmental externalities generated during the production processes are not accounted for. In turn, this suggests that increased TFP growth may not necessarily indicate an environmentally sustainable economic growth in the long-run. In this paper, we estimate Green TFP growth, which is the TFP growth after accounting for the CO2 emissions using data for more than 140 countries across the globe between 1990 and 2019. The Global Malmquist-Luenberger Productivity Index suggests that the Green TFP growth and the conventional TFP growth rates diverge significantly. India's average annual Green TFP growth since 2000 is estimated to be almost zero per cent, while India's conventional TFP growth stands out to be one of the highest globally, at above 2 percent annually. Our findings suggest that mostly the OECD countries may have maintained substantial progress in terms of green TFP, while the emerging Asian economies, including South Asian countries, may be significantly lagging. Despite this, our study suggests that India has improved its green productivity in recent years. Our study highlights the importance of decarbonizing the economic growth process of the emerging economies, including India at a much faster rate to achieve a more sustainable growth in the long-run.

Keywords: Green Total Factor Productivity; Directional Distance Function; Global Malmquist–Luenberger Index.

JEL: Q54, D24, C43

I. Introduction

The rate of technological progress and productivity growth have long been considered important drivers of an economy's sustained growth in output and per-capita income (Solow 1956; Uzawa 1965; Lucas 1988). The long-term viability of a nation's economic growth is achieved through innovations, diffusion of technologies, and growth in the productivity levels of its workforce (McGowan et. al., 2015). Recognizing its importance, the United Nations Department of Economic and Social Affairs included productivity growth among its 17 Sustainable Development Goals (SDGs). The SDGs seek to promote global prosperity by increasing economic productivity through innovation and technological advancement, as well as empowering vulnerable groups through the formalisation and growth of micro, small, and medium enterprises. The term "productivity" appears in SDG 2.3 and 2.4 (agriculture, in particular subsistence agriculture) and in SDG 8.2 (factor productivity). In the broader context, although productivity growth accounts for the distributional aspects of growth, allocative efficiency of available resources, etc., aggregate productivity growth is generally achieved through the advancement and diffusion of technological capabilities within a nation (see McGowan et. al., 2015). The economic policies across the world during the post-World War II era largely focused on the growth rate of per-capita Gross Domestic Product (GDP) through industrialization and technological progress. On the contrary, the environmental implication of this process through the emission of Green House Gases (GHG), deforestation, disposal of harmful chemicals into the soil and water, etc. has come into focus relatively recently. Environmental degradation has long been recognised as having a negative impact on public health, human capital, and thus productivity growth (Jha and Tripathi 2011; Deryugina and Hsiang 2014; and Kumar and Gautam 2014). Therefore, the environmental consequences of a nation's industrialization and productivity growth can potentially limit its ability to utilise its own human and natural resources in the future. In light of this, a wide range of literature provides consensus in accounting for this negative externality on the environment when measuring a country's productivity growth (see Brandt et al. 2014).

Productivity growth has been measured in several ways in the literature. From the welfare point of view, the commonly used measure is average labour productivity, which measures GDP per capita or the output per worker of a nation. However, labour productivity growth comes with limitations when it comes to measuring technological progress and productivity growth. A significant portion

of growth in per-worker output comes from growth in fixed capital stocks, including transport equipment, buildings, etc., which may not necessarily reflect an economy's productivity growth or technological progress. Due to this limitation, total factor productivity (TFP) has gradually taken precedence as a measure of technological progress and productivity growth, following the seminal work of Solow (1956). TFP growth refers to the growth of a country's output, commonly measured by its GDP, after the contributions of both labour and capital are subtracted. Thus, TFP growth accounts for that part of the growth in a country's GDP that is not explained by the growth in its labour force and stock of physical capital. The TFP growth rate, therefore, provides a measure of technological progress and efficiencies in the production processes, collectively called the productivity growth in an economy.

In this paper, we estimate the TFP growth rate for a set of 146 countries after accounting for the possible environmental consequences. We used internationally comparable data on aggregate production sets from Penn World Table 10.0 between 1990 and 2019. The effect of economic growth on the environment can potentially encompass several aspects, including deforestation, land and water pollution through the disposal of chemicals, the depletion of groundwater, and the emission of Green House Gases (GHG). In this paper, however, we account only for the emission of carbon dioxide (CO_2) in deriving our climate-adjusted TFP growth, partly due to the non-availability of reliable and comparable data across countries on other aspects of environmental degradation. We call this measure the "green *TFP growth*" in the remaining part of the paper. In the absence of any direct measure of aggregate externality caused by the emission of CO_2, we assume that this externality is proportional to the volume of the emission. Our methodology broadly follows Oh (2010). This methodology takes all the possible combinations of production set and emission levels at the aggregate country level and comes to an efficient frontier in the form of the Global Malmquist-Luenberger Productivity Index (GMLPI). The green TFP in a country is measured by the "distance" of that country's position from the global frontier.

Several studies in the past, including those by Jeon and Sickles (2004), Kumar (2006), and Oh (2010), estimated green TFP growth by considering a large set of countries, including India. However, these studies mainly focused on the decades prior to 2010. A slew of initiatives has followed since then at the international level in the last decade, following several international protocols and accords, e.g., the Copenhagen Protocol, the Paris Agreement, etc. There has been no

significant empirical evidence available at the international level concerning the growth of green TFPs for the last decade. Our study intends to fill the gap.

Our paper is organised as follows: Section II is a brief review of the literature. Section III is a summary of the stylized facts. Section IV describes the data and methodology used. Section V discusses our findings. We discuss India's key policies towards climate risks in Section VI, while Section VII concludes the paper.

II. Review of Literature

The available literature suggests that stricter environmental laws on account of rising pollution levels adversely impact productivity growth as higher pollution abatement expenditure results in the diversion of resources away from production activities (Eberts and Forgarty (1987), Jaffe et al. (1995), Garofalo and Malhotra (1995), Murty et al. (2006)). Subsequently, a slew of strategies were introduced for modelling environmental externalities in productivity estimates and crediting firms for reducing emissions. The Malmquist-Luenberger Productivity Index (MLPI), empirically estimated as the Global MLPI (Pastor and Lovell 2007; Oh 2010; Zhu et al 2018) Metafrontier MLPI (Oh and Lee 2010); slack-based metrics; and data envelopment analyses (DEA) are among these techniques. These methodologies made it possible to include environmental externalities in the productivity analysis.

