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Performance Evaluation of Fabless CMOS Image Sensor Design Houses by Using an Multiple Objective Programming Based Data Envelopment Analysis

***Abstract**. Complementary Metal Oxide Semiconductor (CMOS) image sensors have widely been used due to the advantages in terms of low power consumption, on-chip signal processing capability, and a comparatively low cost. The market research institutes predicted that the demand for CMOS image sensors will dramatically increase over the next few years. Although the demand continues to increase, the market is becoming daily competitive. Thus, operating efficiently will be very critical for CMOS image sensor vendors to sustain competitiveness. The fabless CMOS image sensor design is one of the fast emerging and most important sectors of the CMOS image sensor industry. Understanding the efficiency of fabless CMOS image sensor design houses is critical for managers of the fabless CMOS image sensor design houses, semiconductor foundries as well as investors. Albeit critical, very few scholars tried to evaluate the performance of the fabless CMOS image sensor vendors. Thus, this paper aims to evaluate the productivity and efficiency of CMOS image sensor firms. A novel Multiple Objectives Programming based Data Envelopment Analysis (DEA) model will be introduced for benchmarking the firms.*

***Streszczenie.** Opisano projektowanie czujnika obrazu CMOS. Wprowadzono nowy algorytm DEA (data envelopment analysis) do oprogramowania MOP (multiple objective programming). (**Ocena właściwości i projektowanie czujnika obrazu CMOS z wykorzystaniem algorytmu DEA**)*

Keywords: CMOS image sensors, Data Envelopment Analysis, Multiple Objective Programming, Efficiency
Słowa kluczowe: czujnik obrazu CMOS, projektowanie typu fabless (bez produkcji).

Introduction

In recent years, the application of digital imaging techniques has experienced explosive growth due to the popularity of camera-equipped mobile phones, notebook webcams, digital still cameras, and internet-based video conferences in consumer as well as business applications [1]. Two most common electronic image sensors for digital imaging are Charge Couple Device (CCD) and Complementary Metal Oxide Semiconductor (CMOS) image sensors. Both image sensors are silicon-based semiconductor devices that convert light to an electric charge for display or storage.

CCDs have traditionally been the dominant image sensor technology [1]. However, advances in semiconductor manufacturing processes and design techniques have led to significant improvements in functional capability and image quality of the CMOS image sensors. Compared to CCDs, CMOS image sensors have numerous advantages. For example, the power consumption of CMOS image sensors ranges from one-third to more than 100 times less than that of CCDs [2]. CMOS image sensors also allow monolithical integration of readout and signal processing electronics [3]. In addition, costs to manufacture CMOS image sensors are lower than those to produce CCDs [3]. Consequently, CMOS image sensors have widely used in mobile phones, notebook webcams, digital camera, portable multi-media devices, and commercial enterprise applications.

The industry analysts predicted that CMOS image sensor demands will triple or quadruple over the next few years. Although CMOS image sensor market continues to grow, the market is intensely competitive. The competition results in rapid technological changes, evolving standards, reductions in selling price, and rapid product obsolescence. Semiconductor memory vendors, especially the dynamic random access memory (DRAM) vendors like Samsung, Hynix and Micron, are producing the products by using the already depreciated 8 inch semiconductor fabrication facilities and pricing the CMOS image sensors significantly below the market levels in order to fully utilize the capacity of the old fabs and gain market share in the short-term. Therefore, CMOS image sensor vendors face additional downward pressure on the price from semiconductor memory vendors.

Fabless CMOS image sensor design houses design and market semiconductor components by relying on contract manufacturers (“foundries”) for the production of their designs. The fabless CMOS image sensor design is one of the fast emerging and most important sectors of the CMOS image sensor industry. Some of the fabless CMOS image sensor design houses like OmniVision, PixArt, Pixelplus, E2V, etc. emerged rapidly during the past decade and have been listed in the stock exchange. Understanding the efficiency of fabless image sensor design houses is critical for managers of the fabless image sensor design houses, semiconductor foundries as well as investors. To meet competitive challenges from dedicated CMOS image sensor vendors with their own semiconductor fabrication facilities as well as DRAM vendors which fabricate the CMOS image sensors by using the already-depreciated fabrication facilities, fabless CMOS image sensor design houses need to design, develop, and outsource-manufacturing the CMOS image sensors efficiently.

