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

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Reserve Bank of India

1 January 2023

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Abstract

The conventional estimate of technological progress and aggregate productivity growth, the total factor productivity, or TFP, can be upwardly biased if environmental externalities generated during the production processes are not accounted for. In this paper, we revisit TFP growth rates across 146 countries in the world between 1990 and 2019 after accounting for their CO_2 emissions. The Global Malmquist-Luenberger Productivity Index suggests that although India's conventional TFP growth stands out to be one of the highest globally, especially since 2000, India's average annual Green TFP growth is lowest, at almost zero per cent since 2000. Our estimates suggest that mostly the OECD countries may have maintained substantial progress in terms of green TFP, whereas the emerging economies in East and Southeast Asia may also be significantly lagging. While the policy tools in India are converging towards the advanced economies, our estimates suggest that India's relative position has improved in terms of Green TFP growth in recent years.

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

JEL: Q54, D24, C43

[1] Authors are affiliated 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. Authors thank the participants of 2nd Biennial Conference on Development, Indira Gandhi Institute of Development Research, Mumbai and the 15th Asian Research Network Workshop organized jointly by the Bank for International Settlements and the Monetary Authority of Singapore for their valuable feedback.

I. Introduction

The rate of technological progress and productivity growth are the pillars of an economy's sustained growth in 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). Economic policies across the globe in the post-World War II era largely focused on growth rate of per-capita Gross Domestic Product (GDP) through industrialization and technological upgradation. On the contrary, environmental implication of this process via emission of Green House Gases (GHG), deforestation and disposal of harmful chemicals into the soil and water have come into focus relatively recently. The adverse impacts of environmental degradation on public health, human capital and labour productivity are well established (Jha and Tripathi 2011; Deryugina and Hsiang 2014; and Kumar and Gautam 2014). Hence, the environmental consequences of a nation's technological progress can potentially limit its ability to utilise its own human and natural resources in the future. A wide range of recent literature builds consensus regarding accounting for the negative externality of technological progress on environment while measuring a country's productivity growth (see Brandt et al. 2014). Our paper provides estimates of GHG emission-adjusted rate of productivity growths across the globe and discussing India's stance in the recent decades.

The existing literature has used several methods to assess productivity growth. From the welfare point of view, a commonly used measure is the average labour productivity which is either GDP per capita or the output per worker of a nation. Labour productivity growth, however, comes with limitations while measuring technological progress and productivity growth. A significant portion of growth in per-worker output may come from growth in fixed capital stocks, including transport equipment and buildings associated with scale expansion, 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 over labour productivity, following the seminal work of Solow (1956). TFP growth refers to the growth of a country's consumable output, commonly measured by its GDP, after adjusting for the contributions of both labour and capital. Thus, TFP growth accounts for that part of the country's GDP growth which is not explained by the growth in its labour force and stock of physical capital. In this paper, we estimate TFP growth rates among a set of 146 countries after accounting for any possible environmental externalities of their aggregate economic growth processes.

While the fundamental idea behind TFP growth relies on the residual growth in output for an entity after the contributions of both labour and capital are accounted for, the research in this domain has also extended an idea of a comparative aggregate 'productive efficiency' of a unit when several decision-making units (DMU) are at work (Charnes et al. 1978). The derivation of green productivity growth in this paper relies on a similar framework. Our methodology broadly follows Oh (2010) which takes all the possible combinations of production set, i.e. factor inputs and output and emission levels at the country-level to estimate a globally 'efficient' frontier in the form of the Global Malmquist-Luenberger Productivity Index (GMLPI). The 'distance' of a country at a given point in time is measured through a directional distance function (DDF), which also measures the relative efficiency of that country compared to the global frontier. The change in a country's efficiency level over time is referred to as the Green TFP (GTFP) growth in the related literature.

