Employment, Wage and Productivity: Analysis of Trend and Causality in Indian Manufacturing Industries

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Abstract

This paper explores the relationship between labour productivity and wage rate and its implication for employment outcomes in registered manufacturing industries in India. We have analysed the trend behaviour of the time series of employment, productivity and wage, and the causal relation between them in the registered manufacturing industries in India since the early 1970s by taking all industries together. We also have estimated the wage-productivity relationship across the industry groups at 2 digit NIC in a panel data framework for the period 1998-2013, the period reasonably after the initiation of the new industrial policy by the union government of the country. This study finds out the differential effects on employment and wage through productivity growth across different industry groups and provides some serious policy implications in the context labour market flexibility.

1. Introduction

1.1 This paper explores the relationship between labour productivity and wage rate and its implication for employment outcomes in registered manufacturing industries in India. The relationship between wage and productivity has serious policy relevance in recent years in the context of neoliberal reforms as initiated in the developing world. The arguments that the wage growth below productivity growth would increase employment level\textsuperscript{2} are particularly important in current policy debate in the light of high unemployment rates in many developing countries following the neoliberal reforms. Faster productivity growth lifted the living standard of the present day advanced industrialised nations in the process of capitalist development and allowed them to eradicate poverty by any historical standards (DeLong, 2002)\textsuperscript{3}. While the technological innovations and capital-intensive investments were the mainsprings of this productivity growth in the advanced capitalist countries, they are responsible for job destruction, particularly for unskilled workers, in the developing world (ibid). India’s disappointing performance in creating jobs along with high productivity growth in the registered manufacturing sector supports this proposition.

1.2 The employment dynamics for productivity growth, however, has not been clear and it is highly difficult to interpret the productivity growth and employment differential across the globe over the past few decades. Some economies performed better in employment

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\textsuperscript{2}The endogenous growth literature highlights that higher wage growth may be one of the factors stimulating capital investment in new technology. In some variants of these models, higher proportional wages growth as compared to productivity growth leads to lower employment in the long-run because of substitution effects towards capital and away from labour at the firm or industry level.

\textsuperscript{3} Malthus and other nineteenth-century thinkers argued that technological progress and capital accumulation began long before the advent of the industrial revolution, but such technological impulses failed to spark growth of income per-capita because of the scarcity of natural-resource or by diminishing returns to capital. Growth impulses at that time led to increases in populations at a substantial rate that pushed down productivity and living standards to their subsistence level.
growth with dismal productivity performance, while some others performed well in terms of productivity growth without generating employment. The higher productivity can crowd out employment and thereby become a source of unemployment, but the empirical evidences of Europe during the 1970s or United States in the second half of the 1990s do not support it. This may raise the question of a trade-off between employment and productivity growth, and also between employment growth and real wage growth (Gordon 1997).

1.3 In this study we have analysed the trend behaviour of the time series of employment, productivity and wage, and the causal relationship between them in the registered manufacturing industries in India since the early 1970s by taking all industries together. We also have estimated the wage-productivity relationship across the industry groups at 2 digit NIC in a panel data framework for the period 1998-2013, the period reasonably after the initiation of the new industrial policy by the union government of the country. This study finds out the differential effects on employment and wage through productivity growth across different industry groups and provides some serious policy implications in the context labour market flexibility, a part of neoliberal reforms in India.

1.4 The study is organised as follows. Section 2 briefly reviews some empirical studies on wages productivity in industries. Section 3 provides the theoretical views on wage, productivity and employment underlying the empirical analysis presented in the paper. Section 4 discusses the methodology used in this study. Section 5 is a short description of the data used in this study. Section 6 interprets the empirical results. Section 7 concludes.

2. Wage productivity relationship – a review of literature

2.1 Most of the empirical studies on wage-employment relationship through productivity growth are based on macroeconomic data from the developed countries. By analysing the US data for the period 1974-94, Zavodny (1999) observed that stronger labour union is associated with smaller increase in wage-productivity gap. In this study the increase in real wage and workers’ compensation is matched more closely the productivity gains in industries where trade unions are more active. Harrison (2009) observed that the widening gap between productivity and real earnings is significantly related to rising  

Any given rate of output growth can be achieved either with high productivity growth and low employment growth, or, with low productivity growth and high employment growth. Thus, higher productivity through technological advancement leads to a decline in employment. Employment in a particular sector will fall if that sector experiences rapid productivity growth and faces stagnant demand at the same time.

5 The phase of rising unemployment coincided exactly with a sharp slowdown of productivity growth in the 1970s in most of the European countries. Similarly, substantial acceleration of productivity growth in the United States coincided with low unemployment rate as recorded very recently. In the second half of the 1990s, the United States experienced a marked acceleration of productivity growth through the rapid expansion of the information and communication technologies. This productivity growth in no way put an end to the employment growth.

