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QUALITY MANAGEMENT: TECHNICAL EFFICIENCY, BENCHMARKING, AND CONTRACTS

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Abstract

Because production processes typically generate quantity flows and quality flows simultaneously, the management of quality flows is potentially as important as the management of quantity flows in the improvement of the performance of firms. Specially, quality is also important in the supply chain in that the quality of products produced by suppliers is one of the most important determinants of the quality of products produced by procurers. If this quality is perfectly observable in market, it will be priced and demanded optimally in the market. Procurers can obtain the quality that they want and suppliers must produce quality in a technically efficient manner. However, quality may be imperfectly observable to suppliers and procurers in the market. In this case, the quality market fails to price quality and there exist only low quality products in the market. As a result, procurers cannot obtain the quality that they want and persistent technical inefficiency exists in the quality production of suppliers.

The objective of this dissertation is to examine the estimation and the improvement of technical efficiency generated from the imperfect observability of quality and the management of quality produced by suppliers in supply chain. To do so, Data Envelopment Analysis (DEA), benchmarking, and contracting are used as base methodologies.

The first essay suggests a new estimation approach for technical efficiency based on DEA when controllable categorical factors are involved in the firm's production process. The new approach can estimate the efficient category level of controllable categorical factors. The second essay examines how firms can improve their technical efficiency by their own effort. New peergrouping approach and new benchmarking approach are developed to help technically inefficient firms improve their technical efficiency based on recent advances in DEA-based benchmarking. The third essay develops a contract model to coordinate the quality flow in supply chain and technical efficiency of suppliers under both symmetric and asymmetric information. Using a simulation method, it is illustrated how the incentives under contract work to manage quality flows and technical efficiency. The simulation results illustrate that incentives under contract can improve the performance of both procurers and suppliers.

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Introduction

Production processes typically generate quantity flows and quality flows simultaneously. This simultaneity in production of quantity and quality often implies that the management of quantity flows will also require the management of quality flows. Quality is important in a supply chain because the quality of products produced by agents at low levels in the supply chain (Suppliers) may affect the quality of products produced by the upper level agents (Procurers). In other words, since products produced by suppliers are used as raw material inputs for products produced by procurers, the quality of products from suppliers may become one of the most important determinants of both the quantity and the quality of products produced by procurers. Therefore, the performance of both quantity and quality in supply chains will be dependent on how the quality of the product produced by suppliers is coordinated throughout supply chains. However, the nature of quality flows often implies that decentralized coordination may result in a failure in supply chain performance and technically inefficient production by suppliers.

I.1. Implications of quality for supply chain performance

As noted, the coordination of product quality flows is an important determinant of the performance of supply chains. Optimal supply chain coordination would induce the production of high quality that is expected by procurers, and is technically and allocatively efficient at each point along the supply chain. If quality were traded in a perfectly competitive market, then a market price would be established that reflects the average cost of quality production and its relative value to consumers. Suppose there were a single perfectly observable quality characteristic for a product. Then, competitive markets might price it. Where observable discrete types of that characteristic occur, markets might price each type. This possibility of pricing quality would induce an optimal supply of quality in the supply chain. However, this is possible only when the quality is measurable (perfectly observable) by all agents along the supply chain, that is, full information on product quality exists throughout the supply chain. Importantly, competitive markets across the supply chain would also result in Pareto-optimal performance. In addition, technically inefficient suppliers would be driven out of perfectly competitive markets because the price of quality would be determined to be equal to the average cost of technically efficient suppliers, a level that would be exceeded by technically inefficient suppliers.

Unfortunately, quality does not often satisfy these conditions for a perfectly competitive market. In many cases, quality is impossible or very difficult for procurers and even suppliers to measure or to characterize perfectly and accurately before they buy and consume a product (Akerlof, 1970). For example, when a customer buys a car, she/he would find it difficult to acquire information concerning the probability of a breakdown in the future. Even after they use a car for a while, they cannot evaluate its quality accurately. That is, a driver does not have full information describing the possibility of a breakdown in the future though she/he can have more information than before buying it. Because quality is imperfectly observable, suppliers and procurers cannot price products. This imperfect information condition causes markets to fail in the pricing and supply of quality.

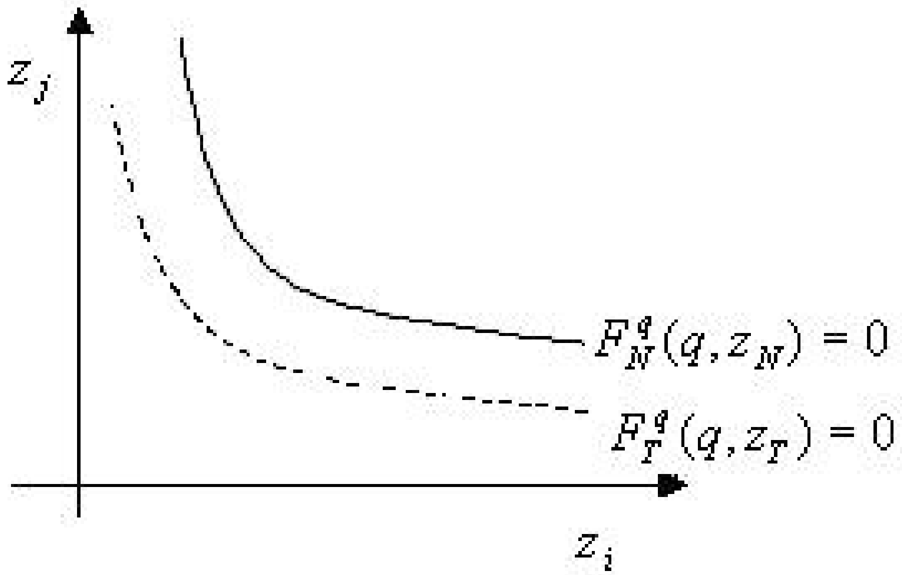
Furthermore, it is possible to think about the case of information asymmetry of quality where suppliers have more information concerning quality than do procurers. In this case, procurers may not be willing to pay for the quality announced by suppliers if procurers suspect suppliers misrepresent their quality to get a higher price. In addition, other characteristics of suppliers that might allow inference concerning the ability to produce quality may be imperfectly observable by procurers.

Another important implication of the imperfect observability of quality flows is that suppliers may be persistently technically inefficient in producing quality. That is, the imperfect observability of quality may lead suppliers to produce quality technically inefficiently because the imperfect observability of quality leads suppliers not to perceive suppliers' quality production function accurately. Persistent technical inefficiency in production of quality will impact production costs at downstream points of the supply chain. Microeconomic production analysis assumes that firms face exogenous incentives and choose production plans to optimize profits or expressions of incentives and elements of the production plan. The result is both allocative and technical efficiency.

Figure I.1 shows how technically inefficient suppliers might persist in a market when imperfect observability of quality exists. Suppose that firms do not have accurate knowledge of the technology of producing quality flows. In Figure I.1, define $F_N^q(q, z_N) = 0$ as an inaccurately perceived quality production function by suppliers and $F_T^q(q, z_T) = 0$ as the true quality production function where q is a vector of the quality outputs and z is a vector of the quality inputs or practices. Under the imperfect observability of quality, a supplier may produce quality q using a vector of quality inputs, z_N though the optimal vector of quality inputs used to produce q is z_T ($<z_N$) because the supplier can not accurately measure quality that she/he produces. The solid line in Figure

I.1 is above the dotted line implying greater use of inputs to produce q than what is optimal. Thus, the supplier produces quality technically inefficiently.

Figure I.1. The accurately perceived function and inaccurately perceived function



To conclude, when quality is imperfectly observable, quality may not be coordinated in a competitive market to optimize social welfare and quality production processes may be technically inefficient. The market failure implies suppliers do not supply the socially optimal quality and, as a result, procurers do not buy the quality. The technical inefficiency caused by the imperfect observability of quality also results in reduced profits for the whole supply chain. The objective of this thesis is to consider approaches to improve quality management, reducing technical inefficiency caused by the imperfect observability of quality. Specifically, this thesis deals with how to measure technical efficiency accurately, how suppliers can manage and improve their technical efficiency, and how to manage quality and technical efficiency in the supply chain effectively through incentive schemes under contracts.

I.2. Outline of dissertation

To cover the above topics, this thesis consists of three essays. Essay one proposes a new approach to estimate technical efficiency when some controllable inputs or practices in the production process are measurable only by categorical factors. Essay two deals with the use of technical efficiency scores as a basis for establishing benchmarks to be used for prescriptive recommendations for how firms might improve their performance. The third essay examines why and how contracts could be used as an approach to improve the coordination of quality and technical efficiency in the supply chain.

In Essay one, the starting point is the fact that recently, many production processes involve categorical factors as well as continuous inputs. That is, some elements in production processes can be measured only by categorical variables. The categorical factors involve categorical inputs with which some inputs may be measurable by polychotomous variables though they are continuous but only observed by intervals, categorical practices with which some inputs may be measurable by use or nonuse, and categorical indicators with which some market environments or production environments can be measured by polychotomous variables. The examples of categorical factors are in Essay one.

Production processes involving quality often involve categorical inputs and practices such as the use of preventive maintenance practices (Mefford, 1991). The adoption of new technology, the use of practices for quality controls, population, and the characteristics of suppliers such as plant location are the examples of categorical factors.

These categorical factors could be classified into controllable categorical factors and uncontrollable categorical factors. The controllable factors are categorical factors that can be controlled by firms such as the adoption of technology and the use of practices for quality controls, and the uncontrollable factors are categorical factors that cannot be controlled by firms such as market environments.

Banker and Morey (1986) included uncontrollable categorical factors in the general DEA model using the same approach as the approach for the quasi-fixed inputs in subvector efficiency model (Fare, Grosskopf, and Lovell, 1994). However, they do not consider uncontrollable categorical factors. Charnes *et al.* (1994) and Cooper, Lovell, and Tone (2000) suggest an approach to evaluate the technical efficiency of controllable categorical factors. Their approach is not to insert some additional constraints to the general DEA model but rather to run the general DEA model with groups of firms previously classified by categorical factors. Though it can evaluate the efficiency of controllable categorical factors, their approach has two important pitfalls. The first one is that efficiency scores for categorical factors in their approach are continuous. The second is that their approach assumes that there exists a clear hierarchical relationship between categories. Thus, their approach cannot give firms any practical insight to the use of categorical factors and does not work when a clear hierarchical relationship between categories is not found.

Therefore, Essay one introduces a new approach based on DEA to deal with controllable categorical factors and compares the results of the new approach with those of the approaches of Banker and Morey (1986), Charnes *et al.* (1994), and Cooper, Lovell, and Tone (2000). The new approach may be sketched as follows. The original data set is fragmented in terms of the observed value of categorical factors. Groups of firms having the same values for categorical factors are available. The technical efficiency of each firm in a group would be evaluated against all groups. Suppose that there are 3 groups. The technical efficiency of a firm in group 1 is evaluated against group 2, group 3 as well as group 1, separately. The same thing has been done for all firms in three groups. It should be examined against which group the technical efficiency score for a firm is minimized.

Two measures of DEA are used, radial and nonradial, because the two measures may give different results about the efficient category level. For radial measure, the category of group that gives a firm the minimum technical efficiency score is the efficient category for the firm. For the nonradial measure, since the technical efficiency score for each input can suggest different efficient category level, the Euclidean distance of the efficient combinations of inputs from the origin could be used unless information on factor prices is available. Thus, using the new approach, the efficient category levels for categorical factors are identified.

The problem in Essay two is to consider how suppliers improve their own technical efficiency. To examine this problem, Essay two suggests a quantitative peergrouping process and benchmarking process for the improvement of technical efficiency. Benchmarking can be defined as the continuous process of evaluating and improving business practices against the toughest competitors or those competitors recognized as industry leaders. The toughest competitors or industry leaders are called ‘benchmarks’. To be a benchmark, a firm should have the best performance and be similar to other firms in the industry. These benchmarks are important in that their performances become a model for other firms that want to improve their performances and remain viable. Thus, the information on the performances of the benchmarks should also be available to other firms. However, though the benchmarking is used broadly in most industries, including the manufacturing and financial industry, it has not been based on the quantitative methods (Rolstadas, 1995). A main contribution of this essay is to propose the new quantitative approach for benchmarking.

The first step in the benchmarking process is the determination of what performance measures will be used as a basis for selection of benchmark firms. The measurability and the absence of the standardized unit for the measurement of performance make the selection of reasonable performance measures more difficult. Financial ratios that have been used for benchmarking are subject to the above problems. Because technical efficiency can avoid all of the above problems, it can be a performance measure for benchmarking. Though this technical efficiency can be measured by a variety of methods, Data Envelopment Analysis (DEA) can find best practices, while parametric methods find only average practices (Horsky and Nelson, 1996).

DEA-based benchmarking has been considered in the past. Some researchers (Golany and Thore, 1997; Ray and Desli, 1997) deal with the benchmarking approach based only on DEA efficiency scores. Others (Athanassopoulos and Ballatine, 1995; Hjalmarsson and Odeck, 1996) deal with the benchmarking approach based on DEA efficiency scores and similarity analysis. Specially, Athanassopoulos and Ballatine (1995), and Volkers and Hickey (1996) presented an approach for identification of benchmarking firms that uses similarity analysis such as the frequency of a firm used as a comparator (the detail on comparator is in Essay two) and the relative distance of a firm from the efficient frontier. Hjalmarsson and Odeck (1996) investigated the efficiency of trucks in road construction and road maintenance using DEA within a framework from which the benchmark is derived. They used wage, fuel, rubber, and maintenance expenditure as inputs and effective hours in production and total transport distance as two alternative outputs. They also used two criteria: the relative distance from the efficient frontier and the frequency used as comparators.

However, these past papers did not use a peergrouping process. The second step of this essay, unlike the general benchmarking approach, is the peergrouping process. Firms in a sample can differ across a variety of important characteristics such as the scale of operation or the pattern of nonradial technical efficiency across variable inputs in DEA. Based on the above literature review, the main contribution to the new DEA-based benchmarking approach proposed in this essay is to present a quantitative peergrouping process that may make the benchmarking results more reasonable. This peergrouping step fragments the data set into sub-sets (groups) that are called peergroups in terms of the scale of operation such as the gross value of sales and gross profit and the pattern of nonradial technical efficiency across variable inputs in DEA that is performed by preliminary nonradial DEA. The two criteria are enforced in a series. That is, the original data set is classified into subgroups by operations scale and each group generated by the scale of operation is finally reclassified into subgroups by the pattern of nonradial technical efficiency across variable inputs in DEA.

After this step, there are multiple peergroups and it is ready for benchmarking process. Before going on to the benchmarking process, it is necessary to verify whether the groups generated by the peergrouping process are different from the other groups or not because the criteria used in peergrouping process are somewhat *ad hoc*. For this verification process, a modified approach of Tulkens and Eeckaut (1995) is used.

In the third step, radial and nonradial technical efficiency for firms in each group are estimated, and the similarity analysis such as the relative distance of efficient firms from the efficient frontier and the frequency used as a comparator of efficient firms are estimated (Anderson and Petersen, 1993). With technical efficiency scores and similarity analysis, the benchmarks for each group are determined. To be a benchmark of a peergroup, a firm must be technically efficient in the use of inputs, the frequency used as a comparator should be quite large (about 15% of total number of firms in a group), and the relative distance from efficient frontier should be quite small (less than two). A firm that satisfies all of three conditions can be identified as a 'perfect' benchmark and a firm that violates one of three conditions slightly can be identified as a 'pseudo' benchmark.

In this essay, the new method and the other DEA-based benchmarking methods are compared. It is expected that benchmarks will be found for each peergroup providing a prescriptive basis for technically inefficient firms to improve their production performance. The main contribution of this essay is to extend the existing DEA-based benchmarking process by adding peergrouping process. The application of the new approach to an agricultural production process illustrates that the peergrouping process can identify the groups that are different in the scale of operation and the different pattern of nonradial technical efficiency across variable inputs in DEA, and the benchmarks identified by the new approach seem to be better than benchmarks identified by the benchmarking approaches based only on technical efficiency scores, based on technical efficiency scores and similarity analysis, or based on the peer grouping and technical efficiency scores in the aspect of similarity to other firms.

The problem in Essay three is to determine how a supply chain might be coordinated to manage the imperfectly observable quality and to improve technical efficiency in quality production of suppliers through an incentive system. As noted, quality flow is typically generated together with quantity flow. Thus, quality should be managed like quantity in the market in most cases. However, quality may be the imperfectly observable, which makes quality markets fail and makes quality production processes technically inefficient.

Imperfect observability of quality makes it impossible to price quality correctly. As a result, quality is not supplied and demanded in an optimal sense. Moreover, imperfect observability prevents suppliers from perceiving their efficient production frontier accurately, which leads suppliers to be able to produce quality technically inefficiently.

For supply chain coordination, vertical organization management alternatives are available. Procurers can own suppliers (vertical integration). However, vertical integration in response to the market failure will not always increase social welfare. Alternatively, procurers can use a strategic alliance with suppliers. However, a strategic alliance is used horizontally rather than vertically. Also, procurers can make a contract with suppliers to coordinate the supply chain. Actually, in many industries, contracts increase the social welfare because procurers can get what they want and suppliers can sell what they produce with stability in the process. That is, they can avoid market risks such as price risk and quantity risk through contracts. Contracts enable procurers to affect the production process of suppliers without incurring extra costs like in a vertical integration and strategic alliance.

In this essay, contracting between procurers and suppliers are examined. Quality may be improved by direct incentives for quality performance and technical efficiency can also be improved by indirect incentives for the use of quality inputs. Therefore, this essay takes both direct incentives and indirect incentives into account. Indirect incentives will be given to the technically efficient part of the use of quality inputs and this scheme can also work for managing the technical efficiency of suppliers. Moreover, the comparison between direct incentives and indirect incentives on performance is examined.

Because procurers can observe the quality after they purchase and use a product, quality may become observable under contracting. In this essay, the contractibility of output comes from two type variables of suppliers: suppliers' ability in quality production and technical efficiency. If information symmetry on supplier types is assumed, contracting has only to set direct incentives for quality to resolve the quality market failure and to set indirect incentives to improve technical efficiency only guaranteeing the reservation profits to suppliers (individual rationality constraints). However, if information asymmetry exists between procurers and suppliers, the incentives should be constrained by incentive compatibility constraints as well as individual rationality constraints to prevent suppliers from lying about their types (adverse selection). To illustrate these contracting schemes empirically, a simulation method is used. The results from simulation illustrate that the optimal incentive schemes can be determined for each type of suppliers, the incentives improve the performance of suppliers and procurer, and the direct incentives has more effect on performance than the indirect incentives.

Essay 1
Efficiency Estimation when Categorical Factors Are Controllable

Production processes in many industries include categorical factors. That is, many elements in production processes could be measured by binary and polychotomous categorical factors. Categorical factors include categorical inputs, categorical practices, and categorical indicators. Some inputs are continuous but measurable by intervals, that is, a continuous variable, x, is measured that if $x \le x^1$, the corresponding categorical factor, c, is 0, if $x^1 < x \le x^2$, c is 1, … (categorical inputs). Categorical practices measure whether some practices are used or not, that is, if a practice is used, the corresponding categorical factor, c, is 1 and otherwise, c is 0. Categorical indicators express the production environments and the characteristics of firms, that is, if the plant of a firm is located in one of multiple cities, the categorical factor of plant location, c, is coded by a polychotomous variable. In fact, these categorical factors enable firms to measure the factors that may not be measured by continuous variables but are important to production processes.

Examples of categorical inputs are the amount of water used by firms and the amount of damage control inputs, such as pesticides and fertilizers, if they are is measured by intervals rather than continuous variables. Examples of categorical practices are the adoption of alternative production technology and the use of special practices for quality control or regulation. Examples of categorical indicators are market population and government regulation. Therefore, these categorical factors are important for firms to describe their production processes accurately, and the evaluation of their performances should be conditioned on categorical factors.

Technical efficiency (productivity) of production processes is conditioned by categorical factors because the efficient frontier that is a basis to evaluate technical efficiency may be different across the different categories of categorical factors. For example, the efficient frontier is different between when biotechnology is used and when it is not used. Moreover, the difference in scale of the use of inputs can make a difference in the efficient frontier. Thus, determining which category of a categorical factor is efficient is an important problem for the firms' decision-making process.

Categorical factors involved in production processes may be classified into controllable categorical factors and uncontrollable categorical factors. Controllable categorical factors as their name implies, can be controlled by firms, such as the adoption of a technology and the use of special practices to manage quality. Uncontrollable categorical factors cannot be controlled by firms, such as the population in the market and government regulations. It is important to evaluate the technical efficiency of controllable categorical factors because they are under control of firms and the efficient category level can improve the productivity of firms. However, it is not possible to evaluate the technical efficiency of uncontrollable categorical factors because they are not under control of firms and may be fixed (exogenous) in short-term. Banker and Morey (1986) suggested an approach to include the uncontrollable categorical factors in DEA model though it has not been used because it is not quite correct.

Many methods are available to measure technical efficiency parametrically and nonparametrically (Charnes *et al.*, 1994; Fare, Grosskopf, and Lovell, 1994; Kumbaker, 1999). Parametric methods are inferior to nonparametric methods in that parametric methods evaluate technical efficiency with respect to average firms, not the best firms.

Therefore, this essay uses a nonparametric method, Data Envelopment Analysis (DEA), to estimate technical efficiency. There has been a considerable amount of literature on estimating technical efficiency using DEA in many industries such as telecommunications (Banker, Chang, and Majumdar, 1996), banking (Berger, Leusner, and Mingo, 1994), agriculture (Fernandez-Cornejo, 1994), and health care (Fizel and Nunnikhoven, 1993), etc.

Categorical factors that are exogenous to the firms are considered in a modification of the general DEA model, the approach of Banker and Morey (1986) based on the subvector efficient model (Fare, Grosskopf, and Lovell, 1994). However, their approach is by definition unable to estimate the efficient category level for controllable categorical factors. Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) suggest an approach for estimation of the technical efficiency of controllable factors. Their approach assumes that there exists a clear hierarchical relationship between categories. It estimates the relative technical efficiency of a firm with respect to firms with at least an equal hierarchical score. Their approach is to define the value for the efficient category based on a weighted average of those category's scores of firms that are participated in estimating technical efficiency of the firm. Thus, the efficient category level of categorical factors would be a continuous value between zero and one, which does not make sense because the efficient category level of categorical factors should be a category. This approach will be compared to the new approach in the following sections.

The objectives of this essay are to develop a new approach to measure the technical efficiency of production processes involving controllable categorical factors of production (including binary and polychotomous factors) and to compare the new approach with existing approaches. The main contribution of this essay is to introduce a new approach to estimate the efficient category of controllable categorical factors. The new approach in this essay is based on the logic with which category a firm can be most technically efficient. Though the new method will be illustrated in section 1.3, firms are classified into subgroups (category groups) in terms of their observed category level. Each firm is evaluated with respect to all groups separately, category group that gives the firm the lowest efficiency becomes the efficient category group, and the category level of the efficient category group is the efficient category level for the firm. In fact, this new method can resolve the limitations of the traditional approaches in that it does not assume the existence of a clear hierarchical relationship, and that it gives the firms categorical efficient category levels for categorical factors.

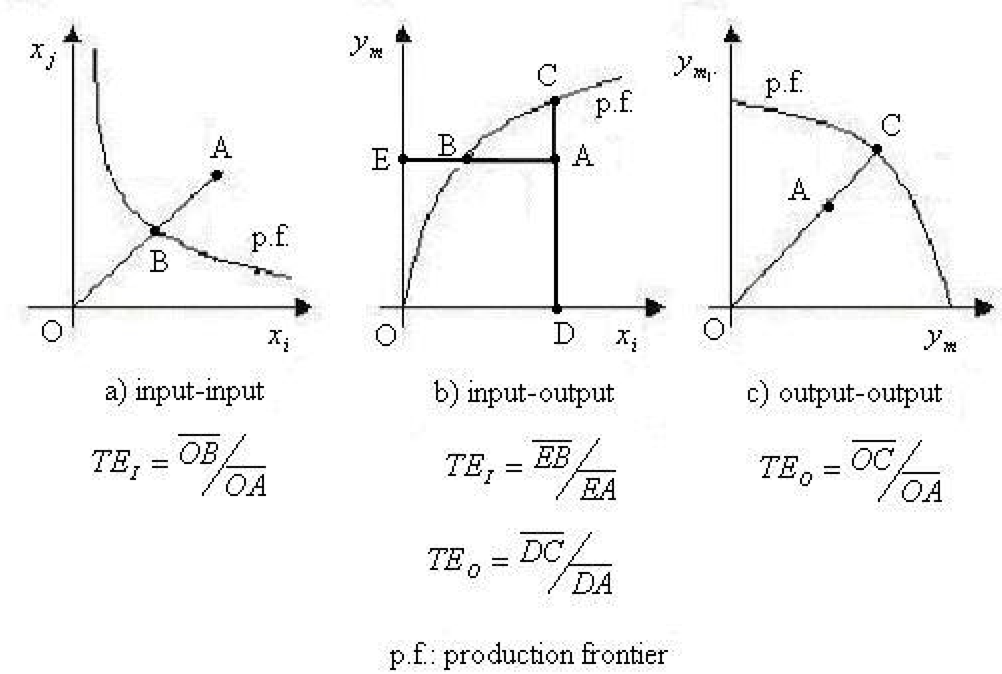
This essay starts from the basic concepts of the production frontier and technical efficiency. The next section describes the changes in the production frontier and technical efficiency when categorical factors are involved in the production processes. Then, the other approaches and new approach are described separately. The comparison between the other approaches and the new approach is illustrated next. Finally, an empirical application is performed to illustrate how to implement the new approach with other data sets and whether Pennsylvania soybean farms are technically efficient in land use practices and environmental quality management or not.

1.1. Basic concepts with respect to the production frontier

The production frontier is defined as follows (Kumbhakar and Lovell, 2000). A production frontier is a function $f(x) = \max\{y : y \in P(x)\} = \max\{y : x \in L(y)\}$ where *P(x)* describes the sets of all output vectors that can be produced with each input vector *x*, and *L(y)* describes the sets of all input vectors that can produce each output vector, *y*. This production frontier provides the upper bound of production possibilities with a given input vector (*x)* and the lower bound of inputs to produce a given output vector (*y*).

Technical efficiency is defined as follows: if the current technique is replaced with the one producing the most in its particular environment, how much less inputs could be used (input-oriented definition) or if only the current technique is replaced with the one producing the most in its particular environment, how much more could be produced (output-oriented definition) (Hall and Winsten, 1959). The input-oriented definition can be expressed as a function $TE_I = \min\{l : l\, x \in L(y)\}$, where l can be a scalar or a vector. If the efficiency score, l, is a scalar, it is the radial measure that leads firms to adjust all inputs equi-proportionally. If l is a vector, it is the nonradial measure that leads firms to adjust each input differently. The details on radial measure and nonradial measure are in appendix 1.1. The output-oriented definition can be expressed as a function $TE_O = \dfrac{1}{\max\{h : h\, y \in P(x)\}}$ where h can be a scalar and a vector. If the efficiency score h is a scalar it is the radial measure that leads firms to adjust their outputs equi-proportionally while if h is a vector it is nonradial measure that leads firms to adjust each output differently (Kumbhakar and Lovell, 2000). Figure 1.1 illustrates input-based technical efficiency (TE_I) and output-based technical efficiency (TE_O) from the perspective of an input-input space, an input-output space, and an output-output space.

Figure 1.1. Production frontiers and technical efficiencies



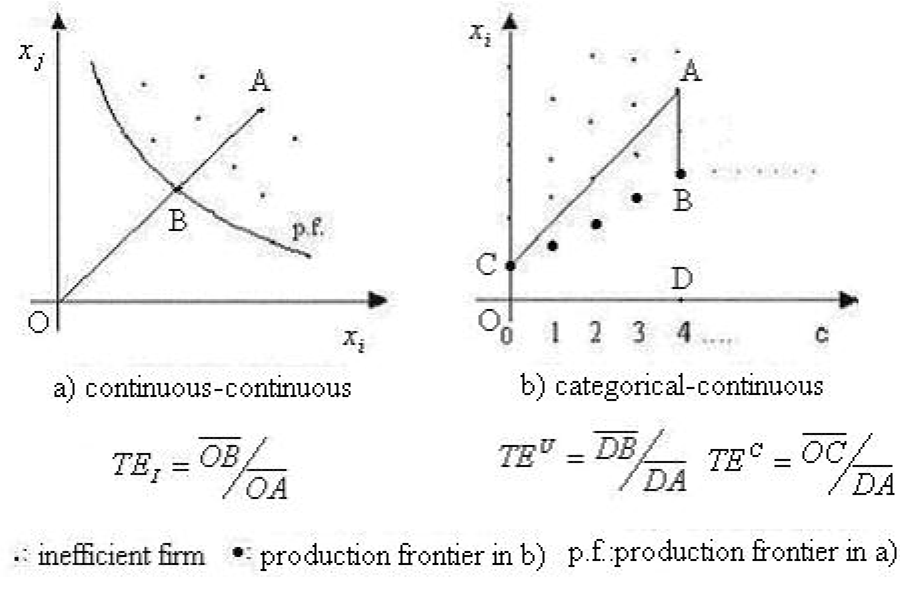
As illustrated in Figure 1.1, input-based technical efficiency is measured conditional on output levels and output-based technical efficiency is measured conditional on input levels.

1.2. Technical efficiency of categorical variables

As noted, considerable research with respect to estimation methods for characterizing production frontiers and technical efficiency has been performed (see Appendix 1.2). However, this past work has not considered categorical factors in a way that acknowledges their endogeneity. If categorical factors are uncontrollable by firms (like market population), it is not necessary to worry about their efficient category level because the factors are not dependent on the firms' decisions.

If they are controllable by firms (like quality control practices), it is important to examine the efficient category for each categorical factor. The estimation of the efficient category level for these categorical factors is very similar to the choice problem among multiple options. The estimation of the efficient category level for a binary factor will lead to binary choice problem and the estimation of efficient category for a polychotomous input will be a choice of a category among multiple categories. Figure 1.2 illustrates technical efficiency in a continuous input-continuous input space and a categorical factor-continuous factor space. x_i and x_j indicate continuous variable inputs, the points indicate firms, and TE_I indicates technical efficiency in the first graph. x_i in the second graph indicates a continuous input and c indicates a categorical factor. TE^u represents technical efficiency when a categorical factor is exogenous, which means that when the current category value must be maintained, a firm in point A should move to point B to become efficient, and TE^c represents technical efficiency when the categorical factor is controllable by firms, which means that a firm in point A should move to point C to become efficient. The line between point A and point C presents the moving path for the firm in point A to move to point C. An important point in b) of Figure 1.2 is that categories in a categorical factor are numbered by their hierarchy. That is, the best technology is numbered by zero and the worse technology is numbered by a higher value.