The Malmquist-Luenberger productivity index, established by Chung et al. (1997) to compute the green productivity index for the Swedish paper and pulp industry, has become the most widely used methodology in the literature. Weber and Domazlicky (2001), Fare et al. (2001), etc. used this approach to estimate green productivity growth in the US. Jeon and Sickles (2004) estimate green productivity using the MLPI for a sample of Asian countries (1980–95) and OECD economies (1980–90). Yue et al. (2006) use aircraft noise to evaluate the productivity of Taiwan's airport industry from 1995 to 1999. Kumar (2006) estimates environmentally sensitive productivity indices for 41 developed and developing countries during 1971–1992. According to these studies, not accounting for unwanted outputs in the analysis of efficient production frontiers can lead to an upward bias in the estimates of productivity growth. Most of these studies also find a divergence between TFP and green TFP in recent decades. They also conclude that a productivity

index that incorporates an increase in desired production and a decrease in undesirable output leads to an increase in the aggregate productivity of a country.

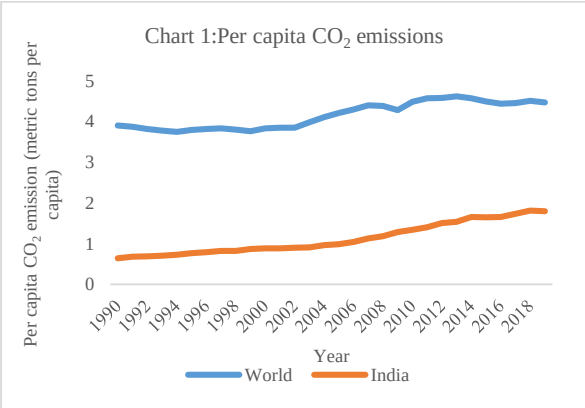
Apart from these studies, there are numerous others that estimate green productivity in China (Li and Tao 2011; Li et al. 2013; Zhang and Choi 2013; Li and Lin 2016). For example, Chen et al. (2018) estimate TFP growth for China's industrial sectors and find that incorporating environmental consequences reduces the industrial TFP by 0.02 percent each year on average. Wang and Shen (2016) find a significant difference in green productivity between polluting and clean production industries, with the former having lower green productivity than the latter. Several studies have examined the adverse impact of the environment on labour and agricultural productivity in India (Datta and Jong 2002; Singh 2016; Kumar and Sharma 2014).

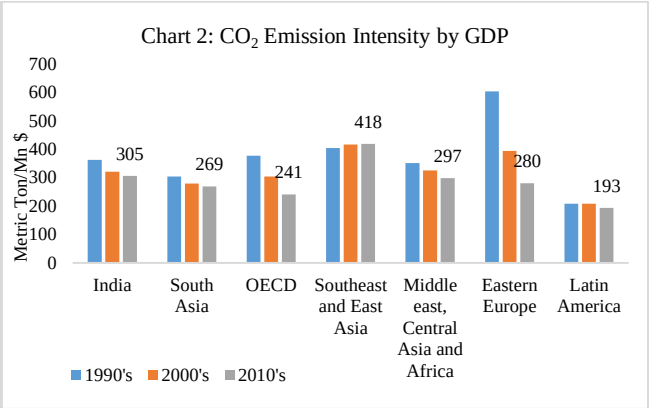
The available literature in this regard has broadly remained concentrated on sectoral estimates for China, the United States, and a select set of OECD and Asian economies and has projected green productivity trends through the early 2000s. There is no significant work after Jeon and Sickles (2004), Kumar (2006), and Oh (2010) that estimated green TFP growth in a large set of countries, including India, especially in the most recent decade, which witnessed a slew of measures by the international, and domestic organizations. Our research attempts to add to the existing literature and policy debates by providing estimates of green TFP growth across the globe for the most recent decades using an internationally comparable Penn World Table dataset. In our discussions, we draw special attention to India's case and provide an international comparison.

III. Stylized Facts

India's per capita CO_2 emissions have historically remained lower than the global average due to India's low share in industrial output and overall GDP. Chart 1 suggests that India's per capita CO_2 emissions, at approximately 1.8 metric tons, were roughly 40 percent of the global average at the end of the last decade, despite increasing since 1990. In contrast, India's CO_2 emission intensity in relation to GDP remained substantially higher than that of the major Asian economies and advanced economies (Chart 2). For instance, India's average CO_2 emission in relation to GDP between 2010 and 2019 was 305 metric tons (MT) per million US dollars, compared to 262 MT per million US dollars in the case of the OECD countries. India's CO_2 emission intensity in relation to GDP was substantially higher than that of other developing nations in South Asia, Latin

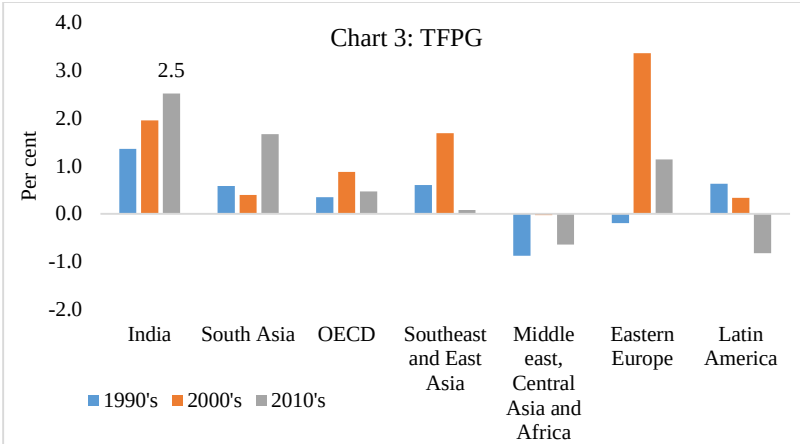
America, and Eastern Europe. Therefore, India's low per capita CO_2 emissions may not necessarily signal the adoption of carbon-sensitive technologies. Indeed, India's low per capita emissions can be attributed to its large population. In fact, as the economy grows at a faster rate than the rest of the world, there could be a risk of higher incremental emissions in the near to medium term.





Source: Author's calculation from Penn World Table 10.0 and World Development Indicators, World Bank.

