CHAPTER SEVEN

PRODUCTIVITY CONVERGENCE IN MANUFACTURING SECTOR ACROSS INDIAN STATES

7.1. Introduction

It has been well recognized that productivity is one of the basic indicators of economic development and as an important tool for the analysis of economic and social problems. Productivity has been receiving increasing attention at the highest level, since it carries a strong connotation of workers efficiency in popular thinking. Since productivity growth is also primarily driven by technological change, vast number of studies relating to cross-country convergence (Baumol 1986, Bernard and Jones 1996a, Dollar and Wolff 1988, Mulder and Groot 2003) show that productivity differences is due to the existence of different technology levels among countries. By analyzing productivity convergence they aimed to gain insight into the potential role of international technology flows in determining cross-country productivity differentials.

Since technological change is the main driving force behind economic growth, the issue of labour or total factor productivity convergence obviously bears important implications for the national welfare distribution. The productivity convergence analysis will help the government to identify whether the manufacturing industries, which are located in poorer states, are converging towards the rich states or not. If the poorer states 'catch up' with the rich states in terms of productivity then it will increase the inter-state competitiveness. As a result, it will have a positive impact on the economy in terms of export promotion and employment generation.

Therefore, the present chapter addresses a key issue in understanding long run productivity performance i.e. whether the process of economic growth tends to involve reductions in productivity differences among states, for example, due to capital accumulation or technology transfers. In the previous chapter, we found a disparity in labour productivity across the sates. Therefore, the major question of this chapter deals with several issues. First, whether there is a significant difference in labour productivity
across the states? Second, whether cross-state productivity differences are persistent or whether they tend to decline over time? Third, what happens to the labour productivity convergence results, when we are relaxing the assumption of steady state growth path? Fourth, what happens to the labour productivity convergence at two digits disaggregates level within manufacturing sector?

In this chapter, we use the partial labour productivity (per capita output) for the convergence analysis. Even if some of the productivity studies literature say that Total Factor Productivity (TFP) is the superior measure than partial labour productivity, but it may not be true always. Both the productivity measures are having their own importance as both the concepts serve different purposes. If we are looking into how efficiently all the input factors of production are utilized then Total Factor Productivity (TFP) is important. “But it is labour productivity that comes closer to the issue of the economy’s ability to increase living standard”.¹ Second reason for not choosing TFP at state level is the issue of measuring capital stock. Recently, some of the scholars in India have measured the TFP at the state level. But it is very difficult to accept the measurement procedure of capital stock, as it is still a debatable issue today.

The chapter is organized as follows. In the section 2 we provide the analytical framework to address the notion of convergence. In section 3 we use the panel data approach to estimate the conditional convergence of labour productivity. Data source and measurement of the variables are presented in the section 4. Estimation results and their interpretation are presented in section 5. In section 6, we use time-series techniques to study the convergence analysis. The last section contains some concluding remarks.

7.2. Analytical Framework

In this section, first we discuss the concept of the convergence in the neoclassical growth model. Then, we have explained the so-called σ-convergence and β-convergence framework in order to measure the labour productivity and wage rate. So in both the

¹ Quoted from Baumol, 1998.
cases the entire methodology are borrowed from Barro and Martin (1992 and 1995) and applied in the context of manufacturing sector of Indian states.

7.2.1. Convergence in the Neoclassical Growth Model

In neoclassical growth models for closed economies, as presented by Ramsey (1928), Solow (1956), Cass (1965) Swan (1956) and Koopmans (1965), the per capita growth rate tends to be inversely related to the starting level of output or income per person. In particular, if economies are similar in respect to preference and technology, then poor economies grow faster than rich ones. Thus there is a force that promotes in levels of per capita product and income. Since the model is familiar, we provide only a brief sketch.

The production function is in intensive form

\[ \hat{y} = f(\hat{k}) \quad (7.1) \]

Where \( \hat{y} \) and \( \hat{k} \) are output and capital per unit of effective labour. In a closed economy, it evolves as

\[ \hat{k} = f(\hat{k}) - \hat{c} - (\delta + x + n)\hat{k} \quad (7.2) \]

Where \( \hat{c} = \frac{C}{Le^t} \), L is labour (and population), and x is the rate of exogenous labour augmenting technological progress. \( \delta \) is the rate of depreciation, and n is the growth rate of L. The representative, infinite-horizon household maximizes utility,

\[ U = \int_0^\infty u(c) e^{-\rho t} dt . \quad (7.3) \]

where \( c = \frac{C}{L}, \rho \) is the rate of time preference, and

\[ u(c) = \frac{e^{1-\theta} - 1}{1-\theta} \quad (7.4) \]

with \( \theta > 0 \), so that marginal utility, \( u'(c) \), has the constant elasticity \(-\theta\) with respect to c.

The first-order condition for maximizing U in equation (7.3) entails

\[ \frac{\hat{c}}{c} = \frac{1}{\theta} \left[ f'(k) - \delta - \rho \right] \quad (7.5) \]
In the steady state, the effective quantities, \( \hat{y}, \hat{k}, \) and \( \hat{c}, \) do not change and the per capita quantities, \( y, k, \) and \( c, \) grow at the rate of \( x. \) The level of \( \hat{k} \) in the steady state satisfies
\[
f'(\hat{k}^*) = \delta + \rho + \theta x \tag{7.6}
\]
If the economy starts with \( \hat{k} \) below \( \hat{k}^* \), then the usual analysis shows that \( \hat{k} \) monotonically approaches \( \hat{k}^*. \) This property carries over unambiguously to the growth rate of output per worker, \( \dot{y} / y, \) if the production function is Cobb-Douglas, that is if
\[
\dot{y} = f(\hat{k}) = Ak^\alpha \tag{7.7}
\]
where \( 0 < \alpha < 1. \) Thus if two economies have the same parameters of preferences and technology, then the key result is that the initially poorer economy—with a lower starting value of \( \hat{k} \) —tends to grow faster in per capita terms.