We used internationally comparable data on aggregate production sets from Penn World Table 10.0 between 1990 and 2019 for 146 countries. The environmental externality on economic growth can potentially encompass several aspects; such as 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, we account for only the emission of carbon dioxide (CO_2) in deriving our climate-adjusted or Green TFP growth, mainly due to the non-availability of reliable and comparable data across countries on other aspects of environmental degradation. 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.

Studies in the past, including Jeon and Sickles (2004), Kumar (2006), and Oh (2010) provided estimates of GTFP growth across the globe, and for India before 2010. A slew of initiatives has followed since then at the international level, 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 on GTFP growth for India vis-à-vis other major economies for the last decade. Our study aims 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 was introduced for modelling environmental externalities in productivity estimates and crediting firms for reducing emissions. The Global Malmquist-Luenberger Productivity Index (GMLPI), (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.

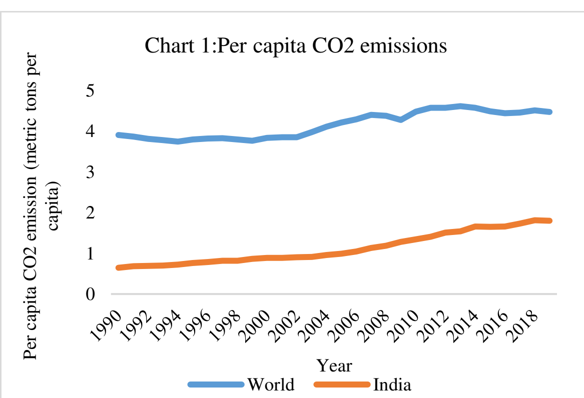
The Malmquist-Luenberger productivity index, established by Chung et al. (1997), has become the most widely used methodology in this domain of empirical literature. Weber and Domazlicky (2001), Fare et al. (2001), etc. used this approach to estimate green productivity growth in the US. Jeon and Sickles (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.

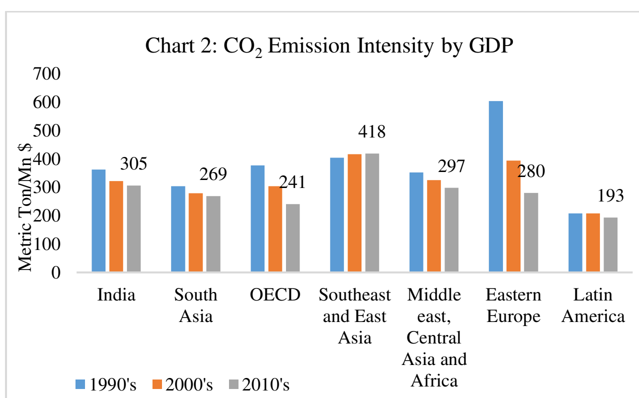
Apart from these studies, there are numerous others that estimate green productivity in China (Li and Tao 2011; Li et al. 2013; Zhang and Choi 2013; Li and Lin 2016). For example, Chen et al. (2018) estimate TFP growth for China's industrial sectors and find that incorporating environmental consequences 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

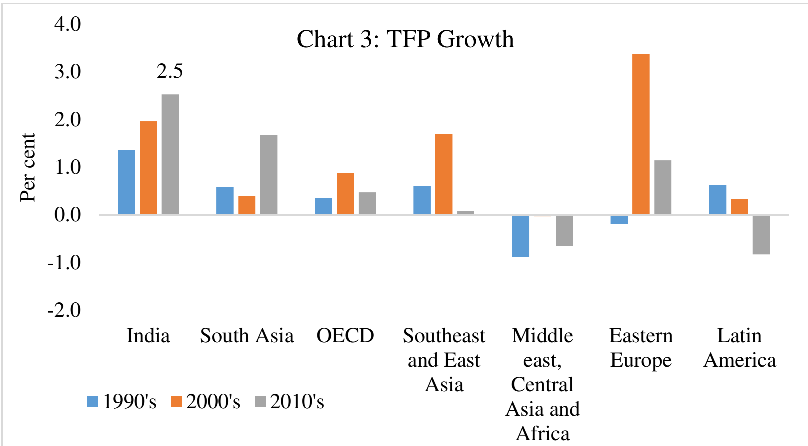
India's per capita CO_2 emission historically remained lower than the global average (Chart 1). India's low per capita emission is attributed to its large population and low per-capita GDP among the major economies. In contrary, India's CO_2 emission to GDP ratio was substantially higher than that of the major Asian economies and advanced economies (Chart 2). India’s CO_2 emission intensity in relation to GDP was also substantially higher than that of other developing nations in South Asia, Latin America, and Eastern Europe, while it was only next to Southeast and East Asia. India's low per capita CO_2 emissions, therefore, may not have necessarily implied an adoption of carbon-sensitive technologies in the country so far.