The available data suggests that the TFP growth rate in India was higher than most of the major economies in recent decades (Chart 3). Since 2000, India's high TFP growth has helped to support the country's high aggregate GDP growth among emerging economies. Chart 3 suggests that India's average TFP growth rates during 1990-2019 were not only the highest in the world, but that the TFP growth rate in India has increased over these decades, in contrast to the developed and most of the developing economies. This relatively higher rate of technological progress in India, as indicated by the TFP growth rates, in conjunction with the high carbon intensities of GDP suggested by Chart 2, suggests that the recent progress may have come at the cost of environmental sustainability. It is well established in the literature that environmental sustainability can lead to better economic growth in the long term. Therefore, in the present context, it may be pertinent to see how much TFP growth India has been able to achieve after we account for the possible environmental consequences of the present growth process. If we do not take into account the environmental damages that the economic growth of the country brings in, the available estimates of productivity growth can be upwardly biased. In this vein, we revisit the estimate of TFP growth after accounting for CO_2 emissions in this paper.



Source: Author's calculation from Penn World Table 10.0.

IV. Methodology and Data

A. Methodology

We estimate green TFP growth (GTFPG) using the methodology of Oh (2010). In this paper, GTFPG is quantified using the Global Malmquist-Luenberger productivity index (GMLPI). This index is estimated on the basis of the directional distance function (DDF), which measures the "distance" of a country at a given point in time from a globally optimum production frontier. The global production frontier consists of the set of outputs maximised with the given sets of inputs. The output may consist of both "good" and "bad" output. A good output may be the outcome of any economic activity that is either welfare-enhancing or has positive externalities, such as the production of consumer goods, intermediate inputs, the delivery of services, works of art, etc. Bad output, on the other hand, is the result of any economic activity that reduces welfare. For instance, emissions of harmful gases, disposal of harmful chemicals into natural resources like waterbodies, etc., and noise pollution can be treated as bad outputs in these estimates.

The index is defined for a production unit as the ratio of DDF between time t and t+1:

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1+D^G(x^t,y^t,b^t)}{1+D^G(x^{t+1},y^{t+1},b^{t+1})} \quad (1)$$

At time s= t and t+1, $x^s, y^s, and\ b^s$ denotes the inputs, good output and bad output, respectively. D^G(.) is the Directional Distance Function (DDF), which measures how far a country is from the production frontier, which represents the global benchmark technology for a given span of years (Fare and Grosskopf 2000). According to the DDF, a country that produces a given set of good

output from a given set of inputs while producing less bad output will be closer to the global technology frontier than a country that can produce the same amount of good output while producing more bad output. The numerator of this GMLPI takes the "distance" of a country from the global frontier as obtained by DDF at period t, while in the denominator, it uses the "distance" of the same country at period t+1. A value of GML greater than 1 indicates higher efficiency in period t+1 compared to period t in producing two outputs using the given set of inputs since the distance of that country's own production frontier from the global frontier in time t+1 is smaller than its distance in time t. On the other hand, if the value of this index is less than 1, it indicates that the country's efficiency has declined from the previous year. The measure of efficiency changes as obtained from the above GMLPI is regarded as the GTFPG, since other than the desirable output y, it also accounts for the production of the undesirable output, which is the emission of greenhouse gases during the country's domestic production processes. A rise in undesirable output while keeping the good output and the set of inputs unchanged would reduce GMLPI. We now briefly describe the methodology for the construction of DDF as given in Fare and Grosskopf (2000). We briefly describe the methodology as in (Chung et al., 1997; Oh, 2010) below.

In the presence of undesirable output, the production technology for a decision-making unit (DMU) producing both desirable and undesirable output from a given set of inputs is represented as follows:

$$P^t(x) = \{(y^t, b^t) \mid x^t can\ produce\ (y^t, b^t)\} \qquad (2)$$

In equation (2), y is the vector of desirable output, b is the vector of undesirable output, and x is the set of inputs available to a particular DMU at a given time. The production technology set provides us with a frontier when a country is producing both desirable and undesirable outputs using the available set of inputs. A global benchmark technology is defined as $P^G = P^1 \cup P^2 \cdots \cup P^T$. This global benchmark technology is an augmented version of Pastor and Lovell (2005), which incorporates undesirable outputs into production.

Some assumptions are imposed on this production technology which are in line with the production theory. First, if inputs are increased, outputs will always increase. Second, desirable outputs cannot be produced if undesirable outputs are not produced. This implies that all production activity leads

to some form of emission, and if there is no emission, there cannot be any production. Third, any proportional decrease in desirable and undesirable output is feasible if the original combination of y and b is in the production technology set for given inputs. Intuitively, this implies that if undesirable output is reduced, then desirable output will also fall. This undesirable output reduction is costly and occurs by diverting resources away from the production of y. Lastly, if the output vector is feasible, then any output vector with less of the desirable output and the same amount of undesirable output is also feasible. This implies that desirable output is freely disposable.

The efficiency of a particular DMU at a given point in time is measured as the distance of that DMU from the global technology frontier. This distance is obtained by a DDF. The DDF shows the efficient point of production for a firm along a predetermined direction. With non-zero bad output, such as pollution, the efficient direction is defined along the path where undesirable output decreases and desirable output increases. For example, let $g = (g_y, g_b)$ be the directional vector[2]. The direction vector determines the direction in which the desirable output should increase and the undesirable output should decrease. Given the direction vector, the DDF is defined as follows:

$$D(x, y, b; g_y, g_b) = \max\{\beta | (y + \beta g_y, b - \beta g_b) \in p(x)\} \quad (3)$$

The function seeks to simultaneously increase the desirable output and reduce the undesirable output. β Is the DDF, it indicates the maximum output which can be produced with minimum emissions. β is estimated using non-parametric optimization techniques such as linear programming. In our paper, we estimate β using linear programming.

Figure 1 pictorially illustrates the DDF. In Figure 1, the solid line indicates the production frontier for a DMU that is producing both good and bad output. The DMU is operating at point F. The distance from the frontier, such as point C, where y is increased and b is decreased, is measured by the DDF, represented by B. The shorter the distance, the more efficient the DMU is. If B decreases over time, then the DMU is improving its green efficiency, whereas if B increases over time, then it means the DMU is deteriorating in its green efficiency.