The transitional dynamics can be quantified by using a log linearization of equations (7.2) and (7.5) around the steady state. The solution for \( \log[\dot{y}(t)] \) in the log-linearized approximation to the model with a Cobb-Douglas technology is
\[
\log[\dot{y}(t)] = \log[\dot{y}(0)] e^{-\beta} + \log(\dot{y}^*). (1 - e^{-\beta}) \tag{7.8}
\]
where the positive parameter \( \beta, \) which governs the speed of adjustment to the steady state, is given by the formula
\[
2\beta = \left\{ \psi^2 + 4 \left( 1 - \alpha \right) \left( \rho + \delta + \theta x \right) \left[ \frac{\rho + \delta + \theta x}{\alpha} \right] \left( n + \delta + x \right) \right\}^{1/2} - \psi \tag{7.9}
\]
where \( \psi = \rho - n - (1-\theta)x > 0. \) The average growth rate of \( y \) over the interval between dates 0 and \( T \) is
\[
\frac{1}{T} \log \left[ \frac{y(T)}{y(0)} \right] = x + \frac{1-e^{-\beta T}}{T} \log \left[ \frac{\dot{y}^*}{\dot{y}(0)} \right] \tag{7.10}
\]
The higher \( \beta, \) the greater the responsiveness of the average growth rate to the gap between \( \log \left( \dot{y}^* \right) \) and \( \log \left[ \dot{y}(0) \right], \) that is, the more rapid the convergence to the steady state.
7.2.2. Beta Convergence

This section deals with the notion of convergence in terms of growth rates. \( \beta \) convergence refers to whether the labour productivity and wage rate of a poor economy tends to grow faster than a rich one, so that the poor country tends to catch up with the rich one in terms of labour productivity and wage rate. In order to measure the \( \beta \) convergence by assuming that labour productivity and wage rate converge towards a unique steady-state for all the states including in the data set, the equation as follows:

\[
\ln \left( \frac{y_i}{y_{i,t-1}} \right) = a - \left( 1 - e^{-\beta} \right) \ln(y_{i,t-1}) + u_i
\]  

(7.11)

where the subscript \( t \) denotes the years, and the subscript \( i \) denotes the state. The theory implies that the intercept, \( a \), equals \( x + (1-e^p) \cdot \left[ \ln(y_i^*) + x(t-1) \right] \), where \( y_i^* \) is the steady state level of \( y_i \).\(^2\) The parameter \( \beta \) can be estimated through both linear (Islam 1995, Baumol 1986, Rao et.al. 1999, Mulder and Groot 2003) as well as nonlinear (Barro and Martin 1992, Mankiw et.al. 1992 and Adabar 2004) form. Following Islam (1995) and Mulder and Groot (2003), the equation (7.11) has been reformulated as

\[
\ln(y_{it}) - \ln(y_{i,t-1}) = a + \beta \ln(y_{i,t-1}) + \epsilon_{it}
\]  

(7.12)

where \( i \) and \( t \) denoting, respectively, the cross state and time-series dimension. \( y_{i,t-1} \) is the initial period value and \( \epsilon_{it} \) represents standard error. The speed of convergence is given by

\[
\frac{d \log(y(t))}{dt} = \lambda \left[ \log(y^*) - \log(y(t)) \right]
\]  

(7.13)

which implies that:

\[
\log(y(t)) = (1 - e^{-\lambda}) \log(y^*) + e^{-\lambda} \log(y(t-1))
\]  

(7.14)

where \( y(t-1) \) is labour productivity or wage rate at the initial period. Subtracting \( \log(y(t-1)) \) from both side yields

\[
\log(y(t)) - \log(y(t-1)) = (1-e^{-\lambda})[\log(y^*) - \log(y(t-1))]
\]  

(7.15)

in which \( - (1-e^{-\lambda}) = \beta \). Hence the speed of convergence, \( \lambda \), is given by \( \lambda = - \left[ 1/T \ln(\beta+1) \right] \) with \( T \) denoting the time period.

7.2.3. Sigma Convergence

The concept of σ-convergence can be defined as a group of economies are converging in the sense of σ, if the standard deviation of logarithm of labour productivity and wage rate tends to decrease overtime. Convergence of β tends to generate the second type of convergence, σ, but the reverse is not true. σ convergence in our study is measured as:

\[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[ \ln(y_{it}) - \ln(\bar{y}) \right]^2} \], where \( \ln(\bar{y}) = \frac{1}{n} \sum_{i=1}^{n} \ln(y_{it}) \) \hspace{1cm} (7.16)

7.2.4. Direct Measures of Convergence

In the literature both σ convergence and β convergence considered as indirect measures. The direct measures of convergence seek to measure convergence directly using a summary statistic of Bourguignon (1979) L-statistics. This measure is aggregative, income zero homogeneity, obey Pigou-Dalton condition and additively decomposable. L-statistics is also not sensitive to the national rate of inflation as it is pure-numbers. Here,

\[ L = \log \left( \frac{1}{n} \sum_{i=1}^{n} wi \right) - \frac{1}{n} \sum_{i=1}^{n} \log wi \] \hspace{1cm} (7.17)

where ‘wi’ is the labour productivity of the ‘i’ th state.

7.3. Specification of Models for Conditional Beta Convergence

In order to measure the conditional β convergence, following Islam (1995), two different models, namely Dynamic Panel Data model and simple Pooled OLS model are used. In the framework of cross section regression, it is not possible to take into account the individual state specific effect. In order to overcome this problem, dynamic panel model can be used.\(^3\) It is well known that in the dynamic case, the LSDV estimator is inconsistent because the lagged endogenous variable is always related with the error term. To investigate the robustness results, we present the dynamic panel data model,\(^4\)

\(^3\) For details, see Islam 1995,1132.
which are estimated using Arellano and Bond (1991) GMM estimation procedure, bearing in mind again the cautions of using dynamic panel estimator in macroeconomic studies where typically the N dimension is short.

Consider the linear dynamic panel data specification given by:

\[ \ln Y_u = \sum_{j=1}^p \rho_j \ln Y_{u-j} + \ln X_u' \beta + \mu_i + \epsilon_u \]  

(7.18)

First-differencing this specification eliminates the individual effect and produces an equation of the form:

\[ \Delta \ln Y_u = \sum_{j=1}^p \rho_j \Delta \ln Y_{u-j} + \Delta \ln X_u' \beta + \Delta \epsilon_u \]  

(7.19)

Where \( x_u' \) is \( 1 \times k \) and \( \beta \) is \( k \times 1 \). \( i = 1 \ldots N; \ t = 1 \ldots T \). The equation (7.19) may be estimated using GMM techniques.