Thus, it is important to evaluate the efficiency and productivity of the fabless CMOS image sensor design houses. However, prior literature focuses mainly on how the sensor technology can be improved [4, 5, 6]. To the best of the authors’ knowledge, no research has tried to evaluate the efficiency of CMOS image sensor vendors. To fill the gap of the literature, the objective of this paper is to evaluate the efficiency of the fabless design houses which focus on designing, developing, marketing as well as outsource-manufacturing CMOS image sensors.

Prior literature has developed various efficiency measurement methods such as Multiple Criteria Decision Making (MCDM) frameworks [7, 8] and the Data Envelopment Analysis (DEA) methods [9, 10]. Among these methods, the DEA methods have been widely used to evaluate productivity and efficiency. The traditional DEA models being proposed by Charnes et al. [11] or Banker et al. [12] evaluate the performance of decision making units (DMUs) by selecting each DMU’s favorable weights. However, such performance evaluation is derived based on different bases of comparisons of DMUs. Thus, the traditional DEA model is not a fair model from the aspect of weight derivations. To overcome the problems in traditional DEA-based performance evaluation, this paper uses the Multiple Objective Programming (MOP) based DEA method [13, 14] to evaluate the performance of the fabless CMOS image sensor firms. The MOP based DEA method provides a unitary weight for all DMUs, which are evaluated by considering an equal standard measure [13, 14].

Based on literature review, the authors summarized the input and output indications being suitable for evaluating the fabless CMOS image sensor design houses (DMUs in this research). The fabless CMOS image sensor design houses were evaluated by the CCR, BCC and the MOP based DEA models using the input and output indicators being obtained from firms' annual reports from 2008 to 2010.

The introduction of the MOP based DEA method is expected to assess the efficiency of the firms reasonably since the same weight being associated with the same input and output belonging to all DMUs. The results being derived by traditional CCR and BCC DEA models serve as the comparisons to demonstrate the discrimination capability of the MOP-based DEA model.

The remainder of this paper is organized as follows. In section 2, the CCR, BCC, and MOP-based DEA methods are introduced. The industrial background and the empirical study process are presented in Section 3. Section 4 presents a discussion, and we conclude with a summary of our results in section 5.

Reseearch Methods

DEA

The DEA is a non-parametric approach and doesn't need assumptions about the inputs and outputs. The CCR model was proposed by Charnes, Cooper, and Rhodes in 1978. This model assumes that production exhibits constant returns to scale. In 1984, Banker, Charnes, and Cooper extended the CCR model by assuming variable returns to scale and named the new model as the BCC model [12]. Both CCR and BCC models of DEA are often used the input-oriented.

1) CCR

The CCR model computes relative efficiency scores h_k of k^{th} DMU $(k \in \{1,2,...,n\})$ based on selected s outputs ($r=1,...,s$) and m inputs ($i=1,...,m$)using the following linear programming expression[13,14]:

(1) Max $h_k = \sum_{j=1}^{s} u_j y_{jk} \Big/ \sum_{i=1}^{m} v_i x_{ik}$

Subject to

$$\sum_{j=1}^{s} u_j y_{jr} \Big/ \sum_{i=1}^{m} v_i x_{ir} \le 1,\ r=1,2,...,n.$$

$$v_i, u_j \ge \varepsilon > 0;$$

$$i=1,...,m;\ j=1,2,\dots,s;\ k,r \in \{1,2,...,n\}.$$

In Eq. (1), it assumes the DMU has **s** outputs and **m** inputs, and there are n DMUs. The definition lets x_{ik} be the i^{th} input ($i=1,2,\dots,m$) and y_{jk} be the j^{th} output ($j=1,2,\dots,s$) in k^{th} DMU; the v_i and u_j are not zero, calculating as $v_i, u_j \ge \varepsilon > 0$, ε is a non-Archimedean number and is 10^{-6} in this paper.

