A DEA Based Approach to Working Capital Management Efficiency

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Abstract

One of the important issues in financial decision making is that of managing working capital. The purpose of this study is to develop a new technique to measure working capital management efficiency based on frontier analysis technique. Data envelopment analysis (DEA) technique is currentlybeing used in numerous studies to measure different forms of technical efficiency but has been ignored in studies related to working capital. We find that the existing measures of working capital management efficiency specially cash conversion cycle has been used by most researchers despite its shortcomings. We use data from 360 firms belonging to four industries in Indian manufacturing sector covering a period of 11 years (2003 to 2013) for our analysis. We found that this new measure based on DEA is able to provide more insights and better analysis opportunities than the existing measures.This may be useful to financial managers, investors and other stakeholders in taking better and more effective decisions. Our study examines the working capital management in an entirely new perspective that has not been previously studied and gives new direction to research in effective measurement of working capital management efficiency.

1. Introduction

Financial decision making involves analysing the financial problems that a firm faces and deciding which course of action should be taken. One of the important issues during the financial decision making process is that of managing working capital (WC). Working capital can be understood as a metric that measures a company's operating liquidity. Working Capital is generally defined as the difference between resources in the form of cash or readily convertible into cash (current assets) and liabilities for which cash will be required soon (current liabilities). Working Capital management (WCM) deals with managing short-term financing and short-term investment decisions of the firm (Sharma & Kumar, 2011). It is the management of short-term financing requirements of a firm. The objective of working capital management is to maintain a balance of each of the working capital components (Filbeck & Krueger, 2005). The overall goal of working capital management is that a firm should be able to continue its operations by managing the interrelationship between current assets and current liabilities. The importance of trade-offs between the two goals of working capital management, i.e., liquidity and profitability has always been stressed in the literature (Smith, 1980).

Working capital management involves decisions regarding:

- Inventory Levels: Deciding between the high costs of stockholding due to inventory pile up vs. the cost of stock outs.
- Receivable levels: Deciding between high levels of receivables to promote sales vs. cost of slow cash inflow.
- Creditor levels: Deciding between the benefits of delaying the payments vs. need to retain goodwill of the suppliers.
- Cash Levels: Deciding between the liquidity benefit of holding cash vs. opportunity cost.

The importance of efficient working capital management can be understood by the statement "Efficient working capital management is an integral component of the overall corporate strategy to create shareholder value" (Hyun-Han Shin & Soenen, 1998). It is very important for working capital management to be effective because it affects the performance and liquidity of the firms (Taleb et al., 2010). The viability of business relies on the ability to effectively manage receivables, inventory and payables (Filbeck & Krueger, 2005). Excessive working capital may have a negative impact on a firm's profitability, whereas a low level may lead to problems of liquidity and stock-outs, resulting in difficulties in maintaining smooth operations (Van Horne and Wachowicz, 2004). Thus to maintain competitiveness firms should improve their WCM efficiency. Therefore it is important for firms to effectively measure the level of their WCM efficiency and identify the benchmark firms.

2. Literature Review: Efficiency of Working Capital Management

Traditionally, the liquidity position of the firm was gauged by a static view of working capital through current ratio. Later the operating cycle view of working capital was introduced by Richards & Laughlin (1980) which gave the concept of the cash conversion cycle (CCC). Most of the studies on working capital have used this cash conversion cycle as a measure of working capital management efficiency. Some later studies, like Gentry, Vaidyanathan & Lee (1990) have used a variation of cash conversion cycle i.e. weighted cash conversion cycle. However, its drawback that it cannot be effectively measured by an analyst outside of the management of the firm has made it less useful. Cash conversion cycle itself has been criticised in many studies, such as Bhattacharya (2004), as it is calculated by adding the ratios which have different denominators. This, according to many authors makes the measure mathematically incorrect. Shin & Soenen (1998) and Erasmus (2010) have discussed an alternative measure Net Trade Cycle (NTC) ((Inventories + Receivables - Creditors)*365/Sales). However NTC suffers from the shortcoming that it assigns equal weightage to all components of working capital and considers only sales as output for working capital investment. A number of studies have however found high correlation between the CCC/NTC and firm performance, whichindicates that overall ranking of firms, calculated using these measures is somewhat correct. Therefore, there is a need for a measure which ranks firms similarly to these methods, but is free from their shortcomings.

