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FACTOR ACCUMULATION AND LONG-RUN OUTPUT: A PANEL COINTEGRATION STUDY OF THE INDIAN MANUFACTURING INDUSTRIES

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Abstract: Using panel cointegration techniques, we show the existence of long-run relationship between output and factor inputs for selected Indian manufacturing industries over the period 1981–1998 using the panel cointegration framework. Based on the panel vector autoregression error-correction model (PVEC), we found that inputs Granger cause output, which identify the production function for each industry under study.

Key words: Panel cointegration, Panel vector autoregression error-correction model, Long-run causality.
JEL Classification Number: C23.

1. INTRODUCTION

Several studies have attempted to empirically estimate the differences in Total Factor Productivity (TFP) for the Indian manufacturing industries in the pre and post-liberalization periods (Ahluwalia, 1991; Balakrishnan and Pushpangandan, 1994; Rao, 1996; Bhalotra, 1998; Krishna and Mitra, 1998; Hulten and Srinivasan, 1999; Topalova, 2004; Rodrik and Subramanian, 2005). In most of these studies, productivity estimates have been made on the assumption of the existence of a neo-classical production structure. A shortcoming of the standard growth accounting framework is that some of the restrictive assumptions have to be made while calculating Total Factor Productivity (TFP)

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level for an economy or industries. Based on a production function, the output elasticity is computed as equal to the relative shares of total income paid to each input, under the assumptions of perfectly competitive factor markets and constant returns to scale. A less restrictive approach is to directly estimate differences across economies or industries in the production function through the use of panel econometric techniques (Islam, 1995; Harrigan, 1999). However, the consistent estimation of production function is a prerequisite for a reliable and consistent measurement of the industrial productivity. The robust estimation of the production function critically hinges on the assumption of the exogeniety of output to factor inputs used in the production structure (Griliches and Mairesse, 1998).

Our objective in this study is to verify the existence of the long-run production function using the recently developed panel cointegration techniques of Pedroni (1999, 2004) for the Indian manufacturing industries but not to estimate their TFP.

Further, we are also able to study the issue of simultaneity between output and factor inputs using the panel vector-autoregressive error-correction model (PVEC). The PVEC enables us to test both the long-run and short-run dynamics of factor inputs and output. The short-run dynamics in our model is introduced through the error-correction form (ECM) that is expected to account for the adjustment of the factor inputs to the economic liberalization policies of the Indian government. One of the key elements of the New Industrial Policy (NIP) of India in 1991 was the abolition of licensing of capital goods which allowed freer import of capital goods. It could also be expected that in the short-run there could be fixity of inputs such as capital stock that takes some time to adjust to the long-run equilibrium (Pattnayak and Thangavelu, 2005).

Our panel cointegration framework follows closely the recent studies by Funk and Strauss (1999) and Christopoulos and Tsionas (2003), which employed annual data to study the long-run causal relationship. Funk and Strauss used the panel cointegration techniques to show the long-run relationship between productivity and capital for the US manufacturing industries. The long-run causal relationship between financial development and economic growth is established by Christopoulos and Tsionas (2003) using the PVEC framework. After establishing the long-run relationship of the variables from panel cointegration, our paper tests for Granger causality (strong exogeniety) between output and factor inputs in a panel vector-autoregressive error-correction model (PVEC). The results of the estimation suggest the existence of a long-run relationship between output and factor inputs, and that the causality runs from factor inputs to output. This result supports the existence of the neo-classical production structure in the Indian manufacturing industries and thereby validates the empirical observation of the impact of the economic liberalization on productivity growth in the Indian manufacturing industries through the production function structure.

The paper is organized as follows: Section 2 outlines the data and methodological framework, section 3 analyzes the empirical results and section 4 concludes.

2. DATA AND METHODOLOGY

The study uses data of 111 industries at 3-digit industrial classification from the Annual Survey of industries (ASI), published by Central Statistical Organization, Ministry of Industry, Government of India for the period 1981 to 1998 for the organized sector of the manufacturing industries. These 111 industries are assigned to 12 industry groups. The panel is created at 3-digit industrial classification and the long-run relationship is established for each panel of industries. Gross output, capital stock, material input, and number of employees were obtained from ASI. Material input variable used in our study consists of both materials and energy inputs used in production.