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 the recent decades (Chart 3), helping the nation achieve one of the highest growth rates in GDP among the major advanced and emerging economies. Chart 3 also suggests that TFP growth rate in India has consistently increased over the last three decades, in contrast to rest of the world. In the context of India's high emission to GDP ratio as shown in Chart 2, it may be interesting 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. Without accounting for these environmental externalities, of India's economic growth, these estimates of TFP growth can potentially 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 GTFP growth following the methodology of Oh (2010). In this methodology, a country's aggregate productivity is defined based on the Global Malmquist-Luenberger productivity index (GMLPI), which is estimated based on the directional distance function (DDF). A DDF provides the 'distance' of a country at a given point in time from a globally optimum production frontier which consists of the set of 'optimum' outputs, given a set of factor inputs. The output consists of both 'good' and 'bad' output. A good output may be the outcome of an economic activity which 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, noise pollution etc. In this framework, a country is defined more productive or efficient, if, given a set of factor inputs, it produces more of the 'good' output, but less of 'bad' output, compared to another country with similar endowment of factor inputs.

The GMLPI 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 any time s, $x^s, y^s, and\ b^s$ 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 global 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 GMLPI 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 percentage growth rate in GMLPI is referred to as the GTFP growth.

The construction of DDF described in Chung *et al.*, 1997 and Oh, 2010 are as follows. In the presence of an 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:

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

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 DMU at a given point of 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 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:

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

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

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

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 a 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.

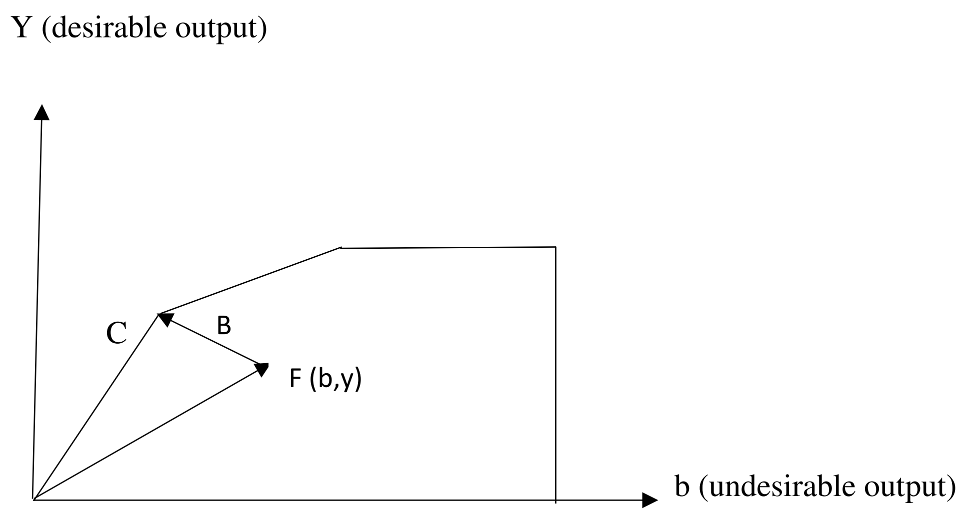


Fig 1: Distance between the optimal frontier and the output vector, denoted by B, is the DDF.