2) Correct CCR based on BCC model

Eq. (1) refers to maximize the ratio of weighted sum of output and input values. Charnes et al.[15] proposed correct CCR model based on input-oriented BBC model:

(2) Max $h_k = \sum_{j=1}^{s} u_j y_{jk} \Big/ \sum_{i=1}^{m} v_i x_{ik}$

Subject to

$$\sum_{j=1}^{s} u_j y_{jr} \Big/ \sum_{i=1}^{m} v_i x_{ir} \le 1,\ r=1,2,...,n.$$

$$u_j \Big/ \sum_{i=1}^{m} v_i x_{ik} \ge \varepsilon > 0,\ j=1,2,...,s.$$

$$v_j \Big/ \sum_{i=1}^{m} v_i x_{ik} \ge \varepsilon > 0,\ i=1,2,...,m.$$

Since it is difficult to solve the fractional programming as Eq. (1) and Eq. (2), we transfer Eq. (1) and Eq. (2) to the linear programming by the following transformations:

Assuming $v_i^0 = t \cdot v_i$ (i.e., $v_i = v_i^0 / t$), $u_j^0 = t \cdot u_j$ (i.e., $u_j = u_j^0 / t$), $t^{-1} = \sum_{i=1}^{m} v_i x_{ik}$, then multiply the numerators and denominators in Eq. (1) by t, and add the consistency condition, $t\sum_{i=1}^{m} v_i x_{ik} = 1$. Thus Eq. (2) can be transferred to Eq. (3).

(3) Max $h_k = \sum_{j=1}^{s} u_j^0 y_{jk}$

Subject to

$$\sum_{j=1}^{s} u_j^0 y_{jr} - \sum_{i=1}^{m} v_i^0 x_{ir} \le 0,\ r=1,2,...,n.$$

$$\sum_{i=1}^{m} v_i^0 x_{ik} = 1.$$

$$u_j^0 \ge \varepsilon > 0,\ j=1,2,...,s.\ v_i^0 \ge \varepsilon > 0,\ i=1,2,...,m.$$

$$v_i^0 = t \cdot v_i;\ u_j^0 = t \cdot u_j;\ t^{-1} = \sum_{i=1}^{m} v_i x_{ik}.$$

The dual formula can be written as follows:

(4) Min $h_k = \left[\theta_k - \varepsilon\left(\sum_{i=1}^{m} S_{ik}^- + \sum_{j=1}^{s} S_{jk}^+\right)\right]$

Subject to

$$\theta_k x_{ik} - \sum_{k=1}^{n} \lambda_k x_{ik} - S_{ik}^- = 0,\ i=1,2,...,m.$$

$$y_{jk} - \sum_{k=1}^{n} \lambda_k y_{jk} + S_{jk}^+ = 0,\ j=1,2,...,s.$$

$$S_{ik}^-,\ S_{jk}^+,\ \lambda_k \ge 0,$$

where S_{ik}^- and S_{jk}^+ are slack variables of input criteria and output criteria.

The dual formula presented by BBC [12] has two primary strengths including the reduction of calculation barriers and the provision of more helpful information for decision makers. When $h_k^* = 1$ an individual DMU$_k$ achieves Pareto's optimality, where "$*$" denotes for the optimal solution; for example, $\{(x_{ik}^*, y_{jk}^*) \mid S_{ik}^- = S_{jk}^+ = 0,$ $i=1,...,m;\ j=1,2,\dots,s$ }, and $S_{ik}^- = S_{jk}^+ = 0$. If a DMU does not achieve Pareto's optimality situation, its limited equation intrinsically includes $x_{ik}^* = \theta^* x_{ik} - S_{ik}^-$ and $y_{jk}^* = y_{jk} + S_{jk}^+$. In order to achieve its efficiency goal of optimality, this specific DMU may either reduce inputs $\Delta x_{ik} = x_{ik} - x_{ik}^*$ or increase output $\Delta y_{ik} = y_{ik}^* - y_{ik}$ to become relatively efficient.

