# Long-run Performance of the Organised Manufacturing Sector in India

## An Analysis of Sub-periods and Industry-level Trends

AMIT BASOLE, AMAY NARAYAN

The Indian manufacturing sector has not increased its share in output or employment along expected lines. The aggregate trends in this sector at the 3-digit level of the National Industrial Classification from 1983 to 2017 are investigated here. Using data from the Annual Survey of Industries obtained from the EPWRFITS, it identifies three sub-periods within the overall period: 1988–96, 1996–2006, and 2006–17. A shift-share decomposition is used to show that most of the decline in the labour to capital ratio can be explained by within-industry changes. Finally, industries are analysed with respect to their capacity to deliver job and wage growth.

The authors thank Arjun Jayadev, Deepankar Basu, the anonymous reviewer for comments, and Zico Dasgupta for help with EViews. Responsibility for errors lies with the authors.

Amit Basole (*amit.basole@apu.edu.in*) is with Azim Premji University, Bengaluru. Amay Narayan (*amaynarayan@outlook.com*) is an independent researcher.

The manufacturing sector, in particular the sub-sector consisting of relatively larger and profit-oriented firms, occupies a place of importance in development economics from the point of view of structural transformation (Lewis 1954). In recent decades, however, it has become clear that many developing countries are failing to increase the share of manufacturing in total value added or employment (Rodrik 2016). In India, for example, the workforce has been shifting from agriculture to the informal economy, mostly in construction and services, such as petty retail and domestic work (Basole et al 2018). Recent evidence also suggests that, since the 1990s, the manufacturing sector is no longer as important a driver of economic growth as it once was (Szirmai and Verspagen 2015). South Asia, in particular, as opposed to East and South-east Asia, seems to be in the service-led structural change category, with India leading the pack (Amjad et al 2015). On the other hand, there is also the view that no country has become high-income on a sustained basis without a substantial increase in manufacturing share of the gross domestic product (GDP) and employment. Hence, developing countries should not give up on manufacturing-led structural change yet; rather there is need for a more nuanced understanding of what works and what does not work, at the policy level (Haraguchi et al 2018).

Table 1 (p 36) shows the share of manufacturing in value added and employment in India since the early 1980s. As can be seen, the sector has failed to expand by either measure. However, analyses at the aggregate level hide substantial variation across different manufacturing industries. Further, if we make a distinction between relatively larger firms in the organised sector versus microenterprises in the unorganised sector, a more complex story emerges. Organised manufacturing employment as a share of total manufacturing employment declined from 25.5% in 1983 to 15.4% in 2004. But, since then has increased to 27.5%. Particularly since 2005, employment in the unorganised manufacturing sector has risen much more slowly compared to the organised sector (Thomas and Johny 2018).

The present study is motivated by two questions. First, which periods in the recent past have seen a relatively better performance of the organised manufacturing sector? Second, which industries have performed relatively better? Both these questions have been, thus far, insufficiently explored in the literature. The answers to these questions can form the basis for policymaking that intends to promote this sector.

**Table 1: Share of Manufacturing (Organised and Unorganised) in Employment and Value Added in India (1983–2015)** (%)

| Year | Employment Share | Value-added Share |
|---|---|---|
| 1983 | 10.6 | 17.3 |
| 1987 | 12.2 | 16.8 |
| 1993 | 10.6 | 16.5 |
| 1999 | 11.0 | 15.8 |
| 2004 | 12.3 | 16.4 |
| 2011 | 12.6 | 16.1 |
| 2017 | 12.1 | 14.9 |

Sources: *National Sample Survey Employment–Unemployment Surveys*, various years; *World Development Indicators*, various years.

The study traces the evolution of key parameters in this sector over a 34-year period from 1983 to 2017 to identify periods of better or worse performance, and industries that have performed better or worse than average. We extend and build upon the analysis of Kannan and Raveendran (2009) and Roy (2016). Using the Bai-Perron test for structural breaks, we show that the entire period can be divided into three clearly different sub-periods. The first period, from 1988 to 1996, is characterised by weak employment growth, rapid substitution of capital for labour, and rising wages. The second period (1996 to 2006) displays loss of employment, slower substitution of capital for labour, and stagnant wages alongside a growing divergence between wages and productivity. The third period (2006 to 2017) shows strong employment growth as well as rising wages, despite a renewed decline in the labour–capital ratio. This is also the only period during which the labour share of income stops falling and even shows a rise in nominal terms.

We also construct a typology of industries based on whether they have managed to deliver employment growth as well as wage growth. We find that large employers such as apparel and knitwear have displayed the capacity to create jobs as well as deliver wage growth. On the other hand, industries such as textiles, machinery, and electrical equipment have failed on both fronts. Other industries show a more mixed profile, delivering on one dimension, but not the other. This diversity calls for further work on elucidating the specific reasons at the policy and industry level.

## Literature Review

Based on several recent studies, the following stylised facts can be highlighted in the Indian organised manufacturing sector: rising capital–labour ratio (capital intensity of production) across all industries, low output elasticity of employment (around 0.5 or less), growing divergence between real wages and labour productivity, falling labour share of income, and rising proportion of contract workers (Abraham and Sasikumar 2017; Goldar and Sadhukhan 2015; Kapoor 2015, 2016; Kapoor and Krishnapriya 2017; Sen and Das 2015).

A question that has been raised in the literature but not satisfactorily answered yet is, to what extent the falling labour–capital ratio at the aggregate level is due to a fall in the ratio within each industry and to what extent it is due to the faster growth of relatively more capital-intensive industries? The latter mechanism is suggested by both Kannan and Raveendran (2009) and ILO (2009) as a mechanism for job-loss growth. The argument is that rising inequality results in greater demand for manufactured commodities that are products of relatively more capital-intensive as well as more import-intensive industries; for example, metal and chemicals-based products, electronics, and vehicles. However, there is some evidence that the capital–labour ratio has increased in capital-intensive as well as labour-intensive industries (Kapoor 2015; Sen and Das 2015). This points to a greater contribution of within industry factors.

The divergence between wages and productivity, the former growing much slower than the latter, has been widely discussed for economies of the Organisation for Economic Co-operation and Development (OECD), but relatively less attention has been paid to this phenomenon in India. One of the first papers to point it out is Kannan and Raveendran (2009). But, the authors do not discuss it much. Abraham and Sasikumar (2017) discuss it in the context of falling wage shares. Nagaraj (2018) also reports the same finding in the context of a discussion on the efficacy of labour laws. His point is that the divergence points to the weak position of Indian labour vis-à-vis capital even within the relatively privileged organised manufacturing working class.

The closely related trend of a fall in labour share of income has, once again, been reported across the globe. Two recent studies have examined this in India. The first study by Abraham and Sasikumar (2017) performs a shift-share decomposition and finds that, of the decline in wage share of 25.6 percentage points, 75.6% is explained by the shift component. That is, the falling share of wages is mostly due to a fall within each industry rather than a faster growth of industries with lower wage shares. The study uses an industry–state–year panel and a first-difference regression model to show that contractualisation, increasing female share in permanent workers, and intensification of work (more days of work in place of more workers) are determinants of the falling wage share. The second study by Jayadev and Narayan (2018) also identifies the rise of contract labour as an important determinant alongside trade openness. It should be noted that the trend of declining wage share goes back to the 1960s (Basu and Das 2015).