[2] Following Chung et al (1997) and Oh (2010), the direction vector used is g=(y,b)

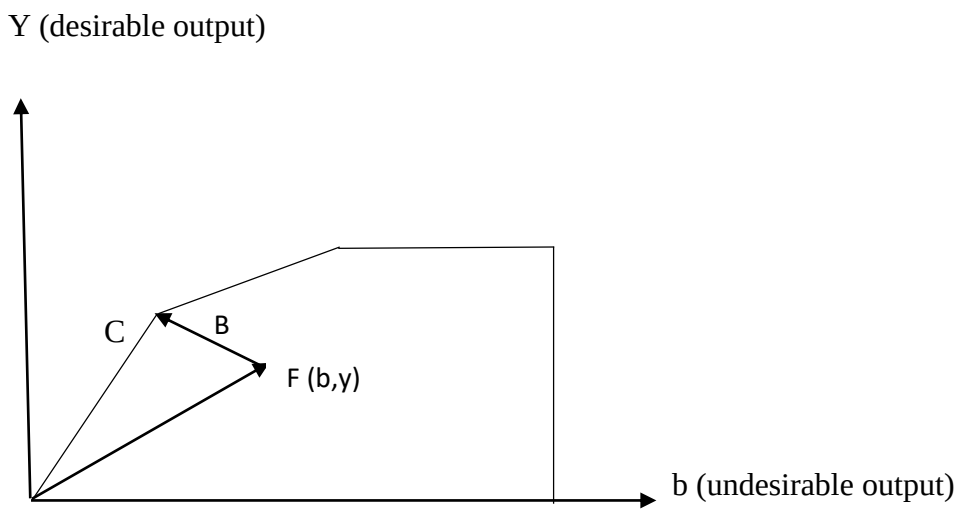


Fig 1: Distance between the optimal frontier and the output vector, denoted by B, is the DDF.

B. Data

In this paper, GTFPG is estimated at the country level. Therefore, in this case, a country serves as a DMU. The implicit assumption underlying a "frontier" among a collection of DMUs is that these DMUs are comparable in terms of the usage and objectives of their technologies and that the "best" among them lies on the frontier. This is a hard assumption to make given that countries around the world vary widely in terms of their economic and scientific developments. For instance, some countries are more dependent on agriculture, while others may be more industrialized. The nature of technologies in an agrarian economy may not be strictly comparable to those in an industrialised country. Despite this heterogeneity, we assume that the population in every country strives to attain a similar standard of living over the long term by utilising the factors of production, namely labour and capital, at their disposal. In addition, globalisation has facilitated the expansion of international connections. This supports the utilisation of a global technology frontier. Earlier applications of the method include (Chung et al. 1997; Fare et al. 2001; Yu et al. 2008).

We collect data on country-wise quantities of inputs, viz., labour and capital; quantities of "undesirable" or "bad" output, which is the emissions of CO_2; and quantities of "desirable" or "good" output. The Penn World Database (version 10.0) is utilised for data on total population, number of employed persons, annual average hours worked by persons engaged in economic activities, indices of human capital based on years of schooling and returns, stock of existing

capital, and indices of capital services based on the internal rate of return to capital in each country. The total population and the number of employed persons were stated in millions, while the capital stocks were reported at 2017 constant national prices converted into USD million. Human capital and capital services indices were expressed as indexes using 2017 as the base year. Penn World Table has had this information for 183 countries since the early 1950s. From this dataset, we exclude 53 countries, which are basically small island nations and countries with a smaller population. We ranked the countries based on their population and eliminated the lowest 20 percent of nations based on population. Afghanistan, Iraq, Syria, and Libya are also omitted from our sample because they suffered large-scale conflict during this period.

We use the World Development Indicators database provided by the World Bank for data on CO_2 emissions. In this database, per-capita emissions of CO_2 measured in metric tonnes were available since 1990 for almost all the countries that were available in Penn World Table 10.0. As a result, we limit our sample to 1990–2019. The final dataset used in this paper is made up of the above information from 143 countries between 1990 and 2019.

We found that the average annual hours worked, capital service, and human capital index were missing for some countries for some significant periods. In these cases, the missing values are estimated using the average value of these variables for the region to which these countries belong. In order to do this, we first divide our sample countries into the following nine geographical regions: OECD excluding Japan, South-East Asia, East-Asia including Japan, the Middle East, North Africa, and Central Asia (MENACA), Africa excluding North Africa, Eastern Europe, Latin America, and South Asia. The assumption is that the working behavior, e.g., the average hours of work, human capital, and returns to capital, would have been similar across countries that share common historical, topographical, and cultural features. Therefore, the average pattern of these variables in the countries in a region could be very similar. Using panel data from 153 countries between 1990 and 2019, we estimate the following regression models to find the time-varying average values of these variables for each region:

$$Human\ Capital\ Index_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \in_{it} \quad (4)$$

$$Capital\ Service_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \in_{it} \quad (5)$$

$$Average\ hours\ worked_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \in_{it} \quad (6)$$

In these models, the estimated coefficients of the region dummies would capture the average value of the variables human capital index, capital services, and the average hours worked for the whole period. The estimated coefficients of the year dummies would provide estimates of by how much these estimates would differ on average in a particular year across all regions. The year dummies, therefore, would capture the year-specific global shocks, both positive and negative, to these variables. The estimated values of human capital, capital service, and average hours worked from these regressions are used to replace the missing fields of these variables among the sample countries. A regression-based estimation of region-specific averages could be advantageous over a simple arithmetic mean for the specified regions for each year, as this regression would separate out the idiosyncratic components that are represented by the error terms of the regressions ($\in_{it}$).

In any productivity estimation, we require information on output and input. In our analysis, we use effective labour and effective capital as inputs into production. This enables us to take into account the quality of labour and capital (Patnaik 2014; Idris and Rahma 2019; Knowles and Owen 1997). To get the actual labour supply in each country, we multiply the number of workers employed by the annual hours of labour supplied by them. And then, to account for labour quality, we multiply by the human capital index.

The effective labor in our study is calculated as:

$$Number\ of\ people\ employed * Hours\ worked * Human\ Capital\ Index \quad (7)$$

These inputs can produce both desirable and undesirable outputs. The desirable output is measured in terms of per capita GDP, while the undesirable output is measured in terms of per capita emissions.

