DATA BASE AND METHODOLOGY

The present chapter explains the theoretical framework related to efficiency and productivity growth of the variables related to the present study. This chapter is divided into three sections. Section 3.1 discusses the sample data, specifications of input and output variables used to measure efficiency and productivity growth and the issues regarding selection of input and output variables. Sections 3.2 explains the techniques used for the measurement of efficiency, justifies the technique i.e., Data Envelopment Analysis (DEA) used in this study and elaborates the theoretical exposition and methodological framework of DEA models applied to analyze various measures of efficiency among Regional Rural Banks (RRBs) in India. This section also explains the Mann-Whitney U-test which is used to study the changes in DEA efficiency scores between two generation reforms periods. Section 3.3 focuses on the theoretical framework of total factor productivity (TFP) growth with a brief discussion on the techniques adopted for measuring productivity change and the model Malmquist Productivity Index (MPI) employed to measure total factor productivity growth of RRBs in India.

SECTION 3.1

3.1.1 Data Base

The study has considered a sample of 50 RRBs which have been uninterruptedly operating since 1991-1992 to 2006-2007 so as to make a balanced panel data set. The sample period is selected up to 2007 as few sample banks were merged after this period. As in the case of studies conducted by Howcroft and Attaullah (2006), Kaur and Jyoti (2005-06) and Zhao et al. (2008) for commercial banks in India, post-liberalization period has been divided into two sub-periods i.e., first-generation reforms period (1991-92 to 1997-98) and second-generation reforms period (1998-99 to 2006-07) to analyze the impact of reforms on the efficiency and behavior of TFP growth and their components among the RRBs. The data for the sample years covers data on financial year basis, i.e., beginning from 1\textsuperscript{st} April of existing year to 31\textsuperscript{st} March of succeeding
year. The list of 50 sample RRBs along with sponsors banks and respective states have been shown in Appendix I. The entire sample RRBs are being raised to be as B1, B2, B3… B50 respectively.

The present study is based upon secondary data. The data have been culled out from various issues of Statistical Tables Relating to Banks in India; Report on Trend and Progress in Banking; Manual on Financial and Banking Statistics; RBI monthly Bulletins published by Reserve Bank of India (RBI) and various issues of Financial Analysis of Regional Rural Banks; Regional Rural Banks Key Statistics and Review of Performance of Regional Rural Banks published by National Bank for Agriculture and Rural Development (NABARD). Apart from above mentioned sources, data has also been compiled from compact disc on “Statistical Tables Relating to Banks in India (including RRBs) 1979 to 2007” available from Reserve Bank of India, Mumbai.

These sources provide us the information on the assets, liabilities, earnings and expenses of banks on individual as well as group basis. Further National Income Statistics published by Center for Monitoring Indian Economy (CMIE) has been used for calculating GDP price deflator (Banking and Insurance). Data on consumer price index (CPI) for urban non-manual employees has been taken from ‘Brochure on Group and Sub-Group CPI Number’, published by Central Statistical Organization, Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

3.1.2 Definitions and Measurement of Inputs and Outputs

The definitions and measurement of inputs and outputs in the banking industry remains a contentious issue among researchers. Banks are typically multi-input and multi-output firms. As a result, defining what constitutes ‘input’ and ‘output’ is filled with difficulties, since many of the financial services are jointly produced and prices are typically assigned to a bundle of financial services. Additionally, banks may not be homogeneous with respect to the types of outputs actually produced. Bergendahl (1998) highlighted this issue by mentioning that there have been almost as many assumptions of inputs and outputs as there have been applications of DEA. Mester (1987) and Berger and Humphrey (1997) identified two main approaches i.e., the production approach (PA) and the intermediation approach (IA) for the specification of input and output
variables whereas Freixas and Rochet (1999) considered another third approach i.e., the modern approach (MA) which is also used in banking literature. The selection of variables in productivity and efficiency related studies, in light of these approaches significantly affects the results.

The production approach is propounded by Benston (1965). Bell and Murphy (1968) defined the banking activities as the production of services to depositors and borrowers. It assumes that a bank by using traditional production factors like land, labour and capital produces desired output in the form of loans and other financial services. This approach recognizes the multiproduct role of the bank as a firm, where output comprises the services provided to customers in the form of number of accounts, types of transactions, documents processed or any specific product over the period. These activities are generally proxy by the number of deposits and loan accounts.

The intermediation approach is based on intermediaries’ role of the bank assuming banking activities as transforming the fund borrowed from depositors into money lent to borrowers (Benston et al., 1982; Kim, 1986; Murray and White, 1983; and Mester, 1987). Deposits and loans have different attributes whereas deposits are typically divisible, liquid, short-term and riskless; on the other hand loans are typically indivisible, illiquid, long-term and risky. It has considered funds generated through deposits and borrowings from financial markets as inputs, and loans and investment outstanding as outputs (Freixas and Rochet, 1999).

The intermediation approach is more appropriate in the case of the main branch which is in charge of transforming the money borrowed from depositors into the money lent to borrowers. Whereas modern approach integrates the specific activities of bank like risk management and information processing agency probe into classical theory of the firm (Mester, 1987; Hughes and Mester, 1993).

The present study is based on intermediation approach which is suitable for bank level efficiency as advocated by Berger and Humphrey (1997). This approach has been extensively used by researches such as Maindiratta (1990), Barr et al. (1994), Sathye (2001), Kumar and Verma (2002-03), Bonin et al. (2005), Matthews and Mahadzir (2006), Pasinras and Sifodaskalakis (2007), Sufian (2007) etc. This approach also
incorporated business objectives of the bank including profit maximization, cost minimization, service provision and intermediation.