Two further questions are interesting from the point of view of policy measures to promote manufacturing jobs. One, are there periods in recent history when the organised manufacturing sector has performed relatively better in terms of job creation? Two, which are the industries that have managed to post job growth in addition to wage and productivity growth? These two questions have been addressed less frequently. Goldar (2011) reports that employment growth rate in organised manufacturing accelerated sharply after 2004–05, while in comparison between 1995–96 and 2003–04, employment in this sector fell at the rate of 1.5% per annum. Das et al (2017) find structural breaks within a two-year window (1997–99) for employment, output, wage rate, and labour productivity. Roy (2016) identifies the top 10 industries that have performed relatively better in delivering output growth, wages, and employment in the period between 2008 and 2012.

## Data and Methods

**Annual survey of industries:** We use data from the Annual Survey of Industries (ASI) concorded series at the 3-digit National Industrial Classification (NIC) level made available by the Economic and Political Weekly Research Foundation's India Time Series database (henceforth, EPWRFITS).

Over the years, the ASI sampling frame and method have changed somewhat, with the most significant change being the exclusion of certain industries starting 1999 (Kannan and Raveendran 2009). These industries have been omitted from our data set in order to retain consistency across the entire period. Our final data set spans 34 years (1982–83 to 2016–17, the most recent year for which the ASI data are available) and 55 industries. For convenience, we refer to a particular financial year by the second calendar year. For example, 2015–16 is referred to as 2016.

**Variables:** We deflate nominal wages and salaries by the consumer price index for industrial workers (CPI-IW), nominal output and value added by the wholesale price index for manufactured products (WPI-MP), and nominal capital stock by the wholesale price index for machines and machinery (WPI-MM). Deflators were obtained from EPWRFITS and rebased to the year 2004–05. Monthly deflator data was averaged for the financial year (April to March) to create the annual series.

The variable "total persons engaged" is used to measure employment trends. But the trends and results are not substantially altered by using production workers only.

Capital stock is calculated by the perpetual inventory method by converting fixed capital at historical cost to replacement cost as outlined in Balakrishnan and Pushpangadan (1994) and Kannan and Raveendran (2009). More details on measuring capital stock from ASI data can be found in Raychaudhuri (1996), Rao (1996), and Datta and Bhattacharya (2007).

We define capital intensity as the capital–labour ratio or the ratio of real fixed capital to total persons engaged. Labour intensity is defined as the inverse of this ratio. We have confirmed that substituting number of workers for total persons engaged does not alter the trends and results. Labour productivity is defined as the ratio of real gross value added (GVA) to number of workers or employees (once again, the trends are similar for both). The wage share is defined as share of wages in real GVA. Using gross output instead of GVA does not substantially alter the productivity or wage share trends.

**Decomposition:** We perform a shift-share decomposition analysis to identify the relative contributions of inter- versus intra-industry changes in the labour to capital ratio. The components of the decomposition are:

$$l^{t+1} - l^t = l_i^t(s_i^{t+1} - s_i^t) + (l_i^{t+1} - l_i^t)s_i^t + (l_i^{t+1} - l_i^t)(s_i^{t+1} - s_i^t) \qquad \ldots(1)$$

where $l = L/K$; $s_i = K_i/K$

The first term is the labour–capital ratio for a given industry multiplied by the change in the share of capital stock of that industry. The second term is the share of a given industry's capital stock multiplied by the change in labour intensity. The third term is an interaction term.

Thus, the change in labour intensity at the aggregate level can be decomposed into an intra-industry component that accounts for within industry changes in labour intensity, an inter-industry component that accounts for the changing importance of a given industry in terms of its share in the total capital stock, and an interaction component.

We also decompose the labour share of income as follows:

$$(wL)/Y = L/K * (wL)/L * K/Y \qquad \ldots(2)$$

where $w$ is the wage rate, $L$ is number of workers, $Y$ is output or value added, and $K$ is the capital stock. Thus, the share of wages in output or value added can be expressed as the product of the labour–capital ratio, the wage rate, and the capital–output ratio. It follows that the growth rate of the wage share can be expressed as the sum of the growth rates of the other three ratios. In the study, we use GVA as a measure of $Y$.

**Analysis of structural breaks:** We are interested in finding out if growth rates of key variables, such as employment and real wages, have changed over time. In particular, it is useful to know if there are statistically distinguishable "regimes," that is, breakpoints at which the growth rate changes. Since these breakpoints are not known in advance, a standard Chow test cannot be performed on the coefficients of a log-linear regression. Further, since the possibility of multiple breaks cannot be ruled out, the supremum Wald (Quandt) test also cannot be used in this case. The Bai-Perron test (Bai and Perron 1998, 2003) has been developed specifically for identifying multiple, unknown breakpoints sequentially. We performed this test on the employment and real wage trends using the EViews software.[1]

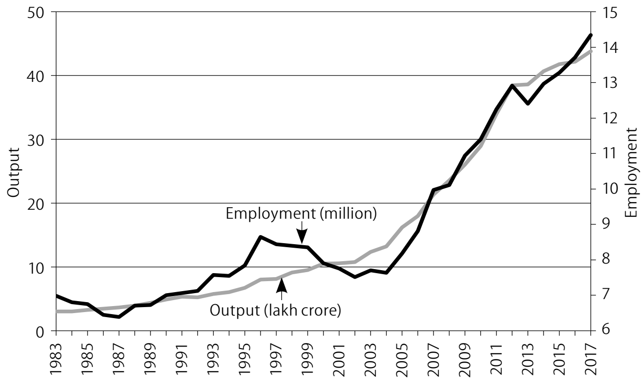
## Aggregate Analysis

**Employment, wage, and labour intensity trends:** Figure 1a (p 38) shows the absolute levels of employment (in million) and output (in lakh crore) in organised manufacturing from 1983 to 2017. Employment includes production workers, managers, supervisors, and clerical staff. After a small initial fall in absolute employment till 1986, there was growth till the mid-1990s. The worst period for organised manufacturing employment was between 1997 and 2002. This decline is not an artefact of the removal of certain industries from ASI coverage (see the section "Data and Methods"). After 2006, employment in this sector grew again.

Growth in employment in any period, however, is much weaker compared to the rise in output, indicating a large increase in labour productivity over the period. This is made clear in Figure 1b (p 38) which shows both trends indexed to the first year (1983). While employment roughly doubles in this period, output goes up nearly 15 times. Thus, the growth elasticity of employment has been low in this sector. The aggregate employment elasticity over the entire period is 0.26. But there is substantial variation from year to year. Figure 2 (p 38) shows annual employment elasticities for the entire period (excluding two outlying years).

