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ARTICLE

Capital misallocation and its implications for India's potential GDP: An evidence from India KLEMS

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Abstract

In this paper, we estimate 'distortions' in the allocation of capital across various economic sectors in India, which has certain predictable impacts on the potential output of an economy. We calibrate our model using the India KLEMS dataset. We show that several industries in India, broadly in the services segments, are possibly 'over-capitalised' in a sense that capital usages here are too high for the output that they produce. In other words, the same level of output in these sectors could also be produced by much lesser capital. On the other hand, several manufacturing sectors are 'under-capitalised' by the similar criteria. Together, it implies that the aggregate output would have been higher if a redistribution of the excess capital from 'over-capitalised' services to the 'under-capitalised' manufacturing sectors was possible. In other words, a shift in the investment that 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 30–35% between 1990 and 1999 from their observed level and by even greater extent of nearly 40% after 2000. Alternatively, if we are able to reduce the 'distortion' to the levels observed before 2005 in India, we may be able to generate an additional 30% output over and above the levels observed between 2005 and 2015. We, therefore, conclude that the government may conduct any further policy on the ease of capital movement with some caution with respect to industries that are 'over-capitalised'.

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1 Introduction

In light of the phenomenal growth in emerging economies during the last couple decades, a number of papers recently shed light on the sources of rapid increases 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 is 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 their ability to infuse larger amount of inputs in the production process or its efficient utilisation that reflects on the higher total factor productivity (TFP). Several papers looked at the efficiency in factor usage from a slightly different perspective. Instead of examining the trend in TFP, they looked at the role of 'distortion' in the allocation of factors of production between firms, industries and sectors to explain the source of output variation (Restuccia and Rogerson 2007; Hsieh and Klenow 2009). The idea is as follows: suppose there are two firms which have access to the same technology. However, due to market segmentation, regulation or imperfect information, firm A finds it hard to raise capital from the market, or it may end up paying too high rates of interest for the capital. This discourages firm A to use more capital. On the other hand, the other firm, say firm B, is not that tightly regulated or may be enjoying favourable 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 excess capital in the production process of firm B. 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 from the factor for the aggregate economy (Banerjee and Esther 2005), and thereby reducing aggregate output (Restuccia and Rogerson 2007). In this paper, we develop a theoretical framework to estimate 'distortion' in the allocation of capital across major sectors in an economy and estimate its possible impact on India's aggregate GDP.

The study on the effects of misallocation or 'distortion' is particularly important for India as it aims for a high growth.[1] Regulatory policies often alter the relative prices of resources across producers, and, therefore, influences how the resources are distributed (Farrell and Susan 2006; Restuccia and Rogerson 2007). In India, majority of the bank credits are extended by the public sector banks. Any underutilisation of the fund eventually puts pressure on the interest rates, fiscal balance, etc., and, therefore, alters the availability of capital to other borrowers. Between

[1] World Economic Outlook report, April 2017 projections for India's growth for 2017 and 2018 are 7.2% and 7.7%, respectively.

2004 and 2011, bank credits to the commercial sector in India have grown by 21%, on average every year, outpacing the growth in nominal GDP at 16%. Similarly, the flows of foreign investments have grown significantly during this period. Net inflows of foreign direct investments (FDI) have grown by 30% on average, every year in US Dollar terms, again outpacing the growth in nominal GDP. The resulting decline in the GDP to capital (in this case, both bank credit and FDI) ratios could be viewed as a resultant of possible 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 Esther 2005; Allen et al. 2012). 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 and find suitable ways which can be addressed in the broader policy framework.

In the relevant literature, 'distortion' is generally perceived as the variation in factor prices across firms within similar industries (Hsieh and Klenow 2009). Hsieh and Klenow (2009) use variations in the TFP across firms as a measure of aggregate impact of 'distortion' in factor and output prices. In estimating 'distortion', Hsieh and Klenow (2009) assume that the factor shares in the value added remains unchanged over time. The assumption, however, is challenged by the available data. Figure 2 in Sect. 2 shows that the share of capital in the gross value added in India has increased since early 2000s, coinciding with the country's high GDP growth phase. A part of this increase might be driven by the changes in technology and labour productivity, which make capital more rewarding. However, our conjecture is that, as capital inflows increased significantly post 2000 in India, the price of capital did not adjust commensurately, resulting in the factor's share to increase. This slower adjustment of factor prices could be related to the factor misallocation similar to Hsieh and Klenow (2009). However, in the present case, possibly the 'distortion' in capital's rent changes over time. When factor shares change over time, the estimation of TFP using a model with constant factor share might be biassed. Therefore, in this paper, we develop a model for measuring the impact of 'distortion' in the allocation of capital on aggregate output, by explicitly accounting for this variation in factor share over time, for the same sector or industry. We show that, the effects of capital misallocation on country's aggregate output can be measured by the intersectoral variation in the share of capital in output, relative to the labour's share. Our contribution to the literature is that, we provide a framework of aggregate effects of misallocation, based on the factor shares, which are directly observable, instead of the TFP, estimation of which can be subject to several assumptions. Major limitation of this paper is that, we restrict our model only to the broad sectors or industrial classification of Indian economy, mainly due to the non-availability of consistent and comparable data on factor shares at more granular level, especially for services. Our formulation of 'distortion' is similar to Dollar and Wei (2007) and Bai et al. (2007) who measure distortion using the cross-sector variation in the capital returns.