In a pooled estimation, it is expected to encounter the problem of heteroscedasticity and autocorrelation (Dielman, 1989). In order to overcome these problems, the pooled estimation assumed nine different assumptions with respect to group-wise heteroscedasticity, cross group error correction and autocorrelation. The nine different assumptions are:

- Homoscedasticity and no autocorrelation,
- Homoscedasticity and common autocorrelation,
- Homoscedasticity and specific autocorrelation,
- Group-wise heteroscedasticity and no autocorrelation,
- Group-wise heteroscedasticity and common autocorrelation,
- Group-wise heteroscedasticity and specific autocorrelation,
- Cross group heteroscedasticity and no autocorrelation,
- Cross group heteroscedasticity and common autocorrelation and
- Cross group heteroscedasticity and specific autocorrelation

The main justification for the assumption of heteroscedasticity in the pooled regression estimation is due to the specific states. Since the dependent variable and the explanatory variables of the respective states are not homogenous, it is sensible to expect that there will be difference in the error variances. The large bodies of cross-sectional empirical econometric studies that take care of the heteroscedasticity problem support to
this fact. Likewise, the presence of autocorrelation in the error term of a given sector cannot be ruled out because observations over time are used while pooling the data.

It is important to note that the panel data estimation of this kind formulate with the assumption of homoscedasticity (constant error variance across countries), absence of cross-group error correlation and also the presence of non-auto correlated errors are too simplistic and misleading. Further, the estimation of the models ignoring the presence of heteroscedasticity, cross-group correlation and auto-correlation might also lead to inconsistent as well as inefficient estimates. In order to obtain efficient and consistent coefficient estimates, the estimation procedure needs appropriate corrections, which is explained in the equation (7.18).

Violation of the assumptions of homoscedasticity and auto-correlation are explained into different possibilities. It includes: (1) Groupwise heteroscedasticity, \( E [\epsilon_i^2] = \sigma_i^2 \), (2) Cross group correlation, \( \text{Cov} (\epsilon_i, \epsilon_j) = \sigma_{ij} \), for \( i \neq j \), (3) Within group autocorrelation, i.e., \( \epsilon_i = \rho \epsilon_{i,t-1} + U_i \). These three cases may be explained in the following manner.

Let \( \Sigma \) be an N×N, period specific covariance matrix, i.e., \( \Sigma = \{ \sigma_{ij} \} \), \( I, j = 1, 2, \ldots, N \). It is possible to impose some restrictions on \( \Sigma \), which may give three possible cases. The first case refers to the classical homoscedastic regression, representing a naive situation where in:

\( S_0 : \Sigma = \sigma^2 I \), where \( I \) is an identity matrix.

In the second case, it stands for group-wise heteroscedasticity, and thus:

\( S_1 : \Sigma = \text{diag} \{ \sigma_{11}, \sigma_{22}, \ldots, \sigma_{NN} \} \)

In the third case, \( \Sigma \) is assumed to be a positive definite matrix signifying cross group correlated errors apart from group-wise heteroscedasticity. That is,

\( S_2 : \Sigma = N \times N \) positive definite matrix.

With respect to autocorrelation, a similar set of assumptions can be considered. Let \( \rho \) be an N×1, vector of group specific autocorrelation coefficients. It is possible to visualize three meaningful restrictions that could be imposed on the \( \rho \) vector. In the first case, \( R_0 : \rho = 0 \), representing a situation where disturbances are non-auto correlated. In the
second case, \( R_1 : \rho = \{\rho, \rho, \ldots, \rho\} \), where all the units have common autocorrelation coefficient. In the third case, \( R_2 : \rho = \{\rho_1, \rho_2, \ldots, \rho_N\} \), where individual unit has specific coefficients.

By combining these two sets of restrictions on \( \Sigma \) and \( \rho \), it is possible to generate nine combinations leading to nine distinct models. They may be represented by \([S_0R_0S_1R_0S_2R_0S_3R_1S_2R_1S_0R_2S_1R_2] \). The last model (i.e., \( S_2R_2 \)) is the most general cases of the first eight models.

A two-step generalized least squares (GLS) and the three-step GLS methods have used for non-auto correlated model and auto correlated model respectively. In order to test the assumption of homoscedasticity and absence of cross-group error-correlation as restriction on the most general case, i.e., \( S_2R_2 \), three diagnostic test statistics, namely, Wald, LM and LR are computed. The test statistics are given by:

\[ \text{WALD} = (T/2) \Sigma_i \left[ S^2 / S_{ii} - 1 \right]^2 \]
\[ \text{LM} = (T/2) \Sigma_{ij} \left[ S_{ij} / S^2 - 1 \right]^2 \quad \text{and} \]
\[ \text{LR} = T \left( N \ln S^2 - \Sigma_i \ln S_{ii} \right) \]

Where \( S^2 \) is the pooled OLS residual variance and \( S_{ii} \) is the OLS residual variance of the \( i^{th} \) industry. All the three test statistics follow the Chi-squared distribution with \((N+R-1)\) degrees of freedom, where \( N \) is the number of units in the panel (in our case number of states), \( R \) is the number of restrictions imposed on the estimated model.

7.4. Data Sources and Measurement of Variables

The database of the study draws from the Annual Survey of Industries (ASI) for the period 1979-80 to 2000-01 across fifteen major states. The bifurcated states are: Bihar, Madhya Pradesh and Uttar Pradesh. Three new states, viz. Jharkhand, Chattisgarh and Uttarachal were carved out of Bihar, Madhya Pradesh and Uttar Pradesh, respectively. For the period of the study, two National Industrial Classification (NIC) codes have been used for data collection. The details of NIC codes (1987 and 1998) of the industries covered in this study are provided in Appendix 7.1. Within the states, for some of the industries, figures are not available for certain years; figures for all the industries have been clubbed together. Since price deflators are not available at the state
level, the appropriate national price indices use in order to obtain real figures. Gross value added figure are deflated by ‘wholesale price index of manufactured products’ (1993-94 =100). The city-wise data on consumer price index of industrial workers are available in RBI bulletin and Bulletin of Food Statistics various issues. There is no specific Consumer Price Index of industrial workers at the state level. So, one general price index number is calculated by taking the average of all available CPI of industrial workers across the cities for a particular state. This index uses as a proxy for representative state. By using the state specific CPI for industrial workers series (1982-83 =100), we converted nominal emolument to real emolument.