In a similar way, the effective capital is measured as:

$$Capital\ service * Capital\ stock. \quad (8)$$

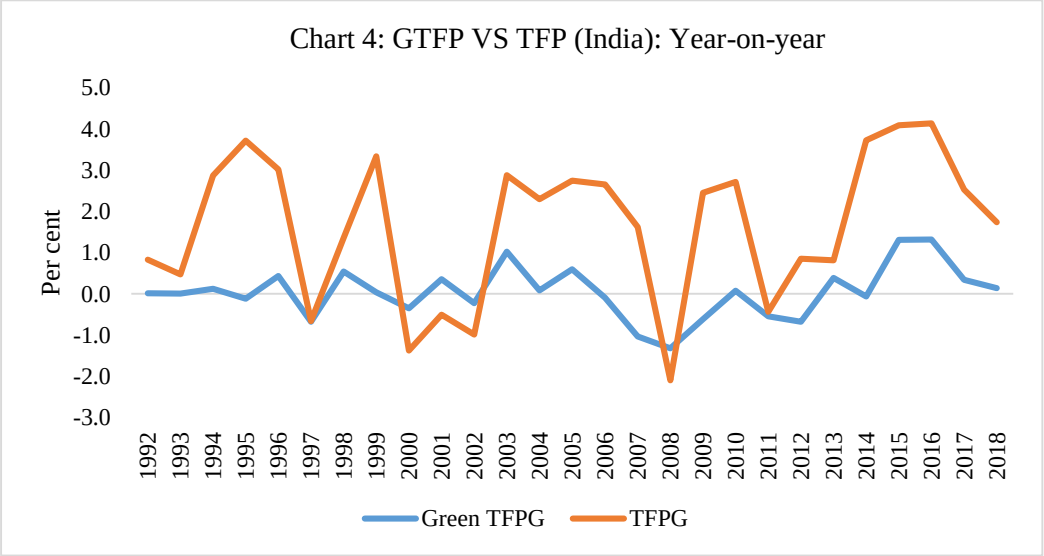
After predicting the missing values, we compute the effective labour and capital using the above formulas.

In addition to accounting for supply-side inputs into production, we also take absorptions into the GDP ratio of each country, where absorption is domestic consumption by end consumers (government, households, and firms).

Based on our data, we estimate the directional distance function of each nation, which indicates the distance of each nation from the global frontier. And from the DDF, we estimate the global Malmquist-Luenberger productivity index (GMLPI), which gives us the measure of green TFP.

V. Results

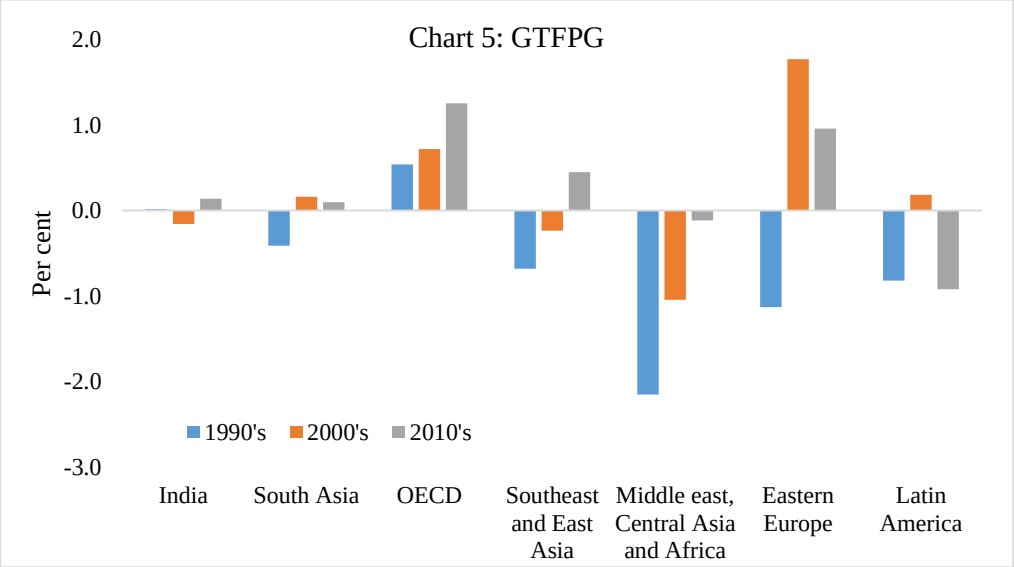
We discuss our estimated results in this section. Our estimates for India in Chart 4 suggest that the GTFP growth remained significantly lower than the TFP growth during the sample period, which is between 1990 and 2019. The TFP growth broadly sums up technological progress and aggregate productivity growth in any country, while the GTFP growth would additionally account for any adverse effect of that technological progress on the environment through the emission of green house gases. Given that almost no industrialization or economic progress can be carried out without some degree of environmental impact, it is logical to have lower GTFP growth than aggregate TFP growth. The gap between the two lines in Chat 4 basically represents that fact. This strand of literature is thus more interested in the relative gap between these two growth rates. The gap between these two, therefore, would represent the cost to the environment from economic growth (see Chart 1a in the Annex).



Source: Author's own calculations based on Penn World Table 10.0.

Chart 5 shows the decadal average growth rate of GTFP from the 1990s to the 2010s. India's green TFPG was negligible at almost 0.0 percent in the 1990s, after which it became negative during the 2000s, when India witnessed phases of high economic growth. It suggests that the economic

growth during the 2000s may have been accompanied by the adoption of technologies that might have provided significant economic growth but were environmentally unsustainable. Notably, most of the environmental regulation, including the National Action Plan on Climate Change (NAPCC, 2008), was adopted in India and globally during the late 2000s. Therefore, the economic activities supporting the high growth phase during the 2000s had limited scope for being regulated from an environmental angle. India's green TFP growth has improved marginally to 0.1 percent during the 2010s, possibly on account of strict implementations of regulatory policies like NAPCC, the Perform, Achieve, and Trade (PAT) scheme, successive stages of BS, etc. The adoption and implementation of these policies may have also been accelerated through the international commitments made under the Kyoto Protocol, the Montreal Protocol, the United Nations Framework Convention on Climate Change, the Paris Agreement, and COP26. These commitments have prompted governments to address the environmental consequences of economic expansion and, as a result, adjust their national policy framework to reduce Green House Gas emissions to adhere to climate-change commitments. It is worth noting that, despite having the highest TFP growth rate compared to the other regions in the 1990s, 2000s, and 2010s, except eastern Europe in the 2000s (Chart 3), India's green TFP growth rate was very low as compared to most of the other regions. This suggests that technological adoption in India may have had a disproportionate impact on the environment over these decades. However, there have been improvements on these grounds in the most recent decade.



Source: Author's calculations based on Penn World Table 10.0 and World Bank.