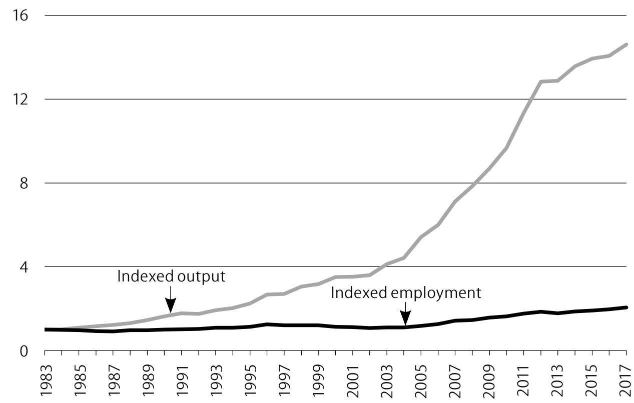
One important reason for low employment elasticity in the organised manufacturing sector has been the rising capital intensity of production. As per ASI data, in the early 1980s,

**Figure 1a: Total Employment (million) and Output (lakh crore) in Organised Manufacturing, 1983–2017**



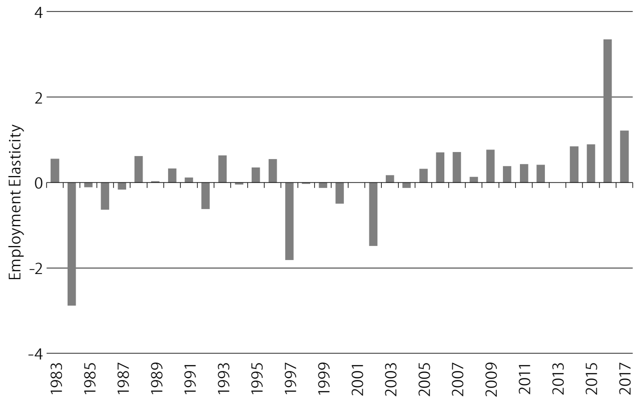

Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**Figure 1b: Indexed Trends in Gross Real Output and Employment (1983 = 1)**



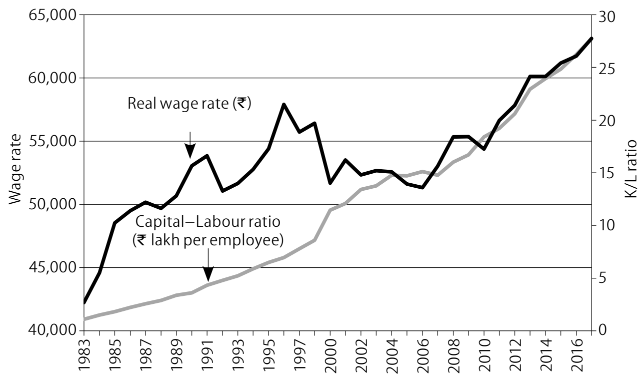

Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**Figure 2: Annual Output Elasticity of Employment across All Industries**




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS. Two outlying values have been removed.

**Figure 3: Real Wage Rate (2005 rupees) and Capital–Labour Ratio, 1983–2017**




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS. Wage data is missing for 1999.

₹2 lakh of invested capital (in 2005 rupees) created one job in this sector. By 2017, this had risen to ₹27 lakh. Putting this in terms of the labour to capital (rather than capital to labour) ratio, around 50–60 jobs were sustained by ₹1 crore of fixed capital (in 2005 rupees) in the early 1980s. This fell to around 11 jobs in 1998 and to less than 5 today. However, the rise in the aggregate capital–labour ratio also shows variation in the three periods identified for employment. And, the same sub-periods can be identified in the real wage rate series as well. Wages grew from the early 1980s till about 1996. After which there was a period of stagnation and even decline, until 2007. Subsequently, they have been increasing (Figure 3).

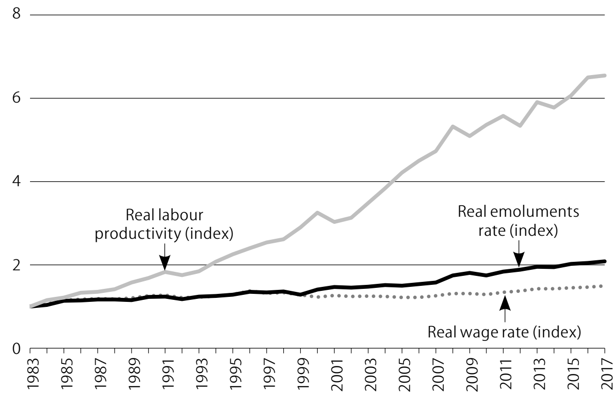
We performed a Bai-Perron structural breakpoint test to identify the break years. The results are given in the Appendix (p 44). Three years emerge as statistically significant breaks in the employment trend: 1988, 1996, and 2006. For the wage rate series, the breaks identified are nearly the same: 1988, 1996, and 2005. We exclude the first period 1983 to 1988 from consideration due to insufficient data and focus on three distinct regimes or sub-periods: 1988 to 1996, 1996 to 2006, and 2006 to 2017. In the first period, employment and wages grew slowly. The second period actually saw a decline in both, and the third, from 2006 to the most recent available year, saw employment and wages growing much faster than at any other time since the early 1980s.

Perhaps unexpectedly, it appears that rising employment–wages regimes are associated with a rising capital–labour ratio while the falling employment–stagnant wages regime is associated with a stagnant ratio. Strikingly, the most recent period (2006 to 2017) demonstrates a rise in the capital intensity, but also a concomitant rise in employment as well as real wage rate. The output elasticity of employment in the first period is 0.22. In the second period, it falls to a mere 0.012 and grows to 0.46 in the third period.

This indicates that rising capital intensity should not straightforwardly be taken to be a negative development from the point of view of employment generation in the manufacturing sector. Rather, if the period also happens to be one of strong output growth, this may result in rising employment and, hence, also rising wages.

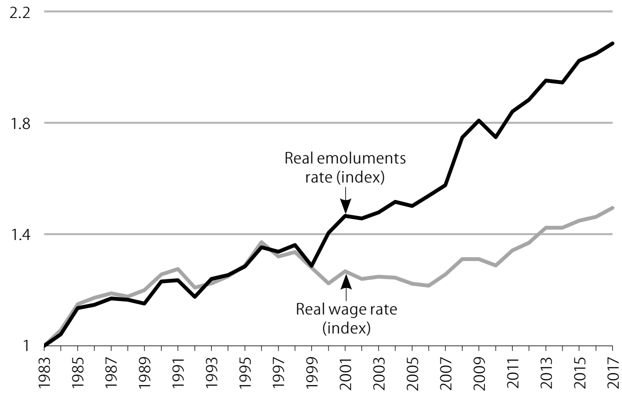
Of course, as might be expected, the rising capital intensity of production has tempered the ability of output growth to generate employment in the sector. An industry fixed effects panel regression (weighted by the initial share of each industry in total employment) shows the average output elasticity of employment over the 34-year period to be 0.23. If we control for capital intensity, the elasticity rises to 0.70. That is, a doubling of output would result in a 70% increase in employment, were capital intensity to remain constant. However, given the rising capital intensity, a doubling of output only increases employment by 23%.