B. Data

In our estimation, ‘good’ and ‘bad’ outputs are represented by a country’s GDP in constant prices and the country’s CO_2 emission, respectively. The factor inputs of a country are the total hours worked by the aggregate workforce of a country during a year, and the stock of available physical capital. The labour inputs represented by the total hours worked are multiplied by the indices of human capital, which is based on the years of schooling and the returns to education. Capital stock is also multiplied by the internal rate of return.

We use World Bank’s World Development indicator to obtain country-wise CO_2 emissions available since 1990. For the remaining variables, we use Penn World Database version 10.0 (PWT

10.0), which provided these data for more than 180 countries since 1950's. For our estimates, we use data only since 1990. We exclude small island nations and countries with very small population from our analysis. To do this, we ranked the countries based on their population and excluded 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. Our final dataset consisted of 146 countries between 1990 and 2019.

PWT 10.0 provided total number of employed persons in million, while both GDP and capital stocks were reported using 2017 constant USD million. Human capital and capital services indices were expressed as indices using 2017 as the base year. We found that the average annual hours worked, index of 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. To compute them, 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. We assume that the behaviour of the economic agents such as the average hours of work, human capital, and returns to capital, would be similar across countries that share common historical, topographical, and cultural features. We use a panel data of 146 countries between 1990 and 2019 and estimate the following regression models. We use the estimated values of average hours worked and the indexes of human capital and capital services to fill up the missing observations.

$$Human\ Capital\ Index_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \epsilon_{it} \tag{4}$$

$$Capital\ Service_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \epsilon_{it} \tag{5}$$

$$Average\ hours\ worked_{it} = \sum Region\ Dummies + \sum Year\ Dummies + \epsilon_{it} \tag{6}$$

In these models, the estimated coefficients of the region dummies would capture the average value of the 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, for 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 (ϵ_{it}).

Following Patnaik 2014; Idris and Rahma 2019; and Knowles and Owen 1997, we account for the differences in quality of factor inputs across countries. The 'effective labour force' and the 'effective capital stock' for a country in a particular year were defined as:

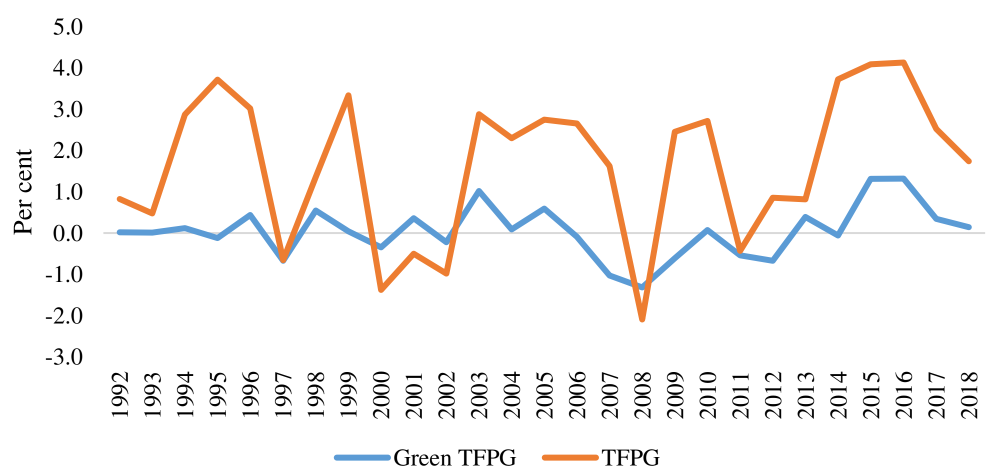
$$Effective\ Labour = Persons\ employed * Average\ hours\ worked * Human\ Capital\ Index \quad (7)$$