Decadal GTFP Growth: International Perspective

Southeast and East Asia, including China, Japan, and South Korea, have seen the most improvement in their GTFP growth, from -0.7 percent in the 1990s to 0.5 percent in the 2010s (Chart 5). Most of these countries except Japan experienced rapid industrialization and economic growth during the late 1980s and early 1990s. This is reflected in the high TFP growth rate (Chart 3). But similar to India during the 2000s, when it experienced higher economic growth, the GTFP growth rate for the Southeast and East Asian countries during the 1990s was actually negative (-0.7 percent) (Chart 5). The cases of India during the 2000s and the Southeast and East Asian countries during the 1990s suggest that the emerging economies in Asia could probably be facing some tradeoffs between high economic growth and environmental sustainability at large, as reflected in relatively high TFP growth but lower GTFP growth during their high growth phases.

Eastern European countries witnessed the second highest GTFP growth during the 2010s. These countries, on the other hand, experienced significant negative GTFP growth in the 1990s and extremely high GTFP growth in the 2000s. Most of the countries in this region are the former Soviet countries, which broke up in the early 1990s. Several of these countries experienced wars and unrest (e.g., Yugoslavia), which is reflected in the negative TFP growth rate during the 1990s (Chart 3). In addition, the war and unrest may have resulted in increased emissions, as reflected in the much lower GTFP growth during the 1990s (Chart 5). When the war and unrest broadly settled in this region during the 2000s, the formation of capital through reconstruction of economic capabilities and the adoption of technologies on top of a very low base due to war and unrest in the prior decade may have resulted in very high growth in both TFP and GTFP growth in the 2000s. The phenomena observed during the 2000s could, therefore, be best described as a "post-war" phenomenon, when the capital stock and technical capacities depleted during the war are being rebuilt, resulting in high TFP growth. In a nutshell, the East European countries were away from their steady states during both the 1990s and 2000s, where the latter may have mostly witnessed a catch-up process fueled by extraordinary growth in GDP and TFP. The situation may have started to stabilise in the 2010s but may still have remained significantly behind their steady states, at least as compared to India and other Southeast and East Asian countries, most of which gained political independence and a relatively stable regime much before the Eastern European

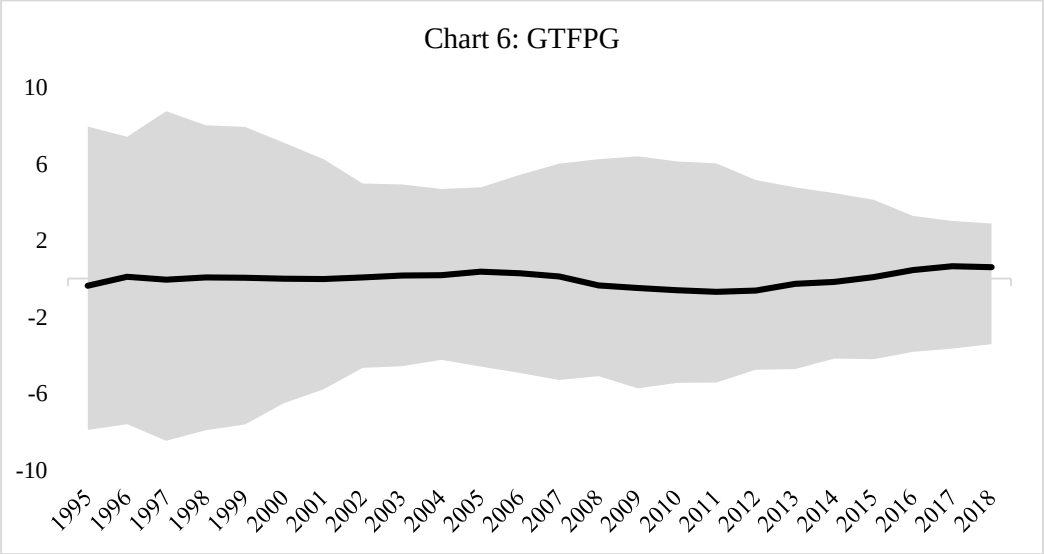
countries. Therefore, large fluctuations in the estimates of GTFP growth in the Eastern European countries may be interpreted with caution.

In this context, the OECD member countries excluding Japan, most of which are advanced economies at present and achieved high-growth phases a long time ago, possibly provide a case of "frontier" or relatively "steady-state" economies in the global context. Since the 1990s, these countries have seen a consistent improvement in GTFP growth. Also, in the last decade, these countries recorded the highest GTFP growth among all the regions considered here. We obtain these higher estimates of GTFP growth for OECD countries despite the fact that TFP growth during the last decade in these countries was lower than in South Asia and Eastern Europe (Chart 3). This suggests that the recent productivity growth in the OECD countries may have occurred with significantly reduced environmental consequences. This may be attributed to the early adoption and improved implementation of environmental policies. For example, the European Union's carbon trading scheme (EU-ETS) was the world's first emission trading system, implemented by EU countries to tackle climate change. These countries were also more successful in implementing other market-based instruments such as carbon trading, effluent taxation, and other command and control instruments. Furthermore, under the umbrella of shared but distinct obligations, these countries have established increasingly ambitious international commitments through significant progress on the NDC. Finally, they have the necessary resources to transition to ecologically friendly technologies.

Countries in the Middle East, Central Asia, and Africa collectively witnessed negative GTFP growth rates during our sample. During this period, these countries also witnessed negative TFP growth rates. However, as a result of global efforts to reduce emissions, GTFP growth in these countries has become less negative over time. For the Latin American countries, negative GTFP growth and negative TFP growth were observed during the 2010s.

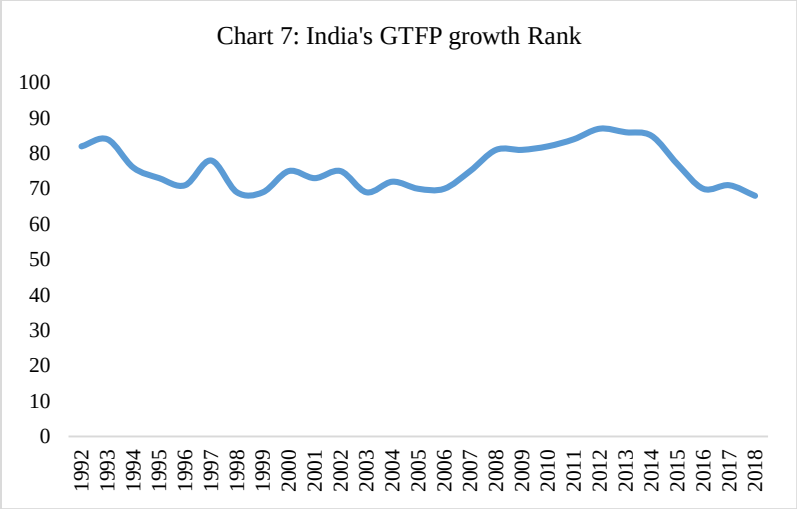
The discussion so far based on Charts 3 and 5 suggests that, although India has witnessed an impressive rate of technological progress and productivity growth since the Economic Liberalization of 1991, which by far remains the largest with respect to the rest of the world (Chart 3), when we account for its adverse effects on the environment, the "net" technological growth, measured by the GTFP growth, remains among the lowest in the world (Chart 5). This suggests