In recent years, there has been a trend towards measuring efficiency using one of the frontier analysis methods. Specifically, the nonparametric data envelopment analysis (DEA) method has been used in many scenariosto measure technical efficiency scores. However, DEA technique has been until now ignored in working capital management studies.

3. Introduction to Data Envelopment Analysis

DEA is a linear programming technique initially developed by Charnes et al. (1978) to evaluate the efficiency scores in cases where there are multiple outputs and inputs and when it is not possible to aggregate these multiple outputs (inputs) into one output (input). DEA is a comparative technique where the comparison of efficiency is carried out among a group of units referred to as Decision Making Units (DMUs). Here, the relative efficiency is measured in terms of the ratio of total weighted outputs and total weighted inputs. DEA is a non-parametric technique, i.e. it does not assume the data to have any particular structure. Thus, unlike other measures no assumption is made regarding the structure of the production function. In DEA the weight vector of inputs and outputs are not fixed.The technique allows each DMU to choose its own weights for inputs and outputs such that the ratio of weighted outputs to weighted inputs is maximised. In other words the standard for judging is set by the DMU itself. However, there is a constraint: the weights assigned should be such that no DMU is able to achieve the ratio of weighted outputs to weighted inputs more than unity. A DMU is efficient if it gets an efficiency score of 1.0. Thus an efficient frontier is created which connects all the DMUs which are efficient and all the DMUs not lying on the frontier are inefficient.

Two main models developed within the DEA technique are the CCR (Charnes, Cooper and Rhodes) model and BCC (Banker, Charnes and Cooper) model. The CCR model was developed by Charnes et al. (1978) and assumes a constant return to scale. The constant return to scale model does not take into consideration differences in scale of operation and assumes that the production frontier is a straight line. It can be used in cases where all DMUs are operating on the same scale and in practical scenarios of varying returns to scale it may not give optimal results.

The BCC model given by Banker et al. (1984) extended the CCR model for technologies that exhibit variable returns to scale. This was done by making the efficient frontier a convex hull instead of a straight line. This is considered an improvement over the CCR model as it allows for variation in returns to scale. Thus in a real life scenario of varying economies of scale the BCC model is more suitable. However its disadvantage is that it leads to a large number of efficient DMUs in comparison to the CCR model. It has two forms, namely output oriented and input oriented. The efficiency score obtained from the above two models don not differ much and in general are inverse of each other. The difference lies in formulation as in input oriented the focus is on minimisation of inputs and in output oriented the focus is on maximisation of output.

The VRS (variable return to scale) BCC model is however not able to rank efficient units as it assigns efficiency of one to all efficient DMUs (DMUs that lie on the efficient frontier).The maximum efficiency score given is one and this can be achieved my more than one DMUs.All those DMUs which lie on efficient frontier will be termed as efficient. Thus we cannot compare and rank the efficient DMUs. To overcome this shortcoming Anderson (1993) introduced a variation of the BCC model to rank efficient DMUs. In this model BCC model is followed, however the DMU under evaluation in not considered (excluded) from the reference set. The model tests that by how much an efficient DMU's inputs can be increasedwithout making the DMU inefficient, i.e. without removing it from the efficient frontier. In other words, it checks the maximum allowable increase in inputs by the efficient DMUs. This allows us to different efficient DMUs which have higher allowable increase in inputs from other efficient DMUs.

4. DEA Based Working Capital Management Efficiency

4.1 Data and Variables

We have used major components of working capital, namely inventory, receivables and sundry creditors as input variables. Sales and cash flow from operations have been used as output variables. The selection of input variables is intuitive as major portion of the investment in working capital is in the form of inventory and receivables. In addition, sundry creditor is considered as an input as it's a short term liability and reduces the required investment in working capital. However, there is a modification needed before using sundry creditors as input. The DEA considers DMU as more efficient, as it uses lesser inputs. However, higher value of sundry creditors represents lesser working capital investment and thus a more efficient DMU. Thus, in our case sundry creditor is a reverse input, i.e. the input, which needs to be increased for higher efficiency. To solve this problem we use a simple transformation technique suggested in literature (Zhu & Cook, 2007) where we take the inverse of the variable(sundry creditors) and use the same as input.

