THE INTERNATIONAL JOURNAL OF BUSINESS & MANAGEMENT

Determinants of Working Capital Management on Profit for Manufacturing Firms

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Abstract:
Management of Working Capital is often influenced by a number of factors. Often due to the large number of measurable factors that influence working capital, it is difficult to ascertain the most significant ones. This paper uses Principal Components Factor Analysis to examine the variables that have an impact on working capital management of Ghanaian manufacturing and industrial firms listed on the Ghana Stock Exchange. Fifteen (15) measurable characteristics that affect working capital management on profit from the Ghana Stock Exchange data is analyzed. It was determined that the Economic factors, short term liquidity, convertibility and operational factors are significant determinants of how a manufacturing company manages its working capital. Policy makers, investors or managers of the firms must focus attention on these areas of working capital that need improvement in order to yield profits.

Keywords: *Working capital management, principal components factor analysis*

1. Introduction

Management of working capital is one of the areas of major concern in financial management. Raheman and Nasr (2007) defined working capital management (WCM) as the administration of a firm's current assets and current liabilities. Measuring the relationship between working capital management and the firms' profitability is a very sensitive area to economist and financial analyst. Filbeck and Krueger (2005) suggested that a firm's progress depends on how managers monitor inventories, payables and receivables. Also, management of working capital ensures that a firm has enough cash flow to settle its operating expenses and short-term debt obligations. Financial analyst uses working capital ratios in assessing the firm's financial value and solvency. Factors that have an impact on the management of working capital are identified by a combination of cash flows and ratios of working capital management. The impact of working capital management on profit and the liquidity position of firms depend on the number of assets a firm has. The ratios connecting to the assets can be used as a factor to examine the importance of WCM. Operational Policies with regard to inventory conversions, debtors and creditors are factors which are important to firms. Also Economic factors such as gross domestic product growth rate and interest rates affect the level of accounts receivable (Walker, 1991).

Several empirical studies are used to assess the association between independent and dependent variables. Multiple regression, correlation, least square, logistic regression among others are mostly used to analyse the impact of working capital management on profit (Akinlo, 2011).There are current and advancing interest in factor analysis applied in different areas of management like leadership, knowledge management marketing and portfolio management (Arunkumarand Radharamanan, 2013). There is few research in using factor analysis to assess the linear dependency and relationship among the independent variables. Over the years, the variables mostly used are related to operational factor, the policy of the firm, ratios of assets and convertibility factors (Ramachandran and Jankiraman, 2009; Yadav et al., 2009; Sen and Oruc, 2009; Falope and Ajilore, 2009; Charitou et al., 2010; Alipour, 2011; Arunkumar and Radharamanan, 2013).

In Ghana, there is limited research that adopts factor analysis in the determination of factors that affect working capital management on profit. This research is novel in Ghana since it goes a step further to apply this methodology to an industry that has seen little research on its management practices. The paper aims at assessing the factors that determine the management of working capital of the manufacturing and industrial firms listed on the Ghana Stock Exchange (GSE) and to determine the most significant variables from the larger pool of measurable characteristics of manufacturing and industrial firms. The obtained significant variablescould be adopted in subsequent multivariate analysis. The variables considered in this study for factor analysis are Leverage (Lev), Inventory

Conversion Period (ICP), Average Payable Period (APP), Cash Conversion Cycle (CCC), Current Ratio (CR), Sales Growth (GR), Company Size (SIZE), Average Conversion Period (ACP), Cash Flow (CF), Interest Rate (IR), Quick Ratio (QR), Current Liabilities to Total Assets (CLTA), Current Assets to Total Assets (CATA), Real Gross Domestic Product Growth Rate (GDPGR) and Current Assets to Total Sales (CATS).
According to (Chong et.al, 2013), factor analysis is a statistical technique employed to examine the variation that exist among observed variables which is catered for by a potentially smaller number of unobserved variables called factors. Therefore, several variables can be grouped into just a single variable.