The study chooses the aggregate manufacturing industry and six two-digits industry groups for investigation. The industries are: (i) Food Products (20-21); (ii) Textiles and textile products (TEXT); (iii) Chemical and chemical products (30); Basic Metals (33); Machinery and other products (35-36) and Transport and parts (37). These six industries are selected based on their share of value added, employment and export performance. The second reason for choosing these industries is the consistency of data across the states.

Y stands for the labour productivity and it is measured by real gross value added divided by total number of employees. CI stands for capital intensity measured as the ratio of total fixed capital to total number of employees. Firm Size (FSIZE) is measured as ratio of total output to number of factories. SKILL manpower represents the trained manpower including supervisory, administrative and managerial staff. It is measured as number of supervisor and managers as a ratio to total employees in percentage. Capacity Utilization (CU) stands as a proxy variable for technology application and is measured as the ratio of gross value of output to productive capital. Wage rate is defined as ratio of real emoluments to total number of employees.
7.5. Estimation Results and Interpretation

Before going to discuss the convergence results, we first highlight the question 'whether the labour productivity across the states is significantly different?' In order to answer this question, one-sample test results for the labour productivity across the states are shown in Table 7.1. Results from the table show that we are rejecting the null of no labour productivity difference across the states over the period of time. This implies the labour productivity across the states is significantly different. In order to see whether the productivity differences across the states are converging or diverging over the period has been presented in the following section.

7.5.1. Direct Measures of Convergence for Aggregate Manufacturing

Figure 7.1 shows the L-statistics of labour productivity for the fifteen major states of India during 1979-80 to 2000-01. The graph shows neither convergence nor divergence over the period of time. The L statistics has increased from 1979-80 to 1981-82, and then it has declined up to period 1987-88. It has again increased after the economic reforms. The economics reforms brought the divergence in labour productivity across the states, which show consistency with our inequality results, presented in the previous chapter.

7.5.2. Sigma Convergence

This section deals with the notion of convergence in terms of levels. Do cross-state differences in labour-productivity levels decrease over time? To answer this question we calculated the cross-state coefficient variation for the log of labour productivity. From Fig.7.2, it's found that the coefficient variation of labour productivity neither shows convergence nor divergence. But this figure shows exactly equal to figure of L-Statistics. But the results are, to some extent, different in case of disaggregate manufacturing (see Fig. 7.3 to 7.8). The food products industry shows that the variation in labour productivity across the states varies from period to period. But the variation in labour productivity is very high between rich and poor states after the economic reforms. The textile and chemical industry shows a divergence in labour productivity. Other two
industries (i.e. machinery and transports) show less variation in labour productivity across the states. But basic metal industry shows convergence in labour productivity.

7.5.3. Beta Convergence

This section presents cross-section absolute beta convergence (Unconditional β-convergence) of labour productivity, assuming that labour productivity converges towards a unique steady-state equilibrium for all the states included in the data set. The results are presented in Table 7.2. Beta convergence has been measured by using Ordinary Least Square method (Equation 7.12) and we have divided the total time period 1979-80 to 2000-01 in to two sub-periods viz., 1979-80 to 1991-92 and 1992-93 to 2000-01.

Table 7.2 unfolds that the coefficient beta for labour productivity growth during pre-reform period is negative and statistically significant. This implies that, across the states, there exists an inverse relationship between growth rates of labour productivity over the period of time with respect to its initial level of productivity. It may be noted that this negative correlation can be interpreted as evidence of convergence. So in the pre-reform period, the states, which were poor in labour productivity “catch up” with the rich states by initially growing faster, and then their growth rates slow down to the common technological progress (resulting in convergence in growth rates). But during the reform period, the labour productivity growth shows neither convergence nor divergence. Furthermore, it is important to note that in the pre-reform period, the productivity convergence is significant only at 10 percent level. During pre-reform period, the speed of convergence in labour productivity across fifteen major states is found to be only 2.25 percent (see implied λ value). The time needed for labour productivity to move halfway its initial level and steady state takes 30.75 years.
Fig 7.9 plots the labour productivity growth rate from 1980 to 2000-01 against log of initial period’s labour productivity. The figure shows, however, that neither convergence nor divergence applies to the Indian states. But for some states there is a strong negative correlation between growth of labour productivity and initial level of labour productivity. From this figure, some interesting observations can be listed. The industrial states like Maharashtra, Gujarat, Tamil Nadu, West Bengal and Karnataka are showing lower labour productivity growth having higher initial labour productivity. The Bihar state, which is poor in terms of per capita income, shows higher labour productivity growth having higher labour productivity in initial period. The reason may be due to the large number of basic metal industries located in Bihar including TATA steel plant. States like Andhra Pradesh, Uttar Pradesh and Kerala, which are low in labour productivity, are growing fast.

The results of the two-digit disaggregate manufacturing sector are presented in Table 7.3. Three industries, viz. food products, textiles and transports and parts show convergence and the coefficients are statistically significant at 10 per cent level. Out of these three industries, the speed of convergence is more in case of Transports and parts. Finally, from this section, it is to be noted that the absolute β convergence does not exist in case of labour productivity during 1979-80 to 2000-01 for aggregate manufacturing.
sector, whereas, three disaggregated industries, viz. food products, textiles and transports and parts show convergence during the same period. The plausible reason for the convergence may be due to the higher wages in 1980s. The results also show that absence of convergence of labour productivity during reform period, which may widen the gap between the rich and poor.

7.5.4. Conditional Convergence

This section considers the empirical determinants of labour productivity convergence. It may be noted that in case of absolute convergence we are assuming that, a similar kind of technology, preferences and institution do exist across the states. But it may not be true in reality. There are some specific factors like industrial location, infrastructures, investment climates and government intervention that vary across the states, which affect the productivity level. All the factors we are considering here as an individual state-specific characteristic. This individual state specific characteristic can be captured through panel data model. Apart from this individual state-specific characteristic, we have taken some other explanatory variables along with the lagged endogenous variable. Here we assume productivity level converge to multiple steady state equilibrium that is conditional on state-specific characteristic. We may note that equation (7) is based on approximation around the steady state and supposed to capture the dynamics towards the steady state.