Rest of the paper is divided into the following sections. In the next section, we provide some details of the India KLEMS dataset, used in our analysis. In Sect. 3, we explain our mode whilst in Sect. 4, we provide our findings. In Sect. 5, we extend certain findings on ‘optimum’ capital share and corroborate our argument of slower adjustment of factor prices, we state in the introduction. We conclude with some policy implications in Sect. 6.

2 Dataset for India

We needed consistent data on labour 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 beginning of 2018.[2] The India KLEMS was envisaged to fulfil the gap in the availability of consistent dataset on productivity across sectors in India. The KLEMS data were 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 and 1981 and 2015 and 2016. The aggregate value of gross output (at current prices) from these 27 sectors covers more than 90% of the GDP at market prices (at current prices) between 1980 and 1981 and 2015 and 2016. 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 2011–2012 prices. In the estimation of TFP, the dataset precisely addresses the quality aspects of the two major inputs viz. labour and capital. The dataset provides separate series on labour employment, labour input, the stock of capital and the capital services. The dataset also provides estimates of the income shares of labour and capital in gross output and gross value added for each year and for each sector, which is the key variable used in our estimation of ‘distortion’. Thus, 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 “Appendix”.

2.1 Some stylised facts

The average annual growth in India’s aggregate gross value added (GVA) was 6.8% between the fiscal years 2000–2001[3] and 2015–2016. During this period, capital

[2] Das et al. (2017), available in https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/KLEMS27032018E6B6C80028604EBCAFDA3A82ACDE9B10.PDF.

[3] The financial year of the government of India runs between April and March. This means, the financial year 2000–2001 would be between April 2000 and March 2001.

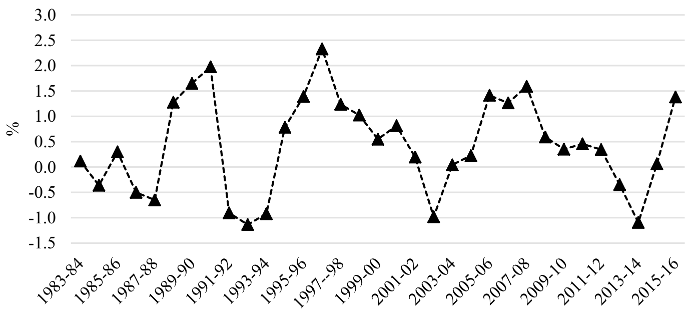

Fig. 1 TFP growth in India (YoY, 3 years moving averaged) Source: India KLEMS. Note: This figure plots the weighted average of annual growth in industry level TFPs, weights being the industry share in all-India real GVA

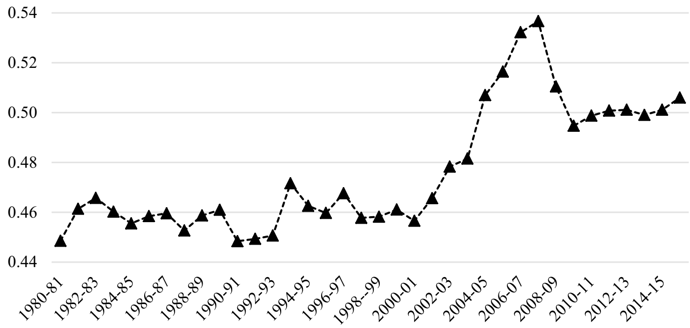

Fig. 2 Capital's share in GVA Source: India KLEMS, authors' calculations. Notes: In this figure, plots the weighted average of industry level capital shares in respective GVA, weights being the industry share in all-India real GVA

inputs grew by 8.8%, far exceeding the growths of GVA (6.8%), TFP (0.5%) and labour inputs (3.3%). Over the longer period, growth in TFP appears to be only cyclical (Fig. 1), often becoming close to zero, or even negative. The average annual GVA growth, persistently above 6%, was mainly driven by the growth in capital inputs or services obtained from the capital stock.

The income share of capital in GVA increased sharply between 1980–1981 and 2015–2016 (Fig. 2). GVA growth across industries and time is positively correlated with the capital's share in that industry (Figs. 3, 4). Theoretically the share of a factor in an economy's GVA increases when an increased usage of a factor is not accompanied by a commensurate decline in its price (real rent in this case). Under a competitive factor market, the real rental of an additional unit of capital must equate to its marginal product. However, under distortions in the factor market, whilst with increased use of capital, the marginal product of the additional unit of capital falls, its real rent does not fall sufficiently (Hsieh and Klenow 2009). In this case, the real rent or the marginal compensation to capital exceeds the marginal product, for the last unit of capital used. This phenomenon results in increases in capital's income

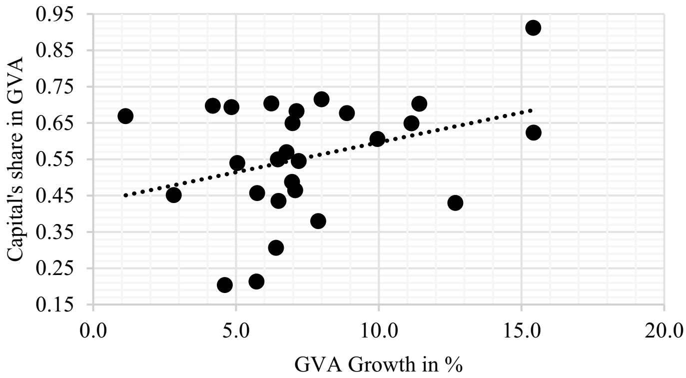

Fig. 3 Capital's share and GVA growth across industries (average 1981–2015) Source: India KLEMS, authors' calculations. Notes: In In this figure, scatters represent industries