There are a number of rules for deciding the proportion of the number of inputs and outputs as well as number of decision making units (DMUs). Charnes and Cooper (1990) stated that proportion should be equal to at least three, Fernandez-Cornejo (1994) argued that it should even exceed five, while Nunamaker, (1985) and Cooper et al. (2000) stated that number of observations should be at least three times the sum of input and output variables. Present study follows these rules and has included a sample of 50 banks and for the estimation of efficiency scores three input and two output variables have been taken.

In this study, the input parameters are defined in terms of loanable funds ($X_1$), fixed assets ($X_2$) and wages ($X_3$) and output parameters are advances ($Y_1$) and total income ($Y_2$). Similar input variables have been taken in the studies by Kumar and Verma (2003) and Rajan et al. (2011) used loanable funds as input variable whereas Das (2005), Chew and Chen (2008) and Matthews and Maahadzir (2006) incorporated fixed assets as input variable. Further wages were taken as input variable by Doshit et al. (2003) and Nago et al. (2012). The output variables used in the study are advances and total income as incorporated in various studies, few among of them are Miller and Noulas (1996) and Bhattacharya (1997) who used advances as output whereas Reddy (2006) and Chiou (2009) used total income as output variable.

The detailed description of input and output parameters has been shown in Table 3.1. The input parameter of loanable fund (purchased fund) are the rupee value of both the deposits and borrowings at the end of the financial year. Deposits consist of demand deposits, saving bank deposits and term deposits. Borrowings include funds collected borrowings from the RBI, commercial banks and other institutions and agencies like Industrial Development Bank of India (IDBI) Export Import Bank (EXIM), NABARD etc. The input variable of fixed assets comprises premises and other fixed assets, including furniture and fixtures. There are number of studies in the existing literature where proxy variables have been used as in the case of Favero and Papi (2002) and Isik and Hassan (2003) which categorized banks as being either big, medium, or small and
Table 3.1: Description of Input and Output Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Assets</td>
<td>Fixed assets comprise premises and other fixed assets, including furniture and fixtures.</td>
</tr>
<tr>
<td>Wages</td>
<td>Wages as a proxy variable of labor incorporated in the form of the staff salaries/wages, allowances, bonus, other staff benefits like provident fund, pension fund, gratuity, leave fare concessions, staff welfare, medical and house rent allowances to staff etc. The amounts paid on interest on deposits, RBI/Inter bank borrowings and others.</td>
</tr>
<tr>
<td>Deposits</td>
<td>Total funds collected on deposits mobilization like demand deposits, saving bank deposits, term deposits and deposits of branches in India.</td>
</tr>
<tr>
<td>Borrowings</td>
<td>Total funds collected through borrowings from different sources like RBI, other banks, other institutions and agencies in India and total funds collected through borrowings outside India.</td>
</tr>
<tr>
<td>Advances</td>
<td>The rupee value of total loans provided in terms of bills purchased and discounted, cash credit, overdrafts &amp; loans and term loans.</td>
</tr>
<tr>
<td>Total Income</td>
<td>Total income comprises interest/discount on advances/bills, income on investments, interest on balances with RBI and inter-bank funds, income from commission, exchange and brokerage etc.</td>
</tr>
<tr>
<td>Total Assets</td>
<td>The rupee value of fixed assets (premises, fixed assets under construction and other fixed assets) and other assets like interest accrued, tax paid stationery and stamps, inter-office adjustments and others.</td>
</tr>
</tbody>
</table>
used dummy variables to represent each category in the regression. Similarly, Miller and Noulas (2000) used the value of total assets to represent the firms’ size and Kumar and Gulati (2008) incorporated non-interest income as a proxy variable of other income.

Following the above studies, we have also incorporated wages as a proxy variable of labor that consists of staff salaries/wages, allowances, bonus, other staff benefits like provident fund, pension fund, gratuity, leave fare concessions, staff welfare, medical and house rent allowances to staff etc. The output parameter of advances includes bills purchased and discounted, cash credits, overdrafts and loans repayable on demand and term loans. The total income includes generation of income from both the banking and non-banking activities. Further, all the input and output variables have been measured in terms of rupee million.

In line with the studies of Das (1997), Das (2000), Feng (2006), Gordan (2008) and Heshmati (2010), price deflator (Banking and Insurance) has been used to deflate two outputs viz., advances and total income and two inputs viz., loan able funds and fixed assets in the present study. In addition, wages have been deflated by CPI for urban non-manual employees. All the nominal data has been converted into real prices (base 1999-2000 = 100) to mitigate the impact of rise in price level. Further, all the input and output variables have been normalized by dividing them by the total assets of individual banks to reduce the effects of random noise due to measurement error in the inputs and outputs.

SECTION 3.2

3.2.1 Measurement of Efficiency

To measure efficiency of banks existing studies have applied either parametric or non-parametric approaches. The difference between these two approaches lies on how they handle random error and their assumption regarding the shape of the efficient frontier (Berger and Humphrey, 1997). Each of the techniques has its own strengths and weaknesses. The advantage of parametric approach is that it allows noise in the measurement of inefficiency, while the advantage of non-parametric is that it is simple and easy to calculate. Another advantage of parametric approach is that any theoretical
test can be tested statistically and so the relationship between inputs and outputs can be shown as functional forms. However, there is no functional form known from production function in many cases. In non-parametric approach, no assumptions are made about the form of the production function. Instead a best practice function is formed empirically from observed inputs and outputs (Norman and Stoker, 1991).

Further, non-parametric linear programming based technique is that frontier is piecewise linear. It illustrates that sample distributions for relevant statistics may be obtained directly without a need to know the exact distribution of the data and this freedom provides wide latitude to develop domain-specific statistics that greatly simplify the direct statement of interesting hypotheses. However, there are some weaknesses associated with a non-parametric approach. First, since a nonparametric method is deterministic and attributes all the variation from the frontier to inefficiency, a frontier estimated by it is likely to be sensitive to measurement errors or other noise in the data. In other words, it does not deal with stochastic noise. Another weakness of a non-parametric method is that it does not permit statistical tests and hypothesis to pertain to production structure and the degree of inefficiency.

