# Growth Appraisals of Indian Sugar Industry and Its Drivers- A Dynamic Panel Data Analysis

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**Abstract**

This research paper is an endeavor to analyze the significance of the growth of Indian sugar industry in overall economic growth of the nation. For analysis purpose, panel data cointegration analysis has been applied on the dataset of 12 major sugar producing states over the period 1974/75 to 2004/05. The empirical analysis reveals that growth of the sugar industry significantly contributes to overall economic growth of states under evaluation. Further, the analysis of the drivers of output growth in Indian sugar industry reveals that given the highest inputs elasticity of sugar output, LNIGIN (i.e., index of growth of inputs) is the most significant variable to accelerate growth of Indian sugar industry. Further, except LNPEIN (managerial efficiency change index), all other variables namely, LNSEIN (scale efficiency change index), LNPTIN and LNIBIN (Indices of Hicks neutral and non-neutral types of technical progress, respectively) contribute positively and significantly to the growth of Indian sugar industry.

**Keywords:** Panel Data Cointegration, Auto-regressive Distributed Lagga Models, Malmquist Productivity Index, Indian Sugar Industry.

**JEL Classification:** C23, D24, L66, O33

The present study has been undertaken with the primary objective to analyze the sources of output growth of Indian sugar industry using the dynamic panel data analysis. The relevance of the study stems from the fact that the development of sugar industry in India can ensures high backward and forward linkages to Indian economy given that sugar industry is: i) second largest agro-based industry in India after the cotton-textile; ii) provides direct employment to 0.5 million and indirect employment to 55 million skilled and unskilled workers (Sanyal et al., 2008); iii) contributes Rs. 25 billion annually to the centre and state exchequer in the form of taxes (ISMA, 2004); iv) potential to generate 5000MW surplus power through the process of cogeneration; and v) supporting the petroleum blending program trough the production of ethanol using molasses (the byproduct of sugar). Despite of these facts, the sugar industry in India has been offended by the ignorance of policy planners and about 35 percent sugar mill in India are running either with the negative net worth or designated as sick units (Standing Committee on Food, Civil Supply and Public Distribution, 2003). Thus, given the appalling status of the health of Indian sugar industry, there is an urgent need to analyze the sources of output growth in the industry (see, Pandey (2007) and, Kumar and Arora (2010) for an introductory review of Indian sugar industry).

The present study is in the lines to fulfill the aforementioned gap in the literature and aimed at analyzing the contribution of the sugar industry in the process of overall economic growth of the 12 major sugar producing states[1] of India. For this, we studied the long-run relationship between the growth of sugar industry and growth of per-capita state domestic product (an indicator of economic growth at the state levels) using dynamic panel data vector autoregressive (VAR) modeling. The present work aiming to assess the

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presence of long-run relationship between growth of sugar industry and regional economic growth in India has been divided into four sections. Section 1 presents methodology used for obtaining empirical results. Section 2 provides the distinct sources of the data and construction of the variables. In Section 3, the empirical results are presented and discussed. The final section concludes the study and provides some noteworthy policy implications.

## 1. Methodology

To check the existence of long-run relationship among different macroeconomic variables and provide robust policy implications, we need first to check for the statistical impurities generally arising from the non-stationary time series. Thus, to avoid the spurious regression we need to check the order of the integration for the given time series variables. The order of integration is the order of differencing at which a non-stationary variable becomes stationary. In a time-series framework, we generally apply Augmented Dickey Fuller (ADF) and Phillip Peron (PP) statistics (see Lütkeophal, 2005; Harris and Sollis 2006; Asteriou and Hall, 2007, for detail on ADF and PP). However, when dealing with panel data, the estimation procedure is more complex than what we use in time series framework. The crucial factor in panel data estimation appears to be the degree of heterogeneity. In particular, it is important to realize that all the individuals in a panel may not have the same properties i.e., they may not all be stationary or non-stationary (or cointegrared or not cointegrated). So if we carry out a panel unit root test where some of the panel have unit root and some do not and the situation becomes more complex (Asteriou and Hall, 2007).

### 1.1 Testing for Unit-Root in Panel Data Framework

In literature, to check for the presence of unit root, different panel data tests like, Levin, Lin and Chu (2002)[2], Maddala and Wu (1999), and Im, Persaran and Shin (2003), have been suggested. However, Levin and Chu (LC), and Im, Persaran and Shin (IPS) test statistics are most widely used statistics to check the presence of unit root in a longitudinal (panel data) variable (Dash and Kumar, 2007). In the present study, we apply the IPS test to check for the order of integration for our panel data variables included into the model The IPS overcomes the major drawback of the LL test which restricts the $\rho$ to be homogeneous across all the cross-sectional units. The IPS test provides separate estimation for each i section, allowing different specifications of parametric values, the residual variance and lag length. Their model is given as:

$$\Delta Y_{it} = a_i + \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \phi_k \Delta Y_{i,t-k} + \delta_i t + u_{it} \qquad (1)$$

While now the null of $\rho_i = 0$ for all $i$ against the alternative of $\rho_i < 0$ for at least one $i$ has been formulated. Im, Persaran and Shin (1997) formulated their model under the restrictive assumption that $T$ should be the same for all cross-sections, requiring a balanced panel to compute the test statistics. Their statistics is nothing else than the average of the individual ADF $t$-statistics for testing $\rho_i = 0$ for all $i$ (denoted by $t_{pi}$):

$$\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{pi} \qquad (2)$$

IPS (1997) also showed that under specific assumptions $t_{pi}$ converges to a statistics denoted as $t_{iT}$ which they assume that is *iid* and that also has finite mean and variance. They then computed values for the mean $(E[t_{iT} / \rho_i = 1])(E[t_{iT} / \rho_i = 1])$ and for the variance $(\text{Var}[t_{iT} / \rho_i = 1])$ of the $t_{iT}$ statistic for different values of $N$ and lags included in the augmentation term in equation:

$$\Delta Y_{it} = a_i + \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \phi_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + u_{it} \qquad (3)$$

Based on those values, they then constructed the IPS statistics for testing unit roots in panel data given by:

$$t_{IPS} = \frac{\sqrt{N}\left(\bar{t} - {}^{1}\!/_{N}\sum_{i=1}^{N} E[t_{it} / \rho_i = 0]\right)}{\sqrt{\text{Var}[t_{it} / \rho_i = 0]}} \qquad (4)$$

which they have proved follows the standard normal distribution as $T \to 0$ followed by $N \to \infty$ sequentially. The values of $(E[t_{iT} / \rho_i = 1])$ and $(\text{Var}[t_{iT} / \rho_i = 1])$ are given in their paper. Finally, they also suggested a group mean Lagrange multiplier test for testing panel unit root. Performing Monte Carlo simulations they proved that both their LM and t statistics have better finite sanple properties than the LL test.