The pooled regression (OLS) models are estimated in the present study. We have chosen the most general model i.e. (S2R2)*. Since adjusted $R^2$ or $R^2$ is not meaningful summary statistic in the context of pooled data, the same is not used and hence not reported.\(^5\) It is striking to note how these results are different to those obtained from single cross section (see Table 7.4). Because of the difference in the time span, we get divergence in labour productivity. In the case of single cross sectional data, the results show neither convergence nor divergence, as the coefficients are not significant during 1979-80 to 2000-01. From these results, we find that inter state wage differentials have

\(^4\) The final model selection criteria rest upon a judicious negotiation between the model diagnostic statistics and desired statistical properties of individual coefficients.

\(^5\) See Roy et.al. (2000), pp. 8.
significant impact on labour productivity divergence. The value of the implied \( \lambda \) indicates
the speed of divergence and the figure is 0.73 percent only.\(^6\) On the other hand, the
implied \( \theta \)\(^7\) is found to be 0.98. Therefore, we find a very low rate of divergence and very
high estimates of the elasticity of labour productivity (implied \( \theta \)) with respect to wage
rate.

The results of dynamic panel regression using GMM estimation are exhibited in
Table 7.5. We control for the potential problem due to the presence of endogenous
regressors, by using the instrument of lagged labour productivity series dated (T-1).
Significant change is observed in GMM results, when we are relaxing the steady state
growth assumption. By comparing GMM model with simple pooled regression model,
we find that apart from wage rate, capital intensity and skilled manpower variables are
also affecting the labour productivity. The speed of divergence is high 3.1 per cent. This
divergence clearly indicates that there is a regional disparity within manufacturing sector.
The productivity gap became wider between rich states and poor states. Apart from the
individual state specific characteristic, wage rate, capital intensity and skill factor were
also responsible for this divergence. In India, most of the rich industrial states are located
in west and southern part. After the liberalization, these states had opened their economy.
As a result, in these states the service sector has grown very fast. The infrastructure
facilities and flow of investment have also increased. Therefore, all these factors have
positive impact on manufacturing sector. The substitution of capital for labour had taken
place\(^8\) in 90s and most of the industries are looked for skilled workers. So these skilled
workers play a significant role in divergence of labour productivity. On the other hand,
the poor states are growing slowly in terms of manufacturing productivity, infrastructure
development and in overall growth process. As India is an agricultural dominated
economy, the growth of manufacturing sector also depends on agriculture. Lack of
transportation is also one of the factors for declining manufacturing output in poor states.

In a nutshell, the above cross section exercise shows that, the results are different
in respect to various assumptions. In case of unconditional convergence, we find there is

\(^6\) Implied \( \lambda = (1/\gamma) \ln (\delta) \), where \( \gamma = t1-t2 \).
\(^7\) \( \theta = \beta/(1-\delta^2) \)
\(^8\) See Nagraj, 2004.
no convergence in labour productivity, whereas, convergence exists in some of the industries. Using a pooled and dynamic panel-data approach, we get to know that labour productivity in rich states grow relatively fast, having relatively high initial productivity level. This evidence of β-convergence does not support the hypothesis that being relatively backward in productivity carries a potential for rapid advance. Furthermore, the results also indicate a divergence to be conditional on cross-state differences in steady-state characteristics, rather than to be unconditional with productivity levels converging to a uniform steady state for all states. In our search for the fundamentals determining the labour productivity divergence, we observe much evidence of a positive relationship between wages and labour-productivity growth. Moreover, we also observe that capital intensity and skilled manpower factors contribute to labour productivity growth, while firm size and capacity utilization do not play any role in explaining cross-state differences in labour productivity growth.

7.6. Time Series Evidence

The literature and cross-section growth regression show that poor region grows faster than rich region in terms of per-capita productivity or income. The result interprets as evidence of convergence. But, cross-sectional convergence result does not imply that the region becomes richer in terms of its per-capita income growth rate or productivity growth rate. In other words, convergence is a dynamic process that should be observable in time-series data. The above statement provides the motivation for this section, which tests the dynamic implications of convergence with time-series data.

Using time-series techniques, Gerald and Mills (1993) look for convergence in per capita incomes in U.S. regions over the 1929-90 periods. They find evidence in support of convergence. Bernard and Durlauf (1995) also use time-series techniques. Using cointegration tests and per capita GDP for fifteen OECD countries, they come across no convergence but do find common trends. Bernard and Jones (1996b) examine the convergence of total factor productivity both at the aggregate national level as well as at the sectoral level for fourteen OECD countries for the period 1970-87. They apply a

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recent advance in unit root econometrics by Levin and Lin (1992). They argue that finding convergence at the aggregate level may be masking differences in sectoral convergence. Using both cross-sectional and time-series techniques, they observe convergence occurring at the aggregate level. However, at the sectoral level they find that convergence is occurring in the non-manufacturing sectors but, surprisingly, little evidence for convergence in manufacturing.

Swaine (1998) investigates the dynamic implications of beta-convergence with time-series data from the 48 contiguous U.S. states. He makes a set of strong assumptions to jump from this cross-sectional correlation to its interpretation as a speed of convergence. The results find that the time-series properties of the data appear to be inconsistent with beta-convergence dynamics. Further, the analysis rejects the assumptions necessary to interpret the cross-sectional correlation as a speed of convergence. Magura (1999) explores whether there is convergence in the productivity of eight sectors in eight midwestern states during 1963-89. He uses both cross-section and time-series techniques. Using cross-section techniques, it is found that convergence did occur for total, state productivity but not for each of the sectors. In particular, convergence did not occur in the productivity of service-related sectors while it did occur in manufacturing and transportation and public utilities. With respect to time-series techniques, he applies the well-known Johansen (1991) cointegration test and found no convergence. However, common trends are present for the total productivity, state productivity and most of the individual sectors.

In this context, the purpose of this study is to investigate the convergence hypothesis for labour productivity by using time-series techniques. The motivation behind this analysis is to see how far the cross-state convergence results, which are presented in earlier section, are corroborating with time-series results. In order to estimate the time-series techniques, we use Levin-Lin and Im, Pesaran and Shin (IPS) panel unit root tests, following Bernard and Jones (1996b).
7.6.1. Theoretical Framework for Testing Unit Roots in Panel Data

Testing for unit root in time series studies is now common practice in applied research and plays an integral part. However, testing for unit root in panel is recent. There are several types of panel unit root tests propounded by Levin-Lin (1992), Im, Pesaran and Shin (1997), Maddala and Wu (1999) and Hadri (1999). As we know for any time-series techniques, we need a long time horizon data. "However, a paper by Levin-Lin (1992) illustrates the relatively straightforward technique of testing unit roots in panel data. The basic findings are twofold: (1) that as both N and T go to infinity, the limiting distribution of the unit root estimator is centered and normal", and (2) the panel setting permits relatively large power improvements.

