Capital Misallocation and its Implications to India's Potential Output: An Evidence from India KLEMS

Rajib Das¹ International Department

Reserve Bank of India

Siddhartha Nath Graduate School of Public Policy University of Tokyo

September 2017

Abstract

In this paper, we provide estimates for the likely 'distortion' in allocation of factors of production, primarily capital, across various economic sectors in India. Existence of such distortion has predictable impact on the potential output of an economy. Using India KLEMS dataset, we show that a number of sectors, broadly in the services segments, are possibly 'over-capitalized' in a sense that capital usages here are too high for the output that they produce, once sectoral performances are compared. In other words, the same level of output in these sectors could be produced by much lesser capital. On the other hand, a number of manufacturing sectors are 'under-capitalized' by the similar criteria. Together, it implies that the aggregate output would have been much higher if a redistribution of the excess capital from 'over-capitalized' services sectors to the 'under-capitalized' manufacturing sectors was possible. In other words, a shift in the investment focus away from select services segments to the manufacturing activities may potentially lift the growth momentum of Indian economy, by correcting some of these 'distortions'. By eliminating this 'distortion' alone, India's aggregate output could have been possibly increased by 20-30% between 1990 and 2004 from their observed level and by even greater extent of nearly 40% after 2005. We, therefore, conclude that a policy framework enabling the ease of capital movement across sectors may be pursued aggressively to achieve growth aspirations.

JEL Classifications: O32, O38, O47

Keywords: Total Factor Productivity, Misallocation

¹ Shri Rajib Das is designated as Director, working in the Reserve Bank of India, Mumbai. Shri Siddhartha Nath is a graduate student at the Graduate School of Public Policy of the University of Tokyo, Japan and previously held a position of Research Officer in the Reserve Bank of India, Mumbai. Shri Nath is currently on leave from the Bank. The views expressed in the paper are those of the authors and not necessarily those of the institution to which they belong. The usual disclaimer applies.

I. INTRODUCTION

In light of India's phenomenal growth in the last decade, a number of papers recently shed light on the sources of rapid increase in output in developing economies (e.g. Bosworth and Collins, 2008). A natural question in this regard would be: if the observed growth during these years are driven only by the increased use of inputs such as capital, or it is a result of more efficient use of the existing inputs, or a combination of both. The growth performances in India and the other developing countries have long been attributed to either on the ability to infuse larger amount of inputs in the production process or its efficient utilization that reflects on the higher total factor productivity (TFP). A number of papers have also looked at the efficiency in factor usage from a slightly different perspective. Instead of examining TFP as a whole, they looked at the role of 'distortion' in the allocation of factors of production between firms, industries and sectors to explain the source of lower output (Restuccia and Rogerson, 2007; Hsieh and Klenow, 2009). The idea is as follows: suppose there are two firms which are subject to the similar technology and therefore, has the same levels of TFP. However, due to market segmentation, regulation or imperfect information, firm A finds it hard to raise capital from the market, or in some cases, it may end up paying too high rate of interest for the capital. This discourages them to use more capital. On the other hand, the other firm, say firm B, is not that tightly regulated or may be enjoying favorable market expectations. As a result, firm B may find it easier to raise capital, sometimes at a much lower rate. Often, this results in the usage of too much of capital in its production process. This is a case of 'distortion' or misallocation of capital. In such an environment, every unit of capital in firm B that is in excess of firm A, will produce lower output in firm B than in firm A. Such misallocation can significantly lower the average return for the factor at the level of aggregate economy (Banerjee and Duflo, 2005) and thereby, reducing the aggregate output (Restuccia and Rogerson, 2007). In this paper, we examine the existence of any possible 'distortion' in the allocation of capital across major sectors and provide estimate of its impact on India's aggregate output.

The study on the effects of misallocation or 'distortion' is particularly important for India as it aims for a high growth². Regulatory policies often alter the relative prices of resources across producers, and therefore, influences how the resources are distributed (Farrel and Susan, 2006; Restuccia and Rogerson, 2007). In India, majority of the bank credits are extended by the public sector banks. Any underutilization of the fund eventually puts pressure on the interest rates, fiscal balance, etc. and therefore, alter the availability of capital to other borrowers. Between 2004 and 2011, bank credits to the commercial sector in India have grown by 21 per cent, on average every year, outpacing the growth in nominal GDP at 16 per cent. Similarly, the flows of foreign investments have grown significantly during this period. Net inflows of foreign direct investments (FDI) have grown by 30 per cent on average, every year in US Dollar terms, again outpacing the growth in nominal GDP. The declining GDP to capital (in this case, both bank credit and FDI) ratios, as indicated by the above facts, could be viewed as a resultant of capital misallocation, under certain circumstances. Often, the nature and improper functioning of the credit market in a developing country like India can become a significant channel of misallocation (Banerjee and Duflo, 2005; Allen et. al. 2007). In case of FDI, for example, capital misallocation is often attributed to the underlying policy priorities and sectoral preferences. In a rapidly growing economy like India, it is, therefore important to identify distortions in the allocation of capital, which can be addressed in the broader policy framework.

² World Economic Outlook report, April 2017 projections for India's growth for 2017 and 2018 are 7.2 percent and 7.7 percent, respectively.

In this paper, we provide a framework to estimate 'distortion' in the allocation of capital across broad sectors in India. We try to assess as to how much the observed output in India deviates from the level, which could be 'attainable' theoretically in an ideal world of no 'distortion'. In this paper, we look at the production function from a 'value added' perspective, and therefore, we choose to analyze 'distortion' in the allocation of capital, instead of focusing on an array of other intermediate inputs, namely the raw materials, energy etc. Earlier papers on this topic, including Hsieh and Klenow (2009), and L., Brandt et. al. (2012) largely focus on the manufacturing sector. We instead look at the aggregate economy, which includes construction activities, services and agriculture. Also, our approach to the estimation of 'distortion' differs significantly from Hsieh and Klenow (2009). In Hsieh and Klenow (2009), the existence of 'distortion' results in lower aggregate manufacturing TFP in India and China, as compared to the USA. The 'distortion' in Hsieh and Klenow (2009) is measured by the variation in TFP across firms. On the contrary, TFP in our production function is a pure 'technology' parameter, which does not change to 'distortion'. We measure aggregate 'distortion' through the cross-sector variation in output's elasticity to the capital usage. At the sectoral level, the 'distortion' is measured by the deviation of observed elasticity from an 'optimum' level. In the Cobb-Douglas production function, the factor elasticity equates the factor's value share in output, under the assumption of constant returns to scale. Therefore, the intuition behind our estimate is as follows: Due to the 'distortion', a firm like firm B in our example may use too much capital. This means that the firm B's total remuneration to the capital is much higher than the firm A. In other words, the share of capital in the gross value added by firm B is likely to be higher than firm A. Therefore, a portion of the cross-sector variation in capital's share may be due to 'distortion', even after taking into account the differences in technology. Within each sector, we assume that the factor share or the factor elasticity may change over time, due to changes in 'distortion'. In Hsieh and Klenow (2009), on the contrary, the share of capital in a firm's output is assumed to remain constant over time, which is a standard assumption in Cobb-Douglas production function. Our concept of 'distortion' is similar to Dollar and Wei (2007) and Bai et. al. (2006) who measure distortion through the cross-sector variation in the capital returns.