### 1.2 Testing for Cointegration in Panel Data Framework

Further, if data is not stationary at their levels then one way of solving the problem of non-stationarity is to difference the time series data until stationarity is not achieved. However, this solution is not ideal. If we difference the variables then the model can no longer give a unique long-run solution (Asteriou and Hall, 2007). To resolve this problem the methodology of Cointegration and Error Correction Mechanism (ECM) has been developed. Non-Stationary variables at levels are said are said to be cointegrated if any linear combination of these non-stationary variables provides us a series which is stationary at levels. This type of relationship is known as long-run relationship between these variables. Granger (1981) introduced a remarkable link between non-stationary processes and the concept of long-run equilibrium; this link is the concept of cointegration. Engle and Granger (1987) further formalized this concept by introducing a very simple test for the existence of cointegrating (i.e. long- run equilibrium) relationships. In such a case, after testing for the existence of cointegration, if it exist, it is necessary to form the model in the equivalent ECM (Error Correction Model) to get casual relationship between time series variables. The Granger representation theorem (see Engle and Granger, 1987) established that any cointegrated series have an ECM and its converse, that cointegration is a necessary condition for an ECM to hold, is also true (see Engle and Granger, 1991).To test for cointegration in between two variables, the study adopts the Engle-Granger approach of cointegration for single equation case.

According to this approach, if the time series variables are integrated[3] of same order, then the next step is to estimate the long-run equilibrium relationship via estimating the following equation (5) and obtain the series of estimated residuals ($\hat{u}_t$):

$$Y_t = \beta_1 + \beta_2 X_t + u_t \tag{5}$$

After, this check for the order of integration of the residuals by performing Dickey Fuller (DF) test on the residual series. The form of the DF test to check for stationarity of the residuals without any constant or time trend is given as in following equation (6):

$$\Delta u_t = a_1 \hat{u}_{t-1} + \sum_{i=1}^{n} \delta_i \Delta \hat{u}_{t-i} + v_t \tag{6}$$

If $\hat{u}_t$ is stationary at levels, i.e., $u_t \sim I(0)$, then we can reject the null hypothesis that the variables $X_t$ and $Y_t$ are not cointegrated. This series of residuals can be used to estimate the error-correction model to analyze the long-run and short-run effects of the variables as well as to see the adjustment coefficient, which is the coefficient of the lagged residual terms of the long-run relationship. But if the series of residuals obtained after estimating equation (5) are not stationary at levels then apply simple Granger Causality test at first differences (as we suppose our time series variables are integrated of order one) to know the short-run two way relationship between time series variables (Mahdavi *et. al*., 1994). Thus, the Engle-Granger (1987) cointegration test is based on an examination of the residuals of a spurious regression performed using $I(1)$ variables. If the variables are cointegrated then the residuals should be $I(0)$. On the other hand if the variables are not cointegrated then the residuals will be $I(1)$. Pedroni (1999, 2004) and Kao (1999) extend the Engle-Granger framework to tests involving panel data.

Pedroni (1999, 2004) proposes several tests for cointegration that allow for heterogeneous intercepts and trend coefficients across cross-sections. Consider the following regression:

$$y_{it} = \alpha_i + \delta_i t + \beta_{1i} x_{1it} + \beta_{2i} x_{2it} + \ldots + \beta_{Mi} x_{Mit} + e_{it} \tag{7}$$

for $t$ = 1, … , $T$; $i$ =1, …, $N$; $m$ = 1, …, $M$; where y and x are assumed to be integrated of order one i.e., $I(1)$. The parameters and are individual and trend effects which may be set to zero if desired. Under the null hypothesis of no cointegration, the residuals will be $I(1)$. The general approach is to obtain residuals from Equation (7) and then to test whether residuals are $I(1)$ by running the auxiliary regression:

$$e_{it} = \rho e_{i,t-1} + u_{it} \tag{8}$$

or

$$e_{it} = \rho e_{i,t-1} + \sum_{j=1}^{p_i} \psi_{ij} \Delta e_{i,t-j} + v_{it} \tag{9}$$

for each cross-section. Pedroni describes various methods of constructing statistics for testing for null hypothesis of no cointegration $\rho_i = 1$. There are two alternative hypotheses: the homogenous alternative, $\rho_i = \rho$ for all $i$ (which Pedroni terms the within-dimension test or panel statistics test), and the heterogeneous alternative, $\rho_i < 1$ for all $i$ (also referred to as the between-dimension or group statistics test).

The Pedroni panel cointegration statistic $\aleph_{NT}$ is constructed from the residuals from either Equation (8) or Equation (9). A total of eleven statistics with varying degree of properties (size and power for different $N$ and $T$) are generated. He shows that the standardized statistic is asymptotically normally distributed,

$$\frac{\aleph_{NT} - \mu\sqrt{N}}{\sqrt{v}} \Rightarrow N(0,1) \quad (10)$$

where $\mu$ and $v$ are Monte Carlo generated adjustment terms. Details for these calculations are provided in the original papers.