We consider the following general model:
\[ y_{it} = \rho_i y_{i,t-1} + z_{it} + u_{it}, \quad i = 1, \ldots, N; t = 1, \ldots, T. \] (7.20)

Where, \( z_{it} \) is the deterministic component and \( u_{it} \) is a stationary process. The \( z_{it} \) could be zero, one, or the fixed effect \( \mu_i \). The Levin-Lin tests assume that \( u_{it} \) are iid(0, \( \sigma_{\mu}^2 \)) and \( \rho_i = \rho \) for all \( i \).

The Levin-Lin tests the null hypothesis
\[ H_0: \rho = 1 \]
against the alternative hypothesis
\[ H_a: \rho < 1. \]

Let \( \hat{\rho} \) and \( t_\rho \) be the OLS parameter estimate and t-statistic from a regression \( y_{it} \) on \( y_{i,t-1} \) including state-specific intercepts. Levin and Lin prove the following lemma:

Lemma 1 (Levin-Lin), When \( \mu = 0 \) and \( \sigma_{\mu}^2 = 0 \) (i.e. the unit root processes have no drift), if \( N \) and \( T \) go to infinity with \( \sqrt{N/T} \) going to zero,

\[ T \sqrt{N \left( \hat{\rho} - \left(1 - \frac{3}{T} \right) \right)} \Rightarrow N(0,10.2) \] (7.21)

\[ \sqrt{1.25t_\rho} + \sqrt{1.875N} \Rightarrow N(0,1) \] (7.22)

Furthermore, this result holds when a common time trend is included in the regression.

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10 For details, see Baltagi and Kao, 2000.
11 Quoted from Bernard and Jones, 1996.
Im, Pesaran and Shin (IPS) Test

For a sample of $N$ groups observed over $T$ time periods, the IPS panel unit root regression of the conventional ADF test is of the following form:

$$
\Delta y_{it} = \alpha_i + \pi_i t + \beta_i y_{i,t-1} + \sum_{j=1}^{k} \psi_{i,j} \Delta y_{i,t-j} + \epsilon_{i,t}
$$

Here, $y$ denotes the time series under consideration, $\Delta$ is the first difference operator, $\epsilon_{i,t}$ is a white noise disturbance term with variance $\sigma^2$, $i = 1,2,\ldots,N$ indexes countries and $t = 1,2,\ldots,T$ indexes times. The $\Delta y_{i,t-j}$ terms on the right hand side of Equation (7.23) allow for serial correlation, with the aim of achieving white noise disturbance term. The IPS panel unit root test is shown to be more powerful than the widely used Levin and Lin (LL, 1992) approach. Unlike the LL test, the IPS test allows for heterogeneous values for all estimated parameters, including the first order autoregressive coefficient that tests the null of a unit root.

The null hypothesis of a unit root in the panel is defined as:

$$
H_0 : \beta_i = 0, \quad \text{for all } i
$$

against the alternative that all series are stationary processes

$$
H_1 : \beta_i < 0, \quad i = 1,2,\ldots,N_1, \quad \beta_i = 0, \quad i = N_1 + 1, N_2 + 2,\ldots,N
$$

This formulation of the alternative hypothesis allows for $\beta_i$ to differ across groups, and is more general than the homogenous alternative hypothesis, namely $\beta_i = \beta < 0$ for all $i$ (Im et al., 2003)

In order to examine the convergence hypothesis in the time-series aspect, we focus on cross-state deviations in labour productivity level. By following Bernard and Jones (1996b), let state 1 denote the benchmark state, our tests follow:

For labour productivity,

$$
\ln L\hat{P}_i(t) = \ln L\hat{P}_1(t) - \ln L\hat{P}_i(t), \quad i = 2,\ldots,N.
$$

Where $L\hat{P}_1(t)$ is the labour productivity of the benchmark state, at the time period $t$ and $L\hat{P}_i(t)$ is the labour productivity of the $i^{th}$ states at the time period $t$. 

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According to Bernard and Durlauf (1995) and Bernard and Jones (1996b), the country $i$ is converging to country 1 in labour productivity if $\ln L\hat{P}_i(t)$ is stationary. In this framework, the model then yields a simple equation for time path of labour productivity:

$$\ln L\hat{P}_i = (\gamma_i - \gamma_1) + (1 - \rho)\ln L\hat{P}_{1-i} + \hat{\epsilon}_i$$

(7.25)

Where a hat indicates a difference of a variable in benchmark state to the same variable in state $i$. The value of $\rho > 0$ provides a movement for “catch-up”. This implies that labour productivity differentials between two states increase the relative growth rate of state with lower labour productivity. “We are testing the null hypothesis of no convergence, which is defined to mean that the deviation in labour productivity levels from benchmark state is a non-stationary process with nonzero drift. The alternative hypothesis is that labour productivity levels are converging in the sense that deviations in labour productivity in levels across the states are in stationary process. In this case of panel estimation, we are not able to examine the hypothesis that all the sub-set of fifteen states is converging because of short time horizon. Rather, we are testing all the states are converging against the alternative that as a group they are not converging”\textsuperscript{12}. The benchmark state chosen is Maharashtra, as the most labour productivity state at the beginning of the sample, 1979-80.

7.6.2. Results Discussion

The results of the time-series tests for convergence are reported in Table 7.6. In order to estimate the Levin-Lin unit root test for panel set of data, we follow Pedroni test procedure as prescribed by Pedroni (1999).\textsuperscript{13} Three types of Levin-Lin results are presented in the table. Similarly, the IPS individual unit root process is estimated through EViewsS. Since the time period is very small (i.e. 22 years) and the analysis is done for the yearly data, it is appropriate to have one lag. The calculated Levin-Lin rho-statistic, Levin-Lin ADF t-statistic and IPS W-statistics for labour productivity is significant, providing evidence against the unit root null of no convergence. This implies in the long

\textsuperscript{12} Quoted from Bernard and Jones, 1996

\textsuperscript{13} For details see Pedroni 1999.
run all the states have the same underlying average growth rates. The states, which are low in labour productivity, are reaching the steady state equilibrium after a period of time.