$$Effective\ Capital\ Stock = Capital\ service * Capital\ stock \quad (8)$$

V. Results

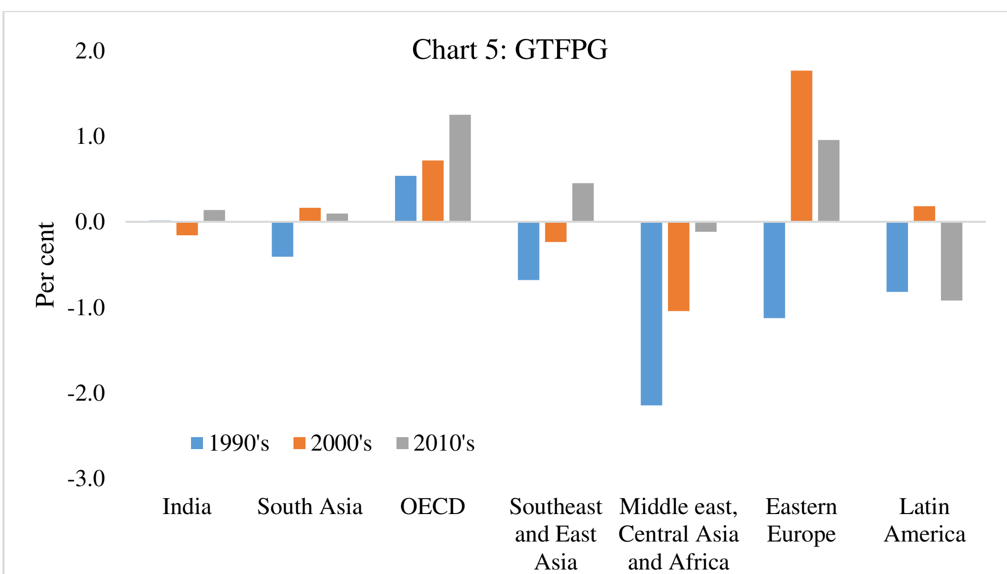
Our estimates for India in Chart 4 suggest that the GTFP growth remained lower than the aggregate TFP growth during most of our sample period between 1990 and 2019. As the environmental impact of economic growth is now internationally recognized, a GTFP growth lower than the aggregate TFP growth, therefore, is consistent with that narrative.

Chart 4: GTFP VS TFP (India): Year-on-year



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

India's GTFP growth is estimated to be almost 0.0 percent for 1990s, further turning to negative during 2000s, when India witnessed phases of high economic growth (Chart 5). 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 may not be environmentally sustainable. 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 GTFP growth improved marginally to 0.1 percent during the 2010s. Although we do not have much empirical evidence, this improvement may have occurred on account of gradual 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.



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

A comparison between Chart 3 and Chart 5 suggests that, while India is estimated to have the highest TFP growth rates compared to other regions during 1990s, 2000s, and 2010s, except eastern Europe in 2000s (Chart 3), India's green TFP growth rate was negligible, especially when compared with OECD countries. This suggest that although India achieved higher rate of technological progress and productivity growth as compared to the advanced economies, the growth may have been more carbon-dependent compared to advanced economies under OECD. Therefore, when the environmental externalities are accounted for, India's GTFP growth falls significantly short of that of OECD, and also Southeast and East Asia for 2010's.

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 trade-offs 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. Therefore, the developing and emerging economies in Southeast and East Asia also witnessed a trajectory similar to India, although they managed to maintain a higher GTFP growth in 2010's.

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). The high TFP growth rate observed in this region during 2000's, thus could best be described as a 'post war' phenomenon when technological capacities and the fixed capital builds up from a depleted, low base. Therefore, large fluctuations in the estimates of both overall TFP and GTFP growth rates in this region 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. Also, at a significantly higher per-capita GDP, these countries may have 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 period. These countries also witnessed negative TFP growth rates. For the Latin American countries, negative GTFP growth and negative TFP growth were observed during the 2010s.