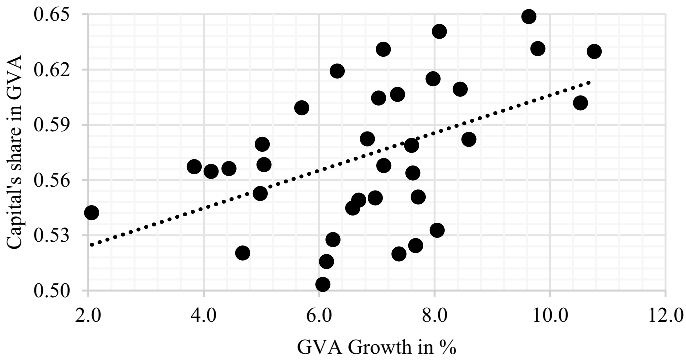

Fig. 4 Capital's share and GVA growth over 1981–2015 (average across industries) Source: India KLEMS, authors' calculations. Notes: In this figure, scatters represent fiscal years

share in GVA. In other words, Figs. 2, 3 and 4 suggests that the growth in certain sectors may have occurred through distortionary usage of capital. The 'distortion', however, may not be uniformly distributed across sectors as some sectors may have attracted 'disproportionately higher' capital during this period, whilst some other may have been capital starved. The last phenomenon is the subject of our assessment in the following sections.

The increased use of a factor may not necessarily be associated with decline in its prices in case of an exogenous shift in its demand. In that case, increased factor usage may be associated with non-declining unit price of the factor, depending upon the shape of its supply curve. Such exogenous shift might be driven by technological growth or growth in labour efficiency, which in turn, demands more capital service.

The growth in labour efficiency[4] in India, however, has been significantly low in recent decades. Das et al. (2016) attested that at least services sector in India witnessed large-scale capital accumulation in some part of 2000s, with declining productivity growth. In addition, the growth in TFP remains cyclical, sometimes being negative (Fig. 1). These facts, together with Figs. 2, 3 and 4 provides motivation for the study on the possible 'distortion' in sectoral capital allocation. How much of the increase in capital's share in GVA is due to the 'distortion', is the subject of this paper.

3 The model

We assume that the production function for the ith sector during the tth period takes the form[5]

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

where the gross value added (GVA) Y is a function of labour 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 labour 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 $\theta_{it} = \frac{P_{it}Y_{it}}{P_t Y_t}$, which is equivalent to the sector's share in the nominal aggre-

[4] The average index of labour quality has increased by only 0.8% annually between 2000–2001 and 2015–2016 (Source: India KLEMS).

[5] 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) emphasised 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.

gate 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.

3.1 The efficient allocation

We express the above sectoral production function in 'per-labour input' form as follows:

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

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

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

An economy maximises aggregate 'per-labour input' GVA, by choosing k_{it} subject to an upper limit $\bar{k}$ on k_{it}. The economy's problem is

$$\text{Max } y_t; \quad \text{subject to } 0 < k_{it} \leq \bar{k},$$

Or

$$\text{Max } \log(y_t); \quad \text{subject to } -\infty < \log(k_{it}) \leq \bar{c}.$$

The Lagrange equation corresponding to this problem is

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

The first-order condition for the social optimisation 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 becomes

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

By solving this condition, we get,[6]

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

[6] Since $\frac{\delta \log(A_{it})}{\delta \log(k_{it})} = \frac{\delta \log(y_{it})}{\delta \log(k_{it})} - \beta_{it}$.

In the above equation, λ shows the weighted average of sectoral capital shares at the distortion-free allocation. This weighted average, in turn, is the'expected' value of a sector's capital share in value added in a sufficiently large sample. Going forward, we call it 'efficient' capital return and denote it by $\bar{\beta}_t$. We allow the 'efficient' capital share to vary over time, as the technology changes and requires varying contribution from the capital. The capital–labour ratio which maximises social welfare may now be called an 'efficient' or 'optimal' capital–labour ratio$\left(\bar{k}_{it}\right)$. We define distortion ($\tau_{it}$) as the percentage deviation of the observed k_{it} from the 'optimal', i.e.$\bar{k}_{it}$. Symbolically;