**Figure 4a: Indexed Real Wage Rate, Emoluments Rate, and Labour Productivity, 1983 = 1**




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**Figure 4b: Indexed Real Wage Rate and Real Emoluments Rate, 1983 = 1**




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**The wage-productivity gap and wage share:** Rising capital intensity is expected to increase labour productivity. Between 1983 and 2017, labour productivity, as measured by real gross value added per employee, went up six times. The question that arises from a quality of jobs perspective is how were the productivity gains shared between labour and capital? For this, we need to look at the relationship between wages and productivity. The growing dominance of capital in the production process suggests that a greater portion of value added would accrue to capital owners as a result. The expected divergence between the real wage rate and real productivity per worker is indeed clearly observed (Figure 4a). On average, the real wage rate grew at the rate of 1.4% per year, while productivity grew at 5.5% per year in real terms. This points to a large shift in distribution in favour of capital. In the panel data set, on average, a doubling of labour productivity is associated with only an 18% rise in wages.

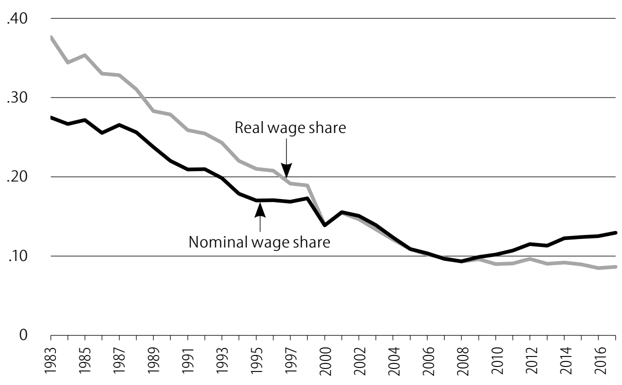
There is another divergence visible in Figure 4a that has not received much attention in the literature, that between wages per worker paid to production workers and emoluments per employee which include benefits and bonuses paid to managerial and supervisory staff. This can be seen more clearly in Figure 4b. After growing in step with each other until the late 1990s, the two diverge. Subsequently, the real wage rate enters a period of stagnation that coincides with the absolute fall in employment discussed earlier, while emoluments rise steadily. The gap between the two has grown steadily since then, even after the wage rate started rising post-2006. The emoluments to wages ratio rose from 1.2 in 1983 to 1.7 in 2016. A possible factor contributing to this divergence is the rise in proportion of contract workers, or workers employed via contractors and not paid through the firm's payroll, that has occurred precisely over the same period. As has been discussed by others, contract workers are paid a fraction of permanent worker wages, often for similar work (Nayanjyoti and Chakraborty 2018; Kapoor and Krishnapriya 2017). Of course, it is also possible that production-line wages have increased far more slowly than salaries and bonuses of the supervisory and managerial staff.

The growing divergence between productivity and wages/emoluments implies a falling share of labour in value added. Figure 5a (p 40) reports the share of wages in gross value added in real as well as nominal terms. The decline in real wage share is steeper than the nominal decline, due to the fact that the CPI has diverged from the WPI over time. Thus, two things are to be noted regarding the declining labour share of income in organised manufacturing. First, that there is a large, secular decline till 2008 in both the nominal and real shares. Afterwards, the nominal share rises slightly, while the real share stagnates. In nominal terms, the share of wages in value added fell from 27% in 1983 to a low of 9.3% in 2008. Subsequently, it has increased to around 13% in 2017. Second, the divergence between the real and the nominal shares has to do with the fact that wages have not increased as much in real terms as has output, due to faster rise in the CPI compared to WPI.

Here, one can ask what part of the trend in labour share is attributable to changes in labour intensity of production, how much to wage trends, and how much to capital productivity. As indicated in the "Data and Methods" section, the wage share of value added can be decomposed into these three ratios. Since the product of the three ratios, the labour–capital ratio (L/K), the wage rate (wL/L), and the inverse of capital productivity (K/GVA) is the wage share of value added (wL/GVA), it follows that the sum of the three growth rates will be the growth rate of the wage share.

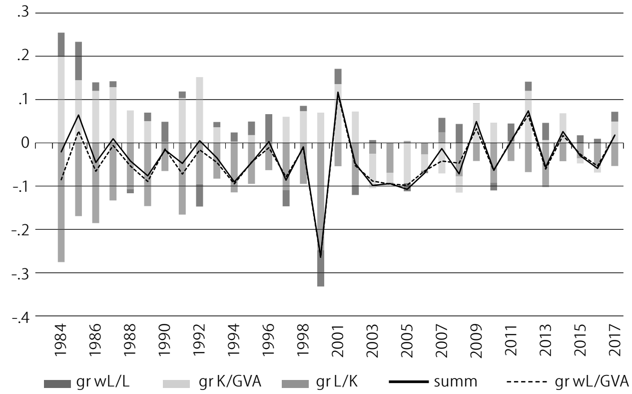
Figure 5b (p 40) shows the results of the decomposition analysis. The real wage-rate trend does not explain much of the decline in wage share. Though, of course, a higher rate of growth of real wages would have counteracted the pull-down effect of the other two variables. Most of the decline in wage share is accounted for by the falling L/K ratio, which is counteracted to a greater or lesser degree by falling capital productivity. Importantly, in the period between 2002 and 2007, when L/K ratio does not fall as rapidly, capital productivity is growing, resulting in a continued fall in the wage share. Further, wage growth is close to zero during this period as well. Only after 2008 does the wage share flatten out. This is a result of contradictory trends: a falling L/K ratio counteracted

Figure 5a: Real and Nominal Wages as a Share of Gross Value Added




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

Figure 5b: Decomposition of the Wage Share




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

by falling capital productivity and rising wage growth. It should be emphasised that the decomposition analysis does not have a causal interpretation. That is, one cannot conclude from the foregoing analysis that the falling L/K ratio causes a decline in the wage share. Rather, it should be seen as an exercise that points to factors that need further investigation. We discuss this further in the "Discussion" section.

## Industry Analysis

In this section, we examine the industry-level variation in five key variables—labour–capital ratio, labour productivity, wage share, real wage rate, and employment elasticity.

**Labour intensity, labour productivity, and wage share:** Rising capital intensity, at the aggregate level, could be the result of a more rapid growth of relatively more capital-intensive industries occurring due to higher demand for products requiring more mechanised methods of production. Typical examples are automobiles and consumer electronics. This hypothesis has been advanced in the literature as an explanation for weak job creation in manufacturing. However, it is also possible that rising aggregate capital–labour ratio is a result of rising capital intensity of production within all industries.

As noted earlier, capital intensity has risen in relatively more labour-intensive as well as relatively more capital-intensive industries. Figure 6a (p 41) shows this phenomenon for a selection of industries. Note that the inverse of the capital–labour ratio (that is, the labour–capital ratio) is displayed. The industries have been chosen to represent a wide range of initial labour intensities from furniture and textiles to vehicles and petroleum products. Note that the textile industry is four times as labour intensive as appliances or vehicles, but it displays very similar dynamics. A scatter of plot of the growth rate of labour–capital ratio against initial level of the same ratio for all 55 industries shows no discernible pattern, confirming the conclusion that the trend towards falling labour intensity is independent of its initial value (data not shown).