Rest of the paper is divided into the following sections. In the next section, we provide details of the India KLEMS dataset, that we use to draw our conclusions. In section III, we explain the framework for our analysis. In section IV, we provide our findings and we conclude with some policy implications for our results in section V.

II. DATASET FOR INDIA

In order to carry out the proposed analysis, we needed consistent data on labor and capital inputs and the estimates of TFP, across sectors and for a sufficiently long time period. For this, we have used the India KLEMS dataset, the latest version of which was made available in the end of 2016³. The India KLEMS was envisaged to fulfill the gap in the availability of consistent dataset on productivity across sectors in India. The KLEMS data was made available by the research team in the Indian Council for Research on International Economic Relations (ICRIER). The productivity measurement was carried out broadly in line with the EU-KLEMS methodology and was made available for the first time in the middle of 2014.

The objective of India KLEMS dataset is to provide a consistent time-series of various inputs of production along with the TFP estimates for 27 broad sectors of Indian economy, between the fiscal years 1980-81 and 2011-12. The aggregate value of gross output (at current prices) from these 27 sectors cover

³ Das et. al., (2015), available in https://rbi.org.in/scripts/PublicationReportDetails.aspx?UrlPage=&ID=855

almost 92% of the GDP at market prices (at current prices) between 1980-81 and 2011-12. The TFP estimates are made available on the basis of both gross output and gross value added for each sector. In our analysis, we have referred to the TFP, which is estimated based on the gross value added for a sector.

Apart from the TFP, India KLEMS dataset provides some key indicators of economic performance such as, gross value added (Rs. Crore) and gross Output (Rs. Crore), both in current prices and in 2004-05 prices. In the estimation of TFP, the dataset precisely addresses the quality aspects of the two major inputs viz. labor and capital. The dataset provides separate series on labor employment, labor input, the stock of capital and the capital services. The dataset also provides estimates of the income shares of labor and capital in gross output and gross value added for each year and for each sector, which is one of the key variables used in our estimation of 'distortion'. Therefore, India KLEMS provides a comprehensive and consistent dataset to study the sources of growth in each sector for a sufficiently long period. We provide a brief description of this dataset in Box 1 of Annex.

Stylised facts from the data

The following stylized facts are drawn from the India KLEMS dataset, in order to substantiate our main question. The average growth in India's aggregate value added was registered at 7.2% between 1999-00 and 2011-12. The growths in TFP, labor and capital inputs were 1.6%, 2.0% and 5.8%, respectively, during this period. Clearly, the growth in capital far exceed the growth in both productivity and aggregate value added. Moreover, over the longer period, growth in TFP appears to be cyclical (fig 1), often becoming close to zero, or even negative. The growth in aggregate value added, on the other hand, has remained persistent, at above 6%, annually in this period. The fact that growth in India are largely driven by the larger input accumulation is also supported by the fact that the income share of capital in GVA increased sharply between 1980-81 and 2011-12 (fig 2). Das, Erumban and Das (2016) also attested that at least services sector in India witnessed large scale capital accumulation in some part of 2000s, with declining TFP growth.



We also observe from India KLEMS that the higher accumulation of capital has translated into differentiated GVA growth across sectors. This means, that the incremental capital during these years had not produced uniform outcome across sectors. We measure the correlation coefficient between capital services and real GVA for each year, with a cross section of 27 sectors. We normalize both the variables to the year 1980-81, for each sector. The average correlation coefficient was only 0.14 between 1999-00 and 2011-12. The stylized facts together validate our question that there may exist some 'distortion' in the allocation of capital

across sector, because of which not only the overall return from capital is low, but also, there exist significant differences in outcome across sectors.

III. ANALYTICAL FRAMEWORK

We assume that the production function for the ith sector during the tth period takes the form4;

$$Y_{it} = A_{it} L_{it}^{1-\beta_{it}} K_{it}^{\beta_{it}}, 0 < \beta_{it} < 1 \forall i \text{ and } t$$

where the gross value added (GVA) Y is a function of labor inputs L and capital services K. The GVA in this function is 'real', which means that it is measured in the prices of a base year. Here L is not only the physical number of employment, but it combines employment with the skills or quality. Therefore, L is a measure of total contribution from the labor in the production process. Similarly, K is the capital's service, rather than just the stock of physical capital. Parameter A represents technology and under the constant returns to scale assumption, β represents the share of capital in GVA. In this production function, we allow β to vary not only across sectors, but also over time. Later we show that variations in β can be explained by the 'distortions'. In absence of such distortions, our production function converges to a standard Cobb-Douglas form.

We assume that the aggregate output is a CES aggregation of the s sectoral GVAs, i.e.

$$Y_t = \prod_{i=1}^{s} Y_{it}^{\theta_{it}}$$

Under the assumption of constant returns to scale, Hsieh and Klenow (2009) show that $\theta_{it} = \frac{P_{it}Y_{it}}{P_tY_t}$, which is equivalent to the sector's share in the nominal aggregate output. In this case, P_{it} is the price of a sector's final output in a perfectly competitive market and $P_t = \prod_{i=1}^{s} P_{it}^{\theta_{it}}$.

In the following subsection, we define the conditions for an 'efficient' or distortions-free factor allocation and how 'distortion' impacts the aggregate output.