Moreover the DEA model does not accept negative valuesof inputs and outputs.However, in our case cashflow from operations may be negative for many firms. To combat this, we use the property of DEA given by Iqbal Ali & Seiford (1990) and Zhu & Cook (2007). According to the above researchers the input oriented model is translation invariant for output data. Thus, if we use an input oriented model we can modify any of the outputs without affecting the results. For each year and for each industry we found the minimum value of cash flow from operations among all the firms. We then added this minimum value incremented by one to the cash flows of all firms making all the negative cash flows non negative.

The selection of output variables is partially based on past working capital measures where sales/revenue is considered as the major output for working capital investment. In addition, we have added a new output measure cash flow from operations (CFO). Literature has suggested that a firm's operating efficiency is not dependent on the liquidation value of its assets, but rather on cash flow generated by those assets (Hyun-Han Shin & Soenen, 1998). It is therefore accepted that one of the main aims of WCM is to generate cash from operating activities. Thus higher the cash flow better is the working capital management of the firm.

All the data for inputs and outputs have been taken from the annual financial statement of firms and collected using CMIE Prowess database. The data comprises of 360 manufacturing sector firms belonging to four industries, namely Food & Agro, Pharmaceuticals, Nonelectric Machinery and Textiles. The time period of study is March, 2003 to March, 2013.

4.2 The Model

In this paper, we have used DEA based input oriented non-decreasing returns to scale (NDRS) super efficiency measure to calculate WCM efficiency. Input oriented model has been used because we are trying to measure efficiency of working capital management and thus our orientation is towards minimising the working capital investment. Moreover, since we have modified the outputs (sundry creditors) we can only use input oriented technique. We expect that in the manufacturing sector, there is variable return to scale. We expect that there can be constant and/or increasing returns to scale in production but not decreasing returns to scale. This means there should be non-decreasing returns to scale and thus we have applied the NDRS model which is a special case of VRS model.

The dual VRS BCC model with modification for super efficiency is

$$\min \ \theta^{super}$$

subject to

$$\sum_{j=1,j\neq 0}^{n} \lambda_j x_y \leq \theta^{super} x_{io} \qquad i = 1, 2, \ldots, m;$$

$$\sum_{j=1,j\neq 0}^{n} \lambda_j y_{rj} \geq \theta y_{ro} \qquad r = 1, 2, \ldots, s;$$

$$\lambda_j \geq 0 \qquad J \neq 0$$

$$\sum_{i=0} \lambda_i = 1$$

Here θ is inverse of efficiency, y and x represent output and inputs and λ represents weights associated with them. x_{ij} represents ith input of jth DMU and y_{rj} represents rth output of jth DMU. x_{io} and y_{ro} are input and output values, respectively, of the DMU to be evaluated (DMUo). There are s outputs and m inputs for all n DMUs

The $\sum_{i=0} \lambda_i = 1$ condition can be changed to $\sum_{i\neq 0} \lambda_i \leq 1$ and $\sum_{i\neq 0} \lambda_i \geq 1$ for non-increasing return to scale (NIRS) and non-decreasingReturns to Scale (NDRS) models respectively according to suitability

Initially, we took the CCC value for each firm grouped by industry for each year. A scatter plot of the data was constructed to identify and remove any outliers. Then, for each year, firms were ranked in the industry according to CCC. Firm with lower CCC were given higher rank and vice versa. The same method was carried for calculating and then ranking firms based on NTC.

For the DEA based model the input and output variables were taken for each firm grouped by industries and input oriented NDRS super efficiency model was run using EMS software to calculate super efficiency measure. This was repeated for each year. Partial output from the DEA model for food and agro industry for the year 2003 is shown in Table 1(we have shown limited info in each table as presenting all tables would have occupied huge space).

