Technology, Jobs and Inequality: Evidence from India's Manufacturing Sector

Radhicka Kapoor

1 Introduction

India's post-reform economic development has seen a sustained increase in the capital intensity of production in the manufacturing sector. The rising capital intensity of production is indeed a well-established fact in the literature (Das et al. 2009; Goldar 2000). The adoption of labour saving and capital intensive techniques of production in an economy that has a comparative advantage in unskilled labour is particularly puzzling and has attracted much attention. In fact, Hasan et al. (2013) have shown that India uses more capital intensive techniques of production in manufacturing than countries at a similar level of development and similar factor endowments.

There exists a vast literature examining the factors that determine the capital intensity of production across industries in the Indian manufacturing sector. Several of these studies have highlighted the significance of factor market imperfections in explaining the rising capital intensity of production (Hasan et al. 2013; Sen and Das 2014). India's labour market regulations, in particular, have attracted much attention in this context. It is believed that the stringencies and rigidities in labour laws have imposed costs on labour use, thereby pushing firms towards greater capital intensity. This, in turn, has reduced labour demand and curtailed gains from trade based on factor-abundance driven comparative advantage. However, it has been argued in the literature that labour regulations cannot alone explain the rising capital intensity of production over time. Sen and Das (2014) attribute the increases in capital intensity to an increase in the ratio of real wage to rental price of capital which was mostly due to a fall in the relative price of capital goods. The decrease was driven by trade reforms in capital goods and falling import tariffs on them in the post-reform period. While these factors are pivotal, it is important to remember that rising capital intensity is also reflective of technological transformation. Technological progress has

R. Kapoor (✉)
ICRIER, New Delhi, India
e-mail: rkapoor@icrier.res.in

S. C. Aggarwal et al. (eds.), *Accelerators of India's Growth–Industry, Trade and Employment*, India Studies in Business and Economics,
https://doi.org/10.1007/978-981-32-9397-7_14

been capital-augmenting rather than labour augmenting during the globalization era. Consequently, Indian firms faced with easier access to foreign technology adopted more capital intensive techniques of production.

While the factors explaining the increasing capital intensity of production in India are well documented in the literature, the implications of this phenomenon for the labour market have attracted relatively less attention. The most immediate concern is the impact of labour saving techniques of production on job creation. Since the followers of Ned Ludd smashed mechanized looms in 1811, workers have worried about automation destroying jobs. In both the industrialized and developing world, there is growing anxiety regarding job prospects for large groups of middle-skilled workers on account of automation, computerization, and new technologies. In India, too, given the intensifying demographic pressures, the adoption of capital intensive methods of production in the manufacturing sector poses a significant challenge to productive job creation. While economists have often reassured that new jobs would be created even as old ones were eliminated, the adoption of capital intensive techniques will not affect all types of workers (unskilled versus skilled workers) uniformly. It has been shown in the literature that capital-augmenting technological change has favoured more skilled workers, replacing tasks performed by unskilled, and increasing the demand for skills. This has increased wage inequality between skilled and unskilled workers. For instance, in the case of the US economy, many commentators see a direct causal relationship between technological changes and the radical shifts in the distribution of wages between 1979 and 1995. The college premium (the wages of college graduates relative to wages of high school graduates) increased by over 25% during this period. Overall earnings inequality also soared: in 1971, a worker at the 90th percentile of the wage distribution earned 266% more than a worker at the 10th percentile. By 1995, this number had risen to 366% (Acemoglu 2002). Moreover, capital-augmenting technological progress has boosted capital's return and its share in the distribution of income. Guscina (2006) has shown that the decline in labour's share in national income over the past two decades in OECD countries has largely been an equilibrium, rather than a cyclical phenomenon, as the distribution of national income between labour and capital adjusted to capital-augmenting technological progress and a more globalized world economy.

In the Indian context, the literature on impact of the adoption of increasing capital intensive techniques of production on distribution of wages and income is limited. This paper attempts to fill this gap by examining the implications of rising capital intensity on wage and income structure in India's manufacturing sector. Using data from a sample of manufacturing firms from the Annual Survey of Industries, this paper presents new empirical evidence on the impact of adoption of capital intensive techniques of production on inequality at the firm level. It is important to mention here that India's manufacturing sector is characterized by dualism, i.e. the prevalence of a formal/organized sector which coexists with a large "unorganized sector". The latter accounts for a disproportionately large share of employment (90%), but a very small share of value added in manufacturing. The formal sector accounts for over 65% of total output and it is this sector which is the focus of analysis in our study. This is because it firmed in this sector which resorted to increasing mechanization and automation, while firms in the unorganized sector continued to employ relatively more labour intensive techniques of production. Moreover, India's labour regulations to which much of the high capital intensity of production is attributable cover only the organized sector. Though it would be useful to study both formal and informal sector firms, given the absence of comparable annual data on the unorganized sector, it is difficult to study both together.[1]

This paper organized as follows. We begin by examining some key trends in the organized manufacturing sector in Sect. 2. Is it the case that the capital intensity of production has increased in industries across the manufacturing sector, or is it just the more capital intensive industries that have resorted to increasing automation leading to greater disparities in the capital-labour ratio across the manufacturing sector? Is it the case that share of value added going to owners of capital have increased as compared to income going to labour? Has the wage differential between skilled and unskilled workers increased? In Sect. 3, we discuss an independent, though important change in India's labour market during this time i.e. the contractualization of India's workforce. This may well have driven some of the stylized facts we present in Sect. 2. In Sect. 4, we outline our empirical strategy to study the impact of rising capital intensity on inequality. We also describe the data used in the empirical analysis and present the main results. Section 5 puts forward some concluding remarks.

2 Key Stylized Facts

2.1 Capital Intensity of Production Increased Across Industries

The increase in the average capital intensity of production in the manufacturing sector is evident in Fig. 1. What is particularly important is that this increase in capital intensity was witnessed across all industries in the manufacturing sector. The trend growth in capital intensity of production across industries at the three-digit level over the last decade shows that the capital-labour ratio[2] has risen for all but eight industries (Fig. 2). Classifying industries on the basis of their capital intensity,[3] we find that this

[1]The National Sample Survey Organization's survey of unorganized manufacturing enterprises covers firms in the unorganized sector but data on this is available only quinquennially.

[2]Capital intensity is defined as the ratio of real fixed capital to total persons engaged. Capital is measured by fixed capital as reported in ASI. This represents the depreciated value of fixed assets owned by the factory on the closing day of the accounting year. It is deflated using WPI for machinery and equipment. Total persons engaged include workers (both directly employed and employed through contractors), employees other than workers (supervisory, managerial and other employees) and unpaid family members/proprietor etc.