However, the limitation of the Pedroni statistics is that it assumes a unique cointegrating vector i.e., a unique type of relationship. Thus, an alternative test i.e., Fisher (combined Johansen) test has also been applied to find out the number of cointegration relationships (vectors) between the variables. Maddala and Wu (1999) used Fisher (1932) combined test, which uses the results of the individual independent tests to propose an alternative approach, to testing for cointegration in panel data by combining tests from individual cross-sections to obtain at test statistic for the full panel. If $\Pi_i$ is the *p*-value from an individual cointegration test for cross-section, then under the null hypothesis of no-cointegration for the panel, $-2\sum_{i=1}^{N}\log(\Pi_i) \rightarrow \chi^2 2n$. By default, the econometrics software EViews-6 reports the $\chi^2$ value based on MacKinnon-Haug-Michelis (1999) *p*-values for Johansen's cointegration trace test (lambda trace) and maximum Eigen (Lambda max) value test (see Lütkeophal, 2005; Asteriou and Hall, 2007 for detail on Johansen test of cointegration).

After obtaining the information about the number of cointegration vectors, the next step deals with the estimation of the cointegration vector. In a panel data framework, it is inappropriate to apply the method of OLS in a two variable framework. Thus, we use the Arellano and Bond (1991) one and two steps procedure to explain the long-run relationship because these estimates are consistent as compare to the other approaches such as pooled OLS, fixed effect and random effect models (see, Baltagi, 2005 pp. 135-163 for detail on dynamic panel data models). After obtaining the point estimates, we check for the existence of unit root in the residual using IPS statistics. If $e_{it} \sim I(0)$ i.e., stationary at levels then the estimated relationship is said to permanent or long-run in nature. However, if the order of integration is different for the exogenous variables to be considered for the long-run relationship then autoregressive distributed lag (ADL) approach has been suggested for the estimation of long-run relationship. However, the estimation procedure for this ADL model also requires dynamic panel data estimation methods. Further, the determination of the cause and effect relationship using vector error correction mechanism (VECM) also requires the Arellano and Bond (1991) method of estimation.

## 1.3 Panel Data Vector Error Correction Mechanism (VECM)

After, obtaining the long-run relationship of policy variables, it becomes pertinent to analyze short-run dynamics of the panel data model with *k* variables. The estimation of the cointegration relationship will provide a series (i.e., series of residuals) which is stationary at levels. This series of residuals can be used to estimate the error-correction model to analyze the long-run and short-run effects of the variables as well as to split the long-run cointegration vector (if vectors are two then we call it cointegration matrix) into a vector of adjustment parameters (explaining the adjustment towards long-run equilibrium) and a vector of long-run coefficients.

Following Banerjee, *et al.* (1993), Shiu and Lam (2004), Wigren and Wihelmsson (2007) and Dash and Kumar (2007), a general bivariate dynamic regression model in the form of vector error correction model (VECM) is equal to:

$$\Delta Y_{it} = \alpha_{1j} + \lambda_{1i} e_{it-1} + \sum_k \beta_{1ik}\Delta Y_{i,t-k} + \sum_k \beta_{2ik}\Delta X_{i,t-k} + \gamma_i + e_{1it} \quad (11)$$

$$\Delta X_{it} = \alpha_{2j} + \lambda_{2i} e_{it-1} + \sum_k \varphi_{1ik}\Delta Y_{i,t-k} + \sum_k \varphi_{2ik}\Delta X_{i,t-k} + \gamma_i + e_{2it} \quad (12)$$

where $\Delta$ denotes first difference operator and *k* is the lag length. The coefficients of the lagged residual terms (obtained from the long-run relationship (5)) signify the adjustment parameter. The sources of causation can be identified by testing for the significance of the coefficients of the dependent variables in above equations (11) and (12). First, the short-run effect can be considered transitory. For short-run causality, we can test the null of $\beta_{lik}$ for all *i* and *k* in equation (11) or $\varphi_{1i/k}$ for all *i* and *k* in model (12). Next, the long-run causality can be tested by looking at the significance of the speed of adjustment $\lambda$, i.e., the coefficient of error-correction term $e_{it-1}$. The significance of $\lambda$ indicates the long-run relationship of the cointegrated process, and so movement along this path can be considered permanent. For long-run causality, we can test $\lambda_{1i} = 0$, for all i in equation (11) or $\lambda_{2i}$ for all *i* in model (12). As we are using panel data, a fixed effect model will be used to account for idiosyncratic state effect (Holtz-Eakin, 1994).

Further, following Lutkepohl (2005), the optimum lag length has been determined using the following equation:

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-k} + A_{p+1} y_{t-k-1} + u_t$$

Here, if $y_t$ is a VAR($k$) process, it is also a VAR($k$ + 1) process given $A_k + 1 = 0$. Therefore, in this model, we will call $y_t$ a VAR($k$) process if $A_k \neq 0$ and for $i > k$ so that $k$ is the smallest possible order. This unique number will be called the VAR order.

It is worth mentioning here that the panel data VECM model is applicable if the variables are cointegrated (i.e., there exist at least one cointegration vector). But if the series of residuals obtained after estimating equation (5) is non-stationary at levels then apply simple Granger Causality test at first differences (as we suppose our time series variables are integrated of order one) to know the short-run two way relationship between time series variables (Mahdavi *et. al*., 1994).

## 2. Database and Construction of Variables

To study the long-run relationship between the growth of sugar industry and economic growth in the macro economy of 12 major sugar producing states, we have used the 7 time series variables which are outlined in Table 1. The variable LNSDP is the log of the index of state domestic product (SDP) growth defined as:

$SDPI_{1974/75}$ =100 (i.e., Output growth index for the year 1974/75 is taken to be 100) and, $SDPI_{t+1}$= $SDPI_t$ ×(1+(Growth rate of $SDP)_{t+1}$)

Taking the log SDPIt the variable of LNSDP has been constructed. It is worth mentioning here that the per capita state domestic products from 1974/75 to 2000/01 have been obtained from the database 'Domestic Products of States of India: 1960-61 to 2000-01' maintained by Economic and Political Weekly (EPW) research foundation, India. However, for the remaining four years, the figures of per capita SDP have been culled out from economic intelligence reports provided by center for monitoring Indian economy (CMIE).