Figure 1.2. The comparison of production frontiers between without categorical inputs and with categorical inputs



As noted, TE^U is the technical efficiency of continuous inputs when categorical factors are uncontrollable, which means that the current values of categorical factors are not changed by firms, and TE^C is the technical efficiency of continuous inputs when categorical factors are controllable, which means that the current values of categorical factors can be changed by firms. As seen in a) of Figure 1.2, while the technical efficiency of continuous inputs is by definition estimated as a continuous value between zero and one ($0 \le TE_I \le 1$), the technical efficiency of categorical factors must be estimated as an integer because the efficient frontier is discrete when categorical factors are considered as seen in panel b) of Figure 1.2. In panel b) of Figure 1.2, the current value of a categorical factor for a firm in point A is 4, which means that the firm uses a category labeled by 4 in the figure. However, the efficient category level in the figure is category 0 because category 0 requires the minimum continuous inputs to produce a fixed output. Thus, for the firm to become efficient, the firm should move to category 0 from category 4. The technical efficiency score of the categorical factor would be 4. In this scheme, the higher score implies lower efficiency. If a firm uses category 3, then it is more efficient than firm that uses category 4 but it is more inefficient than a firm that uses category 2, 1, or 0. Because categorical factors change the efficient frontiers and technical efficiency as illustrated above, their technical efficiency cannot be measured by the general estimation models such as DEA and SFM (SFM) because they focus on the technical efficiency of continuous inputs. As will be noted in next section, the approaches of Banker and Morey (1986), and Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) have not reflected property of categorical factors. Thus, this essay focuses on the development of a new approach based on DEA model.

1.3. Estimation of technical efficiency: Alternative approach

The most well-known estimation methods for the production frontier and technical efficiency are SFM and DEA. Appendix 1.2 includes a brief review of the theory on DEA and of SFM/stochastic distance function model. The second section of the appendix deals with strengths and weaknesses of both models. Table 1.1 summarizes the comparison of the second section of the appendix.

Table 1.1. The summary of the comparison between DEA and SFM

Comparison items	DEA	SFM
Assumption of functional form	No	Yes
Minimum number of samples	No	Yes
Assumptions of error term	No	Yes
The inclusion of multiple outputs	Yes	No
The amount of computations	Small	High
The estimation of T.E. of overall process	Yes	Yes
The estimation of T.E. of individual input	Yes	No
Degree of completeness of data set	High	Low
Estimation of the best practice	Yes	No

To summarize, the reasons why DEA is adopted here as the approach to evaluate the technical efficiency are: DEA can estimate the best practices rather than the average practices unlike SFM, DEA does not need any assumption of functional form for the firm's production function, and DEA can estimate the efficiency of categorical inputs using an integer efficiency score. Moreover, DEA is less restricted to sample size than SFM/stochastic distance function model. Because SFM is based on regression methods (parametric method), it requires a minimum sample size (usually at least, 25) to get significant results. However, since DEA is based on linear programming (a nonparametric method), it is not necessary to worry about a minimum sample size (provided the sample size is not too small, e.g. less than 10. Therefore, DEA is chosen in this essay.

1.4. Traditional DEA approaches to deal with controllable categorical variables

Thus far, some researchers have studied the problem of how DEA can deal with categorical factors. Before going on to review past studies, it is meaningful to discuss the types of categorical factors, namely, controllable factors and uncontrollable factors. Without regard to the type of categorical factors, those factors affect the performance of production processes and service systems considerably. Therefore, it is essential to examine how they affect the performance of production processes.

As the leading research, the approach of Banker and Morey (1986) can be selected. Their approach to include uncontrollable categorical factors in DEA is based on the subvector efficiency model (Fare, Grosskopf, and Lovell, 1994). The subvector efficiency model was originally developed to estimate technical efficiency of firms relative to a subvector of inputs that are not fixed even in short-run rather than relative to an entire vector of all inputs because typical radial measure estimates technical efficiency relative to an entire vector of all inputs including variable inputs and fixed inputs in short-run (Fare, Grosskopf, and Lovell, 1994).

Technical efficiency scores estimated relative to an entire vector including quasi-fixed inputs as well as variable inputs are not reasonable because if firms adjust the level of inputs according to the efficiency scores estimated relative to an entire vector of all inputs including quasi-fixed inputs and variable inputs to become efficient, they should adjust the amount of quasi-fixed inputs as well as the amount of variable inputs. However, it is impossible to adjust the amount of quasi-fixed inputs. Even if firms try to adjust the amount of only variable inputs according to the efficiency scores estimated relative to an entire vector, it would not lead the firms to be efficient. Thus, the subvector efficiency model is reasonable when fixed inputs are involved in production process because it can make firms adjust the amount of variable inputs accurately to become more efficient.

The subvector efficiency model adds the following constraints for quasi-fixed inputs to general DEA model in Table A1.1 instead of dealing with quasi-fixed inputs in the same way as variable inputs: $\sum_{n=1}^{N} z_n \bar{x}_{ns} \leq \bar{x}_{n_o s}$ where n is the index of firms, s is the index of quasi-fixed inputs, $\bar{x}_{ns}$ is the value of the sth quasi-fixed input of firm n, n_0 is the evaluated firm, and z_n is the intensity of firm n to construct the efficient frontier, which implies that in the subvector efficiency model, quasi-fixed inputs affect the shape of the efficient frontier.

This subvector efficient model may be useful to measure the technical efficiency of firms when uncontrollable categorical factors are involved in their production process in that because uncontrollable categorical factors are fixed at least in short-run, technical efficiency must be estimated relative to a subvector of variable inputs not an entire vector of variable inputs and uncontrollable categorical factors like quasi-fixed inputs.

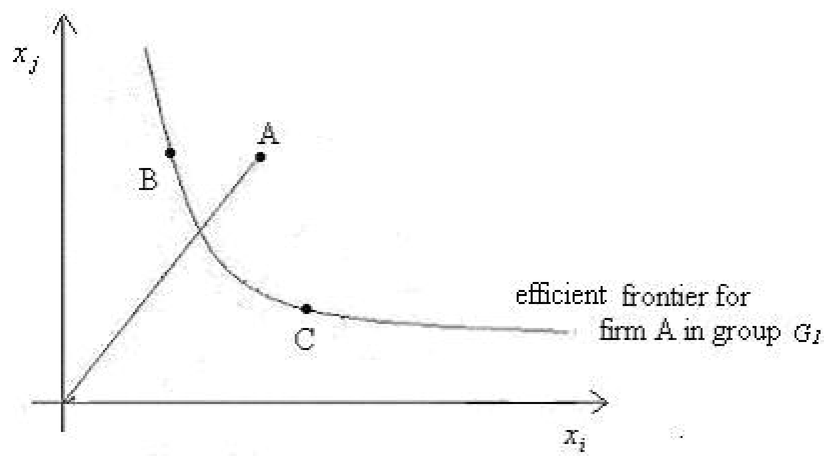
Banker and Morey (1986) developed and used the above subvector efficiency approach to evaluate the technical efficiency of 69 pharmacies in the state of Iowa. That is, $\sum_{n=1}^{N} z_n c_{nk} \le c_{n_0 k}$ where n is the index of firms, k is the index of categorical factors, c_{nk} is the value of kth categorical factor of firm n, n_0 is the evaluated firm, and z_n is the intensity of the firm n to construct the efficient frontier is inserted in the general DEA model. The categorical factor used by them is the market population that is classified into 11 categories. In their approach, categories are coded by as many binary variables as the number of categories minus one. If there are 11 categories in a categorical factor, category 0 is coded by 0000000000 where each binary number makes up of a binary variable, category 1 is coded by 1000000000, category 2 is coded by 1100000000, …, and category 10 is coded by 1111111111. That is, the categorical factor is coded by 10 binary variables.

However, Kamakura (1988) pointed out that their approach is not quite correct in that firms with category zero are evaluated with respect to firms with the same category while firms with category one can be evaluated with respect to firms with both category zero and one. When $c_{nk} = 0$, if firms with category one participate in evaluation, constraints $\sum_{n=1}^{N} z_n c_{nk} \le c_{n_0 k}$ will not be satisfied and there is no feasible solution. Moreover, subvector efficiency model is not good for dealing with controllable categorical factors because it rules out controllable categorical factors from estimating their technical efficiency though their technical efficiency should be estimated. Even if technical efficiency is estimated relative to a vector of variable inputs and controllable categorical factors, it is not reasonable in that technical efficiency of categorical factors is measure by a continuous value between zero and one like variable inputs. Charnes *et al.* (1994) suggest an approach to estimate the technical efficiency of controllable categorical factors. Because of this weakness of Banker and Morey (1986), their approach has not been used.

Here, the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) is illustrated. Their approach does not apply any more constraints to the general DEA model but uses the general radial DEA model. Their primal assumption is that a clear hierarchy between categories exists. Suppose that a controllable categorical factor, c, takes on values ($0, 1, \ldots, L-1$) where the lowest value of category is regarded as better because it leads to more productivity. The original data set (G) can be expressed as follows: $G = \bigcup_{l=0}^{L-1} G_l$ where G_l is the group of firms with category l. Of course, $G_m \cap G_l = f$ (empty set) if $m \neq l$. This notation is relevant to categorical factors because firms with an equal categorical value consist of a group. That is, the firms would be considered to have different characteristic from firms with different categorical value.

With these groups, the efficiency of a firm in G_0 is evaluated with respect to firms in G_0, firms in G_1 with respect to $\bigcup_{l=0}^{1} G_l$, …, and firms in G_{L-1} with respect to $\bigcup_{l=0}^{L-1} G_l$. The efficient category level (technical efficiency) can be calculated using the intensity values (weights: z_n in Table A1.1) of firms that participated in the evaluation of the firm. That is, $l^c_{nlk} = \sum_{n=1}^{n_0+\ldots+n_l} z_n c_{nk}$ where l^c_{nlk} is the technical efficiency of kth categorical factor of firm n in group G_l, and n_l is the number of firms in group G_l. That is, if a firm in G_1 participates in evaluation for a firm with the intensity of 0.3 and a firm in G_0 participates in evaluation with the intensity of 0.7, the efficient category level of the firm is 0.3 $(= 1 \times 0.3 + 0 \times 0.7)$. However, 0.3 does not make sense to the use of this categorical variable. A graphical illustration of the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) for a binary factor is shown in Figure 1.3.

Figure 1.3. The approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) for a binary factor



In Figure 1.3, suppose that there is a binary factor. There are two groups: G_0 and G_1. Firm A belongs to G_1, which means that the current value of the categorical factor is one. Suppose that the efficient frontier for firm A is formed by two firms B in group G_0 and C in group G_1 and the intensity values of B and C (z_B, z_C) are 0.3 and 0.7, respectively. Then the efficient category level of firm A is 0.3 $(= 1 \times 0.3 + 0 \times 0.7)$. However, 0.3 is not feasible for a binary categorical factor.

Moreover, another important pitfall of the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) is that where the assumption of the existence of a clear hierarchical relationship between categories is violated, they do not present the clear approach. If there does not exist a clear hierarchy between categories it is impossible to express categories by numbers. As a result, it is also impossible to measure technical efficiency with categories labeled by characters. Suppose that two categories are labeled by a and b. Then, $0.3\times a+0.7\times b$ is not meaningful.

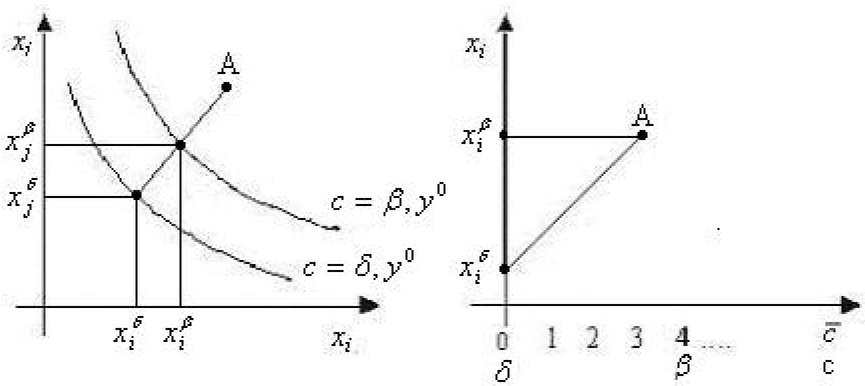
1.5. New DEA-based approach

As noted, the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) may be criticized for its assumption of the existence of a hierarchy across categories and its computation of continuous efficient category levels for categorical factors. A new DEA-based approach is developed in this section. Categories of a categorical factor are assumed to be coded arbitrarily in the original data set. For example, in a binary variable the response 'yes' can be coded as one and the response 'no' is coded as zero, and in a polychotomous variable each category can be coded by an integer from zero to the number of categories without reflecting any information on the impact of categories on output. Thus, this coding system does not reflect any hierarchical relationship between categories that is essential to estimate the technical efficiency of categorical factors in the other approaches of Charnes *et al*. (1994) and Cooper, Seiford, and Tone (2000).

In order to go on, suppose that categories of categorical variables are coded by a, b, c, d … in original data set instead of the number coding system. There are two cases: the production frontiers for categories are parallel (the existence of an unambiguous hierarchical relationship) and the production frontiers for categories are not parallel but crossed one time (the existence of no unambiguous hierarchical relationship).

The first case is that the production frontiers for categories are parallel. Because each category has different average production, each category can be coded by the size of average production. Note that category d always has $y^0 / x_i^d > y^0 / x_i^b$ where y^0 is a vector of fixed outputs, x_i^d is the technically efficient level of x_i on the efficient frontier of category d and x_i^b is the technically efficient level of x_i on the efficient frontier of category b. Though their average production changes as x_i is changed (average production is not constant), still, it is possible to code them by number in order of the size of average production. Graphically,

Figure 1.4. The parallel production frontiers

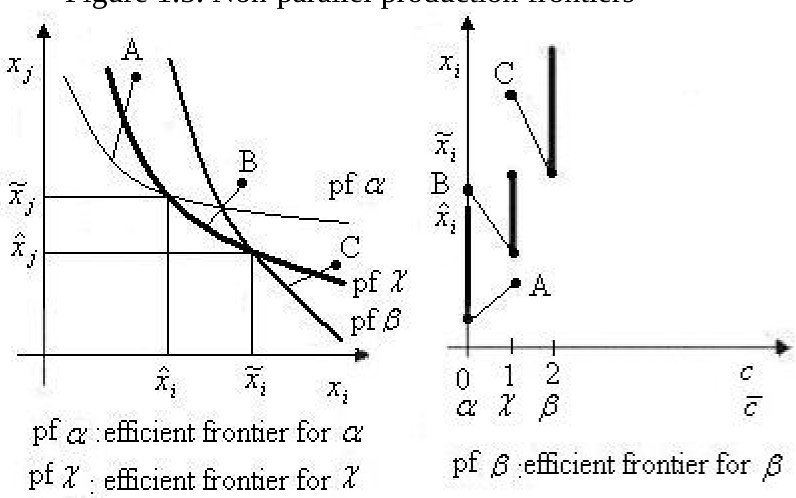


Here, it is possible to consider the relationship between the parallel distinction of isoquants and homotheticity. By Hanoch (1969), the homotheticity in outputs y is defined by the following relation: $F(y\,(m,x)\cdot y, mx) = 0$ where $F(y,x)$ is a production function, y is a vector of outputs, x is a vector of inputs, $m > 0$, $y\,(m,x) > 0$,

$\partial y(m,x) \big/ \partial m > 0$, and $y(1,x) = 1$. The parallel distinction of isoquants in Figure 1.4 is expressed by $F(y^0, x) = 0$ and $F(y^0, mx) = 0$ where if it is assumed that m >1, $F(y^0, x) = 0$ is the production function for category d and $F(y^0, mx) = 0$ is the production function for category b. That is, the parallel distinction of isoquants is a special case of homotheticity of outputs where $y(m,x)$ is always equal to one regardless of the values of m. Though the amount of inputs used by firms increase by $(m-1)x$, outputs are not increased by difference in categorical factors (practices or technology). Therefore, the production function of this case would be expressed by $F(y, x \mid c) = 0$ (different production function conditioned on categorical factors, c) rather than by the homotheticity of $F(y, x) = 0$. In the first figure of Figure 1.4, since firms should choose technology that gives them the highest average productivity, the efficient level of categorical factors is determined by selecting c such that its corresponding production function requires the least amount of variable inputs used by firms. Figure 1.4 illustrates that the values taken by a categorical factor (c) can be mapped to an integer number ($\bar{c}$) in terms of the average production. Category d is mapped to zero (best hierarchy) because when it is chosen, the least amount of continuous inputs is required to produce the given output and category b is mapped to four (worst hierarchy) because when it is chosen, the most amount of continuous inputs is required. Because categorical inputs are controllable and firms try to be technically efficient in the case illustrated, technical efficiency for all firms should be measured against the production frontier when technology is d. Thus, firm A should move along the line to become efficient.

The second case to be considered occurs when no unambiguous hierarchical relationship exists. Unlike in the first case, the production frontiers for categories are crossed and not parallel with each other. For example, suppose that there exist three alternative production technologies in an industry. If their performance is conditioned on the intensity of inputs, it is impossible to determine which technolo gy is better than other technologies. In other words, suppose that a technology is more labor-intensive and the other technology is more capital-intensive. Then, the labor-intensive technology may not be said to be always better than the capital-intensive technology. Graphically,

Figure 1.5. Non-parallel production frontiers



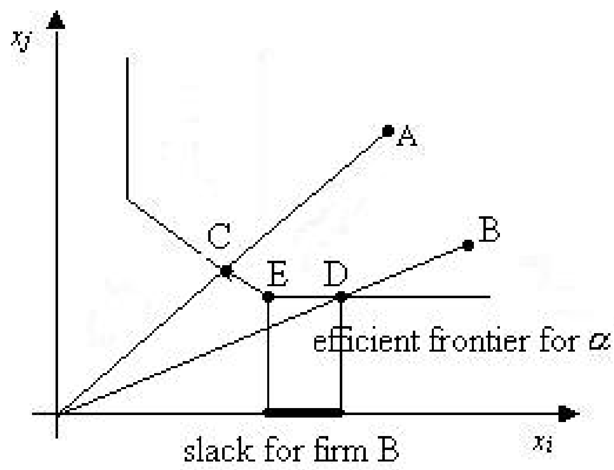
As seen in Figure 1.5, in two cases, the efficient value of the categorical factor differs over the range of the continuous inputs. When $x_i \le \hat{x}_i$ and $x_j > \tilde{x}_j$ technology a is the efficient category level, when $\hat{x}_j < x_j \le \tilde{x}_j$ and $\hat{x}_j < x_j \le \tilde{x}_j$ technology b is the efficient category level, and when $x_i > \tilde{x}_i$ and $x_j \le \hat{x}_j$ technology c is the efficient category level. Firms A, Firm B, and Firm C should move along the lines in Figure 1.5 to become technically efficient. Since a, b, and c are mapped to integer numbers in terms of the range of x_i , that is, a category that is efficient in the lowest range of x_i is mapped to zero, a category that is efficient in the second lowest range of x_i is mapped to one, and a category that is efficient in the highest range of x_i is mapped to two. a is mapped to zero, b is two, and c is mapped to one in the second figure of Figure 1.5.

In both cases, the most important problem is the selection of the efficient level of the categorical factor for each firm. This essay introduces a new approach based on an extension of the approach of Charnes *et al*. (1994) and Cooper, Seiford, and Tone (2000). Suppose that a categorical factor has 3 categories (a , b , and c). The original data set (G) can be expressed as follows: $G = G_a \cup G_b \cup G_c$ where G_l is the group of firms for which category value is l (= a , b , c). Of course, $G_m \cap G_l = f$ if $m \neq l$. In the new approach, a firm in a group is evaluated with respect to all of groups G_a, G_b, G_c , separately. Thus, there are 3 efficiency scores computed for each evaluated firm. Define TE_n^a, TE_n^b, TE_n^c where TE_n^l indicates the technical efficiency for categorical factor of firm n evaluated with respect to firms in group G_l. If the radial measure is used, TE_n^l is a scalar (= RTE_n^l) and otherwise, TE_n^l is a vector (= $NRTE_n^l$ =($NRTE_{n1}^l, \ldots NRTE_{ni}^l, \ldots, NRTE_{nI}^l$)). Intuitively, the determination of the efficient category level for firm n can be done by comparing $RTE_n^a, RTE_n^b, RTE_n^c$, or $NRTE_n^a, NRTE_n^b, NRTE_n^c$.

The reason why both radial and nonradial measures are used deserves explanation. Consider Figure 1.6. Suppose it is necessary to find the efficient category level for firm A and firm B, i.e. c_A^* and c_B^*. Since the radial efficient category level (a)

for firm A leads firm A to have no slack on the efficient frontier, the radial measure is relevant. However, because the radial efficient category level (a) for firm B leads firm B to have some slack on the efficient frontier, the radial measure is not relevant and it is necessary to use the nonradial measure to find the efficient category level that results in the firm having no slack.

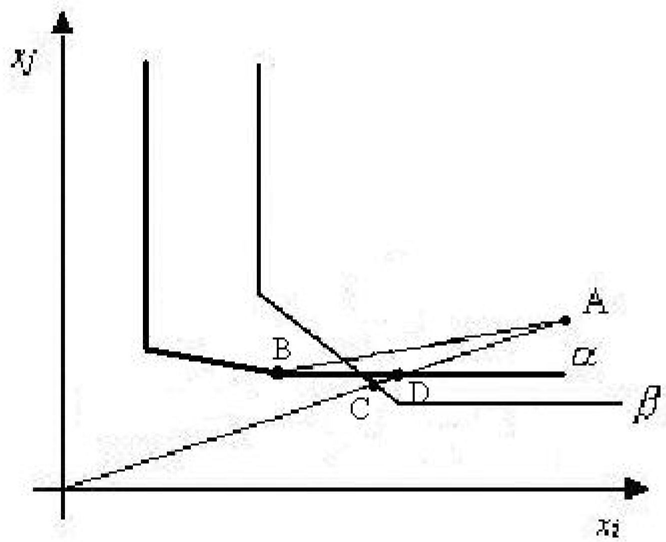
Figure 1.6. The relevancy of radial measure



A: firm A, B: firm B, $C = e^{a}_{R,A}$, $D = e^{a}_{R,B}$, $e^{a}_{R,A}$ is the radially efficient pair of input x_i and x_j when firm A is evaluated with respect to the efficient frontier of a, $e^{a}_{R,B}$ is the radially efficient pair of input x_i and x_j when firm B is evaluated with respect to the efficient frontier of a

Moreover, the efficient category level for categorical factors identified by radial measure may be different from the efficient category level identified by nonradial measure. Figure 1.7 illustrates this case.

Figure 1.7. The case where the efficient category level by radial measure is different from the efficient category level by nonradial measure



$B = e^{\alpha}_{NR,A}$ $\quad C = e^{\beta}_{R,A} = e^{\beta}_{NR,A}$ $\quad D = e^{\alpha}_{R,A}$

A: firm A, $e^{a}_{R,A}$ is the radially efficient pair of input x_i and x_j when firm A is evaluated with respect to the efficient frontier of a , $e^{a}_{NR,A}$ is the nonradially efficient pair of inputs x_i and x_j when firm A is evaluated with respect to the efficient frontier of a , $e^{b}_{R,A}$ is the radially efficient pair of inputs x_i and x_j when firm A is evaluated with respect to the efficient frontier of b , and $e^{b}_{NR,A}$ is the nonradially efficient pair of inputs x_i and x_j when firm A is evaluated with respect to the efficient frontier of b .

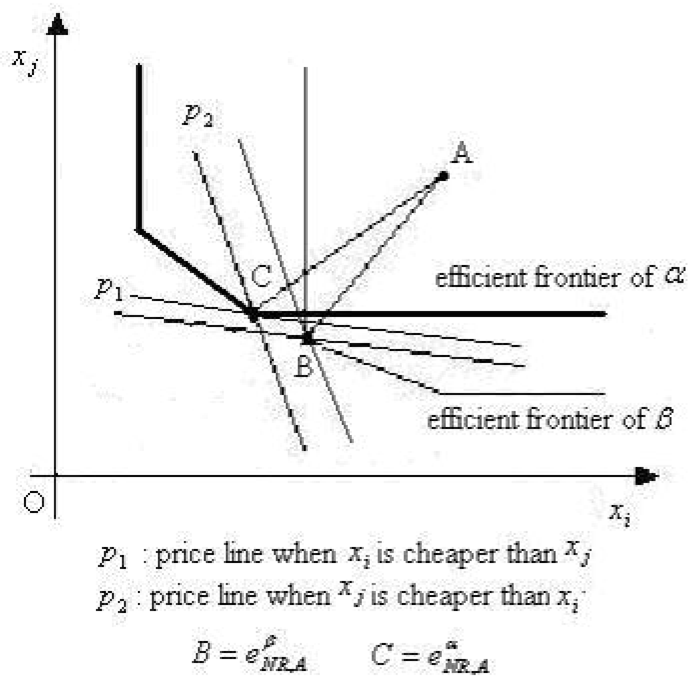
In Figure 1.7, while the efficient category level for firm A identified by radial measure is b because $RTE^{a}_{n} > RTE^{b}_{n}$, the efficient category level for firm A identified by nonradial measure may be a . Use of nonradial measure is also problematic because each input may have different efficient category level. That is, in Figure 1.7 the efficient category level for x_i identified by nonradial measure is b because x_i^{b} in point C is less than x_i^a in point B while the efficient category level for x_j identified by nonradial measure is a because x_j^a in point B is less than x_j^b in point D. An approach is, therefore, needed that provides a single category level that is efficient for all inputs. An approach is illustrated below.

To begin, the problem deserves more careful definition. For radial measure, the category that gives the firm the minimum technical efficiency becomes the efficient category level. That is, $c^*_{R,n}$ is the superscript of RTE_n^l that has the minimum value of $RTE_n^a, RTE_n^b, \ldots$ where $c^*_{R,n}$ is the efficient category level for firm *n* by radial measure. If category a gives us the minimum radial technical efficiency value, $c^*_{R,n}$ becomes a. For nonradial measure, a problem can occur because each input factor can make a different decision on the efficient category level. For example, the case of $NRTE_{ni}^a < NRTE_{ni}^b$ but $NRTE_{nj}^a > NRTE_{nj}^b$ can occur when $i \neq j$, where *i* and *j* are index for input type.

Next, two approaches are considered to resolve this problem. The first possible criterion is total input cost ($\sum_{i=1}^{I} p_i x_{ni}^l$ where p_i is the price of *i*th input and x_n^l (=($x_{n1}^l, \ldots, x_{ni}^l, \ldots, x_{nI}^l$)) that is a vector of the efficient input levels for firm *n* when firm *n* is evaluated with respect to the efficient frontier for category *l*) when information on the factor prices is available. That is, $c^*_{NR,n}$ is the superscript of the vector of x_n^l that has the minimum total input cost where $c^*_{NR,n}$ is the efficient category level for firm *n* by nonradial measure. Figure 1.8.1 and Figure 1.8.2 illustrate the use of total input cost and

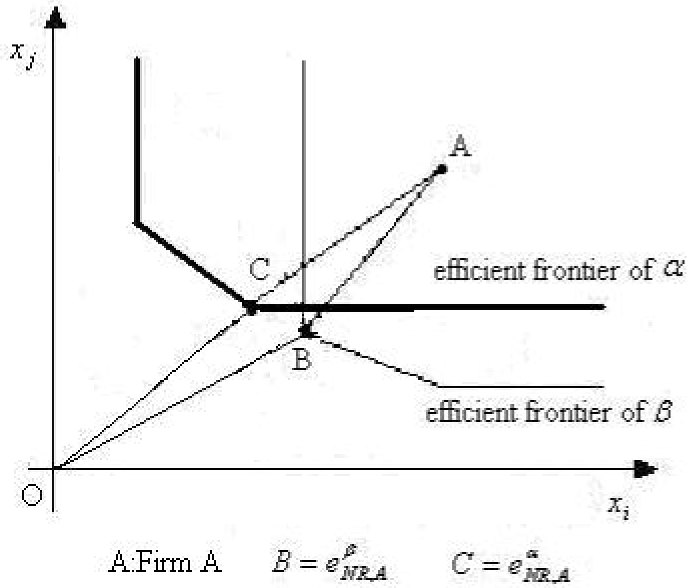
Euclidean distance for the determination of the efficient category level by nonradial measure.

Figure 1.8.1. The determination of nonradial efficient category level using the information on factor prices



When x_i is cheaper than x_j, because point B has the minimum input cost, point B is better than point C and *b* is the efficient category level identified by nonradial measure. When x_j is cheaper than x_i, because point C has the minimum input cost, point C is better than point B and *a* is the efficient category level identified by nonradial measure.

Figure 1.8.2. The determination of nonradial efficient category level using the Euclidean distance



When the information on factor prices is not available, Euclidean distance of point B and point C from the origin can be used to decide the efficient category level identified by nonradial measure. Assuming the factor prices are equal, the shorter distance of $ED_n^a = \overline{OC}$ and $ED_n^b = \overline{OD}$ determines the efficient category level.

In Figure 1.8.1, it may be impossible to decide which is better of $e^a_{NR,A}$ and $e^b_{NR,A}$ if $NRTE^a_{Ai} < NRTE^b_{Ai}$ but $NRTE^a_{Aj} > NRTE^b_{Aj}$ as shown in Figure 1.7. However, by using the factor prices it is possible to determine which one is better of $e^a_{NR,A}$ and $e^b_{NR,A}$. If x_i is cheaper than x_j (price line p_1), $e^b_{NR,A}$ (point B) becomes better than $e^a_{NR,A}$ (point C) and the efficient category level identified by nonradial measure is b. If x_j is cheaper than x_i (price line p_2), $e^a_{NR,A}$ (point C) becomes better than $e^b_{NR,A}$ (point B) and the efficient category level identified by nonradial measure is a. Therefore, total input cost can be used as a criterion. However, if the information on factor prices is not available, total input cost cannot be used. Thus, in order to solve this situation, the second criterion can use the Euclidean distance of the efficient pair from the origin. This Euclidean distance can determine the distance of the efficient point on the efficient frontier for each category level from the origin. When the nonradial measure does not identify an efficient category level, Euclidean distance determines on which efficient frontier the efficient point is closest to the origin of the efficient frontiers for all category levels assuming the factor price of x_i and x_j is equal. That is, $c^*_{NR,n}$ is the superscript of the vector of x^l_n that has the minimum Euclidean distance. In Figure 1.8.2, the Euclidean distance of point B and C that are nonradially efficient point on the efficient fontier for category b and a are measured by $\overline{OC}$ and $\overline{OB}$, respectively. Assuming that the factor price of x_i and x_j is equal, if $\overline{OC} < \overline{OB}$ a becomes the efficient category level identified by nonradial measure and otherwise, b becomes the efficient category level identified by nonradial measure.