Pedroni (1999, 2004) provides the cointegration test for the panel analysis, which is used in our study. The cointegration test is based on the null hypothesis that each individual component of the series are not co-integrated, as opposed to the alternative hypothesis that there is a single co-integrating vector which differs across the individual components. The main purpose of the panel co-integration is to pool information to determine the common long-run relationship and at the same time allow for heterogeneity across the individual components in the panel.

The formulation by Pedroni (1999) allows us to investigate heterogeneous panels, in which heterogeneous slope coefficients, fixed effects and individual specific deterministic trends are permitted. In its most simple form, this consists of taking no cointegration as the null hypothesis and using the residuals derived from the panel analogue of an Engle and Granger (1987) static regression to construct the test statistic and tabulate the distributions. The panel cointegration test is carried out for the following equation:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} k_{it} + \beta_{2i} l_{it} + \beta_{3i} m_{it} + e_{it} \tag{1}$$

where $y_{it}, k_{it}, l_{it}, m_{it}$ are the logarithm of output, capital, labor and material inputs respectively. The panel cointegration test is conducted with and without deterministic heterogeneous trends. Based on the cointegration residuals, Pedroni (1999) develops 7 panel cointegration statistics[1]. The asymptotic distributions of these panel cointegration statistics are derived in Pedroni (2004). Under an appropriate standardization, based on the moments of the vector of Brownian motion functionals, these statistics are distributed as standard normal distribution. Although the results are robust across the 7 test statistics, due to brevity, in this paper we only report 3 out of the 7 panel cointegration test in Table 1.

In Table 1, we report panel ν-statistics, panel ρ-statistics, and group ρ-statistics of Pedroni. It must be noted that for panel-ν statistics, the alternative hypothesis diverges to a positive infinity, and consequently the right tail of the normal distribution is used

[1] See Pedroni (1999), pp. 659–662 for the testing procedure and the complete formulation of test statistics. Pedroni (2004) derives the asymptotic distributions and explores the small sample performances of 7 different statistics for testing null-hypothesis of no co-integration. Panel ν-Statistic, Panel ρ-Statistic, Panel t-Statistic (non-parametric) and Panel t-Statistic (parametric) are commonly referred to as *within*-dimension or panel co-integration test. The remaining three test statistics—Group ρ-Statistic, Group t-Statistic (non-parametric) and Group t-Statistic (parametric), are based on pooling along what is commonly referred to as between-dimension or group mean panel statistics.

Table 1. Panel co-integration results for Indian manufacturing industries: 1981–1998

Industry	Panel ν-Stat	Panel ρ-Stat	Group ρ-Stat	Panel ν-Stat	Panel ρ-Stat	Group ρ-Stat
	No Trend			Heterogeneous Trend		
Food & Food Products ($n = 18$)	55.63* (0.008)	−14.32* (0.001)	−13.56* (0.005)	86.01* (0.001)	−16.54* (0.000)	−15.55* (0.002)
Beverages, Tobacco ($n = 10$)	41.84* (0.009)	−12.33* (0.003)	−11.58* (0.001)	64.40* (0.0012)	−13.77* (0.002)	−13.65* (0.003)
Wool, Silk, etc. ($n = 9$)	39.74* (0.001)	−10.08* (0.000)	−9.31* (0.001)	51.74* (0.002)	−12.31* (0.000)	−11.45* (0.006)
Textile ($n = 10$)	41.84* (0.000)	−13.14* (0.003)	−15.87* (0.0002)	64.40* (0.0026)	−14.12* (0.009)	−16.01* (0.007)
Paper Products ($n = 8$)	37.59* (0.001)	−7.12* (0.0001)	−9.22* (0.0012)	57.84* (0.002)	−12.14* (0.0067)	−13.06* (0.008)
Rubber, Plastic, etc. ($n = 7$)	37.59* (0.000)	−13.21* (0.003)	−11.07* (0.002)	57.84* (0.001)	−14.08* (0.000)	−13.11* (0.001)
Chemical Products ($n = 8$)	39.74* (0.006)	−10.11* (0.004)	−11.14* (0.003)	51.74* (0.001)	−14.05* (0.005)	−13.43* (0.001)
Non-Metallic Minerals ($n = 7$)	32.25* (0.002)	−9.34* (0.009)	−9.08* (0.0067)	54.10* (0.007)	−10.34* (0.008)	−12.23* (0.004)
Basic Metal & Alloys ($n = 8$)	37.59* (0.000)	−7.98* (0.005)	−8.33* (0.004)	57.84* (0.0023)	−11.01* (0.007)	−10.11* (0.002)
Metal Products ($n = 7$)	35.25* (0.0065)	−9.17* (0.001)	−11.01* (0.000)	54.10* (0.002)	−10.39* (0.001)	−12.26* (0.000)
Machinery & Equipments ($n = 10$)	41.84* (0.001)	−8.98* (0.013)	−9.77* (0.000)	64.40* (0.004)	−11.49* (0.0012)	−10.14* (0.002)
Electrical Machinery & Products ($n = 9$)	39.74* (0.016)	−11.02* (0.000)	−13.46* (0.001)	51.74* (0.003)	−12.02* (0.000)	−14.44* (0.004)