**Table 1. Summary of Variables**

| *ABBREVIATION OF VARIABLE* | *VARIABLES DESCRIPTION* |
|---|---|
| LNSDP | Log of Real Gross State Domestic Product |
| LNSUGAR | Log of Sugar Output |
| LNPEIN | Log of Pure Efficiency Change Index |
| LNSEIN | Log of Scale Efficiency Change Index |
| LNPTIN | Log of Hicks Neutral Type of Technical Change Index |
| LNIBIN | Log of Hicks Non-neutral Technical Change Index |
| LNIGIN | Log of the Inputs Growth Index |

*Source:* Author's Elaboration

Further, the following Malmquist productivity index (13) has been utilized to construct the indices of different components of TFP growth.

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)} \sqrt{\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}} \qquad (13)$$

where,

$$\text{Technical Efficiency Change} = ECH = \frac{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_o^t\left(x^t, y^t\right)} \qquad (14)$$

$$\text{Technological Change} = TCH = \sqrt{\frac{D_o^t\left(x^{t+1}, y^{t+1}\right)}{D_o^{t+1}\left(x^{t+1}, y^{t+1}\right)} \frac{D_o^t\left(x^t, y^t\right)}{D_o^{t+1}\left(x^t, y^t\right)}} \qquad (15)$$

As given in model (13), in order to calculate the MPI for state $k$ between $t$ and t + 1 for a constant returns-to-scale (CRS) technology, the four different distance functions that make up the index (i.e., $D_o^t(x^{k',t}, y^{k',t})$, $D_o^{t+1}(x^{k',t+1}, y^{k',t+1})$, $D_o^t(x^{k',t+1}, y^{k',t+1})$, and $D_o^{t+1}(x^{k',t}, y^{k',t})$) are required to be calculated using linear programming approach. For calculating output-oriented distance functions for the sugar producing state , four different linear programming problems can be stated as:

$$\left.\begin{aligned}
&D_o^{t+j}(x^{k',t+j}, y^{k',t+j})^{-1} = \max\ \theta^{k'} \\
&\text{subject to} \\
&\theta^{k'} y_m^{k',t+j} \le \sum_{k=1}^{K} z^{k,t+i} y_m^{k,t+i}, \qquad m = 1,\ldots,M; \\
&\sum_{k=1}^{K} z^{k,t+i} x_n^{k,t+i} \le x_n^{k',t+j}, \qquad n = 1,\ldots,N; \\
&z^{k,t+i} \ge 0, \qquad k = 1,\ldots,K.
\end{aligned}\right\} \quad (16)$$

where $(i, j) = (0,0)$ for solving for $(D_o^t(x^{k',t}, y^{k',t}))^{-1}$ ;

$(i, j) = (1,1)$ for solving for $(D_o^{t+1}(x^{k',t+1}, y^{k',t+1}))^{-1}$;

$(i, j) = (0,1)$ for solving for $(D_o^t(x^{k',t+1}, y^{k',t+1}))^{-1}$; and

$(i, j) = (1,0)$ for solving for $(D_o^{t+1}(x^{k',t}, y^{k',t}))^{-1}$ .

In the above linear programming problems, $z^{k,t}$ is an intensity variable indicating the intensity at which a particular state is employed in constructing the frontier of the technology set. The technology specified here is non-parametric but assumes constant returns-to-scale and strong disposability of inputs and outputs. In above formulation $\theta$ is the efficiency score and take value between 0 and 1. Following Afrait (1972), one may allow for variable returns to scale (increasing, constant or decreasing) by having $\sum Z_k = 1$ as a restriction in all of the linear programs. Thus, estimation of distance functions defined by model (16) along with the restriction $\sum Z_k = 1$ enables us to decompose the ECH into PECH and SECH given as:

$$ECH = \underbrace{\frac{D_o^{t+1}(x^{t+1}, y^{t+1}/VRS)}{D_o^t(x^t, y^t/VRS)}}_{PECH} \times \underbrace{\frac{S_o^{t+1}\left(x^{t+1}, y^{t+1}\right)}{S_o^t\left(x^t, y^t\right)}}_{SECH} \quad (17)$$

Moreover, estimating two additional distance functions $(D_o^t(x^{k',t+1}, y^{k',t}))^{-1}$ and $(D_o^{t+1}(x^{k',t+1}, y^{k',t}))^{-1}$ makes it possible to decompose TECH into Hicks neutral and non-neutral types of technical progress, given as:

$$TECH = \underbrace{\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}}_{Hicks\ Neutral} \times \underbrace{\sqrt{\frac{D_o^{t+1}(x^t, y^t)}{D_o^t(x^t, y^t)} \times \frac{D_o^t(x^{t+1}, y^t)}{D_o^{t+1}(x^{t+1}, y^t)}}}_{Hicks\ Non-neutral} \quad (18)$$

The $x^t$ and $y^t$ are input and output variables sets, respectively (For details on the construction of these variables see Kumar and Arora, 2009).

Following the procedure outlined by Sharma and Upadhyay (2008), the indices for the components of TFP have been constructed as follows:

$PECHI_{1974/75}$=100 (i.e., Pure Efficiency Change Index for 1974/75 is taken to be 100)

and, $PECHI^{t+1} = PECHI_t(1+(PECH-1)_{t+1})$

where PECHI is pure efficiency change index and PECH-1 represents the growth of pure efficiency. Similarly, the indices for the remaining components of output growth viz., scale efficiency change (SECH), Pure technical change (i.e., MATECH component an indicator of Hicks neutral type of technical progress), and input bias technology change (i.e., IBTECH an indicator of Hicks non-neutral type of technical progress) have been constructed using same method.

## 3. Empirical Results

In the first step, we test the presence of unit-root in the aforementioned macroeconomic variables using the IM, Pesaran and Shin (IPS) panel unit root test. Testing of the presence of unit-root is essential i) to get exact order of integration so as to get rid of the problem of spurious regression; ii) to check the existence of cointegration relationship between the growth of Indian sugar industry and economic growth of India; and iii) to identify the relevant policy variables for augmenting the growth of Indian sugar industry. Table 2 presents the results pertaining to IPS panel unit-root test. From Table 2, we note that the application of IPS test refutes the presence of unit-root for the two variables LNSEIN and LNIBIN, and thus, found to be stationary at levels. However, the remaining variables are found to be non-stationary (i.e., I(1)) i.e., they attain stationarity after first differencing. Therefore, the inclusion of LNSEIN and LNIBIN is not feasible (because they are I(0)) to determine long-run cointegrating relationship between output and indices of the components of output growth using Johansen cointegration framework.