Therefore, in order to identify the efficient category level for a categorical factor of a firm, the following steps must be implemented.

Step 1. Calculate the efficient category level for firm n by radial measure ($c^*_{R,n}$).

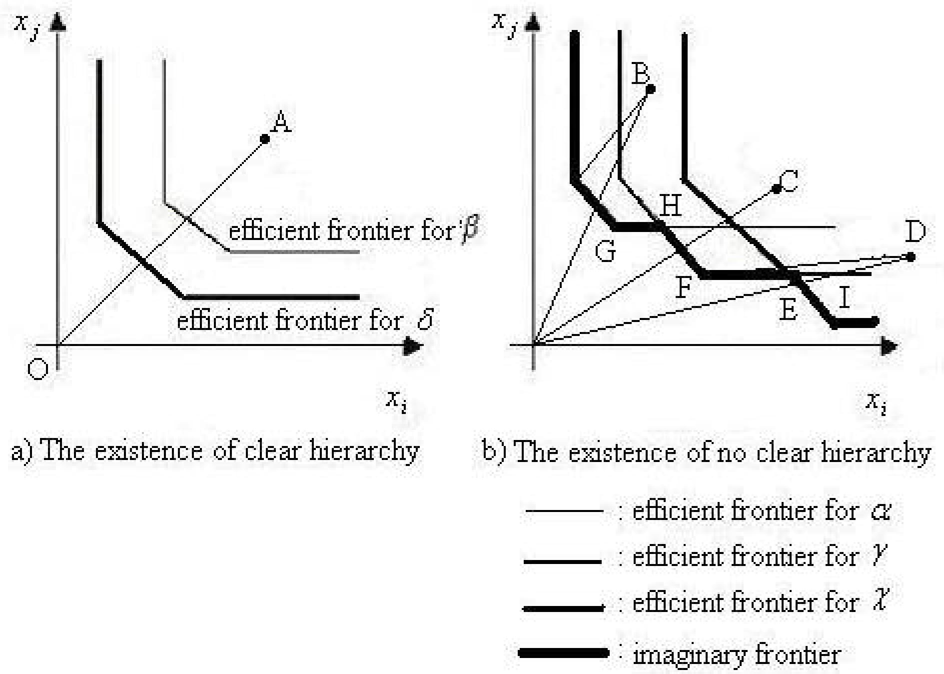
Step 2. Calculate the efficient category level for firm n by nonradial measure ($c^*_{NR,n}$). $c^*_{NR,n}$ is determined in terms of total input cost if information on factor prices and otherwise, $c^*_{NR,n}$ is determined in terms of Euclidean distance.

Step 3. If the efficient category level by radial measure is equal to the efficient category level by nonradial measure ($c^*_{R,n} = c^*_{NR,n}$), then the category level is the efficient level ($c^*_n = c^*_{R,n} = c^*_{NR,n}$). Otherwise ($c^*_{R,n} \neq c^*_{NR,n}$), go to step 4.

Step 4. If the efficient category level by radial measure is not equal to the efficient category level by nonradial measure (see Figure 1.8.2), then the efficient category by nonradial measure becomes the efficient category level ($c^*_n = c^*_{NR,n}$) because nonradial measure always show at least the equal opportunity for adjustment to radial measure (see Appendix 1.1).

Figure 1.9 illustrates the expected results from the application of the new approach in the case of the existence of a clear hierarchical relationship between categories and in the case of the existence of no clear hierarchical relationship between categories.

Figure 1.9 Efficient frontiers by DEA for both cases



Portion G-H-F on imaginary frontier and portion F-E-I are nonconvex portions on imaginary frontier

As seen in Figure 1.9, when there exists a clear hierarchical relationship between categories, the efficient category level for firm A identified by both radial measure and nonradial measure is d . When there exists no clear hierarchical relationship, the efficient category level for firm B identified by both radial measure and nonradial measure is a and the efficient category level for firm C identified by both radial measure and nonradial measure is g . However, the efficient category level for firm D identified by radial measure (c , point E) is different from the efficient category level for firm D identified by nonradial measure (g , point F). In this case, g is the efficient category level for firm D by the protocol of the above. In figure b) of Figure 1.9, the 'imaginary' frontier, the thickest line connecting the efficient part of the efficient frontier for each category, indicates the hypothetical efficient frontier perceived by firms though it does not exist. As seen in Figure 1.9, nonconvex portions may exist on imaginary efficient frontier. Portion G-H-F on imaginary frontier and portion F-E-I are nonconvex portions. Though these portions look nonconvex on imaginary efficient frontier, they are each portions of the convex frontier relevant for a particular category. As noted, because all analyses to identify the efficient category level are implemented based on the efficient frontier for each category not on the imaginary frontier, it is not necessary to worry about the existence of nonconvex portions on imaginary efficient frontier. In fact, the imaginary efficient frontier is literally 'imaginary' but it does not affect the decision of firms.

Those nonconvex portions are irrelevant because each of them belongs to two efficient frontiers. The imaginary frontier in Figure 1.9 should be partitioned into three portions of -G-H, H-F-E, and E-I- that are all convex. In fact, technical efficiency of a firm is evaluated with respect to one of the three potions but not with respect to a nonconvex portion because each of the three portions belongs to the efficient frontier for each category. For example, firm C in Figure 1.9 is evaluated with respect to portion H-F-E not G-H-F because portion H-F-E belongs to the efficient frontier for category g while portion G-H-F belongs to the two efficient frontiers for category a and g. It should be noted that each firm is evaluated with respect to the efficient frontier for each category separately and technical efficiency with respect to each efficient frontier is compared.

1.6. Empirical Application

The objectives of this empirical application are to verify the value of the new approach by demonstrating its use in a real production setting and by comparing it with results from the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000). The empirical application will provide results that examine how efficiently environmental quality management practices are used in an agricultural setting. A series of hypotheses will be tested. First, the hypothesis that the new approach provides better and more reasonable results than the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) will be examined. Second, the hypothesis that there exist possibilities for improvement in the use of categorical factors as well as variable inputs in a real production setting will be considered. Results will also provide estimates of efficiency in the use of categorical factors and prescription for the direction of adjustment.

Data come from the 1999 Agricultural Resource Management Survey in Pennsylvania. This survey includes data regarding production practices for soybeans such as acres planted, the use of damage control inputs (pesticides and fertilizers), land use practices, environmental total quality management (TQM) practices, and the use of genetically modified operations. These data include both continuous variables and categorical variables. Since the markets for soybeans are very competitive in the world, efficiency issues are critical for firms. The number of firms in the survey is 136 (N). The original data set includes 199 firms. However, this essay analyzes only 136 firms because 63 firms were excluded due to missing values and zero value for critical input variables such as seeding rate and acres planted in data. Since DEA cannot allow the missing values to be included in model, they must be eliminated from analysis. Thus, the data set that is used in this essay is a subsample of the original data set that does not have any missing values. The notable thing is that while this data set does not include any specific quality output factors, the quantity output factor (yield/acre) reflects the impact of damage control inputs and environmental TQM practices on production.

Soybean production process consists of selection of seed varieties, planting, fertilization, pest management such as weed management, insect management, and disease management, and harvesting, drying, and storage (Kansas State University Agricultural Experiment Station and Cooperative Extension Service, 2002).

In the selection of seed varieties, whether genetically modified (GM) seeds are used or not may be decided. In planting, seeding rate, timing, and method may be decided. In fertilization, the amount of fertilizers applied is decided. In pest management, the amount of pesticides applied and the timing of applications are decided. Moreover, though all of the three processes, practices for quality control and environment protection may be implemented. In harvesting and drying, the method and the timing of harvesting and drying are decided. In storage, the method and period of storage are decided.

Because the yield per acre is determined right before harvesting, this essay is interested in the estimation of efficiency from the selection of seed varieties to pest management. Therefore, the production function for soybean production should involve the above factors. A theoretical production function of soybean is developed following the neoclassical production function, and the production function for damage control inputs of Carpentier and Weaver (1997) as follows: $F(y, x, z, e, s) = 0$ where y is a vector of outputs (yield/are), x is a vector of continuous variable inputs used by firms (acres planted and seeding rate), z is a vector of continuous damage control inputs applied (pesticides and fertilizers), e is a vector of environmental TQM practices (Remove crop residue by bailing, etc., Use contour firming, Scout for weeds, Use of tilling, chopping, mowing, and burning, Use of tilling, chopping, mowing, and burning, Cleaning the equipment after implementing field work, Rotation of crops in 1999), s is a vector of the characteristics of seed (Consideration of pest resistance, Treatment of seed for disease control, Genetically modified seeds). While all the variables for y, x, and z are continuous, all the variables for e and s are categorical factors. Definitely, the variable inputs and damage control inputs affect yield of firms. That is, more inputs used by firms will give more yields to firms. The characteristics of seed also affect yield. However, 'Cleaning the equipment after implementing field works' in environmental TQM practices can look like affecting yield of next year rather than this year. If cleaning is performed after each day of work, it can affect the yield of this year. In this empirical application, the focus is on how to deal with categorical factors in e and s using the approach of Charnes *et al*. (1994) and Cooper, Seiford, and Tone (2000), and the approach of Banker and Morey (1986), and the new approach. Actual data used is reported in Table A1.3. A summary of the data is in Table A1.2.

In order to examine the credibility of data set used in this essay, the descriptive statistics in Table A1.2 are compared to those available from other sources. Categorical factors are not compared because descriptive statistics from other sources are not available. Yield per acre (32.65 bushels) in Table A1.2 looks consistent with the average yield per acre (29 bushels) from Pennsylvania Agricultural Statistics Service (http://www.nass.usda.gov:81/ipedb/) though two values are not exactly equal. Seeding rate per acre (56.63 lbs.) in Table A1.2 also looks consistent with seeding rate per acre

(54.27 lbs.) of Virginia State in 2001 (Source: Virginia Cooperative Extension - http://www.ext.vt.edu/departments/agecon/spreadsheets/crops/soybean.html). The amounts of nitrogen, potash, and phosphate used (19.38 lbs, 70.57 lbs., and 51.57 lbs.) in Table A1.2 are consistent with those (no data, 60 lbs., and 35 lbs.) of Virginia State in 2001. The amount of pesticides used (3.65 lbs.) in Table A1.2 looks consistent with that (2.25 lbs.) of Virginia State in 2001. Moreover, it is possible to predict that descriptive statistics in Table A1.2 that are not compared to those from other sources are consistent with those from other sources. Therefore, the data set used in this essay is consistent with data reported for similar production systems that is available for comparison.

Table 1.2 illustrates the average efficiency and the percentage of efficient firms when DEA is run with the approach of Banker and Morey (1986). Note, based on Banker and Morey (1986), that all categorical factors are regarded as uncontrollable.

Table 1.2. Radial and nonradial efficiency of continuous inputs by the approach of Banker and Morey (1986)

Measure		Average efficiency	% of efficient firms
Radial		0.8052	55.88
Nonradial	Inputs		
	Acres planted in selected field	0.7607	58.82
	Standardized seed rate/acre	0.7491	58.09
	Applied amount of potash/acre	0.7145	54.76
	Applied amount of nitrogen/acre	0.8246	78.26
	Applied amount of phosphate/acre	0.7829	56.41
	How much was applied/acre? -1st pesticide	0.7263	58.82
	How much was applied/acre? -2nd pesticide	0.8413	81.25
	Applied amount of manure/acre	0.7014	58.82

Categorical factors: Remove crop residue by bailing, etc., Use contour farming, Scout for weeds, Use of tilling, chopping, mowing, and burning, Use of tilling, chopping, mowing, and burning, Cleaning the equipment after implementing field work, Consideration of pest resistance, Treatment of seed for disease control, Rotation of crops, and Genetically modified seeds in 1999

In this case, the radial average efficiency is about 81%, which implies that an average firm can reduce 19% of its use of overall inputs and still achieve the same output. About 56% of firms are radially technically efficient in the use of overall continuous inputs. Nonradial average efficiency of acres planted in selected field is about 76%, which implies that an average firm can reduce 24% of acres planted in selected field to produce its current output, and about 59% of firms are nonradially technically efficient in the use of acres planted in selected field.

The main difference between the new approach and the approach of Banker and Morey (1986) is generated when categorical factors are included in the analysis. As noted, because the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) calculates the technical efficiency of categorical factors by using weights of each firm, the efficient category level is a value between zero and one. Table 1.3 illustrates the results of the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) using the same data set as in Table 1.2 but the estimation method is different from Table 1.2, as noted in section 1.4. In other words, the technical efficiency of variable inputs is estimated without including the constraints for categorical factors in the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) unlike the approach of Banker and Morey (1986). The difference in the technical efficiency of variable inputs between in Table 1.2 and Table 1.3 comes from this difference in including the constraints for categorical factors in DEA model. Table 1.3 illustrates the results of the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000).

Table 1.3. The efficiency of categorical factors and continuous inputs by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000)

Description (Categorical factors)	Average of efficient category level	% of firms that category 1 is efficient	% of firms that category 0 is efficient
Remove crop residue by bailing, etc.	0.2502	6.62	30.88
Use contour farming	0.2448	5.88	30.88
Scout for weeds	0.6125	18.38	2.94
Use of tilling, chopping, mowing, and burning	0.4200	8.82	19.12
Cleaning the equipment after implementing field work?	0.1322	4.41	61.03
Consideration of pest resistance?	0.2502	11.03	34.56
Use of treated seed for disease control?	0.0935	3.68	70.59
Rotation of crops?	0.6448	19.85	4.41
Genetically modified seeds in 1999?	0.6023	19.12	5.15

Description (Variable inputs)		Average efficiency	% of efficient firms
Radial		0.5475	17.65
Nonradial	Inputs		
	Acres planted in selected field	0.6294	31.62
	Standardized seed rate to lbs/acre	0.4658	18.38
	Pounds of potash/acre	0.6717	50.00
	Pounds of nitrogen/acre	0.7707	75.00
	Pounds of phosphate/acre	0.6275	46.15
	How much was applied/acre? (lbs.)-1st pesticide	0.6061	37.93
	How much was applied/acre? (lbs.)-2nd pesticide	1.0000	100.00
	Gallons of manure applied/acre	0.5097	38.46

The second column illustrates that an average firm should do about 61% of scouting for weeds. This does not make sense because scouting should be done (1) or not (0). The same thing is true for all values in the second column. The third column and the fourth column present the percent of firms whose efficient category level one or zero, respectively. The results illustrate that about 18% of firms should do scouting for weeds and about 3% of firms do not need to scout for weeds. Therefore, the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) does not give any recommendation on the use of scout for weed to about 29 of firms in the sample.

The new approach provides each firm with information on which level of each categorical factor is efficient for it indicating the technology or practice that is efficient. Table 1.4.1 and Table 1.4.2 illustrate the selection of the efficient category level for binary factors. Table 1.4.1 presents results for radial measure and Table 1.4.2 presents results for nonradial measure. There are radial technical efficiency scores for each categorical factor for each firm when each firm is evaluated with respect to firms using category a (no) and firms using category b (yes), and the information on which category is efficient for firms in Table 1.4.1. There are Euclidean distance values between nonradially efficient pairs and the original point for each categorical factor when each firm is evaluated with respect to firms using category a and firms using category b, and the information on which category is efficient in Table 1.4.2 because the information on the factor prices is not available. In Table 1.4.1 and Table 1.4.2, subscript k is an index of categorical factors because there may be multiple categorical factors.

Table 1.4.1. Radial choice process of new approach

Firm	Remove crop residue by bailing, etc.			Use contour farming			Cleaning the equipment after implementing field work?		
	C 1	C2	$c^*_{R,nk}$	C1	C2	$c^*_{R,nk}$	C1	C2	$c^*_{R,nk}$
1	1.0000	0.8702	b	0.8702	1.0000	a	0.8990	1.0000	a
2	0.5528	0.7118	a	0.5528	0.8618	a	0.5605	0.7595	a
3	0.6080	0.9300	a	0.6080	0.9467	a	0.6169	0.6585	a

C1: Radial technical efficiency of firm *n* evaluated with respect to efficient frontier of category a of *k*th categorical factor (RTE^a_{nk}), C2: Radial technical efficiency of firm n evaluated with respect to efficient frontier of category b of *k*th categorical factor (RTE^b_{nk}), $c^*_{R,nk}$: the efficient category level for *k*th categorical factor of firm *n* identified by radial measure. For example, because C2 (0.8702) of firm 1 for remove crop residue by bailing, etc. is less than C1 (1.0000), the efficient category level becomes b .

Table 1.4.2. Nonradial choice process of new approach (Euclidean distance)

Firm	Remove crop residue by bailing, etc.			Use contour farming			Cleaning the equipment after implementing field work?		
	C1	C2	$c^*_{NR,nk}$	C1	C2	$c^*_{NR,nk}$	C1	C2	$c^*_{NR,nk}$
1	56.29	14.53	b	15.59	56.29	a	14.53	56.29	a
2	54.05	9.52	a	54.05	9.52	a	9.52	60.03	a
3	76.04	12.06	b	76.04	12.06	b	12.06	76.04	a

C1: Euclidean distance of nonradial efficient point of firm *n* evaluated with respect to efficient frontier of category a of *k*th categorical factor from the origin (ED^a_{nk}), C2: Euclidean distance of nonradial efficient point of firm *n* evaluated with respect to efficient frontier of category b of *k*th categorical factor from the origin (ED^b_{nk}), $c^*_{NR,nk}$: the efficient category level for *k*th categorical factor of firm *n* identified by nonradial measure. For example, because C2 (14.53) of firm 1 for remove crop residue by bailing, etc. is less than C1 (56.29), the efficient category level becomes b .

Table 1.4.1 illustrates that the efficient category for Firm 1 should be b category for remove crop residue by bailing, etc. (p976), and a category for use contour farming (p993) and cleaning the equipment after implementing field work (p1057) because $RTE^a_{1,p976}(1.0000) > RTE^b_{1,p976}(0.8702)$, $RTE^a_{1,p993}(0.8702) < RTE^b_{1,p993}(1.0000)$, and $RTE^a_{1,p1057}(0.8990) < RTE^b_{1,p1057}(1.0000)$. The choices of Firm 2 and Firm 3 can be interpreted in the same way. Table 1.4.2 illustrates that the efficient category for Firm 1 should be b (yes) category for remove crop residue by bailing, etc. (p976), and a (no) category for use contour farming (p993) and cleaning the equipment after implementing field work (p1057) because $ED^{a}_{1,p976}(56.29) > ED^{b}_{1,p976}(14.53)$, $ED^{a}_{1,p993}(15.59) < ED^{b}_{1,p993}(56.29)$, and $ED^{a}_{1,p1057}(14.53) < ED^{b}_{1,p1057}(56.29)$. Firm 2 and Firm 3 can be interpreted in the same way. As noted in section 1.4, there exist firms whose efficient category level identified by radial measure is different from the efficient category level identified by nonradial measure, such as the categorical factors of Remove crop residue by bailing, etc. and Use contour farming of Firm 3 in Table 1.4.1 and Table 1.4.2. As noted in section 1.4, the efficient categorical level identified by nonradial measure overrules the efficient categorical level identified by radial measure.

Table 1.5 illustrates the concordance of the observed value of categorical factor, the efficient category level identified by radial measure, and the efficient category level identified by nonradial measure. The concordance is determined by examining whether the observed value and the efficient category level are equal or not. This concordance has been used in probit and logit analysis. In other words, if the estimate of dependent variable estimated by probit or logit model is equal to the observed value of dependent variable, it is concordant and otherwise, it is discordant (Zhang, 1998). 'Efficient firms' means that all of the observed value, the efficient category level identified by radial measure, and the efficient category level identified by nonradial measure are equal, 'Observed not concordant' means that only the observed value is different from the other two values, 'Radial not concordant' means that only the efficient category level identified by radial measure from the observed value and the efficient category level identified by nonradial measure, and 'Nonradial not concordant' means that only the efficient category level identified by nonradial measure from the observed value and the efficient category level identified by radial measure. Therefore, 55 firms (about 40%) for remove crop residue by bailing, etc. (p976), 51 firms (about 38%) for use contour farming (p993), and 87 firms (about 64%) for cleaning the equipment after implementing field work (p1057) currently use the efficient category level. The reasons why the new approach is better compared to the approach of Banker and Morey (1986) and the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) are that the new approach can identify the efficient category level for categorical factors of each firm and identify which firms are efficient and which firms are inefficient.

Table 1.5. The concordance between data and the efficient category levels

Description ($N=136$)	Efficient firms (N_{eff})	Observed not concordant (N_{data})	Radial not Concordant (N_R)	Nonradial not Concordant (N_{NR})	% of efficient firms
Classification criteria	$c_k = c^*_{R,k} = c^*_{NR,k}$	$c^*_{R,k} = c^*_{NR,k}$	$c_k = c^*_{NR,k}$	$c_k = c^*_{R,k}$	N_{eff}/N
Remove crop residue by bailing, etc.	55	45	10	26	40.44
Use contour farming	51	48	10	27	37.50
Scouting for weeds	78	48	3	7	57.35
Use of tilling, chopping, mowing, and burning	47	51	19	19	34.56
Cleaning the equipment after implementing field work?	87	45	1	3	63.97
Consideration of pest resistance?	51	64	13	8	37.50
Treatment of seed for disease control?	78	28	6	24	57.35
Rotation of crops?	95	35	2	4	69.85
Genetically modified seeds in 1999?	80	49	3	4	58.82

c_k: current value of kth categorical factor, $c^*_{k,R}$: efficient category level for kth categorical factor identified by radial measure, $c^*_{k,NR}$: efficient category level for kth categorical factor identified by nonradial measure, N_{eff}: the number of efficient firms that are concordant and identical classification, N_{data} : the number of firms with nonconcordant observed data, N_R: the number of firms with the nonconcordant radial efficient category level, N_{NR}: the number of firms with the nonconcordant nonradial efficient category level, N: the number of all firms.

Next, as a method to evaluate the new method, it is examined if the continuous technical efficiency scores estimated by the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994) can predict the efficient category levels estimated by the new approach of this essay. If the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994) can predict the efficient level identified by the new approach, both approaches can be considered to be equivalent (identical). To examine that, a graphic approach is used from Figure 1.10.1 to Figure 1.12.3. The figures cover the first three categorical factors among nine categorical factors used in this essay. The x-axis of the figures presents the technical efficiency estimated by the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (2000) and the y-axis presents the number of firms as indicated by blocks where lines indicate fitted normal curve of frequency and play a role of illustrating the rough characteristics of a frequency distribution such as skewness and the shape etc. By reviewing the characteristics of the fitted normal curves and the pattern of blocks, it is possible to determine whether a frequency distribution is similar to other frequency distributions or not. The figures allow consideration of whether technical efficiency estimated by the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994) predict the efficient category level for a categorical factor estimated by radial model ($c^{*}_{R,nk}$) and nonradial model ($c^{*}_{NR,nk}$) in the new approach. In these figures, if there exists difference in the pattern of the frequency distributions between two subfigures in each figure, it can be said that the technical efficiency estimated by the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994) predict the efficient category level for a categorical factor identified by radial measure and nonradial measure in the new model. However, as seen in the figures, since the subfigures in each of figure have very similar pattern of frequency distribution, it may not be said that technical efficiency estimated by the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994) predicts the efficient category level for a categorical factor estimated by radial model and nonradial model. These results imply that the new approach is different from the approach of Charnes *et al.* (1994) and Cooper, Lovell, and Tone (1994).

Figure 1.10.1. The distribution of the technical efficiency for the variable 'Remove crop residue by bailing, etc.' (p976) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the observed value is zero and one

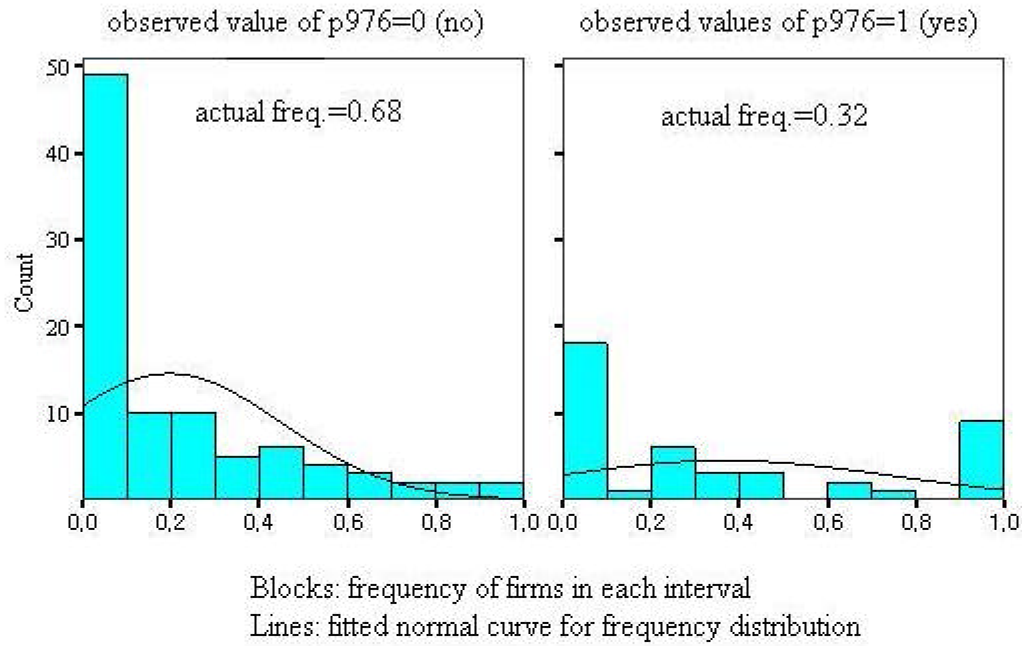


Figure 1.10.2. The distribution of the technical efficiency for the variable 'Remove crop residue by bailing, etc.' (p976) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by radial measure is zero and one

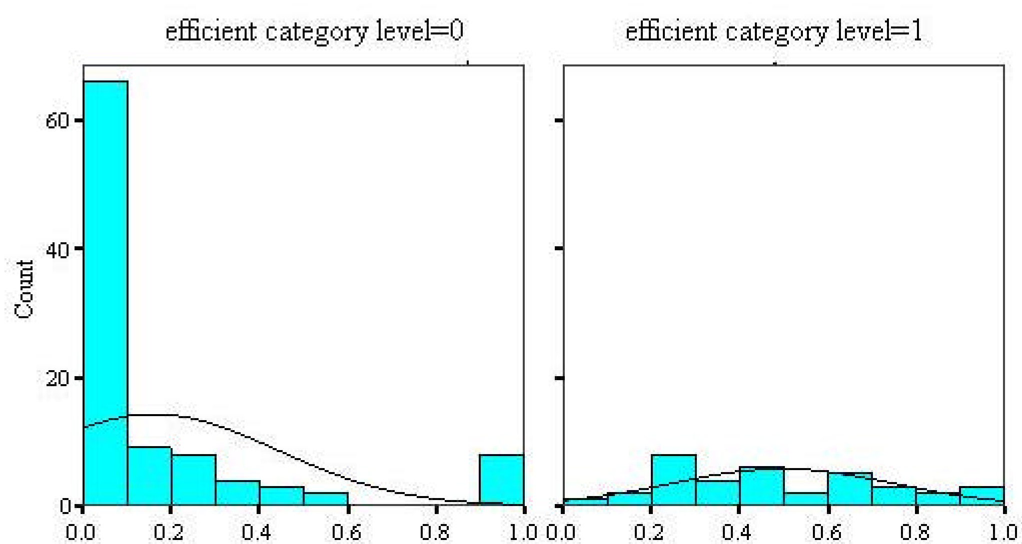


Figure 1.10.3. The distribution of the technical efficiency for the variable ‘Remove crop residue by bailing, etc.’ (p976) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by nonradial measure is zero and one

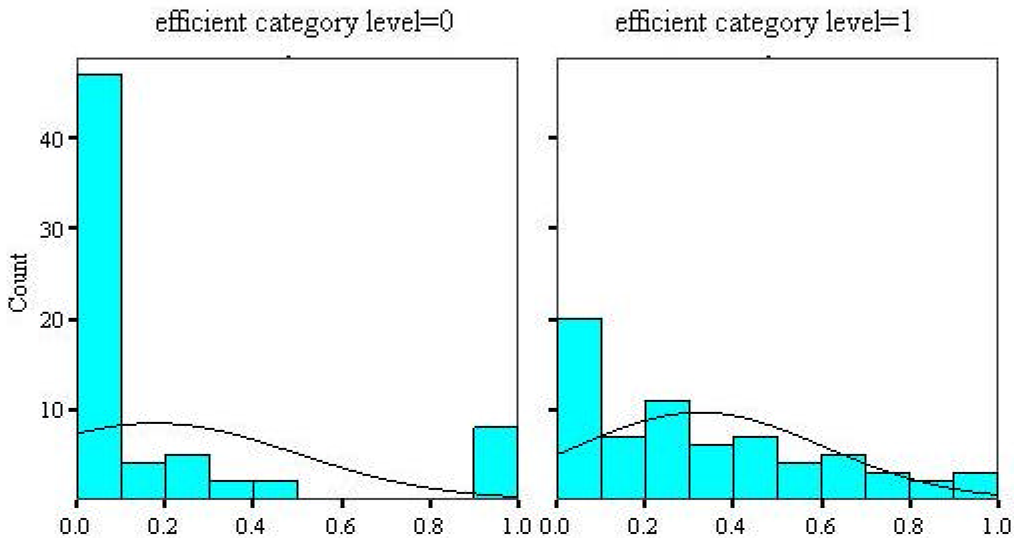


Figure 1.11.1. The distribution of the technical efficiency for the variable ‘Use contour farming’ (p993) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when current value is zero and one