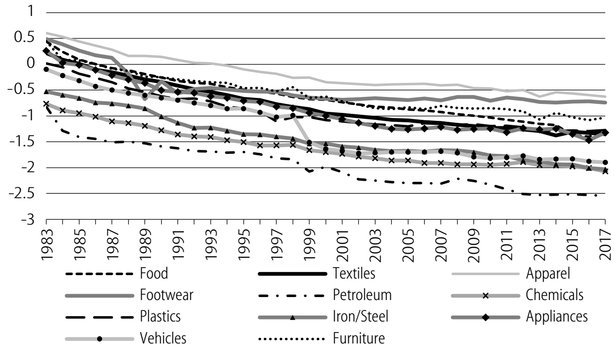
To further test this, we perform a shift-share decomposition of the labour–capital ratio to estimate the relative contributions of the within and between industry components in the decline of the aggregate ratio (see "Data and Methods" for details). The results of this analysis are presented in Figure 6b (p 41). The jagged lines show actual growth rates year on year and the sum of the three components. As expected, the two lines coincide exactly. Each bar is split into three components, intra-industry change in labour–capital ratio, inter-industry change, and the interaction term.

As we saw before, the labour–capital ratio declines for most of the 1980s and 1990s, is steady in the early 2000s, and starts declining again after 2008. But, more importantly, we see that the fall in the intra-industry component dominates for almost every year in the sample. The inter-industry component is positive for some years, indicating that labour-intensive industries actually grew faster, contrary to the hypothesis that falling aggregate labour intensity has to do with faster growth of relatively more capital-intensive industries. Thus, one can conclude from the decomposition analysis that the decline in the L/K ratio is due to rising capital intensity within each industry rather than due to faster growth of more capital-intensive industries.

As expected from growing mechanisation, there have been large gains in labour productivity across all industries. From the point of view of welfare, it is important to know the division of these productivity gains between wages and profits. In general, it is clear that wage growth is much lower than productivity growth for all industries. Figure 7 (p 41) shows this relationship in a scatter plot along with a line of best fit and a line of equality.[2] The fact that nearly all industries lie above the line of equality means that wage gains have not kept pace with productivity gains anywhere in organised manufacturing. Thus, it is not surprising that there is an almost universal decline in the wage share (data not shown). The line of best fit shows the average relationship between the two variables and the dispersion in both directions shows which industries are better or worse than average at translating productivity gains into wage gains.

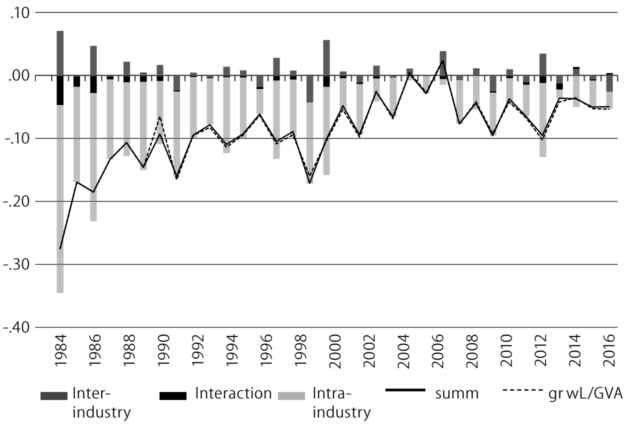
Some industries such as petroleum (NIC 232), tobacco (NIC 160), non-ferrous metals (NIC 272), and motor vehicles (NIC 341) lie far above the line of best fit, indicating a worse performance in translating productivity increases into wage increases. On the other hand, some big employers such as knitwear (NIC 173), leather (NIC 191), and footwear (NIC 192) lie below the line, indicating lower productivity growth, but a better-than-average

**Figure 6a: Log Labour–Capital Ratio for Selected Industries over Time**



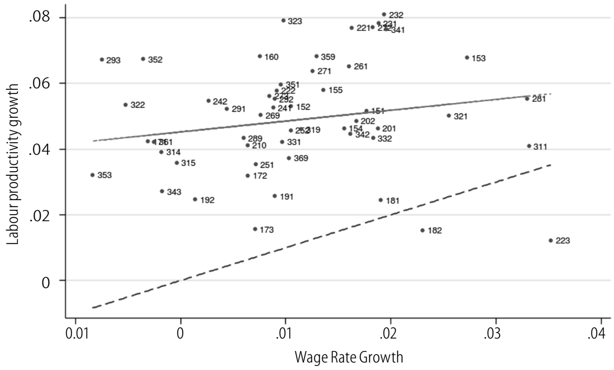

Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**Figure 6b: Shift-share Decomposition of the Labour–Capital Ratio**




Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

**Figure 7: Relationship between Growth Rate of Labour Produtivity and Growth Rate of Wages by Industry**




Straight line indicates Best Fit, dotted line is the Line of Equality.
Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

performance translating it into wage growth. Other important employment-intensive industries like textiles (NIC 171) and food (NIC 151–154) lie very close to the line, indicating an average performance.

**Employment elasticity and wages:** Thus far, we have seen that certain aggregate trends such as falling labour intensity, rising productivity and wages, and falling wage share are seen in almost every industry, albeit to varying degrees. Industries also differ widely in their employment growth over the data period. Employment in apparel increased 14 times over the entire period, while employment in textiles as well as food actually fell. It is probably not a coincidence that these same two industries (food and textiles) are the largest employers in the informal sector. It should also be noted that apparel and footwear, two industries that have done well on the employment front, are also the two least capital-intensive industries.

However, as noted earlier, capital intensity is only one determinant of employment. Both textiles and plastics are very similar in their capital intensities but very different in their employment performances. Employment in plastics grew nine times over the period while, as noted before, employment in textiles has fallen. Clearly, output growth is the relevant factor to consider here. While plastics still employed only half as many workers as textiles in 2017, in output terms the former has grown 48 times over the entire period, while textiles has only grown six times.

But, even controlling for output growth, there is wide variation in employment generation capacity from knitwear (NIC 173) with a healthy elasticity of 0.7 to saw-milling and planing of wood (NIC 201) with a value of -0.5. Some important employers that have posted very lacklustre elasticities are textiles (NIC 171) and food (NIC 154), while large employers displaying robust elasticities are knitwear (NIC 173), other textiles (NIC 172), leather (NIC 191), and footwear (NIC 192).