The efficient allocation

We express the above sectoral production function in 'per-labor unit' form as,

$$y_{it} = A_{it} k_{it}^{\beta_{it}}$$

where y and k are the GVA and capital services, per unit of labor, respectively. Similarly, the aggregate 'per labor unit' GVA can be expressed as

⁴ Following Hsieh and Klenow (2009), we assume a neoclassical production function for the sectors. We follow the similar set of assumptions about the production function as laid down in Hsieh and Klenow (2009). It may be noted that, Hsieh and Klenow (2009) emphasized on the firm-level productivity and factor reallocation, using the plant level data, for manufacturing sector. We, on the other hand, restrict our study to the broad sectors or industries, due to the data constraints for the aggregate economy.

$$y_t = \prod_{i=1}^s y_{it}^{\theta_{it}}$$

We assume that, a society maximizes the aggregate 'per-labor unit' GVA, by appropriately choosing the k_{it} . Therefore, the problem that a society faces is to maximize y_t ; subject to $0 < k_{it} \le \bar{k}$, where \bar{k} is a hypothetical upper-limit on k_{it} , beyond which it is almost impossible for the capital-labor ratio to reach. Alternatively, we write our problem as;

Maximize
$$\log(y_t)$$
; subject to $-\infty < \log(k_{it}) \le \bar{c}$

The Lagrange equation corresponding to this problem is;

$$L = \log(y_t) + \lambda \{ \bar{c} - \log(k_{it}) \}$$

The first order condition for the social optimization requires $\frac{\delta L}{\delta \log(k_{it})} = 0.$

Given that $y_t = \prod_{i=1}^{s} y_{it}^{\theta_{it}}$ and $y_{it} = A_{it}k_{it}^{\beta_{it}}$, the first order condition for welfare maximization can be written as;

$$\sum_{i=1}^{S} \theta_{it} \frac{\delta \log(A_{it})}{\delta \log(k_{it})} + \sum_{i=1}^{S} \theta_{it} \beta_{it} = \lambda$$

By solving this condition, we get⁵,

$$\sum_{i=1}^{S} \theta_{it} \frac{\delta \log(y_{it})}{\delta \log(k_{it})} = \lambda$$

At the optimum allocation, the weighted average of sectoral capital returns converges to a constant or a 'socially desirable' capital return, which we write $\overline{\beta}_t$ going forward. Therefore, at the optimal allocation, factor elasticities tend to equalize across sectors, in a stochastic sense⁶. Note that we still require the 'efficient' capital return to vary over time, as the technology changes and requires varying contribution from the capital. The capital-labor ratio which maximizes social welfare may now be called an 'efficient' or 'optimal' capital-

⁶ Note that, at the optimum allocation, $\bar{y}_{it} = A_{it}\bar{k}_{it}^{\bar{\beta}}$ and therefore, $\bar{k}_{it} \propto \frac{1}{\bar{y}_{it}}$. In our model, even if factor returns equalize

across sectors, optimum allocation (i.e. \bar{k}_{it}) may still differ due to the differences in technology. Factor allocation tend to be higher in a sector where technological progress is relatively lagged. We make marginal deviation from L., Brandt et. al. (2009) while stating this optimality condition. In a study of factor allocation across sectors and provinces in China, L. Brandt et. al. (2009) show that, at the efficient allocation, factor share in a sector is equal to the sector's TFP share. Indexing sector and province by j and i, respectively, L. Brandt et. al. (2009) show; $\frac{L_{ij}}{L_i} = \frac{K_{ij}}{K_i} = \pi_{ij}$ and $\frac{L_i}{L} = \frac{K_i}{K} = \pi_i$ where $\sum_{i,j} L_{ij} = L$ and $\sum_{i,j} K_{ij} = K$, are the aggregates across sectors and provinces. The optimality conditions above imply $\frac{L_{ij}}{K_{ij}} = \frac{L_i}{K_i}$ and $\frac{L_i}{K_i} = \frac{L_i}{K_i}$ and $\frac{L_i}{K_i} = \frac{L_i}{K_i}$ or,

the labour-capital ratio in a sector is identical to the ratio in a province, which in turn is equal to the ratio at the economy. Putting in simple words, at the optimum allocation, capital-labor ratio in L. Brandt et. al. (2009) is equal for all sectors and provinces. Our model relaxes this condition. However, in our model, homogeneous technologies would refer to a condition similar to the L. Brandt et. al. (2009), i.e. the capital-labor ratio would equalize across sectors.

⁵ since $\frac{\delta \log(A_{it})}{\delta \log(k_{it})} = \frac{\delta \log(y_{it})}{\delta \log(k_{it})} - \beta_{it}$

labor ratio (\bar{k}_{it}). We define distortion (τ_{it}) as the percentage deviation of the observed k_{it} from the 'optimal', i.e. \bar{k}_{it} . Symbolically;

$$k_{it} = (1 + \tau_{it})\bar{k}_{it} \tag{1.1}$$

In the following exercise, we show that the 'unobserved' distortions in the capital-labor ratio can be gauged in terms of the 'observed' capital returns (β_{it}) and technology (A_{it}). Since β_{it} is capital's elasticity to the output, we can write;

$$\beta_{it} = M P_k \frac{k_{it}}{y_{it}} \tag{1.2}$$

Marginal product of k_{it} under the efficient allocation \bar{k}_{it} is the first order partial derivative of the function $y_{it} = A_{it}(k_{it})^{\beta_{it}}$, with respect to k_{it} , evaluated at $k_{it} = \bar{k}_{it}$ and for $\beta_{it} = \bar{\beta}_{it}$.

$$MP_k = A_{it}\beta_{it}(k_{it})^{\beta_{it}-1}$$
, for any k_{it}

This expression can be rewritten as;

$$MP_{k} = A_{it}\bar{\beta}_{it}\frac{\beta_{it}}{\bar{\beta}_{it}} \{(1 + \tau_{it})\bar{k}_{it}\}^{\beta_{it}-1} \qquad (\text{using (1.1)})$$

$$= A_{it}\bar{\beta}_{it}\frac{\beta_{it}}{\bar{\beta}_{it}}(\bar{k}_{it})^{\bar{\beta}_{it}-1}(\bar{k}_{it})^{\beta_{it}-\bar{\beta}_{it}}(1 + \tau_{it})^{\beta_{it}-1}$$

$$= (MP_{k})_{k_{it}=\bar{k}_{it}}\frac{\beta_{it}}{\bar{\beta}_{it}}(\bar{k}_{it})^{\beta_{it}-\bar{\beta}_{it}}(1 + \tau_{it})^{\beta_{it}-1} \qquad .$$
Or, $\frac{MP_{k}}{(MP_{k})_{k_{it}=\bar{k}_{it}}} = (1 + \tau_{it})^{\beta_{it}-1}\frac{\beta_{it}}{\bar{\beta}_{it}}(\bar{k}_{it})^{\beta_{it}-\bar{\beta}_{it}} \qquad (1.3)$

Equation 1.3 implies that, when the <u>actual k_{it} is higher than the 'efficient' level \overline{k}_{it} in a sector (i.e. $\tau_{it} > 0$), the marginal product of k_{it} is lower than the 'efficient' situation, as $\beta_{it} - 1 < 0$.</u>

Equation (1.3) implies;

⁷ For simplicity, we trite the marginal product of capital-per labour input for the ith sector in tth period as MP_k , i.e. without indexing by i and t.