2. Materials and Methods

Computed ratios from 13 manufacturing and industrial firms listed on the Ghana Stock Exchange between 2009 and 2014 was analyzed. Audited annual financial reports from the Fact Book of the Ghana Stock Exchange and the institutions' web portals are also employed in this research. Management of working capital is necessary for manufacturing and industrial firms since majority of its assets is made up of current assets (Horne and Wachowitz, 2000).
Fifteen variables captured from the stock exchange fact book and those listed on the institutions' web portals are selected for the study. The selected variables are expected to be significant in the explaining the impact of working capital management on profit (Akinlo, 2011). Table 1 presents the variables used in the analysis, various categories and how they are calculated. The Variables are grouped under four main categories to represent the firm's convertibility of assets into cash, operating asset efficiency, short term liquidity and movement of Debtors and Creditors, the policy of the firm (Arunkumar and Radharamanan, 2013).

No.	Variable	Code	Category	Computation Method
1	Account Payable Period	APP	Policy factor	$\frac{Average\ Accounts\ Payable}{Net\ Sales} \times 365$
2	Cash Conversion Cycle	CCC	Short term Liquidity	$ACP + ICP - APP$
3	Current Ratio	CR	Convertibility factor	$\frac{Current\ Assets}{Current\ Liabilities}$
4	Inventory Conversion Period	ICP	Operational factor	$\frac{Average\ Inventory}{Net\ Sales} \times 365$
5	Sales Growth	GR	Short term Liquidity	$\frac{Sales_t - Sales_{t-1}}{Sales_{t-1}}, t = 1, 2, \ldots$
6	Leverage	LEV	Operational factor	$\frac{Total\ Debt}{Total\ Assets}$
7	Company Size	SIZE	Convertibility factor	Natural Logarithm of Total Assets
8	Account Collection Period	ACP	Policy factor	$\frac{Average\ Accounts\ \mathrm{Re}ceivable}{Net\ Sales} \times 365$
9	Interest Rate on Loans	IR	Economic factor	$Cost\ of\ borrowing\ money \times Loan\ Amount$
10	Real GDP Growth Rate	GDPGR	Economic factor	$\frac{GDP}{1 + Inflation\ \sin ce\ base\ year}$
11	Cash Flow	CF	Short term Liquidity	$\frac{Operating\ Cash\ Flow}{Total\ Sales} \times 100$
12	Current Assets to Total Assets	CATA	Convertibility factor	$\frac{Current\ Assets}{Total\ Assets}$
13	Current Liabilities to Total Assets	CLTA	Convertibility factor	$\frac{Current\ Liabilities}{Total\ Assets}$
14	Quick Ratio	QR	Short term Liquidity	$\frac{Cash + Short\ Term\ Investment + \mathrm{Re}ceivables}{Current\ Liabilities}$
15	Current Assets to Total Sales	CATS	Convertibility factor	$\frac{Current\ Assets}{Total\ Sales}$

Table 1: Variables Used in the Analysis

3. Factor Analysis Techniques

Factor Analysis is a multivariate statistical technique employed to group variables which have high correlation among themselves but low correlations with all other variables (Rencher, 2002).

3.1. Orthogonal Factor Model

Suppose each of the observed financial statements of the selected firms is a value of the random vector $Z=(z_1,z_2,...,z_k)'$ with mean vector $\mu=(\mu_1,\mu_2,...,\mu_k)'$ and covariance matrix $\sum$.

The factor analysis model expresses every variable as a linear combination of unobserved variables called factors $f_1,f_2,...,f_n$ with an additional error $\varepsilon_1,\varepsilon_2,...,\varepsilon_k$ (Rencher, 2002).

The factor analysis model is

$$\begin{aligned} z_1-\mu_1 &= \alpha_{11}f_1+\alpha_{12}f_2+\ldots+\alpha_{1n}f_n+\varepsilon_1 \\ z_2-\mu_2 &= \alpha_{21}f_1+\alpha_{22}f_2+\ldots+\alpha_{2n}f_n+\varepsilon_2 \\ \vdots & \qquad \vdots \\ z_k-\mu_k &= \alpha_{k1}f_1+\alpha_{k2}f_2+\ldots+\alpha_{kn}f_n+\varepsilon_k \end{aligned} \tag{1}$$

The coefficient α_{kn} is called the loading of the k^{th} variable on the n^{th} factor with ε_k being the k^{th} specific error associated with the k^{th} response z_k.