Note: The parenthesized values are the respective p-values obtained by stochastic simulation of 100,000 replications. * −5% level of significance.

to reject the null hypothesis. Therefore, in the panel-ν statistic a large positive value might imply that the null of no cointegration might be rejected. For each of the other 2 test statistics, the test statistics diverges to a negative infinity under the alternative hypothesis and consequently the left tail of normal distribution is used to reject the null hypothesis. In this case a large negative value might imply that a null of no cointegration might be rejected. It is important to note that the standardized test statistic reported in Pedroni (1999) is based on the simulated moments μ and ν with $T = 1000$. However, given the limited time series data available by industry, the time period in our sample for each industry consists of only $T = 17$, which is much smaller than that reported in Pedroni (1999). Although a longer time span will provide better long-run dynamics, the limitation of long time series hampers the causality study more in a univariate analysis as compared to the panel analysis. The conventional unit-root tests are normally used to study the stationary properties in a single equation framework. However, it is a well known fact that these tests have low power when the root is very close to one, and the power of ADF test critically relies on T being large to provide a reliable test statistic (Shiller and Perron, 1985). The idea of increasing the data span of say an annual time-series data set using pooled cross-section data has been proposed in the context of unit root testing by Quah (1994). The key advantage that was pointed out in the implementation of a unit root test on a pooled cross section data set rather than performing separate unit root tests for each individual series is that it can provide 'dramatic improvements in the statistical power'. Thus, the panel cointegration that combines the dynamics of both times series and cross sectional data is expected to overcome the problem of short time series by pooling both the time series and cross sectional data and improve the power of the test (Pedroni, 1999). The main purpose of the panel cointegration is to pool information to determine the common long-run relationship and at the same time allow for sufficient heterogeneity across the individual components in the panel. Further, the span of 17 years in our study is expected to be sufficient to capture the impact of the liberalization on the production structure of the manufacturing industries in India. To improve on our analysis we provide robust critical values by conducting Monte Carlo simulations to get the exact critical values for the non-standardized test statistics for our empirical sample of different sizes of N and $T = 17$ (see Rajaguru (2003)). The panel co-integration test results clearly indicate that we could reject the null of no cointegration for all the selected industries in our study[2].

Having established the long-run relationship, we turn to the issue of causality. Since in each industry the series (y, k, l, m) are individually non-stationary but together are co-integrated, we know from the Granger representation theorem, (Engle and Granger, 1987) that these series can be represented in the form of a dynamic error correction model. To estimate the error correction form we employ a two-step procedure.

The advantage of the two-step estimation procedure, first estimating the co-integrating relationship and then the error correction mechanism, is that all the variables in equation system (2–5) are stationary. Asymptotically, the fact that we use the estimated disequilibrium rather than the true disequilibrium in (2–5) does not affect the standard properties of our estimates, due to the well known super-consistency properties of the estimator of the co-integrating relationship[3] It follows that we can carry out standard hypothesis tests on the coefficients estimated in the system. By exploiting the co-integrating relationship we are able to summarize the long-run effects of the innovations in the variables in terms of the parameters such as λ_i.

[2] The results of the Monte Carlo simulations are available from the authors upon request.