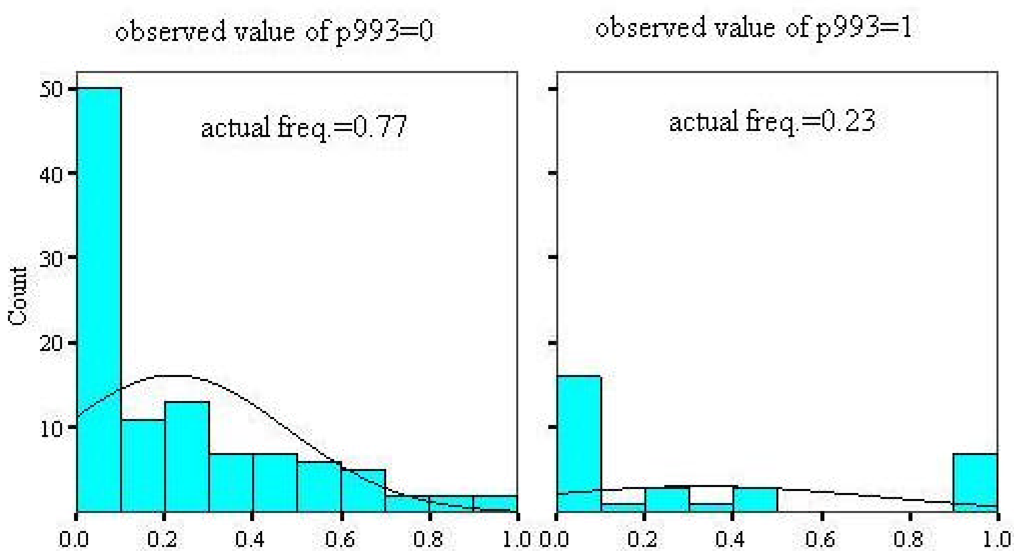


Figure 1.11.2. The distribution of the technical efficiency for the variable 'Use contour farming' (p993) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by radial measure is zero and one

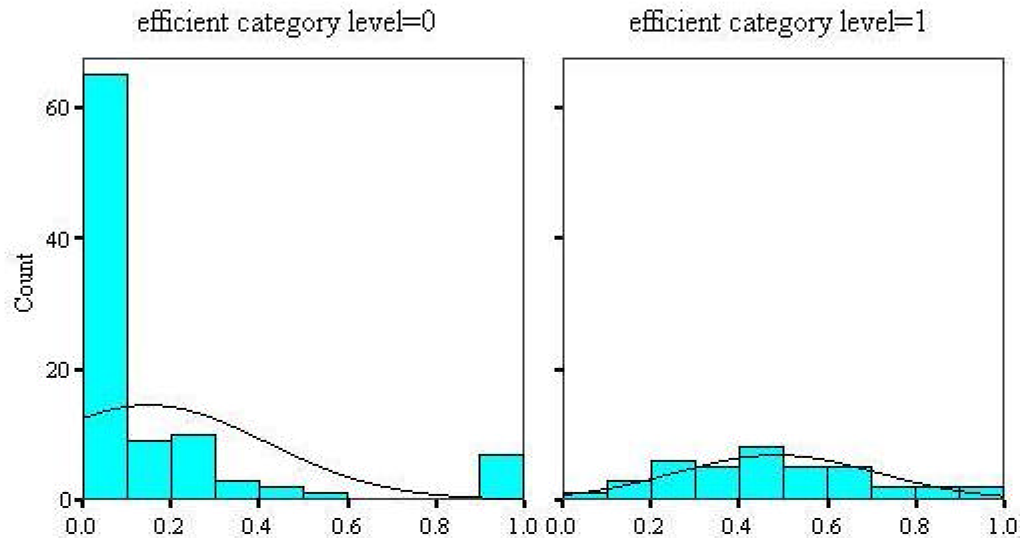


Figure 1.11.3. The distribution of the technical efficiency for the variable 'Use contour farming' (p993) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by nonradial measure is zero and one

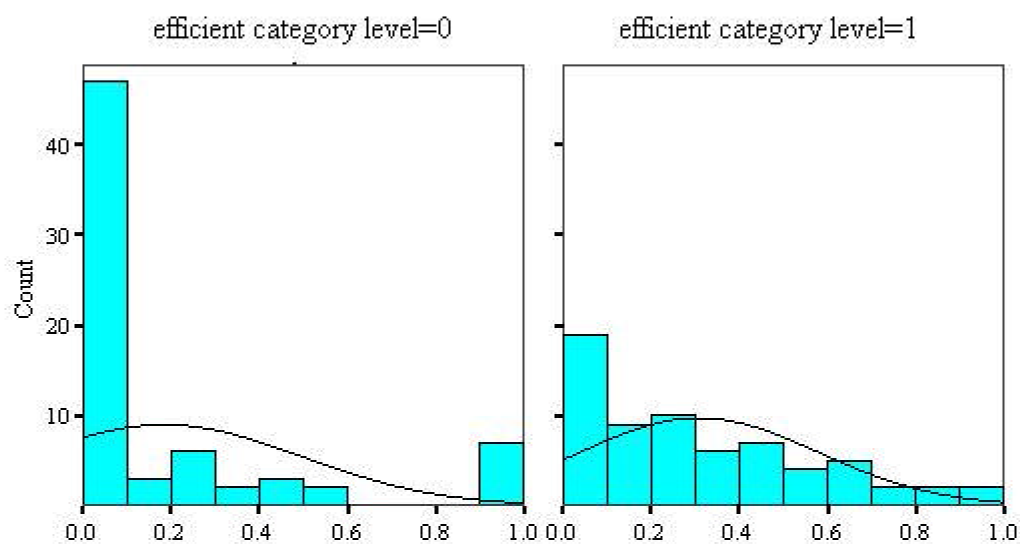


Figure 1.12.1. The distribution of the technical efficiency for the variable 'Scouting for weeds' (p1031) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when current value is zero and one

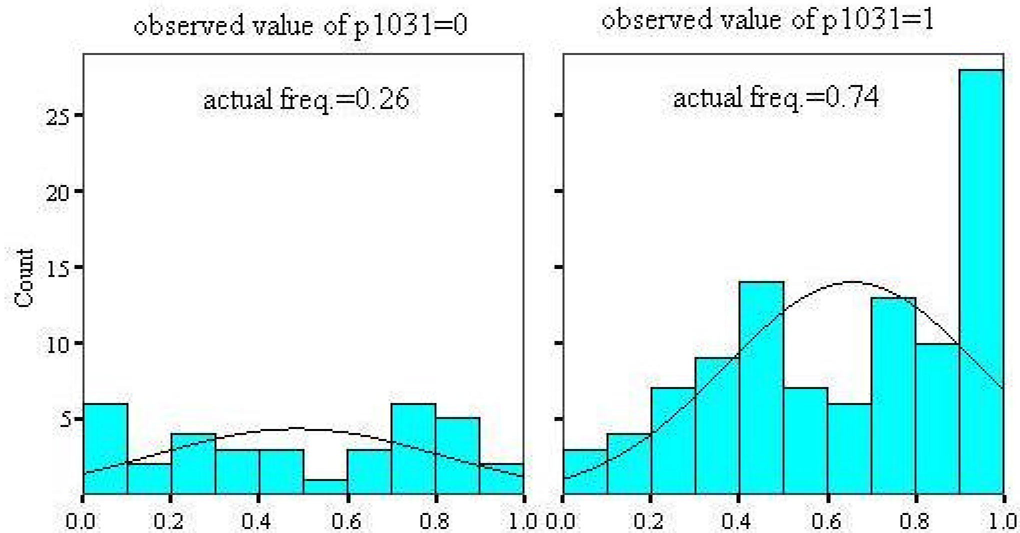


Figure 1.12.2. The distribution of the technical efficiency for the variable 'Scouting for weeds' (p1031) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by radial measure is zero and one

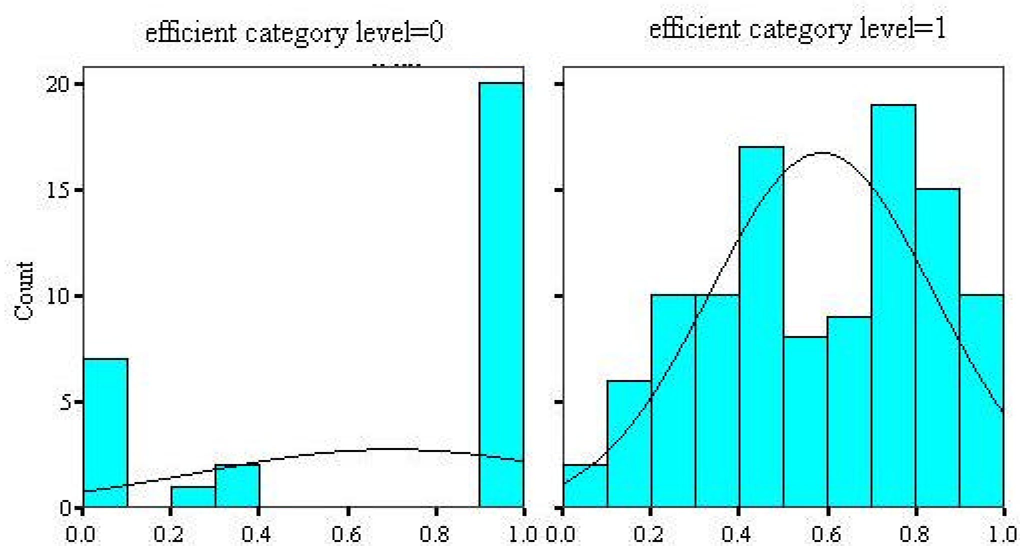
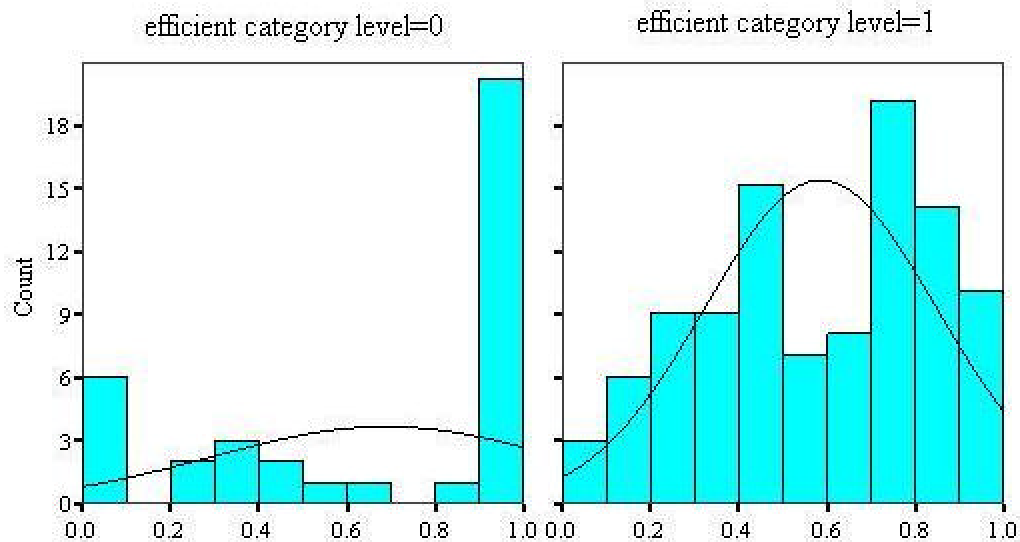


Figure 1.12.3. The distribution of the technical efficiency for the variable 'Scouting for weeds' (p1031) by the approach of Charnes *et al.* (1994) and Cooper, Seiford, and Tone (2000) when the efficient category level identified by nonradial measure is zero and one



1.7. Conclusion

The problem of essay one is the estimation of technical efficiency (the determination of efficient category level) for categorical factors involved in production processes. If quality is regarded as output for a production process, more categorical factors can be included in production process. These categorical factors can be classified into uncontrollable categorical factors (market environments) in that they are not controlled by firms and controllable categorical factors (adoption of technologies) in that they can be controlled by firms. It is not necessary to estimate the technical efficiency of uncontrollable categorical factors because they cannot be adjusted by firms. However, the technical efficiency (efficient category level) for controllable categorical factors must be evaluated to improve the efficiency of firms. In fact, the selection of efficient category level for categorical factors involved in production process affects the amount of continuous inputs used by firms.

The critical past literature on the inclusion of categorical factors in the estimation of technical efficiency is the paper of Banker and Morey (1986), Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000). Banker and Morey (1986) suggest an approach to include uncontrollable categorical factors into Data Envelopment Analysis (DEA) model based on the subvector efficiency model (Fare, Grosskopf, and Lovell, 1994). However, the approach of Banker and Morey has not been used because it is not correct in that categorical factors are dealt with like continuous factors in their approach. Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000) suggest an approach to evaluate the technical efficiency (the efficient category level) for controllable categorical factors assuming the existence of a clear hierarchical relationship between categories. In their approach, firms are classified into groups in terms of their currents value of categorical factors and the technical efficiency of each firm in a group is evaluated with respect to firms in groups whose category is equal to or worse (lower hierarchy) than category of the evaluated firm by DEA. The intensity values of firms participated in the evaluation of the evaluated firm are collected and the efficient category level of the firm is the summation of the multiplication of intensity values and category levels of firm participated in the evaluation of technical efficiency. The limitations of the approach of Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000) are that the efficient category level for categorical factors is a continuous value, which cannot give any reasonable insight to the adjustment of the values of categorical factors, and the assumption of the existence of a clear hierarchical relationship between categories, which implies that if there is no clear hierarchical relationship between categories, their approach may not be applicable.

Because the past approaches have the limitations described, it is necessary to develop a new approach to overcome the limitations of the past limitations and to identify the efficient category level of categorical factors. The new approach in this essay starts from the idea that efficient frontier may be different between category levels. Like the approach of Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000), firms are classified into groups in terms of their current value of categorical factors. However, firms in a group are evaluated with respect to firms in other groups separately. Thus, the technical efficiency of a firm is evaluated as many as the number of groups. For radial measure, the category level of group that gives a firm the minimum technical efficiency becomes the efficient category level. For nonradial measure, because each input may have the different efficient category level, the category level of group that gives a firm the minimum total input costs or the minimum Euclidean distance becomes the efficient category level. If the efficient category level identified by radial measure is different from that identified by nonradial measure, the efficient category level identified by nonradial measure becomes the efficient category level. Since the efficient category level identified by the new approach is not a continuous value but a category level, the new approach can give firms a reasonable insight to the adjustment of categorical factors. Moreover, the assumption of the existence of a clear hierarchical relationship between categories is not needed in the new approach.

An empirical application of the new approach is implemented using the data from the 1999 Agricultural Resource Management Survey for soybean production in Pennsylvania. The results of the empirical application illustrate how many percent of firms are efficient in the use of categorical factors, and what is the efficient category level for categorical factors if a firm is not efficient in the use of categorical factors. In fact, a considerable percent of firms are inefficient in the use of categorical factors in the Pennsylvania soybean production and it is possible to lead them to adjust the categorical factors in order to become efficient by the results of the empirical application.

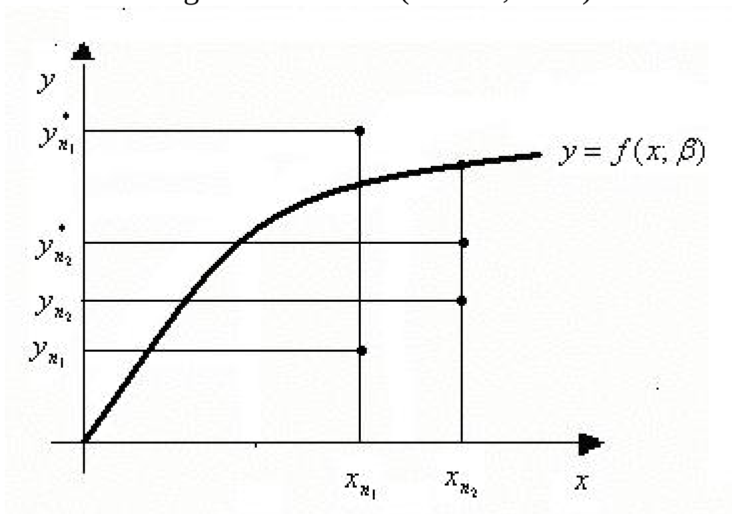
The new approach is quite different approach from the approach of Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000) because the results from the approach of Charnes *et al*. (1994), and Cooper, Lovell, and Tone (2000) cannot predict the results of the new approach as illustrated in the empirical application. Moreover, since the new approach has the advantages in that it does not need the assumption of the existence of a clear hierarchical relationship between categories and in that it can give firms a reasonable insight to the adjustment of categorical factors, the new approach can be a contribution to production economics.

Appendix 1.1. Basic theory of estimation models for production frontier

As noted, to estimate the production frontier and measure technical efficiency, there has been much research parametrically and nonparametrically, so far. Here, reviewed are the two most famous methods that can be a representative of parametric methods and nonparametric methods respectively: the SFM/stochastic output distance functions and DEA.

SFM/stochastic output distance function may be a representative of parametric methods. The former is used for the single output case to estimate the production frontier and measure technical efficiency, and the latter is used in the multiple output case to measure technical efficiency. SFM is defined as $y = f(x; b)\exp(v - u)$ where *f()* is an assumed functional form of the production function, v is a random error which is associated with factors not under the control of the firm, *u* is a non-negative random error associated with firm-specific factors that contribute to the firm not attaining maximum production, *f* is the production function with parameter b to be estimated (Battese, 1992). The deterministic frontier model is expressed as $y = f(x; b)\exp(-u)$. v is normally distributed with zero as the mean and s_v^2 as the variance, *u* is the non-negative truncation of $N(0, s^2)$ or exponentially distributed with a positive mean, and *v* and *u* are mutually independent. The reason why this model is called SFM is that y is bounded above by the stochastic quantity, $f(x; b)\exp(v)$. Graphically,

Figure A1.1. SFM (Battese, 1992)



In Figure A1.1, the stochastic frontier production ($y_{n_1}^*$ or $y_{n_2}^*$) can be greater or less than the deterministic frontier production, $y = f(x; b)$. The stochastic frontier production for Firm n_1 ($y_{n_1}^*$) is when n_{n_1} is positive and $y_{n_2}^*$ is when n_{n_2} is negative. y_{n_1} and y_{n_2} represent the observed output for Firm n_1 and n_2, respectively. Technical efficiency with both the deterministic frontier model and SFM is measured as follows:

$T.E. = \dfrac{y}{y*} = \dfrac{f(x; b)\exp(v-u)}{f(x; b)\exp(v)} = \exp(-u)$. Therefore, technical inefficiency is associated with firm-specific factors and $0 \le \exp(-u) \le 1$. The stochastic output distance function model is literally based on an output distance function. The estimable regression model is $|y|^{-1} = D_o(x, \dfrac{y}{|y|}; b) \cdot \exp(u-v)$ where $|y|$ is the norm of output vector and $D_o()$ is an output distance function that measures technical efficiency when multiple outputs are produced. Therefore, this model does not estimate the production frontier but only measures technical efficiency. Moreover, SFM/stochastic distance function model measures overall technical efficiency rather than the technical efficiency of an individual input.

DEA is the most popular nonparametric method. It is not necessary to worry about the number of outputs in DEA. DEA models are defined as follows: in Table A1.1, n is the index of firms ($n=1, \ldots, N$), i is the index of variable inputs, m is the index of outputs, and z_n is the weight for firm n to estimate the production frontier.

Table A1.1. DEA formula for radial measure and nonradial measure

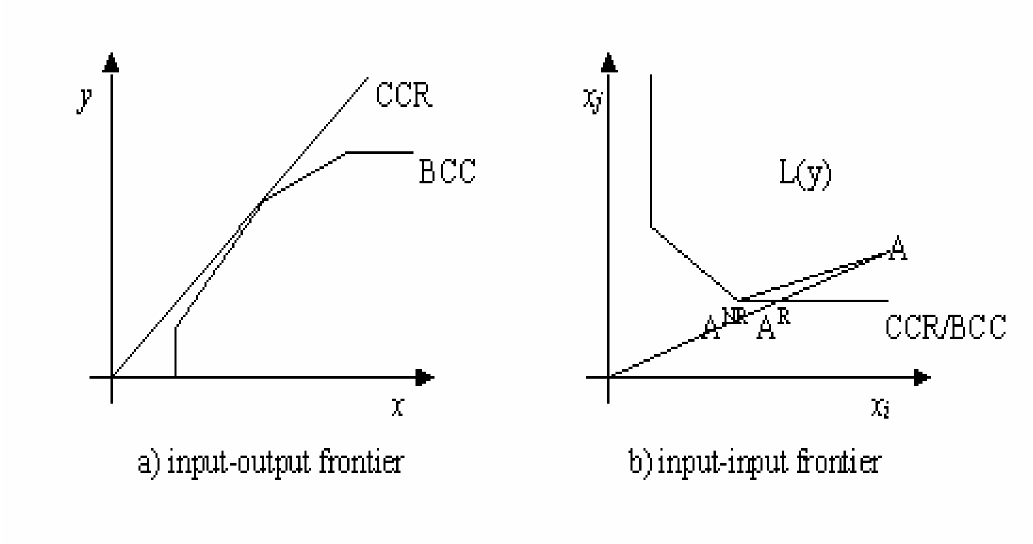
Measure	Definition	Linear Program (Input-oriented CCR)
Radial	$R(y,x) = \min\{ l : l\, x \in L(y)\}$ where l is scalar	Objective function $\underset{l,z}{Min}\ l$ Constraints $\sum_{n=1}^{N} z_n x_{ni} \le x_{n_0 i}\, l$, i =1,2,…,I: Variable inputs, n_0: the evaluated firm $y_{n_0 m} \le \sum_{n=1}^{N} z_n y_{nm}$, m =1,2,…, M: Outputs Non-negative constraints
Non-radial	$NR(y,x) = \min\{ l : l\, x \in L(y)\}$ where l is a $1 \times I$ vector	Objective function $\underset{l,z}{Min} \sum_{i \in \{h \mid x_{n_0} \neq 0\}} \frac{l_i}{I^+}$ Constraints $\sum_{n=1}^{N} z_n x_{ni} \le x_{n_0 i}\, l_i$, i=1,2,…,I: Variable inputs $y_{n_0 m} \le \sum_{n=1}^{N} z_n y_{nm}$, m=1,2,…,M: Outputs $\sum_{i=1}^{I^+} l_i \le I^+$, Non-negative constraints

I^+: The number of non-zero variable inputs.

Table A1.1 illustrates the DEA models developed by Charnes, Cooper, and Rhodes (1978) that are called CCR models; these are the most basic models of DEA, assuming the constant returns to scale. Moreover, the above models are input-oriented *CCR* models because they measure the technical efficiency of inputs when the given outputs are produced. In fact, output-oriented DEA models exist that measure the technical efficiency of outputs when the given inputs are used for production. As seen in Table A1.1, DEA is a linear programming-based model without any assumptions about the functional form of the production function. Constraints set (estimate) the piecewise linear production frontier determining the optimal weights for each firm, and the objective function represents radial and nonradial technical efficiency that will explained below.

In addition to *CCR* models, it is possible to think about the models suggested by Banker, Charnes, and Cooper (1984) that are called *BCC* models. The *BCC* model is different from *CCR* in that *BCC* models assume variable returns to scale, which implies that returns to scale is changed in the amount of inputs used. Thus, *BCC* models are obtained only by adding the constraints $\sum_{n=1}^{N} z_n = 1$ to *CCR* models. It can be said that that these two models are basic DEA models. In addition to these two basic models, a variety of models are available such as the Free Disposal Hull model (FDH) that explains the assumption of returns to scale in the production function. In Figure A1.2, the first figure illustrates the shape of production frontier in CCR and BCC.

Figure A1.2. Production frontiers in DEA



In DEA, technical efficiency can be defined in two ways: radial measure and nonradial measure. Farrell's measures of technical efficiency provide insights for total factor employment and propose equi-proportional reduction of all factors necessary to attain technical efficiency (Fare, Grosskopf, and Lovell, 1994). While this type of measure of technical efficiency may be useful for some questions, the differential impacts of agricultural inputs on the environment would seem to beg for a measure of input specific potential for the adjustment of input use. The former is called radial technical efficiency (RTE) and the latter is called non-radial technical efficiency (NRTE) or Russell's measure. As noted, radial measure adjusts the input vector back toward the origin. These radially technically efficient points (A^R) belong to the weak efficient points in that they may have slacks (Fare, Grosskopf, and Lovell, 1994). In Figure A1.2, although A^{NR} does not have any slack, A^R has the slack by A^{NR}-A^R. Because of this existence of slacks in RTE, it may seem to look incomplete. However, RTE is meaningful in that it can give us the overall technical efficiency of firms. In order to obtain a more complete (not weak) measure, it is possible to think about a nonradial measure of technical efficiency. Each input factor is reduced in a different proportion. In Figure A1.2, the adjustment from A to A^{NR} represents the nonradial adjustment. These nonradial technically efficient points (A^{NR}) belong to the efficiency points in that they do not have any slack. NRTE is also meaningful in that it can give us insight into the source of the technical inefficiency of firms. This nonradial technical efficiency measure collapses to the radial measure when all technical efficiencies for all inputs are equal to the radial technical efficiency. Since nonradial measures can shrink an input vector at least as the radial measure can, the relationship between them is $0 < NRTE \leq RTE \leq 1$. The models for both radial measures and nonradial measures are in Table A1.1. This distinction between radial measure and non-radial measure comes from the piecewise linear property of the production frontier estimated by DEA.

Appendix 1.2. Comparison of estimation models: DEA vs. SFM

This part deals with a comparison between the mentioned models (SFM/stochastic distance function model and DEA), and describes the strengths and weaknesses of each model.

As noted, because SFM/stochastic distance function model is a parametric model, the assumptions of parameters and functional forms are essential. It is natural that the validity and accuracy of the assumption can be a problem. However, by using distribution assumptions, SFM/stochastic distance function model can involve and classify the controllable errors and the uncontrollable errors in the model. Because uncontrollable events that affect productivity may always occur during the production process, this property of SFM/stochastic distance function model can be a good strength. SFM can estimate the production frontier with an assumed form of the production function. The estimated frontier may have curvature similar to the 'ideal' true production frontier while because the production frontier estimated by DEA is piecewise linear it is difficult to reflect the true production frontier. Moreover, the estimation results for the production frontier and technical efficiency from SFM can give us interval estimates as well as point estimates, and can be subject to statistical inference tests for their statistical significance. Thus, it is possible to have the significant interval for the estimated production frontier and technical efficiency (interval estimates) and the degree of confidence of them. In spite of these advantages of SFM, this model has some weaknesses as follows: it deals with only the single output case, and it may be troubled by problems generated by the fact that it is a parametric method such as collinearity and heteroskedasticity (Olesen, 1995). In the multiple output case, the stochastic distance function model does not estimate the production frontier, though it estimates technical efficiency. This is a common problem for regression-based estimation methods. Except the canonical correlation method, regression-based estimation methods are not allowed to have multiple dependent variables. Therefore, all parametric approaches to estimate the production frontier have been specified with the single output case. Though it is possible to find two papers attempting to develop a multiple-output-multiple-input SFM such as Kumbhakar (1987) and Lovell and Sickles (1983), there seems to be almost nothing to gain (Olesen, 1995). Moreover, when a prior knowledge is known that a production process is a joint production process, it is very difficult to assume an accurate functional form for the production function or distance function that reflects the jointness. Thus, jointness can degrade the robustness and accuracy of estimates by the stochastic production frontier and stochastic distance function. Though it is difficult to find previous research on categorical variables in SFM and stochastic distance function model, it is also hard to measure the technical efficiency of categorical variables because SFM and stochastic distance function model estimate the radial technical efficiency of all inputs (Kumbhakar and Lovell, 2000). In the view of amount of calculation, SFM and stochastic distance function take much more time than DEA. For example, the calculation amount of a maximum likelihood estimate is increased by a geometric progression in the number of parameters to be estimated and in the complexity of the assumed functional form.

Since DEA is a nonparametric method, it is not necessary to assume the functional form of the random error distribution function. Moreover, it is not necessary to worry about the functional form of the production function or distance function. These properties enable DEA to handle large number of variables and relations in the data set and to handle a data set whose size is from very small (about 10) to large, while SFM needs at least 25 samples to guarantee that degree of freedom. However, these properties make DEA require better-conditioned sets of data than parametric models because of the lack of stabilizing effect from a chosen functional form. DEA cannot give us interval estimates or statistical inferences but just point estimates. DEA can deal with the multiple output case easily to estimate the production frontier and measure technical efficiency, identify sources and amounts of inefficiency in each input and each output, and identify the peergroup of each firm variably not predetermined. The most important strength of DEA relative to SFM and stochastic distance function is its ability to represent a production process with a joint technology of multiple outputs from a consumption of multiple inputs. Namely, the estimated production frontier by DEA can involve the economies of jointness/scope or diseconomies of jointness/scope (Olesen, 1995). Moreover, because DEA can estimate the technical efficiency of individual inputs, it is easier for DEA to deal with categorical variables than for SFM and stochastic distance function model.

Appendix 1.3. Summary of data and data set analyzed

There are 136 observations, nine categorical variables, eight continuous input variables, and one output variable.