Johnson and Wichern (2007) stated that when $n<k$, the parsimonious explanation of the variables as functions of a few underlying factors are attained. The matrix notation of the orthogonal factor model is

$$\underset{(k\times 1)}{Z-\mu} = \underset{(k\times n)}{\alpha}\;\underset{(n\times 1)}{F} + \underset{(k\times 1)}{\varepsilon} \tag{2}$$

Where Z,μ and ε have earlier been explained,

$$\alpha=\begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{k1} & \alpha_{k2} & \cdots & \alpha_{kn} \end{bmatrix}$$

$$F=(f_1,f_2,...,f_k)'$$

A number of assumptions about model (2) made by the factor analyst such as F and ε are independent, $E(F)=0, Cov(F)=I, E(\varepsilon)=0, Cov(\varepsilon,F)=0$ and $Cov(\varepsilon)=\lambda$, where λ is a diagonal matrix.

The Covariance structure for the orthogonal factor model is given by

$$\begin{aligned} &i)\,Cov(Z_i,Z_k)=\alpha_{i1}\alpha_{k1}+\ldots+\alpha_{in}\alpha_{kn} \\ &Var(Z_i)=\alpha_{i1}^2+\ldots+\alpha_{in}^2+\lambda_i \\ &ii)\,Cov(Z_i,F_j)=\alpha_{ij} \end{aligned} \tag{3}$$

Where $\alpha_{i1}^2+\alpha_{i2}^2...+\alpha_{in}^2$ is the sum of squares of the loadings of the i^{th} variable or portion of the variance of the i^{th} variable contributed by the n common factors called the i^{th} communality and λ_i = specific variance.

3.2. Estimating the Parameters in the Factor Model

The unknown factor loadings and the error variances are estimated from the sample data. The sample correlation matrix is mostly used as compared to the sample covariance matrix. Several methods such as Principal Component, Principal Factor, Maximum-likelihood, Iterated Principal Factor, etc. are used for estimation of factor model but this study chose the Principal Component Method because it does not make strong assumptions about the distribution (Nortey et. al., 2014). The results are rotated in order to make it easy to interpret the factors.

3.3. The Principal Component Method

Let $\sum$ have eigenvalue-eigenvector pairs (β_i,e_i) with $\beta_1\geq\beta_2\geq\ldots\geq\beta_k\geq 0$, then $\sum$ can be decomposed as a linear combination of the Eigen value- Eigen vector pairs as follows:

$$\sum = \beta_1 e_1 e_1^{'} + \beta_2 e_2 e_2^{'} + \ldots + \beta_k e_k e_k^{'}$$

$$= \left[\sqrt{\beta_1 e_1} \; \vdots \sqrt{\beta_2 e_2} \vdots \cdots \; \vdots \sqrt{\beta_k e_k} \right] \begin{bmatrix} \sqrt{\beta_1 e_1^{'}} \\ \ldots\ldots\ldots \\ \sqrt{\beta_2 e_2^{'}} \\ \ldots\ldots\ldots \\ \vdots \\ \ldots\ldots\ldots \\ \sqrt{\beta_k e_k^{'}} \end{bmatrix} \qquad (4)$$

So if $\alpha = \left[\sqrt{\beta_1 e_1} \; \vdots \sqrt{\beta_2 e_2} \vdots \cdots \; \vdots \sqrt{\beta_k e_k} \right], then \sum = \alpha \alpha^{'}$

For $n < k$ factor model, $\alpha = \left[\sqrt{\beta_1 e_1} \; \vdots \sqrt{\beta_2 e_2} \vdots \cdots \; \vdots \sqrt{\beta_n e_n} \right]$, then the Principal factor estimate of α is

$$\alpha = \left[\sqrt{\beta_1 e_1} \; \vdots \sqrt{\beta_2 e_2} \vdots \cdots \; \vdots \sqrt{\beta_n e_n} \right] \qquad (5)$$

Where $(\beta_i, e_i), \mathrm{i} = 1, 2, \ldots, \mathrm{n}$ is the eigenvalue-eigenvector of the sample covariance matrix S.