[3]In order to classify industries as labour or capital intensive, we calculate the capital intensity for all industries in the organized manufacturing sector for every year from 1999 to 2011. An industry is classified as labour intensive if its capital intensity is below the median value for the manufacturing sector throughout the decade. Similarly, an industry is classified as capital intensive

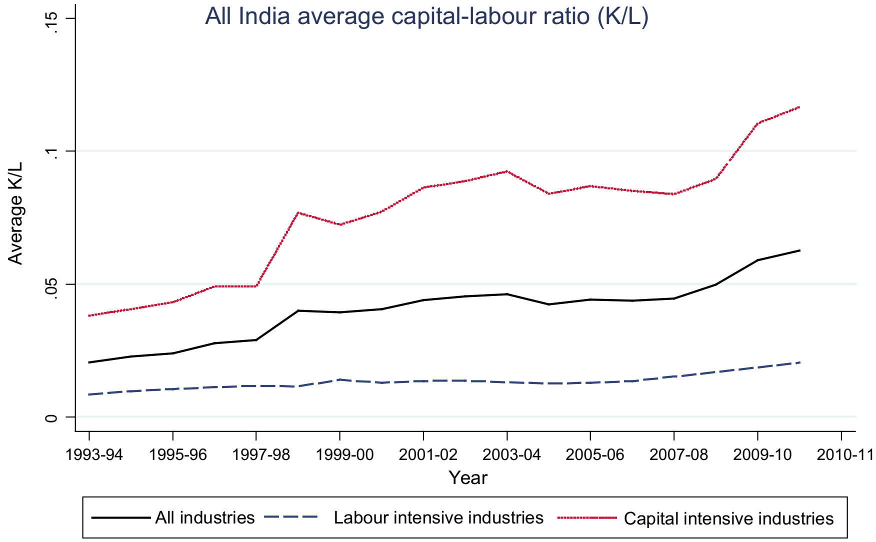

Fig. 1 Capital intensity of production. *Source* Author's calculations based on ASI publishes statistics, MOSPI

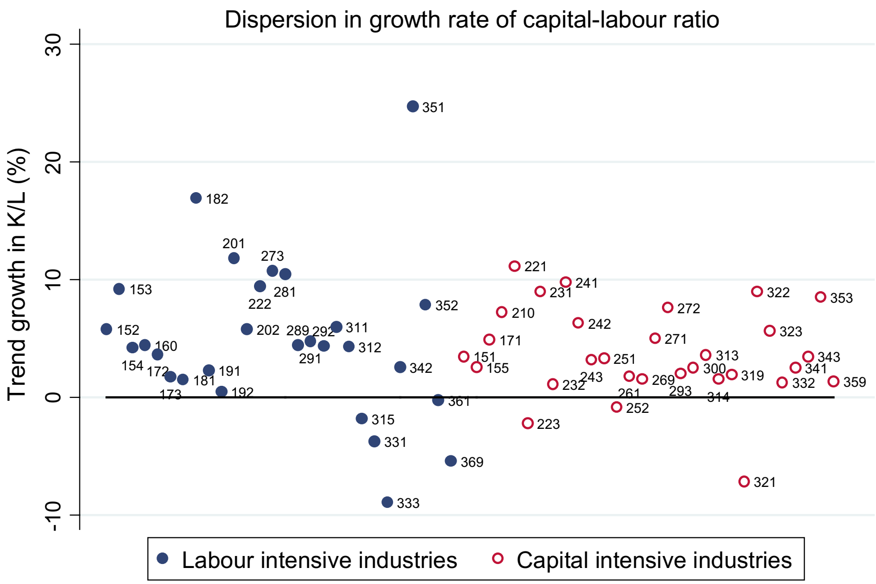

Fig. 2 Trend growth rate in capital intensity of production by industry (NIC-2004). *Source* Author's calculations based on ASI publishes statistics, MOSPI

ratio has increased not just in capital intensive but also labour intensive industries. Rising capital intensity of production, especially in labour intensive industries, is a cause of concern as it raises doubts about the capacity of the manufacturing sector to absorb labour and create jobs.

2.2 Labour Intensive Industries Grew Slower Than Capital Intensive Industries

The rising capital intensity of production in the manufacturing sector has been accompanied by another important phenomenon. Capital intensive industries have also grown significantly faster than labour intensive industries in terms of gross value added (GVA) (Kapoor 2015). This is contrary to what one would expect in an economy where labour is a source of comparative advantage. The rising capital intensity of production, coupled with the fact that labour intensive industries grew slower than capital intensive industries further makes the task of creating productive jobs for India's largely low-skilled and unskilled workforce more challenging (Fig. 3).

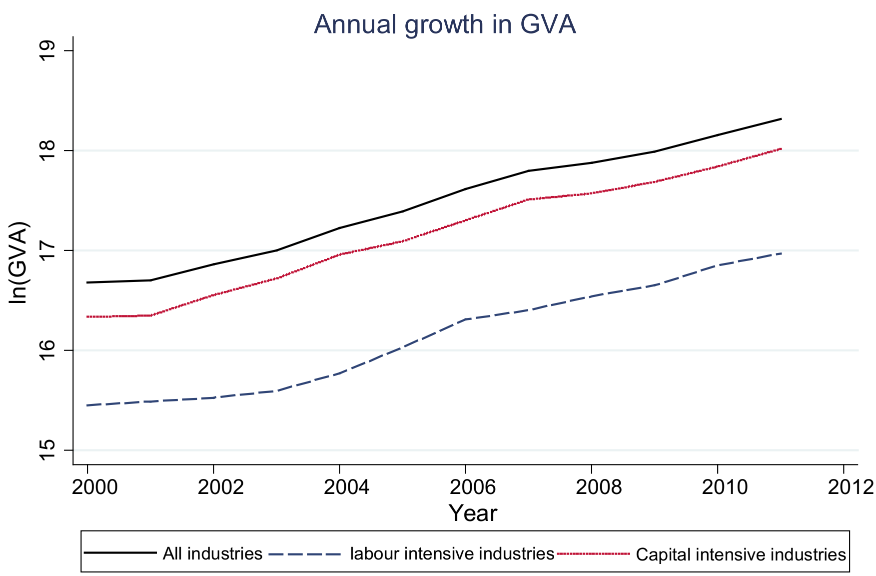

Fig. 3 Growth of value added in the manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

---

if its capital intensity is above the median value for the manufacturing sector throughout the decade. The remaining industries are classified as ambiguous.