Table A1.2. Summary of variables for DEA

Description	Name	Unit	Type*	N	Min	Max	Mean[1]	St Dev
Remove crop residue by bailing, etc.	p976	N/A	*c*	136	0	1.00	0.32	-
Use contour farming	p993	N/A	*c*	136	0	1.00	0.23	-
Scouting for weeds	p1031	N/A	*c*	136	0	1.00	0.74	-
Use of tilling, chopping, mowing, and burning	p1056	N/A	*c*	136	0	1.00	0.38	-
Cleaning the equipment after implementing field work?	p1057	N/A	*c*	136	0	1.00	0.36	-
Consideration of pest resistance?	p1059	N/A	*c*	136	0	1.00	0.49	-
Treatment of seed for disease control?	p1060	N/A	*c*	136	0	1.00	0.23	-
Rotation of crops?	p1065	N/A	*c*	136	0	1.00	0.87	-
Genetically modified seeds in 1999?	p949_1	N/A	*c*	136	0	1.00	0.71	-
Acres planted in selected field	p935	Acre	*x*	136	0.50	60.00	9.03	7.96
Standardized seed rate/acre	p944_1	Lbs.	*x*	136	5.60	132.00	56.63	38.40
Applied amount of potash/acre	klbsacre	Lbs.	*x*	53	3.60	480.00	70.57	67.01
Applied amount of nitrogen/acre	nlbsacre	Lbs.	*x*	45	0.14	60.00	19.38	14.61
Applied amount of phosphate/acre	plbsacre	Lbs.	*x*	48	3.96	240.00	51.57	34.58
How much was applied/acre? - 1st pesticide	p308_1a	Lbs.	*x*	85	0.02	5.00	2.16	0.95
How much was applied/acre? - 2nd pesticide	p308_2a	Lbs.	*x*	32	0.02	5.00	1.49	1.30
Applied amount of manure/acre	manuacre	Ton	*x*	55	0.14	30.00	3.67	5.01
Yield/acre	p954	Bushel	*y*	136	4	65.00	32.65	12.79

*. N/A: not applicable, *c*: categorical factors, *x*: variable inputs, *y*: output

[1]. For binary variable, it means the percentage of 'yes' responses.

Table A1.3. Data set analyzed

Name	Description	Type	F1	F2	F3	F4	F5	F6	F7
ID	Firm identification number	ID	3000 10730	3000 16500	3000 36350	3000 40400	3000 68850	3000 90000	3000 91350
p976	Remove crop residue by bailing, etc.	C	0	0	0	0	0	0	0
p993	Use contour farming	C	1	0	0	1	0	0	0
p1031	Scout for weeds	C	1	0	0	1	0	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0	0	1	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	1	0	0	0	0	0
p1059	Consideration of pest resistance?	C	1	1	0	0	1	0	0
p1060	Treatment of seed for disease control?	C	0	1	0	0	0	1	1
p1065	Rotation of crops?	C	1	1	0	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	1	1	1	1	1
p935	Acres planted	X	15	4	5	3	2.3	4	3.5
p944_1	Standardized seeding rate (lbs.)	X	13.33	60	132	14.87	90	80	8.47
klbsacre	Pounds of potash/acre	X	0	0	0	0	0	95	0
nlbsacre	Pounds of nitrogen/acre	X	52.5	0	0	0	0	15	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	0	0	40	0
p308_1a	How much was applied/acre? (lbs.)	X	0	2	2	2	2	2	2.8
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	1	0	0	0
manuacre	Tons of manure applied/acre	X	3.03	2	0	0	0	0	0
p954	Yield/acre (Bushel)	Y	45	30	38	18	40	32	40

Name	Description	Type	F8	F9	F10	F11	F12	F13	F14
ID	Firm identification number	ID	3000 92860	3001 00360	3001 10580	3001 24500	7700 34170	7700 40540	7701 01780
p976	Remove crop residue by bailing, etc.	C	0	1	1	0	0	0	0
p993	Use contour farming	C	1	1	0	1	1	0	0
p1031	Scout for weeds	C	0	1	1	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0	0	1	0	0
p1057	Cleaning the equipment after implementing filed work?	C	1	0	0	1	1	0	1
p1059	Consideration of pest resistance?	C	0	0	0	1	1	0	1
p1060	Treatment of seed for disease control?	C	0	0	1	1	0	0	1
p1065	Rotation of crops?	C	1	0	1	1	1	0	1
p949_1	Seed variety in 1999?	C	0	1	0	0	1	1	1
p935	Acres planted	X	3	12	8	15.4	6	7	0.5
p944_1	Standardized seeding rate (lbs.)	X	100	13.33	13.33	75	72	100	70
klbsacre	Pounds of potash/acre	X	0	0	0	0	6	0	40
nlbsacre	Pounds of nitrogen/acre	X	0	0	9	0	10.4	0	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	0	25.2	0	40
p308_1a	How much was applied/acre? (lbs.)	X	2	0	2	1	0	2.5	3
p308_2a	How much was applied/acre? (lbs.)	X	0.25	0	0	0.4	0	3	0
manuacre	Tons of manure applied/acre	X	1.67	0	0.75	2	0	0	2
p954	Yield/acre (Bushel)	Y	36	20	25	50	45	9	40

Name	Description	Type	F15	F16	F17	F18	F19	F20	F21
ID	Firm identification number	ID	7701 25600	7701 46320	7701 50790	7701 78610	7702 08020	7702 08430	7702 28500
p976	Remove crop residue by bailing, etc.	C	0	0	0	0	0	0	0
p993	Use contour farming	C	0	0	1	1	0	1	1
p1031	Scout for weeds	C	1	1	1	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	1	0	0	1	1
p1057	Cleaning the equipment after implementing filed work?	C	1	0	1	1	1	1	0
p1059	Consideration of pest resistance?	C	1	0	0	1	0	1	0
p1060	Treatment of seed for disease control?	C	0	1	0	1	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	0
p949_1	Seed variety in 1999?	C	1	0	1	1	1	0	1
p935	Acres planted	X	15	20	3.5	25	4	1.5	16
p944_1	Standardized seeding rate (lbs.)	X	13.33	80	132	12.67	12	75	11.67
klbsacre	Pounds of potash/acre	X	90	0	60	75	0	0	0
nlbsacre	Pounds of nitrogen/acre	X	30	1.32	10	22.5	0	0	0
plbsacre	Pounds of phosphate/acre	X	90	0	30	57.5	0	0	0
p308_1a	How much was applied/acre? (lbs.)	X	3	2	2.75	3	2	2	2
p308_2a	How much was applied/acre? (lbs.)	X	0	1	5	0	2	2	0
manuacre	Tons of manure applied/acre	X	0	0	0	0	0	0	0
p954	Yield/acre (Bushel)	Y	30	10	35	48	20	10	53

Name	Description	Type	F22	F23	F24	F25	F26	F27	F28
ID	Firm identification number	ID	7702 38660	7702 43500	7702 49990	7702 59520	7703 09560	7704 68720	7709 27410
p976	Remove crop residue by bailing, etc.	C	1	1	0	0	0	0	0
p993	Use contour farming	C	0	0	0	0	1	0	1
p1031	Scout for weeds	C	1	1	1	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	0	0	0	0	0	1
p1057	Cleaning the equipment after implementing filed work?	C	1	0	1	0	0	0	1
p1059	Consideration of pest resistance?	C	0	0	0	1	1	1	1
p1060	Treatment of seed for disease control?	C	0	0	1	1	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	0	1	1	1	1	1
p935	Acres planted	X	8	1.5	8	6.7	5	12	10
p944_1	Standardized seeding rate (lbs.)	X	90	14.67	90	90	12.47	13.33	13.33
klbsacre	Pounds of potash/acre	X	0	0	0	0	100	0	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	0	10	0	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	0	50	0	0
p308_1a	How much was applied/acre? (lbs.)	X	4	2	2.25	2	3	2	2
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	0.5	0	2	2.03	0	0	0
p954	Yield/acre (Bushel)	Y	4	20	35	65	33	20	33

Name	Description	Type	F29	F30	F31	F32	F33	F34	F35
ID	Firm identification number	ID	7709 73740	7710 63100	7715 62250	7716 00970	7718 99410	7720 01650	7900 55390
p976	Remove crop residue by bailing, etc.	C	0	0	1	1	0	0	0
p993	Use contour farming	C	1	0	0	0	1	0	1
p1031	Scout for weeds	C	1	1	1	1	1	0	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	1	0	1	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	0	0	0	0
p1059	Consideration of pest resistance?	C	0	1	1	1	1	1	1
p1060	Treatment of seed for disease control?	C	0	0	0	0	1	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	1	1	1	1	0
p935	Acres planted	X	7	4	10	4	3	20	3
p944_1	Standardized seeding rate (lbs.)	X	75	12	13.33	80	60	75	70
klbsacre	Pounds of potash/acre	X	105	0	0	0	40	0	0
nlbsacre	Pounds of nitrogen/acre	X	10.5	0	50	0	32	0	0
plbsacre	Pounds of phosphate/acre	X	52.5	0	0	0	16	0	0
p308_1a	How much was applied/acre? (lbs.)	X	2	4	3	3	4	2.4	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0.09	0	1	0.02	0
manuacre	Tons of manure applied/acre	X	0	2	1.14	0	0	0	8
p954	Yield/acre (Bushel)	Y	28	55	35	32	31	30	15

Name	Description	Type	F36	F37	F38	F39	F40	F41	F42
ID	Firm identification number	ID	7900 63170	7900 66330	7900 89860	7900 90260	7901 50590	7902 19210	7902 19750
p976	Remove crop residue by bailing, etc.	C	0	1	0	0	0	1	1
p993	Use contour farming	C	0	0	0	0	1	1	0
p1031	Scout for weeds	C	0	1	0	1	1	1	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	1	0	0	1	1	1
p1057	Cleaning the equipment after implementing filed work?	C	1	0	0	0	0	1	0
p1059	Consideration of pest resistance?	C	0	0	1	0	1	0	1
p1060	Treatment of seed for disease control?	C	0	0	0	1	0	1	0
p1065	Rotation of crops?	C	0	1	1	0	1	1	1
p949_1	Seed variety in 1999?	C	1	1	1	1	1	1	0
p935	Acres planted	X	3	10	4	16	8.2	5	6
p944_1	Standardized seeding rate (lbs.)	X	70	12	12.33	76	11.67	132	58.3
klbsacre	Pounds of potash/acre	X	60	0	90	120	14.3	37.5	0
nlbsacre	Pounds of nitrogen/acre	X	30	0	0.21	0.14	4.4	37.5	0
plbsacre	Pounds of phosphate/acre	X	60	0	0	0	17.6	37.5	0
p308_1a	How much was applied/acre? (lbs.)	X	0	0.03	2	2	0.03	2	1
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0.63	0	2
manuacre	Tons of manure applied/acre	X	0	0.25	0	0	0	1.89	2.5
p954	Yield/acre (Bushel)	Y	35	12	35	50	4	45	20

Name	Description	Type	F43	F44	F45	F46	F47	F48	F49
ID	Firm identification number	ID	7902 65220	7902 66070	7903 47690	7903 69320	7903 87670	7903 97280	7903 97290
p976	Remove crop residue by bailing, etc.	C	1	1	0	0	0	0	1
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	0	1	1	1	0	0	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	1	0	0	0	1	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	1	0	0	0
p1059	Consideration of pest resistance?	C	1	0	1	1	0	0	0
p1060	Treatment of seed for disease control?	C	0	1	0	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	0
p949_1	Seed variety in 1999?	C	1	1	1	1	1	0	0
p935	Acres planted	X	3	14	7	30	8.9	4	4
p944_1	Standardized seeding rate (lbs.)	X	15	97	70	90	12	90	85
klbsacre	Pounds of potash/acre	X	0	0	0	11.62	0	0	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	0	0	0	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	8.3	0	0	0
p308_1a	How much was applied/acre? (lbs.)	X	0.5	2	0.31	2	0.11	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	3	0	0	0	0
manuacre	Tons of manure applied/acre	X	2.27	0	1.14	0	1.89	0.21	0.57
p954	Yield/acre (Bushel)	Y	25	15	38	30	55	50	40

Name	Description	Type	F50	F51	F52	F53	F54	F55	F56
ID	Firm identification number	ID	7904 65070	7904 80420	7905 25780	7905 44300	7905 72060	7905 75500	7905 82690
p976	Remove crop residue by bailing, etc.	C	0	1	1	0	1	1	0
p993	Use contour farming	C	1	0	0	0	0	1	1
p1031	Scout for weeds	C	0	1	0	1	1	0	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	1	1	1	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	1	1	0	0
p1059	Consideration of pest resistance?	C	0	1	0	1	0	1	0
p1060	Treatment of seed for disease control?	C	0	1	0	0	0	1	0
p1065	Rotation of crops?	C	0	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	0	1	0	0	1
p935	Acres planted	X	7	16	5	7	2.5	3	2
p944_1	Standardized seeding rate (lbs.)	X	12.67	13.67	80	8.33	66	70	120
klbsacre	Pounds of potash/acre	X	0	0	0	30	5	0	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	30	5	0	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	60	10	0	0
p308_1a	How much was applied/acre? (lbs.)	X	5	0.5	0.02	1	2	2	1
p308_2a	How much was applied/acre? (lbs.)	X	0	0.03	0.02	2	2	0	2
manuacre	Tons of manure applied/acre	X	0	0	15	0	1.2	0.25	0
p954	Yield/acre (Bushel)	Y	30	47	45	35	20	15	37

Name	Description	Type	F57	F58	F59	F60	F61	F62	F63
ID	Firm identification number	ID	7905 83410	7905 96030	7906 16650	7906 48870	7906 55510	7906 73520	7907 15650
p976	Remove crop residue by bailing, etc.	C	0	0	0	0	1	1	0
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	1	0	1	1	1	0	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	0	1	1	1	1	0
p1057	Cleaning the equipment after implementing filed work?	C	1	1	1	1	0	0	1
p1059	Consideration of pest resistance?	C	1	1	1	0	0	0	0
p1060	Treatment of seed for disease control?	C	1	0	0	0	1	1	0
p1065	Rotation of crops?	C	1	0	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	0	0	0	1	0
p935	Acres planted	X	5	11	36	8	21	5	2
p944_1	Standardized seeding rate (lbs.)	X	10.67	90	90	80	87	75	80
klbsacre	Pounds of potash/acre	X	75	60	3.6	0	42.75	0	40
nlbsacre	Pounds of nitrogen/acre	X	0	0	0.54	0	42.75	0	20
plbsacre	Pounds of phosphate/acre	X	75	60	3.96	0	42.75	0	40
p308_1a	How much was applied/acre? (lbs.)	X	2	2.25	3	2	2.96	2.5	2.5
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0.23	0	0
manuacre	Tons of manure applied/acre	X	0	0	0	10	0.14	0	4
p954	Yield/acre (Bushel)	Y	48	35	15	50	33	35	35

Name	Description	Type	F64	F65	F66	F67	F68	F69	F70
ID	Firm identification number	ID	7907 24710	7907 53500	7954 01450	7955 00300	7956 01110	8270 21150	8373 05090
p976	Remove crop residue by bailing, etc.	C	0	0	1	1	0	1	1
p993	Use contour farming	C	0	0	0	0	0	1	0
p1031	Scout for weeds	C	1	0	1	1	0	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	0	1	0	1	0	1
p1057	Cleaning the equipment after implementing filed work?	C	1	1	1	0	0	0	0
p1059	Consideration of pest resistance?	C	0	0	1	0	1	0	0
p1060	Treatment of seed for disease control?	C	0	0	1	0	0	0	0
p1065	Rotation of crops?	C	1	1	0	1	1	1	1
p949_1	Seed variety in 1999?	C	0	0	1	1	1	0	1
p935	Acres planted	X	4	3	5	4	4.5	3	5
p944_1	Standardized seeding rate (lbs.)	X	90	120	15	13.33	85	130	16.67
klbsacre	Pounds of potash/acre	X	0	0	0	0	33.12	0	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	0	8.28	0	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	0	24.84	0	0
p308_1a	How much was applied/acre? (lbs.)	X	2	3	3	3	2	2	3
p308_2a	How much was applied/acre? (lbs.)	X	1	0	0	0	2	0	0
manuacre	Tons of manure applied/acre	X	0	0	0	2.95	0	0	1
p954	Yield/acre (Bushel)	Y	40	45	8	20	25	25	10

Name	Description	Type	F71	F72	F73	F74	F75	F76	F77
ID	Firm identification number	ID	8373 06910	8373 17780	8373 22250	8373 23430	8373 29450	8474 06940	8474 08670
p976	Remove crop residue by bailing, etc.	C	0	1	0	0	1	0	0
p993	Use contour farming	C	1	0	0	0	0	1	0
p1031	Scout for weeds	C	0	1	1	1	0	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0	1	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	1	0	0	0
p1059	Consideration of pest resistance?	C	1	0	0	1	0	0	0
p1060	Treatment of seed for disease control?	C	1	0	1	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	0
p949_1	Seed variety in 1999?	C	1	1	0	1	1	0	0
p935	Acres planted	X	2	6	13	6	13	7	3
p944_1	Standardized seeding rate (lbs.)	X	5.6	12	70	15	11.67	15	5.6
klbsacre	Pounds of potash/acre	X	0	0	100	80	0	0	8
nlbsacre	Pounds of nitrogen/acre	X	0	0	12.5	17	0	0	8
plbsacre	Pounds of phosphate/acre	X	0	0	37.5	80	0	0	24
p308_1a	How much was applied/acre? (lbs.)	X	3	3.5	0	3	2	3	1.25
p308_2a	How much was applied/acre? (lbs.)	X	0	2	0.02	0	0	0	0
manuacre	Tons of manure applied/acre	X	10	5.83	0	0	0	0	0
p954	Yield/acre (Bushel)	Y	28	48	10	30	35	40	40

Name	Description	Type	F78	F79	F80	F81	F82	F83	F84
ID	Firm identification number	ID	8474 09230	8474 10640	8474 12880	8474 16250	8474 25410	8474 26630	8575 00050
p976	Remove crop residue by bailing, etc.	C	0	0	1	0	0	0	1
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	0	1	1	1	0	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	1	1	0	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	1	1	1	0	0
p1059	Consideration of pest resistance?	C	1	0	1	0	0	1	1
p1060	Treatment of seed for disease control?	C	0	0	1	0	0	1	0
p1065	Rotation of crops?	C	0	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	0	1	1	1	1	1
p935	Acres planted	X	9	25	25	8	2	20	12
p944_1	Standardized seeding rate (lbs.)	X	13.33	90	75	13.33	60	100	75
klbsacre	Pounds of potash/acre	X	0	0	0	480	0	80	90
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	60	0	20	0
plbsacre	Pounds of phosphate/acre	X	0	0	0	240	0	80	0
p308_1a	How much was applied/acre? (lbs.)	X	2	2	0	2	2	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0.38	1	0	0	0	0	4
manuacre	Tons of manure applied/acre	X	0	2	2.27	0	3	0.8	10
p954	Yield/acre (Bushel)	Y	40	35	30	35	15	40	35

Name	Description	Type	F85	F86	F87	F88	F89	F90	F91
ID	Firm identification number	ID	8575 01620	8575 02550	8575 10160	8575 10260	8575 13280	8575 14970	8575 26220
p976	Remove crop residue by bailing, etc.	C	1	0	0	0	0	0	0
p993	Use contour farming	C	0	1	0	0	0	0	0
p1031	Scout for weeds	C	1	1	1	1	1	1	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0	0	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	1	0	1	0	0	1
p1059	Consideration of pest resistance?	C	0	0	0	0	0	0	0
p1060	Treatment of seed for disease control?	C	0	1	1	1	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	0	0	1	1	0
p935	Acres planted	X	15	14.6	30	11	18	3	5
p944_1	Standardized seeding rate (lbs.)	X	14.67	70	80	110	120	8	132
klbsacre	Pounds of potash/acre	X	0	0	0	0	16	60	120
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	0	8	0	15
plbsacre	Pounds of phosphate/acre	X	0	0	0	0	24	60	45
p308_1a	How much was applied/acre? (lbs.)	X	2	0	0	0	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	1	0	2	0	0	0	3
manuacre	Tons of manure applied/acre	X	2.08	0	1.51	1.51	0	0	0
p954	Yield/acre (Bushel)	Y	30	45	40	45	35	50	25

Name	Description	Type	F92	F93	F94	F95	F96	F97	F98
ID	Firm identification number	ID	8579 06890	8579 11850	8579 13410	8579 18540	8676 01840	8676 09780	8676 12790
p976	Remove crop residue by bailing, etc.	C	0	1	0	1	0	0	0
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	1	1	1	1	0	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	0	0	0	0	1	1
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	1	0	1	1
p1059	Consideration of pest resistance?	C	1	1	1	1	1	1	1
p1060	Treatment of seed for disease control?	C	0	0	0	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	0	1	1	1
p949_1	Seed variety in 1999?	C	1	0	1	1	1	0	1
p935	Acres planted	X	20	10	18	20	12	7	2.5
p944_1	Standardized seeding rate (lbs.)	X	75	70	12.33	12	75	13.33	100
klbsacre	Pounds of potash/acre	X	90	0	60	0	0	0	0
nlbsacre	Pounds of nitrogen/acre	X	9	0	30	0	0	0	0
plbsacre	Pounds of phosphate/acre	X	45	0	60	0	0	0	0
p308_1a	How much was applied/acre? (lbs.)	X	0.75	2	2	0	4	0	2
p308_2a	How much was applied/acre? (lbs.)	X	3.5	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	0	3.03	0	1.42	10	0.32	0
p954	Yield/acre (Bushel)	Y	35	30	30	50	60	32	50

Name	Description	Type	F99	F100	F101	F102	F103	F104	F105
ID	Firm identification number	ID	8676 22350	8676 38700	8676 71800	8777 00240	8778 22920	8778 33800	8778 41770
p976	Remove crop residue by bailing, etc.	C	0	0	0	1	1	0	0
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	1	1	1	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	1	0	0	1	1	1
p1057	Cleaning the equipment after implementing filed work?	C	0	0	0	1	0	1	0
p1059	Consideration of pest resistance?	C	0	1	0	0	0	1	1
p1060	Treatment of seed for disease control?	C	1	0	1	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	0	1
p949_1	Seed variety in 1999?	C	1	1	1	0	0	1	1
p935	Acres planted	X	5	5	5	4	4.5	10	17
p944_1	Standardized seeding rate (lbs.)	X	12	75	70	100	75	80	75
klbsacre	Pounds of potash/acre	X	0	0	90	78	0	120	48
nlbsacre	Pounds of nitrogen/acre	X	0	0	15	18	0	20	12
plbsacre	Pounds of phosphate/acre	X	0	0	45	78	0	60	48
p308_1a	How much was applied/acre? (lbs.)	X	0	1.5	2	3	3.14	0.63	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0.05	0
manuacre	Tons of manure applied/acre	X	2.84	0	0	0	2.22	0	0
p954	Yield/acre (Bushel)	Y	35	35	38	45	30	40	20

Name	Description	Type	F106	F107	F108	F109	F110	F111	F112
ID	Firm identification number	ID	8878 47720	8878 76660	8878 77890	8978 95340	9070 09630	9070 12300	9070 12940
p976	Remove crop residue by bailing, etc.	C	0	1	1	0	1	0	0
p993	Use contour farming	C	0	0	1	1	0	1	1
p1031	Scout for weeds	C	1	0	1	1	0	1	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	1	0	1	1	0	0
p1057	Cleaning the equipment after implementin g filed work?	C	1	1	1	0	1	0	0
p1059	Consideration of pest resistance?	C	0	1	1	1	0	1	0
p1060	Treatment of seed for disease control?	C	0	0	0	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	0	1	1
p949_1	Seed variety in 1999?	C	0	1	0	1	0	1	1
p935	Acres planted	X	4	10	2	60	2.5	5	3
p944_1	Standardized seeding rate (lbs.)	X	90	13.33	120	8	72	70	80
klbsacre	Pounds of potash/acre	X	0	48	0	0	62.5	0	56
nlbsacre	Pounds of nitrogen/acre	X	0	0	0	0	15	0	0
plbsacre	Pounds of phosphate/acre	X	0	48	0	0	62.5	0	56
p308_1a	How much was applied/acre? (lbs.)	X	2.5	0	0	0	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	2.27	0	15	2.21	0	2.35	0
p954	Yield/acre (Bushel)	Y	40	40	30	45	10	20	30

Name	Description	Type	F113	F114	F115	F116	F117	F118	F119
ID	Firm identification number	ID	9170 01610	9177 34270	9270 05720	9270 07420	9270 88670	9271 30630	9271 47340
p976	Remove crop residue by bailing, etc.	C	0	1	0	0	0	1	1
p993	Use contour farming	C	0	0	1	1	0	0	1
p1031	Scout for weeds	C	1	1	1	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0	0	0	1	1
p1057	Cleaning the equipment after implementing filed work?	C	1	0	0	0	0	0	0
p1059	Consideration of pest resistance?	C	1	1	1	0	0	1	0
p1060	Treatment of seed for disease control?	C	0	0	0	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	0	1	1	1
p949_1	Seed variety in 1999?	C	1	1	1	1	0	1	1
p935	Acres planted	X	5	2	4.1	6	3	8	5
p944_1	Standardized seeding rate (lbs.)	X	70	14.67	67.5	75	70	70	11.67
klbsacre	Pounds of potash/acre	X	90	75	120	0	80	0	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	36	0	0	0	0
plbsacre	Pounds of phosphate/acre	X	30	0	0	0	80	0	0
p308_1a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	1	30	0	0	0	0	0
p954	Yield/acre (Bushel)	Y	47	30	10	20	30	20	40

Name	Description	Type	F120	F121	F122	F123	F124	F125	F126
ID	Firm identification number	ID	9272 20240	9273 61280	9273 62960	9273 63310	9273 63590	9273 63800	9273 75720
p976	Remove crop residue by bailing, etc.	C	0	0	1	0	1	0	1
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	1	1	0	1	1	1	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	1	0	1	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	1	0	0	1	0	0	0
p1059	Consideration of pest resistance?	C	1	1	0	1	1	0	1
p1060	Treatment of seed for disease control?	C	1	0	0	0	0	0	0
p1065	Rotation of crops?	C	1	1	1	1	1	1	1
p949_1	Seed variety in 1999?	C	1	1	0	1	1	1	1
p935	Acres planted	X	10	9	8.5	20	12	10	7
p944_1	Standardized seeding rate (lbs.)	X	12	50	100	12	75	75	13.33
klbsacre	Pounds of potash/acre	X	0	0	39	0	0	42	0
nlbsacre	Pounds of nitrogen/acre	X	0	0	7.5	0	9.24	40	0
plbsacre	Pounds of phosphate/acre	X	0	0	39	0	0	40	0
p308_1a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	1.89	0	0	0	0	0	2.27
p954	Yield/acre (Bushel)	Y	20	45	20	35	40	40	10

Name	Description	Type	F127	F128	F129	F130	F131	F132	F133
ID	Firm identification number	ID	9370 02700	9370 06550	9370 06700	9370 24480	9470 10810	9570 11600	9570 12750
p976	Remove crop residue by bailing, etc.	C	0	1	1	0	1	0	0
p993	Use contour farming	C	0	0	0	0	0	0	0
p1031	Scout for weeds	C	1	1	1	0	1	0	1
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	0	0	0	1	0	0	0
p1057	Cleaning the equipment after implementing filed work?	C	1	1	0	1	0	0	0
p1059	Consideration of pest resistance?	C	0	1	1	0	0	1	0
p1060	Treatment of seed for disease control?	C	0	0	0	1	0	0	0
p1065	Rotation of crops?	C	1	1	0	1	0	1	1
p949_1	Seed variety in 1999?	C	1	1	1	0	0	1	1
p935	Acres planted	X	16	9.2	10.1	15	8	3	4
p944_1	Standardized seeding rate (lbs.)	X	90	76	14.67	65	13.33	10.67	14
klbsacre	Pounds of potash/acre	X	60	154	0	60	0	12	48
nlbsacre	Pounds of nitrogen/acre	X	30	0	0	30	0	12	0
plbsacre	Pounds of phosphate/acre	X	60	68	0	60	0	36	48
p308_1a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0	0	0	0	0
manuacre	Tons of manure applied/acre	X	0	0	0	0	2.5	0	3
p954	Yield/acre (Bushel)	Y	20	51	25	30	48	40	20

Name	Description	Type	F134	F135	F136
ID	Firm identification number	ID	9670 03480	9670 11830	9670 18720
p976	Remove crop residue by bailing, etc.	C	0	0	0
p993	Use contour farming	C	0	0	0
p1031	Scout for weeds	C	0	0	0
p1056	Use of tilling, chopping, mowing, and burning etc.?	C	1	0	0
p1057	Cleaning the equipment after implementing filed work?	C	0	0	1
p1059	Consideration of pest resistance?	C	0	1	0
p1060	Treatment of seed for disease control?	C	0	0	0
p1065	Rotation of crops?	C	1	1	1
p949_1	Seed variety in 1999?	C	1	0	0
p935	Acres planted	X	8	7	6
p944_1	Standardized seeding rate (lbs.)	X	15.33	120	100
klbsacre	Pounds of potash/acre	X	40	0	0
nlbsacre	Pounds of nitrogen/acre	X	16	0	0
plbsacre	Pounds of phosphate/acre	X	80	0	0
p308_1a	How much was applied/acre? (lbs.)	X	0	0	0
p308_2a	How much was applied/acre? (lbs.)	X	0	0	0
manuacre	Tons of manure applied/acre	X	0	0	8.33
p954	Yield/acre (Bushel)	Y	45	11	50

Essay 2
Quantitative Peergrouping and DEA-based Benchmarking

The objective of this essay is to present a new approach for evaluating the performance of firms that reveals potential for performance improvements as well as implementing the improvements. While Essay one deals with how to measure the technical efficiency of the firms' production process including categorical factors, this essay develops a new quantitative approach for peergrouping and benchmarking to improve technical efficiency. That is, the new approach consists of two stages: peergrouping and Data Envelopment Analysis (DEA)-based benchmarking. The peergrouping process results in a classification of firms into subgroups based on their characteristics, such as the scale of operation and the pattern of nonradial technical efficiency across variable inputs in DEA. DEA-based benchmarking determines benchmarks for each peergroup using DEA scores and similarity analysis (the relative distance of a firm from the efficient frontier of other firms and frequency of a firm used as a comparator[2]).

Benchmarking is characterized by the comparison of the performance of a firm with that of other firms. The microeconomics of benchmarking can be described based on the profit function of firms. Subject to the technology and given output prices and factor prices, the firm maximizes $p = py - r_x x - kF(x, y \mid q)$ where p is a vector of output prices, r_x is a vector of factor prices, k is a Lagrange multiplier, $F(y, x \mid q) = 0$ is production function, and q is a vector of firm characteristics such as the scale of

2. The term 'Comparator' comes from the paper of Athanassopoulos and Ballantine (1995). Comparator is defined as a firm that is involved in the efficient frontier during the evaluation of the other firm. That is, if firm A participates in the evaluation of firm B (that is, firm B is involved in the efficient frontier), firm A becomes a comparator of firm B.

operation (Lau, 1972a). The maximized value of p is the profit function $V(p, r_x) = 0$ and is given by $Max p = py^* - r_x x^* = V(p, r_x)$ where the * signifies the optimized value (Lau, 1972a). In this setting, the firm with the maximum profit or at least the closet profit (the best profit) to the maximum profit becomes a benchmark for other firms with the similar characteristics (q) to the firm. If multiple firms have the maximum or best profit, multiple benchmarks can exist. Therefore, in a broad manner, benchmarking would consist of identifying the firms with similar characteristics (peergrouping), identifying the benchmarks, and implementing the adjustment of production processes to the production process of benchmarks.