In spite of all these weaknesses, a large number of studies have been conducted on the efficiency measurement of financial institutions in last few decades based upon non-parametric technique. Färe et al. (1989) and Chavas and Cox (1990) mentioned that non-parametric techniques perform better than parametric techniques in some situations. And it does not require an assumption about the mathematical form of the production function.

Common parametric approaches are the Stochastic Frontier Approach (SFA), the Thick Frontier Approach (TFA) and the Distribution Free Approach (DFA), while the common non-parametric technique is the Data Envelopment Analysis (DEA). In SFA, TFA and DFA, the production function is defined by the set of explanatory variables (inputs, outputs and other possible explanatory variables as well as the form of the function is arbitrarily chosen) and the two components of this regression’s composite error term-the random error and the inefficiency term. SFA assumes two-sided distribution (usually normal with zero mean) of the error term and one-sided distribution of the non-negative inefficiency term leaves on author’s decision (for
instance half-normal, truncated-normal, normal exponential, or normal-gamma distribution). DFA, used in panel data, relaxes composite error term of distributional assumptions. The core inefficiency is distinguished from random error by the assumption of core inefficiency being persistent over time, while random errors tend to average out over time. TFA also does not impose distributional restrictions on the composite error term but assumes that inefficiency term is different in the highest (thick frontier) and lowest efficiency quartile of the observed decision-making units and the random error is present within these quartiles.

According to Zhu (2002) among various non-parametric techniques, DEA has become popular. Over the past three decades, various DEA models have been widely used to evaluate the technical efficiency or technical effectiveness of decision making units (DMUs) in different organizations or industries. Its popularity is mainly attributable to its flexibility in application, and ability to deal with multiple inputs and outputs. This feature makes it very practical because it is usually hard to determine the functional relationship between the productive factors and the product. In view of this, researchers prefer DEA, non-parametric frontier approach to measure efficiency of any business undertaking. In the present study too, DEA, non-parametric frontier approach has been applied to examine the performance measures of RRBs in India.

3.2.2 Components of Efficiency

DEA is a methodology based upon an application of linear programming. It was originally developed for performance measurement. It has been successfully employed for assessing the relative performance of a set of firms that used a variety of identical inputs to produce a variety of identical outputs. In a production process, a production function describes the technical relationship between inputs and outputs. To maximize outputs (or to minimize inputs), however, the production unit needs to convert inputs into outputs efficiently. The study of the efficiency of financial system and in particular banks has gained a lot of popularity in recent times. In an economy, banks normally serve as a main channel for financial inter-mediation (Chen and Yen, 2000). A firm is said to be technically efficient if it derives the maximum output from the given set of inputs within given technology i.e., if it attains the highest possible productivity output.
(or decrease an input) by decreasing another output or increasing another input simultaneously otherwise it is said to be technically inefficient. It is the ability of a firm to avoid wastage of available resources by producing as much output as possible, or by using as little input as production allows (Koopmans, 1951). However, empirical studies frequently showed that in real world, some firms are more efficient than others (Caves, 1989).

Nunamaker (1985) defines technical efficiency as a measure of the ability of a micro level unit (referred to as a firm, observation or DMU) to avoid waste by producing as much output as input usage will allow, or using as little input as output level will allow. Technical efficiency (TE) is based upon the assumption of constant returns to scale (CRS) which indicates the combined effect of pure technical efficiency (PTE) and scale efficiency (SE). Increasing returns to scale (IRS) exist when a proportional increase in all inputs causes outputs to increase by a greater proportion. Decreasing returns to scale (DRS) is the situation when a proportional increase in all inputs causes output to increase by a smaller proportion. Following, Singh, S.K. (2000) it is noteworthy that concept of returns-to-scale (RTS) and economies of scale has been used interestingly in present study. The decomposition of TE also indicates that inefficiencies come from different sources. In case of PTE, inefficiencies come from the inefficient operation of the DMU and in case of SE these come from due to some adverse conditions in the DMU (Cooper, Seiford and Tone, 2000).

3.2.3 Technical and Scale Efficiency-DEA Model

DEA is a non-parametric mathematical programme. The piecewise-linear convex hull approach to frontier estimation was originally proposed by Farrell (1957), but failed to gain popularity until reformulated into a mathematical programming problem in a paper by Charnes, Cooper and Rhodes (1978), which has become known as the DEA approach (Seifort and Thrall, 1990). For a given set of input and output variables, DEA produces a single comprehensive measure of performance (efficiency score) for each DMU. This is done by constructing an empirically based best-practice or efficient frontier as a result of identifying a set of efficient DMUs (on the efficient frontier) and inefficient DMUs not on the efficient frontier (Wagner & Shimshak,
The efficient DMUs retain their efficiency scores equal to one whereas inefficient DMUs retain their efficiency scores in the range of zero and one.

Consider, Figure 3.1, which illustrates nine DMUs 1, 2, 3, 4, 5, 6, 7, 8, and 9. Each DMU utilizes a single input to produce a single output. Those DMUs which lie on the frontier are termed as efficient ones and those DMUs that do not lie on the frontier are inefficient ones. Figure 3.1, clearly shows that five DMUs viz; 1, 2, 3, 4 and 5 lie on the frontier are termed as efficient and others four DMUs viz; 6, 7, 8 and 9 do not lie on the frontier are inefficient. The inefficient DMUs can improve their operations either by reducing their input or augmenting their output.