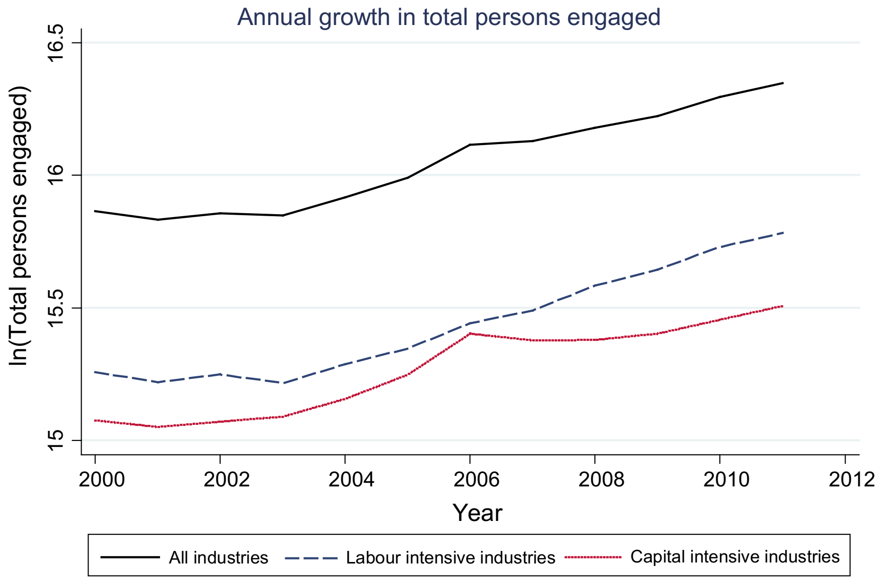

Fig. 4 Growth of employment in the manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

However, when we look at the performance of industries in terms of employment generation, we find that despite having lower employment elasticity of output, capital intensive industries have generated reasonably high rates of employment growth (Fig. 4). Perhaps, this is because output growth in these industries was significantly higher. Table 1 shows that the industry which generated the highest employment growth over the last decade was in fact the most capital intensive industry i.e. manufacture of motor-vehicles, trailers, and semi-trailers. In fact, the trend growth of employment in capital intensive industries appears to be as high as in labour intensive industries. Of course, it is important to mention that the higher growth rates of employment in capital intensive industries could also be partly a result of the base effect i.e. lower initial values of employment. The disconnect between growth of employment and gross value added in the manufacturing sector during this period of rising capital intensity is also worth noting. Results from ASI show that while employment grew at the rate of about 4.6% p.a. between 2000 and 2012, real value added in organized manufacturing grew at almost double the rate (10.2% p.a.).

2.3 Changes in Distribution of Income

With growing capital intensity and the adoption of labour saving techniques of production, the importance of labour relative to capital is likely to decline. Consequently,

Table 1 Trend growth rate of employment across industries

	Industry	Trend growth of employment (%)
Labour intensive	Mf of food products and beverages	2.6
	Mf of tobacco products	−1.8
	Mf of wearing apparels; dressing and dyeing of fur	8.5
	Tanning and dressing of leather; Mf of luggage, handbags, saddlery, harness and footwear	7.6
	Mf of wood and products of wood and cork, except furniture; Mf of articles of straw and plaiting materials	5.1
Capital intensive	Mf of coke and refined petroleum products and nuclear fuel	6.4
	Mf of chemicals and chemical products	0.4
	Mf of rubber and plastic products	7.4
	Mf of basic metals	5.4
	Mf of office, accounting and computing machinery	8.4
	Mf of motor-vehicles, trailers and semi-trailers	10.7

Source Author's calculations based on ASI published data

one would expect the shares of income earned by equipment owners/owners of firms to rise relative to that of labourers. This is exactly what we observe in the Indian manufacturing sector (Fig. 5). The share of total emoluments paid to workers declined from 28.6 to 17.4% of GVA between 2000–2001 and 2011–2012. Significantly, the share of wages to workers in GVA declined steeply from 22.2 to 14.3% over the same period. The interest paid out by firms dwindled from about 29 to 19% of GVA.[4] Importantly, the share of profits in GVA rose from 19.9% in 2000–2001 to 46.2% in 2011–2012. The declining bargaining power of workers vis-à-vis capitalists reflected in these figures raises the issue of equity in the distribution of income. However, it needs to be examined whether these trends were indeed a result of higher capital intensity of production, or there were some other factors at play.

[4]It is beyond the scope of this study to understand the impact of interest rate policy on these estimates.

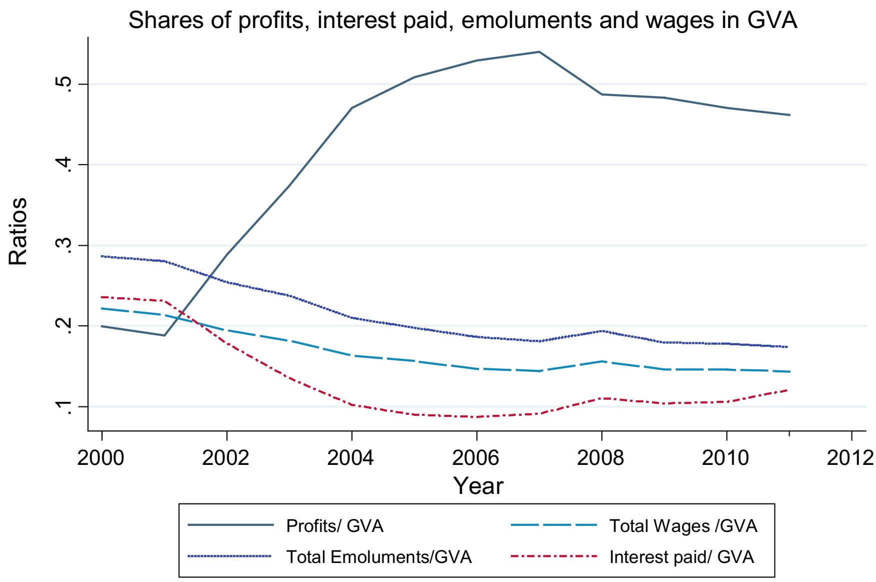

Fig. 5 Changes in key distribution of value added. *Source* Author's calculations based on ASI publishes statistics, MOSPI

2.4 Skilled Versus Unskilled Workers

While the adoption of capital intensive techniques of production may have diluted the importance of labour, the impact of mechanization has been differential across various categories of workers. Capital-augmenting technological progress is not just about introduction of machines but also about the workers who have developed a set of machine-specific skills. While machines are generally substitutes for unskilled labour, they are also complements to skilled labour. Across the world, mechanization has resulted in rising importance of a new portfolio of occupations i.e. engineers, machine builders, toolmakers and a wide range of skilled machine operators who maintain and manage these machines. The increasing role of this portfolio of occupations vis-à-vis production workers has led to the former enjoying a larger share of the total wage pie. The share of wages to production workers has fallen from 57.6% of the total wage bill to 48.8%, while that of supervisory and managerial staff[5] increased from 26.1 to 35.8% between 2000 and 2012. The rising disparity in the wages of supervisory and managerial staff, and production workers is also reflected in the fact that the wages of the latter type of workers remained roughly flat over the last decade, while those of the former category rose sharply (Fig. 6). The ratio of the average wages of supervisory and managerial staff to production workers increased from 3.57 to 5.82 over the last decade.