Table 1: Part Output from DEA Run Using EMS (Food and Agro Industry 2003)

DMU	Efficiency	Inventory	Receivables	Sundry Creditors	Cashflow from ops.	Sales	Benchmarks
Upper Ganges Sugar & Inds. Ltd.	72.71%	0.28	0.09	0.63	0.73	0	41 (0.13) 44 (0.86) 83 (0.03)
Uttam Sugar Mills Ltd.	64.38%	0.25	0.41	0.34	0.64	0	41 (0.33) 55 (0.27) 81 (0.42)
Vishnu Sugar Mills Ltd.	93.21%	0.66	0.12	0.22	0.93	0	41 (0.29) 50 (0.67) 55 (0.05)
B & A Ltd.	128.32%	0.47	0.11	0.42	1.28	0	17
Jay Shree Tea & Inds. Ltd.	50.66%	0.41	0.37	0.22	0	0.18	7 (0.81) 8 (0.07) 43 (0.11) 83 (0.00)
Joonktollee Tea & Inds. Ltd.	85.77%	0.08	0.5	0.42	0.86	0	40 (0.01) 63 (0.71) 64 (0.29)
Neelamalai Agro Inds. Ltd.	96.41%	0.45	0.09	0.45	0	0.02	56 (0.63) 64 (0.05) 66 (0.01) 69 (0.30)
Rossell India Ltd.	168.68%	0.43	0.32	0.25	0	0.69	10
Scottish Assam Ltd.	197.38%	0.72	0.28	0	0.82	1.15	1
Stanes Amalgamated Estates Ltd.	123.12%	0.83	0	0.17	1.01	0.22	4
Tata Global Beverages Ltd.	108.98%	0.07	0.21	0.72	1	0.09	4
Ajanta Soya Ltd.	97.99%	0.9	0	0.1	0	0.76	4 (0.19) 72 (0.08) 81 (0.72)
Avanti Feeds Ltd.	42.25%	0.27	0.15	0.58	0.35	0.08	7 (0.01) 8 (0.06) 43 (0.05) 81 (0.90)
Jayant Agro-Org. Ltd.	57.59%	0.46	0.18	0.36	0	0	7 (0.09) 8 (0.55) 81 (0.36)
K S E Ltd.	114.19%	0.43	0.41	0.16	0	0.34	4
K S Oils Ltd.	40.05%	0.29	0.1	0.61	0.39	0.01	7 (0.44) 8 (0.42) 41 (0.03) 83 (0.11)
Marico Ltd.	80.93%	0.04	0.47	0.48	0.36	0.45	8 (0.04) 19(0.06) 44(0.09) 83(0.86)
Modi Naturals Ltd.	83.64%	0.35	0.33	0.32	0	0.44	4 (0.06) 43(0.15) 55(0.12) 64(0.67)

Thereafter, for each year the firms were ranked in the industry, according to super efficiency with higher super-efficient firms getting a higher rank. An example of such rank table is shown in Table 2.

5. Model Analysis

5.1 Rank Analysis

We calculated Spearman's rank correlation for each year between (i) firms'ranks according to CCC and according to NTC (ii) firms'ranks according to NTC and according to DEA (iii) firms' ranks according to CCC and according to DEA. We then compared the correlation measure with the critical values.Table3 and Table 4 show the Spearman rank correlation between (i) CCC and DEA ranks and (ii) NTC and DEA ranks respectively.

We find that the correlation between ranks according to NTC and CCC are fairly high, suggesting a similarity in the ranking. We can infer from this that both the traditional measures, though calculated differently are ranking the firms in an almost similar manner. The correlation between DEA based ranking and the two traditional measures (CCC & NTC) are also high. We find that both the correlations (DEA with CCC and NTC) for each of the four industries are more than the critical values at 99% confidence interval. This strongly suggests that the DEA measure is able to rank the firms similar to the ranks of NTC and CCC.

A number of researchers have examined the relationship between CCC/NTC ranking and firm performance and have found strong evidence of a positive relationship. Since profitability is a performance measure, the positive relationship suggests that the traditional measures are able to rank the firms correctly according to their WCM efficiency. The DEA measure being highly correlated to the traditional measures is thus also able to rank the firms according to their WCM efficiency. However the DEA analysis produces results which are free from the shortcoming of the traditional measures and in addition are able to provide much more information about the working capital management efficiency of firms.