3.2.3.1 Non-Increasing Returns to Scale Formulation (NIRS)-DEA Model

Information about returns to scale whether an observation with scale inefficiencies is operating under increasing or decreasing returns to scale can be obtained from a variant of the variable returns to scale (VRS) formulation called the non-increasing returns to scale (NIRS) formulation. This form of the DEA linear programming involves the modification of the VRS constraint from a strict equality governing the sum of the linear combination parameters to one of being less than or equal to one. Comparing variable and non-increasing returns efficiency scores allows judgments of the nature of returns to scale for each observation in the sample. Figure 3.2 illustrates the decomposition of overall technical efficiency (OTE) into PTE and SE in a single output space. As shown in Figure 3.2, the input oriented TE of the point P is distance PPC and under VRS input oriented technical inefficiency would only be Pv. The difference between Pc and Pv is put down to scale inefficiency.

The presentation of above diagram can also be expressed as in ratio of efficiency measure:

\[
\begin{align*}
\text{TE}_{(\text{CRS})} &= \frac{\text{AP}_C}{\text{AP}} \\
\text{TE}_{(\text{VRS})} &= \frac{\text{AP}_V}{\text{AP}} \\
\text{SE} &= \frac{\text{AP}_C}{\text{AP}_V}
\end{align*}
\]
Figure 3.1: Efficiency Frontier
[Figure 3.2: Technical and Scale Efficiency Measure];

Adapted from Coelli, T. (1996)
where all these measures will be bounded by zero and one. It should also be noted that

\[ \text{TE}_{(\text{CRS})} = \text{TE}_{(\text{VRS})} \times \text{SE} \]

Because

\[ \frac{\text{AP}_C}{\text{AP}} = (\frac{\text{AP}_V}{\text{AP}}) \times (\frac{\text{AP}_C}{\text{AP}_V}). \]

While it is possible to use these results to decompose technical efficiency into scale and other effects, the results offer no information about whether an observation with scale inefficiencies is operating under increasing or decreasing returns to scale. Information about returns-to-scale can be obtained from a variant of the VRS formulation called the NIRS formulation. This can be done by altering the DEA model of equation (1) by substituting the \( N1' \lambda = 1 \) restriction with \( N1' \lambda \leq 1 \), to provide:

Min. \( \theta \),

Subject to: \[-y + Y \lambda \geq 0,\]

\[ \theta x_i - X \lambda \geq 0, \]

\[ N1' \lambda = 1 \]

\[ \lambda \geq 0, \]

\[ \theta \leq \theta \leq \theta \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]

\[ \lambda \leq 1 \]

\[ \lambda \geq 0, \]
3.2.3.2 Charnes, Cooper and Rhodes (CCR) Input-Oriented DEA Model

The Charnes, Cooper and Rhodes (1978) paper reformulated Farrell's original ideas into a mathematical programming problem, allowing the calculation of an efficiency score for each observation in the sample. This score is defined as the percentage reduction in the use of all inputs that can be achieved to make an observation comparable with the best, similar observation(s) in the sample with no reduction in the amount of output.

In order to illustrate CCR input-oriented DEA model, a set of decision making units (DMUs) \( m=1, 2 \ldots b \) is taken as utilizing quantities. We can denote \( u_{nm} \) the amount of \( n^{th} \) input used by \( m^{th} \) DMU and \( V_{po} \), the amount of \( p^{th} \) output produced by \( m^{th} \) DMU.

**CCR Efficiency Measure**

Max.

\[
Z_0 = \frac{\sum_{p=1}^{t} W_p V_{pma}}{\sum_{n=1}^{d} Z_p u_{nma}}
\]

Subject to

\[
\frac{\sum_{p=1}^{t} W_p V_{pn}}{\sum_{n=1}^{d} Z_n u_{nm}} \leq 1
\]

\( W_p, Z_n \geq m =1,2,\ldots, n, p =1,2,\ldots, t, i =1,2,\ldots d \)

\( w_p, z_n = \) weights given to output \( p \) and input \( n \).

\( v_{po} = \) quantity of output \( p \) achieved by unit \( o \)

\( u_{nm} = \) quantity of input \( n \) used by unit \( m \)

\( b = \) number of DMUs

\( t = \) number of outputs
- $d =$ number of inputs
- $\varepsilon =$ an infinitesimal constant

The efficiency scores of different DMUs are computed by determining the values of weights $(w_p, z_n)$. The key feature of these models is that the weights $w_p$ and $z_n$ are positive and unknown. The main purpose is to obtain weights so as efficiency of DMUs is maximized. In order to apply linear programming algorithms, the above fractional form can be transformed to a linear programming problem (LPP) which can be written as:

**CCR Efficiency Measure (LPP Form)**

$$\text{Max } Z_0 = \sum_{p=1}^{t} w_p v_{pma}$$

Subject to:

$$\sum_{n=1}^{d} z_n u_{nma} = 1$$

$$\sum_{p=1}^{t} w_p v_{pn} - \sum_{n=1}^{t} z_n u_{nm} \leq 0$$

$$w_p \geq \varepsilon \quad z_n \geq \varepsilon$$

For the above linear programming problem, the dual form can be written as:

**Dual form of LPP**

$$\text{Mini. } \theta_{jo} - \varepsilon \left( \sum_{p=1}^{t} S_p^+ + \sum_{n=1}^{d} S_i^- \right)$$

Subject to:

$$\sum_{m=1}^{b} \lambda_m u_{nm} + S_n^- = \theta_\text{ma} u_{nm}$$
\[ \sum_{m=1}^{b} \lambda_m v_{pm} + S_p^+ = v_{pma} \]

\[ m_j \geq 0 \]

\[ S_p^+, S_n^- \geq 0 \]

\[ 0 \leq \varepsilon \leq 1 \]

\[ m = 1, 2 \ldots b, n = 1, 2 \ldots d, p = 1, 2 \ldots t \]

To solve the CCR model it is suggested to do it by using the dual form known as envelopment form (Cooper et al., 2000) which is easier and simpler to solve as it has \( s+1 \) fewer constraints than the primal. The primal problem has \( b+d+t+1 \) constraints while dual form has \( d+t \) constraints, popularly known as multiplier form. It is evident that both primal and dual form has the same solution. The number of DMUs should be considered larger than the number of inputs and outputs \( (d+t) \) in order to provide a fair degree of discrimination of results.