Clearly, the slack variable analysis of the DEA method provides DMUs related information for improvement. When a DMU does not achieve Pareto's optimality, we can make some improvement or innovation based on Eq. (4). This can help individual DMU achieve Pareto's optimality in the relative efficiency, i.e.,

$$x_{ik}^* = \theta^* x_{ik} - S_{ik}^-;\ i=1,2,...,m;\ i=1,2,...,m.$$

$$y_{jk}^* = y_{jk} + S_{jk}^+,\ j=1,2,...,s.$$

Multiple Objective Programming Based DEA

The MOP based DEA method provides a unitary weight (u^*, v^*) for all DMUs, which are evaluated by considering an equal standard measure [13, 14]. By using this approach, this research can obtain the efficiency rating of each DMU more fairly. Moreover, all DMUs can be treated simultaneously, which makes it effectiveness in handling large number of DMUs.

Model 1

$$\text{(5)}\quad \left.\begin{aligned} &\text{Max } z_1 = \sum\nolimits_{j=1}^{s} u_j y_{j1} / \sum\nolimits_{i=1}^{m} v_i x_{i1} \\ &\vdots \\ &\text{Max } z_k = \sum\nolimits_{j=1}^{s} u_j y_{jk} / \sum\nolimits_{i=1}^{m} v_i x_{ik} \\ &\vdots \\ &\text{Max } z_n = \sum\nolimits_{j=1}^{s} u_j y_{jn} / \sum\nolimits_{i=1}^{m} v_i x_{in} \end{aligned}\right\}$$

Subject to

$$\sum\nolimits_{j=1}^{s} u_j y_{jk} / \sum\nolimits_{i=1}^{m} v_i x_{ik} \le 1,\ k = 1,2,...,n.$$
$$v_i, u_j \ge \varepsilon > 0;\ i = 1,2,...,m;\ j = 1,2,...,s.$$

The definition of y_{jk} is the observed amount of output of j^{th} (j=1,2,...,s) type for the k^{th} DMU (k=1,2,...,n). The x_{ik} is the observed amount of input of i^{th} (i =1,2,…,m) type for the k^{th} DMU (k=1,2,...,n). v_i is the parameter of multiplier or weight of the i^{th} input and u_j is the parameter of multiplier or weight of the j^{th} output. The ε is a non-Archimedean quantity.

Then multiplying the numerators and denominators in CCR model [11] is established the multiple objectives programming model and is shown as Eq. (5). It is considered by the efficiencies of all DMUs and established a Multiple Objective Linear Fractional Programming model, as shown in Model 1 (Eq. (5)). According to the research of Sakawa and Yumine[16], such problem can be solved by the Multiple Objective Linear Programming (MOLP) approach proposed by Zimmermann [17]. MOLP with DEA approach adopts to obtain common weights, which can maximize all DMUs' efficiencies.

The concept of MOLP utilizes membership function transfers of multiple objective functions into one objective function. The membership function is as follows:

$$\text{(6)}\quad \mu(z_k) = \begin{cases} 0 & ; \quad z_k \le z_k^L \\ \dfrac{z_k - z_k^L}{z_k^R - z_k^L}; & \quad z_k^L \le z_k \le z_k^R \\ 1 & ; \quad z_k \ge z_k^R \end{cases}$$

where z_k^L and z_k^R are the negative ideal solution (the worst value) and the positive ideal solution (the aspiration level), respectively. For the value of the objective function z_k, the degree of membership function is [0, 1].