5.2 Mathematically Correct Calculation

The most widely used measure cash conversion cycle (CCC) has been criticised in literature for being mathematically flawed. This is because CCC is calculated by summing three ratios namely inventory days, receivable days and negative of payable days. This, according to many researchers is flawed as all of the three components have different denominators and thus cannot be added. It assumes that inventory consumption

Table 2: Part of Ranking Table (Food and Agro Industry 2003)

	DEA Efficiency	Rank DEA Efficiency	NWC	Rank NWC	NTC	Rank NTC
C C L Products (India) Ltd.	0.5571	67	109.57	52	0.2609	54
Tata Coffee Ltd.	0.3773	78	146.32	64	0.4164	70
B C L Industries & Infra Ltd.	0.8896	36	24.54	16	0.1175	29
Divya Jyoti Inds. Ltd.	1.5727	10	30.75	20	0.0447	12
Flex Foods Ltd.	0.3519	82	233.62	79	0.3497	65
Gujarat Ambuja Exports Ltd.	0.5561	68	85.77	45	0.2611	55
Harrisons Malayalam Ltd.	1.5105	11	-15.47	5	0.0182	8
J V L Agro Inds. Ltd.	1.1012	24	11.05	11	-0.0201	7
K R B L Ltd.	0.4888	73	290.28	83	0.8375	84
Kesar Enterprises Ltd.	0.6256	63	210.76	74	0.3865	68

Table 3: Correlation Between CCC Based Ranks and DEA Based Ranks

Year	Industry			
	Food and Agro (86 firms)	Textiles (87 firms)	Pharma (102 firms)	Non-Elec. Mac. (85 firms)
2003	0.4173	0.6493	0.3686	0.5954
2004	0.4701	0.4715	0.5139	0.6240
2005	0.3642	0.5777	0.5696	0.5491
2006	0.4199	0.6609	0.3358	0.5203
2007	0.5471	0.6061	0.3711	0.6280
2008	0.6340	0.6100	0.3741	0.6718
2009	0.4892	0.6390	0.3933	0.6205
2010	0.4163	0.6345	0.4911	0.5854
2011	0.4107	0.5466	0.4248	0.6439
2012	0.3980	0.5200	0.3732	0.4935
2013	0.5406	0.6402	0.3775	0.4146
Critical Value (99%)	0.278 (85 pairs)	0.278 (85 pairs)	0.256 (100 pairs)	0.278 (85 pairs)

Table 4: Correlation Between NTC Based Ranks and DEA Based Ranks

Year	Industry			
	Food and Agro (86 firms)	Textiles (87 firms)	Pharma (102 firms)	Non-Elec. Mac. (85 firms)
2003	0.6067	0.7157	0.5278	0.6225
2004	0.7473	0.5992	0.7586	0.6009
2005	0.6032	0.6770	0.6507	0.5406
2006	0.6375	0.7631	0.4752	0.5001
2007	0.7330	0.7921	0.6281	0.6268
2008	0.7286	0.7013	0.5832	0.6667
2009	0.6887	0.7700	0.5335	0.4978
2010	0.5274	0.6965	0.6526	0.3625
2011	0.4750	0.7148	0.5595	0.4519
2012	0.5139	0.6882	0.4024	0.3524
2013	0.6014	0.7082	0.4403	0.4337
Critical Value (99%)	0.278 (85 pairs)	0.278 (85 pairs)	0.256 (100 pairs)	0.278 (85 pairs)

days and days of sales (debtors' period) can be added i.e. days in all working capital components are universal and comparable, which is mathematically incorrect. Moreover, sometimes it can lead to negative CCC, which is absurd (Bhattacharya, 2004). The DEA based measure in contrast, is derived from linear programming and is mathematically correct. The method is non-parametric in nature and is not dependent on the units of inputs/ outputs. Moreover, it has been proved that whatever be the units of measurement of inputs and outputs the efficiency measure will remain same (provided these units are same for all firms) (Cooper, Seiford, & Tone, 2006).