The characteristic of the CCR ratio model is the reduction of the multiple-outputs/multiple inputs situation, for each DMU, to a single virtual output and a single virtual input ratio. For a given DMU, this ratio provides a measure of efficiency which is a function of multiplier. The objective is to find the largest sum of weighted outputs of DMUs while keeping the sum of its weighted inputs at the unit value, thereby forcing the ratio of the weighted output to the weighted input for any DMU to be less than one. The CCR method is based upon the assumption of constant returns to scale which is only appropriate when all DMUs operate at optimal scale that is a portion increase in input results in a proportionate increase in output. But, the prevalence of imperfect competition does not allow a DMU to operate at an optimal scale. So, BCC model modifies CCR model simply by adding an additional convexity constraint of \( \sum_{s=1}^{x} \lambda s = 1 \) in the formulation of original models. BCC model provides the performance measures of OTE, PTE and SE.
3.2.3.3 Banker, Charnes and Cooper (BCC) Model

The Banker Charnes and Cooper (1984) model, is employed to take into account the effect of VRS. By examining the sum of weights which are determined in the CCR model, they modified the original CCR model by arguing that if the sum of weights of inputs and outputs in the CCR model add up to more than 1, the scale size of the DMU is DRS. To achieve CRS or optimum productive size a DMU should reduce the excess use of inputs. However, if the sum of weights adds up to less than 1, a DMU is said to have IRS. To achieve the most productive size i.e. 1, this DMU should expand or increase the use of productive resources. This modification to get the returns to scale in DEA is called the BCC model named after Banker, Charnes and Cooper.

The input-oriented BCC model in the envelopment form is given by

\[
\text{Minimize } \theta_{ma} - \varepsilon \left( \sum_{p=1}^{i} S_p^+ + \sum_{n=1}^{d} S_n^- \right)
\]

Subject to

\[
\begin{align*}
\sum_{m=1}^{b} \lambda_m U_{nm} + S_n^- = \theta_{ma} U_{nm} \\
\sum_{m=1}^{b} \lambda_m V_{pm} - S_p^+ = V_{pma} \\
\sum_{m=1}^{b} \lambda_m \geq 1 \\
\lambda_{m1} S_p^+, S_n^- \geq 0 \\
0 \leq \varepsilon \leq 1
\end{align*}
\]

m = 1, 2..., b p = 1, 2..., t, n=1, 2...d

Note that if a DMU is CCR efficient, then it will also be BCC efficient. However, if a DMU is BCC efficient, then it will not also be CCR efficient. Further, technical efficiency of a DMU obtained from the CCR model is always less than technical efficiency obtained from the BCC model (Cooper, Seiford, and Zhu, 2004).
DEA can be a powerful tool when used wisely. A few of the characteristics that make it powerful are; First, DEA is a multivariate technique that can take multiple inputs and outputs into account (Liu and Zhuang 1998). Second, it is used to measure the efficiency of decision making units (DMUs) and evaluate their relative efficiency (Charnes et al., 1978; Cooper et al., 2004; Duzakin, 2007; Podinovski, 2007; Wagner and Shimshak, 2007 and Zhou et al., 2008). Third, DEA has been extensively used to compare the efficiencies of nonprofit and profit organizations such as schools, hospitals, shops, bank branches and other environment in which there are relatively homogeneous DMUs (Baker and Talluri, 1997; Cooper et al., 2000). Fourth, DEA can estimate scale efficiency without using the input prices. Fifth, DEA has also been used to supply new insights into activities (and entities) that have previously been evaluated by other methods (Cooper, Seiford and Tone, 2000).

The various characteristics that make DEA powerful tool can also create problems. However, DEA has some drawbacks. First, it is highly sensitive to the data used. So, the input and output data should be chosen cautiously considering theoretical and practical issues and the measurement errors in the data should be minimized. Second, since DEA is a non-parametric technique, statistical hypothesis tests are difficult. Third DEA is good at estimating relative efficiency of a DMU but it converges very slowly to absolute efficiency. In other words, it can tell you how you are compared to your peers but not compared to a theoretical maximum. Fourth, since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive.

3.2.4 Mann-Whitney U-test

To decide whether there is a difference between the samples, a non-parametric test known as Mann-Whitney U-test has been applied. It is outlined as:

\[ U_1 = N_1N_2 + \frac{N_1(N_1+1)}{2} - R_i \]

\[ U_2 = N_1N_2 + \frac{N_2(N_2+1)}{2} - R_i \]
where, $N_1$ and $N_2$ are the sizes of sample 1 and sample 2 respectively and $R_1$ and $R_2$ are the respective sums of the ranks of the first and second samples. Ranks are assigned after arranging all the values of combined samples 1 and 2.

If $N_1$ and $N_2$ are both at least equal to 8, it turns out that the distribution of $U$ is nearly normal with the parameters $\bar{U} = \frac{N_1 N_2}{2}$ and $\sigma_U^2 = \frac{N_1 N_2 (N_1 + N_2 + 1)}{12}$. Now the null hypothesis and both samples come from the same population can be tested using $Z$-test:

$$Z = \frac{U - \bar{U}}{\sigma_U}$$

If $Z > Z_\alpha$ (critical value of $Z$), then the null-hypothesis of common population is rejected i.e. there is significant difference among the sample banks between two sub-periods and vice-versa.