The degree of membership function of z_k^L in $\mu(z_k)$ refers to the achievement level of the efficiency ratio for DMU$_k$. The problem of obtaining the maximum decision is to choose parameter vector $(\boldsymbol{u}^*, \boldsymbol{v}^*)$, such that

Model 2

$$\text{(7)}\quad \underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \underset{k}{\text{Min}}\ \mu(z_k);\ k = 1,2,...,n.$$

Subject to

$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \le 1,\ k = 1,2,...,n.$$
$$v_i, u_j \ge \varepsilon > 0;\ i = 1,2,...,m;\ j = 1,2,...,s.$$

If $\mu(z_k) = \alpha$, z_k is a convex combination of z_k^L and z_k^R, i.e. Eq. (6) via variable transformation can be transformed $z_k = \alpha \cdot z_k^R + (1-\alpha)\cdot z_k^L$; Eq. (7) can be rewritten as Eq. (8). According to the concept of multiple objective linear programming, we can determine the weight vectors ($u = (u_1,...,u_j,...,u_s)$ and $v = (v_1,...,v_i,...,v_m)$) that satisfy all DMUs' restrictions. The weights vector $(\boldsymbol{u}^*, \boldsymbol{v}^*)$ is the common weights of all DMUs, which are evaluated on a consistent standard of ranking.

$$\underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \underset{k}{\text{Min}}\{z_k = \sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \,|\, k = 1,2,...,n\}$$

(8) Subject to

$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \le 1,\ k = 1,2,...,n.$$
$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \ge \alpha \cdot z_k^R + (1-\alpha)\cdot z_k^L,\ k = 1,2,...,n.$$
$$v_i, u_j \ge \varepsilon > 0;\ i = 1,2,...,m;\ j = 1,2,...,s.$$

By introducing the auxiliary variable α, Eq. (8) can be transformed into the following equivalent conventional mathematical programming problem:

$$\text{(9)}\quad \underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \alpha$$

Subject to

$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \le 1,\ k = 1,2,...,n.$$
$$\sum\nolimits_{j=1}^{s} u_j y_{jk} - [\alpha \cdot z_k^R + (1-\alpha)\cdot z_k^L]\cdot \sum\nolimits_{i=1}^{m} v_i x_{ik} \ge 0.$$
$$k = 1,2,...,n;\ 0 < \alpha \le 1;$$
$$v_i, u_j \ge \varepsilon > 0;\ i = 1,2,...,m;\ j = 1,2,...,s.$$

When we set the worst value $z_k^L = 0$ and the aspiration level $z_k^R = 1$, Eq. (9) can be rewritten as Eq. (10).

$$\underset{\boldsymbol{u},\boldsymbol{v}}{\text{Max}}\ \alpha$$

(10) Subject to

$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \le 1,\ k = 1,2,...,n.$$
$$\sum\nolimits_{j=1}^{s} u_j y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i x_{ik} \ge \alpha,\ k = 1,2,...,n.$$
$$0 < \alpha \le 1;\ v_i, u_j \ge \varepsilon > 0;\ i = 1,2,...,m;\ j = 1,2,...,s.$$

After solving Eq. (10), we can find the common multipliers vector $(\boldsymbol{u}^*, \boldsymbol{v}^*)$ to calculate the efficiency achievement level for DMUs. Define the efficiency achievement for each DMU$_k$ as follow:

(11) $\alpha_k = \sum\nolimits_{j=1}^{s} u_j^* y_{jk} \Big/ \sum\nolimits_{i=1}^{m} v_i^* x_{ik}$ or $\alpha_k = \boldsymbol{u}^{*\prime} \boldsymbol{y}_k \Big/ \boldsymbol{v}^{*\prime} \boldsymbol{x}_k$.

Evaluting the CMOS image sensor firms by the MOP based DEA

Background of the CMOS Image Senor Industry

The two mainstream electronic image sensors in the market are CCD and CMOS image sensors. One of critical differences between CCD and CMOS image sensors is the way in which each processes an electrical signal. CCDs require an additional integrated circuit to convert a signal from analog to digital format. In contrast, CMOS image sensors are able to integrate the full signal processing circuit such as amplification, noise correction, analog-digital converter on the same substrate as the detector[2]. Moreover, compared to CCDs, CMOS image sensors are more power-efficient, more cost-effective, and smaller. Thus, CMOS image sensors are widely used in mobile phone, notebook webcams, military surveillance, entertainment applications, digital still cameras and medical applications.

Due to advances in semiconductor manufacturing processes and design techniques, the performance and image quality of CMOS image sensors have significant improvements. Consequently, CMOS image sensors not only develop its own application market but also continue to overtake the market occupied by CCD.