⁸ We write $(MP_k)_{k_{it}=\bar{k}_{it}}$ as $MP_{\bar{k}}$.

The optimum values such as \bar{k}_{it} , $\bar{\beta}_{it}$ and $MP_{\bar{k}}$ are given for any sector, and can be treated as constant in this case. Therefore, we replace the term $\left\{\frac{(\bar{k}_{it})^{\bar{\beta}_{it}}}{MP_{\bar{k}}}\right\}$ with \in , a constant. Given (1.1), $\frac{(k_{it})^{\beta_{it}}}{(\bar{k}_{it})^{\beta_{it}}}$ can be written as $(1 + \tau_{it})^{\beta_{it}}$. Also, we simplify the expression $\left\{\frac{MP_k}{(k_{it})^{\beta_{it}}}\right\}$ by substituting k_{it} in terms of y_{it} . Therefore, we write (1.4) as;

$$\frac{\beta_{it}}{\bar{\beta}_{it}} = (1 + \tau_{it})\beta_{it}(y_{it})^{1/\beta_{it}}(A_{it})^{1 - (1/\beta_{it})} \in$$
(1.5)

Equation (1.5) implies that, once the capital allocation is decided and the output is produced, the distance between the observed shares of capital in GVA from the 'optimal' capital share is directly proportional to the 'distortion' but inversely proportional to the technology. Equation (1.5) implies;

$$\frac{\beta_{it}}{\bar{\beta}_{it}} \propto \frac{(1+\tau_{it})}{A_{it}}$$

Now, the first order condition for the welfare maximization states that, $\bar{\beta}_{it}$ for all the sectors converge to an average value $\bar{\beta}_t$.⁹ With this, we express the above relation in the following way;

$$\tau_{it} \propto \left(\frac{A_{it}\beta_{it}}{\beta_t} - 1\right) \tag{1.6}$$

In each sector, 'distortion' in the capital allocation is proportional to the distance between the observed and 'efficient' capital returns, adjusted for technology. In the annex, we provide charts comparing the 'optimal' capital-labour ratio to the observed capital-labour ratio, for each sector. In order to arrive at those charts, we use relations (1.1), (1.6) and (2.1) (equation (2.1) is derived in the next section). In deriving those charts, we assume an equality in (1.6). It does not hinder our inference, as the precise measure of the distortion or, τ_{it} is directly proportional to this ratio.

Aggregate misallocation

We assume that the firms within a sector produce homogeneous products and maximize their profits. For simplicity, we assume no distortion in the price of the final product, which is sold in the perfectly competitive market. Also, within a sector, firms face roughly the same factor price. In turn, this means that the sectoral profits are maximized when the individual firms maximize their profits. By assuming W and R to be the unit cost of labor and capital, respectively, we write the sectoral profit as

$$\Pi_{it} = P_{it}Y_{it} - W_{it}L_{it} - R_{it}K_{it}$$

The first order conditions for the profit maximization solve for the following:

$$\frac{K_{it}}{L_{it}} = \frac{W_{it}}{R_{it}} \frac{\beta_{it}}{1 - \beta_{it}}$$
(2.1)

⁹ In the following subsection, we show, given the β_{it} s, how we can derive an estimate for the $\overline{\beta}_t$.

Or,
$$\log K_{it} = \log L_{it} + \log \left(\frac{W_{it}}{R_{it}} \frac{\beta_{it}}{1 - \beta_{it}}\right)$$
 (2.2)

Under the assumption of constant returns to scale, we use the expression $\beta_{it} = \frac{K_{it}R_{it}}{P_{it}Y_{it}}$ and subsequently expand Y_{it} to get;

$$P_{it} = \frac{\frac{W_{it} \left(\frac{K_{it}}{L_{it}}\right)^{-\beta_{it}}}{(1-\beta_{it})}$$
(2.3)

$$L_{it} \propto \frac{\frac{P_{it}}{W_{it}} A_{it} \left(\frac{K_{it}}{L_{it}}\right)^{\beta_{it}}}{(1-\tau_{it})}$$
(2.4)

Conditions (2.1) to (2.4) are the standard conditions for profit maximization. Equation (2.1) produces the profit maximizing level of capital-labor ratio for each sector. The ratio $\frac{W_{it}}{R_{it}}$ is the relative per unit remuneration to the labor relative to the capital. Precisely, it represents the <u>labor quality</u> in a sector. Equation (2.3) tells us that, given the factor allocation and technology, price of the final produce is a fixed markup over the unit labor cost. Condition (2.4) states the labor input is directly proportional to this markup.

Now, we expand the aggregate growth equation $Y_t = \prod_{i=1}^{s} Y_{it}^{\theta_{it}}$ in the following way;

$$\log(Y_t) = \sum_{i=1}^{s} \theta_{it} \log(A_{it}) + \sum_{i=1}^{s} \theta_{it} (1 - \beta_{it}) \log(L_{it}) + \sum_{i=1}^{s} \theta_{it} \beta_{it} \log(K_{it})$$
(3)

With the help of expressions (2.1), (2.2) and (2.4); equation (3) can be rewritten as;

$$\log(Y_t) = 2\sum_{i=1}^s \theta_{it} \log(A_{it}) + 2\sum_{i=1}^s \theta_{it} \beta_{it} \log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^s \theta_{it} \log\left(\frac{P_{it}}{W_{it}}\right) - 2\sum_{i=1}^s \theta_{it} \beta_{it} \log\left(\frac{1-\beta_{it}}{\beta_{it}}\right) - \log\prod_{i=1}^s \tau_{it}^{\theta_{it}} \theta_{it} \log\left(\frac{1-\beta_{it}}{\beta_{it}}\right) - \log\left(\frac{1-\beta_{it}}{\beta_{$$

In equation (4), $\prod_{i=1}^{s} \tau_{it}^{\theta_{it}}$ is the geometric mean of the sectoral distortions. In a multi-sector model such as this, if we assume that the aggregate supply of labor and capital in the economy is fixed for a certain period, then this measure is likely to be very close to unity and therefore, the expression $\log \prod_{i=1}^{s} \tau_{it}^{\theta_{it}}$ doesn't have any significance in (4). It doesn't mean that there exists no distortion for the aggregate economy, it rather means that the factors are always fully employed, while the inter-sectoral allocation of resources are subject to 'distortion'.