The estimated specific factors are approximated as $\sum \approx \alpha \alpha^{'} + \lambda$

$$= \left[\sqrt{\beta_1 e_1} \; \vdots \sqrt{\beta_2 e_2} \vdots \cdots \; \vdots \sqrt{\beta_k e_k} \right] \begin{bmatrix} \sqrt{\beta_1 e_1^{'}} \\ \ldots\ldots\ldots \\ \sqrt{\beta_2 e_2^{'}} \\ \ldots\ldots\ldots \\ \vdots \\ \ldots\ldots\ldots \\ \sqrt{\beta_k e_k^{'}} \end{bmatrix} + \begin{bmatrix} \hat{\lambda}_1 & 0 & \cdots & 0 \\ 0 & \hat{\lambda}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \hat{\lambda}_k \end{bmatrix} \qquad (6)$$

Where $\hat{\lambda}_i = s_{ii} - \sum_{j=1}^{n} \hat{\alpha}_{ij}^2 \text{ for } i = 1, 2, \ldots, k$

The estimated communalities are $\hat{h}_i^2 = \hat{\alpha}_{i1}^2 + \hat{\alpha}_{i2}^2 + \ldots + \hat{\alpha}_{in}^2, i = 1, 2, \ldots, k$ (7)

With $Var(V_i) = S_{ii} = \hat{h}_i^2 + \hat{\lambda}_i$

3.4. Rotation Matrix

Rotation of the factors is mostly employed to facilitate in the interpretation of the analysis. Factor rotation does not have an effect on the number of variance and factors extracted.

The orthogonal rotation method is used since our main aim is data reduction and the result is a matrix of the factor loadings.The most popular and frequently used orthogonal method called Varimax will be used in this study. It maximizes the variance of the squared loadings for all the variables conditioned on the communality of each variable remaining the same. Every factor attained will have either small or large loadings of any of the variables. Assessing the Varimax Outcome will guide the researcher to identify easily every variable with a single factor.

4. Analysis and Results

4.1. Descriptive Statistics

Table 2 below shows the descriptive statistics of 13 manufacturing and industrial firms over a period of 10 years. The mean, the standard deviation, skewness and kurtosis are computed for all the 15 independent variables that is expected to affect profit.

Variables	N	Mean	S. D	Skewness	Kurtosis
CATS	130	0.15138	0.039723	-0.045	0.158
SIZE	130	11.173462	3.3636656	0.757	-0.026
CCC	130	57.556692	15.4812699	-0.020	-0.297
ACP	130	42.189615	15.4011036	-0.046	-0.301
APP	130	81.801308	42.5434519	0.104	-1.181
CR	130	2.79115	1.201976	0.496	-0.461
ICP	130	86.70462	32.335357	0.340	-0.785
LEV	130	0.384715	0.4200055	1.480	0.906
GR	130	0.136885	0.0702745	2.594	8.626
CATA	130	0.400759	0.1995896	1.453	1.072
IR	130	0.241977	0.0411014	-0.086	0.684
GDPGR	130	0.214885	0.0356898	-0.043	0.198
CLTA	130	0.170654	0.0380658	-0.080	0.363
CF	130	0.169562	0.0404793	-0.449	1.428
QR	130	0.288062	0.0357974	-0.036	0.425

Table 2: Descriptive Statistics

4.2. Factor Analysis Results

This section displays the results of the factor analysis which include the number of factors selected and the total variance explained by the chosen factors. From SPSS, the factor analysis method was used with Principal Component Analysis as the extraction method and Varimax as the rotation method.

The value of the sample adequacy test measured by Kaiser-Meyer -Olkin is 0.850 which indicate that the sample is accepted for factor analysis to be performed. Also, the Bartlett's Test of Sphericity has a significant value of 0.00 which is anindication that the correlation matrix is not an identity matrix.

Table 4 below shows the data for the communalities. The Communalities shows how much of the variance in the variables that affect profit are explained by the extracted factors. For instance, over 97.2% of the variance in IR is explained and accounted for while 65.8% of the variance in GR is also explained and accounted for.