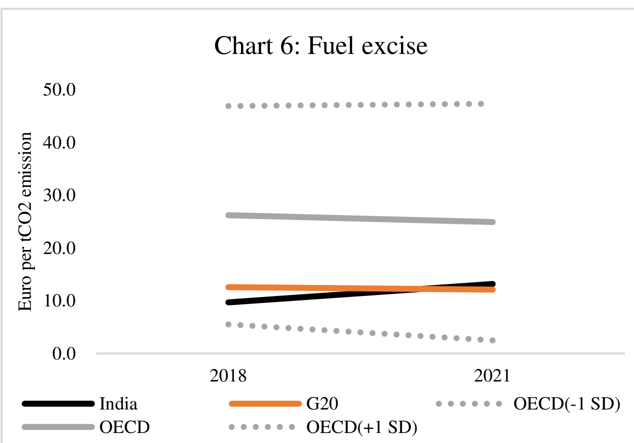
The relatively lower GTFP growth, particularly for the emerging and developing economies in Asia needs discussion. The priority for relatively less industrialised economies in South Asia, including India, rests in rapid economic progress to escape relatively larger scale of poverty and catching up their global peers at the current juncture. These priorities may entail some compromises on their environmental goals, at least in the medium term. A disproportionate focus on the environmental causes would invariably shift significant portion of resources away from the general economic growth and infrastructure, hurting the objective of inclusive growth in the country whose per-capita income is almost 1/20th of the OECD countries[3]. This, however, does not mean that the environmental degradation, especially the emission of GHG can be compromised over a longer horizon. The recent policy communications, especially in India, provided hints towards maintaining these balances (GOI 2022). In the next section, we briefly discuss how the

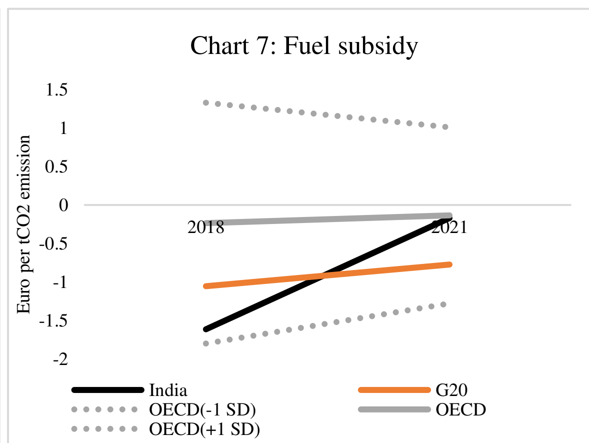
[3] Based on the Per Capita GDP (current US$) published by World Bank.

policy instruments in India have started converging to the OECD nations, indicating the country's continued effort to meet climate commitments.

VI. Discussions on Policy

Globally, several forms of carbon-pricing have emerged to limit carbon-demand within the countries. The estimates available from the Carbon Pricing Dashboard (World Bank 2022), 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, covered 54.7 per cent of emissions in 2021, while fossil fuel subsidies covered 2.5 per cent of emissions in 2021 in India (OECD 2022). The available data suggests that the fuel excise rates in India have moved closer to the average rate prevailing across OECD countries (Chart 6). On the other hand, India has drastically slashed fuel subsidies to almost match the OECD average subsidy rate[4] (Chart 7).





Source: OECDStat.
Note: SD: Standard Deviation. G20 excludes Saudi Arabia.