6 With labour market flexibility, labour laws are increasingly relaxed in favour of the employers. The firms having one thousand workers do not require government’s permission for laying anyone off.
earnings inequality. Lopez and Silva (2011) found that wage increases have exceeded productivity growth for permanent workers, while the opposite is true for temporary workers because of their low bargaining power by analysing a macroeconomic panel of OECD countries between 1985 and 2007. Elgin et al. (2012) have analyzed wage-productivity gap in the context to Turkish manufacturing industries over the period 1950-2009 in terms of inflation, capital deepening, size of the informal sector and taxes. The bargaining power of workers is one of the crucial determinant in explaining the gap in their study.

2.2 The empirical study on the similar issues is very much limited in India mainly because of non-availability of appropriate data. Bhalotra (1998) had tested empirically the equality between the wage elasticity of output and employment elasticity of output for the Indian labour market by following optimality rule. Pal (2004) examined the effect of technological change on wage differential in Indian manufacturing using the data from National Sample Survey Office for the years 1983-84, 1987-88 and 1993-94 and observed that introduction of new technology worked against the educated workers. Goldar et al. (2005) revealed a positive relationship between labour productivity and wage rate, but the marginal effect of labour productivity on wage rate was very low. Bhattachary et al. (2011) investigated the long-run relationship between labour productivity and real wages for Indian manufacturing sector at two digit level of disaggregation by using ASI data for the period 1973-74 to 1999-2000, and found long run relationship between labour productivity and wage as well as between productivity and employment. They observed that flexible labour market had a significant influence on productivity, employment and real wages in Indian manufacturing industries. Das et al. (2015) observed a mismatch between output and employment growth with a significant regional disparity in India. The present study is an extension of Das et al. (2015) by taking industry groups in the registered sector at two digit level of disaggregation.

3. Theoretical views

3.1 Theoretically, wage is closely related to labour productivity. The neoclassical model suggests that labour demand would increase if productivity per unit of labour input increased at a given wage rate. Given a fixed labour supply, the increased labour demand would result in higher pay, until a new profit-maximising equilibrium is reached at which wage rate again equals marginal productivity. In the medium and long-run, firms can alter not only their employment levels, but also their capital stock. As a result, changes in wages or interest rates can lead firms to substitute labour for capital or vice versa. Thus, while in the short-run wage increases have only a scale effect, in the medium- and long-run they result in both scale and substitution effects. At exogenously-given price level on goods markets under perfect competition, both the scale and the substitution effects of an increase in wages on labour demand are unambiguously negative. In practice, even though the assumptions of economic theory are not always satisfied\(^7\), this kind of relationship has been used to justify wage-setting rules.

3.2 Wages are important in determining employment, but, in Keynesian reasoning, wages and also employment in the short run are determined by the real effective demand,
not by the productivity. In the medium-term, however, labour market equilibrium strongly depends on the relation of real wage aspirations to aggregate labour productivity. The long-term concept of an equilibrium growth path takes into account the endogenous response of capital formation to the evolution of both employment and productivity. Modern developments in the theory of endogenous growth open a number of avenues along which links between productivity growth and employment growth can be investigated. In this theoretical framework, capital includes not just the sum of all tangible physical assets required for the production of goods and services, but also the non-tangible investments that generate productive payoffs to the economy, in particular human capital (education) and know-how (research and development).

3.3 The efficiency wage theory as developed in Shapiro and Stiglitz (1984) rejects the premise that wages are associated to the marginal productivity of workers under perfect competition. In contrast, this theory argues that paying higher-than-market wages is a rational choice for firms to get more productive effort from workers. In this framework wages are set to get a specific productivity in the presence of labour market institutions like unemployment benefits. In this sense, efficiency wage models imply a reverse causality from wage to productivity. According to this model, an increase in labour market flexibility or a reduction of unemployment benefits reduces the wages that increase employment levels.

4. Data

4.1 The data used in this study are obtained from the Annual Survey of Industry (ASI), the main data source for registered manufacturing industries in India, published by the Central Statistical Office (CSO) under the Ministry of Statistics and Programme Implementation of the Union Government of India. The ASI distinguishes between the census sector which corresponds to the larger units and the sample sector which consists of units below the size that qualifies a factory as a member of the census sector. The coverage of the factory units in ASI under census sector was changed in 1997-98. In carrying out empirical exercise we have used ASI data from 1998 to 2013 simply because the major change in national industrial classification (NIC) appeared in 1998-99. In constructing balanced panel 22 manufacturing groups at 2 digit classification of NIC 2004 are taken as cross section units as shown in Table A1 in appendix. By using the concordance table provided by the CSO we make NIC 98 and NIC 04 comparable with NIC 08.

4.2 In this study, gross value added in real terms is used as output variable. Among the input variables, gross value of plant and machinery is used as capital input. In ASI, it includes the book value of newly installed plants and machinery and the approximate value of rented in plants and machinery without adjusting depreciation. The ASI data contain number of workers and employees separately and the corresponding annual wages and emoluments. The real values of the variables are calculated by deflating the nominal values by the consumer price index for industrial workers. Two distinct types of labour inputs, namely, manufacturing workers and non-manufacturing workers (supervisors and engineers) are used in this study. Productivity is measured by observed gross value added per worker. The relevant indicator to capture wage growth used in this study is the wage share as a percentage of gross value added.
5. Methodology

5.1 We analyse, first, the data generating process (DGP) or the trending behaviour of the series before estimating the relationship between the time series variables of wage, productivity and employment taken from all manufacturing industries in the registered sector. While the most widely used model to analyse the stochastic behaviour of economic time series is based on Dickey and Fuller (1979), we have carried out unit root test using the methodology developed in Zivot and Andrews (1992) after locating structural break, if any, by following Andrews (1993)\(^8\).