that India's technological progress may have been more carbon-dependent compared to the rest of the world, especially the east-Asian and OECD countries. Although it is well recognised that OECD countries are far ahead of India in terms of economic progress and technological abilities to turn their economic activities into more environmentally sensitive ones, critically examining India's environment-related policies vis-à-vis the OECD countries may provide sufficient scope for improving India's position in this respect. Chart 6 suggests that India's GTFP growth remained within the 1 standard deviation band around the median GTFP growth rate across all the sample countries. In the long run, we also find a convergence in GTFP growth across countries. This could be due to the implementation of climate finance, which allows developing nations to access climate finance through the Green Climate Fund, the Adaptation Fund, and the Global Environment Facility.



Source: Author's calculations based on Penn World Table 10.0 and World Bank.

Chart 7 suggests that, out of 146 countries in our sample, India ranked between 70th and 80th for most of the 1990s and the years prior to the global financial crisis. It deteriorated between 2006 and 2012 but improved afterwards to reach below 70 again towards the end of the 2010s.



Source: Author's calculations based on Penn World Table 10.0 and World Bank.

Despite these recent improvements, India's rank in terms of GTFP growth remains behind all the major emerging and advanced economies. This suggests heavy carbon-dependence of the aggregate growth process in the Indian economy. In the long run, this would require a robust system of carbon-pricing to limit the carbon-demand in India. The estimates as at end of 2022 available from the Carbon Pricing Dashboard, World Bank Group suggest that 70 carbon-pricing initiatives are implemented globally, covering 47 national jurisdictions. India, however, does not levy an explicit carbon price till date (OECD 2022). Fuel excise taxes, an implicit form of carbon pricing, cover 54.7 per cent of emissions in 2021, unchanged since 2018, while fossil fuel subsidies cover 2.5 per cent of emissions in 2021, unchanged since 2018 (OECD 2022). This underlines the need for stepping up an active and direct carbon-price mechanism in India. In this vein, we discuss some of the existing fiscal, monetary and macroprudential frameworks existing in India towards the nation's goal for transition to a greener economy.

VI. Policy Developments in India

India started sensitising the issue of climate change and green finance as early as 2008. The National Action Plan on Climate Change (NAPCC) was formulated in 2008 with a vision to outline the broad policy framework for mitigating the impact of climate change. Subsequently, the Climate Change Finance Unit (CCFU) was formed in 2011 within the Ministry of Finance as a coordinating agency among the main actors responsible for green finance in India, viz., the Ministry of Finance, the Ministry of Environment, Climate Change, and Forests, the State Governments, the Reserve Bank of India, the Security and Exchange Board of India, and the Insurance Regulatory and

Development Authority of India. There are several policy measures in place to reduce the carbon dependence in the country, which can be broadly classified into two: the combined fiscal-monetary incentives and the macroprudential regulations. In the absence of any direct carbon-pricing in the country (OECD 2022), these measures are expected to bring some initial fruit towards the goal of achieving sustainable growth in the country. Some major policies that are in place, are as follow:

Fiscal and Monetary Frameworks

The Government of India has committed to a net-zero target of 2070 and has been implementing several initiatives to achieve this target. For instance, the International Solar Alliance; reducing emissions in railways; the LED bulb campaign; and widening the geographical coverage of BS IV, etc. Moreover, the GoI launched two phases of the Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) scheme in 2015 and 2019. The FAME schemes are aimed at reducing the up-front purchase price of all vehicles and developing the infrastructures (such as charging stations) to encourage green vehicle production and sales. The Production Linked Incentive (PLI) scheme by the Government of India covers the production of electric vehicles. In 2021, PLI included manufacturing of Advanced Chemistry Cell (ACC) under its coverage which is expected to bring down the prices of battery in the country. Recently, the Goods and Services Tax (GST) on electric vehicles has been reduced from 12 per cent to 5 per cent, while the tax on chargers/charging stations are reduced from 18 per cent to 5 per cent. Increasing thrust and policy supports in green vehicle segment augur well for its demand in the future, leading to increased scope for lending into this segment. In India, the Energy Conservation Building Code, introduced in 2007 targets energy efficiency of the buildings and is expected to have a major impact towards green building initiatives. The Green Rating for Integrated Habitat Assessment (GRIHA) is a national rating system developed to rate commercial, institutional and residential buildings in India emphasising on the environmental concerns.

The Reserve Bank of India included the small renewable energy sector under its Priority Sector Lending (PSL) scheme in 2015. Under this scheme, firms in the renewable energy sector are eligible for loans up to INR 30 crore, while households are eligible for loans up to INR 10 lakh for investing in renewable energy. However, the exposure of the banking sector has so far been very

limited to alternative sources of energy. At the all-India level, less than 10 percent of the bank credit deployed in the electricity industry is for non-conventional energy production[3].

Macroprudential Policies

Disclosure Requirements

One of the prominent policy initiatives at the international level includes the formation of the Financial Stability Board's Taskforce on Climate-related Financial Disclosures (TCFD). Building on the recommendations of TCFD, the International Sustainability Standards Board (ISSB) has already released its first set of standards, encompassing industry-based disclosure requirements derived from the Sustainability Accounting Standards Board (SASB) for implementation by countries. Currently, the TCFD encourages companies to use its recommended frameworks. However, implementation of these recommendations has not been made mandatory so far in most cases. The major strategic move in India in this respect was the implementation of sustainability disclosure requirements in 2012. Since 2012, the Security and Exchange Board of India (SEBI) has made it mandatory for the top 100 listed entities based on market capitalization at the BSE and NSE to publish annual business responsibility reports and has revised it from time to time. In its latest revision as of March 2021, titled "*Business Responsibility and Sustainability Reporting by Listed Entities*" (BRSR), the Security and Exchange Board of India (SEBI) sought disclosures on a listed entity's overall management of environment, social, and governance (ESG)-related risks, the approach taken to mitigate those risks, and its performance on those grounds. The Ministry of Corporate Affairs also mandated reporting of the progress on corporate social responsibilities (CSR) under the Companies Act, 2013. In October 2017, the Report of the Committee on Corporate Governance proposed that the board of directors meet at least once a year to specifically discuss strategy, budgets, board evaluation, risk management, and succession planning.