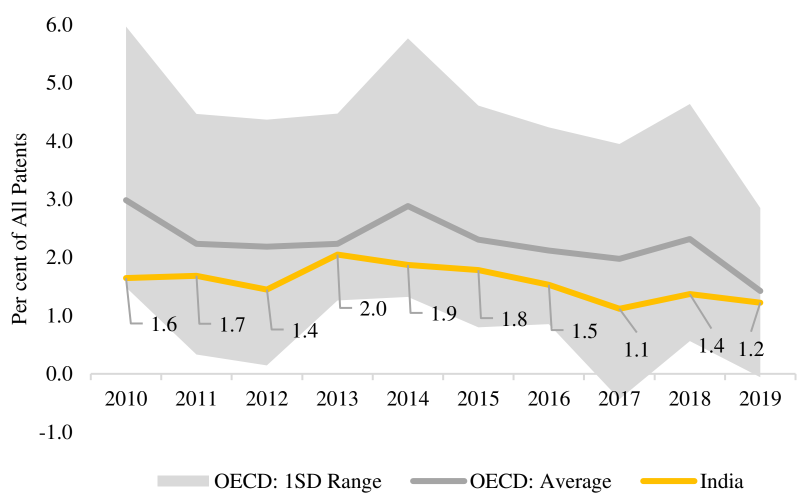
Although India has not implemented any direct trading schemes for GHGs yet, several mechanisms are at place. For instance, the state of Gujarat has already implemented an emission trading scheme for Particulate Matters (PM) – the particulate pollutants PM2.5 and PM10 (particles 2.5 microns and particulate 10 microns wide), which is first-of-its-kind in the world. India has also introduced, Perform, Achieve and Trade scheme (PAT) scheme, which works

[4] A negative rate means that the subsidy exists.

through the issuance of tradable certificates for the excess energy savings by certain energy intensive sectors. There also exists a Renewable Energy Certificate (REC) mechanism which is also a market-based instrument like ETS but focused on renewable energy instead of GHG emissions.

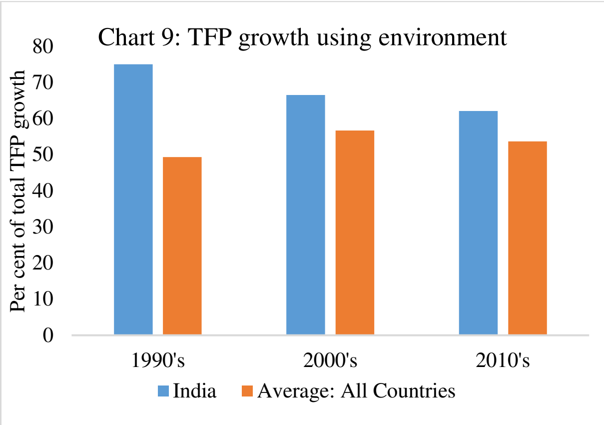
Apart from the market-based mechanisms, the innovations in emission reductions have continued to take place in India. Chart 8 suggests that roughly 1 to 2 per cent of all the patent applications from India were on account of air pollution abatement in the last decade. For the OECD countries, the average figure for this period stood higher at 2 to 3 per cent, except only in 2019, when it fell to 1.4 per cent (Chart 8). Despite India's low ratio as compared to the OECD average, the ratio of the number of patents on air pollution abatement technologies to all patents' applications from India remained within one standard deviation range for the OECD countries. Available data from the World Bank suggests that India's forest coverage has increased by 0.3 per cent annually, on average between 2000 and 2016, compared to 0.1 per cent for OECD countries. In contrast, the forest coverage has declined by 0.1 per cent annually on average at the global level between 2000 and 2016.

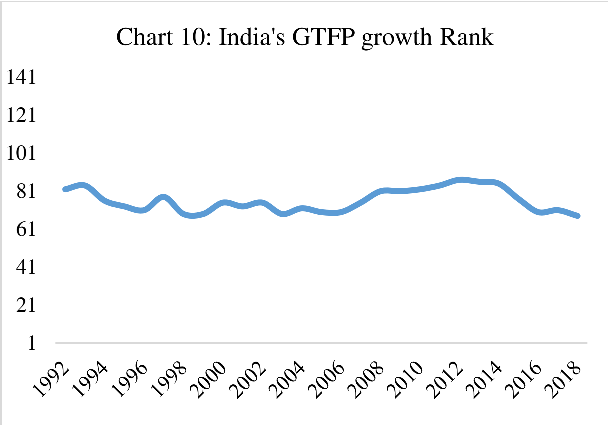
Chart 8: Number of Patents in Air Pollution Abatement



Source: OECDStat.
Note: SD: Standard Deviation.