5.2 Zivot and Andrews (1992) considered three models of structural break under the null and alternative hypotheses to test for a unit root.

A change in the level of the series (intercept):

\[
\Delta Y_t = \phi_0 + \rho \Delta Y_{t-1} + \beta t + \eta_1 D_p + \eta_2 D_L + \sum_{j=1}^{k} \gamma_j \Delta Y_{t-j} + \varepsilon_t \tag{1}
\]

A change in the rate of growth (slope):

\[
\Delta Y_t = \phi_0 + \rho \Delta Y_{t-1} + \beta t + \eta_3 D_T + \sum_{j=1}^{k} \gamma_j \Delta Y_{t-j} + \varepsilon_t \tag{2}
\]

A change in both intercept and slope:

\[
\Delta Y_t = \phi_0 + \rho \Delta Y_{t-1} + \beta t + \eta_1 D_p + \eta_2 D_L + \eta_3 D_T + \sum_{j=1}^{k} \gamma_j \Delta Y_{t-j} + \varepsilon_t \tag{3}
\]

The intercept dummy \(D_L\), pulse dummy \(D_p\) and slope dummy \(D_T\) are defined by assuming \(T_b\) as the break point as

\[D_L = 1, \text{if } t > T_b\]
\[= 0, \text{if } t \leq T_b\]

\(^8\)The Augmented Dickey-Fuller (ADF) form of the model with lag length \(p\) is

\[
\Delta Y_t = \alpha + \rho \Delta Y_{t-1} + \eta_1 \Delta Y_{t-1} + \eta_2 \Delta Y_{t-2} + \ldots + \eta_{p-1} \Delta Y_{t-p+1} + \beta T + \varepsilon_t
\]

The ADF test sometimes gives a wrong signal, particularly when the t-statistic is very close to its critical value because of the presence of structural break. An important development in the literature about unit roots in macroeconomic time series is provided by Perron (1989), who presented a model to test for unit roots in the presence of an exogenous break in the series. In this case, the basic assumption is that outlying events can be separated from the noise function and be modeled as one-time changes in the deterministic part of the time series model. The importance of Perron’s work lies in the fact that unit root tests are biased toward non-rejection of the unit root null when there are structural breaks in the series. If a series contains any structural break, the ADF test will be biased in favour of non-rejecting the null hypothesis of the presence of unit root. A time series can also appear to exhibit unit root behaviour owing to the presence of structural break. Perron’s work has received some criticism in the literature, based on the fact that the breaking point is exogenously selected.
5.3 Andrews (1993) derived the asymptotic distribution of the likelihood ratio (LR), Wald (W) and Lagrange Multiplier (LM) tests for one-time structural change with an unknown break point. In the case of a simple AR(1) model, the Andrews’ three tests are based on the following specification: The stochastic process for the whole period is described as

\[ y_t = \phi y_{t-1} + \epsilon_t, \quad t=1,2,\ldots,T \quad (4) \]

Let we allow a single break at point \( T_b \). The behaviour of \( y_t \) before and after break are specified respectively as

\[ y_t = \phi_1 y_{t-1} + \epsilon_{1t}, \quad \text{for } t=1,2,\ldots,T_b \quad (5) \]

and

\[ y_t = \phi_2 y_{t-1} + \epsilon_{2t}, \quad \text{for } t=T_b+1, T_b+2\ldotsT \quad (6) \]

In testing for structural break, the null hypothesis is

\[ H_0 : \phi_1 = \phi_2 \]

Under the null of no structural change we estimate this equation by OLS. Let \( \hat{\epsilon}_t \), \( \hat{\epsilon}_{1t} \), and \( \hat{\epsilon}_{2t} \) be the estimated residual for the whole period, the period before break and the period after break respectively.

Let we define \( S = \hat{\epsilon}_t', \hat{\epsilon}_t, S_1 = \hat{\epsilon}_{1t}', \hat{\epsilon}_{1t} \) and \( S_2 = \hat{\epsilon}_{2t}', \hat{\epsilon}_{2t} \) as the sum of squared residuals for equations (4), (5) and (6) respectively.

The supremum values of the test statistics are

\[ Sup\text{LR} = \max_{\pi} T \left( \frac{S}{S_1 + S_2} \right) \]

\[ Sup\text{W} = \max_{\pi} T \left( \frac{S - S_1 - S_2}{S_1 + S_2} \right) \]
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\[ SupLM = \max_{\pi} T \left( \frac{S - S_1 - S_2}{S} \right), \] Here, \( \pi = \frac{T_b}{T} \)

5.4 It is customary to take \( \pi \in (0.15, 0.85) \), so that breaks toward the ends are ruled out. The intuition behind this test is to compare the maximum sample test with what could be expected under the null hypothesis of no break. The test statistic a function of the sample statistics computed over a range of possible break dates. Andrews (1993) recommended a symmetric trimming of 15 percent when the researcher has no other information on good trimming values.