To sum up, the time-series evidence shows reverse results with cross-section analysis as its definition of convergence is different from cross-section approach. Thus, we conclude that the estimated cross-sectional correlation should not be interpreted as a dynamic speed of convergence. However, our results do not necessarily reject the convergence hypothesis in case of labour productivity. After discussing the alternative models and the assumptions underlying them, the question of choosing best approach is difficult. But this study chooses the cross-section results and thus finds a divergence in productivity of manufacturing sector across the Indian states. The justification for choosing cross-sections divergence results rather than time-series convergence results is based on the findings of the post-liberalization results. Secondly, findings of our cross-section results also corroborate with some of the earlier studies (Goldar, 2004 and Trivedi, 2004).

7.7. Conclusions

In this chapter, we have tried to assess the convergence of labour productivity in case of Indian manufacturing sector by taking fifteen major states' data from 1979-80 to 2000-01. We have tested the convergence hypothesis by using both cross-sections as well as time series techniques. Again, in cross-section analysis, we have examined the convergence hypothesis by taking both absolute and conditional convergence. The results indicate that the absolute $\beta$ convergence of labour productivity does not exist in case of aggregate manufacturing during 1979-80 to 2000-01, whereas, there is convergence in case of food products, textiles, and transports and parts disaggregate manufacturing level during the same period. The results also show that absence of convergence of labour productivity during reform period may widen the gap between the rich and poor.

In case of conditional convergence using panel data approach, we observed that labour productivity in rich states grow relatively fast with relatively high initial productivity level. This evidence of $\beta$-convergence does not support the hypothesis that
being relatively backward in productivity carries a potential for rapid advance. Furthermore, the results show a divergence to conditional on cross-state differences in steady-state characteristic, rather than to be unconditional with productivity level converging to a uniform steady state for all states. Moreover, we also found that wages, capital intensity and skilled manpower factors influence labour productivity growth for divergence, while firm size and capacity utilization do not play any role in explaining cross-state differences labour productivity growth. The cross-section results have again verified with time-series analysis. The time-series evidence shows that labour productivity is converging across the states. Because of the time-series results, we can say that beta convergence dynamics may not be able to explain the cross-sectional results.

Above all, it seems that the issue has several policy implications. First, our analysis found that an inter-regional wage differential within the manufacturing is one of the causes of the productivity divergence. Even though, our government brought the reforms and integrated our economy with global economy, still there are lot of restrictions with respect to privatization, liberalization and investment policy. Most importantly, these policies also differ across the states because some of the industries within manufacturing are owned by the public. This may be one of the reasons for low foreign direct investment flows in poor states. So, the government should remove the barriers like wage rigidity, state interference and rigidity in labour market and make the economy more open with special attention to the poor states. There is necessity to provide wage incentives to the workers. Of course, Indian industries are following several incentive systems like piece-rate system, payment of production bonus, etc. But all the systems have several pitfalls, which should be rectified.

Second, this study also observed that labour productivity in manufacturing sector shows divergence especially after the 1991 economic reform. The role of capital and labour mobility play the main cause for divergence. In case of southern and western regions, the manufacturing sector is producing more output using more capital and skilled manpower. These two regions are also dominated by IT sector in India. The service sector has positive impact on the manufacturing sector because software depends on hardware processing. As a result, the manufacturing sector is performing better in this
group as compared to other group (i.e. north and east regions). So, the government should enhance the productivity in poorer states by bringing more capital inflows, generating employment in the manufacturing sector and set up IT sector in poor regions.

Third, the study also found that three disaggregated industries Viz. chemical and chemical products, basic metals and machinery and equipments are not converging. These industries are basically heavy industries, which are coming under public sector in India. The performance of chemical and machinery industries has slowed down recently in terms of industrial production. So, the government should give importance to these industries in order to enhance the productivity across the states.
Fig. 7.1: L-Statistics for Labour Productivity Across Indian Sates

![L-Statistics for Labour Productivity Across Indian Sates](image)

Fig. 7.2: Coefficient Variation of Log Labour Productivity for Aggregate Manufacturing Across Indian States

![Coefficient Variation for Labour Productivity Across Indian States](image)
Fig. 7.3: Coefficient Variation of Labour Productivity for Food Products Across Indian States

Fig. 7.4: Coefficient Variation of Labour Productivity for Textile Industry Across Indian States
Fig. 7.5: Coefficient Variation of Labour Productivity for Chemical Industry Across Indian States

![Graph showingCV of LP for Chemical Industry from 1980-81 to 2001-02.](image)

Fig. 7.6: Coefficient Variation of Labour Productivity for Basic Metals Industry Across Indian States

![Graph showing CV of LP for Basic Metals Industry from 1980-81 to 2001-02.](image)
Fig. 7.7: Coefficient Variation of Labour Productivity for Machinery and Machine Tools Across Indian States

Fig. 7.8: Coefficient Variation of Labour Productivity for Transports and Parts Across Indian States
Table 7.1. One Sample Test for Labour Productivity

<table>
<thead>
<tr>
<th>Test value = 0</th>
<th>t</th>
<th>Significance (2-tailed)</th>
<th>Mean Difference</th>
<th>95% Confidence interval of the difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Lower</td>
</tr>
<tr>
<td>LP</td>
<td>41.936</td>
<td>0.000</td>
<td>4.47</td>
<td>4.25</td>
</tr>
</tbody>
</table>

Table 7.2. Unconditional Beta Convergence for Aggregate Manufacturing

<table>
<thead>
<tr>
<th>Labour Productivity</th>
<th>Period</th>
<th>( \beta )</th>
<th>S.E.</th>
<th>( R^2 )</th>
<th>Implied ( \lambda )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1979-80 to 2000-01</td>
<td>-0.1527</td>
<td>0.22</td>
<td>0.034</td>
<td>0.00789</td>
</tr>
<tr>
<td></td>
<td>1979-80 to 1991-92</td>
<td>-0.2371***</td>
<td>0.11</td>
<td>0.23</td>
<td>0.02255</td>
</tr>
<tr>
<td></td>
<td>1992-93 to 2000-01</td>
<td>0.090901</td>
<td>0.10</td>
<td>0.05</td>
<td>-0.0108</td>
</tr>
</tbody>
</table>

Source: Researcher’s Calculation. Asterisks denote level of significance; * (1%), ** (5%), *** (10%).