CCD image sensor components have long been dominated by Japanese companies [18]. Unlike the competitive landscape for CCD, strong competition for CMOS image sensors comes from U.S., Korea, Japan, Taiwan, and China. Main firms in the CMOS image sensor industry include Aptina, Crysview, E2V, GalaxyCore, Hynix, Invensense, PixArt, Pixelplus OmniVision, Samsung, SETi, Sharp, Sony, and STMicroelectronics.

Fabless CMOS image sensor design houses focus on designing, developing, marketing and outsource manufacturing CMOS image sensors. For example, OmniVision outsources the wafer fabrication of its products to Taiwan Semiconductor Manufacturing Company (TSMC). PixArt outsources the wafer fabrication of its products to United Microelectronics Corporation (UMC). Other companies such as the traditional semiconductor memory vendor (e.g. Samsung and Micron) own and operate their own fabrication facilities. These companies have the ability to price their products more aggressively and can respond more rapidly to changing market opportunities [19].

Although CMOS image sensor market continues to grow, the market is intensely competitive. The competition results in rapid technological change, evolving standards, reductions in selling price, and rapid product obsolescence. Semiconductor memory vendors, especially the DRAM vendors like Samsung, Hynix and Micron, produce the products by using the already depreciated 8 inch semiconductor fabs and price the CMOS image sensors significantly below the market levels in order to fully utilize the capacity of the old fabs and gain market share in the short-term. Fabless CMOS image sensor design houses face additional downward pressure on price from new entrants. To maintain and grow their businesses, fabless CMOS image sensor design houses need to design, develop, and manufacture sensors efficiently.

Performance Evaluation of the Major CMOS Image Sensor Design Houses

In the following, the performance evaluation procedure of four major fabless CMOS image senor design houses is introduced. At first, the firms are selected according to the *CMOS Image Sensors Technologies & Markets-2010 report*. Aptina, Crysview, GalaxyCore and SETi are unlisted firms, which do not provide financial reports publicly. Thus, we exclude these firms from our analysis. Finally, OmniVision, PixArt, Pixelplus, and E2V serve as the DMUs. The performance evaluation results by the MOP based DEA are demonstrated in Table 1.

Table 1. Evaluation results being derived by using the traditional CCR, BCC efficiency and the MOP based DEA method

DMUs	CCR	Rank	BCC	Rank	MOP	Rank
Omnivision 2010	0.819	9	1.000	1	0.725	9
Omnivision 2009	0.724	10	0.894	11	0.678	10
Omnivision 2008	0.670	11	0.863	12	0.670	11
Pixart 2010	0.922	5	0.929	8	0.922	3
Pixart 2009	0.962	4	0.971	6	0.962	2
Pixart 2008	1.000	1	1.000	1	1.000	1
Pixelplus 2010	1.000	1	1.000	1	0.815	5
Pixelplus 2009	0.858	8	1.000	1	0.761	7
Pixelplus 2008	0.566	12	0.905	10	0.566	12
e2V 2010	1.000	1	1.000	1	0.828	4
e2V 2009	0.904	7	0.906	9	0.739	8
e2V 2008	0.904	6	0.943	7	0.778	6

Discussion

Performance evaluation is a critical issue for firms and their stakeholders. According to the results of performance evaluation, firms can compare themselves with other firms in the same industry and then to develop strategic plans to improve their efficiency. In recent years, many models for performance evaluation have been developed. DEA is one method which is extensively used by the academics. Researchers apply DEA method in a variety of input-output models. Nevertheless, one major problem for these papers using traditional DEA models is the selection of favorable weights to each DMU. Results for performance evaluation may be biased due to unrealistic weight distributions.

In contrast to traditional CCR and BCC DEA, the MOP based DEA approach depends on the assumptions of fair weights for each input and output. Thus, in our empirical test, we find that the results obtained from traditional CCR and BCC DEA are different from those using the MOP based DEA approach. Apparently, the MOP based DEA model is considered as a better method compared to the traditional CCR or BCC DEA models.