5.5 In carrying out unit root test with the possibility of break we have chosen lag length \((k)\) in equations (1), (2) and (3) by following minimum AIC rule. The null hypothesis to be tested is

\[ H_0 : \rho = 0, \beta = 0 \]

Against the alternative

\[ H_1 : \rho < 0, \beta \neq 0 \]

5.6 The null hypothesis in the three models is \( \rho = 0 \), where all the series contains a unit root with a drift that excludes any structural break, while the alternative hypothesis \( \rho < 0 \) where all the series having a trend stationary process with a one-time break which occurring at an unknown point in time. Model (1) permits an exogenous change in the level of series, model (2) allows an exogenous change in the slope of the trend function and model (3) admits both change in the level and the slope of the trend function. The rejection of \( H_0 \) implies that the series follows trend stationary process (TSP) exhibiting deterministic trend along with stationary fluctuations around this trend. If on the other hand \( H_0 \) is not rejected the series belongs to the class difference stationary process (DSP) exhibiting stochastic trend. The presence of stochastic trend has a serious macroeconomic implication: the effect of external shock on the time series of employment, for example, has been long lasting.

5.7 After examining the stochastic behaviour of the time series variables as mentioned above we have applied cointegration theory developed in Engle and Granger (1987) to estimate the meaningful relationship between them. The Johansen (1995) methodology is used to test for the existence of cointegration. This test is based on the estimation of the ECM by the maximum likelihood, under various assumptions about the trend or intercepting parameters, and the number \( k \) of cointegrating vectors.

5.8 To capture the unobserved heterogeneity, mostly technological heterogeneity, by industry groups in wage-productivity relationship the study uses panel data econometric model. The fixed effect model is selected on the basis of Housman (1978) test. Fixed effect explores the relationship between predictor and outcome variables within an industry group.

\(^9\)Two variables are cointegrated if each is non-stationary but a linear combination of the two is stationary. For the validity of the relationship in a causal sense the variables should be cointegrated of order one, or else they will be drifting further apart over time, in which case the regression relationship between them may not be meaningful and indeed becomes spurious.
Each industry group has its own individual characteristics that may or may not influence the predictor variables. Instead of demeaning the data, one could include a dummy for every $i$:

$$y_{it} = \beta_0 + \mu_i + \beta' x_{it} + \varepsilon_{it}$$

$$= \alpha_i + \beta' x_{it} + \varepsilon_{it}$$

(7)

In vector form,

$$y_i = e\alpha_i + X_i\beta + \varepsilon_i$$

(8)

Here, $e' = [1 \ 1 \ \ldots \ \ 1]$ $\alpha_i$ is a $1 \times 1$ scalar constant representing the effects of those variables characterising the $i$th individual in more or less the same fashion over time. The error term, $\varepsilon_{it}$, represents the effects of the omitted variables that will change across the individual units and time periods. We assume that $\varepsilon_{it}$ is uncorrelated with $x_{it}$ and can be characterized by an independently identically distributed random variable with mean zero and variance $\sigma^2$.

The OLS estimators of $\alpha_i$ and $\beta_i$, called the least-squares dummy-variable (LSDV) estimator, are obtained by minimizing

$$S_e = \sum_{i=1}^{N} e_i'e_i = \sum_{i=1}^{N} (y_i - e\alpha_i - X_i\beta)'(y_i - e\alpha_i - X_i\beta)$$

(9)

5.9 We get estimates for the $\mu_i$ which may be of substantive interest. The least square dummy variable model (LSDV) provides a good way to understand fixed effects. The effect of $x$ is mediated by the differences across industry groups. By adding the dummy for each industry group we are estimating the pure effect of $x$ (by controlling for the unobserved heterogeneity). Each dummy is absorbing the effects particular to each industry group.

6. Empirical Findings

6.1 Analysis of trend

6.1.1 The trend pattern of employment, output and productivity as defined above could be visualized, although grossly, if we plot the time series of these variables. The time paths of the series are displayed in Figure 1. The gap between total persons engaged and number of workers represents employment in managerial and technical activities in the factories. We observe that the gap remains roughly constant over time. The employment of all types of workers declined since the mid-1990s and continued to show a negative growth till the early 2000s; however, the employment in registered manufacturing improved exhibiting positive trend thereafter. With liberalisation, labour laws are increasingly relaxed in favour of the employers. The companies having one thousand workers do not require government’s permission for laying anyone off. Many big companies have reduced their labour force. For example, Tata Engineering and Locomotive has reduced its staff by 10,000 (29 per cent) between 1996 and 2000. Similarly Mahindra and Mahindra, Bajaj Auto, and Associated Cement Companies reduced the labour force by 30 per cent during the same period.
6.1.2 Total manufacturing output started to grow since the late 1990s after a period long stagnation. Employment growth increased because of output growth. Thus, the registered manufacturing sector in India experienced a positive output growth by displacing labour during the late 1990s and early 2000s. The visual inspection of the movements of real wage rate and labour productivity suggests that there has been a significant gap between them, and the gap widened gradually since the late 1990s. Productivity grew at a much higher rate than the growth in wage rate since 1998. Although it is difficult to show directly with ASI data, one of the reasons for the rising gap between productivity and wage rate may be the decline in bargaining power of the worker’s union because of labour market flexibility. However, this simple graphical presentation shown in Figure 1 indicates that output growth in registered manufacturing was led by productivity growth during the late 1990s and early 2000s.