[5]The supervisory and managerial staff reported in the ASI dataset captures the category of skilled workers, while the production workers capture unskilled workers.

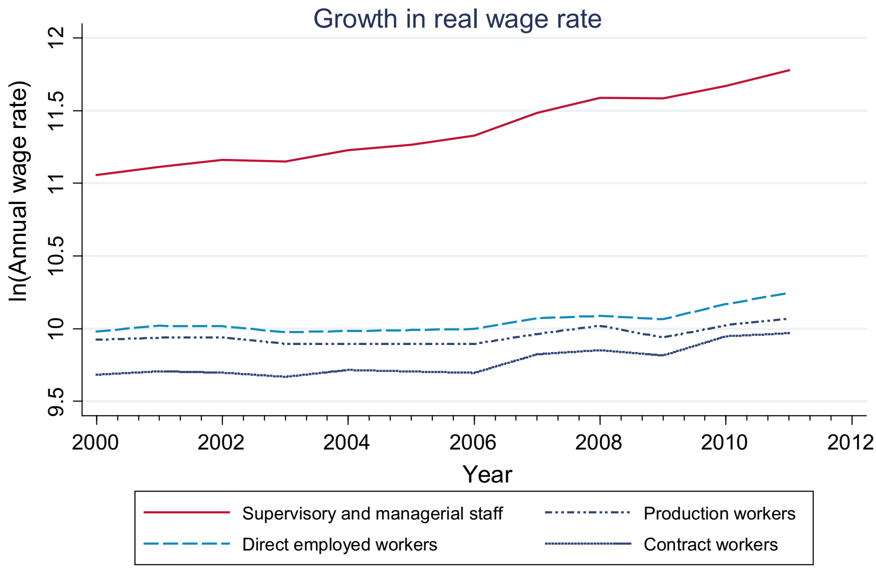

Fig. 6 Growth in real wage rates across various categories of employees. *Source* Author's calculations based on ASI publishes statistics, MOSPI

3 The Contractualization of the Workforce

As mentioned before, this study attempts to identify the implications of rising capital intensity of production on inequality. The preceding section outlines some key stylized facts in India's manufacturing sector pertaining to the distribution of income and wages. However, these changes cannot be attributable to increases in the capital intensity of production alone. There may have been other changes in the labour market during this period which can explain these trends. It is therefore imperative to acknowledge the independent effects of such factors alongside the rising capital intensity. One such critical factor is the increased contractualization of India's workforce.

Production workers in India's manufacturing sector are divided into two categories—permanent and contract workers. The latter are hired via contractors, can be hired and fired at the will of the owners of firms and receive wages which are about half those of permanent workers. The last decade witnessed a sharp increase in the share of contract workers at the expense of regular employment in the organized manufacturing sector (Fig. 7). The share of contract workers in total employment in the organized manufacturing sector rose from 15.7% in 2000–2001 to 26.47% in 2010–2011, while that of directly employed workers fell from 61.12 to 51.53% in the same period. More significantly, the increase in contract workers accounted for about 47% of the total increase in employment in the organized manufacturing sector over

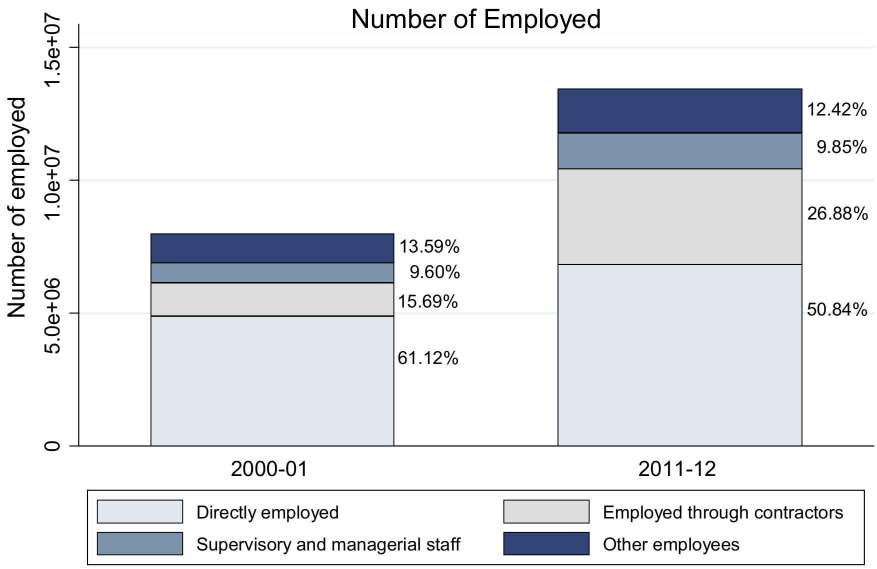

Fig. 7 Composition of employment in organized manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

the last decade.[6] Two reasons have been attributed to this increasing informalization. First, the use of contract workers provides a means of getting around stringent labour regulations, particularly the Industrial Disputes Act, as contract workers do not come under the purview of labour laws that are applicable to directly employed workers in labour markets. Second, increased import competition has led to informalization of industrial labour since the lower wages of informal workers and the savings made on the expenditure of worker benefits helps in reducing costs and thus improving competitiveness (Goldar and Aggarwal 2012).

The contractualization of the workforce though not an implication of the rising capital intensity of production, may well have affected or driven some of the changes we see in the distribution of income and wage inequality in the following manner: contract workers are significantly cheaper, performing the same task as permanent workers. This lowers the average wages paid to production workers. Furthermore, their presence in the workforce helps the firms' management diminish the bargaining power of regular workers and exert downward pressure on their wages. Through these two channels, contract workers help firms lower their wage bill and improve profitability. By putting downward pressure on the average wages of production workers, they may also contribute to rising wage inequality between production workers and the supervisory and managerial staff. Given these effects of contractualization, we

[6]The number of contract workers in the organized manufacturing sector increased from 1.17 million in 2000–2001 to 3.04 million in 2010–2011, while the number of directly employed workers increased from 4.55 to 5.91 million over the same period. The total persons engaged increased from 7.42 to 11.41 million.

need to control for this phenomenon independently, while studying the effect of rising capital intensity on distribution of income and wages.