**Table 2.** **IM, Pesaran and Shin (IPS) Panel Unit Root Test**

| VARIABLES | WITHOUT TREND | | WITH TREND | | |
|---|---|---|---|---|---|
| | AT LEVEL | 1ST DIFFERENCE | AT LEVEL | 1ST DIFFERENCE | ORDER OF INTEGRATION |
| LNSDP | 2.11 | –11.35** | 0.17 | –9.37** | I(1) |
| LNSUGAR | –1.87* | –16.17** | –5.53** | –14.59** | I(1) |
| LNPEIN | –3.23** | –4.55** | –0.22 | –3.05** | I(1) |
| LNSEIN | –2.56** | –7.10** | –5.41** | –5.43** | I(0) |
| LNPTIN | 1.55 | –4.14** | 0.13 | –2.70** | I(1) |
| LNIBIN | –2.30* | –6.68** | –5.75** | –4.51** | I(0) |
| LNIGIN | 1.85 | –12.51** | –1.13 | –11.84** | I(1) |

Notes: i) The critical values for the panel unit root test at the 1 percent and 5 percent levels of significance are -2.326 and -1.645, respectively; and ii) ** denotes significant at 1 percent level and * refers to significance at 5 percent level.

*Source:* Author's Calculations

## 3.1 Long-run Dynamics, i.e. Cointegration Analysis

Table 3 provides the results of Pedroni test to ascertain the existence of cointegration (i.e., long-run relationship) between the sugar output and per capita SDPs. Three alternative models i) without trend and time dummy; ii) with time dummy; and iii) with trend and time dummy, have been used to explore the existence of long-run relationship between three variables. It has been observed that out of 7 alternative statistics, 6 statistics reveal the existence of cointegration for the without trend and time dummy model. Even for the other two models, majority of the test statistics supports the existence of cointegration between growth of sugar industry and per capita SDP. Thus, the macroeconomic analysis pertaining to the contribution of growth performance of Indian sugar industry in overall process of economic growth of India at aggregate and disaggregate (regional) levels carries a worth in the light of presence of long-run relationship between these variables. Thus, the results can be used to draw significant policy implications for augmenting the rate of economic growth in the macro economy of major sugar producing states.

**Table 3.** **Pedroni Test of Cointegration between Ex-factory Sugar Output and Per-capita State Domestic Products**

| STATISTICS | WITHOUT TREND AND TIME DUMMY | WITH TIME DUMMY | WITH TREND AND TIME DUMMY |
|---|---|---|---|
| Panel v-Statistic | –0.121 | –1.581 | 9.703** |
| Panel rho-Statistic | –2.934** | –2.126* | –3.278** |
| Panel PP-Statistic | –2.867** | –2.281* | –4.466** |
| Panel ADF-Statistic | –2.270* | –1.397 | –0.582 |
| Group rho-Statistic | –0.474* | –1.506 | –1.789 |
| Group PP-Statistic | –2.629* | –2.259* | –4.000** |
| Group ADF-Statistic | –2.103* | –1.982 | –0.630 |

**Note:** i) ** denotes null of no Cointegration is rejected at 1 percent level and * denotes null of no Cointegration is rejected at 5 percent level of significance; and ii) the decision about the rejection or not rejecting the null of no Cointegration is based upon the corresponding p-values.

*Source:* Author's Calculations

We supplemented the results of Pedroni test with Fisher (combined Johansen) test. Table 4 provides the lambda trace and Lambda max statistics for the Indian sugar industry. It has been observed that both of the tests reject the null hypothesis of no cointegration. However, the null hypothesis of at most one cointegration vector has not been rejected at 5 percent level of significance. Thus, the results support the existence of long-run relationship between the growth of sugar output and growth of per-capita SDP.

**Table 4. Fisher (combined Johansen) Test of Cointegration between Ex-factory Sugar Output and Per-capita State Domestic Products**

| *HYPOTHESIS* | *TRACE TEST* | *LAMBDA-MAX TEST* |
|---|---|---|
| No Cointegration Vector | 40.36* | 36.08* |
| | (0.0195) | (0.0480) |
| At most 1 Cointegration Vector | 36.11 | 36.11 |
| | (0.0535) | (0.0535) |

**Note:** i) * refers significance at 5 percent level; and ii) figures in parenthesis of type ( ) are p-values.

*Source:* Author's Calculations

After determining that there exists a unique cointegration vector, we estimated the model $Y_{it} = \beta_1 + \beta_2 X_{it} + u_{it}$ using the five alternative models namely, i) pooled OLS; ii) Fixed Effect; iii) random Effect; iv) Arellano and Bond one step procedure; and v) Arellano and Bond two step procedure. The estimation of a panel data model requires introduction of idiosyncratic cross-sectional or time specific (or both) effects and, thus, needs to apply either fixed effect or random effect models. Further, if the matter is to obtain dynamic panel estimates, the fixed effect or random effect estimators cannot be applied because of the presence of lagged endogenous variable due to which the estimates are biased (Nickell, 1981). However, the appropriate method of estimation is instrumental variable estimators as proposed by Anderson and Hsiao (1982) or the generalized methods of moments (GMM) estimators as proposed by Arellano and Bond (1991) (see Hayashi (2000) and Baltagi (2005), for details on Arellano and Bond procedure). To check the order of integration for the estimated residual ($\breve{u}_{it}$), IPS panel data unit-root test has been applied. If the $\breve{u}_{it} \sim I(0)$ then the null hypothesis of no cointegration is rejected and we can infer that, the estimated parameters provide a long-run relationship between the two variables.