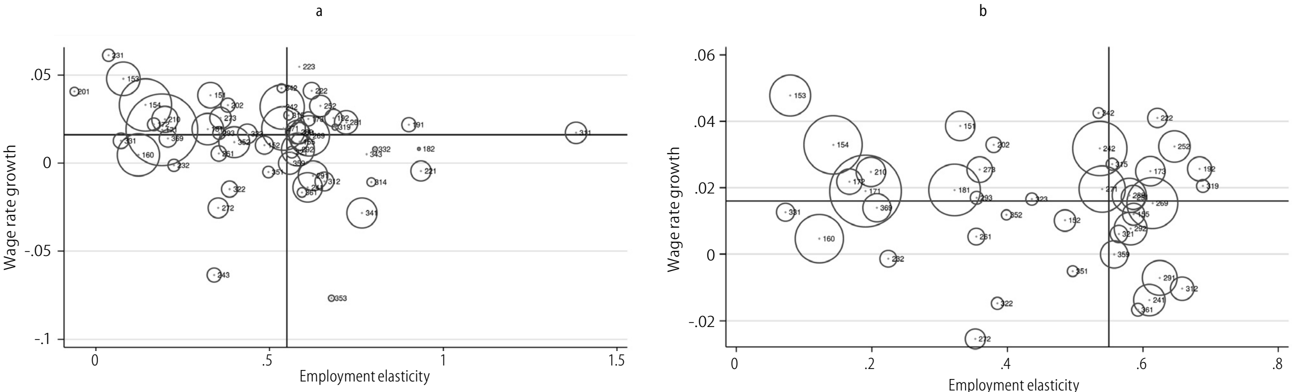
Combining the elasticity and wage-rate data, we can answer the question of which industries have been relatively better at both job creation and delivering wage growth. We do this analysis only for the most recent sub-period that has seen rapid employment and wage growth.

Figures 8a and 8b (p 42) show a scatter plot of elasticity versus wage-rate growth. Each data point is an industry labelled with its 3-digit NIC, and the size of the circle indicates the share of an industry in total employment in 2006. The horizontal and vertical lines are median values.

Several points are worth noting. First, note that the majority of industries display positive elasticity and wage growth. Second, there is large variation in this overall pattern. As we have seen already in the previous analysis, some important industries, such as apparel (NIC 181) and knitwear (NIC 173), have performed quite well on both fronts, placing them in or near the top-right quadrant. Other industries that had a big share of employment in 2006, such as textiles (NIC 171), have performed poorly on both fronts with zero wage growth and almost no employment generation capacity in the organised factory sector. And then, there are big employers such as food processing and products (NIC 153, 154) that perform better in terms of wage growth than employment generation.

Several large employers (in 2006) such as machinery (NIC 291), paper (NIC 210), and chemicals (NIC 241) are underperformers on both fronts. And, others such as processing of fruits, vegetables, meat (NIC 151), iron and steel (NIC 271), and glass (NIC 261) have displayed low elasticities, albeit with above median growth in wages. Others, such as other chemicals (NIC 242) and non-metallic minerals (NIC 269), have shown better than median elasticities, but very

**Figure 8: Output Elasticity of Employment versus Wage Growth for All Industries (2006–2017)**




Size of the circle represents share of the industry in total employment in 2006.
Source: Authors' calculations based on ASI 3-digit concorded data from EPWRFITS.

Zoomed in to the nearest median values for clarity.

low wage growth. We comment further on this typology in the next section.

## Discussion

**Sub-periods in the aggregate trends:** The analysis of aggregate trends, using the Bai-Perron structural breakpoint test, reveals three distinct sub-periods in the entire period from 1983 to 2017. The first period from 1988 to 1996 is characterised by employment growth (albeit weak), rapid substitution of capital for labour, and rising wages and emoluments. The second period (1996 to 2006) displays the weakest employment generation, slower substitution of capital for labour, and stagnant wages alongside emerging divergence between wages and emoluments. The third period (2006 to 2017) shows strong employment generation as well as rising wages, despite a renewed decline in the labour–capital ratio and a steadily growing divergence between wages and emoluments as well as wages and productivity. This is also the only period during which the labour share of income stops falling and even shows a rise in nominal terms.

What factors may be relevant in explaining these differences? While it is true that the early 1980s was a period of declining employment and the subsequent increase in jobs was weak, leading to the earliest discussion on "jobless growth" (Nagaraj 2000), the transition that takes place in the mid-1990s is much larger. This decline in employment is not an artefact of the coverage changes in ASI around this time because our analysis excludes the industries that were dropped from coverage and even industries, such as apparel, that show strong employment growth over the entire period stagnated during this period. So far as we know, there is no satisfactory explanation for this in the literature. Rani and Unni (2004) analysed output and employment trends in three sub-periods, 1985 to 1990, 1990 to 1995, and 1995 to 2000. The authors attribute weak employment growth in the last period to labour law reforms that allowed firms with more than 100 workers to retrench more easily and to public sector downsizing. They also note that by the mid-1990s, import tariffs had been reduced in most industries, including consumer goods. Vashisht (2016) also discusses the gradually increasing nature of trade liberalisation in the 1990s and, notes that the manufacturing sector downturn became more pronounced when quotas on imported consumer goods were removed.

The improvement in performance, in wages as well as employment, starting 2005–06, has also been widely commented on, but once again, satisfactory explanations for it are lacking. On the employment front, an important factor is the shift in the labour force from the unorganised to the organised sector. Thomas and Johny (2018) note that the pattern of employment growth in the manufacturing sector is very different in this recent period compared to the 1990s. Whereas, earlier factory employment was comparatively stagnant and employment in the unorganised sector was increasing, the pattern was more or less reversed after 2005. This indicates a redistribution of employment away from the unorganised to the organised sector.

This does not imply, however, that the new jobs were formal jobs. It seems likely that the relaxation of the labour law implementation resulted in a shift away from subcontracting work to small firms in the unorganised sector to production in-house with contract workers.

**Industry-level analysis:** Industry-level analysis corroborates that the aggregate trends for the labour–capital ratio and the wage share are observed for the overwhelming majority of industries. Thus, the main lesson based on this study (labour–capital ratio) and Abraham and Sasikumar (2017) (wage share) is that within industry factors are the main drivers of the decline in both cases. This suggests that policy variables that affect all industries equally, such as the national and international

**Table 2: A Typology of Industries**

| Type A | Type B | Type C | Type D |
|---|---|---|---|
| Leather | Meat, fish, fruits, etc | General purpose machinery | Tobacco |
| Footwear | Grain, mill products | Basic chemicals | Non-ferrous metals |
| Plastics | Other food products | Electricity distribution apparatus | Man-made fibres |
| Knitwear | Apparel | Motor vehicles | |
| Iron and steel | Textiles | Publishing | |
| Other chemical products | | | |

Type A: above median wage growth and elasticity; Type B: above median wage growth and below median elasticity; Type C: below median wage growth and above median elasticity; Type D: below median wage growth and below median elasticity.

macroeconomic climate, ease of borrowing, or labour legislation may be more important factors than industry-specific variables such as technology or differential demand. However, there is some variation in the extent of decline of the labour–capital ratio, and it would be of interest to see how it is related to capital subsidies received by particular industries or the extent of exposure to the global market.

The across-industry variation is much larger for employment elasticity and wage rate. This observation prompted us to examine the relationship between growth in the wage rate and employment elasticity in order to construct the typology of industries shown in Table 2 (p 42). Here, we focus on the most recent 10-year period, though other periods may also hold interesting lessons for policy. Industries are categorised as Type A, B, C, or D as follows. Only industries with a relatively large employment share are discussed.