**SECTION 3.3**

Productivity consists of measuring the change in ratio of outputs over inputs used in a production process over time. No doubt increase in inputs, if used efficiently, will produce productivity growth. The two most commonly used measures of productivity are single factor productivity (SFP) and multi factor productivity (MFP). The partial or single factor productivity (or SFP) is defined as the ratio of the volume of output (or value-added) to the quantity of the factor of production for which productivity is to be estimated (i.e., labour productivity or capital productivity). When the proportion in which the factors of production are combined (i.e., labour and capital) undergoes a change, partial measures of productivity provide a distorted view of the contribution made by these factors in changing the level of production. In a situation where capital-labour ratio follows an increasing trend, productivity of labour is overestimated and that of capital is underestimated. For instance, capital deepening (shifts in technique of production) can lead to a rise in labour productivity and fall in capital productivity over time. In this case, a change in labour productivity is merely a reflection of substituting one factor by another (Majumdar, 2004). Similarly, improvements in labour productivity could also be due to changes in scale economies
(Mahadevan, 2004). In short, the partial measure does not provide overall changes in productive capacity since it is affected by changes in the composition of inputs.

The concept of multifactor or total factor productivity (TFP) tries to circumvent the problem encountered in the interpretation of SFP estimates in the event of changing factor intensities. TFP is defined as the ratio of output (or value added) to a weighted sum of the inputs used in the production process. TFP is deemed to be the broadest measure of productivity and efficiency in resource use. It aims at decomposing changes in production due to changes in quantity of inputs used and changes in all the residual factors such as change in technology, capacity utilization, quality of factors of production, learning by doing, etc.

Most commonly used method to estimate TFP can be classified into parametric and non-parametric approaches. By applying these methods, the output growth is decomposed into technical efficiency change, technological change and input growth. The parametric approach employs econometric technique and in this approach, the deviation of actual output from the maximum output is decomposed into two parts, viz., the statistical noise and inefficiency. The various alternatives within the parametric approach are as follows: (a) econometric frontier approach; (b) thick frontier approach; and, (c) distribution free approach. Each of these approaches involves arbitrary assumptions regarding the distribution of the noise and inefficiency components. The prime difficulty in using the econometric approach lies in separating the noise from the inefficiency. The empirical evidence suggests that the most common non-parametric methods to measure total factor productivity growth are Tornquist index, Fisher Ideal Index and Malmquist index. Tornquist and Fisher approach are mainly used because it does not require the specification of a particular functional form for the relevant function (e.g., production function, cost function, revenue function, distance functions or other functions) like parametric approach. And secondly, both can be calculated directly from price and quantity data (Sufian, 2009). The Malmquist index has three main advantages relative to the Tornquist and Fischer Indices that (i) it does not require the profit maximization or the cost minimization assumption; (ii) it does not require information on the input and output prices; (iii) if the researcher has panel data, it allows the decomposition of productivity changes into various components.
The measurement of total factor productivity index is comprised of multiplication of change value in technical efficiency and technical change value (Angelidis and Lyroudi, 2005). The constituents of total factor productivity: technical efficiency change and technological changes being more than 1 represent improvement in technology and technical efficiency and its being less than 1 implies retrogression. In other words, technical efficiency change index being more than 1 depicts the capability of the organization in satisfying the production limit. Likewise, technological change index being more than 1 shows that the organization successful in hoisting its efficiency level. Technological change index having a negative change value means that there has been a reduction in the output produced by the similar amount of input (Karacabey, 2002). On the other side, technical efficiency change is decomposed further into pure technical efficiency change and scale efficiency change. Multiplication of these divisions renders technical efficiency change index. Managerial competence in pure technical efficiency questions whether the organization works with suitable scale and shows the result in producing within the appropriate scale. Decrease in pure technical efficiency signals the distortion in managerial competence. The observation of decay in scale efficiency is a glimpse of organizations’ scale problem. MPI is the geometric mean of two TFPC indices, one evaluated with respect to the technology (efficiency frontier) in the current period \( t \) and the other with respect to the technology in the base period \( t_0 \). The DEA, based MI is one of the prominent indexes for measuring the relative productivity change of DMUs in multiple time periods which indicates the performance of an organization.

### 3.3.1 Malmquist Total Factor Productivity Index

The Malmquist total factor productivity (TFP) index is the most commonly used measure of productivity change (Casu and Girardone, 2004). Caves, Christensen and Diewert (CCD) initially introduced the DEA based MPI approach in 1982. They named these indexes after Malmquist, who proposed to construct input quantity indexes as ratios of distance functions (Malmquist, 1953). The distance function, introduced by Shephard in 1970 allows estimation of the relative efficiency of firms in relation to the technological frontier. Distance functions describe as multi-input, multi-output production technology without making behavioural assumption (such as cost
minimization or profit maximization) which is especially suitably in regulated industries. Another important advantage of distance function is that it does not require the information regarding input and output prices. The distance function can take an input orientation or an output orientation. An input-oriented distance function characterizes the production technology by looking at a minimal proportional contraction of the input vector given an output vector whereas an output-oriented distance function considers a maximal proportion expansion of the output vector given on input vector. This study adopts the input-oriented Malmquist productivity index. The Malmquist index is an index of the geometric mean of TFP index from period ‘t’ to t+1. When the index is greater (MPI>1) than one, this indicates an improved productivity and lower than one (MPI<1) is a decline in productivity and finally, equal to one means no change (constant) in productivity. The Malmquist index is derived with the help of an available computer program called Data Envelopment Analysis Program (DEAP) version 2.1 (Coelli, 1996).

For finding the input-distance function of Malmquist productivity index, we take let S be the production technology available at period t = 1, 2,..., T such that S_t = (x_t, y_t): x_t can produce y_t at time t), describes all feasible set of input/output factors.