6.1.3 We analyse the trend behaviour of labour employment, real values of ex-factory output, gross value added, wage per worker and labour productivity during the period 1975-2014 by allowing structural break which may appear endogenously in the series. The trend growth rates of these variables are estimated by taking log linear trend model over the whole period and the sub-periods after finding out structural break by applying the methodology developed in Andrews (1993). The estimated growth rates for the overall period are shown in column 1 of Table 1. Both output and gross value added grew at significantly higher rates than the growth rates of labour (both worker and non-worker). Labour productivity also grew at a higher rate than wage rate.

6.1.4 In terms of supremum Wald statistic in Andrew’s (1993) test for unknown break point we have located break points in the trend paths as shown in the last column in Table 1. After identifying structural break in the trend path we have estimated growth rates separately for the periods before break and after break. The growth rates of the major indicators of registered manufacturing as shown in Table 1 increased markedly excepting for the growth of wage rate. The trend wage growth declined significantly after 1998, while labour productivity increased from its negative value to 6.8 percent. Growth rates of output, value added in real terms and labour productivity were negative during the period before structural break in their trend paths. The structural break in the underlying productivity trend is potentially an important source of disturbances in labour markets.

6.1.5 The stochastic behaviour of the time series mentioned above is examined by carrying out ADF unit root test in the presence of structural break by following the methodology developed in Zivot and Andrews (1992). By following the minimum AIC rule, the optimum lag length is found to be 1 for all the series used in this study. The estimated test statistics of the variables in log form both at levels and first differences are shown in Table 2. We have found that all the variables described above are integrated of order 1 exhibiting stochastic trend along with the deterministic trends. The presence of stochastic trend has serious macroeconomic implications: the effects of external shocks, industrial policy for example, will be long lasting.

6.2 Causality between wage rate and productivity

6.2.1 We have shown in Table 2 that the time series of employment, wage rate and productivity are integrated of order 1. Therefore, they will exhibit similar type of stochastic trend and by Engle-Granger’s (1987) theorem they may be cointegrated. To investigate the number of cointegration relations between the series we have carried out Johansen (1995)
likelihood ratio (LR) test based on Gaussian assumptions and its modifications. The estimated
eigen values and trace statistics are shown in Table 3. By comparing trace statistics with
the critical values at 5 percent level we fail to reject the no cointegration null between
employment, wage rate and productivity. Thus, there is no significant causal relation between
employment, wage rate and productivity in registered manufacturing industry in India.
Wage rate is not determined by following the productivity rule as suggested in the theory
of firms’ behaviour. In many cases wages are fixed by the administration in an arbitrary
manner.

6.3 Wage productivity relationship by industry groups: panel data estimation

6.3.1 By analysing data for all manufacturing industry in the registered sector we have
shown that wage rate is not causally related to labour productivity. In this section we are
looking into the wage productivity relationship by taking unobserved heterogeneity of the
manufacturing groups at 2 digit NIC level in a panel data framework over the period 1998-
2014. Industries differ in terms of technology, efficiency, skill and inputs use pattern. Many
firm specific characters, like firms’ efficiency, are unobserved. We have taken 22
manufacturing industry groups as shown in Table A1 in the appendix. The Housman test
confirms that the fixed effect error component model is best fitted in the data set. Thus, the
relationship is estimated by applying fixed effect panel regression model. To estimate industry
specific effects on wage productivity relationship we have estimated fixed effects in a frame
of least square dummy variable (LSDV) model. We have constructed 21 dummy variables
(Di, i denotes NIC08 at 2 digit) corresponding to 21 industry groups to avoid dummy
variable trap. In our estimate the manufacturing of furniture (36) is taken as the base industry
group. Wage rate and labour productivity both in logarithmic form, log(w) and log(p), are
used as dependent variable and independent variables respectively. We need to incorporate
interaction dummies, Di_log(p), to find out the industry specific differential effects of
productivity on wage rate.