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

In the following exercise, we show that the 'unobserved' distortions in the capital–labour ratio can be obtained in terms of the 'observed' capital returns (β_{it}) and technology (A_{it}). Since β_{it} is also the capital's elasticity to output, we can write[7]

$$\beta_{it} = MP_k \frac{k_{it}}{y_{it}}. \tag{2}$$

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

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

This expression can be rewritten as follows:

$$\begin{aligned} MP_k &= A_{it}\bar{\beta}_{it}\frac{\beta_{it}}{\bar{\beta}_{it}}\left\{(1+\tau_{it})\bar{k}_{it}\right\}^{\beta_{it}-1} \\ &= A_{it}\bar{\beta}_{it}\frac{\beta_{it}}{\bar{\beta}_{it}}\left(\bar{k}_{it}\right)^{\bar{\beta}_{it}-1}\left(\bar{k}_{it}\right)^{\beta_{it}-\bar{\beta}_{it}}\left(1+\tau_{it}\right)^{\beta_{it}-1} \\ &= \left(MP_k\right)_{k_{it}=\bar{k}_{it}}\frac{\beta_{it}}{\bar{\beta}_{it}}\left(\bar{k}_{it}\right)^{\beta_{it}-\bar{\beta}_{it}}\left(1+\tau_{it}\right)^{\beta_{it}-1} \\ \text{or, } MP_k\Big/\left(MP_k\right)_{k_{it}=\bar{k}_{it}} &= \left(1+\tau_{it}\right)^{\beta_{it}-1}\frac{\beta_{it}}{\bar{\beta}_{it}}\left(\bar{k}_{it}\right)^{\beta_{it}-\bar{\beta}_{it}}. \end{aligned} \tag{3}$$

Equation 3 implies that when the actual k_{it} is higher than the 'efficient' level $\bar{k}_{it}$ in a sector (i.e.$\tau_{it} > 0$), the marginal product of k_{it} is lower than the 'efficient' situation, as$\beta_{it} - 1 < 0$.

Equation (3) implies[8]

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

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

$$\begin{aligned}\frac{\beta_{it}}{\bar{\beta}_{it}} &= \left(1+\tau_{it}\right)^{1-\beta_{it}}\left(MP_k/MP_{\bar{k}}\right)\left(\bar{k}_{it}\right)^{\bar{\beta}_{it}-\beta_{it}} \\ &= \left(1+\tau_{it}\right)^{1-\beta_{it}}\left\{\frac{MP_k}{\left(\bar{k}_{it}\right)^{\beta_{it}}}\right\}\left\{\frac{\left(\bar{k}_{it}\right)^{\bar{\beta}_{it}}}{MP_{\bar{k}}}\right\} \\ &= \left(1+\tau_{it}\right)^{1-\beta_{it}}\left\{\frac{MP_k}{\left(k_{it}\right)^{\beta_{it}}}\right\}\frac{\left(k_{it}\right)^{\beta_{it}}}{\left(\bar{k}_{it}\right)^{\beta_{it}}}\left\{\frac{\left(\bar{k}_{it}\right)^{\bar{\beta}_{it}}}{MP_{\bar{k}}}\right\}.\end{aligned} \tag{4}$$

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 €, a constant. Given (1.1), $\frac{(k_{it})^{\beta_{it}}}{(\bar{k}_{it})^{\beta_{it}}}$ can be written as $\left(1+\tau_{it}\right)^{\beta_{it}}$. Also, we simplify the expression $\left\{\frac{MP_k}{(k_{it})^{\beta_{it}}}\right\}$ by substituting k_{it} in terms ofy_{it}. Therefore, we write (4) as follows:

$$\frac{\beta_{it}}{\bar{\beta}_{it}} = \left(1+\tau_{it}\right)\beta_{it}\left(y_{it}\right)^{1/\beta_{it}}\left(A_{it}\right)^{1-(1/\beta_{it})}€. \tag{5}$$

Equation (5) implies that, once the capital allocation is decided and the output is produced, the distance between the 'observed' capital share from the 'optimal' capital share is directly proportional to the 'distortion' but inversely proportional to the technology. Equation (5) implies

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

Now the first-order condition for the maximisation problem requires $\bar{\beta}_{it}$ to converge to $\bar{\beta}_t$ for all sectors[9]. With this, we express the above relation in the following way[10]

$$\tau_{it} \propto \left(\frac{A_{it}\beta_{it}}{\overline{\beta_t}} - 1\right) = \hat{\tau}_{it}. \tag{6}$$

In each sector, 'distortion' in the capital allocation is proportional to the distance between the 'observed' and the 'efficient' capital returns, adjusted for the technology.

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

10 We derive expression for $\overline{\beta_t}$ in the next section (Eq. 7).

In the Table 1 in "Appendix", we tabulate this measure of $\hat{\tau}_{it}$ (we call it capital/labour distortion factor) for the industries and infer whether any specific industry is 'over' or 'under' capitalised. Although we do not directly observe the capital services to labour input ratios (i.e. k_{it} and $\bar{k}_{it}$), our inference still remains valid since the actual 'distortion' τ_{it} is directly proportional to $\hat{\tau}_{it}$, i.e. the observed 'capital/labour distortion factor'. By definition, an industry is 'under' ('over') capitalised if $\hat{\tau}_{it} < 0\ (>0)$, i.e. $k_{it} < (>) \bar{k}_{it}$.