The main objective of benchmarking is to help a firm adjust its intermediate performances ($t(d)$) that are the functions of a vector of decision variables (d) to the levels ($t(d^*)$ where d^* is a vector of optimal levels of decision variables) of firms with the best final performances (W^*) by changing its decision variables to minimize the difference between the best final performances and the final performances (W) of the firm (Cross and Iqbal, 1995). Mathematically, $\underset{t(d)}{Min}\, W^*(t(d^*)) - W(t(d))$. Here, the final performance measures can be defined as the performance measures that firms try to optimize ultimately. For example, many firms set profit maximization as their ultimate goal and, in this case, the final performance measure becomes profit.

Intermediate performance measures present the performance measures that may be evaluated during production to examine the status of firms though they are not the final performance measures. For example, financial ratios and technical efficiency can be the intermediate performance measures. Generally, though they are not set as a final performance measure, they are used for checking the current status of firms. These intermediate performance measures should be related to the final performance measures (profit) as well as, as noted, should be a function of a vector of decision variables (inputs). That is, better performance in intermediate performance measures should be related to better performance in the final performance measures or the worse performance. For example, better technical efficiency or better financial ratios as intermediate performance measures should be related to better profit as a final performance measure.

The reason why intermediate performance measures are used for adjustment rather than the final performance measures for adjustment is that the relationship between decision variables and the intermediate performance measures can be found more easily than the relationship between decision variables and the final performance measures. In fact, though it is very hard or almost impossible to observe the profit function of firms that defines the relationship between decision variables and profit, the relationship between decision variables and financial ratios or technical efficiency has well been defined in economics (Whittington, 1980; Hall and Winsten, 1959). In the profit maximization problem, technical efficiency is defined as ${x^*}/{x}$ if output is assumed to be y where x is the amount of an input used by firms that do not have the maximum/best profit and x^* is the amount of an input used by firms that have the maximum/best profit, and the financial ratios are defined as ${py - r_x x}/{py}$ (ratio of profit to sales) and ${py - r_x x}/{r_x x}$ (ratio of profit to cost) for firms that do not have the maximum/best profit, and $\frac{py^* - r_x x^*}{py^*}$ (ratio of profit to sales) and $\frac{py^* - r_x x^*}{r_x x^*}$ (ratio of profit to cost) for firms that have the maximum/best profit.

Firms with the best performance (benchmarks) play an important role in benchmarking process. They are identified by the final performance measures (W) or the intermediate performance measures ($t(d)$) among firms with the similar characteristics (q). Thus, at first, firms should be classified into subgroups in terms of their q. If both performance measures are available, the benchmarks are identified by the final performance measures and the intermediate performance measures are used only for the adjustments. If the final performance measures are not available, the intermediate performance measures can be used for both the identification of benchmarks and the adjustment. Thus, for a firm to become a benchmark, the firm must have the best final performances or the best intermediate performances among firms with similar characteristics to the firm. These benchmarks are used as a target for firms with not best performance. Their performance is a model that other firms must follow. Moreover, for a firm to be a benchmark, the information on the performances of the firms would need to be available to other firms. Other firms change their decision variables to the decision variables of benchmarks to improve performance.

Benchmarking has been widely adopted as a means of improving firm level performance. For example, Korea benchmarked against the Japanese semiconductor industry to build the Korean semiconductor industry in 1980s and Japan benchmarked against the Korean semiconductor companies, such as Samsung, to keep track of the development of new memory chips (Cho, Kim, and Rhee, 1998). Manhattan hotels are surviving intense competition through benchmarking between each other (Baum and

Ingram, 1998). Cross and Iqbal (1995) report on the successful use of benchmarking by the Xerox company. Lewis and Samuel (1995) present results of an application of the important core technological activities of a small manufacturer engaged in batch production of discrete products such as the assembly of oil tanks. Hirsch *et al.* (1995) investigate the benchmarking of bid preparation for capital goods such as trains. Other examples include the software development industry, steel production industry, and machine tool building industry.

Benchmarking requires the selection of a performance measure that provides a basis for evaluation of the relative performance of firms in a group. Given this performance measure, a selection of benchmark firms is made that identifies firms with the best practices and are representative in a group of firms (Athanassopoulos and Ballantine, 1995). Because of the availability of data and measurability, financial ratios and technical efficiency may be a performance measure used for benchmarking. In this essay, a technical efficiency performance measure-based criterion for benchmarking is considered because financial ratios are subject to two important pitfalls: the proportionality assumption of financial ratios and the absence of standardized units across firms (Whittington, 1980; Schefczyk, 1993; Horsky and Nelson, 1996). The detail of this is presented in section 2.2.

Horsky and Nelson (1996), Golany and Thore (1997), Ray and Desli (1997), and Smith (1997) introduced the benchmarking approach based only on DEA efficiency scores. However, since there exist many efficient firms in their approach, inefficient firms will have difficulty in selecting the benchmarks for themselves among many efficient firms because inefficient firms do not have any information on the similarity of efficient firms to themselves. To solve this problem, Athnassopouls and Ballatine (1995) and Hjalmarsson and Odeck (1996) suggested the following similarity analysis in addition to DEA scores, the frequency of an efficient firm used as a comparator for the evaluation of other firms and the relative distance of an efficient firm from the efficient frontier. Though their approach may reduce the number of potential benchmarks and increase the quality of benchmarks, their similarity analysis cannot identify any differences in firm characteristics (q) between firms because the similarity analysis is based on DEA and DEA assumes that all firms are homogeneous in characteristics. Thus, this essay tries to add a quantitative peergrouping process to other benchmarking approaches in order to identify firms with similar characteristics before DEA analysis.

This new process is the main contribution of this essay. As noted, the new approach involves peergrouping process, DEA efficiency score estimation, and similarity analysis such as the frequency of a firm used as a comparator analysis and the relative distance from the efficient frontier analysis. After all of the above analyses are completed, benchmarks for the peergroups of firms are identified.

Past literature provides substantial evidence of persistent technical inefficiency in many industries (Weaver and Kim, 1999; Fuss, 1994; Fernandez-Cornejo, 1994). If firms can eliminate this technical inefficiency, they can improve their profitability without any extra cost or effort. It follows that benchmarking based on technical efficiency may enable firms to reduce production costs by reducing the amount of production inputs used, resulting in increased profit.

The use of DEA is wide-spread. Most of research may estimate the technical efficiency of firms with respect to other firms in a sample without considering peers within the same industry. Research on technical efficiency-based benchmarking may be classified into two streams, as noted: benchmarking approach based only on technical efficiency scores (Golany and Thore, 1997; Ray and Desli, 1997; Smith, 1997) and benchmarking approach based on technical efficiency scores and similarity analysis (Athanassopoulos and Ballantine, 1995; Hjalmarsson and Odeck, 1996). However, all of these other technical efficiency-based benchmarking approaches have an important weakness: they preliminarily assume that the firms in a data set are homogeneous. Instead, this essay assumes that firms are heterogeneous and introduces a quantitative process for identifying similar firms. Furthermore, the essay introduces a quantitative approach for selecting benchmarks. After peergroups are identified for a data set, the benchmarking approach based on the approach of Athanassopoulos and Ballantine (1995), and Hjalmarsson and Odeck (1996) is presented.

This essay proceeds as follows. First, the role and importance of benchmarking is reviewed. Second, the conditions for a performance measure to become a benchmarking criterion are discussed. Third, the conditions for a firm to become a benchmark are presented. The final two sections present an application of the new DEA-based benchmarking approach and the comparison with the other approaches.

This application is performed using the data from the 1999 Agricultural Resource Management Survey for soybean production in Pennsylvania, including the data for the scale of operation, damage control input use, and quality control input use. The peergrouping process is implemented. Radial and nonradial technical efficiency for firms in each group are estimated by DEA to decide which firms in each group are efficient. Technically efficient firms in each group become candidates for a benchmark for the group. Next, similarity analysis is performed to determine the final benchmark. Similarity analysis consists of two analyses, the frequency of the efficient firms used as a comparator and the relative distance of the efficient firms from the efficient frontier. The empirical application is meaningful in that it illustrates how the new benchmarking approach is performed, compares the new approach to the other approaches numerically, and finds benchmarks for a data set on Pennsylvania soybean production operations in 1999.

2.1. The importance of benchmarking

Survival in a competitive market environment requires that firms maintain the best possible level of economic performance. As the environment changes, this environment requires that firms search for opportunities to improve their performance and to implement the improvements. Though a firm may have the best level, unless it makes effort to keep track and adjust to changes in the environment it will not survive competition. The opportunities for improvement can be identified from a within firm analysis or by the comparison across a set of competitors. However, when such opportunities are identified from within firm analysis, they follow from an information base that may have already been exploited by management. In contrast, comparison with competitors broadens the firm's information set, providing sights for new opportunities (Pettersen, 1995). Thus, as noted, this essay focuses on the opportunities from the comparison with competitors.

Zulch, Grobel, and Jonsson (1995) suggested and compared four methods to reveal potentials for the implementation of performance improvements: control, branch comparison, benchmarking, and simulation. Control includes performance evaluation of the production process under investigation within the firm, usually performed by pre-determined indicators such as financial ratios and quality performance within a firm. While this is easy to perform, this has a critical weakness in that there is no possibility to compare the performance of a firm to that of other firms because a direct comparison to other firms is almost impossible if the structure of the firm is not similar and comparable.

Industry comparison is the comparison of estimates of performance to the average of those achieved by other firms within the same economic industry. The data is typically collected from the surveys initiated by industry associations. This comparison approach can be uninformative when firms are heterogeneous within the industry. While this may be a kind of benchmarking in a general sense, it fails to provide benchmarks for a firm when it is not easy to find a group of similar firms within an industry because there exist differences between firms in an industry, and the average performance will not guarantee the best practices within industry.

Benchmarking tries to recognize a process or sub-unit in other similar firms that represents the best practice to characterize those practices, and to improve the process of the firm by following the best practice. However, because firms used for comparison are competitors, they are often unwilling to disclose their internal data. Therefore, it is impossible or very difficult to compare a whole firm to other firms. When the focus of data collection is on a production process or sub-unit in a firm, data may be more easily collected and used to support benchmarking.

Simulation is related to the need for proving the economic value of a new solution before it is realized. Because the production processes can be simulated based on different adjustment scenarios, alternative configurations can be evaluated without monetary risk. However, this simulation approach has two important pitfalls. First, the model used for simulation must be justified. The selected functional forms for the production functions, cost functions, and random processes must be justified and the parameters for the production functions, cost functions, and profit function must also be justified. Moreover, sensitivity analysis to examine how the simulation results change with a change of parameters is needed (Canova, 1995; Gautier and Granot, 1995). Second, a simulation approach cannot guarantee the optimal solution of the problem. Unlike the optimization approach that searches for decision variable values that optimize an objective function, the simulation approach computes the objective function value associated with decision variable values and model parameter values. Therefore, if the decision variable values do not include the optimal values, the simulation approach cannot find the optimal solution.

Based on the above review of Zulch, Grobel, and Jonsson (1995), this essay chooses the benchmarking approach as the implementation tool for performance improvement because it seems to be the best tool in the aspects of the accessibility to data and the possibility of comparison with competitors. In fact, while this comparison-based approach may not guarantee the optimal performance it can guarantee the best performance among competitors.

2.2. The performance measures for benchmarking

One of the main challenges in benchmarking is the selection of an appropriate performance measure. An appropriate performance measure should reflect the objectives of the firm it purports to describe (Browne, Sackett, and Wortmann, 1995; Holsky and Nelson, 1996). Further, a systematic framework for the estimation of the performance measure should be available (Bogetoft, 1997; Lewin and Seiford, 1997; Golany and Thore, 1997). As noted, final performance measures may fail to be performance measures for benchmarking because of the absence of a systematic framework for the estimation.

There are many alternative performance measures that might be adopted. Performance measure for benchmarking has varied over time reflecting what firms in particular industry view as important. For example, in the 1970s, production cost was considered to be important, in the 1980s, financial ratios were considered to be important, and after the 1990s, customer satisfaction has been considered to be important (Browne, Sackett, and Wortmann, 1995). The measure selected should be accurately estimable and observable by other firms or a representative of them (e.g. industry association). Measures that are not observable outside a firm or are not objectively estimable, will not provide a basis for a benchmarking criterion (Hansen and Riis, 1995). Two measures that have been considered to satisfy the above conditions across a variety of industries have been considered by Athanassopoulos and Ballantine (1995) and Horsky and Nelson (1996), respectively.

Accounting data were employed to compute financial ratios to be used for measuring relative performance in 1980s and 1990s (Athanassopoulos and Ballantine, 1995). Financial ratios measure the relationship between two numbers in a financial statement, such as profit-sales ratios, liability-asset ratio, and profit-investment ratios. The profit-sales ratio indicates the profitability per sales, and is interpreted as an estimate of how efficient a firm is; if the profit-sales ratio of a firm is relatively low compared to that of other firms, the firm may be regarded as inefficient. The liability-asset ratio indicates the ratio of total liabilities of a firm to total assets. This ratio is interpretable as an indicator of the solvency of a firm. If this ratio is very high, the firm is more likely to become bankrupt than other firms. The profit-investment ratio indicates the ratio of profit to new investment for a financial period. If this ratio is relatively low compared to other firms' ratios in the same industry, the firm should modify its investment strategy to remain competitive with other firms. Each of these ratios has been used to track change in performance of firms over time, as well as used as a relative performance measures to identify opportunities for improvement efforts by firms.

Financial ratios enable performance to be considered from a number of perspectives such as profitability and liquidity (Athanassopoulos and Ballantine, 1995). They provide a basis for a benchmarking criterion. Houghton and Woodliff (1987) found that financial ratios can predict the success and failure of a firm in the future. However, the usefulness of financial ratios can be criticized by two limitations of them. First, the basic assumption of financial ratio analysis is that a proportionate (linear) relationship exists between two values whose ratio is calculated (Whittington, 1980). This implies that financial ratios provide poor criteria for benchmarking when the relationship between the two values is not linear or when there exists a constant term though the relationship is linear. Second, the units and criteria with which firms measure financial status vary across firms and industries, and are not standardized (Horsky and Nelson, 1996). For example, there may be difference in the criteria when a revenue comes true between firms or between industries. Some firms record a revenue when they sell products even before payment by buyers while other firms record a revenue after payment by buyers. The second limitation reduces the compatibility between firms.

These limitations of financial ratios motivate the exploration for new measures. An important alternative is technical efficiency, (see Essay one). Because firms are interested in the improvement of technical efficiency and because technical efficiency is measured easily based on an industry data set, technical efficiency satisfies the above two conditions to become a benchmarking criterion. Firms are willing to reveal information describing their production process to gain access to estimates of their efficiency relative to the industry.

Mathematically, technical efficiency can be measured by ${x_i^*}/{x_{ni}}$ for variable inputs and ${z_k^*}/{z_{nk}}$ for quality inputs where n is the index of firms, i is the index of variable inputs, k is the index of quality inputs when outputs of firm n are assumed to be equal to outputs of efficient firms, x_i^* is the efficient level of ith variable input, and z_k^* is the efficient level of kth quality input. Technical efficiency can be measured parametrically and nonparametrically.

This essay chooses a nonparametric method, – DEA, for the same reasons as reviewed in Essay one. DEA can provide estimates of the efficiency of a firm relative to a best practice frontier, rather than an average practice. Further, DEA does not depend on knowledge of the functional relationship between inputs and outputs (See Appendix 1.1). Technical efficiency measured by DEA can resolve both the limitations of financial ratios that implied financial ratios provide weak bases for benchmarking criteria. Further, DEA is not sensitive to differences in measurement units across firms.

Athanassopoulos and Ballantine (1995) suggest the combined use of financial ratios (profit-sales ratio), DEA efficiency scores, the relative distance from the efficient frontier, and the frequency used as a comparator as a basis for constructing benchmarking criteria.

2.3. The conditions for identification of benchmark firms

For a firm to be a benchmark, the firm should have the best performance among firms. Given a performance measure for benchmarking, a criterion for the selection of firms as benchmarks must be established. Benchmarks can come from within a firm, among firms in the same industry (competitors), or among firms in other industries. Because of the value of external information available from a comparison with competitors, this essay will restrict the range of selection to other firms in the same industry. However, benchmarks must be drawn from those firms that have the similar characteristics, such as the scale of operation and pattern of nonradial technical efficiency across variable inputs in DEA (Athanassopoulos and Ballantine, 1995; Hjalmarsson and Odeck, 1996). Intuitively, an automobile company with a conveyor assembly system should not benchmark a company with a batch production system. Moreover, it is not reasonable for a small firm (the scale of operation) to benchmark to a large firm.

Past studies of DEA-based benchmarking have not considered a quantitative approach for identifying groups of firms that may be viewed as having the similar charactersitics, i.e. as a peergroup. Athanapoulos and Ballantine (1995), and Hjalmarsson and Odeck (1996) used similarity analysis (the frequency used as a comparator and the relative distance from the efficient frontier) to identify benchmarks, however they do not consider a peergrouping process that precedes the estimation of technical efficiency. To proceed, a new quantitative benchmark selection process is introduced that includes peergrouping as well as a similarity analysis for identification of benchmarks as developed by Athanapoulos and Ballantine (1995), and Hjalmarsson and Odeck (1996). The next sections describe the new benchmarking process and illustrate an empirical illustration of the benchmarking process.

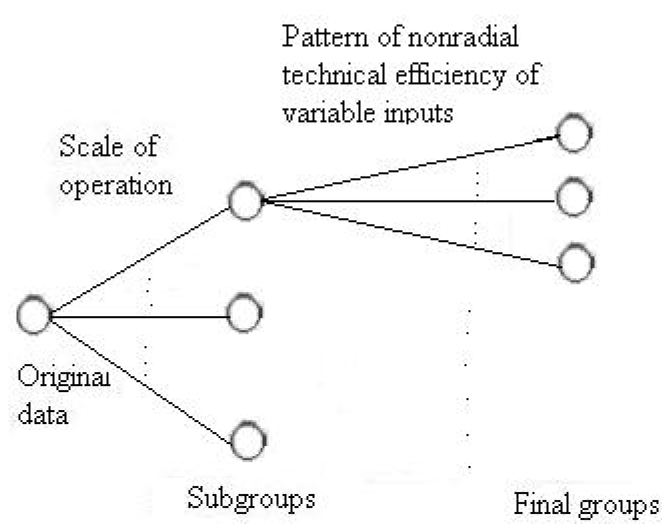
2.4. Peergrouping approach

As noted, some literature on DEA-based benchmarking exists. The main difference between these approaches and the new approach introduced here is the application of a quantitative peergrouping process that precedes the benchmarking process. In other words, the new DEA-based benchmarking in this essay consists of two stages: 1) peergrouping and 2) the estimation of efficiency and other criteria for benchmarking, and the determination of benchmarks. This section describes the peergrouping process and next section describes the benchmarking process. The peergrouping process can be regarded as a process that classifies firms in terms of their characteristics.

Criteria for peergrouping in this essay are the scale of operation and the pattern of nonradial technical efficiency across variable inputs in DEA. In fact, the two criteria may not identify different peergroups because the criteria are selected arbitrarily. For example, if data were collected from a homogeneous region, all firms can have the similar scale of operation though they may not have exactly same scale of operation. In this case, the criteria will not work well to identify the different peergroups. Moreover, it is also possible to use other characteristics for peergrouping process. Thus, it is necessary to validate whether peergroups identified by the two criteria are really different from each other or not. This validation approach is illustrated in section 2.5 in detail.

These two criteria are considered serially. That is, the scale of operation classifies firms into subgroups, and each subgroup made by the scale of operation is also reclassified into more than one subgroup by the pattern of nonradial technical efficiency across variable inputs in DEA. Figure 2.1 illustrates this peergrouping process graphically.

Figure 2.1. Peergrouping process

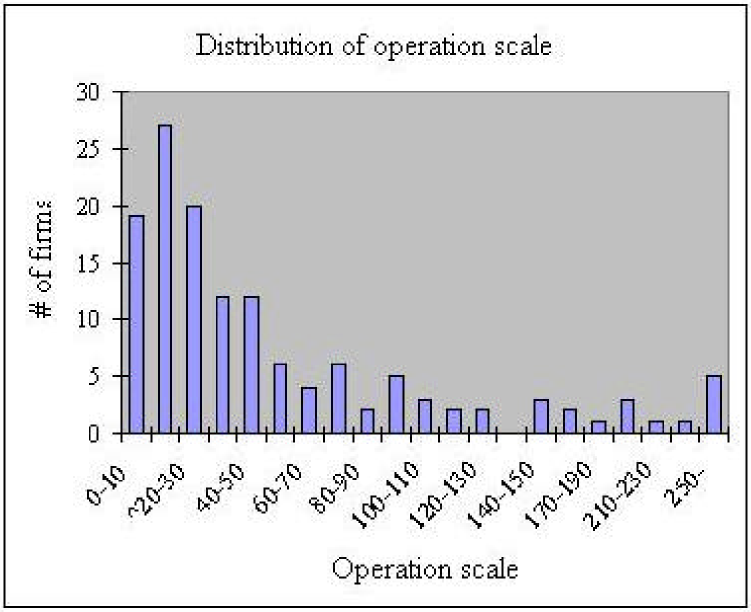


The scale of operation can be taken for peergrouping as an indicator of the overall size or scale of firms. Darr and Chern (2002) use the scale of operation (the gross value of sales) to classify the firms that produce soybeans in Ohio State into subgroups. This classification of firms by the scale of operation is meaningful in that there may exist differences in production processes between firms with the different scale of operation.

The motivation of using the scale of operation as a basis for peergrouping comes from the homotheticity of production function. Hanoch (1969) defines the homotheticity in outputs y by the following relation: $F(y\ (m,x)\cdot y, mx)=0$ where $F(y,x)$ is a production function, y is a vector of outputs, x is a vector of inputs, m >0, $y(m,x) > 0$, $\partial y(m,x) / \partial p > 0$, and $y(1,x) = 1$. In this notation, $y(m,x) \cdot y$ can be regarded as a scale of operation because it reflects total output of a firm that may indicate overall size of the firm.

If a production function of firms in an industry is homothetic in outputs, the efficient frontiers for groups generated by the scale of operation can be derived from the efficient frontier of a group because the vector of efficient inputs for firms whose scale of operation is $y(m,x) \cdot y$ becomes mx^* where x^* is the vector of efficient inputs for firms whose scale of operation is y. Otherwise, if the production function is not homothetic, the vector of efficient inputs for firms whose scale of operation is $y(m,x) \cdot y$ cannot be derived from the vector of efficient inputs for firms whose scale of operation is y (Hanoch, 1969). Thus, the efficient frontier for each group generated by the scale of operation must be estimated separately and firms with different scale of operation must be classified into different groups. This scale of operation can be measured using a variety of indicators: e.g. the gross value of sales, total profits, total planted acres in agricultural industries, the amount of raw iron ore processed in steel industry, and the amount of crude oil processed by a refinery. In order to classify firms into subgroups by the scale of operation, a histogram analysis is used to look at the distribution of firms by the scale of operation. Figure 2.2 illustrates an example of the distribution of a scale of operation measure. As illustrated in the figure, while some intervals have a large number of firms, others do not.

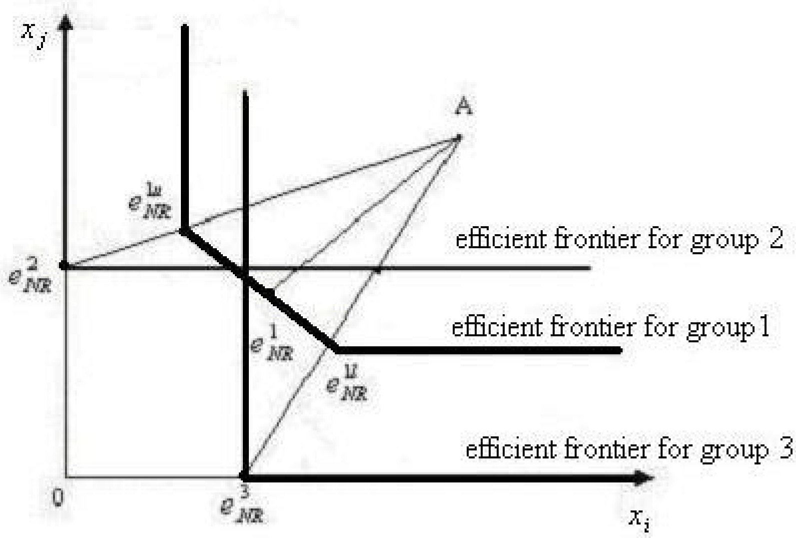
Figure 2.2. An example of distribution of the scale of operation



To make sure that each group has the enough number of firms for DEA, the intervals should be modified. The modification of the intervals in Figure 2.2 is shown in Figure 2.7.2. Figure 2.7.2 reduces 11 intervals to 4 intervals to make sure that each group has the enough number of firms to implement DEA. In fact, DEA is implemented with data set whose size is less than 10 because DEA is a nonparametric method. However, because DEA requires better-conditioned set of data than parametric models because of the lack of a stabilizing effect from a chosen functional form, a considerable size of samples is needed to obtain the better-conditioned set of data (Cooper, Seiford, and Tone, 2000: see Appendix 1.2). Though there is no previous study on this topic, 15 firms have been considered to be reasonable by some empirical application (Cooper, Seiford, and Tone, 2000).

The second basis for peergrouping is to use preliminary nonradial DEA to identify the difference in the pattern of nonradial technical efficiency of variable inputs between firms. That is, the result from the preliminary nonradial DEA indicates the pattern of nonradial technical efficiency of variable inputs of firms. Figure 2.3 illustrates this point. Three imaginary groups are presented in Figure 2.3. Group 1 in Figure 2.3 illustrates a pattern of nonradial technical efficiency of two variable inputs (x_i, x_j) on which the efficient level of both inputs are positives, group 2 illustrates a pattern of nonradial technical efficiency of two variable inputs on which the efficient level of x_i is zero, and group 3 illustrates a pattern of nonradial technical efficiency of two variable inputs on which the efficient level of x_j is zero. As seen in Figure 2.3, the efficient frontier for each group can be different in location and shape from the efficient frontier for other groups. The efficient frontier for group 2 and group 3 has only one nonradial efficient point (e^2_{NR}, e^3_{NR} where e^g_{NR} is the nonradial efficient point of group g) because there does not exist the part for the substitution relationship between two inputs in the efficient frontier. That is, the slope of efficient frontier for them will be zero or infinity. If firm A in Figure 2.3 is involved in group 2, the nonradial efficient point is e^2_{NR} and if firm A in Figure 2.3 is involved in group 3, the nonradial efficient point is e^3_{NR}. The efficient frontier for group 1 has the part of the substitution relationship between two inputs, as seen in Figure 2.3. Thus, the nonradial efficient point of group 1 (e^1_{NR}) can be put the interval between e^{1l}_{NR} and e^{1u}_{NR} in Figure 2.3. If firm A is involved in group 1, the nonradial efficient point is e^1_{NR}. Therefore, firms with different patterns of nonradial technical efficiency of variable inputs must be classified into different groups.

Figure 2.3. Alternative patterns of nonradial technical efficiency across variable inputs



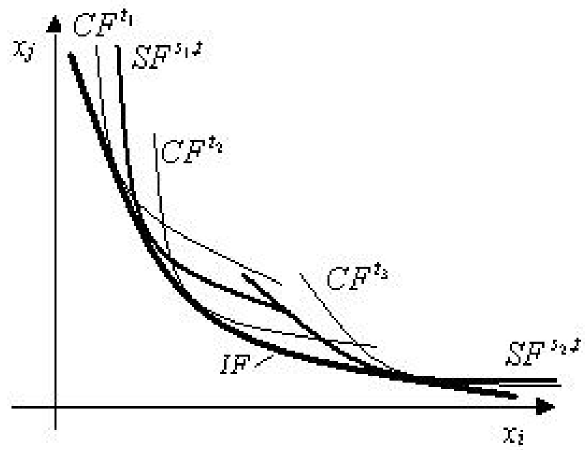
e_{NR}^{g} : the nonradial efficient point of group g

The DEA approach of Fare, Grosskopf, and Lovell (1994) is used to implement this analysis. Their approach gives one ($l_{ni} = 1$: the nonradial technical efficiency score for ith input of firm n) as the efficient score to an input not used by a firm ($x_{ni} = 0$: the amount of ith input used by firm n) while general DEA approach gives zero ($l_{ni} = 0$). In fact, the technical efficiency of not used input ($x_{ni} = 0$) cannot be computed because $l_{ni} = x_{ni}^{e} / x_{ni} = 0/0$ where x_{ni}^{e} is the nonradially efficient point for ith input of firm n. Thus, it is possible to determine the nonradial efficiency score arbitrarily because it will not affect the results of DEA and most research has determined it as zero. However, if the nonradial technical efficiency score for not used inputs is set as zero, it is impossible to distinguish the case where $l_{ni} = 0$ when $x_{ni} > 0$ from the case where $l_{ni} = 0$ when $x_{ni} = 0$ in the results from this preliminary analysis in this essay. Therefore, the approach of Fare, Grosskopf, and Lovell (1994) is used to set the technical efficiency score for not used inputs.

2.5. Validation of peergroups

An important issue raised by the above peergrouping process is that because the peergrouping criteria in this essay are *ad hoc*, it is necessary to verify if they identify peergroups that differ. Most importantly, verification is needed to establish that each peergroup faces a different frontier. A similar problem has been considered by Tulkens and Eeckaut (1995). They studied how to identify the efficient frontier for panel data and how to evaluate the progress or regress of technology over time using efficient frontiers. A contemporaneous frontier is constructed from data for each time period, a sequential frontier from data from the first time period up until another time period (not current period), and an intertemporal frontier from data for all time periods. They also introduce the approach to determine technology progress or regress. Figure 2.4.1 illustrates the frontiers. Suppose that there are N firms and T time periods are considered. Total number of observations is $N \times T$. $F^1 = ... = F^t = ... = F^T$ where $F^t = (F_1^t, ..., F_N^t)$ is the group of firms in each time period and F_n^t is the nth firm in time period t. Thus, there are T contemporaneous frontiers (CF^t), ${}_T C_2$ sequential frontiers (SF^{st}: a sequential frontier from time s till time t), and one intertemporal frontier (IF).