6.3.2 The estimated coefficients are shown in Table 4. The coefficient for log(p) measures
the impact of labour productivity on wage rate in the manufacturing of furniture. The
coefficient is positive and statistically significant at less than 1 percent level implying that
labour productivity has positive effect on wage rate in this industry group. The coefficients
for interaction dummies measure the differential effects of productivity on wage rate in
different industry groups with respect to the effect observed in furniture industry. The
effect is highly significant and found to be greater in the manufacturing of food products
(15), tobacco products (16), leather (19), wood products (20) and rubber (25) as compared to
the effect of productivity on wage rate in furniture industry. But, the productivity effect on
wage is lower in the manufacturing of machinery (29), motor vehicles (34) and transport
equipment (35) than the effect in furniture industry. There is no significant relationship
between wage rate and productivity in many manufacturing industries like petroleum (23),
chemicals (24), paper (21), printing (22), fabricated metals (28) and the manufacturing of
electrical equipment (31).

6.4 Relation between employment and wage-productivity gap

6.4.1 It is argued that wage rate increases at lower proportional rate than the rate of
productivity growth that causes wage-productivity gap. The higher gap enhances
employment growth. In this study the relationship between wage-productivity gap and
employment is estimated by allowing heterogeneous effect across the manufacturing groups
in the ASI sector. By taking number of workers (L) as dependent variable and wage-productivity gap (G) as independent variable, both in logarithmic terms, we have estimated the LSDV model where the 22 manufacturing groups are differentiated by 21 group dummies as defined above. Here, again the manufacturing of furniture is taken as the base industry group. We measure wage-productivity gap as the ratio of labour productivity to wage rate. Here, we have constructed the dummy variables interacted with log(G) to estimate industry specific differential effect of wage-productivity gap on employment.

6.4.2 Table 5 presents the estimated results based on this LSDV model. The coefficient for log(G) measures the effect of wage-productivity gap on employment. It is positive and significant at less than 5 percent level (as indicated by the P-value 0.038) implying that wage-productivity gap has employment enhancing effect in furniture manufacturing. The employment enhancing effect is higher than the effect in furniture industry in wood products industry (20), printing (22), computer (30), medical equipment (33) and transport equipment (35). But, in many industries like food products (15), tobacco products (16), textiles (17), leather (19), paper products (21), the wage-productivity gap has negative significant effect on employment. It might be possible because increase in productivity may lead to less labour requirement to produce the same level of output. In some cases the fall in wage rate in particular industry group may be the cause of transference of workers from this industry group to some other industries. In some industries like apparel (18), petroleum products (23), television (32), the effect of wage-productivity gap on employment is not statistically significant.

7. Conclusions

7.1 In this paper we have estimated the relationship between labour productivity and wage rate and its implication for employment outcomes in registered manufacturing industries in India. The study analyses the trend behaviour of the time series of employment, productivity and wage, and the causal relationship between them in the registered manufacturing industries in India. The links between wage, productivity and employment growth as discussed in this paper are central to the overarching theme of poverty reduction and productivity in the ILO World Employment Report 2004.

7.2 The study observes that employment of all types of workers declined since the mid-1990s and continued to show a negative growth till the early 2000s. There has been a significant gap between wage rate and labour productivity, and the gap widened gradually since the late 1990s. Productivity grew at a much higher rate than the growth in wage rate since 1998. The trend wage growth declined significantly after 1998, while labour productivity increased from its negative value to 6.8 percent.

7.3 We also observe no significant causal relation between employment, wage rate and productivity in registered manufacturing industry in India. Wage rate is not determined by following the productivity rule as suggested in the theory of firms’ behaviour. In many cases wages are fixed by the administration in an arbitrary manner. We have estimated the wage productivity relationship by taking unobserved heterogeneity of the manufacturing groups at 2 digit NIC level in a panel data framework over the period 1998-2014. We observe no significant relationship between wage rate and productivity in many manufacturing industries, while in some industries positive significant relation is observed.
The relationship between wage growth and productivity growth has serious policy relevance in recent years in the context of neoliberal reforms as initiated in the developing world. The argument that wages increase at lower proportional rate than the rate of productivity growth will increase employment levels are particularly important in current policy debate, in the light of high unemployment rates in many developing countries following the neoliberal reforms. In this study we observe that in many industries the wage-productivity gap has negative significant effect on employment.

References


Figure 1: Time Paths of Employment, Output and Productivity

![Time Paths of Employment, Output and Productivity](image)

Source: ASI time series data, CSO

Table 1: Trend Growth Rates: 1975-2014

<table>
<thead>
<tr>
<th>Variables</th>
<th>Growth rate for overall period</th>
<th>Growth rate before break</th>
<th>Growth rate after break</th>
<th>Break year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing workers</td>
<td>1.4</td>
<td>1.3</td>
<td>4.7</td>
<td>1999</td>
</tr>
<tr>
<td>Nonmanufacturing workers</td>
<td>1.4</td>
<td>2.0</td>
<td>4.5</td>
<td>1999</td>
</tr>
<tr>
<td>Ex-factory real output</td>
<td>4.3</td>
<td>-0.5</td>
<td>11.0</td>
<td>1997</td>
</tr>
<tr>
<td>Real gross value added</td>
<td>3.3</td>
<td>-0.6</td>
<td>9.3</td>
<td>1997</td>
</tr>
<tr>
<td>Real wage rate</td>
<td>0.9</td>
<td>2.5</td>
<td>0.7</td>
<td>1998</td>
</tr>
<tr>
<td>Labour productivity</td>
<td>2.9</td>
<td>-1.8</td>
<td>6.8</td>
<td>1998</td>
</tr>
</tbody>
</table>