4 Data and Econometric Analysis

4.1 Data

The stylized facts presented above outline the rising capital intensity of production and the changes observed in the labour market vis-à-vis the distribution of income and wage inequality. However, the question of whether these changes were indeed the effects of the increasing mechanization and automation is best answered through an empirical analysis. We address this issue using plant-level data from the Annual Survey of Industries (ASI). The database covers all factories registered under Sections 2m(i) and 2m(ii) of the Factories Act, 1948 i.e. those factories employing 10 or more workers using power; and those employing 20 or more workers without using power. This database provides a wide array of information on each plant. For each year, firms provide detailed information on aspects such as output, value added, fixed capital, investment, materials, fuel, total persons engaged, workers and wages and salaries to all employees (directly employed workers, contract workers, supervisory and managerial staff and unpaid family workers) It also provides information on the type of ownership, the type of organization, as well as the start year of each plant. The ASI reports the book value of plant and machinery both at the beginning and at the end of the fiscal year (net of depreciation).

Our measure of capital in this study is the net value of plant and machinery at the end of the fiscal year. Employment is measured as the total numbers of persons engaged in a plant. This is divided into two broad categories: production workers(further subdivided into directly employed workers and contract workers) and non-production workers(supervisory and managerial staff). We use these two categories of workers to distinguish between skilled labour (non-production workers) and unskilled labour (production workers). Of course, this categorization is not ideal as skills are best captured by classifications based either on educational characteristics or on a much more detailed classification by working tasks. However, the ASI dataset does not provide us any information on the education or skill level of workers, therefore the only option we have is to rely on this categorization. The classification of workers into 'production' and 'non-production' groups in order to approximate skilled and unskilled labour respectively is not an uncommon one in the literature.[7] International evidence indicates a close relationship between the production/non-manual status of workers and their education level (Goldberg and Pavenik 2007). Therefore, in our analysis we use the wage differential between non-production and

[7]Meschi et al. (2011).

production workers as a measure of skill wage gap. This has been considered a suitable measure for analyzing the impact of globalization on wage inequality in the literature.[8]

The time period under consideration in this study is from 2000–2001 to 2010–2011. There are three different industrial classifications used in the ASI dataset during this time period. For the surveys between 1998–1999 and 2003–2004 the industrial classification used was NIC-1998, between 2004–2005 and 2007–2008 it was NIC-2004, and 2008–2009 onwards it was NIC-2008. In this study, we undertake a concordance exercise across these different classifications to make the dataset comparable as per the NIC-1998 classification.

The data collected from the ASI are at current prices and any analytical work requires deflating these variables. An obvious candidate for this is the wholesale price index (WPI) series. However, we cannot use the WPI as a deflator directly because while ASI follows the NIC classification of industries, WPI is constructed with a view to capturing price movements based on nature of commodities and final demand. Therefore, we create a WPI for each of the industries in the analysis by approximating commodities based on the nature of economic activities and map NIC activities to WPI commodities.[9] To deflate wages, however, we use the Consumer Price Index of Industrial Workers.

The raw data consist of about 384,000 observations over 10 years, with an average of about 38,000 plants surveyed each year. We only study observations corresponding to open plants and plants with positive values of output, plant and machinery and total persons engaged. A problem in the ASI dataset is the presence of a large number of outliers. To reduce their influence in our estimates, we winsorize the data, following Dougherty et al. (2011). This procedure essentially involves top-coding and bottom-coding the 1% tails for each plant-level variable. In other words, for each year and each variable we replace outliers in the top 1% tail (bottom 1% tail) with the value of the 99th (1st) percentile of that variable. This procedure was applied separately to each 2-digit industry.

4.2 Econometric Framework

The proposed empirical specification is as follows:

$$\ln Y_{fist} = \beta_i + \beta_1 (K/L)_{fist} + \beta_2 (CW/TW)_{fist} + \beta_3 (Age)_{fist} + \beta_4 (Size\ Dummy)_{fist} + \mu T + \varepsilon_{fist}$$

The outcome variable, $\boldsymbol{Y_{fist}}$, varies over firm $\boldsymbol{f}$ belonging to industry $\boldsymbol{i}$ in state $\boldsymbol{s}$ at time $\boldsymbol{t}$. The dependent variables, which are of interest are the share of profits in

[8]It may well be the case that this measure is an underestimate of the wage gap since production workers may include some skilled workers.

[9]Capital is deflated using the WPI created for industry, NIC 29.

GVA; share of wages in GVA; ratio of skilled (non-production workers) to unskilled (production workers) and the ratio of their wage rates. We also look at the shares of the wage bill accruing to skilled and unskilled workers separately. As mentioned previously, the former is the share of the wage bill paid to managerial and supervisory staff, while the latter is share of the wage bill paid to production workers. We also control for share of contract workers in total production workers (*CW/TW*) in our specification given the discussion in Sect. 3. T represents the linear time trend, while β_i denotes industry fixed effects. We include industry fixed effects to account for any time invariant industry-specific effects such as industry technology differences, market structure and degree of competition. In addition to the above, we control for the age of the factory and its size. We create a dummy variable for the size of the firm and classify factories into three categories (small, medium and large)[10] on the basis of total persons engaged in them. We also introduce a state-level time variant infrastructure control (log of tele-density[11]) in our specification.

Importantly, this model cannot be estimated using Ordinary Least Squares (OLS). The reason for this is as follows. The firm's decision of the technology it adopts for production or its capital intensity of production is not an exogenous factor. In other words, it is simply not an outside force but an outcome of decisions made by firms, i.e. it is endogenous. Firms may well be responding to profit incentives while making decisions about technology they choose to adopt.[12] That technological change is not an outside force acting on the labour market and wage inequality, but in fact, endogenous has been discussed in the literature (Acemoglu 2003). For instance, the spinning and weaving machines of the nineteenth century were invented because they were profitable. They were profitable because they replaced the scarce and expensive factors—the skilled artisans—by relatively cheap and abundant factors—unskilled manual labour of men, women, and children. Similarly, electrical machinery, air-conditioning, large organizations all were introduced because they presented profit opportunities for entrepreneurs. Similarly, the share of contract workers may well be endogenous, and a result of firms response to profit incentives. Reverse causality may arise as firms with low profits may be incentivized to hire more contract workers to improve profitability. Similarly, firms with a disproportionately large labour share in their wage bill might prefer witching to contract workers to reduce their wage bill.