Sustainable or ESG stock indices are definitive steps in measuring risks and implementing macroprudential policies. The ESG stock indices were adopted across the globe as part of the Sustainable Stock Exchange initiative, which recommends the signatory countries recognise ESG leaders from time to time. Two major stock exchanges in India, the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), are part of this initiative and publish separate ESG

[3] Based on data published by Reserve Bank of India as on March 2022.

indices. The leading stock exchanges, financial market regulators, and ministries dealing with corporate affairs in China (2008), Hong Kong (2012), the UK (2012), India (2012), the Philippines (2013), Vietnam (2013), and Singapore (2016) were among the nations to implement the framework for disclosure of ESG-related risks by the listed companies in their jurisdiction (Volz, 2018).

Tracking of Risks

India currently uses platforms such as PAT (perform, achieve, trade) and RPO (renewable purchase obligations) for tracking GHG emissions. The implementation of national MRV (measurement, reporting, and verification) to track both domestic and international climate finance is under consideration. However, there is a need for a unified statistical framework, including a consistent and comparable taxonomy, regular disclosures, and monitoring. India would require a significant amount of work in this respect.

Way Forward

An improved macroprudential framework would require a better assessment of the risk. In this respect, standardising climate-related disclosures and making them mandatory would probably be a major push (Krogstrup and Oman (2019)). Current prudential frameworks generally do not explicitly take climate-related risks into account. Climate risk can be incorporated into stress tests in this regard (ESRB 2016, NGFS 2019). Banco Central do Brasil already requires commercial banks to incorporate environmental risk factors in capital need calculations (Banco Central do Brasil 2011), while the Bank of England is conducting stress tests using climate scenarios (Bank of England 2019a, b). Additional tools such as reserve, liquidity, and capital requirements, loan-to-value ratios, caps on credit growth, especially for "brown" industries, and sectoral capital buffers targeting credit to particularly climate-exposed sectors may also be considered (Galati and Moessner (2017), Cerutti et al. (2017). In this regard, China published the world's first national-level green bond taxonomy in 2015 (NGFS 2019) to address the challenge of correctly pricing climate risks. With the aim to increase banks' demand for financing green investments and reduce demand for non-green investments, the EU High-Level Expert Group on Sustainable Finance (2018) considered introducing a "*green supporting factor*" and a "*brown penalising factor*" in

prudential rules. Aglietta and Espagne (2016) proposed the introduction of international requirements for a minimum amount of "green" assets on bank balance sheets.

VII. Conclusion

In this paper, we provide estimates of green total factor productivity (GTFP) growth, which is the growth in a country's total factor productivity (TFP) after accounting for its environmental consequences, generally measured by the emission of greenhouse gases, using nationally aggregate data for 146 countries across the globe between 1990 and 2019. Our estimates using the Global Malmquist-Luenberger Productivity Index suggests that GTFP growth generally differs significantly from the aggregate TFP growth across the globe. In case of India, our estimates suggest that India's average annual GTFP growth rate since 2000 is lowest among the major emerging and advanced economies in the world at almost zero per cent, while India's conventional TFP growth stands out to be one of the highest globally, at above 2 percent annually. This means, although India witnessed an impressive rate of technological progress and productivity growth since the Economic Liberalization of 1991, this progress may have been more carbon-dependent compared to the rest of the world, especially the east-Asian and OECD countries. Our findings suggest that India's technological progress may have been more carbon-dependent compared to the rest of the world, especially the east-Asian and OECD countries. In this vein, this paper discusses some possible policy aspects to appropriately cap the carbon-dependence in the economy. Although it is well recognised that OECD countries are far ahead of India in terms of economic progress and technological abilities to turn their economic activities into more environmentally sensitive ones, critically examining India's environment-related policies vis-à-vis the OECD countries may provide sufficient scope for improving India's position in this respect. Despite being low, India's GTFP growth improved in the last decade, i.e., the 2010s. The improvement bodes well for India's international commitments under successive climate deals at the international level and India's efforts towards achieving climate-sensitive growth trajectories. In recent years, we have seen convergence in GTFP growth across countries. This could be due to the implementation of several key initiatives on this front, including climate finance, which allows developing nations to access climate finance through the Green Climate Fund, the Adaptation Fund, and the Global Environment Facility. This exercise, therefore highlights the importance of

incorporating environmental degradation into the productivity estimates and macroprudential actions by the rapidly industrialising nations.

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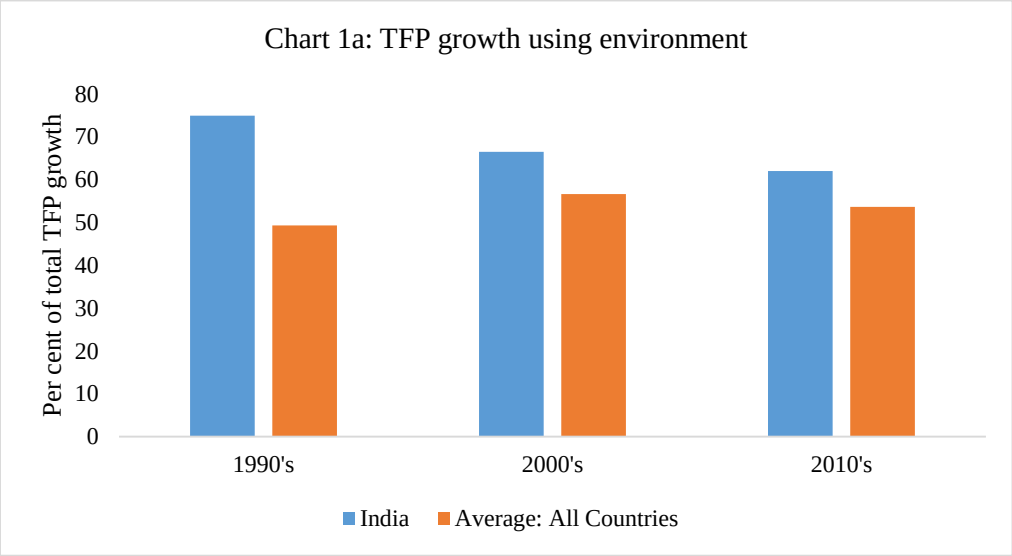
Annex



Source: Author's calculation