Note: Growth rates are estimated by applying log linear trend model.
Source: Authors' estimate with ASI time series data

Table 2: Unit Root Test with Break

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF Test (Test Statistic, P-value)</th>
<th>ADF Test (1st diff) (Test Statistic, P-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real wage rate</td>
<td>-2.22, 0.033</td>
<td>-6.478, 0.000</td>
</tr>
<tr>
<td>Productivity</td>
<td>-1.1, 0.28</td>
<td>-4.429, 0.000</td>
</tr>
<tr>
<td>Real output</td>
<td>-0.31, 0.757</td>
<td>-4.875, 0.000</td>
</tr>
<tr>
<td>Real gross value added</td>
<td>-0.69, 0.492</td>
<td>-5.13, 0.000</td>
</tr>
<tr>
<td>Manufacturing workers</td>
<td>-0.97, 0.34</td>
<td>-4.987, 0.000</td>
</tr>
<tr>
<td>Nonmanufacturing workers</td>
<td>-0.93, 0.32</td>
<td>-4.358, 0.000</td>
</tr>
</tbody>
</table>

Source: As for Table 1
Table 4: Estimated Coefficients of Wage Productivity Relation by 2-Digit Industry Groups: 1998-2013

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.09</td>
<td>-4.17</td>
<td>0.000</td>
</tr>
<tr>
<td>log(p)</td>
<td>0.29</td>
<td>9.73</td>
<td>0.000</td>
</tr>
<tr>
<td>D15_log(p)</td>
<td>0.26</td>
<td>7.89</td>
<td>0.000</td>
</tr>
<tr>
<td>D16_log(p)</td>
<td>0.20</td>
<td>5.91</td>
<td>0.000</td>
</tr>
<tr>
<td>D17_log(p)</td>
<td>0.07</td>
<td>2.04</td>
<td>0.042</td>
</tr>
<tr>
<td>D18_log(p)</td>
<td>0.07</td>
<td>2.04</td>
<td>0.041</td>
</tr>
<tr>
<td>D19_log(p)</td>
<td>0.12</td>
<td>3.61</td>
<td>0.000</td>
</tr>
<tr>
<td>D20_log(p)</td>
<td>0.24</td>
<td>7.09</td>
<td>0.000</td>
</tr>
<tr>
<td>D21_log(p)</td>
<td>0.02</td>
<td>0.43</td>
<td>0.669</td>
</tr>
<tr>
<td>D22_log(p)</td>
<td>0.01</td>
<td>0.39</td>
<td>0.698</td>
</tr>
<tr>
<td>D23_log(p)</td>
<td>-0.02</td>
<td>-0.35</td>
<td>0.723</td>
</tr>
<tr>
<td>D24_log(p)</td>
<td>-0.06</td>
<td>-1.16</td>
<td>0.248</td>
</tr>
<tr>
<td>D25_log(p)</td>
<td>0.10</td>
<td>2.51</td>
<td>0.012</td>
</tr>
<tr>
<td>D26_log(p)</td>
<td>0.07</td>
<td>1.93</td>
<td>0.054</td>
</tr>
<tr>
<td>D27_log(p)</td>
<td>-0.06</td>
<td>-1.56</td>
<td>0.120</td>
</tr>
<tr>
<td>D28_log(p)</td>
<td>0.00</td>
<td>-0.04</td>
<td>0.965</td>
</tr>
<tr>
<td>D29_log(p)</td>
<td>-0.09</td>
<td>-2.34</td>
<td>0.019</td>
</tr>
<tr>
<td>D30_log(p)</td>
<td>0.28</td>
<td>2.47</td>
<td>0.014</td>
</tr>
<tr>
<td>D31_log(p)</td>
<td>-0.02</td>
<td>-0.45</td>
<td>0.653</td>
</tr>
<tr>
<td>D32_log(p)</td>
<td>-0.10</td>
<td>-2.21</td>
<td>0.027</td>
</tr>
<tr>
<td>D33_log(p)</td>
<td>-0.08</td>
<td>-2.27</td>
<td>0.023</td>
</tr>
<tr>
<td>D34_log(p)</td>
<td>-0.07</td>
<td>-2.12</td>
<td>0.035</td>
</tr>
<tr>
<td>D35_log(p)</td>
<td>-0.26</td>
<td>-7.79</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Note: D15 =1 for food products, D16=1 for tobacco, D17 =1 for textiles, D18= 1 for apparel, D19=1 for leather, D20 =1 for wood products, D21 =1 for paper products, D22=1 for printing, D23=1 for petroleum, D24=1 chemical, D25=1 for rubber, D26=1 for nonmetal, D27=1 for basic metal, D28=1 for fabricated metal, D29=1 for machinery, D30=1 for computer, D31=1 for electrical equipment, D32=1 for television, D33=1 for medical equipment, D34=1 for motor vehicles, D35=1 for transport equipment