3.2 Aggregate misallocation

We assume that the firms within a sector produce homogeneous products and maximise 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 maximised when the individual firms maximise their profits. By assuming W and R to be the unit cost of labour 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 maximisation solve for the following:

$$\frac{K_{it}}{L_{it}} = \frac{W_{it}}{R_{it}}\frac{\beta_{it}}{1-\beta_{it}}, \tag{7}$$

$$\text{Or,}\quad \log K_{it} = \log L_{it} + \log\left(\frac{W_{it}}{R_{it}}\frac{\beta_{it}}{1-\beta_{it}}\right). \tag{8}$$

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

$$P_{it} = \frac{\frac{W_{it}}{A_{it}}\left(\frac{K_{it}}{L_{it}}\right)^{-\beta_{it}}}{\left(1-\beta_{it}\right)}, \tag{9}$$

$$L_{it} \propto \frac{\frac{P_{it}}{W_{it}}A_{it}\left(\frac{K_{it}}{L_{it}}\right)^{\beta_{it}}}{\left(1-\tau_{it}\right)}. \tag{10}$$

Conditions (7)–(10) are the standard conditions for profit maximisation. Equation (7) produces the profit maximising level of capital–labour ratio for each sector. The ratio $\frac{W_{it}}{R_{it}}$ is the relative per unit remuneration to the labour relative to the capital. Precisely it represents the labour quality in a sector. Equation (9) tells us that, given the factor allocation and technology, price of the final produce is a fixed markup over the unit labour cost. Condition (10) states that the labour 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:

$$\log(Y_t) = \sum_{i=1}^{s} \theta_{it}\log(A_{it}) + \sum_{i=1}^{s} \theta_{it}(1-\beta_{it})\log(L_{it}) + \sum_{i=1}^{s} \theta_{it}\beta_{it}\log(K_{it}). \quad (11)$$

With the help of expressions (7), (8) and (10); Eq. (11) can be rewritten as:

$$\begin{aligned}\log(Y_t) = 2\sum_{i=1}^{s} \theta_{it}\log(A_{it}) + 2\sum_{i=1}^{s} \theta_{it}\beta_{it}\log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^{s} \theta_{it}\log\left(\frac{P_{it}}{W_{it}}\right) \\ - 2\sum_{i=1}^{s} \theta_{it}\beta_{it}\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right) - \log\prod_{i=1}^{s} \tau_{it}^{\theta_{it}}.\end{aligned} \quad (12)$$

In Eq. (12), $\prod_{i=1}^{s} \tau_{it}^{\theta_{it}}$ is the geometric mean of the sectoral distortions. In a multi-sector model such as this, if we assume that the aggregate supply of labour 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 $\log\prod_{i=1}^{s} \tau_{it}^{\theta_{it}}$ does not have any significance in (12). It does not mean that there exists no distortion for the aggregate economy; it rather means that the factors are always fully employed whilst the inter-sectoral allocation of resources are subject to 'distortion'.

In Eq. (12), 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 labour 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 labour return in the economy. The basic assumptions about the parameters in our production function states that labour 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, Eq. (12) means that, on an average, the higher the share of labour in output, lower is the aggregate output.[11]

If $\frac{1-\beta_{it}}{\beta_{it}}$ are lognormally distributed,[12] then the closed form solution for the expectation of $\log(Y_t)$ is[13]

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

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

[13] We can express any random variable X in the form $X = E(X) + \sqrt{\mathrm{Var}(X)}Z$ where Z is the standardised random variable with $E(Z) = 0$.

$$E(\log(Y_t)) = 2\sum_{i=1}^{s}\theta_{it}\log(A_{it}) + 2\sum_{i=1}^{s}\theta_{it}\beta_{it}\log\left(\frac{W_{it}}{R_{it}}\right) + \sum_{i=1}^{s}\theta_{it}\log\left(\frac{P_{it}}{W_{it}}\right) - 2\sum_{i=1}^{s}\theta_{it}\beta_{it}\left\{E\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right) + \frac{1}{2}\text{Var}\left(log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)\right\}\sqrt{\text{Var}(X)}. \quad (13)$$

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 labour 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 $\text{Var}\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$, which summarises the variation in labour share around its mean $E\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$. Therefore, $\text{Var}\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$ measures the 'distortion' in factor allocation and the loss in aggregate output because 'distortion' is measured by $\sum_{i=1}^{s}\theta_{it}\beta_{it}\text{Var}\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$. The 'efficient' or 'optimal' allocation is represented by $E\left(\log\left(\frac{1-\beta_{it}}{\beta_{it}}\right)\right)$, and hence, we solve

$$\bar{\beta}_t = \frac{1}{1+e^{\alpha_t}}, \quad (14)$$

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

At the sectoral level, we can estimate the profit-maximising capital–labour ratio using Eq. (7), given the estimates for labour 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–labour ratio, using (1), (6), (7) and (14).

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

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

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.

2. 'Distortion' in the allocation of capital in sector i for the period t: $\tau_{it} \propto \left(\frac{A_{it}\beta_{it}}{\bar{\beta}_t} - 1\right)$,

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.

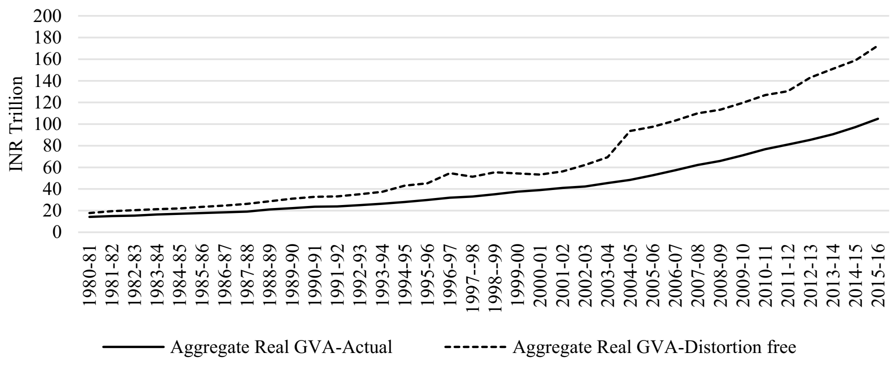

Fig. 5 Real output gap due to distortion Source: India KLEMS, authors' calculations

4 Evidence from India KLEMS data

Our estimates using the latest India KLEMS data suggest that between 1991 and 2000[14] 'loss' to the aggregate output in India was about 30–35% due to the 'distortion' in allocation of capital across sectors. This means, the aggregate output in India was 30–35% 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 about 40% between 2001 and 2016.