To address the endogeneity problem, we use Instrumental Variable (IV) estimation in our analysis. We use three instruments in our analysis here—labour market regulations, minimum wages of the state and the level of financial development. The rationale for using these instruments is as follows. Given the argument that it is stringencies in labour legislations that have discouraged firms from hiring workers and instead adopting more capital intensive techniques of production, we use a

[10]Small firms are defined as those having less than 50 employees, medium firms have 50–199 employees and large firms are defined as those having 200 or more workers.

[11]The tele-density variable captures the state-wise telephones statistics per 100 population.

[12]There are also no compelling theoretical reasons to expect technological change always and everywhere to be skill-biased. On the contrary, if replacing skilled workers is more profitable, new technologies may attempt to replace skilled workers, just as interchangeable parts did.

measure of the rigidity of labour market regulations of the state the firm is located in as an instrument. Typically, one would expect the firms which are located in states with inflexible labour regulations to adopt more capital intensive techniques of production. Similarly, it has been argued that it is firms in states with more stringent labour regulation which are incentivized to substitute permanent workers with contract workers (Sen et al. 2010). Quantifying differences in LMR across states is a contentious subject in the existing literature. In our analysis, we use an index of labour market rigidity constructed by Gupta et al. (2008). They create a composite measure of LMR across states by combining information from three key studies.[13] On the basis of this composite index, they categorize states' LMR as flexible, neutral and inflexible assigning scores of 1, 0 and -1.[14]

The choice of the level of financial development as an instrument is driven by the fact that firms located in financially developed states would have increased attractiveness to invest in capital. Data on index of financial development is obtained from Kumar (2002). Finally, we include the minimum wage rate of the state as an instrument in our analysis. As is the requirement of a good instrument, the minimum wage rate[15] in a state is highly correlated with the wages of contract workers. The Contract Labour Act (1970) mandates that wages of contract workers must not be lower than the prescribed minimum wage, therefore states with higher minimum wages observe lower share of contract workers in their workforce (Sen et al. 2010). Data on minimum wages is obtained from the Labour Bureau Statistics (various years).

4.3 Results

As explained in the previous section, the reverse causality between the dependent variables on one hand and capital intensity of production and share of contract workers, on the other hand, taints the OLS results and provides inconsistent estimates. We therefore estimate the above-mentioned equation using Instrumental Variables

[13]They examine state-level indexes of labour regulations developed by Besley et al. (2008), and OECD (2007). The Besley and Burgess measure relies on amendments to the IDA as a whole. Bhattacharjea's measure focuses exclusively on Chapter VB of the IDA—i.e., the section that deals with the requirement for firms to seek government permission for layoffs, retrenchments, and closures. Bhattacharjea considers not only the content of legislative amendments, but also judicial interpretations to Chapter VB in assessing the stance of states vis-à-vis labour regulation. The OECD study is based on a survey of experts and codes progress in introducing changes in recent years to not only regulations dealing with labour issues, but also the relevant administrative processes and enforcement machinery. The regulations covered by the survey go well beyond the IDA and include the Factories Act, the Trade Union Act, and Contract Labour Act among others.

[14]Andhra Pradesh, Rajasthan, Tamil Nadu, UP and Karnataka are classified as having flexible labour regulations. Maharashtra, Orissa and West Bengal are classified as having inflexible labour regulations. Assam, Bihar, Gujarat, Haryana, Kerala, Madhya Pradesh and Punjab are classified as the neutral states.

[15]These wages are determined by respective state governments and vary across states and over time—background as to how minimum wages are determined.

(Table 2). The Wu-Hausman test statistic at the bottom of the table is statistically significant in each of the specifications confirming that the endogenous regressors in the model are in fact endogenous and need to be instrumented.

In the first column, the dependent variable is the share of profits in GVA, i.e. ln(Profits/GVA). The coefficient of the capital intensity of production is negative and statistically significant, suggesting that profitability was in fact lower in firms which witnessed relatively larger increases in the capital-labour ratio. The coefficient on ln(K/L) suggests that if firms increase their capital-labour ratio by 1% their profitability will decline by 0.08%. This may well be a result of the fact that firms require greater financial resources to adopt more capital intensive techniques of production and this lowers their profits in the short-run. The coefficient on the share of contract workers in total workforce is positive and significant. This is not surprising following the discussion on the role of contract workers in improving firm profitability in Sect. 3. This result is noteworthy as it seems to suggest that it is the substitution towards cheaper workers that are driving higher profits and making owners of firms wealthier and not the substitution towards capital (in the short-run). The coefficient on the size dummy is positive and statistically significant suggesting that larger

Table 2 Instrumental variable analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Profit/GVA)	ln(All wages/GVA)	ln(Wage bill to (NPW)/GVA)	ln(Wage bill to PW/GVA)	ln(NPW/PW)	ln(NPW wage/PW wage)
ln(K/L)	-0.08^{b} (0.04)	-0.25^{c} (0.04)	0.23^{c} (0.04)	-0.30^{c} (0.03)	0.21^{c} (0.06)	0.10^{b} (0.05)
ln(Contract workers/Total workers)	1.01^{c} (0.19)	0.74^{c} (0.19)	0.43^{b} (0.20)	−0.15 (0.17)	0.54^{b} (0.25)	0.74^{c} (0.22)
ln(Age of firm in years)	0.04^{c} (0.02)	0.08^{c} (0.01)	0.24^{c} (0.01)	-0.04^{c} (0.01)	0.19^{c} (0.01)	0.06^{c} (0.01)
Size dummy	0.30^{c} (0.05)	0.26^{c} (0.06)	-0.19^{c} (0.06)	0.12^{b} (0.05)	-0.30^{c} (0.08)	0.26^{c} (0.07)
ln(Tele-density)	−0.03 (0.02)	0.08^{c} (0.01)	0.09^{c} (0.02)	0.03^{b} (0.01)	0.11^{c} (0.02)	−0.02 (0.02)
ln(Real Minimum Wage)		0.18^{c} (0.03)		0.11^{c} (0.03)		-0.09^{c} (0.03)
Time	-0.05^{c} (0.01)	-0.03^{c} (0.01)	-0.02^{c} (0.01)	−0.01 (0.01)	-0.06^{c} (0.01)	0.02^{b} (0.01)
N	63339	71319	64913	71331	68102	68102
RMSE	1.46	1.10	1.26	0.97	0.99	0.87
Wu-Hausman	24.21^{c}	28.15^{c}	147.02^{c}	32.81^{c}	86.41^{c}	165.23^{c}
Cragg-Donald statistic	27.13^{b}	21.99^{b}	15.95^{b}	21.91^{b}	8.55^{b}	8.5^{b}
Sargan chi-square	0.14		0.16		0.21	

Robust *t* statistics are given in brackets. [a]significant at 10%; [b]significant at 5%; [c]significant at 1%

firms are more profitable. Importantly, we need to verify if our estimates suffer from a weak instrument problem, meaning that the explanatory power of the excluded instruments in the first stage regression is too low to provide reliable identification. The Cragg and Donald minimum eigenvalue statistic reported at the bottom of the table is a test of weak instruments and from this, we can reject the null hypothesis that the set of instruments is weak.[16] In addition to the requirement that instrumental variables be correlated with the endogenous regressors, the instruments must also be uncorrelated with the structural error term. Since our model is over-identified, meaning that the number of additional instruments exceeds the number of endogenous regressors, we can test whether the instruments are uncorrelated with the error term. The over-identification test reports Sargan's chi-square tests. The insignificant test statistic suggests that our instruments are not invalid.