In equation (4), the term $\sum_{i=1}^{s} \theta_{it} \beta_{it} \log \left(\frac{1-\beta_{it}}{\beta_{it}} \right)$ is of particular interest. The term $\log \left(\frac{1-\beta_{it}}{\beta_{it}} \right)$ measures the percentage deviation of labor returns from the capital returns. Therefore, the expression $\sum_{i=1}^{s} \theta_{it} \beta_{it} \log \left(\frac{1-\beta_{it}}{\beta_{it}} \right)$ is the weighted average labor return in the economy. The basic assumptions about the parameters in our production function states that labor returns always vary between zero and one. Therefore,

the term $\sum_{i=1}^{s} \theta_{it} \beta_{it} \log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)$ is always positive. In other words, equation (4) means that, on an average, the higher the share of labor in output, lower is the aggregate output¹⁰.

If $\frac{1-\beta_{it}}{\beta_{it}}$ are lognormally distributed¹¹, then the closed form solution for the expectation of $\log(Y_t)$ is;

$$E(\log(Y_t)) = 2\sum_{i=1}^{s} \theta_{it} \log(A_{it}) + 2\sum_{i=1}^{s} \theta_{it} \beta_{it} \log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^{s} \theta_{it} \log\left(\frac{P_{it}}{W_{it}}\right) - 2\sum_{i=1}^{s} \theta_{it} \beta_{it} \left\{ E\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) + \frac{1}{2} Var\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) \right\}_{i=1}^{12} \left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) = 2\sum_{i=1}^{s} \theta_{it} \log(A_{it}) + 2\sum_{i=1}^{s} \theta_{it} \log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^{s} \theta_{it} \log\left(\frac{P_{it}}{W_{it}}\right) - 2\sum_{i=1}^{s} \theta_{it} \beta_{it} \left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) + \frac{1}{2} Var\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) = 2\sum_{i=1}^{s} \theta_{it} \log(A_{it}) + 2\sum_{i=1}^{s} \theta_{it} \log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^{s} \theta_{it} \log\left(\frac{W_{it}}{W_{it}}\right) + 2\sum_{i=1}^{s} \theta_{it} \log\left(\frac{W_{it}}{R_{it}}\right) = 2\sum_{i=1}^{s} \theta_{it}$$

The downside risk to the aggregate growth comes from two sources. First, $\sum_{i=1}^{s} \theta_{it} \beta_{it} E\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$, i.e. the average labor returns in the economy. Intuitively, $\sum_{i=1}^{s} \theta_{it} \beta_{it} E\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$ is a parameter of structural change in the economy. The second source of the risk comes from $Var\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$, which summarizes the variation in labor share around its mean $E\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$. Therefore, $Var\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$ measures the 'distortion' in factor allocation and the loss in aggregate output due to 'distortion' is measured by $\sum_{i=1}^{s} \theta_{it} \beta_{it} Var\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$. The 'efficient' or 'optimal' allocation is represented by $E\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$ and hence, we solve;

$$\bar{\beta}_t = \frac{1}{1 + e^{\alpha_t}} \tag{6}$$

where α_t is the simple average of $log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)$ across all the sectors.

At the sectoral level, we can estimate the profit-maximizing capital-labor ratio using equation (2.1), given the estimates for labor quality and capital's share in output, i.e. β_{it} . Further, given the estimates of TFP, i.e. A_{it} , we can infer whether the observed capital-labour ratio in a sector is equal to, higher or lower than the 'optimum' capital-labor ratio, using (1.1), (1.6), (2.1) and (6).

To summarize, the key relationships that we obtain from this exercise are:

(1) Loss in <u>aggregate output</u> (in %) from the 'distortion': $\sum_{i=1}^{s} \theta_{it} \beta_{it} Var\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$

where s indicates the number of sectors in the economy and θ_{it} is the share of the sector i in the aggregate GVA at period t, measured in the current prices.

¹¹ If $\frac{1-\beta_{it}}{\beta_{it}}$ are lognormally distributed then the mean and variance of the distribution are $e^{E\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)+Var\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)/2}$ and $(e^{Var\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)}-1)(e^{2E\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)+Var\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)})$, respectively.

¹⁰ We arrive at this condition particularly, since we expressed the capital input in 'per-labor unit' form, i.e. keeping capital constant, increase in labor input means that the effective capital usage for each labor unit reduces.

¹² We can express any random variable X in the form $X=E(X) + \sqrt{Var(X)}Z$ where Z is the standardized random variable with E(Z)=0.

(2) The 'distortion' in the allocation of capital in sector i for the period t: $\tau_{it} \propto (\frac{A_{it}\beta_{it}}{R} - 1)$

where,
$$\bar{\beta}_t = \frac{1}{1+e^{\alpha_t}}$$
 and α_t is the simple average of $log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)$ across all the sectors.

Given information on β_{it} , A_{it} and the GVA (current prices) for 27 sectors, in India KLEMS dataset, we can obtain both these measures. We provide our key findings in the following section.

IV. EVIDENCE FROM INDIA KLEMS DATA

Using the latest India KLEMS data, we estimate that, between 1981 and 2004¹³, 'loss' to the aggregate output in India was about 25-30% due to the 'distortion' in allocation of capital across sectors. This means, the aggregate output in India was 25-30% lower than what could be achieved if there was no 'distortion' in the allocation of capital between sectors. Our estimate suggests that the output 'loss' increased to 35-40% between 2005 and 2011.



Fig 3 shows that simply a more 'efficient' reallocation of the existing capital could increase India's aggregate output by a significant margin, without any changes in TFP. The gap between the observed real GVA and the dotted line, representing the 'optimum' or 'distortion-free' output, represents the output loss that we estimate. Interestingly, post-2005, although the supply of capital improved significantly, gains to the output was limited, as the gap between actual and optimum output widened. As this figure suggests, the increased supply of capital could raise India's output significantly (see the 'optimum'). However, the actual output did not increase commensurate to that increase, as most of this extra capital were allocated in sectors which were already capital rich, or were subject to the lower marginal product for the additional capital for some other reasons. Das, Erumban and Das (2016), on the contrary finds evidence of significant capital reallocation, where, the findings from the observed TFP growth decomposition suggests expansion of investment in sectors with high returns from capital, since 1994. Our findings do not contradict Das, Erumban and Das (2016). Our conclusions are mostly drawn from the optimality point of view, wherein, we say, how much 'could have been achieved' if misallocation could have been completely eradicated. This may hold true even if some degree of reallocation is happening in reality.