A: Above median wage growth and elasticity.
B: Above median wage growth and below median elasticity.
C: Below median wage growth and above median elasticity.
D: Below median wage growth and below median elasticity.

On the positive side, large employers such as leather, footwear, and knitwear have displayed good wage growth as well as employment growth in the organised sector in the past decade. It is possible that this has come at the expense of employment in the unorganised sector. On a more mixed note, employment-intensive industries such as food processing, textiles, and apparel have shown a weak capacity for employment generation while posting higher than median rates of wage growth. The opposite is the case for motor vehicles where job creation has been strong, but wage growth has been low, possibly coming from a reliance on contract labour.

Interestingly, apparel and knitwear, leather and footwear were also the industries that performed better than average in translating productivity growth into wage growth. This result seems somewhat counter-intuitive given the reputation of these industries for sweatshop conditions.

## Conclusions

The role of the manufacturing sector in bringing about a structural transformation in developing economies by absorbing surplus labour from the agriculture and informal sector has been debated extensively in recent years (Haraguchi et al 2018). India is often cited as an example of an economy that has "missed the manufacturing bus" and has instead experienced service-led growth (Cantore et al 2017; Ministry of Finance 2015). On the other hand, many scholars have also argued in favour of a renewed strategic industrial policy to actively promote manufacturing in India (Mehrotra 2020; Nagaraj 2017; Thomas 2019).

In this article, we have tried to show that there is much to learn from a detailed analysis of the organised manufacturing sector. The distinct differences between the three sub-periods show that the policy regime and the international environment may have dramatic effects, even given the same geographical and institutional conditions. Further, industries differ widely in their ability to create jobs and deliver wage growth amidst generalised productivity increases. In India, some stories, such as the decline of organised textile manufacturing and the rise of the informal power-loom sector, are well known. But, others such as the performance of apparel or food are less so. They deserve further investigation in order to identify the factors that contributed to job growth and wage growth simultaneously.

In conclusion, the recent performance of Indian organised manufacturing suggests that this sector may yet serve an important role in India's structural transformation. We hope that this study will stimulate efforts at addressing this issue further.

### NOTES

1 For details, see EViews users guide, http://www.eviews.com/help/helpintro.html#page/content/preface.html (viewed on 5 February 2020).

2 The NIC 3-digit codes used in Figure 7, Figure 8a, and Figure 8b are defined at http://www.epwrfits.in/ASITreeview_ThreeDigitIndustry.aspx (viewed on 11 February 2020).

### REFERENCES

Abraham, V and S Sasikumar (2017): "Declining Wage Share in India's Organized Manufacturing Sector: Trends, Patterns and Determinants," International Labour Organization (ILO) Asia-Pacific Working Paper Series.

Bai, Jushan and Pierre Perron (1998): "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica*, Vol 66, pp 47–78.

— (2003): "Computation and Analysis of Multiple Structural Change Models," *Journal of Applied Econometrics*, Vol 18, No 1, pp 1–22.

Balakrishnan, P and K Pushpangadan (1994): "Total Factor-Productivity Growth in Manufacturing Industry: A Fresh Look," *Economic & Political Weekly*, Vol 29, No 31, pp 2028–35.

Basole, Amit, Arjun Jayadev, Anand Shrivastava and Rosa Abraham (2018): *The State of Working India 2018*, Bengaluru: Azim Premji University.

Basu, Deepankar and Debarshi Das (2015): "Profitability in India's Organized Manufacturing Sector: The Role of Technology, Distribution, and Demand," Political Economy Research Institute Working Paper 380.

Cantore, N, Michele Clara, Alejandro Lavopa and Camelia Soare (2017): "Manufacturing as an Engine of Growth: Which Is the Best Fuel?"

STATEMENT about ownership and other particulars of newspaper ECONOMIC & POLITICAL WEEKLY as required to be published in the first issue of every year after the last day of February.

FORM IV (*See Rule 8*)

| | |
|---|---|
| 1 Place of publication: | Mumbai |
| 2 Periodicity of its publication: | Weekly |
| 3 Printer's name: | Gauraang Pradhan for Sameeksha Trust |
| Whether citizen of India: | Yes |
| Address: | 179/14 Hindu Colony, Shakti Niwas, Sir Bhalchandra Road, Dadar, Mumbai 400 014 |
| 4 Publisher's name: | Gauraang Pradhan for Sameeksha Trust |
| Whether citizen of India: | Yes |
| Address: | As above |
| 5 Editor's name: | Gopal Guru |
| Whether citizen of India: | Yes |
| Address: | 2001 Daffodil, Neelkanth Gardens, Shankeshwar Parshwanath Rd., Govandi (E), Mumbai 400 088 |
| 6 Name and address of individuals who own the newspaper and partners or shareholders holding more than one per cent of the total capital: | Sameeksha Trust, 320–322, A to Z Industrial Estate, Ganpatrao Kadam Marg, Lower Parel, Mumbai 400 013. |

I, Gauraang Pradhan, hereby declare that the particulars given above are true to the best of my knowledge and belief.

Mumbai
March 7, 2020

(Gauraang Pradhan)
*Signature of Publisher*

*Structural Change and Economic Dynamics*, Vol 42, pp 56–66.

Das, P, R Basu and A Halder (2017): "Employment, Wage and Productivity: Analysis of Trend and Causality in Indian Manufacturing Industries," *Journal of Industrial Statistics*, Vol 6, No 1, pp 41–56.

Datta, A and A Bhattacharya (2007): "Measurement of Service Capital," *Journal of Income and Wealth*, Vol 29, No 1, pp 55–72.

Goldar, B (2011): "Growth in Organised Manufacturing Employment in Recent Years," *Economic & Political Weekly*, Vol 46, No 7, pp 20–23.

Goldar, B and A Sadhukhan (2015): "Employment and Wages in Indian Manufacturing: Post-reform Performance," Technical Report 185, International Labour Organization, Geneva.

Haraguchi, N, B Martorano and M Sanlippo (2018): "What Factors Drive Successful Industrialization? Evidence and Implications for Developing Countries," *Structural Change and Economic Dynamics*, Vol 49, pp 266–76.

ILO (2009): *Towards an Employment Strategy for India*, Technical Report, International Labour Organization, Geneva.

Jayadev, A and A Narayan (2020): "The Evolution of India's Industrial Labour Share and Its Correlates," *Development and Change*, Forthcoming.

Kannan, K and G Raveendran (2009): "Growth Sans Employment: A Quarter Century of Jobless Growth in India's Organised Manufacturing," *Economic & Political Weekly*, Vol 44, No 10, pp 80–91.

Kapoor, R (2015): "Creating Jobs in India's Organised Manufacturing Sector," *Indian Journal of Labour Economics*, Vol 58, No 3, pp 349–75.

— (2016): "Technology, Jobs and Inequality: Evidence from India's Manufacturing Sector," Technical Report 313, Indian Council for Research on International Economic Relations, New Delhi.

Kapoor, R and P Krishnapriya (2017): "Informality in the Formal Sector: Evidence from Indian Manufacturing," Technical Report F-35316-INC-1, International Growth Centre.