In the second column, the dependent variable is the share of wage bill to all employees in GVA i.e. ln(All Wages/GVA). Here, we find that the share of total wage bill in GVA was lower in firms witnessing relatively larger increase in capital-labour ratio. The coefficient on ln K/L indicates that as firms increased their capital-labour ratio by 1%, the share of wages in GVA declined by 0.25%. This suggests that the higher capital intensity of production was squeezing the share of labour in GVA. It is important to mention that we are unable to use the logarithm of real minimum wages as an instrument here. Doing so, misspecifies the equation, as this variable should in fact be included in the structural equation, and not be an excluded exogenous variable.[17] This is because firms in states with a higher minimum wage will typically have to pay higher wages, resulting in the wage bill eating into a larger share of GVA. The coefficient on the log of real minimum wages is positive and statistically significant, confirming this. The other two instruments (index of labour market regulations and level of financial development of the state) are valid. Also, from the Cragg–Donald minimum eigenvalue statistic, we can reject the null hypothesis of weak instruments. The coefficients on the age of the firm and the size dummy are positive and statistically significant suggesting that older and larger firms have a larger share of wage bill in their GVA.

Next, we disaggregate the wage bill into two components, i.e. wage bill accruing to non-production workers/skilled workers (ln(Wage Bill to NPW/GVA)) and that accruing to production workers/unskilled workers (ln(Wage Bill to PW/GVA)). Here, we find that the share of wage bill going to skilled workers is higher in firms witnessing relatively larger increases in the capital-labour ratio (column 3).[18] On the

[16]The null hypothesis of each Stock and Yogo's tests is that the set of instruments is weak. To perform these tests, we must first choose either the largest relative bias of the 2SLS estimator we are willing to tolerate or the largest rejection rate of a nominal 5% Wald test we are willing to tolerate. Since the test statistic exceeds the critical value in each case, we can conclude that our instruments are not weak.

[17]The Sargan&Basmann's chi-square test reports a statistically significant test statistic when we include real minimum wages as an instrument, suggesting that we either have an invalid instrument or incorrectly specified structural equation.

[18]In this equation, we use the log of real minimum wages as an instrument since the Sargan&Basmann's chi-square test report a statistically insignificant test statistic.

other hand, the share of wage bill going to unskilled workers was lower in such firms (column 4).[19] It is worth noting that the coefficient on the variable age of the firm, is positive and significant in column 3, but negative and significant in column 4. This suggests that the share of the wage bill going to supervisors and managers in older firms is greater than in younger firms. On the other hand, the share of wage bill going to production workers is higher in younger firms. Also, larger firms have a bigger share of their wage bill being paid out to production workers as compared to smaller firms. Not surprisingly, the log of real minimum wage bill is positive and statistically significant in column 4 as higher minimum wages drive up the wages of production (and not non-production workers).

In the fifth column, the dependent variable is the ratio of non-production/skilled to production/unskilled workers (ln(NPW/PW)). Here, we find that firms experiencing relatively larger gains in capital-labour ratio observed relatively larger increases in proportion of skilled to unskilled workers. A 1% increase in the capital intensity of production resulted in a 0.21% increase in the ratio of skilled to unskilled workers. This result underlines the existence of capital-skill complementarity, which means that ceteris paribus, firms with higher capital intensity also employ a higher share of skilled workers. We also find that older firms have a higher ratio of skilled to unskilled workers as compared to younger firms. The coefficient on the size dummy is negative and statistically significant suggesting that larger firms have a lower ratio of skilled to unskilled workers.[20] In this equation, we use all three instruments as they are valid and not weak.

In the last column, we find that the rising capital intensity of production has also exacerbated wage inequality and resulted in growing divergence in wages earned between skilled and unskilled workers. The coefficient on the capital intensity of production is positive and statistically significant suggesting that firms observing relatively larger increases in the capital-labour ratio saw relatively larger increases in wage differential between production and non-production workers (ln NPW wage/PW wage). It needs to be noted here that though statistically significant, the size of the coefficient on the capital-labour ratio (0.10) is smaller than the size of the coefficient on the share of contract workers (0.74). This suggests that hiring of contract workers accentuates wage inequality between the production workers and supervisory and managerial staff. This is a result of the fact that greater presence of contract workers in the firms' workforce helps reducing the average wages of production workers not only because this category of workers receives lower wages, but also because they exert a downward pressure on wages of directly employed workers (Sen et al. 2010 and Saha et al. 2013). Importantly, we find that the wage disparity between skilled and unskilled workers is higher in older and larger firms. Furthermore, in this specification we cannot use the log of real minimum wages as an

[19]Here, we cannot use the log of real minimum wages as an excluded exogenous variable as the Sargan & Basmann's chi-square test report a statistically significant test statistic. It needs to included in the structural equation.

[20]Firm size is largely driven by the production workers and not non-production workers, as the latter are quite small as a percentage of total persons engaged.

excluded exogenous variable. We therefore include it in the structural equation and find its sign to be negative and significant. This is because a higher minimum wage put upward pressure on the average wages of production workers, thereby reducing inequality between production and non-production workers.

The results of the first stage of the IV are reported in the appendix and they are not surprising. The coefficient on the labour regulation index is negative and statistically significant in both columns suggesting that firms in states with more inflexible labour regulation are incentivized to use more capital intensive techniques of production and have a greater share of contract workers in their workforce. Also, firms in states where the level of the minimum wage rate is higher, employ a greater share of contract workers. However, we do not find the coefficient on the level of the financial development of the state to be statistically significant.

5 Conclusion

That mechanization and automation of production processes threaten employment for India's low-skilled/unskilled workforce is a well-known fact. However, doomsday prediction of the world in which everything is done by machines is also unrealistic. Nevertheless, such prospects are hugely worrying in a country such as India looking to create employment for its rapidly increasingly working age population. Not only has the capital intensity of production been increasing sharply, but recent economic growth has benefited industries which rely more on skilled workers and capital as opposed to unskilled/low-skilled workers. As technology makes it easier to substitute capital for labour, an increase in capital intensity of production over time is inevitable and we can certainly not resist the adoption of new technology only to preserve jobs.

