APPENDIX TO CHAPTER 4

Appendix 4-A

Questions used in this study

17. At what degree does your company consider the following factors in determining the target profit under target costing? Please put circle in the appropriate cell relating to each factor.

	Lower utilization	Medium utilization	Wider utilization
1. Target return on sales ratio determined in medium and long term profit planning.			
2. Target return on sales determined based on past actual return on sales ratio of the related product.			
3. Target reduction rate of cost of the existing and similar product.			

18. In your company, which formula is being used in determining target cost? Please put circle to the appropriate one.

    1. Target cost is determined by subtracting the target profit from target sales price.
    2. The difference between the target profit and target sales price is considered as allowable cost. This allowable cost is compared with drifting cost (which is the estimated cost calculated at the present technological level) to determine the target cost.
    3. Target cost is calculated by applying the (1 – target reduction rate of cost) to the drifting cost, which is predicted by the present technological level.

20. Presently at what degree does your company achieve target cost? Please put circle to the appropriate one.

    1. About 60% of target cost
    2. About 70% of target cost
    3. About 80% of target cost
    4. About 90% of target cost
    5. Almost 100% (or more) of target cost

Appendix 4-B

Data showing the number of companies using each target profit and cost method at each level of target cost achievement

Target Profit Methods	Target Cost Methods (TC)	Target Cost Achievement Level (TCAL)			
		About 70%	About 80%	About 90%	Almost 100% or more
TP1					
L	SUB	2	3	3	0
M	SUB	1	3	2	1
H	SUB	2	1	3	6
TP1					
L	COM	7	9	6	2
M	COM	0	8	3	1
H	COM	2	4	6	9
TP1					
L	ADD	3	6	8	2
M	ADD	3	6	6	0
H	ADD	2	3	4	1
TP3					
L	SUB	1	1	1	1
M	SUB	3	4	3	1
H	SUB	1	2	4	5
TP3					
L	COM	1	3	3	4
M	COM	5	13	4	3
H	COM	3	2	8	5
TP3					
L	ADD	4	2	2	0
M	ADD	3	8	8	1
H	ADD	1	4	8	2
TP2					
L	SUB	1	0	2	1
M	SUB	2	5	2	1
H	SUB	2	2	4	5
TP2					
L	COM	1	2	4	1
M	COM	6	10	5	7
H	COM	2	9	6	4
TP2					
L	ADD	3	4	5	0
M	ADD	2	7	4	2
H	ADD	3	3	9	1

Appendix 4-C

Statistical issues

Estimation Approach

The dependent variable or response Y (target cost achievement level) is by design restricted to one of four possible values representing the achievement level of 70% or fewer, between 71% and 80 %, between 81% and 90%, and between 91% to 100%. These categories are clearly ordered, but it does not make sense to compare the distance between the first and second categories with that between, say, the third and fourth. It is therefore safe to regard the variable as the one measured by ordinal scales. This eliminates the possibility of applying ordinary least squares(OLS). The standard approach (McCullagh and Nelder, 1989) is to transform the cumulative response probabilities $\gamma_j = \Pr(Y \leq j)$, where $j = 1,\ldots,4$ is the number of categories, rather than the category probabilities $\pi_j = \Pr(Y = j)$, by the logistic function $\log(\gamma_j/1-\gamma_j)$ and regress them on the explanatory variables x_k, $k = 1,\ldots,p$.

The choice of 70%, 80%, and 90% in separating response categories in our survey could be construed as subjective. If we are to arrive at meaningful conclusions, it is essential that the nature of those conclusions not to be dependent upon the particular number and/or choice of these response categories. That is to say, if a new category is formed by combining neighboring categories of the old scale, the inherent character of the conclusions should not be altered. Such considerations naturally lead to models based on the cumulative response probabilities.

The model we employed is referred as the proportional-odds model and involves parallel regressions on the chosen ordinal scale

$$\log\{\gamma_j(X)/1-\gamma_j(X)\} = \theta_j - \beta^T X, j = 1,\ldots,k-1$$

where $\gamma_j(X) = \Pr(Y \le j|X)$ is the cumulative probability up to and including category j, when the independent variable vector is X. The name of the model originates from the fact that the odds of the event $Y \le j$ at $X = X_1$ relative to those at $X = X_2$ can be written as

$$\frac{\gamma_j(X_1)/\{1-\gamma_j(X_1)\}}{\gamma_j(X_2)/\{1-\gamma_j(X_2)\}} = \exp\{-\beta^T(X_1 - X_2)\},$$

and is independent of the choice of category (j). The negative sign in front of the β is a convention that guarantees large values of $\beta^T X$ generates an increase in probability of the higher-numbered categories. Both θ and β are unknown parameters to be estimated. The θ must satisfy $\theta_1 \le \theta_2 \le \cdots \le \theta_{k-1}$ because they represent the average values of cumulative response probabilities. We can use only $k-1$ categories out of the total k to estimate θ and β because the cumulative probabilities adds up to unity by definition.