Variables	IR	GR	ICP	CR
Initial	1.000	1.000	1.000	1.000
Extraction	0.971	0.658	0.862	0.679

Table 4: Communalities Before and After Extraction

Table 5 shows the importance of each of the 15 principal components using the eigen values. The first four have Eigen values over 1.00 which explains over 80.515% of the total variability in the data. Hence we can conclude that a four factor solution will be adequate in determining the management of profits in the manufacturing industry.

Component	Total	Initial Eigen	Values
		% of Variance	Cumulative %
1	7.375	49.168	49.168
2	2.149	14.328	63.495
3	1.488	9.917	73.413
4	1.065	7.102	80.515
5	0.779	5.195	85.710
6	0.718	4.789	90.499
7	0.398	2.650	93.149
8	0.292	1.948	95.097
9	0.261	1.742	96.838
10	0.159	1.062	97.901
11	0.117	0.781	98.681
12	0.097	0.650	99.331
13	0.055	0.370	99.701
14	0.041	0.273	99.974
15	0.004	0.026	100.000

Table 5: Total Variance Explained

Table 6 below shows the detailed results of the factor loadings of the 15 variables that result from Varimax rotation. From the output, it is clear that, CATS, IR, CF, CLTA, QR, and 0.898 are significant in the first factor.ICP, LEV, CATA constitute the major components of the second factor while ICP and APP constitute the most significant factors in factor 3. Factor four comprises CR and ACP as having significant weight.

Variables	Factors			
	1	2	3	4
CATS	0.967	0.121	0.119	0.078
SIZE	0.359	0.155	0.242	-0.555
CCC	0.409	0.343	0.267	0.597
ACP	0.625	0.067	0.119	0.613
APP	0.235	0.461	0.782	0.068
CR	0.456	0.070	0.064	**0.680**
ICP	-0.021	-0.003	**0.928**	-0.006
GR	0.000	**-0.759**	0.097	-0.268
LEV	0.362	0.674	0.277	-0.402
IR	**0.968**	0.130	0.101	0.089
CF	0.948	0.061	0.101	0.117
CATA	0.167	0.737	0.258	-0.049
CLTA	0.905	0.091	0.030	0.087
QR	0.939	0.148	0.079	0.128
GDPGR	0.898	0.270	0.034	0.023

Table 6: Rotated Component Matrix

Table 7 shows the SPSS results of the selected variables, their factor loadings and the categories they belong to after using factor analysis method with the extraction method from the Principal Component Analysis and Varimax as the rotation method. The variables are grouped into four factors, namely, economic factor, short term liquidity, convertibility factor and operational factor.

Factor	Variables	Code	Factor Loading	Category
1	Interest Rate	IR	0.968	Economic factor
2	Sales Growth	GR	-0.759	Short Term Liquidity
3	Inventory Conversion Period	ICP	0.928	Operational factor
4	Current Ratio	CR	0.680	Convertibility factor

Table 7: Selected Variables after Factor Analysis

5. Conclusion

It is clear that principal component factor analysis is an efficient tool in the determination of a significant smaller set of variables from observed variables that affect working capital management on profit of manufacturing and industrial firms. The application of the methodology on 15 selected variables from 13 manufacturing and industrial firms on the Ghana Stock Exchange indicates that short term liquidity, convertibility and operational factors are significant in the management of a manufacturing company's capital on profit. The results showed that some variables are more significant in two or more of the firms and that at least economic factors, are chosen in the representative set of the variables after factor analysis. Sampling adequacy was also identified to be acceptable and that the correlation matrix is not an identity matrix.

The factors extracted using principal component analysis will assist policy makers, investors or managers of the firms to identify areas of working capital that need improvement in order to yield profits. Although the variables captured are significant in profit yield of manufacturing companies, a number of factors (such as company good will, scandals, marketing strategy etc.) often not captured by stock exchanges may also influence profitability.

This paper will contribute to a better understanding of the nature and features of variables that affect working capital management on profit of manufacturing and industrial firms in Ghana and perhaps in the African environment as there are very few researches and studies conducted in this field in Ghana and Africa as a whole.

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