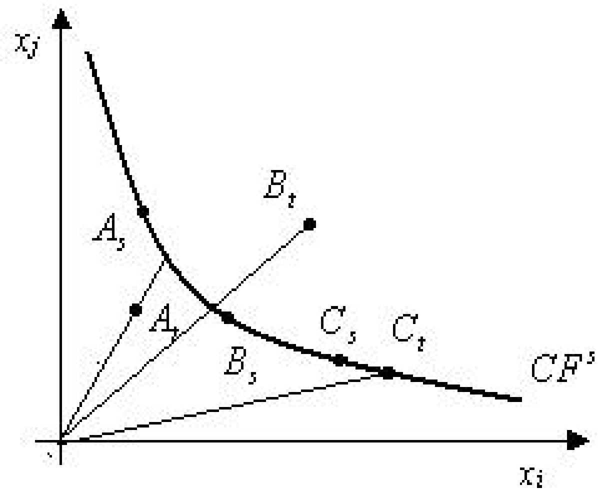
Figure 2.4.1. The efficient frontiers for the approach of Tulkens and Eeckaut (1995)



IF: intertemporal frontier, $SF^{s,t}$: sequential frontier over period from time point *s* till time point *t*,(s=s_1,s_2), CF^{t} : contemporaneous frontier in time point *t* (t= t_1,t_2,t_3)

The objective of Tulkens and Eeckaut (1995) is to examine whether each contemporaneous frontier is different from other contemporaneous frontiers or not, and whether each sequential frontier is different from other sequential frontiers or not. Moreover, they try to find which frontier is more efficient than other frontiers. For the implementation of the analysis, they estimate the relative distance of the efficient firms in a group (period) from the efficient frontiers of other groups (periods), and if the distance of a firm is greater than one then the firm is said to make progress during the period, if the distance is less than one then the firm is said to make regress during the period, and it the distance is equal to one then the firm is said to make no change. Figure 2.4.2 illustrates this approach. Firm A, Firm B, and Firm C are efficient in time point *s*. Compared to the efficient firms in time point *s*, Firm A in the figure made progress during the period between time point *s* and time point *t*, Firm B made regress, and Firm C made no change.

Figure 2.4.2. The approach of Tulkens and Eeckaut (1995)



CF^s : contemporaneous frontier in time point s, A_s: the input pair of firm A in time point s, A_t: the input pair of firm A in time point *t*, B_s: the input pair of firm B in time point *s*, B_t: the input pair of firm B in time point *t*, C_s: the input pair of firm C in time point *s*, and C_t: the input pair of firm C in time point *t*.

The concrete algorithm of their approach is as follows. Because the problem in this essay is similar to the determination of progress or regress with a contemporaneous frontier, their approach is briefly described to compare the efficient frontier in time *t* with that in time *s* ($t>s$).

Step 1. Estimate using DEA the technical efficiency of firms with data for time *t*. Here, DEA model used in this approach is different from general DEA model in that DEA in this approach allows the efficiency score is greater than one by dropping the constraint that the efficiency scores should be between zero and one from general DEA model.

Step 2. It is not necessary to worry about inefficient firms because they are not on efficient frontier. Keep efficient firms in time *t*. Suppose that the group of efficient firms in time *t* is $E^t = (E_1^t, ..., E_{m_t}^t)$ where m_t is the number of efficient firms in time *t*.

Step 3. Estimate the technical efficiency of firms with data in time *s* using DEA.

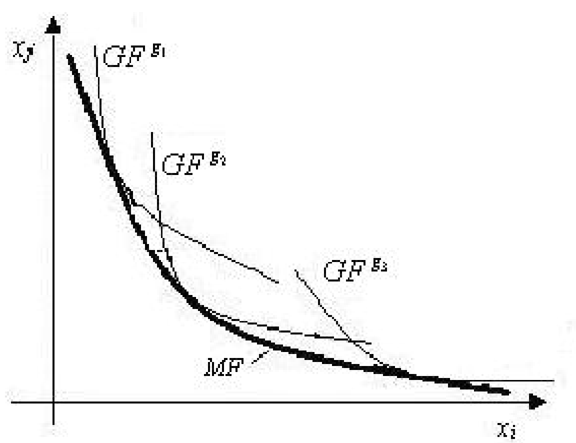
Step 4. It is not necessary to worry about inefficient firms because they are not on an efficient frontier. Keep efficient firms in time *s*. Suppose that the group of efficient firms in time *s* is $E^s = (E_1^s, ..., E_{m_s}^s)$ where m_s is the number of efficient firms in time *s*.

Step 5. Estimate the relative distance of firms in group E^t from the efficient frontier for group E^s using Andersen and Petersen formulation (Andersen and Petersen, 1993). If the distance is greater than one, Firm *m* made progress in technology in time *t* rather than in time *s*, if the distance is less than one, Firm *m* made regress in technology in time *t* rather than in time *s*, and if the distance equals one, Firm *m* uses the same technology in time *t* as in time *s*.

This approach should be modified to be applied to this essay because each group has different firms in this essay, and the objective is not to find technology progress or regress but to find the difference between groups in one period. That is, $F^g \cap F^h = f$ (empty set) if $g \neq h$ for all *g* and *h*, and $\bigcup_{g=1}^{G} F^g = F$ where *g* is the index of groups and *F* is the group of all firms. There exist two types of frontiers: mega frontier (*MF*) that is formed by all firms (*F*) and group frontier (GF^g) that is formed by a group *g*.

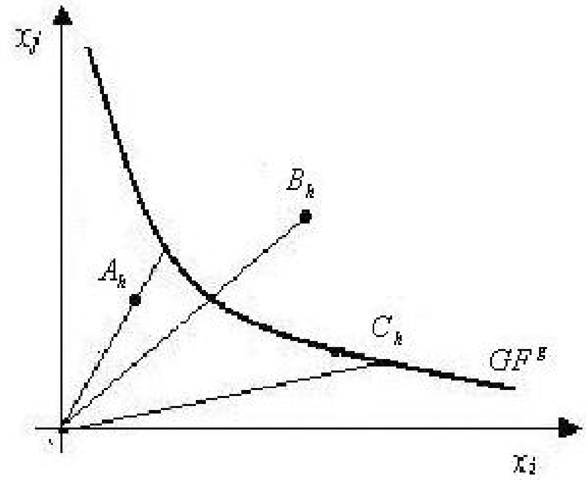
The objective of this approach is to examine whether there exist the difference between GF^g for all *g*. Though the approach is almost similar to the approach of Tulkens and Eeckaut (1995), this approach is different in two points. The first one is that this approach has only to examine whether the distance is one or not and the second one is that all efficient firms in a group must not have the distance of one from the efficient frontier for other groups in order for them to be different. The first one is that this approach has only to examine whether the distance is one or not and the second one is that all efficient firms in a group must not have the distance of one from the efficient frontier for other groups in order for them to be different. If an efficient firm in a group has the distance of one from the efficient frontier for the other group, the firm is on the efficient frontiers for both groups. Moreover, if all efficient firms in a group have the distance of one from the efficient frontier for the other group, the two groups have the same efficient frontier, which implies that they are not different groups. Figure 2.5.1 and Figure 2.5.2 illustrate the efficient frontiers and approach. Figure 2.5.1 and Figure 2.5.2 illustrate the efficient frontiers and approach.

Figure 2.5.1. The efficient frontiers for the new approach in peergroup verification



GF^{g} : group frontier for group g (g=g_1,g_2,g_3), and MF: mega frontier.

Figure 2.5.2. The new approach in peergroup verification



GF^g : group frontier for group g, that does not include firm A_h, firm B_h, and firm C_h, A_h: the input pair of firm A in group h, B_h: the input pair of firm B in group h, and C_h: the input pair of firm C in group h.

The modified approach is as follows:

Step 1. Estimate using DEA the technical efficiency of firms in each peergroup. DEA model used in this approach is different from general DEA model in that DEA in this approach allows the efficiency score is greater than one by dropping the constraint that the efficiency scores should be between zero and one from general DEA model.

Step 2. It is not necessary to worry about inefficient firms in each group because they are not on an efficient frontier. Keep efficient firms for each group. Suppose that the group of efficient firms in group g is $E^g = (E_1^g, ..., E_{m_g}^g)$ where m_g is the number of efficient firms in group g ($g=1, \ldots, G$).

Step 3. Estimate the relative distance of firms in E^g with respect to firms in group E^h $(g \neq h)$ using the Anderson and Peterson formulation. The fact that the distance is not equal to one implies that firm m in group g is not equal to the firms in group h. That the distance equals one implies that firm m in group g is equal to the firms in group h. If all firms in group g is different from firms in group h, group g can be said to be different from group h.

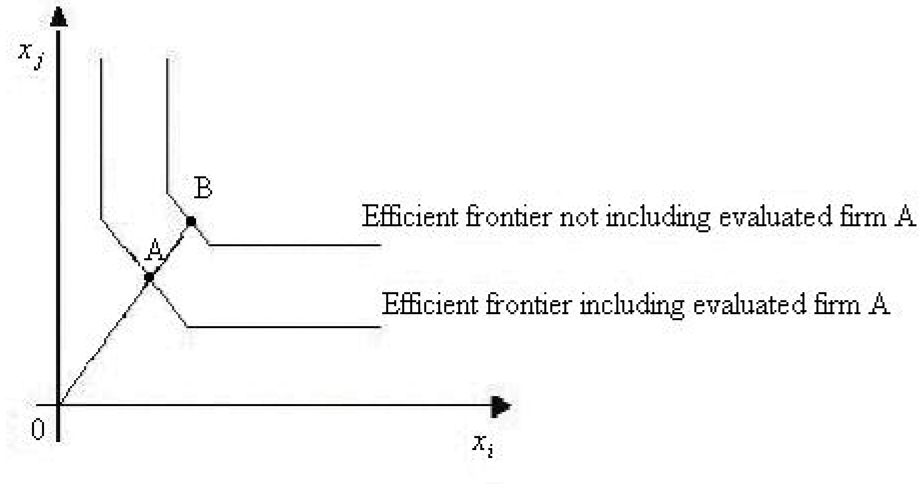
Step 4. Repeat step 3 until all groups are compared. Therefore, step 3 should be repeated ${}_{G}C_{2}$ times.

2.6. Identification of benchmark firms

After the above peergrouping process, the final peergroups of firms are composed and attention is next turned to finding benchmarks for each group. With these peergroups, DEA estimates of the technical efficiency for each group are computed. Firms found to be technically efficient from DEA results are regarded as candidates for benchmarks within a group. However, Athanassopoulos and Ballantine (1995) claim that more thorough analyses based on the properties of efficient firms are necessary. They suggest two further analyses to complement the technical efficiency: 1) the distance of the firm from the efficient frontier and 2) the frequency that a firm is used as a comparator.

The relative distance from the efficient frontier analysis uses the formulation of Anderson and Peterson (1993), see Appendix 2.1. The intuition of this approach is to compute the technical efficiency of a set of firms excluding the firm being evaluated. This measure is used for determining the similarity of an efficient firm to the other efficient firms within a group. If the efficient firm is similar to other efficient firms, the distance of the firm from the efficient frontier excluding it would be short and otherwise, the distance would be relatively long. Figure 2.6 illustrates how this distance is measured and how different this distance is from general technical efficiency.

Figure 2.6. Efficient frontiers with or without evaluated firm



A: firm A that is efficient when it is evaluated with respect to firms including it, B: the radial efficient point for firm A when the efficient frontier is formed not including firm A.

Suppose firm A is an efficient firm when it is evaluated with respect to group of firms including itself. When firm A is excluded from the group, because firm A is an efficient firm the new frontier will be contained by the original frontier, 'efficient frontier not including evaluated firm A'. Therefore, the distance of firm A from the new efficient frontier is greater than one. That is, $\overline{OB}/\overline{OA} \geq 1$ where B is the radial efficient point on the efficient frontier not including firm A for firm A. The efficient firms whose relative distance from the efficient frontier is close to one become candidates for benchmarks because as noted, they are similar to other efficient firms. In order for an efficient firm to be a benchmark, this distance should not be large. It must be less than two (2), which is called the ‘relative distance condition’ in this essay. The reason why two (2) is selected as the critical value for relative distance condition is arbitrary. In fact, Athanassopoulos and Ballantine (1995) and Hjalmarsson and Odeck (1996) do not present any clear criterion for the critical value of relative distance condition. In this essay, two (2) is selected because Athanassopoulos and Ballantine (1995) regarded the firms with the distance of greater than 2 as firms with high relative distance and the firms with the distance less than 2 as firms with not substantial distance.

Another criteria for identify benchmark firms to complement the relative distance measure is the frequency of an efficient firm used as a comparator for other firms within a group (Athanassopoulos and Ballatine, 1995; Hjalmarsson and Odeck, 1996). The frequency of an efficient firm used as a comparator in the evaluation of other firms should be considered. This frequency is a measure of the similarity of a firm to other firms including both other efficient firms and inefficient firms. If the frequency of a firm is high, the firm participates in the evaluation of other firms more often, which means that the firm is similar to other firms. This frequency is measured by counting the number of intensity values of firms (z_n, $n=1,\ldots, N$, where n is the index of firms, see Table A1.1) that are greater than zero for each efficient firm in each group. When the efficiency of firm n is estimated, constraints in DEA form a piecewise linear production frontier with the data of firms in a group determining the optimal intensity of each firm. This intensity value can be used as an indicator of whether an efficient firm participates in evaluating the technical efficiency of other firms. Generally, in order to be identified as a benchmark, an efficient firm should be used as a comparator for over 15% of the total number of firms in the same group. This criterion is called the ‘frequency condition’ in this essay. Also, the selection of '15%' is another arbitrary selection for the same reason as the relative distance condition. The reason why 15% is selected is based on the experience of DEA implementation. In other words, it has been found during DEA implementation for other data sets that firms that participate in the evaluation for other firms maximally do that about 15% of total number of firms. Therefore, if a number less than 15 is selected, too many firms may pass the frequency condition and if a number greater than 15 is selected, too few firms may pass the frequency condition.

One important issue for the approach proposed here is how to select benchmarks for firms (unique firms) that are not included in any peergroup. Since they are not included in any peergroup, their technical efficiency may not be estimated. Thus, the first step to select benchmarks for unique firms is to estimate the technical efficiency for them with respect to all firms in the original data set, F. The second step is to identify the benchmarks using the benchmarking approach of Athanassopoulos and Ballantine (1995), where the benchmarks are identified using DEA scores, the frequency condition, and the relative distance condition. Once the benchmarks from the benchmarking approach of Athanassopoulos and Ballantine (1995) are identified, the third step is to compare the set of benchmarks from the benchmarking approach of Athanassopoulos and Ballantine (1995) (B^{AB}) to the set of benchmarks from the new approach ($\bigcup_{g=1}^{G} B_g^{new}$, where B_g^{new} is a set of benchmarks for group g identified by the new approach). The benchmarks identified by the new approach would be eliminated from the benchmarks from the benchmarking approach of Athanassopoulos and Ballantine (1995). That is, $B^{Unique} = B^{AB} - \bigcup_{g=1}^{G} B_g^{new}$ where B^{Unique} is a set of benchmarks for unique firms, B^{AB} is a set of benchmarks identified by the benchmarking approach of Athanassopoulos and Ballantine (1995), and B_g^{new} is a set of benchmarks for group g identified by the new approach. Because B^{AB} will not be equal to $\bigcup_{g=1}^{G} B_g^{new}$ in most cases, $B^{Unique} \neq f$. All elements of B^{Unique} cannot be benchmarks for unique firms. After the scale of operation and the technology are reviewed, the closest firms (elements) of B^{Unique} to a unique firm will become benchmarks for the unique firm. This approach may be motivated in that the benchmarks for unique firms could be determined with respect to mega frontier in Figure 2.5.2 instead of group frontier because unique firms are not involved in any group. Moreover, because the benchmarks identified for other groups by the new approach are ruled out for the benchmarks for unique firms, benchmarks for unique firms are not overlapped with the benchmarks identified by the new approach. In fact, since the benchmarking approach of Athanassopoulos and Ballantine (1995) has been used frequently so far, this approach for unique firms is reasonable.

Another important issue is why inefficient firms should move to benchmarks identified by the new approach instead of to efficient but non-benchmark firms. This issue is to evaluate the utility of benchmarks and is raised because the relative distance condition and the frequency condition are also somewhat *ad hoc*. In fact, it can be said that the benchmarks identified by the new approach is more similar to other firms in a group as well as they are efficient. However, it does not always imply that the benchmarks identified by the new approach are better than efficient but non-benchmark firms. Therefore, it is necessary to establish an approach to compare the utility of benchmarks identified by the new approach to efficient but non-benchmark firms. In order to that, it is possible to use the approach used to find the efficient category level from nonradial model in Essay one. In other words, if the information on factor prices is available, it is possible to evaluate the goodness of benchmarks against other efficient firms by computing total input cost of benchmarks and other efficient firms. If total input costs of benchmarks are always less than those of other efficient firms, then benchmarks identified by the new benchmarking approach can be considered to be better than other efficient firms, and the new benchmarking process works well. However, in many cases, the information on prices is not available. In fact, the data set for this essay does not have the information. In this case, it is almost impossible to evaluate the difference between benchmarks and other efficient firms accurately. One suggestible approach is to compare the Euclidean distance of the benchmarks identified by the new benchmarking approach and the efficient but non-benchmark firms from the original points. If the distance of benchmarks identified by the new approach is always shorter than that of other efficient firms, benchmarks can be said to be better than other efficient firms. The motivation of these criteria is in Essay one.

2.7. Empirical illustration

An empirical illustration of DEA-based benchmarking is presented to illustrate how the new benchmarking approach is performed and to evaluate the new approach using a production data set through a comparison of the benchmarking approach based only on DEA scores and the benchmarking approach based on DEA scores and similarity analysis. The illustration provides a basis for considering whether the peergrouping process improves the quality of benchmarks, whether the similarity analysis improves the quality of benchmarks, and whether the scale of operation and preliminary nonradial DEA matter in benchmarking process.

For an application, data for soybean production in Pennsylvania in 1999 are used. Data follow from the 1999 Agricultural Resource Management Survey (ARMS). This data set is described in more detail in Essay one. The data set includes measures of soybean output, the scale of operation, variable input use, and damage control input use, including pesticides and fertilizers. The data set includes sufficient information to implement benchmarking based on measures of the scale of operation and of the pattern of nonradial technical efficiency across variable inputs in DEA.

Given the same data set that is used as in Essay one except that categorical variables are not used in this essay, the summary of data is also the same as in Essay one (see Appendix 1.3). Recently, the use of damage control inputs is an important issue in agricultural production related to environmental protection (Carpentier and Weaver, 1997). That is, the claim is that the efficient use of damage control inputs can contribute to reducing the pollution of soil and water. This data set can illustrate how to control the use of damage control inputs in agriculture through the benchmarking process. In fact, the results of benchmarking with this data set illustrate that there exist the overuse of damage control inputs in the soybean production of Pennsylvania and firms can reduce the use of them through benchmarking.

2.7.1. Peergrouping protocol

Two criteria are used to set peergroups in this essay: the scale of operation and the pattern of nonradial technical efficiency across variable inputs. These two criteria are used serially to set peergroups for the benchmarking process. The original data set is partitioned into subgroups in terms of the scale of operation and each group made by the scale of operation is also partitioned into subgroups in terms of the results of preliminary nonradial DEA. The result is a partitioning that establishes multiple groups, each containing more than one firm. As a result of this process, some firms cannot be classified with a group. In this case, such a firm is called 'a unique firm'.

As noted, for peergrouping the scale of operation of all (*N=136*) firms is first examined. The gross value of sales and total planted acres are used as the scale of operation variables. As a result, two sets of benchmarking results are generated one for each measure of scale of operation. Darr and Chern (2002) used the gross value of sales as a measure of the scale of operation for Ohio state soybean firms. Total planted acres also reflect the scale of operation.

Both the gross value of sales and total planted acres classify firms into four groups. The groups made by gross value of sales are illustrated in Figure 2.7.2, and the groups made by total planted acres are illustrated in Figure 2.7.1. Based on sales, the first group (up to $50,000) consists of 30 firms, the second group (Between $50,000 and $100,000) consists of 28 firms, the third group (Between $100,000 and $250,000) consists of 38 firms, and the fourth group (Over $250,000) consists of 40 firms for the gross value of sales. Based on acreage, the first group (up to 20 acres) consists of 46 firms, the second group (Between 20 acres and 40 acres) consists of 32 firms, the third group (Between 40 acres and 80 acres) consists of 28 firms, and the fourth group (Over 80 acres) consists of 30 firms for total planted acres. In the survey instrument, gross value of sales is measured as a categorical variable. These categories are used to partition the sample into subgroups. In contrast, total planted acres are measured as a continuous variable is in the survey. As noted in section 2.4, this frequency interval schemes is chosen to make sure that each group includes the enough number of firms to implement DEA.

Figure 2.7.1. Distribution of firms in terms of the gross value of sales

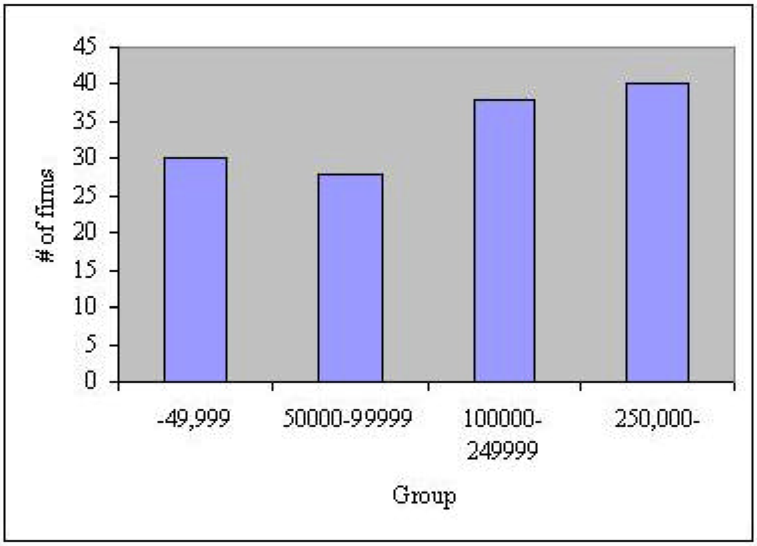
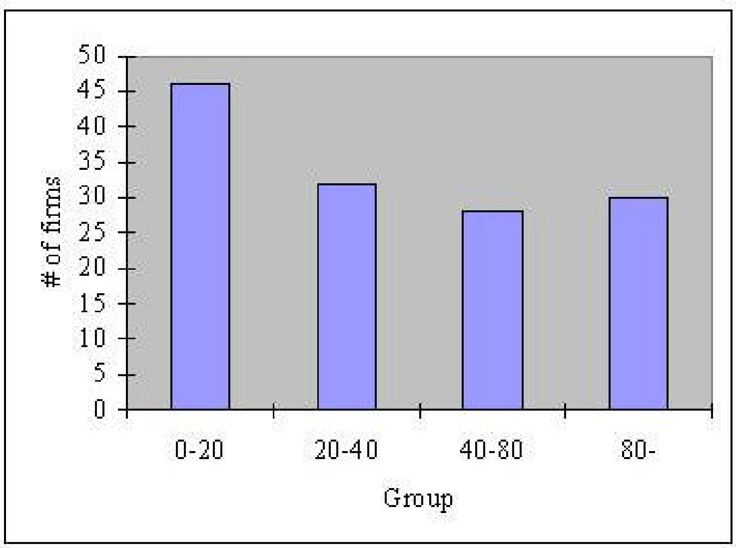


Figure 2.7.2. Distribution of firms in terms of total planted acres



The next criterion for peergrouping is the pattern of nonradial technical efficiency across variable inputs performed by the preliminary nonradial DEA for each group made by the scale of operation. Table 2.1 illustrates a sample of the results from this analysis for each group made by the gross value of sales. Each cell indicates the technical efficiency of each input for each firm. As noted in the section 2.4, it is possible to identify the different patterns of nonradial technical efficiency across variable inputs of firms.

The results for four firms in each of the first two groups of firms are presented in Table 2.1. As illustrated in Table 2.1, Firm 33 and Firm 54 in group 1 have different pattern of nonradial technical efficiency across variable inputs to produce current output because the efficiency scores for potash, nitrogen, phosphate, and the first use of pesticides are zero. Firm 61 in group 2 has a different pattern of nonradial technical efficiency across variable inputs because the efficiency scores for potash, nitrogen, phosphate, the use of pesticides, and manure are zero. On this basis, these firms are regrouped with firms having the same pattern of efficient frontier. However, during this regrouping process, because some firms may not find members in any group, these firms will be labeled as unique firms. For example, if Firm 54 of group 1 in Table 2.1 does not find a firm with the same pattern within group 1 it should be a unique firm.

Table 2.1. Estimates of nonradial DEA groups based on gross value of sales for the scale of operation

Description of variable inputs	Group 1 (Firm # in data)				Group 2 (Firm # in data)			
	F33	F36	F45	F54	F61	F69	F70	F76
Acres planted in selected field	0.9042	1.0000	1.0000	0.4000	0.3143	1.0000	0.3236	1.0000
Standardized seed rate to lbs/acre	0.1094	1.0000	1.0000	0.6061	0.4215	1.0000	0.1309	1.0000
Pounds of potash/acre	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000
Pounds of nitrogen/acre	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000
Pounds of phosphate/acre	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000
How much was applied/acre? (lbs.)-1st pesticide	0.5425	1.0000	1.0000	0.4000	0.0000	1.0000	0.0067	1.0000
How much was applied/acre? (lbs.)-2nd pesticide	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	1.0000	1.0000
Gallons of manure applied/acre	1.0000	1.0000	1.0000	0.0000	0.0000	1.0000	0.3436	1.0000

After the above two analyses, there exist three peergroups with more than 15 firms and a set of unique firms with the gross value of sales for peergrouping, and two peergroups with more than 15 firms and a set of unique firms with total planted acres. The reason for the selection of 15 firms is discussed in section 2.4. The three peergroups for the gross value of sales consist of one from the interval less than $49,999 (19 firms), one from the interval between $100,000 and $249,999 (19 firms), and one from the interval of more than $250,000 (26 firms). Thus, 64 firms are included in peergroups and 72 firms are left as unique firms. Two peergroups for total planted acres consist of one from the interval less than 20 acres (26 firms) and one from the interval between 40 acres and 80 acres (21 firms). Thus, 47 firms are included in peergroups and 89 firms are left as unique firms.

2.7.2. Peergroup verification and benchmark identification

Before going on to the stage to find benchmarks for each group, it is necessary to verify whether the peergroup approach identified firms that in fact face different production frontiers. Table 2.2 presents the results of the verification test for the case of the gross value of sales for the scale of operation by using the verification approach described in section 2.5. The firms presented in Table 2.2 are the efficient firms in each group and the values under the title of 'distance from the efficient frontier for group #' indicate the distance of a firm in each group from the efficient frontier for that group #. For example, Firm 7 in group 1 has the distance of 2.0000 and 2.6894 from the efficient frontier for group 2 and 3, respectively. It implies that Firm 7 is different from the firms in group 2 and 3 because the distance of Firm 7 from the efficient frontiers for group 2 and group 3 is never one. In conclusion, it can be said that each group is different from other groups because no firm in each group has the distance of one from the efficient frontiers for other groups. This implies that these three groups indeed face different production frontiers and the peergrouping protocol was effective in grouping firms that differ by the frontier they face.

Table 2.2. Results of verification of difference between peergroups with the gross value of sales for the scale of operation

Group 1			Group 2			Group 3		
Firm	Distance from the efficient frontier of group 2	Distance from the efficient frontier of group 3	Firm	Distance from the efficient frontier of group 3	Distance from the efficient frontier of group 1	Firm	Distance from the efficient frontier of group 1	Distance from the efficient frontier of group 2
F7	2.0000	2.6894	F18	0.6795	1.2171	F12	7.0000	1.4401
F14	6.4000	4.8000	F25	2.3881	1.1111	F21	8.5690	4.2845
F36	0.8750	0.7000	F32	0.7549	0.5410	F23	1.0172	1.9925
F45	0.6178	0.9572	F38	1.8211	1.1572	F43	1.8003	1.0806
F56	2.9388	1.9923	F39	0.8557	1.3158	F51	5.3066	3.6576
F57	5.5636	0.7323	F47	18.1818	8.3333	F65	0.7500	3.0000
F77	1.9041	2.2404	F48	6.7619	39.6667	F72	6.8078	1.2312
F89	0.3281	0.4430	F69	0.7447	0.4839	F78	1.3196	1.2918
F98	3.6000	4.4500	F76	1.3723	0.9035	F86	1.0714	0.7143
F108	1.2000	2.5000	F99	1.1667	5.8333	F90	10.0000	8.9583
F112	1.8039	0.6345	F121	1.6222	1.5000	F95	8.3333	7.5000
F113	1.0168	1.0330	F123	3.5279	6.2500	F97	10.4125	1.5587
F116	0.6667	1.0815	F128	0.8824	1.0526	F100	0.9009	1.1133
F125	0.5143	0.6186	F132	2.2228	7.0291	F109	11.2500	6.2500
F133	0.6848	0.4032				F129	5.1125	1.0720
F136	0.9000	3.3333				F131	7.2018	5.5514
						F134	4.8924	2.6331

The values in table are the relative distance of efficient firms in each group from the efficient frontier for other groups. Since there is no distance of one, groups are different from other groups.

In order to find benchmarks for each group, four values generated by DEA estimates are computed for each group: 1) radial and 2) nonradial DEA efficiency scores, 3) frequency used as a comparator in both radial model and nonradial model, and 4) the relative distance from the efficient frontier. Table 2.3.1 and Table 2.3.2 illustrate the results of the analyses for group 1 identified by the gross value of sales and by total planted acres for the scale of operation. Based on both radial and nonradial measure, group 1 with the gross value of sales for the scale of operation has 16 technically efficient firms out of 19 firms, and group 1 with total planted acres has 19 technically efficient firms out of 26 firms. Because technical efficiency scores from nonradial measure are always at least equal to those from radial measure (Fare, Grosskopf, and Lovell, 1994), nonradially efficient firms are also radially efficient. Among these firms (16 for sales and 19 for acreage), benchmarks are selected based in 1) the frequency that the firms are used as a comparator and 2) the relative distance of the firms from the efficient frontier. As noted in section 2.6, to become a 'perfect' benchmark, an efficient firm should be used as a comparator for over 15% of the number of firms in the group, and the relative distance from efficient frontier should be less than two (2).