According to our results, the efficiency scores of five DMUs are equal to 1 in the BCC model. The efficiency scores of three DMUs in the CCR model are equal to 1. In contrast, only one DMU achieves optimal efficiency by using the MOP based DEA model.

OmniVision and E2V, two CMOS image sensor firms with higher revenue, do not always achieve optimal efficiencies in all three DEA models. In particular, OmniVision are ranked the least efficient firm in all of three years based on results derived from the MOP based DEA model. There are two possible reasons for the inefficiency. First, because competition of the CMOS image sensors continues to intensify, average selling price of OmniVision's products will be lower. Due to a reduction in gross margin, the company may invest less R&D expenditure than what it should do. We find that the ratio of R&D expenditure to total revenues declined from 16.73 percent in year 2008 to 9.25 percent in year 2010. Insufficient R&D investment may be unable to timely introduce new products or develop more cost-effective technology. Second, the mobile phone market accounted for more than 60 percent of OmniVision's revenue in year 2010 [19]. However, it is expected an increased demand for CMOS image sensors in other applications such as entertainment, security, medical, and automobile industries. OmniVision seems not to take aggressive strategies for these emerging markets.

While cutting R&D expenditure, OmniVision devotes itself to reducing manufacturing costs. The ratio of cost of goods sold to total revenues reduced from 76.76 percent in year 2008 to 70.93 percent in year 2010. Because a decrease in manufacturing costs offsets the negative impact of the decline in R&D investment, the efficiency of OmniVision gradually improved.

E2V was inefficient in 2009. Possible reason is the decline in R&D expenditure. The management implemented the accelerated business improvement program including the closure of the CCD wafer fabrication in Grenoble. The business improvement program helped E2V reduce the manufacturing costs and further improved its efficiency in 2010.

Pixelplus experienced huge losses in year 2008. However, the company aggressively improves its efficiency through developing new products, penetrating new markets, and securing new design wins. The efficiency of Pixelplus has improved.

PixArt is the most efficient fabless CMOS image sensor design house from year 2008 to year 2010. One possible reason is that PixArt expands R&D in developing new products. Although PixArt achieved the optimal efficiency in year 2008, the efficiency gradually declined. The possible reason is that compared to other competitors, the ratio of cost of goods sold to total revenues increases. Higher manufacturing costs may lead to lower gross margin. The company should work with its outsourcing partners to implement advance manufacturing process in order to reduce the manufacturing costs.

Conclusions

The application of digital imaging has become more prevalent as evidenced by the popularity of camera-equipped mobile phones, notebook webcams, and portable multi-media devices over the past decades. CCD and CMOS image sensors are the two most common electronic image sensors. Continuous improvement in the technology has led CMOS image sensors to be the dominant image sensing device. Although the demand for CMOS image sensors continues to increase, competition from U.S., Korea, Taiwan and China is intense. To meet competitive challenges and lower the threat from new entrants, fabless CMOS image sensor design houses need to formulate strategies to improve the efficiency of the design and development.

Thus, it is critical for CMOS image sensor firms to evaluate their efficiency. Albeit important, no researchers evaluate the performance of the fabless CMOS image sensor design houses. This research bridges the gap and evaluates the performance using the DEA method. The results derived from the traditional CCR and BCC DEA approach may be biased due to selecting favorable weights to each DMU. Thus, this paper introduces a MOP based DEA approach which overcomes the shortage of the traditional CCR and BCC DEA models.

The analytical results derived from the MOP based DEA model indicate that PixArt was the most efficient firm from 2008 to 2010. However, the efficiency declines due to an increase in manufacturing costs. Pixelplus was the least efficient firm in year 2008; however, its efficiency continued to enhance. Although E2V was inefficient in 2009, the firm improved its efficiency in 2010 due to implementation of business improvement programs. OmniVision is the most inefficient firm. However, the firm devotes itself to reducing the manufacturing costs. The efficiency gradually improved in 2009 and 2010. According to our results, we suggest that the fabless CMOS image sensor design houses should not only expand R&D in new products and technology but also reduce its manufacturing costs for wafer foundries.

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