**Table 5. Long-Run Relationship between Ex-factory Sugar Output and Per Capita SDP**

| *PARAMETER* | | *ARELLANO AND BOND ONE STEP* | *ARELLANO AND BOND TWO STEP* | *POOLED OLS* | *FIXED EFFECT* | *RANDOM EFFECT* |
|---|---|---|---|---|---|---|
| Constant ($\beta_1$) | | n.a. | 0.679** (0.000) | 0.478* (0.015) | 1.361** (0.000) | 1.053** (0.000) |
| Output ($\beta_2$) | | 0.440** (0.000) | -0.007 (0.542) | 0.376** (0.000) | 0.264** (0.000) | 0.303** (0.000) |
| IM, Pesaran and Shin (IPS) Panel Data Unit-Root Test for Residual→ | Individual Intercept | -6.773** (0.000) | -9.276** (0.000) | -0.097 (0.461) | -0.705 (0.240) | 0.839 (0.799) |
| | Intercept and trend | -7.862** (0.000) | -9.658** (0.000) | -6.571** (0.000) | -4.069** (0.000) | -6.122** (0.000) |

**Note**: i) ** and * refer significant at 1 percent and 5 percent levels of significance respectively; ii) # refers estimators obtained using the time specific effects as fixed; and iii) figures in parenthesis of type ( ) are p-values.

*Source:* Author's Calculation

Table 5 provides the estimates of the parameters using aforementioned 5 alternative methods. It has been observed that the null hypothesis of the presence of unit-root in ($\breve{u}_{it}$) has been strongly rejected using the Arellano and Bond (1991) one step and two step procedures (i.e., both without trend and with trend IPS statistics are negative and significant). Thus, the estimates of GMM are preferred over the estimates obtained using pooled OLS, fixed and random effect models. Further, the estimates obtained from GMM one step method are consistent but not efficient whereas the GMM two steps procedure provides efficient estimators. Thus, the estimates obtained using Arellano and Bond two steps (GMM two steps) procedure have been used to explain the long-run relationship between the growth of sugar output and growth of per-capita SDP. The estimates of cointegration relationship support the inference that growth of sugar output is positively affecting the growth of per-capita SDPs of sugar producing states. Since, the variables are in logarithmic form, the estimated coefficients thus, represent the output elasticity of growth of SDP. On the basis of above results, we conclude that 1 percent growth in sugar output bring theoretically a 0.44 percent increase in per-capita SDP of 12 major sugar producing states of India. Although, the results seems to be overstating the scenario yet the positive and significant relationship has been identified by 4 out of the five techniques applied.

## 3.2 Cointegration between the Output Growth and its Sources in Indian Sugar Industry

The above analysis clearly provide a long-run relationship between the growth of sugar industry in terms of output and growth in per-capita SDP in the macro economy of major sugar producing states. Given the long-run relationship between the growth in sugar output and per capita SDPs, it has now become pertinent to analyze the long-run determinants of growth in sugar production in these states. For this purpose, we again conducted a cointegration analysis using the variable LNSUGAR as dependent variable and the variables LNPEIN, LNSEIN, LNPTIN, LNIBIN, and LNIGIN as independent variables. We expect that all these variables affect LNSUGAR positively and significantly. However, application of IM, Pesaran and Shin (IPS) panel unit root test provides that two variables LNSEIN and LNIBIN are integrated of order zero (see, Table 2) i.e., stationary at levels and the remaining variables are stationary of order one. Therefore, the Johansen procedure for testing the existence of cointegration is not appropriate. However, the long-run relationship among the variables with different order of integration can be explored with the autoregressive distributed lag (ADL) model. The ADL model for two variables for a time series framework is given as:

$$Y_t = a_0 + \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{i=0}^{n} \beta_i X_{t-i} + \varepsilon_t$$

where, $\alpha_i$ and $\beta_i$ are coefficient and $\varepsilon_t$ is an error term. Estimating this equation using the method of OLS helps to obtain the long-run coefficient given as:

$$a_0^* = \frac{\hat{a}_0}{1 - \sum_{i=1}^{n} \hat{\alpha}_i} \quad \text{and} \quad \beta^* = \frac{\sum_{i=0}^{n} \hat{\beta}_i}{1 - \sum_{i=1}^{n} \hat{\alpha}_i}$$

However, the same methodology can be extended in a multiple dynamic panel data regression framework. Instead of applying OLS, we use Arellano and Bonds (1991) type of estimates to obtain the long-run vector or relationship. However, the alternative techniques such as pooled estimates, fixed effect and random effect have also been utilized to check the sensitivity of the results.

Table 6 provides the estimates of ADL model. It has been observed that the estimates obtained using Arellano and Bonds' one step procedure satisfy *a-priori* expectations about the direction of the impact of independent variables. However, the remaining three models do not satisfy a-priori expectations. The long-run relationship provided by the Arellano and Bonds' estimates confirms that input growth elasticity of output (i.e., the coefficient of LNIGIN) dominates all other remaining components of output growth. A one percent increase in inputs has been observed to increase sugar output by 4.803 percent. However, baring the pure efficiency change elasticity of output (i.e., coefficient of LNPEIN), the remaining elasticities are positive[4] and unitary less elastic. The policy implication of above results is that any long-run policy to augment sugar output must be in direction to enhance input growth first. However, in the light of the observations of Kumar and Arora (2009), we must say that among inputs, the increase in the supply of the raw material (i.e., sugarcane) is pre-requisite for reaching at the levels of potential capacity output and then for augmenting the sugar production. Due to inadequate supply of sugarcane, the existing plant capacity of most of the sugar mills is not properly utilized and they sometimes cease off their production operations even during the mid of a sugar year.