Figure 5 shows that simply a more 'efficient' allocation 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 'optimum' or 'distortion-free' GVA measures the output 'loss' that we estimate. Interestingly, post-2005, although the supply of capital improved significantly, gains to the output were 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 the commensurate to that increase, as most of this extra capital was 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 et al. (2016), on the contrary find evidence of significant capital reallocation, where the findings from the observed TFP growth decomposition suggest expansion of investment in sectors with high returns from capital, since 1994. Our findings do not contradict Das et al. (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 taking place.

Our estimates suggest the maximum possible gains from eliminating every possible 'distortion' in the economy. In practice, however, it is not possible for any

[14] For simplicity, we express the financial year 2004–2005 as the year ending in March, 2005; or simply 2005, and so on.

economy to achieve a perfect 'distortion-free' allocation of every factor of production. In that case, the potential gains from removing the 'distortion' at least partially would lie in the range suggested by the paper. For example, if we can reduce the 'distortion' to the level prior to 2004, a simple calculation reveals that we may generate additional 30% output over the output levels observed from the years 2005.

Our estimates at the sectoral level further suggest that the services activities were 'over-capitalised' (see Table 1 in "Appendix"), whilst host of other activities were capital starved. Controlling for the technology, we see that activities such as trade, hotels and restaurants, transport and storage, financial and business services continue to use 'excess' capital. Some exceptions within the services are public administration, defence and social security; education and health and social work, which were 'under-capitalised'. Most of the manufacturing activities, as we see, except the electrical and transport equipment, chemical products were 'under-capitalised'.[15]

A mix of government policy and sector specific characteristics is generally argued as the factor behind capital misallocation. Banerjee and Esther (2005) noted that the average marginal product of physical capital in India may have been as low as 22%, though for large firms, it was in the range from 60 to 100%, in the early years of liberalisation of Indian economy. As the private investment picked up, this huge variation in capital productivity has naturally given rise to distortionary capital formation in the absence of proper market information. Banerjee and Esther (2005) also noted huge inefficiency in the banking and retail businesses in the early years of liberalisation. In the later years too, Das and Ghosh (2009) noted low profit efficiency of Indian banks. The inefficiency is likely to be largely on account of priority sector lending and governments' direction to the public sector banks to operate in the rural and semi-urban areas at much subsidised lending rates. Over the years, financial services, mainly that extended by the banking and insurance sectors, have been dominated by the public sector with capitalization being met through governments' active participation. In 2015, government of India has increased the sectoral cap of foreign direct investment (FDI) in the insurance sector to 74% whilst for the private banks, the government raised the limit for the institutional investment limit to 74%. However, in the absence of a marked efficiency improvement, these measures have likely contributed to 'over-capitalisation' of these sectors. In the context of manufacturing sectors, Hsieh and Klenow (2009) noted that in India, variations in markup and adjustment costs with the plant size and age resulted in distortionary capital allocation. Many of these explanations hold true for the services activities such as business and professional services, transport services, etc. as well. Whilst the aggregate productivity continued to be low for these sectors, the gradual opening up of the market has increased the stock of capital, including the FDI and domestic capital for these services. Naturally, this increase in capital stock without much improvement in the productivity levels has resulted in over-capitalisation of those activities. Apart from these services activities, allocation of capital in the manufacturing sectors is also subjected to certain sector-specific characteristics such

[15] For detailed discussion on the causes behind misallocation in India at the macro level, see Banerjee 2005.

as variation in the degree of external exposure.[16] For instance, excess capital in chemical 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. India’s signing of TRIPS agreement on the WTO and subsequent creation of R&D capabilities in the pharmaceutical sectors may have resulted in large investment, including FDI. However, the pharmaceutical industries face tough regulation overseas as well as domestically, reducing its potential to grow despite heavy investments. It is, in fact, evident in our results that the output loss due to the capital misallocation increased markedly since 2005, which coincides with the period when the FDI policies started to be relaxed.