5.3 Data Type of Efficiency Measure

We know that there are four major data types, namely nominal, ordinal, interval and ratio. The traditional measures of CCC and NTC were not ratio type data, i.e. one cannot perform all types of mathematical operations with the measures. For example in case of CCC one cannot say that a person with CCC of 10 is twice as efficient as a firm with CCC of 20. This is because the CCC is calculated by adding three ratios which are unequal and are thus is only able to tell that a firm with lower CCC is better than the one with higher CCC, but cannot tell how much better. However, DEA based efficiency measure is a pure ratio type data and thus we can do multiplication and division type mathematical operation and can thus say that firm with efficiency 50% is twice as efficient as a firm with 25% efficiency.

5.4 Component Weightage and Analysis

Another shortcoming of these traditional measures is that they give equal weightage to each component of working capital. In CCC we just add the three components, assigning equal weights. Similarly, in NTC, we add inventory and receivables and subtract payables and then divide the result by revenue, again giving equal weights to all WC components. This may not be optimal. We cannot say with surety that a value of 5 for inventory days is same as the value of 5 for payable days. For each firm there is different level of liquidity associated with its WC components. For some firm it may be easier for it to liquidate inventory and for some it may be easier to recover receivables. Thus assigning equal weights to components for all firms is a restricting condition. The DEA based analysis provides the freedom to each firm to choose the weight for its inputs and outputs such that it maximises the efficiency scores. A firm which is efficient in inventory management gets assigned higher weights for inventory input and so on.

For example (see Table 1) the entry for the firm Avanti Feeds Ltd. shows that the firm is giving different weights to WC components with 0.27 to inventory, 0.15 to receivable and 0.58 to creditors.

In addition, the DEA results are able to show what weights were assigned to each of the inputs/outputs for a particular firm. Thus we can know that in a particular year, which of the inputs were managed more efficiently by the firm and which were not. The input(s) with least weights are not managed efficiently as they have been least used to calculate efficiency. Such inputs need to be worked upon by the firm's management in order to improve the firm's efficiency.Thus, in the above case Avanti Feed Ltd has creditors as most efficient input and receivables as least efficient.

5.5 Sensitivity Analysis

The DEA based measure is able to carry out sensitivity analysis, which may be very useful to a firm for planning improvements and preparing budgets. Sensitivity analysis for a particular input gives a sensitivity value (m) ($0<m<1$) for each firm.This value m is the multiple by which the input of the firm has to be multiplied to make the DMU efficient. In other words, if we reduce the input (say p) of a firm to value equal to m x p then the DMU will become efficient.

In addition to this, the DEA measure gives for each inefficient DMU, a list of benchmark DMUs. These DMUs act as benchmarks to the DMU under consideration. The lambda values (as shown in Table 5) associated with these benchmarks reveal the point on the efficient frontier where the DMU under consideration will reach if the input is decreased (by multiplying input with sensitivity value). Since such a point should be a linear combination of efficient DMUs therefore these lambda values act as weights. These weights when multiplied by benchmark DMUs' inputs will indicate the point on the frontier where the inefficient DMU under consideration can reach after becoming efficient (i.e. after reducing its input). Such type of analysis is not possible in traditional WCM measures. Moreover, the DEA measure is also able to provide sensitivity analysis for efficient firms. It provides information about the allowable increase (decrease) in inputs (outputs) so that the firm remains efficient.

Table 5 shows a sample of sensitivity analysis on receivables carried out for food and agro industry for the year 2012. In Table 5 Kesar Enterprises Ltd. can