Our estimates at the sectoral level further suggests that the services activities were 'over-capitalized' (see sectoral charts in the Annex), while host of other activities were capital-starved. Controlling for technology, we see that activities such as trade, hotels and restaurants, transport and storage, financial and

¹³ For simplicity, we express the financial year 2004-05 as the year ending in March, 2005; or simply 2005, and so on.

business services continue to use 'excess' capital. Some exception within the services are public administration, defense, and social security; education; and health and social work, which were 'under-capitalized'. Most of the manufacturing activities, as we see, except the electrical and transport equipment, chemical products were 'under-capitalized'¹⁴.

This is broadly consistent with the nature of sectoral characteristics in India. Due to their rapid growth in last few decades, trade and miscellaneous other services activities attracted disproportionate investment, both domestic and external. They may also be subjected to the investors' over-optimism in some part, leading to over capitalization. Dominance of public sector in financial services too may be a possible reason for its overcapitalization in relation to sectoral value added. Varied degree of external exposure is also visible within manufacturing sectors' capital intensity¹⁵. For instance, excess capital in chemical products' sector can be possibly explained by its greater inward orientation, as compared to 'textile' where markets are mostly export oriented imposing greater capital discipline, and risk. Public administration and defense services are subject to tighter budget constraint, making them one of the 'under-capitalized' sectors. On the other hand construction activities were seriously capital starved and its high growth in last decade is driven by the increasing contribution from labor. Agriculture remained mildly 'under-capitalized' as compared to the manufacturing and construction sectors.

We also provide an alternative explanation for the aggregate 'distortion'. Alongside the differences in the allocation of capital services across sectors, we find that the share of capital in aggregate output increased rapidly since mid-1990s. A part of this increase could be driven by the structural change in the economy, led by the use of more capital intensive techniques, higher inflows of foreign capital, fast credit growth etc. However, a large part of this capital is misallocated in relation to the 'observed' level of output. In fig 4, we plot the average level of capital's share in output, i.e. the β_{it} , adjusted for TFP, and the optimum capital share, i.e. $\overline{\beta}_t$. We derive our intuition from the equation (1.6), that despite improvement in technology (i.e. higher TFP) if a sector continues to exhibit same level of β_{it} , we say that the 'effective' capital share in that sector has gone up. Therefore, we 'adjust' the β_{it} s by multiplying them with the sector's TFP.



Fig 4 can be divided into three phases. First, before 1995, when the capital's share was broadly aligned with the 'optimum'. It started deviating from the 'optimum' since then and post-2005, the pace of deviation accelerated. Using the India KLEMS data we show that the use of capital services are largely inelastic to the real rent that is being paid on capitals. Therefore, at times of rising real rent (e.g. post-1997 in fig. 5.1),

¹⁴ For detailed discussion on the causes behind misallocation in India at the macro level, see Banerjee and Duflo, 2005.

¹⁵ For the theoretical explanation of the impact on trade on intra-industry reallocation, see Melitz (2003)

the use of capital services did not fall commensurately, as we see from the very low correlation coefficient (fig. 5.2). Fig 5.2 shows the correlation coefficient between the real rent of capital and the capital service, normalized to the real output. Both the variables are indexed to the year 1981. The correlation coefficients are calculated for each year separately, by using observations on all 27 sectors. Fig 5.2 shows that, with increases in real rent, the capital consumption, in general does not fall adequately. Over the sample period, the average correlation coefficient is only -0.3. As result, at a high level, capital continues to be used sub-optimally, i.e. with lower marginal product than the rent paid on it. This phenomenon gives rise to the output gap (i.e. actual deviating from the 'potential') as we show in fig 3.



V. CONCLUSION

Capital misallocation in the growth process is of particular importance in India as the country aims for a high growth despite having constraint on the availability of capital. In a rapidly growing economy like India, it is therefore important to look at the issue of misallocation purely from the perspective of growth aspirations as also to identify various sources of distortions in capital allocations in policy framework. In this context, this paper made an empirical assessment to measure the extent of output loss in the Indian economy purely arising from capital misallocation.

In order to carry out the analysis, we use India KLEMS dataset on labor and capital inputs and TFP estimates across 27 sectors of the economy, between 1980-81 and 2011-12. The quality aspects of the two major inputs viz. labor and capital are also captured in this dataset. The dataset also provides income shares of labor and capital in output for each year and for each sector.

We first measure the correlation coefficient between the capital service and the real GVA for each year across 27 sectors. We observe that the average correlation coefficient is only 0.14 between, 1999-00 and 2011-12. This provides us the first evidence of possible capital misallocation. In further exercise, we estimate the gap between the observed real GVA to the 'optimum' or 'distortion-free' GVA, which confirms significant output loss in the Indian economy purely through the misallocation of capital. Although the supply of capital improved significantly since -2005 and output grew faster, our calculation suggests that the gap between observed and 'optimum' output has widened since then. In other words, misallocation of capital went up in the more recent period, despite improvements in the supply of capital.

Our estimates at the sectoral level further suggests that the services activities were generally 'overcapitalized', with the exception of public administration, defense, and social security; education; and health and social work. We find evidence that activities such as trade, hotels and restaurants, transport and storage, financial and business services carry relatively larger share of capital, which is not commensurate with their returns on capital. Most of the manufacturing activities, on the other hand, except the electrical and transport equipment, chemical products remains 'under-capitalized'. This implies that, possibly higher investments in these segments could yield larger GVA growth. Agriculture remained mildly 'under-capitalized' as compared to the manufacturing and construction sectors. It is possible that economic sectors subjected to restricted entry, inwardly oriented or intensively regulations are more prone to over capitalization. At the aggregate level, we observe that the sensitivity of use of capital services to the real rent paid on capitals is low, possibly substantiating our findings on 'distortion'. It is estimated that by eliminating this 'distortion' alone, India's aggregate output could possibly be lifted by 20-30% between 1990 and 2004 from their observed level and by even greater extent of nearly 40% after 2005.

The study brings out an important dimension of growth process in the Indian economy in that the aggregate output may potentially be increased simply by redistributing the excess capital from the 'over-capitalized' services sectors to the 'under-capitalized' manufacturing sectors. In other words, it implies that a larger focus on the manufacturing investments in India may potentially lift the growth momentum of the economy, without any fresh infusion of capital, but just by shifting capital from select services segments. Although the finding is a theoretical possibility and a complete elimination of 'distortion' may not be feasible in practice, we still held that a policy framework enabling financial liberalization may be pursued aggressively to achieve the growth aspirations of the economy (see Galindo et. al. 2007).

Annex

Following charts compare capital-labor ratio for the sectors which are broadly characterized as 'under-capitalized'.