Lewis, W A (1954): "Economic Development with Unlimited Supplies of Labour," *The Manchester School*, Vol 22, No 2, pp 139–91.

Mehrotra S (2020): "Manufacturing: The Cornerstone of a Planning Strategy for the 21st Century," in *Planning in the 20th Century and Beyond: India's Planning Commission and NITI Aayog*, Santosh Mehrotra and Sylvie Guichard (eds), Cambridge University Press.

Ministry of Finance (2015): *Economic Survey 2014–15*, Government of India.

Nagaraj, R (2000): "Organised Manufacturing Employment," *Economic & Political Weekly*, Vol 35, No 38, pp 3445–48.

— (2017): "Economic Reforms and Manufacturing Sector Growth," *Economic & Political Weekly*, Vol 52, No 2, pp 61–68.

— (2018): "Of 'Missing Middle,' and Size-based Regulation: A New Frontier in the Labour Market Flexibility Debate," Centre for Sustainable Employment Working Paper 2018–7, Azim Premji University, Bengaluru.

Nayanjyoti and A Chakraborty (2018): "Changes in Production Regimes and Challenges to Collective Bargaining: A Study of the Gurgaon Industrial Belt," Centre for Sustainable Employment Working Paper 2018–18, Azim Premji University, Bengaluru.

Rani, U and J Unni (2004): "Unorganised and Organised Manufacturing in India: Potential for Employment Generating Growth," *Economic & Political Weekly*, Vol 39, No 41, pp 4568–80.

Rao, J M (1996): "Manufacturing Productivity Growth: Method and Measurement," *Economic & Political Weekly*, Vol 31, No 44, pp 2927–36.

Raychaudhuri, B (1996): "Measurement of Capital Stock in Indian Industries," *Economic & Political Weekly*, Vol 31, No 21, pp M2–M6.

Rodrik, D (2016): "Premature Deindustrialization," *Journal of Economic Growth*, Vol 21, No 1, pp 1–33.

Roy, S (2016): "Faltering Manufacturing Growth and Employment: Is 'Making' the Answer?" *Economic & Political Weekly*, Vol 51, No 13, pp 35–42.

Sen, K and D K Das (2015): "Where Have All the Workers Gone?" *Economic & Political Weekly*, Vol 50, No 23, pp 108–115.

Szirmai, A and B Verspagen (2015): "Manufacturing and Economic Growth in Developing Countries, 1950–2005," *Structural Change and Economic Dynamics*, Vol 34, pp 46–59.

Thomas J (2019): "How to Revive Indian Manufacturing? On the Need for Industrial Policy," *State of Working India 2019*, Azim Premji University, Bengaluru.

Thomas, J and C Johny (2018): "Labour Absorption in Indian Manufacturing: The Case of the Garment Industry," Centre for Sustainable Employment Working Paper 2018–15, Azim Premji University, Bengaluru.

Vashisht, P (2016): "Creating Manufacturing Jobs in India: Has Openness to Trade Really Helped?" *Journal of Asian Economics*, Vol 42, pp 53–64.

Yusuf, Anam, Dev Nathan, Rashid Amjad, Salim Raihan, Sher Verick and Sunil Chandrasiri (2015): "What Holds Back Manufacturing in South Asia," *Economic & Political Weekly*, Vol 50, No 10, pp 36–45.

## Appendix

1

Dependent Variable: LOG_AGG_EMP
Method: Least Squares with Breaks
Date: 10/21/19 Time: 15:01
Sample: 1983 to 2017
Included observations: 35
Break type: Bai-Perron tests of L+1 vs L sequentially determined breaks
Break selection: Trimming 0.15, Significance level 0.05
Breaks: 1988, 1996, 2006
HAC standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

| Variable | Coefficient | Standard Error | t-Statistic | Probability |
|---|---|---|---|---|
| 1983–87—5 observations | | | | |
| TIME | -0.023096 | 0.000775 | -29.78263 | 0.0000 |
| C | 15.78247 | 0.002161 | 7302.150 | 0.0000 |
| 1988–95—8 observations | | | | |
| TIME | 0.022790 | 0.000980 | 23.24716 | 0.0000 |
| C | 15.57140 | 0.009898 | 1573.142 | 0.0000 |
| 1996–2005—10 observations | | | | |
| TIME | -0.011968 | 0.004345 | -2.754279 | 0.0104 |
| C | 16.12154 | 0.074774 | 215.6027 | 0.0000 |
| 2006–17—12 observations | | | | |
| TIME | 0.039487 | 0.004053 | 9.742092 | 0.0000 |
| C | 15.11947 | 0.123829 | 122.1001 | 0.0000 |
| R-squared | 0.986380 | Mean dependent variable | | 15.97950 |
| Adjusted R-squared | 0.982849 | Standard deviation of dependent variable | | 0.249541 |
| Standard error of regression | 0.032680 | Akaike information criterion | | -3.806468 |
| Sum squared residual | 0.028836 | Schwarz criterion | | -3.450960 |
| Log likelihood | 74.61319 | Hannan-Quinn criterion | | -3.683746 |
| F-statistic | 279.3461 | Durbin-Watson statistic | | 1.871946 |
| Prob (F-statistic) | 0.000000 | | | |

2

Dependent Variable: LOG_AGG_WAGE
Method: Least Squares with Breaks
Date: 10/21/19 Time: 15:09
Sample: 1983 to 2017
Included observations: 35
Break type: Bai-Perron tests of L+1 vs L sequentially determined breaks
Break selection: Trimming 0.15, Significance level 0.05
Breaks: 1988, 1996, 2005
HAC standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth = 4.0000)

| Variable | Coefficient | Standard Error | t-Statistic | Probability |
|---|---|---|---|---|
| 1983–87—5 observations | | | | |
| TIME | 0.044894 | 0.005969 | 7.521629 | 0.0000 |
| C | 10.62113 | 0.018258 | 581.7101 | 0.0000 |
| 1988–95—8 observations | | | | |
| TIME | 0.008344 | 0.002650 | 3.148515 | 0.0040 |
| C | 10.78191 | 0.027050 | 398.5925 | 0.0000 |
| 1996–2004—9 observations | | | | |
| TIME | -0.011940 | 0.002464 | -4.846854 | 0.0000 |
| C | 11.11269 | 0.044680 | 248.7200 | 0.0000 |
| 2005–17—13 observations | | | | |
| TIME | 0.017470 | 0.000499 | 35.02033 | 0.0000 |
| C | 10.44301 | 0.014661 | 712.2827 | 0.0000 |
| R-squared | 0.951409 | Mean dependent variable | | 10.88839 |
| Adjusted R-squared | 0.938812 | Standard deviation of dependent variable | | 0.084420 |
| Standard error of regression | 0.020882 | Akaike information criterion | | -4.702182 |
| Sum squared residual | 0.011774 | Schwarz criterion | | -4.346674 |
| Log likelihood | 90.28819 | Hannan-Quinn criterion | | -4.579461 |
| F-statistic | 75.52310 | Durbin-Watson statistic | | 1.698229 |
| Prob (F-statistic) | 0.000000 | | | |