**Table 6.** **Estimates of ADL Models and Long-Run Relationship between Components of Output Growth and Ex-factory Sugar Output**

| *VARIABLE* | *ARELLANO AND BOND* | | *POOLED OLS* | | *FIXED EFFECT* | | *RANDOM EFFECT* | |
|---|---|---|---|---|---|---|---|---|
| | *ADL* | *LONG-RUN* | *ADL* | *LONG-RUN* | *ADL* | *LONG-RUN* | *ADL* | *LONG-RUN* |
| a) Costant | 2.605* | a/b=8.218 | 1.744* | a/b=22.358 | 1.541* | a/b=13.059 | 1.736* | a/b=22.545 |
| LNSUGARt-1 | 0.895* | | 1.077* | | 1.016* | | 1.077* | |
| LNSUGARt-2 | –0.21* | | –0.155* | | –0.134* | | –0.154* | |
| b) 1-Sub Total | 0.315 | | 0.078 | | 0.118 | | 0.077 | |
| LNPEINt | 4.206* | c/b=(–)0.044 | 3.414* | c/b=(–)1.064 | 3.691* | c/b=(–)0.390 | 3.417* | c/b=(–)1.091 |
| LNPEINt-1 | –5.893* | | –4.704* | | –5.335* | | –4.715* | |
| LNPEINt-2 | 1.673* | | 1.207* | | 1.598* | | 1.214* | |
| c) Sub Total | –0.014 | | –0.083 | | –0.046 | | –0.084 | |
| LNSEINt | 4.081* | d/b=0.105 | 3.414* | d/b=(–)1.064 | 3.736* | d / b = ( – )0.797 | 3.735* | d/b=(–)2.494 |
| LNSEINt-1 | –6.516* | | –4.704* | | –5.833* | | –5.4* | |
| LNSEINt-2 | 2.468* | | 1.207* | | 2.003* | | 1.473* | |
| d) Sub Total | 0.033 | | –0.083 | | –0.094 | | –0.192 | |
| LNPTINt | 4.244* | e/b=0.156 | 3.392* | e/b=(–)0.590 | 3.726* | e/b=(–)0.415 | 3.396* | e/b=(–)0.597 |
| LNPTINt-1 | –5.817* | | –4.536* | | –5.296* | | –4.546* | |
| LNPTINt-2 | 1.622* | | 1.098* | | 1.521* | | 1.104* | |
| e) Sub Total | 0.049 | | –0.046 | | –0.049 | | –0.046 | |
| LNIBINt | 4.871* | f/b=0.317 | 3.879* | f/b=(–)2.154 | 4.212* | f/b=(–)1.288 | 3.885* | f/b=(–)2.169 |
| LNIBINt-1 | –7.174* | | –5.314* | | –6.434* | | –5.33* | |
| LNIBINt-2 | 2.403* | | 1.267* | | 2.07* | | 1.278* | |
| f) Sub Total | 0.1 | | –0.168 | | –0.152 | | –0.167 | |
| LNIGINt | 1.421* | g/b=4.803 | 1.651* | g/b=(–)0.846 | 1.503* | g/b=0.347 | 1.648* | g/b=(–)0.844 |
| LNIGINt-1 | –1.53* | | –1.887* | | –1.65* | | –1.883* | |
| LNIGINt-2 | 1.622* | | 0.17* | | 0.188* | | 0.170* | |
| g) Sub Total | 1.513 | | –0.066 | | 0.041 | | –0.065 | |
| Unit-Root | Model1 | | –7.948* | | –10.595* | | –10.284* | –10.615* |
| Test | Model2 | | –9.380* | | –10.653* | | –10.454* | –10.695* |

Notes: * refers significant at 5 percent level of significance;

*Source:* Author's Calculations

### 3.3 Short-Run Dynamics

After exploring the long-run relationship between growth of sugar output and its components, we concentrate on the short-run dynamics of the panel data model with LNSUGAR as dependent variable and LNPEIN, LNSEIN, LNPTIN, LNIBIN, and LNIGIN as independent variable. The estimation of ADL (GMM1) model provides a residual, which has been observed stationary at levels (see Table 6). This series of residuals can be used to estimate the error-correction model to analyze the long-run and short-run effects of the variables as well as to see the adjustment coefficient, which is the coefficient of the lagged residual terms of the long-run relationship.

We also operationalise the pooled mean group (PMG) based methodology developed by Engle and Granger (1987) and Following Banerjee, *et al*. (1993), Shiu and

Lam (2004), Wigren and Wihelmsson (2007) and Das and Kumar (2007), a general dynamic regression model in the form of vector error correction model (VECM) given by equations (11) and (12) have been estimated. The panel data VECM model given by equations (11) and (12) has been extended for six variables case and the Wald $\chi^2$ — *statistics* have been reported for testing Granger type of causality between the aforementioned variables in Table 7. Using the appropriate lag length of one for VECM, the analysis reports that except input growth, the remaining components of output growth in Indian sugar industry are significantly causing the growth of sugar output in the short-run. Nevertheless, the transitory (i.e., short-run) impact of inputs growth is relatively feeble because in short-run: i) instantaneous increase in sugarcane output is not possible and requires gradual changes at institutional level particularly at farm level; ii) fixed factor of production i.e., capital cannot be increased; and iii) labour input cannot be increased because of already observed frictional type of unemployment in sugar industry. Further, the significance of long-run impact parameter (i.e., the coefficient of error correction term) also confirms the importance of all the components (including inputs growth) of output growth, to augment the performance of sugar industry in the long-run.

An important inference that can be drawn from the significant $\chi^2$—*statistics* of error-correction term equal to 98.22 that the input growth[5] is significantly affected by the growth of sugar output and as well as of its component. Further, both types of effects i.e., transitory and permanent, have been observed significant for inputs growth as dependent variable. The direct connotation of this result is that the problem of acute inputs shortage can be resolved via improving the performance of sugar industry. Thus, we can safely infer that there exists a significant cause and effect relationship between the inputs growth and growth of sugar industry. If the rising excess capacity and technical inefficiency is caused by the shortage of inputs then the shortage of inputs has also been caused primarily by the poor performance of sugar mills. Given the abundant capacity, the shortage of inputs is primarily attributed to the shortage of sugarcane. Thus, the major component of input growth is sugarcane output. Nevertheless, farmers are not ready to grow sugarcane because of the untimely payments to the farmers by sugar mills and mounting sugarcane arrears. Being a more profitable crop, farmers will prefer to grow sugarcane as compare to the indigenous crops wheat and rice, if sugar firms pay the farmers in time. Thus, the performance of sugar industry can solve the problem of shortage of sugarcane, and vice-versa.