Following charts compare capital-labor ratio for the sectors which are broadly characterized as 'over-capitalized'.



Following charts compare capital-labor ratio for the sectors where are capital is broadly 'optimally' allocated.



Box 1: Brief Description of the India KLEMS database and the variables 16

Introduction to KLEMS

The KLEMS methodology is being applied recently, both internationally and in India, as an alternative to the traditional methodology to obtain the productivity measure, where the "value added" is used as a measure of output, with capital (K) and labour (L) as inputs. In KLEMS methodology, the "gross output" is seen as a measure of output with capital (K), labour (L), energy (E), materials (M) and services (S) as inputs. The objective of India KLEMS project is to provide the KLEMS dataset for industries comprising the economy of India. These datasets are envisaged to be used for analyzing the sources of growth across sectors in India and also to serve as a supplement to the system of the national accounts. The dataset is prepared for use in the growth accounting methodology for estimating total factor productivity, which allows a decomposition of output growth into the contributions of different inputs and total factor productivity. The industrial classification in India KLEMS with 27 broad industries in this project was built according to the several rounds of NIC (National Industrial Classification) and was made aligned to the EU KLEMS to ensure compatibility with other studies under the World KLEMS initiative. The industrial disaggregation consists of one agriculture, one mining and quarrying, thirteen manufacturing, one sector covering electricity, gas and water supply, one construction and nine services industries. In its present form, India KLEMS database provides time-series of all inputs under the definition of KLEMS, gross output (GO) and gross value added (GVA), between fiscal years 1980-81 and 2011-12. The dataset has been constructed on the basis of National Accounts Statistics (NAS), Annual Survey of Industries (ASI), National Sample Survey Organisation (NSSO) rounds and input-output tables. In the following sub-sections, we provide the definition and some details about the key series that we use in our estimation.

I. Gross Value Added and Gross Output

Gross value added or GVA of an industry is defined as the value of output less the value of its intermediary inputs. The NAS brought out by the CSO, Government of India is the basic source of data for the construction of series on GVA in India KLEMS dataset. NAS provides disaggregated GVA measures in both current and constant (2004-05) prices at the broad industry level. A higher level of disaggregation in some cases have been obtained by using information from ASI and NSSO rounds, for registered and unregistered manufacturing sectors, respectively.

Gross output: Estimates of gross output in India KLEMS for sectors agriculture, hunting, forestry and fishing, mining and quarrying, construction and manufacturing sectors are directly obtained from NAS at current and constant prices. For splitting some sectors, as in the case of value added, additional information is used from ASI and NSSO. For other sectors, mainly service sectors, where there was no output information available from NAS, input-output transaction tables, which provides output and value added, are used. The ratio of these two is applied to value added in NAS to obtain consistent estimates of gross output. The benchmark input output tables for the years 1978, 1983, 1989, 1993, 1998 2003 and 2007 are used for this purpose, and for the intermediate years the ratios are linearly interpolated.

¹⁶ Inputs and information for this box is broadly obtained from Das et. al., (2015). The authors' presentation in Reserve bank of India, Mumbai to explain the characteristics of India KLEMS dataset and the methodology to estimate TFP is acknowledged. For detailed implementation method and exact formulae, please refer to Das et. al., (2015).

II. Labour Input

India KLEMS database provides separate index of labour input (1980-18=100) for each industry for the period 1980-81 to 2011-12. In estimating the index, two dimensions of the labour input are taken into account - labour persons and educational attainment of the workers, in order to distinguish one type of labour from the other. Employment data in India KLEMS is based on usual principal and subsidiary status (UPSS) concept, and are obtained from the quinquennial rounds of Employment and Unemployment Surveys (EUS) published by National Sample Survey Office (NSSO). The aggregate labor input, used in this study is obtained as the weighted sum of employment growth rates of workers of various educational levels. The idea is to take into account the embodied human capital in each person, which could be through investment in education, experience, trainings, etc. The contribution from each person to the output comes from this embodied capital and accordingly the wages and earnings vary. Therefore, the project aims at separating out these differences in labour to clearly understand the underlying differences in labour characteristics. Das et.al. (2015) defines the aggregate labour input by applying the Törnqvist index of persons worked by individual labour type. In this methodology, the aggregate labour input turns out to be a multiplication of labour employment and labour quality. In the present case, Das et. al. (2015) considers only the educational attainment as the aspect of labour quality. For the estimation of labour input across various industries in India, several rounds of the large scale Employment and Unemployment Surveys (EUS) by the NSSO and the estimated population series based on the decennial population census have been used. Available data from these sources enabled the authors to estimate the persons employed in each industry and adjust it for changes in labour skill by calculating the labour education index, and thereby obtaining the education corrected labour input.

III. Capital Services

Capital services: Capital services for the aggregate economy and for industries in India KLEMS are arrived at from industry level investment in three different asset types – construction, transport equipment, and machinery are gathered from NAS for broad sectors of the economy, the Annual Survey of Industries (ASI) covering the formal manufacturing sector, and the National Sample Survey Office (NSSO) rounds for unorganized manufacturing. These industry level data are used to construct capital stock using perpetual inventory method

Aggregate <u>capital services</u> growth rate is derived as a <u>weighted growth rate of individual capital assets</u>, the weights being the compensation shares of each asset-type. Das et. al. (2015) uses the Törnqvist approximation to the continuous Divisia index under the assumption of instantaneous adjustability of capital. In the following steps, Das et. al. (2015) derives capital stock estimates for detailed asset types and the shares of each of these assets in total capital remuneration, which is used for calculating capital services growth:

As the first step towards obtaining the industry-level estimates for capital services, Das et. al. (2015) defines <u>total investment</u> by asset-category for each industry. The primary source of data in this regard is the NAS, which provides information on aggregate capital formation under 9 broad sectoral heads. However, in order to bring larger disaggregation (as there are 27 industries in India KLEMS), detailed data on industry and assets were collected from CSO, ASI and NSSO. Broadly, Das et. al. (2015) defined the following asset types: construction, transport equipment, and machinery and equipment¹⁷, for both private sector and public sector,

¹⁷ Das et. al. (2015) includes software in the machinery and equipment, as the approach does not distinguish between ICT and non-ICT assets.