An input distance function D_t at time t is defined as

\[ D_t(x_t, y_{t+1}) = \min_{\theta_j} S_{th} \]

An input distance function D_{t+1} at time t+1 is defined as

\[ D_{t+1}(x_{t+1}, y_{t+1}) = \min_{\theta_j} S_{t+1} \]

Mixed-period distance functions could be written as:

\[ D_0(x_{t+1}, y_{t+1}) = \min_{\theta_j} S_{t+1} \]

And

\[ D_{t+1}(x_{t+1}, y_{t+1}) = \min_{\theta_j} S_{t+1} \]

If mixed-period distance function is greater than one, it may be due to technological progress or shift in production frontier between t and t+1 period.
Figure 3.3: The Input based Malmquist Productivity Index;
Adapted from Fare, et al. (1992)
Following Fare et al. (1992), the input-oriented MPI could be written as input distance functions between two periods as shown in equations 5 and Figure 3.3.

\[ M_i(x_t, y_t, x_{t+1}, y_{t+1}) = \left[ \frac{D_i^t \left( \frac{\epsilon_{t,1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)}{D_i^t \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)} \right]^{\frac{1}{2}} \] …………5

We can now derive the input distance function with CRS assumption from Figure 3.3 and could be written as

- TE in period t relative to frontier t = \( D_i^t \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right) \)
- TE in period t+1 relative to frontier t+1 = \( D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right) \)
- TE in period t relative to frontier t+1 = \( D_i^t \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right) \)
- TE in period t+1 relative to frontier t = \( D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right) \)

We can now express the change in TFP and its components geometrically as below

The change in TE can be expressed geometrically as:

\[ \frac{D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)}{D_i^t \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)} \]

And change in technology can be expressed geometrically as:

\[ \left[ \frac{D_i^t \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)}{D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)} \right]^{\frac{1}{2}} \left[ \frac{D_i^{t+1} \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)}{D_i^t \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)} \right]^{\frac{1}{2}} \]

We know that change in total factor productivity is the product of change in technical efficiency (catching up) and change in technology (frontier effect). Therefore, it can be expressed geometrically as:

\[ \frac{D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)}{D_i^t \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)} \left[ \frac{D_i^t \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)}{D_i^{t+1} \left( \frac{\epsilon_{t+1}, y_{t+1}}{\epsilon_{t}, y_{t}} \right)} \right]^{\frac{1}{2}} \left[ \frac{D_i^{t+1} \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)}{D_i^t \left( \frac{\epsilon_{t}, y_{t}}{\epsilon_{t+1}, y_{t+1}} \right)} \right]^{\frac{1}{2}} \]

Where the quotient outside the brackets measured the change in technical efficiency and the ratios inside the brackets measured the shift in the frontier between
period's t and t +1. In literature, there were several extended versions of MPI approach. Here, we have followed Fare et al. (1994) to calculate the values of distance functions using linear programming techniques. For a given panel of k observations using inputs and outputs \((x_{nk}^{kt}, y_{mk}^{kt})\), \(\lambda k\), t is an intensity variable that serves to form the convex combinations of observed inputs and outputs, the frontier technology in period t can be constructed as:

\[
S' = \{x_{t}, y_{t}, y_{m}' \mid y_{m}' \leq \sum_{k=1}^{k} \lambda^{kj} y_{m}^{kj} \}
\]

\[
\theta^{k}_{m} \geq \sum_{k=1}^{k} \lambda^{kj} X_{m}^{kj}
\]

\[
\sum_{k=1}^{k} \lambda^{kj} \leq 1; \lambda^{kj} \geq 0,
\]

\[\text{ sway } \] (m = 1, 2, -----, M, n = 1, 2, -----, N, k = 1, 2, -----, K)

MPI distance functions are reciprocal to traditional Farrell input-oriented measure; in that case, the distance function would be as:

First equation would be as:

\[
\begin{bmatrix}
\phi_{t} & \xi_{t} & \gamma_{t} \\
\end{bmatrix} = \min_{\phi \lambda} \theta
\]

S.T \(\varphi x_{kl} - x_{i} \lambda \geq 0\)

\(- \gamma_{kl} + \gamma_{i} \lambda \geq 0\)

\(\lambda \geq 0\)

Second equation would be as:

\[
\begin{bmatrix}
\phi_{t+1} & \xi_{t+1} & \gamma_{t+1} \\
\end{bmatrix} = \min_{\phi \lambda} \theta
\]

S.T \(\varphi x_{kl+1} - x_{i+1} \lambda \geq 0\)

\(- \gamma_{k+1} + \gamma_{i+1} \lambda \geq 0\)

\(\lambda \geq 0\)
Third equation would be as:

\[
\begin{bmatrix}
\tilde{y}_{i} \\
\tilde{t}_{i} \\
\tilde{r}_{i} \\
\end{bmatrix} = \min \phi \lambda \theta
\]

S.T. \( \varphi x_{kt+1} - x_{kt} \geq 0 \)

\[- \gamma_{kt+1} + \gamma_{kt} \lambda \geq 0 \]

\[\lambda \geq 0\]

And fourth equation would be as:

\[
\begin{bmatrix}
\tilde{y}_{t+1} \\
\tilde{t}_{t+1} \\
\tilde{r}_{t+1} \\
\end{bmatrix} = \min \phi \lambda \theta
\]