In this paper, we attempt to examine the effects of growing capital intensity (and associated technological change) on inequality of wages and earnings in organized manufacturing in India. The theoretical expectation is that growing capital intensity would not only increase the share of capital in value added, but also skill premium, thus increasing inequality. The increase in the wage gap between the managerial and supervisory staff (high-skilled) and production workers (low-skilled), and the reduction in share of aggregate value added going to labour, in our dataset, is consistent with this expectation. However, the share of managerial and supervisory staff in total employment seems to have remained stagnant, while the share of contract workers in production workers has increased sharply over the last decade. Arguably, had there been no growth of contract workers, the wage gap between the managerial and supervisory staff and the production workers would have increased much less. In other words, it is not just the growth of capital intensity but also the growth of contract workers that explains the growth of inequality. At the same time, it is also possible that the salaries of the managerial and supervisory staff were growing not so much because of growing demand from manufacturing but intensifying competition with the services sector for such staff.

It is important to mention that in India, unlike in the developed world, skill-biased technological change was not accompanied by a large increase in the supply of more educated workers. This may well have exacerbated wage disparity. The serious supply-side constraint is evident from the fact that only 4% of total workers engaged in the manufacturing sector have any technical education and only 27% of workers in manufacturing are vocationally trained, of which 86% are non-formally trained (Mehrotra et al. 2013).

The government's ambitious Skill India program, with a target to skill 40 crore workers over the next five years attempts to address this gap. However, assembly line methods of skill development which produce large numbers of electricians, machine operators, plumbers, carpenters, electricians and other such narrowly skilled and certified persons will not address India's skills challenge. In an uncertain and dynamic world where new technologies will disrupt old forms of production and alter processes of production, it is not possible to predict what the nature of jobs will be in the future and precisely what skills workers will need to perform these jobs. Consequently, workers may end up being imparted skills they may actually not put to any use. For skill development systems to be effective, they need to be able to respond to technological changes in the economy. This requires providing young workers with a broad foundation of basic skills and a minimum level of educational attainment so that they are able to learn the requisite skills in the enterprises where the jobs are being created. Increasing the supply of skilled workers in such a manner will help reduce the growing divergence in wages of skilled and unskilled workers. However, the phenomenon of contractualization poses a serious threat to the skilling challenge. Workers are discouraged from acquiring skills as they feel that even though skilling-up may result in improved productivity, it may not translate into higher wages as firms will prefer to hire them as cheap contract labour.

Acknowledgements I am grateful to Prof. Suresh Aggarwal, Prof. Biswanath Goldar and Dr. Ajit Ghose and P.P. Krishnapriya for their helpful comments and suggestions.

Appendix A

First stage regression from IV analysis

	(1) ln(K/L)	(2) ln(CW/TW)
Labour regulations index	−0.36*** (0.01)	−0.06*** (0.00)
Financial development index	0.19*** (0.01)	−0.02*** (0.01)
ln(Real minimum wage)	−0.59*** (0.03)	−0.04*** (0.02)
ln(Age of firm in years)	−0.47*** (0.01)	−0.09*** (0.00)

(continued)

(continued)

	(1) ln(K/L)	(2) ln(CW/TW)
Size dummy	0.59*** (0.01)	−0.14*** (0.00)
ln(Tele-density)	0.27*** (0.01)	−0.01 (0.01)
Time	−0.01 (0.00)	0.03*** (0.00)
N	212851	77545

Robust *t*-statistics are given in brackets. *significant at 10%; **significant at 5%; ***significant at 1%

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature, 40,* 7–72.

Acemoglu, D. (2003). *Technology and Inequality, N.B.E.R. Reporter Winter 2002/2003* (pp. 12–16).

Bhattacharjea, A. (2008). How do Indian firms respond to employment protection legislation? Mimeo.

Das, D. K., Wadhwa, D., & Kalita G. (2009). *The employment potential of labor intensive industries in India's organized manufacturing* (Labor Economics Working Papers 22913). East Asian Bureau of Economic Research.

Dougherty, S., Robles, V., & Krishna, K. (2011). *Employment protection legislation and plant-level productivity in India* (NBER Working Papers No. 17693). National Bureau of Economic Research, Inc.

Goldar, B. (2000). Employment growth in organised manufacturing in India. *Economic and Political Weekly, 35*(14), April 1–7.

Goldar, B., & Aggarwal, S. (2012). Informalization of industrial labour in India: Effect of labour market rigidities and import competition. *Developing Economies,* 141–69.

Goldberg, P., & Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature, 45*(1), 39–82.

Gupta, P., Hasan, R., & Kumar, U. (2008). Big reforms but small payoffs: Explaining the weak record of growth in Indian manufacturing. In S. Bery, B. Bosworth, & A. Panagariya (Eds.), *India policy forum* (Vol. 5, pp. 59–108). Delhi: Sage.

Guscina, A. (2006). *Effects of globalization on labor's share in national income* (IMF Working Paper No. 294).

Hasan, R., Mitra, D., & Sundaram, A. (2013). The determinants of capital intensity in manufacturing: The role of factor market imperfections. *Indian Growth and Development Review* 11/2013.

Kapoor, R. (2015). Creating jobs in India's organised manufacturing sector. *The Indian Journal of Labour Economics, 58*(3), 349–375.

Kumar, R. (2002). The impact of regional infrastructure investment in India. *Regional Studies, 36*(2).

Meschi, E., Taymaz, E., & Vivarelli, M. (2011). Trade, technology and skills: Evidence from Turkish microdata. *Labour Economics, 18*(2011) S60–S70.

Mehrotra, S., Gandhi, A., & Sahoo, B. K. (2013). *Estimating the skill gap on a realistic basis for 2022* (IAMR Occasional Paper No. 1/2013).

Organization for Economic Co-operation and Development. (2007). *OECD Economic Surveys: India. 2007*(14).

Saha, B., Sen, K., & Maiti, D. (2013). Trade openness, labour institutions and flexibilisation: Theory and evidence from India. *Labour Economics, 24*, 180–195.

Sen, K., Saha, B., & Maiti, D. (2010). Trade *Openness, labour institutions and flexibility: Theory and evidence from India* (BWPI Working Paper No. 123). Brooks World Poverty Institute, University of Manchester.

Sen, K., & Das, D. (2014). *Where have all the workers gone? The puzzle of declining labour intensity in organized Indian manufacturing* (DEPP Working Paper No. 36). www.seed.manchester.ac.uk/subjects/idpm/research/publications/wp/depp/depp-wp36/.