Table 7.3. Unconditional Beta Convergence for Disaggregate Manufacturing

<table>
<thead>
<tr>
<th>Labour Productivity</th>
<th>INDUSTRY</th>
<th>( \beta )</th>
<th>t</th>
<th>( R^2 )</th>
<th>Implied ( \lambda )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Food Products</td>
<td>-12.85***</td>
<td>1.74</td>
<td>0.13</td>
<td>0.1194</td>
</tr>
<tr>
<td></td>
<td>Textiles</td>
<td>-7.75***</td>
<td>1.90</td>
<td>0.16</td>
<td>0.0986</td>
</tr>
<tr>
<td></td>
<td>Chemical</td>
<td>-4.39</td>
<td>0.21</td>
<td>0.003</td>
<td>0.0765</td>
</tr>
<tr>
<td></td>
<td>Basic Metals</td>
<td>-2.87</td>
<td>0.63</td>
<td>0.03</td>
<td>0.0615</td>
</tr>
<tr>
<td></td>
<td>Machinery</td>
<td>-2.03</td>
<td>1.41</td>
<td>0.07</td>
<td>0.0503</td>
</tr>
<tr>
<td></td>
<td>Transports</td>
<td>-38.40***</td>
<td>1.85</td>
<td>0.15</td>
<td>0.1669</td>
</tr>
</tbody>
</table>

Source: Researcher’s Calculation. Asterisks denote level of significance; * (1%), ** (5%), *** (10%).
Table 7.4. Pooled Regression from a Panel of Five-Year Span Data

<table>
<thead>
<tr>
<th>Model</th>
<th>Constant</th>
<th>Y0</th>
<th>CI</th>
<th>FSIZE</th>
<th>SKILL</th>
<th>CU</th>
<th>WAGE</th>
<th>LR test Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>S₂R₂</td>
<td>0.16</td>
<td>0.96</td>
<td>-0.25</td>
<td>0.31</td>
<td>0.39</td>
<td>-0.25</td>
<td>4.50* (14.44)</td>
<td>83.78</td>
</tr>
</tbody>
</table>

Implied $\lambda = 0.00729$; Implied $\theta = 0.99$

Note: Figures in Parentheses refer to t-ratios. * Significant at 1 % level. For degrees of freedom 6, the critical values at 0.99 and 0.95 levels are 16.81 and 12.59 respectively.

Source: Researcher’s Calculation

Table 7.5. Arellano-Bond Dynamic Panel Data Estimation

<table>
<thead>
<tr>
<th>Variables</th>
<th>GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y0</td>
<td>0.43* (4.82)</td>
</tr>
<tr>
<td>CI</td>
<td>0.29** (2.97)</td>
</tr>
<tr>
<td>FSIZE</td>
<td>- 0.45 (-1.49)</td>
</tr>
<tr>
<td>SKILL</td>
<td>0.45*** (1.87)</td>
</tr>
<tr>
<td>CU</td>
<td>- 0.46 (-1.11)</td>
</tr>
<tr>
<td>WAGE</td>
<td>3.57* (6.62)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.06* (2.47)</td>
</tr>
<tr>
<td>Sargan test Chi-square</td>
<td>6.35</td>
</tr>
</tbody>
</table>

Implied $\lambda = 0.0310$, Halfway life = 22.35 years

Numbers in Parentheses are the t-statistics. *, **, *** Denotes that coefficients are significant at 1%, 5% and 10 % level respectively. GMM assumes regressors are exogenous.

Source: Researcher’s Calculation
Table 7.6. Panel Unit Root Results

<table>
<thead>
<tr>
<th></th>
<th>Labour Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levin-Lin rho-stat</td>
<td>-10.04*</td>
</tr>
<tr>
<td>Levin-Lin PP stat</td>
<td>-4.4845</td>
</tr>
<tr>
<td>Levin-Lin ADF stat</td>
<td>-3.8084**</td>
</tr>
<tr>
<td>IPS W-stat</td>
<td>-17.43*</td>
</tr>
</tbody>
</table>

The critical value for ADF test at 1%, 5% and 10% are -4.06, -3.46 and -3.15 respectively. *, ** denotes statistical significance at the 1 per cent and 5 per cent level. The critical value for rho-stat is -6.98. Source: Researcher’s Calculation
Appendix 7.1

Classification of Industries

The database of the study is drawn from Annual Survey of Industries (ASI), which is based on the National Industrial Classification NIC-1987 and NIC-1998.

<table>
<thead>
<tr>
<th>Name of the Industry</th>
<th>NIC 1987 (Two digit)</th>
<th>NIC 1998</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Products</td>
<td>20-21</td>
<td>151+152+153+154</td>
</tr>
<tr>
<td>Beverages</td>
<td>22</td>
<td>155+160</td>
</tr>
<tr>
<td>Cotton Textiles</td>
<td>23</td>
<td>171</td>
</tr>
<tr>
<td>Woolen Textiles</td>
<td>24</td>
<td>171</td>
</tr>
<tr>
<td>Jute Textiles</td>
<td>25</td>
<td>171</td>
</tr>
<tr>
<td>Textiles Products</td>
<td>26</td>
<td>172+173+181</td>
</tr>
<tr>
<td>Wood Products</td>
<td>27</td>
<td>201+202+361</td>
</tr>
<tr>
<td>Newspaper Products</td>
<td>28</td>
<td>210+221+222+223</td>
</tr>
<tr>
<td>Leather Products</td>
<td>29</td>
<td>182+191+192</td>
</tr>
<tr>
<td>Chemical Products</td>
<td>30</td>
<td>241+242+243</td>
</tr>
<tr>
<td>Rubber, Petroleum, and Coal products</td>
<td>31</td>
<td>23+25</td>
</tr>
<tr>
<td>Non-metallic Minerals</td>
<td>32</td>
<td>261+269</td>
</tr>
<tr>
<td>Basic Metals</td>
<td>33</td>
<td>271+272+273+371</td>
</tr>
<tr>
<td>Metal Products</td>
<td>34</td>
<td>28</td>
</tr>
<tr>
<td>Machinery (other prds.)</td>
<td>35-36</td>
<td>29+30+31+32</td>
</tr>
<tr>
<td>Transport and Parts</td>
<td>37</td>
<td>34+35</td>
</tr>
<tr>
<td>Other Manufacturing</td>
<td>38</td>
<td>33+369</td>
</tr>
</tbody>
</table>

Source: Central Statistical Organization