Table 5: Example of Sensitivity Analysis Sheet Using DEA Frontier Software

DMU Name	Efficiency Sensitivity	Optimal Lambdas with Benchmarks		Optimal Lambdas with Benchmarks		Optimal Lambdas with Benchmarks	
Kesar Enterprises Ltd.	0.36620	0.437	J V L Agro Inds. Ltd.	0.076	Rajshree Sugars & Chemicals Ltd.	0.592	S B E C Sugar Ltd.
Kohinoor Foods Ltd.	0.03811	0.714	J V L Agro Inds. Ltd.	2.000	United Provinces Sugar Co. Ltd.		
Monsanto India Ltd.	0.60654	0.093	Simbhaoli Sugars Ltd.	0.061	Tata Global Beverages Ltd.	1.552	Ruchi Infrastructure Ltd.
Rei Agro Ltd.	0.02180	0.552	J V L Agro Inds. Ltd.	3.844	United Provinces Sugar Co. Ltd.		
Vikas Granaries Ltd.	0.19978	0.021	Riga Sugar Co. Ltd.	0.164	Devon Plantations & Inds. Ltd.	0.815	Rossell India Ltd.
Vikas W S P Ltd.	0.27095	0.375	Rajshree Sugars & Chemicals Ltd.	0.578	Shree Renuka Sugars Ltd.	0.467	Rasoi Ltd.
Balrampur Chini Mills Ltd.	3.37481	0.088	E I D-Parry (India) Ltd.	0.716	Mawana Sugars Ltd.	0.197	Triveni Engineering & Inds. Ltd.
Bannari Amman Sugars Ltd.	0.04076	0.634	J V L Agro Inds. Ltd.	0.529	United Provinces Sugar Co. Ltd.		
Dalmia Bharat Sugar & Inds.Ltd.	0.34949	0.135	J V L Agro Inds. Ltd.	1.108	S B E C Sugar Ltd.	0.646	Simbhaoli Sugars Ltd.
Dhampur Sugar Mills Ltd.	0.69937	0.285	Balrampur Chini Mills Ltd.	0.067	Andrew Yule & Co. Ltd.	0.647	Ruchi Infrastructure Ltd.
Dharani Sugars & Chemicals Ltd.	0.63975	0.571	Rajshree Sugars & Chemicals Ltd.	0.319	S B E C Sugar Ltd.	0.109	United Provinces Sugar Co. Ltd.

become efficient by reducing its receivable levels to 36.62% of its initial level. It can then reach a point on efficient frontier which is referenced by: 0.437 times JVL Agro Inds. Ltd. receivables + 0.076 times Rajshree Sugars Chemicals Ltd. receivables + 0.592 times SBEC Sugar Ltd receivables.

5.6 Benchmarking

The DEA results as shown in Table 1show a benchmark column for each firm under consideration. This column gives two types of information: (i) for firms with efficiency less than 100% it gives a list of benchmark firms with weights. If the weights of benchmark firms are multiplied by their particular inputs, thenthe resulting value is the target the inefficient DMU under consideration. If this target is achieved by the inefficient firm, then it will become 100% efficient.(ii) For firms with efficiency score more than 100% it gives the number of firms for which it is a benchmark firm. Thus, overall this DEA method of WCM efficiency is able to tell a firm about where to improve, how much to improve and which peers to look up to, in order to become more efficient. The firm can use this information to decide which inputs and by how much they need to be decreased in order to become an efficient firm. This is a clear advantage over traditional measures like CCC and NTC since they just provided efficiency measures with no information about how much to increase or decrease the input to become more efficient.

For example in Table 1 Avanti Feeds Ltd has benchmarks 7 (0.01), 8 (0.06), 43 (0.05), 81 (0.90) which means that DMU/Firm no. 7, 8, 43 and 81 are the benchmarks for Avanti Feeds Ltd and it can become efficient if it reduces its inputs to a value which isequal to 0.01 time DMU 7 input + 0.06 times DMU 8 input +0.05 times DMU 43 input + 0.90 times DMU 81 input.

5.7 Model Extendibility

The DEA based WCM efficiency measure can be extended and modified according to the requirement.

(i) Return to scale: In our analysis, we assumed Non Decreasing returns to scale (NDRS) in the industry. However,depending upon the requirement and type of analysis, we can change the model to constant return to scale or to other forms of variable return to scale. At this point it is important to mention that the constant return to scale model measures both technical and scale efficiency where a variable return to scale model measures pure technical efficiency (Ramanathan, 2003).

(ii) Change of weights: In our analysis the weights of inputs and outputs were not restricted, i.e. they could take any value between 0 and 1. The model can be modified to restrict the weights to a maximum or minimum value. Also conditions can be applied e.g. Weights of inventory $\geq$ 2x weight of receivables, etc. This can help in finding efficiency under a set of conditions. For example, in case a firm that more weightage should be given to inventory than receivables as they are more liquid.