separately. Total investment in each asset category is then calculated as the sum of private and public sector investments. Second, the estimates of capital service required time-series data on asset-wise capital stock, which has been constructed using the perpetual inventory method (PIM), where capital stock (S) is defined as a weighted sum of past investments with weights given by the relative efficiencies of capital goods at different ages. This aggregation required data on current investment, investment prices and depreciation rate by assettype. For the implementation of PIM, Das et. al. (2015) takes the NAS estimate of real net capital stock in 1950 as the benchmark capital stock for non-manufacturing sectors while the same for the year 1964 is taken as the benchmark capital stock for manufacturing sector. The current period investment is already estimated in the previous step. The investment price deflator in each case has been derived using the investment data in current and constant prices by industry and asset-type, as provided by CSO to the India KLEMS team. The depreciation rates for the non-ICT assets have been derived using the detailed information on assumed life by asset-type, provided by NAS. Lastly, the final aggregation to arrive at the capital services requires estimates of rental prices. The rental price of capital stock is equal to the investment price in current period times the rate of nominal return, adjusted for the depreciation rate, less the changes in investment price of the asset-type from previous period. The compensation to each asset-type is calculated by multiplying the capital stock with the rental price. Having obtained (i) the capital stock in step 2 and (ii) the rental prices/compensation in the last step, Das et. al. (2015) expresses the index of capital services (1980-81=100) by using the Törnqvist index for each industry.

IV. Factor income shares

The factor income share is defined as the ratio of total remuneration to a factor of production, to GVA. Under the assumption of constant returns to scale with two factors of production i.e., labour and capital, the sum of labour income share and capital income share is 1. India KLEMS dataset provides detailed estimates of labour income share for all 27 industries over 1980-81 to 2011-12. The capital income share is obtained as one minus the labour income share.

Das et.al. (2015) provides following details about the estimation of labour income share. There are no published data on factor income shares in Indian economy at a detailed disaggregate level. National Accounts Statistics (NAS) publishes the Net Domestic Product (NDP) series comprising of compensation of employees (CE), operating surplus (OS) and mixed income (MI) for the NAS industries. The income of the self-employed persons, i.e. MI is not separated into the labour component and capital component of the income. Therefore, to compute the labour income share out of value added, one has to take the sum of the compensation of employees and that part of the MI which are wages for labour. The computation of labour income share for the 27 study industries involves two steps. First, estimates of CE, OS and MI have to be obtained for each of the 27 study industries from the NAS data which are available only for the NAS sectors. Second, the estimate of MI has to be split into labour income and capital income for each industry for each year

It is already pointed out that NAS classifies the aggregate GVA into 9 broad sectors. Therefore, in the present exercise, a number of these sectors were further disaggregated to obtain 27 industries in total, using the methodology already discussed in sub-section I. In these cases, the CE, OS and MI for a particular sector in NAS has been distributed among the newly classified sectors in KLEMS, according to the gross value added by these smaller industries. In the following step, MI has been split into labour income and capital income, by assuming that labour income in an industry is a constant (i.e. not varying over time) proportion of the MI. The estimation of this proportion has been done with the help of NSS survey-based estimates of employment of

different categories of workers (number of persons and days of work) and the wage rates. Finally, the total compensation to labour is obtained as a sum of CE and the portion of MI classified as labour income.

V. Total factor productivity

Having obtained the series for gross value added, indices of labour input, capital services and shares of labour and capital into GVA, Das et. al. (2015) obtains estimated for the total factor productivity by using the standard growth accounting methodology. For an individual or industry, productivity measure can be based on a value added concept. In this concept, GVA is considered as the industry's output which is generated and shared by only the primary inputs such as labour and capital. The productivity measures obtained by using the GVA can be valid complements to gross output based measures.

References

Aghion, Philippe, Robin Burgess, Stephen Redding, and Fabrizio Zilibotti, "The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India," American Economic Review, 98 (2008), 1397–1412.

Alfaro, Laura, Andrew Charlton, and Fabio Kanczuk, "Plant-Size Distribution and Cross-Country Income Differences," NBER Working Paper No. w14060, 2008.

Allen, F., Chakrabarti R., De S., Qian J., and Qian M. (2007), Financing Firms in India, manuscript, University of Pennsylvania.

Bai et. al. (2007), "The Return to Capital in China", NBER Working Paper No. 12755.

Banerjee, A., and Esther D. (2005), "Growth Theory through the Lens of Development Economics," in Handbook of Economic Growth, Vol. 1 A, (Elsevier, Chap. 7).

Bosworth, B., S.M. Collins (2008), Accounting for growth: Comparing China and India, Journal of Economic Perspectives, 22(1): 45-66.

Boybeau-Debray, G. and Wei, S-J, (2004), "Can China Grow Faster? A Diagnosis of the Fragmentation of Its Domestic Capital Market", IMF Working Paper, 04/76, May 2004.

Brandt, L. et. al. (2012), "Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing", Journal of Development Economics 97, pg. 339–351.

Das, D.K. et. al., (2015), "Measuring Productivity at the Industry Level: The India KLEMS database", Data Manual 2015, Version 2.

Das, D.K., Erumban, A. A. and Das, P.C. (2016), "Productivity Dynamics in Indian Industries – Input Reallocation and Structural Change".

de Vries, G. J., Erumban, A. A., Timmer, M. P., Voskoboynikov, I., and Wu, H. X. (2012), "Deconstructing the BRICs: Structural transformation and aggregate productivity growth", Journal of Comparative Economics, 40(2), 211-227.

de Vries, G.,M.P Timmer and de Vries, K (2015), "Structural Transformation in Africa: Static Gains, Dynamic Losses", The Journal of Development Studies, 51(6).

Dollar, D. and Wei, S. (2007), "Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China", IMF Working Paper, No. WP/07/9.

Farrell D., and Susan L. (2006), "China's and India's Financial Systems: A Barrier to Growth," McKinsey Quarterly, November, 1–12.

Galindo, A., Fabio S., and Andrew W. (2207), "Does Financial Liberalization Improve the Allocation of Investment? Micro-Evidence from Developing Countries," Journal of Development Economics, 83, 562–587.

Hsieh, C and Klenow, P. J. (2009), "Misallocation and Manufacturing TFP in China and India", The Quarterly Journal of Economics, Vol. CXXIV, Issue 4, November.

Kochar, Kalpana, Utsav Kumar, Raghuram Rajan, Arvind Subramanian, and Ioannis Tokatlidis (2006), "India's Pattern of Development: What Happened, What Follows," NBER Working Paper No. w12023.

Melitz, Marc J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity," Econometrica, 71, 1695–1725.

McMillan, M.S. and Rodrik, D. (2011), "Globalization, Structural Change and Productivity Growth", NBER Working Paper, No. 17143, June.

Restuccia, D. and Rogerson, R. (2007), "Policy Distortions and Aggregate Productivity with Heterogeneous Plants", NBER Working Paper, No. 13018, April.