S.T. \( \varphi \lambda x_{kt} - x_{kt+1} \lambda \geq 0 \)

\[- \gamma_{kt} + \gamma_{kt+1} \lambda \geq 0 \]

\[\lambda \geq 0\]

where, \( Y_{kt} \) is a MxI vector of output quantities for the observation k at time t; \( X_{kt} \) is a NxI vector input quantities for the observation k at time t; \( Y_{t} \) is a KxM matrix of output quantities for all observations at time t; \( X_{t} \) is a KxN matrix of output quantities for all observations at time t; \( \lambda \) is a KxI vector of weights and \( \varphi \) is a scalar. The Malmquist productivity change index in case of VRS can be further decomposed into three components:

\[M_i (X_{t+1}, Y_{t+1}, X_{t}, Y_{t}) = TECH \ast PEFFCH \ast SEFFCH\]

In which \( TECH \) represent technological change, \( PEFFCH \) represent pure efficiency change and \( SEFFCH \) represent scale efficiency change. The scale efficiency change and pure efficiency change components were decompositions of efficiency change calculated relative to constant returns to scale: \( EFFCH=PEFFCH \ast SEFFCH \). \( EFFCH \) referred to efficiency change calculated under constant returns to scale, and \( PEFFCH \) is pure efficiency change calculated under variable returns to scale. To derive the full decomposition, including the scale-change components, two additional programming problems are required to be these are conducted.
$D_{1}(Y_{i},X_{i})$ and $D_{1}^{i+1}(Y_{1+i},X_{1+i})$ relative to the technology of variable return to scale [(Fare et al., (1994), Coelli, (1996), Bushara and Mohaydin, (2007)]. Both the concepts have been illustrated in Figure 3.4 by adding two VRS frontiers and obtained the following equation of distance functions.

$$
\Delta M = \frac{D_{v}^{i+1}(x_{i+1}, y_{i+1})}{D_{v}^{i}(x_{i}, y_{i})} \left[ \frac{D_{c}^{i+1}(x_{i+1}, y_{i+1})}{D_{c}^{i}(x_{i}, y_{i})} \right]^{1/2}
$$

(1)

$$
\Delta M = \frac{D_{v}^{i+1}(x_{i+1}, y_{i+1})}{D_{v}^{i}(x_{i}, y_{i})} \left[ \frac{D_{c}^{i+1}(x_{i+1}, y_{i+1})}{D_{c}^{i}(x_{i}, y_{i})} \right]^{1/2}
$$

(2)

$$
\Delta M = \frac{D_{v}^{i+1}(x_{i+1}, y_{i+1})}{D_{v}^{i}(x_{i}, y_{i})} \left[ \frac{D_{c}^{i+1}(x_{i+1}, y_{i+1})}{D_{c}^{i}(x_{i}, y_{i})} \right]^{1/2}
$$

(3)

The first term represents the PTE under VRS technology, second term represents the SEFCH under CRS and VRS technology and the third term represent the shift in the frontier due to innovations under CRS technology. All the terms are between the periods $t$ and $t+1$. We can derive the distance functions with VRS assumptions from Figure 3.4.

TE in period $t$ relative to frontier $t = D_{i}^{i}(x_{i}, y_{i}) = \frac{MB}{MA}$

TE in period $t+1$ relative to frontier $t+1 = D_{i}^{i+1}(x_{i+1}, y_{i+1}) = \frac{NE}{NH}$

TE in period $t$ relative to frontier $t+1 = D_{i}^{i+1}(x_{i}, y_{i}) = \frac{MC}{MA}$

TE in period $t+1$ relative to frontier $t = D_{i}^{i}(x_{i+1}, y_{i+1}) = \frac{NF}{NH}$

TE in period $t$ relative to VRS $t = D_{v}^{i}(x_{i}, y_{i}) = \frac{MD}{MA}$

TE in period $t+1$ relative to frontier $t+1: D_{v}^{i+1}(x_{i+1}, y_{i+1}) = \frac{NG}{NH}$
We can now express the change in TFP and its components geometrically with VRS assumption as below:

The change in TE can be expressed geometrically as:

\[
\frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} \times \frac{NE}{NH} \times \frac{MA}{MB}
\]

The change in PTE can be expressed geometrically as:

\[
\frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} = \frac{NG}{NH} \times \frac{MA}{MD}
\]

The change in SE can be expressed geometrically as:

\[
\frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} \times \frac{NE}{NG} \times \frac{MB}{MD}
\]

The change in technology can be expressed geometrically as:

\[
\frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} = \left( \frac{NF}{NH} \times \frac{NE}{MA} \right)^{\frac{1}{2}} \times \left( \frac{MB}{MA} \times \frac{MC}{NE} \right)^{\frac{1}{2}} = \left( \frac{NF}{NE} \times \frac{MB}{MC} \right)^{\frac{1}{2}}
\]

and finally, the change in malmquist productivity index can be expressed geometrically as:

\[
\frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} = \left( \frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} \right)^{\frac{1}{2}} \times \left( \frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} \right)^{\frac{1}{2}} = \left( \frac{D_{t+1}^i \left( \epsilon_{t+1}, y_{t+1} \right)}{D_i^j \left( \epsilon_t, y_t \right)} \right)^{\frac{1}{2}}
\]
[Figure 3.4: Input-Oriented Malmquist Productivity Index under VRS]
The DEA based techniques of efficiency and productivity measurement are best used in the present study. DEA is a methodology based upon an application of linear programming, method has two advantages over parametric stochastic techniques in measuring productivity change (Fare and Primont, 1997). When parametric techniques were used, the choice of functional form for specifying the technology and the choice of the error structure both influenced the degree of efficiency (Coelli, 1995). Linear programming techniques enveloped the data without the specification of a restrictive functional form and were free from distribution bias. Malmquist productivity index construct distance functions which is described as multi-input, multi-output production technology without making behavioural assumption such as cost minimization or profit maximization. Further, it does not require the information regarding input and output prices. The DEA methodology allowed the recovery of various efficiency and productivity measures in a commendable manner. Specifically, it was able to answer questions related to technical efficiency, scale efficiency and productivity changes.

************