Estimation Methodology

All regression coefficients are estimated by maximizing logarithm of the likelihood function

$$l(\gamma|Z) = \sum l(\gamma_i|z_i) = \sum_i \sum_j \left(z_{ij} - z_{i(j-1)}\right)\log\left(\gamma_{ij} - \gamma_{i(j-1)}\right),$$

where we suppose that there are n independent multinomial vectors, each with k categories. The i-th observations are denoted by $y_1,\ldots,y_n$, where $y_i = (y_{i1},\ldots,y_{ik})$.

The cumulative response vectors are $z_{ij} = \sum_{k=1}^{j} y_{ik}$ and the binomial index $\sum_j y_{ij} = m_i$ is fixed for each i. Differentiating the log likelihood with respect to γ_{ij} and the Lagrange multiplier λ subject to the constraint $\sum_{j=1}^{k} \left(\gamma_{ij} - \gamma_{i(j-1)}\right) = 1$ gives

$$\frac{\partial l(\gamma|Y)}{\partial \gamma_{ij}} = m_i \Gamma^{-} \left(\sum_{l}^{i} y_{il} - m_i \gamma_i \right),$$

where the Γ^{-} is a $k \times k$ symmetric Jacobi or tri-diagonal matrix as follows.

$$\Gamma^{-} = \frac{1}{m_i} \begin{bmatrix} \pi_{i1}^{-1} + \pi_{i2}^{-1} & -\pi_{i2}^{-1} & 0 & \cdots & 0 \\ -\pi_{i2}^{-1} & \pi_{i2}^{-1} + \pi_{i3}^{-1} & \ddots & \ddots & \vdots \\ 0 & \ddots & \ddots & -\pi_{i(k-1)}^{-1} & 0 \\ \vdots & \ddots & -\pi_{i(k-1)}^{-1} & -\pi_{i(k-1)}^{-1} + -\pi_{ik}^{-1} & 0 \\ 0 & \cdots & 0 & 0 & 0 \end{bmatrix}.$$

It is the Moore-Penrose inverse of the covariance matrix $\Gamma = \{\gamma_{rs}\} = m_i \gamma_r (1 - \gamma_s)$.

Let $\beta^* = (\theta_1, \ldots, \theta_{k-1}, -\beta_1, \ldots, -\beta_p)$, then the proportional-odds model can be written as

$$\log\{\gamma_{ij} / 1 - \gamma_{ij}\} = \sum_r x_{ijr}^* \beta_r^*$$

where x_{ijr}^* is the components of a matrix X^* of order $n(k-1) \times p^*$ where p^* is the dimension $p^* = (k-1) + p$ of β^*. The j-th row in the i-th block of the matrix X^* can be written as $(0, \ldots, 1, \ldots, 0, x_{i1}, \ldots, x_{ip})$, the first $k-1$ columns are zero except the

j -th, which has unity, and the remaining p columns has values of the independent or explanatory variables corresponding i -th cell count.

Finally differentiating the log likelihood with respect to β^* gives

$$\frac{\partial l}{\partial \beta_r^*} = \sum_i \sum_j x_{ijl}^* \gamma_{ij} \left(1 - \gamma_{ij}\right) \frac{\partial l}{\partial \gamma_{ij}},$$

Setting the derivatives equal to zero and solving with respect to β^* by applying iterative re-weighted least squares with starting values $\hat{\beta}^{*(0)}$ until convergence obtains the result. The estimate $\hat{\beta}^*$ of β^* are normally fairly accurate after a few cycles of iteration.

Lack of convergence is seldom an issue unless at least one component of the estimate $\hat{\beta}^*$ is infinite, which usually implies that the data are sparse and $y_i = 0$ or $y_i = m_i$ for certain components of the response vector. Irregular convergence or oscillation could occur and normally indicates that the log likelihood is either very flat or has an asymptote. Three dimensional graphical representation of likelihood surface should detect such a phenomenon. A slight change in convergence criterion is often enough to address the problem.