From the discussion above, it appears that the sector-specific characteristics such as inter-firm variation in the capital return, variation in markup and profitability are probably the leading factors behind sustained ‘distortion’ in the allocation of capital. Whilst it is not a viable option for the government to curb the inflows of foreign capital and restrict domestic investment, an entirely free flow of capital may worsen the situation on misallocation. Although the government has limited scope to act upon such issues concerned with the firm productivity, steps including improving aggregate labour productivity, imposing certain disciplines on the investment activities in sectors that we identify as ‘over-capitalised’ and divert investment and perhaps equity capital to the capital-starved industries might be a better solution to reduce such ‘distortion’. Singh and Kaur (2014) noted that although there exist overall industrial and agricultural policies in India, there is no integrated service policy, especially towards improving labour productivities. Also, government may focus on building information symmetry between firms and investors. As the productivity in services and manufacturing firms had already been lower prior to 2000, liberalisation of capital movements since 2000 has naturally showed up as an immediate increase in ‘distortion’. As Hsieh and klenow (2009) noted significant lags in the effectiveness of liberalisation on reducing distortion, we may expect some moderation in the misallocation in the coming years. It may be relevant for the government not to pursue further easing of capital movement until the firm level productivities are improved, inter-firm productivity dispersions are minimised and information asymmetry between firms and the financial institutions is reduced. It may also be appropriate for the government to conduct some checks and balances on the investment profitability scenario on an ongoing basis, especially for the sectors which contribute relatively heavily to the aggregate GDP, such as financial, business and professional services, transport storage and trade-related services. Lastly, the government may conduct any further policy on the ease of capital movement with some caution with respect to certain industries.

5 Real rent and capital share

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

[16] For the theoretical explanation of the impact on trade on intra-industry reallocation, see Melitz (2003).

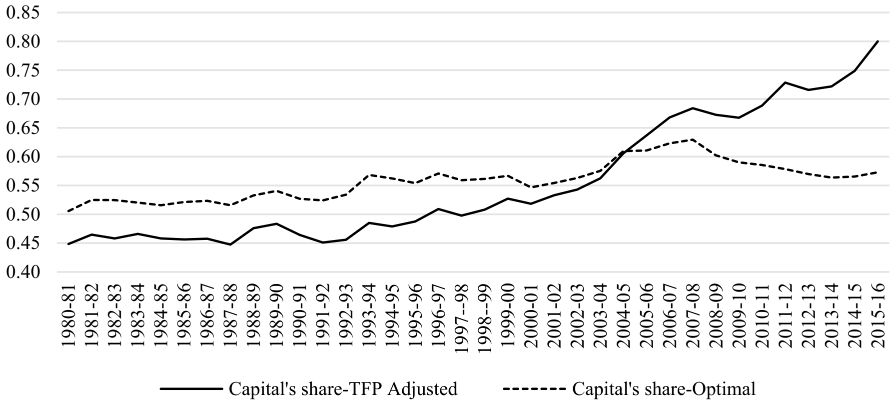

Fig. 6 Capital's share in GVA Source: India KLEMS, authors' calculations

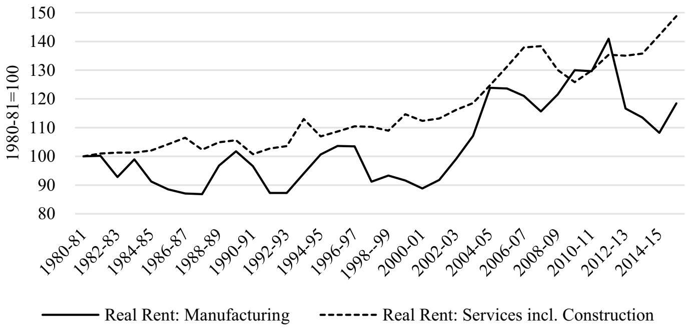

Fig. 7 Real rent of capital in India Source: authors' calculations based on India KLEMS

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. 6, 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 Eq. (6), that despite the 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.

Figure 6 can be divided into two phases. First, before 2003, when the capital's share was actually lower than the 'optimal'. It started deviating from the 'optimum' since then and post-2007, 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[17]

[17] Real rent on capital $= \frac{(\text{Capital share on GVA})*(\text{sectoral GVA})}{(\text{Index of capital service})*\left(\frac{\text{sectoral GVA at current price}}{\text{sectoral GVA at constant price}}\right)}$. The sectoral real rents are aggregated using the sectors' share in aggregate GVA as weight.

that is being paid on capitals. The pace of increase in real rental on capital increased post 2000 (Fig. 7). However, we estimate a very low average correlation coefficient of -0.26[18] between real rent on capital and the use of capital services (1980 = 100) between 2000 and 2016. It is clear that the usage of capital services grew (8.8% annually on average) despite rising real rental on the capital. Given very low growth in TFP (0.5% annually on average) in this period, we can exclude any possibility of a positive exogenous demand shock on the capital. Therefore, the 'weak' correlation between real rental and usage of capital services that we observe in the data can possibly explain the 'distortion' at aggregate levels.

6 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.

To carry out the analysis, we use India KLEMS dataset on labour and capital inputs and TFP estimates across 27 sectors of the economy, between 1980–1981 and 2015–2016. The quality aspects of the two major inputs viz. labour and capital are also captured in this dataset. The dataset also provides income shares of labour 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 1999–2000 and 2011–2012. 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 suggest that the services activities were generally 'over-capitalised', with the exception of public administration, defence 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 remain

[18] Median correlation coefficient between 2000–2002 and 2015–2016. We estimate the correlation coefficients for each year separately, by using observations on all 27 sectors.

'under-capitalised'. This implies that, possibly higher investments in these segments could yield larger GVA growth. Agriculture remained mildly 'under-capitalised' as compared to the manufacturing and construction sectors. It is possible that economic sectors subjected to restricted entry, inwardly oriented or intensive regulations are more prone to over-capitalisation. 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 30–35% between 1990 and 1999 from their observed level and by even greater extent of nearly 40% after 2000.