[3] Toda and Phillips (1993, 1994) study the properties in the context of more conventional dynamic Granger causality tests in co-integrated systems. See also Urbain (1992) for a related discussion on testing causality in error correction models.

3. RESULTS OF PVEC

The presence of cointegration is consistent with causality running in one or in all possible directions. Once a long run relationship has been detected, it became relevant to determine the actual direction of causality. In particular, we are interested in assessing if the inputs are Granger-causing output or if the variables Granger cause each other in the long run. Given the non-stationary features of our variables, we test for causality within the framework of panel vector error-correction mechanism (PVEC) model. We can represent the panel analysis as a system of cointegrated variables in the form of a dynamic ECM model. The PVEC model is estimated based on a two-step procedure. In the first step, the long run relationship between output, capital, labour and material inputs is estimated and residuals are derived. In the second stage, we estimate the PVEC model for each variable of interest. The PVEC model is given as:

$$\begin{aligned} \Delta y_{it} &= c_1 + \lambda_1 \widehat{\varepsilon_{i,t-1}} + \sum_{j=1}^{p} \beta_{11,j} \Delta y_{i,t-j} + \sum_{j=1}^{p} \beta_{12,j} \Delta k_{i,t-j} \\ &\quad + \sum_{j=1}^{p} \beta_{13,j} \Delta l_{i,t-j} + \sum_{j=1}^{p} \beta_{14,j} \Delta m_{i,t-j} + u_{1it} \end{aligned} \tag{2}$$

$$\begin{aligned} \Delta k_{it} &= c_2 + \lambda_2 \widehat{\varepsilon_{i,t-1}} + \sum_{j=1}^{p} \beta_{21,j} \Delta k_{i,t-j} + \sum_{j=1}^{p} \beta_{22,j} \Delta y_{i,t-j} \\ &\quad + \sum_{j=1}^{p} \beta_{23,j} \Delta l_{i,t-j} + \sum_{j=1}^{p} \beta_{24,j} \Delta m_{i,t-j} + u_{2it} \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta l_{it} &= c_3 + \lambda_3 \widehat{\varepsilon_{i,t-1}} + \sum_{j=1}^{p} \beta_{31,j} \Delta l_{i,t-j} + \sum_{j=1}^{p} \beta_{32,j} \Delta y_{i,t-j} \\ &\quad + \sum_{j=1}^{p} \beta_{33,j} \Delta k_{i,t-j} + \sum_{j=1}^{p} \beta_{34,j} \Delta m_{i,t-j} + u_{3it} \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta m_{it} &= c_4 + \lambda_4 \widehat{\varepsilon_{i,t-1}} + \sum_{j=1}^{p} \beta_{41,j} \Delta m_{i,t-j} + \sum_{j=1}^{p} \beta_{42,j} \Delta y_{i,t-j} \\ &\quad + \sum_{j=1}^{p} \beta_{43,j} \Delta k_{i,t-j} + \sum_{j=1}^{p} \beta_{44,j} \Delta l_{i,t-j} + u_{4it} \end{aligned} \tag{5}$$

Where, the error-correction term is given as $\widehat{\varepsilon_{t-1}} = y_{it-1} - \widehat{c_i} - \widehat{\alpha_i} k_{it-1} - \widehat{\beta_i} l_{it-1} - \widehat{\gamma_i} m_{it-1}$ and in the case of cointegrated series at least one of the λ_i parameters is expected to be significant. We may note here that all the variables appearing in equations (2–5) are stationary, which suggests that the standard inference on the estimated coefficients could be performed. We may also note that the long-run dynamics are captured

Table 2. The results of PVEC model for Indian manufacturing industries from 1981–1998: Estimated coefficient for the error-correction term (λ)