**Table 7. Panel Data VECM Granger Causality/Block Exogeneity Wald Tests**

| *CAUSE VARIABLE* | *EFFECT VARIABLES* | | | | | |
|---|---|---|---|---|---|---|
| | *D(LNSUGAR)* | *D(LNPEIN)* | *D(LNSEIN)* | *D(LNPTIN)* | *D(LNIBIN)* | *D(LNIGIN)* |
| D(LNSUGAR) | n.a. | 1.698<br>(0.4279) | 0.080<br>(0.9608) | 1.924<br>(0.3821) | 0.067<br>(0.9673) | 25.684**<br>(0.000) |
| D(LNPEIN) | 18.325**<br>(0.000) | n.a. | 1.743<br>(0.4183) | 19.124**<br>(0.000) | 0.901<br>(0.6374) | 22.836**<br>(0.000) |
| D(LNSEIN) | 16.128**<br>(0.000) | 7.744*<br>(0.021) | n.a. | 7.383*<br>(0.025) | 5.114<br>(0.0775) | 8.960*<br>(0.011) |
| D(LNPTIN) | 19.797**<br>(0.000) | 18.835**<br>(0.000) | 1.290<br>(0.5246) | n.a. | 0.900<br>(0.6376) | 25.203**<br>(0.000) |
| D(LNIBIN) | 17.497**<br>(0.000) | 9.548**<br>(0.008) | 8.466**<br>(0.0145) | 10.521**<br>(0.005) | n.a. | 9.954**<br>(0.007) |
| D(LNIGIN) | 1.807<br>(0.4051) | 0.120<br>(0.9419) | 0.063<br>(0.9686) | 0.059<br>(0.971) | 0.0295<br>(0.9854) | n.a. |
| eit-1 | 36.428**<br>(0.000) | 32.013**<br>(0.000) | 15.834<br>(0.105) | 31.474**<br>(0.000) | 8.785<br>(0.553) | 98.212**<br>(0.000) |

**Note:** i) values are Wald -statistics; ii) figures in parenthesis of type are p-values; and iii) * and ** refers significant at 5 percent and 1 percent levels of significance, respectively.

*Source:* Author's Calculations

As observed earlier, that there exists a significant cause and effect relationships between the six variables included into the model, the regression diagnose provide a reasonably good fit for each model. Thus, to ascertain the relative importance of each component to augment the output growth in sugar industry, the impulse response analysis has been utilized through formulating a 2-lag VAR with Cholesky identification scheme. Given the objective to find out relative importance of each factor augmenting output growth, the response of one standard deviation shock in each factor to output growth spanning over the forthcoming 10 years has been reported[6] in Table 8.

It is evident from Table 8 that the policy needed to improve the performance of sugar industry must have the spirit to boost up the input growth. It has been observed that the impact of inputs growth persists over the period of 7 years given the impact of output itself dies down in 6 years, pure efficiency change (i.e., LNPEIN) in 5 years, scale efficiency change (i.e., LNSEIN) in 3 years, Hick neutral type of technical progress (i.e., LNPTIN) in 5 years, and Hick non-neutral type of technical progress (i.e., LNIBIN) in first year. Thus, the analysis reiterates our earlier finding that inputs growth driven by increase in the supply of sugar cane is relatively most important source to achieve sustainable and permanent growth in the sugar manufacturing of India.

**Table 8. Impulse Response to Output Growth**

| *RESPONSE OF ±1SD SHOCK TO* | *PERIOD* | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | *t* | *t+1* | *t+2* | *t+3* | *t+4* | *t+5* | *t+6* | *t+7* | *t+8* | *t+9* | *t+10* |
| LNSUGAR | 0.169 | –0.074 | –0.024 | 0.020 | 0.006 | –0.009 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNPEIN | 0.000 | –0.001 | 0.002 | 0.000 | –0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNSEIN | 0.002 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNPTIN | 0.002 | 0.002 | –0.002 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNIBIN | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| LNIGIN | 0.088 | –0.041 | –0.003 | 0.009 | 0.002 | –0.004 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 |

**Note:** The responses to remaining variables have been ignored because the discussion about those is beyond the scope of the objectives of present study.

*Source*: Author's Calculations

## 4. Conclusions and Policy Implications

The overall conclusion that emerges from the study of macroeconomic framework is that there exists a significant long-run nexus between the growth of sugar industry and economic growth of the 12 sugar producing states of India. Further search for the relative importance of the components of output growth in explaining the growth of Indian sugar industry reveals that input growth is the most important and significant factor causing output growth in both long-run as well as in short-run. The Granger causality analysis reveals that there exists bi-directional relationship between output growth and inputs growth. The direct connotation of this fact is that if the improvement of sugar industry requires the substantial inputs growth then the inputs growth is also possible through the expansion of sugar industry.

In the light of the above results, we suggest that government policy should aim to solve the problems creating shortage of sugarcane. In this direction, the need of the hour is to encourage the farmers to opt for farming of sugarcane on large scale basis. The areas which require major focus are: i) timely and remunerative payments for the purchase of sugarcane; ii) rehabilitation of the sick sugar firms through providing funds to the sugar firms; and iii) stressing upon the total cane concept and production of sugar must be treated as the byproduct of the sugar firms. Once farmers will get the timely and assured payments for their produce, they will routinely diversify their production towards the cultivation of sugarcane in comparison to other indigenous crops such as wheat and rice. It will not only solve the problem of lack of the sugarcane supply for the sugar mills but will also help to diversify the Indian agriculture: a critical need of Indian agriculture.

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## Endnotes

[1] The 12 major sugar producing states are Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu and Uttar-Pradesh.

[2] Levin and Lin (1992) presented their test in a working paper in year 1992. However, their work was finally published in 2002 with Chu as another coauthor.

[3] Integrated of order one means that time series variables are stationary when taken at first difference.

[4] Although elasticities can never be negative, yet to represent the slope of dependent variable with respect to the given independent variable, negative word has been used.

[5] As the variables are in logarithmic forms, their first difference will represent average annual growth over one year.

[6] The response of one standard deviation shock in each variable to the remaining 5 variables (except output) has not been reported to save space and also due to the irrelevance of the matter to justify the given objectives.