The study brings out an important dimension of growth process in the Indian economy in that the future path of aggregate output may potentially be lifted simply by curbing the excess accumulation of capital to the 'over-capitalised' services sectors and by improving capital flows to the 'under-capitalised' manufacturing sectors. However, the most important aspect of reducing the existing imbalance in capitalisations of the broader sectors is to help improve the firm-level productivities, minimise the productivity dispersion across firms and building information symmetry between firms and investors. It may also be useful to impose certain disciplines on the investment activities in sectors that we identify as 'over-capitalised', divert investment and equity capital to the capital-starved industries. The government may conduct some checks and balances on the investment profitability scenario on an ongoing basis, especially for the sectors which contribute relatively heavily to the aggregate GDP, such as financial, business and professional services, transport storage and trade-related services. Lastly, the government may conduct any further policy on the ease of capital movement with some caution with respect to certain industries.

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Appendix

See Table 1 here.

Table 1 (Capital/Labour) distortion factor: industry classification on capital usage using India KLEMS

India KLEMS Industry	1980-81 to 1989-90	1990-91 to 1999-2000	2000-01 to 2015-16	All-India GVA Share (%): 2000-01 to 2015-16
Wood and Products of wood				0.3
Coke, Refined Petroleum Products and Nuclear fuel				1.7
Construction				9.0
Rubber and Plastic Products				0.5
Education				3.3
Health and Social Work				1.5
Other Non-Metallic Mineral Products				1.1
Public Administration and Defense; Social Security				6.1
Machinery, nec.				1.2
Textiles, Textile Products, Leather and Footwear				2.1
Basic Metals and Fabricated Metal Products				3.1
Mining and Quarrying				3.6
Agriculture,Hunting,Forestry and Fishing				20.4
Manufacturing, nec; recycling				0.4
Other services				9.8
Pulp, Paper,Paper products,Printing and Publishing				0.4
Hotels and Restaurants				1.1
Trade				9.8
Food Products, Beverages and Tobacco				2.0
Transport Equipment				1.4
Transport and Storage				4.9
Business Service				4.8
Electricity, Gas and Water Supply				2.2
Electrical and Optical Equipment				0.9
Financial Services				4.9
Chemicals and Chemical Products				2.1
Post and Telecommunication				1.0

Source: Authors' Calculations based on India KLEMS.

Notes on colors:

	Severely Under-capitalised: (Capital/Labour) Distortion Factor < -30%
	Less Severely Under-capitalised: (Capital/Labour) Distortion Factor between -20% and -30%
	Moderately Under-capitalised: (Capital/Labour) Distortion Factor between -10% and -20%
	Almost Optimally capitalised: (Capital/Labour) Distortion Factor between 10% and -10%
	Moderately Over-capitalised: (Capital/Labour) Distortion Factor between 10% and 20%
	Less Severely Over-capitalised: (Capital/Labour) Distortion Factor between 20% and 30%
	Severely Over-capitalised: (Capital/Labour) Distortion Factor > 30%

In this table, we provide estimates for the (capital/labour) distortion factor as elaborated in Eq. (6)

Box 1: Brief description of the India KLEMS database and the variables[19]

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 analysing 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 1 agricultural, 1 mining and quarrying, 13 manufacturing, 1 sector covering electricity, gas and water supply, 1 construction and 9 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 1980–1981 and 2011–2012. 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.

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 (2004–2005) prices at the broad industry level. A higher level of disaggregation in some cases have been obtained using information from ASI and NSSO rounds, for registered and unregistered manufacturing sectors, respectively.

[19] 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)

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.

Labour input

India KLEMS database provides separate index of labour input (1980–1918 = 100) for each industry for the period 1980–1981 to 2011–2012. In estimating the index, two dimensions of the labour input are taken into account—labour persons and educational attainment of the workers, to distinguish one type of labour from the other. Employment data in India KLEMS are 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 labour 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) consider 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.

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 unorganised manufacturing. These industry level data are used to construct capital stock using perpetual inventory method.

Aggregate capital services growth rate is derived as a weighted growth rate of individual capital assets, the weights being the compensation shares of each asset type. Das et al. (2015) use the Törnqvist approximation to the continuous Divisia index under the assumption of instantaneous adjustability of capital. In the following steps, Das et al. (2015) derive 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) define total investment 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 nine broad sectoral heads. However, 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 equipment,[20] for both private sector and public sector, 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 asset type. For the implementation of PIM, Das et al. (2015) take the NAS estimate of real net capital stock in 1950 as the benchmark capital stock for non-manufacturing sectors whilst 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, to reduce 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 (1) the capital stock

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

in step 2 and (2) the rental prices/compensation in the last step, Das et al. (2015) express the index of capital services (1980–1981 = 100) using the Törnqvist index for each industry.

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 one. India KLEMS dataset provides detailed estimates of labour income share for all 27 industries over 1980–1981 to 2011–2012. The capital income share is obtained as one minus the labour income share.

Das et al. (2015) provide 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 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 nine 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 have been distributed amongst 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.

Total factor productivity

Following the estimations of gross value added, indices of labour input, capital services and shares of labour and capital into GVA, Das et al. (2015) obtain estimation for the total factor productivity for the 27 industries over the sample period. 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 using the GVA can be valid complements to gross output-based measures.

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