Industry	Δy (Equation-2)	Δk (Equation-3)	Δm (Equation-4)	Δl (Equation-5)
Food & Food Products	−0.032* (−3.530)	−0.045 (−0.67)	−0.017 (−1.07)	−0.003 (−0.08)
Beverages, Tobacco	−0.351* (−3.12)	−0.159* (−4.14)	−0.172 (−0.88)	0.007* (5.48)
Wool, Silk, etc.	−0.885* (−2.55)	−0.006 (−1.51)	−0.004 (−1.26)	−0.491* (−2.09)
Textiles	−0.033* (−2.15)	−0.002 (−0.45)	−0.002 (−0.539)	−0.001 (−0.13)
Paper & Products	−0.257* (−6.09)	−1.522* (−4.78)	−0.001 (−1.71)	−0.326* (−2.21)
Rubber, Plastic, etc.	−0.02* (−2.22)	−0.001 (−1.09)	−0.002 (−1.57)	−0.003 (−1.57)
Chemical Products	−0.046* (−3.68)	−0.008 (−1.41)	−0.172 (−0.73)	−0.061 (−0.33)
Non-Metallic Minerals	−0.211* (−4.39)	−0.001 (−1.11)	−0.0009 (−0.35)	−0.009 (−1.11)
Basic Metal & Alloys	−0.042* (−4.78)	−0.479 (−1.83)	−0.001 (−0.73)	−0.0006 (−0.58)
Metal Products	−0.012* (−2.47)	−0.007 (−1.03)	−0.0003 (−0.08)	−0.007 (−0.012)
Machinery & Equipments	−0.901* (−2.25)	−0.004 (−1.22)	−0.006* (−2.13)	−0.001 (−0.588)
Electrical Machinery & Products	−0.038* (−2.86)	−0.007 (−1.55)	−0.014 (−1.71)	−0.008 (−1.71)

Note: t-statistics in the parenthesis. * −5% level of Significance.

by the λ_i parameters, which is distinct from the short-run dynamics given by the β_i coefficients. The advantage of the PVEC is that we could test for both the short-run and long-run dynamics. The long-run causal relationships between variables are determined by the joint significance of the respective cointegrating vectors and the error-correction coefficients. In our case, we are only interested in establishing the long-run bi-directional relationship from factor inputs to output. Thus the long-run causality in our model could be tested by restricting $\lambda_i = 0$ for each of the respective equations given above in the PVEC model.

The estimated error adjustment terms are reported in Table 2 for value of output, capital, labour, and material inputs for all the manufacturing industries. We have used 2–3 lag length while estimating the error correction model. We could clearly observe that in the output equation (2), the coefficient of error-correction term λ_i is negative and highly significant across all the industries. As compared to the output equation, the coefficient of the error-correction term is not statistically significant for most of the factor inputs and of very low magnitude. These results provide some evidence in favour of the existence of a long-run relationship from inputs to output, supporting the evidence for the existence of the production function. However, we could also observe λ_i to be significant for factor input equations such as Beverages and Tobacco (industry 22), and paper, paper products and publishing (industry 28), which suggest feedback from output to factor inputs. To establish robustness of the long-run relationship, we conduct the long-run causality test (Wald test) by imposing $\lambda_i = 0$ in the above PVEC model.

The details of the causality issue reveal that there is only a uni-directional effect from inputs to output. Given the statistical significant of λ_i in Table 2, we could conclude the following. The low p-values clearly suggest that the null hypothesis of no long-run effects from production inputs in question on output is rejected consistently for all the selected industries indicating that inputs are exogenous with respect to output. The null hypothesis of no long-run relationship from production inputs on output is rejected. The null hypothesis of no long-run effects of output, capital and material inputs on labor is not rejected for all industry groups. The null hypothesis of no long run effects is not rejected for most of the industry groups. Our results also do not reject the null hypothesis of no long-run relationship of output, capital and labor on material inputs in almost all industries

4. CONCLUSION

The study provides strong evidence of long-run relationship from factor inputs to output in the Indian manufacturing industries on the basis of the cointegration test and long-run causality test, thereby establishing the existence of a neo-classical production function. We also found that inputs Granger cause output, thus identifying the production function for each industry under study. This supports the studies that adopt the neo-classical production framework to study the economic liberalization in the Indian manufacturing industries.

The results also indicate that there are strong short-run adjustments in the accumulation of factor inputs to the long-run equilibrium, thereby providing some evidence that economic liberalization might be providing some impetus for this adjustment. However, due to limited time series data in our study, the current panel cointegration study could be extended if longer time series were available by industries. The results of the paper could also be extended to study the long-run relationship between productivity improvements and economic liberalization. As in the case of the economic liberalization in India, this result is also important to trace the existence of relationship between productivity and capital, which has important policy implications for allocation of resources.

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