(iii) Inclusion of outside variables: The model can be extended to include regression model or a Tobit model (Lee, 2005) to take into consideration effect of outside or uncontrollable factors. These models are usually called two stage models and will be able to provide pure technical efficiency as the effect of uncontrollable factors will be removed.

6. Practical Implications

The DEA based technique because of its support for different type of analysis would prove useful to the regulator, i.e. government for policy framing and also to individual firms for effective management of short term resources. The government can make use of the measure to calculate the overall trend in efficiency of industry. This can be achieved by calculating the average of efficiencies of all firms for each year. For example Table 6 gives the average super efficiencies for Food and Agro industry for each year and the overall average efficiency. The table shows that the average efficiency of the industry is around 95%. This efficiency can be compared to the efficiencies of Food and Agro industries worldwide to get an idea of the competitiveness of the Indian industry. This can be used to either grant or withdraw incentives to the industry and to frame bank credit policy. Moreover the efficiency figure can be used to compare different industries to frame incentive policy. If it is found that an industry has a low average WCM

Table 6: Average WCM Efficiency of Food and Agro Industry

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Average Super Efficiency	97.9%	87.7%	85.1%	98.1%	100.0%	95.4%	99.9%	99.9%	93.9%	94.0%	99.8%
Overall Average	95.65%										

efficiency, then the government can take appropriate steps like building of public storage facilities. These warehouses can store the raw materials and firms can purchase from them as and when required. This will reduce inventory of firms and thus improve WCM efficiency.

The sensitivity analysis and working capital component wise analysis can help the regulators in understanding the expected changes in efficiency of firms due to small changes in inventories and/or availability of credit. This may help them in better forecasting the effect of the credit crunch or a shortage in raw material for inventory purpose. The component wise analysis for example in case of Food and Agro industry (Table 1) reveal that most of the firms have large weights associated with creditors and inventory and small weights associated with receivables. This reveals that overall industry is not managing the receivables efficiently and therefore appropriate steps can be taken like framing banking policies for easier and quicker discounting of receivables through banks etc. in order to improve the industry's WCM efficiency.

For individual firms like those in Food and Agro industry, it is possible for firms to benchmark themselves with respect to their peers. E.g. If the efficiency of a firm is below 97% in year 2003, then it can know that the short term fund management of the firm is not as per industry standards and that there is room for improvement. Moreover the DEA technique also aids in providing information to a less efficient firm about the amount of improvement required in order to become efficient.For example, from Table 1 we can see that Upper Ganges Sugar & Inds. Ltd. is less efficient firm and needs to improve to become efficient like DMU nos. 41 and 44. Similarly the firms can come to know that which of the inputs are not being used in an effective manner by checking the component analysis as suggested in section 5.4 above.

This will help the financial and operations manager in better planning the purchase and storage of raw materials and other inventory items, improved management of receivables and creditors for effective utilisation of funds.

The technique however needs to be applied carefully in order to achieve correct results. Since the DEA technique measures relative efficiency, it is essential that the sample size should be as large as possible in order to include all types of firms. The technique has the disadvantage that its results are only as good as the reference sample. Moreover, since some industries like Foods and Agro industry have to go for seasonal purchase of raw material, therefore the inventory value may be extremely high at one point of time and very low in another. Using inventory value at just one particular time of year may yield suboptimal results and therefore quarterly or monthly average value of inventory, debtors and receivables need to be considered in such cases.

7. Conclusion

This paper proposes a new method for measuring working capital management efficiency based on DEA where we have used non decreasing return to scale input oriented super efficiency model. The paper shows that the new model is able to overcome most of the shortcomingsof traditional measures (cash conversion cycle and net trade cycle) like mathematical flawed calculation and equal weights to inputs/outputs. In addition the paper presents superiority of the model over others due to its property of unit invariance, ratio type data output, ability to carry out sensitivity analysis and benchmarking. Further, the paper shows that the model can be extended to incorporate different types of return to scale, put conditions on weights of inputs and outputs and to include the effect of outside uncontrollable variables. Our study examines the working capital management efficiency in an entirely new perspective and opens new direction of research in effective working capital management.

End Note

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