Source: As for Table 1
Table 5: Relation between Employment Growth and Wage-Productivity Gap

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Coefficients</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>11.01</td>
<td>0.000</td>
</tr>
<tr>
<td>log(G)</td>
<td>0.41</td>
<td>0.038</td>
</tr>
<tr>
<td>D15_log(G)</td>
<td>-1.41</td>
<td>0.000</td>
</tr>
<tr>
<td>D16_log(G)</td>
<td>-1.61</td>
<td>0.000</td>
</tr>
<tr>
<td>D17_log(G)</td>
<td>-1.93</td>
<td>0.000</td>
</tr>
<tr>
<td>D18_log(G)</td>
<td>-0.03</td>
<td>0.900</td>
</tr>
<tr>
<td>D19_log(G)</td>
<td>-0.64</td>
<td>0.013</td>
</tr>
<tr>
<td>D20_log(G)</td>
<td>0.64</td>
<td>0.028</td>
</tr>
<tr>
<td>D21_log(G)</td>
<td>-1.23</td>
<td>0.000</td>
</tr>
<tr>
<td>D22_log(G)</td>
<td>0.49</td>
<td>0.073</td>
</tr>
<tr>
<td>D23_log(G)</td>
<td>-0.19</td>
<td>0.487</td>
</tr>
<tr>
<td>D24_log(G)</td>
<td>-0.43</td>
<td>0.174</td>
</tr>
<tr>
<td>D25_log(G)</td>
<td>-1.17</td>
<td>0.000</td>
</tr>
<tr>
<td>D26_log(G)</td>
<td>-0.99</td>
<td>0.000</td>
</tr>
<tr>
<td>D27_log(G)</td>
<td>-1.07</td>
<td>0.000</td>
</tr>
<tr>
<td>D28_log(G)</td>
<td>-1.11</td>
<td>0.000</td>
</tr>
<tr>
<td>D29_log(G)</td>
<td>-0.89</td>
<td>0.001</td>
</tr>
<tr>
<td>D30_log(G)</td>
<td>2.30</td>
<td>0.058</td>
</tr>
<tr>
<td>D31_log(G)</td>
<td>0.19</td>
<td>0.410</td>
</tr>
<tr>
<td>D32_log(G)</td>
<td>-0.03</td>
<td>0.903</td>
</tr>
<tr>
<td>D33_log(G)</td>
<td>0.85</td>
<td>0.000</td>
</tr>
<tr>
<td>D34_log(G)</td>
<td>-0.35</td>
<td>0.134</td>
</tr>
<tr>
<td>D35_log(G)</td>
<td>0.49</td>
<td>0.021</td>
</tr>
</tbody>
</table>

Note: D15 = 1 for food products, D16 = 1 for tobacco, D17 = 1 for textiles, D18 = 1 for apparel, D19 = 1 for leather, D20 = 1 for wood products, D21 = 1 for paper products, D22 = 1 for printing, D23 = 1 for petroleum, D24 = 1 chemical, D25 = 1 for rubber, D26 = 1 for nonmetal, D27 = 1 for basic metal, D28 = 1 for fabricated metal, D29 = 1 for machinery, D30 = 1 for computer, D31 = 1 for electrical equipment, D32 = 1 for television, D33 = 1 for medical equipment, D34 = 1 for motor vehicles, D35 = 1 for transport equipment.

Source: As for Table 1

Appendix


<table>
<thead>
<tr>
<th>NIC</th>
<th>Industry group</th>
<th>NIC</th>
<th>Industry group</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>Food products and beverages</td>
<td>26</td>
<td>Other non-metallic mineral products</td>
</tr>
<tr>
<td>16</td>
<td>Tobacco products</td>
<td>27</td>
<td>Basic metals</td>
</tr>
<tr>
<td>17</td>
<td>Textiles</td>
<td>28</td>
<td>Fabricated metal products</td>
</tr>
<tr>
<td>18</td>
<td>Wearing apparel</td>
<td>29</td>
<td>Machinery and equipment</td>
</tr>
<tr>
<td>19</td>
<td>Leather</td>
<td>30</td>
<td>Office, accounting and computing machinery</td>
</tr>
<tr>
<td>20</td>
<td>Wood and wood products</td>
<td>31</td>
<td>Electrical machinery</td>
</tr>
<tr>
<td>21</td>
<td>Paper and paper product</td>
<td>32</td>
<td>Radio, television and communication equipment</td>
</tr>
<tr>
<td>22</td>
<td>Publishing and printing</td>
<td>33</td>
<td>Medical and optical instruments</td>
</tr>
<tr>
<td>23</td>
<td>Coke and refined petroleum products</td>
<td>34</td>
<td>Motor vehicles</td>
</tr>
<tr>
<td>24</td>
<td>Chemical and chemical products</td>
<td>35</td>
<td>Other transport equipment</td>
</tr>
<tr>
<td>25</td>
<td>Rubber and plastic products</td>
<td>36</td>
<td>Furniture</td>
</tr>
</tbody>
</table>