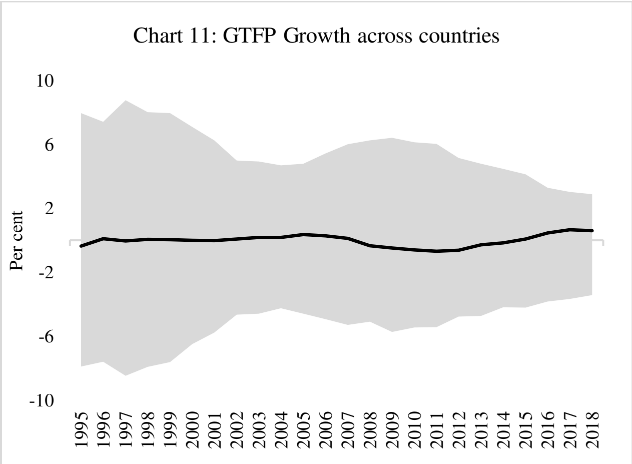
The gap between aggregate TFP growth and GTFP growth in Chart 4 would show how much of the TFP growth could have come at the cost of the environment. In Chart 9, we show the estimated gap between aggregate TFP and GTFP growths, as percentage of aggregate TFP. Chart 9 suggests, although India’s TFP growth may have come at a higher cost to the environment as compared to the rest of the world, the cost may have persistently and significantly declined in case of India. Chart 10 suggests that India’s rank in GTFP growth has improved since the beginning of last decade.





Source: Author’s calculations based on Penn World Table 10.0 and World Bank.
Based on a sample of 146 countries. So, the relative ranking is shown in a scale of 1-146. A lower value of the rank indicates a better position.

Globally, there is a convergence in GTFP growth rates in the later part of the last decade (Chart 11). In Chart 11, the grey area shows the one standard deviation band around average GTFP growth for 146 countries in our sample. The black line in Chart 11 shows the GTFP growth in India. The grey area in Chart 11 has narrowed down since 2010, which suggests possible convergence in emission-adjusted productivity and technology growths across the countries in the world. There is a visible improvement in India’s GTFP growth among this set of countries since 2011.



VII. Conclusion

In this paper, we provide estimates of green total factor productivity (GTFP) growth using nationally aggregate data for 146 countries across the globe between 1990 and 2019. The GTFP growth estimates a country's total factor productivity (TFP) growth, a measure of technological progress and aggregate productivity growth, after accounting for their environmental consequences, generally measured by the emission of greenhouse gases. Our estimates using 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, although India's conventional TFP growth stands out to be one of the highest globally, especially since 2000, the country's average annual GTFP growth rate remained close to zero between 1990 and 2019. This means, although India may have 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 paper acknowledges that, for India, a relatively higher carbon-dependence may be unavoidable at the current juncture while keeping in mind the objectives of rapid economic growth, poverty reduction and inclusive growth to catch-up the living standards of the advanced economies. Therefore, it may be challenging for India to replace the current carbon-dependent growth path to greener technologies at a pace which developed countries could have achieved in last two or more decades. At the same time, our paper also brings out the fact that the policy tools in India are also significantly converging towards the advanced economies. The slew of counter-emission measures undertaken by India would probably balance the country's emission per unit of GDP and the carbon dependence.

Our paper suggests convergence in GTFP growth in last decade across our sample of 146 countries around the world. This could be on account of greater climate awareness and the implementation of several initiatives at the global front. India's relative position in GTFP growth has, in fact, improved during the last decade among these countries.

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