It is possible for no benchmark identified for a group because no efficient firms in a group can pass both the relative distance condition and the frequency condition. For that case, if one of the above conditions is satisfied and the other one is not satisfied by a small margin, or one condition is satisfied very definitely though the other condition is not satisfied, the firm can be labeled as a 'pseudo' benchmark. The importance of pseudo benchmarks is that they can be used as benchmarks when there does not exist any perfect benchmark within the group. However, this does not imply that perfect benchmarks always dominate pseudo benchmarks. This issue is also related to the utility of benchmarks problem discussed in section 2.6. Which one dominates could be determined by evaluating the utility of benchmarks using approaches suggested in section 2.6.

In Table 2.3.1 and Table 2.3.2, '*V*' indicates that the firm is a perfect benchmark and $'\tilde{V}'$ indicates the firm is a pseudo benchmark. Firm 98 in Table 2.3.1 satisfies all conditions to be benchmark because they are efficient, are used as comparators over 15% of the number of firms in group, and the relative distance from efficient frontier of them is less than 2. Firm 36 and Firm 89 in Table 2.3.1 satisfy conditions for being perfect benchmarks. Firm 36 violates the frequency condition by a small margin while it satisfies the relative distance condition. Firm 45 satisfies conditions for being a pseudo benchmark because the relative distance condition and the frequency condition in nonradial measure are satisfied definitely but the frequency condition in radial measure is not satisfied. Table 2.3.2 report one perfect benchmark and three pseudo benchmarks. Firm 108 is the perfect benchmark. Firm 7, Firm 71, and Firm 132 in Table 2.3.2 satisfy conditions for being pseudo benchmarks. Firm 7 and Firm 132 violate the relative distance condition while they satisfy the frequency condition. Firm 71 satisfies the relative distance condition definitely because the relative distance of them from the efficient frontier is very close to one (1) but they do not satisfy the frequency condition by a small margin.

Table 2.3.1. Benchmarking result of group 1 with the gross value of sales for the scale of operation

Benchmark	DEA efficiency		Frequency used as a comparator		Relative distance
	Firm	Score	Radial	Nonradial	
	F7	1.0000	3	1	9.4451
	F14	1.0000	1	1	4.0000
$\tilde{\boldsymbol{V}}$	F36	1.0000	3	3	1.4167
	F45	1.0000	1	4	1.4688
	F56	1.0000	1	1	1.3455
	F57	1.0000	1	1	2.2933
	F77	1.0000	3	2	1.9548
V	F89	1.0000	5	3	1.2426
	F98	1.0000	1	1	1.3236
	F108	1.0000	1	1	1.8000
	F112	1.0000	1	1	2.0000
$\tilde{\boldsymbol{V}}$	F113	1.0000	3	1	1.7933
	F116	1.0000	3	2	2.0000
	F125	1.0000	1	1	1.2950
	F133	1.0000	1	1	2.1277
	F136	1.0000	1	1	1.9500

V: perfect benchmark, $\tilde{\boldsymbol{V}}$: pseudo benchmark

Table 2.3.2. Benchmarking result of group 1 with total planted acres for the scale of operation

Benchmark	DEA efficiency		Frequency used as a comparator		Relative distance
	Firm	Score	Radial	Nonradial	
$\tilde{V}$	F7	1.0000	5	4	3.3160
	F9	1.0000	4	2	1.6671
	F14	1.0000	1	1	5.3333
	F25	1.0000	2	2	2.8508
	F48	1.0000	2	2	2.8409
$\tilde{V}$	F56	1.0000	1	4	1.8500
	F65	1.0000	1	1	1.3667
	F71	1.0000	3	4	1.2211
	F72	1.0000	1	1	2.9430
	F77	1.0000	2	1	1.6211
	F102	1.0000	1	2	2.7845
	F107	1.0000	1	1	2.6671
	F108	1.0000	4	6	1.2000
	F113	1.0000	1	2	1.0236
	F114	1.0000	1	1	2.5917
	F117	1.0000	1	1	2.0000
	F120	1.0000	1	1	1.1537
	F121	1.0000	1	1	2.6666
$\tilde{V}$	F132	1.0000	6	7	2.9267

Table 2.4.1 and Table 2.4.2 present the benchmarking results for group 2. With the same logic as in the results for group 1, Firm 69 in Table 2.4.1 satisfies the conditions for being a perfect benchmark in group 2. Firm 123 and Firm 128 in Table 2.4.2 satisfy conditions for being pseudo benchmarks. Table 2.4.2 have one perfect benchmark and three pseudo benchmarks. Firm 26 is the perfect benchmark. Firm 21, Firm 53, and Firm 109 in Table 2.4.2 satisfy conditions for being pseudo benchmarks.

Table 2.4.1. Benchmarking result of group 2 with the gross value of sales for the scale of operation

Benchmark	DEA efficiency		Frequency used as a comparator		Relative distance
	Firm	Score	Radial	Nonradial	
$\tilde{V}$	F18	1.0000	1	1	1.0586
	F25	1.0000	1	1	2.9683
	F32	1.0000	1	1	1.1679
	F38	1.0000	1	1	1.4997
V	F39	1.0000	1	1	2.5527
$\tilde{V}$	F47	1.0000	1	1	1.6740
	F48	1.0000	1	1	1.8269
	F69	1.0000	4	3	1.0870
	F76	1.0000	1	1	2.0690
	F99	1.0000	1	1	2.3887
	F121	1.0000	1	1	2.2222
	F123	1.0000	3	4	3.2407
	F128	1.0000	3	1	1.3509
	F132	1.0000	2	2	3.6143

Table 2.4.2. Benchmarking result of group 2 with total planted acres for the scale of operation

Benchmark	DEA efficiency		Frequency used as a comparator		Relative distance
	Firm	Score	Radial	Nonradial	
$\tilde{V}$	F21	1.0000	3	4	2.1479
	F23	1.0000	2	1	4.0252
	F26	1.0000	3	5	1.0660
	F47	1.0000	1	1	1.2998
	F49	1.0000	2	2	1.9648
	F51	1.0000	1	1	1.6604
	F53	1.0000	2	6	1.1877
	F63	1.0000	1	1	1.5000
	F89	1.0000	1	1	2.7407
	F96	1.0000	2	2	2.6050
	F97	1.0000	1	1	1.4665
	F101	1.0000	1	1	2.9575
	F109	1.0000	4	3	1.5621
$\tilde{V}$	F129	1.0000	2	2	2.0000
	F131	1.0000	1	3	1.6999
	F134	1.0000	1	1	5.4300

As seen so far, there may exist multiple benchmarks in each group even with the new approach because the new approach also regards a firm as a benchmark if and only if it passes the described conditions. Because the problem how the ‘best’ benchmark can be identified is also related to the utility of benchmarks described in section 2.6, this problem can be solved by using the approach suggested in section 2.6.

Table 2.5 presents the benchmarking results for group 3 with the gross value of sales for the scale of operation. With the same logic as in the results in the above table, Firm 78 and Firm 100 satisfy the conditions for being perfect benchmarks in group 3. Firm 23 and Firm 43 satisfy conditions for being pseudo benchmarks. Firm 43 satisfies the relative distance condition but it violates the frequency condition. Firm 23 satisfies the frequency condition though it violates the relative distance condition.

Table 2.5. Benchmarking result of group 3 with the gross value of sales for the scale of operation

Benchmark	DEA efficiency		Frequency used as a comparator		Relative distance
	Firm	Score	Radial	Nonradial	
	F12	1.0000	1	0	1.9939
V	F21	1.0000	5	3	1.6230
$\tilde{\boldsymbol{V}}$	F23	1.0000	7	6	2.2200
$\tilde{\boldsymbol{V}}$	F43	1.0000	2	4	1.1625
	F51	1.0000	1	1	1.5589
	F65	1.0000	2	2	1.6905
	F72	1.0000	1	3	1.2695
$\tilde{\boldsymbol{V}}$	F78	1.0000	4	5	1.0761
	F86	1.0000	1	1	2.6918
	F90	1.0000	2	2	4.4148
	F95	1.0000	1	1	1.2578
V	F97	1.0000	1	1	1.4904
	F100	1.0000	4	5	1.0591
	F109	1.0000	2	2	1.3500
	F129	1.0000	1	1	2.6509
	F131	1.0000	3	1	1.6412
	F134	1.0000	1	1	2.9238

This new benchmarking process successfully identifies benchmarks for each group. In this data set, because using the gross value of sales as the scale of operation measure gives us better results than using total planted acres, the results using the gross value of sales for the scale of operation are used for comparison to the other approaches.

The illustration of the benchmarks for unique firms with the gross value of sales for the scale of operation is as follows. The results from the benchmarking approach by Athanassopoulos and Ballantine (1995) present the fact that Firm 7, Firm 48 and Firm 98 are perfect benchmarks, and Firm 30, Firm 90 and Firm 119 are pseudo benchmarks (see Table A2.2).

2.7.3. Empirical comparison between the new approach and other approaches with 1999 ARMS soybean production data in Pennsylvania

This subsection illustrates the comparison of results between from the new approach and other approaches in empirical application to 1999 Pennsylvania ARMS soybean production data. This subsection is meaningful in that the differences in the results from alternative benchmarking approaches are illustrated. That is, the new benchmarking approach is comparatively evaluated to other benchmarking approaches empirically. This subsection is based on the results from the case where the gross value of sales is used as a measure of the scale of operation.

First, the benchmarking approach based only on DEA efficiency scores by Horsky and Nelson (1996) is compared to the new benchmarking approach. The results of the benchmarking approach based only on DEA efficiency scores illustrate that there are 25 benchmarks identified for the sample (See Table A2.1). It is difficult for an inefficient firm to find a firm to benchmark because the firm does not have any information which of 25 benchmarks is similar to itself.

Second, the benchmarking approach based on DEA scores and similarity analysis by Athanassopoulos and Ballantine (1995) is compared to the new benchmarking approach. While their approach can reduce the number of benchmarks from 25 of the benchmarking process based only on DEA efficiency scores by Horsky and Nelson (1996) to 6 (3 perfect benchmarks and 3 pseudo benchmarks: see Table A2.2) through similarity analysis, benchmarks identified by the new approach can be regarded as better benchmarks because they were identified from peergroups of similar firms and the peergrouping process was verified that it could identify different peergroups (see Table 2.2). Though the number of benchmarks is reduced and it is possible to find benchmarks for each group by the new approach, the problem of identifying the best benchmark for each inefficient firm still remains to be addressed when multiple benchmarks are found.

Third, the benchmarking approach based on preliminary nonradial DEA for peergrouping not the scale of operation, and DEA scores and similarity analysis is compared to the new approach. This approach gives us 2 benchmarks for only 41 firms among 136 firms because of the existence of unique firms while the new approach gets benchmarks for 64 firms. Preliminary nonradial DEA generates 95 unique firms because it was run without previously grouping firms in terms of the scale of operation (See Table A2.3). Compared the benchmarking approach based on preliminary nonradial DEA for peergrouping not the scale of operation to the benchmarking approach using only the scale of operation for peergrouping not preliminary nonradial DEA, and using DEA scores and similarity analysis, the approach can get benchmarks for all 136 firms.

However, it is important to examine the difference in pattern of efficient frontier in DEA between firms.

2.8. Conclusion

The problem in Essay 2 is to consider how firms improve their own technical efficiency through their own efforts. In order to examine this problem, this essay suggests a quantitative peergrouping approach and benchmarking approach for the improvement of technical efficiency. Benchmarking can be defined as the continuous process of evaluating and improving business practices against the firms with the best performance. The firms with the best performance are called 'benchmarks'. The performance measure for benchmarking is technical efficiency scores estimated by Data Envelopment Analysis. The main reason why DEA is selected as an estimation method of technical efficiency is that DEA can find the firms with the best technical efficiency while parametric methods just estimate the average performance firms.

DEA-based benchmarking has been considered in the past. Some researchers (Golany and Thore, 1997; Ray and Desli, 1997) concentrate on the benchmarking approach based only on DEA efficiency scores. In the research, only if a firm is technically efficient, the firm becomes a benchmark. Other researchers (Athanassopoulos and Ballatine, 1995; Hjalmarsson and Odeck, 1996) deal with benchmarking approach based on DEA efficiency score and similarity analysis such as the relative distance from the efficient frontier and the frequency used as a comparator. Athanassopoulos and Ballatine (1995), and Volkers and Hickey (1996) presented an approach for identification of benchmarking firms that uses similarity measures such as the frequency of a firm used as a comparator and the relative distance of a firm from the efficient frontier.

Hjalmarsson and Odeck (1996) investigated the efficiency of trucks in road construction and road maintenance using DEA within framework of which benchmark is derived. They used wage, fuel, rubber, and maintenance as inputs and effective hours in production and total transport distance as 2 alternative outputs. They also used two criteria: the relative distance from efficient frontier and the frequency used as comparators. However, these past researches did not use a peergrouping process.

The new benchmarking approach consists of two stages. The first stage is the peergrouping. Firms in a data set can differ across a variety of important characteristics such as the scale of operation and the pattern of nonradial technical efficiency across variable inputs in DEA. Based on the above literature review, the main contribution to the new DEA-based benchmarking approach proposed in this essay is to present a quantitative peergrouping process that may make the benchmarking results more reasonable. This peergrouping step fragments the data set into groups that are called peergroups in terms of the scale of operation and the pattern of nonradial technical efficiency across variable inputs in DEA. The two criteria are enforced in a series. That is, the original data set is classified into subgroups by the scale of operation and each group generated by the scale of operation is finally reclassified into subgroups by the pattern of nonradial technical efficiency across variable inputs in DEA. Before going on to the benchmarking process, it is necessary to verify whether the groups generated by the peergrouping process are different from the other groups or not because the criteria used in peergrouping process are somewhat *ad hoc*. For this verification process, a modified approach of Tulkens and Eeckaut (1995) is used. The second stage, radial and nonradial technical efficiency for firms in each group are estimated, and the similarity analysis such as the relative distance of efficient firms from efficient frontier and the frequency used as a comparator of efficient firms are estimated. With technical efficiency scores, similarity measure, and relative distance from efficient frontier, the benchmarks for each peergroup are determined. That is, in order to be a benchmark of a peergroup, a firm must be technically efficient in the use of inputs, the frequency used as a comparator should be quite large, and the relative distance from efficient frontier should be quite small. A firm that satisfies all of three conditions can be identified as a 'perfect' benchmark and a firm that violates one of three conditions slightly can be identified as a 'pseudo' benchmark.

It is expected that benchmarks are found for each peergroup providing a prescriptive basis for technical inefficient firms to improve their production performance. An empirical application of the new approach is also implemented using the data from the 1999 Agricultural Resource Management Survey for soybean production in Pennsylvania. The empirical application illustrates that the peergrouping process can identify the peergroups that are different in the scale of operation and the different pattern of nonradial technical efficiency across variable inputs in DEA, and the benchmarks identified by the new approach seem to be better than benchmarks identified by the benchmarking approaches based only on technical efficiency scores, based on technical efficiency scores and similarity analysis, or based on the peergrouping and technical efficiency scores in that benchmarks identified by the new approach have the similar characteristics (the scale of operation and the pattern of nonradial technical efficiency across variable inputs in DEA). However, the utility of benchmarks should be evaluated using total input cost or Euclidean distance like in Essay 1.

The main contribution of this essay is to extend other DEA-based benchmarking approaches by adding peergrouping approach to benchmarking. If the peergrouping approach can identify the different peergroups, this new benchmarking approach works to find benchmarks.

Appendix 2.1. Andersen and Petersen (AP) model

The original objective of the AP model is to fix or eliminate the errors in the data set. After determining the specification of the DEA model, it is necessary to screen the observations with the potential of errors and fix or eliminate them from data file. That is, some observations can have errors for various reasons that can corrupt the result. In order to do that, the super-efficient AP formulation is used (Andersen and Petersen, 1993). This model is different from the general DEA model in that the evaluated firm does not participate in forming the efficient frontier. Therefore, this model can estimate the distance of a firm from the efficient frontier not including itself.

AP model (Anderson and Petersen model)

$$\underset{l,z}{Min}\ l$$

Constraints

$$\sum_{n \neq n_0}^{N} z_n x_{ni} \leq x_{n_0 i}\, l\ ,\ i = 1,2,\ldots,I\text{: Variable inputs}$$

$$y_{n_0 m} \leq \sum_{n \neq n_0}^{N} z_n y_{nm}\ ,\ m = 1,2,\ldots,M\text{: Outputs}$$

Non-negative constraints

How to find error data through AP model is not described here because this essay is not interested in that. In addition to the detection of error data, the AP model can be used to estimate the relative distance of firms from the efficient frontier and can be used to verify the difference between peergroups as described in this essay. Also, Tukens and Eeckaut (1995) used the AP model to verify the difference in technology between periods.

Appendix 2.2. Summary of other benchmarking approaches

Table A2.1. Benchmarks identified by benchmarking approach based on only DEA scores

Benchmarks	F1, F7, F12, F14, F21, F23, F25, F30, F47, F48, F51, F56, F71, F77, F90, F95, F98, F108, F109, F114, F119, F121, F128, F131, F132

Table A2.2. Benchmarks identified by benchmarking approach based on DEA scores and similarity analysis

Benchmarks	DEA efficiency		Frequency		Relative distance
	Firm	Score	Radial	Nonradial	
$\tilde{\boldsymbol{V}}$	F7	1.0000	31	26	1.4177
	F12	1.0000	1	1	2.8036
$\tilde{\boldsymbol{V}}$	F14	1.0000	3	3	4.0000
	F21	1.0000	11	7	1.1080
$\tilde{\boldsymbol{V}}$	F23	1.0000	4	3	1.0172
$\tilde{\boldsymbol{V}}$	F25	1.0000	2	1	2.7986
V	F30	1.0000	21	13	1.1946
	F47	1.0000	9	6	1.2376
	F48	1.0000	29	23	1.4307
$\tilde{\boldsymbol{V}}$	F51	1.0000	1	2	2.9380
$\tilde{\boldsymbol{V}}$	F56	1.0000	2	5	1.1935
	F71	1.0000	5	9	1.0811
V	F77	1.0000	15	9	1.4580
	F90	1.0000	33	21	2.3959
	F95	1.0000	5	7	1.0798
	F98	1.0000	43	34	1.2471
	F108	1.0000	4	2	1.2000
	F109	1.0000	5	4	1.3500
	F114	1.0000	4	1	1.6455
	F119	1.0000	79	69	2.6546
	F121	1.0000	4	2	2.7222
$\tilde{\boldsymbol{V}}$	F128	1.0000	1	1	2.4948
	F131	1.0000	6	5	1.0206
	F132	1.0000	12	6	1.3699

Table A2.3. Benchmarks identified by benchmarking approach based on preliminary nonradial DEA, DEA scores and similarity analysis

Benchmark	DEA efficiency		Frequency		Relative distance
	Firm	Score	Radial	Nonradial	
	F2	1.0000	1	1	1.4177
	F4	1.0000	1	1	0.8036
	F5	1.0000	1	1	4.0000
	F6	1.0000	1	1	1.1080
	F7	1.0000	2	1	1.0172
	F8	1.0000	2	1	0.7986
V	F9	1.0000	2	1	1.1946
	F10	1.0000	3	2	1.2376
	F11	1.0000	5	3	1.4307
	F13	1.0000	1	1	0.9380
	F14	1.0000	1	1	1.1935
	F18	1.0000	1	1	1.0811
V	F19	1.0000	1	1	1.4580
	F22	1.0000	3	1	2.5952
	F23	1.0000	2	1	1.0798
	F25	1.0000	4	6	1.2471
	F26	1.0000	1	1	1.2000
	F27	1.0000	1	1	1.3500
	F29	1.0000	1	2	1.6455
	F33	1.0000	12	9	2.6546
	F34	1.0000	2	1	0.7222
$\tilde{V}$	F36	1.0000	1	1	0.4948
	F38	1.0000	2	2	1.0235
	F39	1.0000	1	1	1.3699

Essay 3
Supply Chain Contracting to Manage Quality and Technical Efficiency

Production processes typically generate quantity flows and quality flows simultaneously. This simultaneity in production of quantity and quality often implies that the management of quantity flows will also require the management of quality flows. Quality is important in a supply chain because the quality of products produced by suppliers may affect the quality of products produced by procurers. In other words, since products produced by suppliers are used as raw material inputs for products produced by procurers, the quality of products supplied from suppliers may become one of the most important determinants of both the quantity and quality of products produced by procurers. Therefore, the performance of both quantity and quality in supply chains will be dependent on how the quality of product produced by suppliers is coordinated through supply chains. However, the nature of quality flows often implies that decentralized coordination may result in a failure in supply chain performance and technically inefficient production by suppliers.

As noted, the coordination of product quality is an important determinant of the performance of supply chains. Optimal supply chain coordination would induce production of high quality that is expected by procurers, and is technically and allocatively efficient at each point along the supply chain. If quality were traded in a perfectly competitive market, then a market price would be established that reflects the average cost of quality production. This possibility of pricing quality would induce optimal supply of quality in the supply chain. However, this is possible only when the quality is perfectly observable along the supply chain. Importantly, in this case, competitive markets along the supply chain would result in socially Pareto-optimal performance. In addition, technically inefficient suppliers would be driven out of perfectly competitive markets because the price of quality would be determined to be equal to the average cost of technically efficient suppliers, a level that would be exceeded by technically inefficient suppliers.

However, quality may not satisfy the conditions for a perfectly competitive market. In many cases, it is impossible or very difficult for procurers and even suppliers to observe perfectly and accurately before procurers consume a product (Akerlof, 1970). For example, when a customer buys a car, she/he would find it difficult to acquire information concerning the probability of a breakdown in the future. Even after they use a car for a while, they cannot evaluate its quality accurately. That is, a driver does not have full information concerning the possibility of a breakdown in the future though she/he can have more information than before buying it. If quality is imperfectly observable, it cannot be priced in the market. This imperfect observability of quality causes market failure in the pricing and supply of quality.

Another important implication of the imperfect observability of quality is that suppliers may be persistently technically inefficient in producing quality. The imperfect observability of quality may lead suppliers to produce quality technically inefficiently because the imperfect observability of quality leads suppliers not to perceive their quality production function accurately. Persistent technical inefficiency in production of quality will impact production costs at downstream points of the supply chain. The first two essays focus on the estimation of technical efficiency when persistent technical inefficiency generated by imperfectly observable quality exists and the improvement of such technical efficiency by firm's own efforts. This essay focuses on the management of quality and technical efficiency in supply chain through contracts.

The types of quality and implications for the market performance of the various types of quality as an output flow or product characteristic have been considered from a variety of perspectives. One strand of literature has focused on the question of imperfect observability of quality and quality market failure. Akerlof (1970) claims that where it is imperfectly observable, markets will fail and poor quality products (lemons) will drive out high quality products. The quality is regarded as an experience good when quality is imperfectly observable (Ungern-Sternberg and Weizsacker, 1985; Allen, 1988). The demand of this experience good is based on the assumption that if a supplier has supplied good quality in past, she/he will supply good quality in the future (Ungern-Sternberg and Weizsacker, 1985). Moreover, quality may have the properties of reputation goods (Satterthwaite, 1979; Pauly and Satterthwaite, 1981) if the quality is not perfectly observable to consumers or procurers in the market but there exist some associates who have information on suppliers unlike the experience good. The reputation good is defined as the product that is differentiated across suppliers and the information affecting the decision of purchase comes primarily from other associates who know much about each supplier. In this case, the increasing monopoly phenomenon can occur in market. The increasing monopoly phenomenon is defined that as the number of suppliers increases the price of the product increases in monopolistic competition (Pauly and Satterthwaite, 1981). This is totally different result from general microeconomic theory. Therefore, if quality is a reputation good, quality price in the market is increased as the number of suppliers increases. As a result, consumers or procurers will pay more for the same quality. This may also be regarded as a kind of market failure.

If quality is perfectly observable, it can be regarded as a search good like quantity (Nelson, 1970) and can be priced in the market socially Pareto-optimally, as noted. Spence (1975) claims that if quality is perfectly observable, the supply of quality is based on the consumers' marginal valuation of quality. Leland (1977) and Hueth and Ligon (1999) use the 'characteristics approach' to describe the quality instead of treating different quality levels of a product as different goods. This characteristics approach has a metric to determine the closeness of different products. Dorfman and Steiner (1954), and Douglas and Miller III (1974) insert quality into demand function as an argument. Therefore, the price of product is also a function of quality. As a different approach to include quality in economic analysis, many studies such as Schoenberger (1990), Zeithaml, Parasuraman, and Berry (1990), and Lederer and Rhee (1995) measure quality by customer satisfaction.

In this essay, quality is considered to be imperfectly observable to suppliers and procurers in the competitive market. As a result, quality is not priced in the market and is not supplied and demanded socially Pareto-optimally in the market, and quality may be produced technically inefficiently. Procurers cannot obtain the quality that they want from suppliers and suppliers cannot get the price for quality that they produced. This market failure is only to degrade the performance of supply chain. To solve this problem, vertical organization management alternatives are available. Procurers and suppliers can be vertically integrated (vertical integration). Vertical integration occurs when a firm includes two single output production processes in which either the entire output of the supplier is employed as part or all of the quantity of one intermediate input to the procurer, or the entire quantity of one intermediate input to the procurer is obtained from part or all of the outputs of the supplier (Perry, 1989). Thus, vertical integration tries to maximize the joint profit of supplier and procurer, $Max\, p_p + p_i$ where p_p is the profit of procurer and p_i is the profit of supplier integrated by the procurer. Some more research is available to examine the properties of vertical integration. Grossman and Hart (1986) define vertical integration as the ownership and complete control over assets. Perry (1989) takes three determinants of vertical integration: technological economies, transactional economies, and market failure. Perry (1989) and Royer (1998) claim that vertical integration in response to technological or transactional economies would generally increase welfare, while vertical integration in response to market failure may increase or decrease welfare. Because the problem in this essay deals with quality market failure from the imperfect observability of quality, using vertical integration to resolve this problem cannot guarantee an improvement in social welfare. Actually, transaction cost analysis of vertical integration by Williamson (1979) illustrates the relative advantage of contracts to vertical integration. The study can be a motivation of contracts as a tool to resolve market failure.

Contracts are a good compromise of two extreme cases (competitive market and vertical integration) and can increase social welfare (Williamson, 1979). In fact, contracts increase the social welfare in many industries because procurers can get what they want and suppliers can sell what they produce with stability in the process (Lazear, 1996; Banker, Lee, and Potter, 1996; Fernie and Metcalf, 1996). Both procurers and suppliers can avoid market risks such as price risk and quantity risk through contracts.

Contracts enable procurers to affect the production process of suppliers without incurring additional costs unlike in a vertical integration. Therefore, a contract scheme is also designed between suppliers and procurers in this essay.

The basic story of the contract is that suppliers produce a product to supply to procurers (quality is imperfectly observable to suppliers and procurer), procurer purchases the product from suppliers, procurer measures the quality of product after the product arrived (quality is known to both suppliers and procurer), procurer determines the direct incentives for quality achievement (still persistent technical inefficiency exists in suppliers). Thus, under contract, quality achievement can be priced (direct incentives) and procurers can encourage suppliers to improve quality by giving them direct incentives. While these direct incentives can control the quality achievement and lead suppliers to report their production ability truly, suppliers are still technically inefficient in the use of quality inputs because of imperfect observability of quality. This technical inefficiency can lead suppliers to have higher production cost and procurers to spend more money in procuring quality. In order to control this technical inefficiency, procurer may give the incentives for the technically efficient part of quality input use to suppliers (indirect incentives). These indirect incentives can help improve quality because more technically efficient suppliers can have the capability to use more quality inputs.

Proposed is an analysis of 'indirect' incentives for quality inputs used by suppliers to control technical efficiency as well as 'direct' incentives to improve the quality achievement. Technical efficiency for quality inputs of suppliers in a contract pool is measured by the procurer after quality is measured and suppliers notify the amount of quality inputs used by them to the procurer. Nobody has studied this topic though there has been a lot of literature written about the effects of incentives on performance.

However, there may exist information asymmetry between procurer and suppliers on two things: the ability of suppliers, and the technical efficiency of suppliers. The information asymmetry on quality production ability of suppliers implies that suppliers can lie about their quality production ability to procurer when suppliers can obtain extra profit by reporting their production ability untruthfully, where quality production ability is not changeable by the supplier themselves in the short-term. The information asymmetry on the technical efficiency of suppliers implies that suppliers can lie about their technical efficiency to procurer when suppliers can obtain extra profit by reporting their technical efficiency untruthfully, where suppliers with the same production ability could have different technical efficiency in the production of quality. In this essay, because of the indirect incentives, it is possible for suppliers to obtain the extra profit by reporting their technical efficiency untruthfully. Reporting their technical efficiency untruthfully is possible by notifying the amount of quality inputs used by them untruthfully to procurer. If procurer cannot observe the production process of suppliers, this information asymmetry on quality production ability of supplier and the amount of quality inputs used by suppliers (technical efficiency) may occur. In the case of information symmetry, a contract works to guarantee the social Pareto-optimality and, otherwise (information asymmetry), suppliers can pretend to be the other type for getting extra profits (adverse selection, multitasking). Therefore, contract model must be designed to be able to resolve this problem.

Summarily, Contracting between procurers and suppliers are examined with two incentives: direct incentives for the quality achievement and indirect incentives for the technically efficient part of quality input use. As noted, if only direct incentives are used in contracts, persistent technical inefficiency exists in the quality production of suppliers. Thus, indirect incentives are needed. On the contrary, if only indirect incentives are used, it is impossible to manage the quality achievement for each type of suppliers. Therefore, both direct incentives and indirect incentives are needed in contracting models. In these processes, the information asymmetry on the types of suppliers (quality production ability and technical efficiency) can be inserted. The information asymmetry on quality production ability can exist if suppliers report their ability falsely. The information asymmetry on technical efficiency can exist if suppliers report the amount of quality inputs used by them falsely. If indirect incentives are not included in contract model, there is no motivation to report the amount of quality inputs used by them falsely because all suppliers want to produce efficiently. However, if indirect incentives are included in model, there may exist motivation to report the amount of quality inputs used by suppliers falsely because suppliers can get more profit by improving their technical efficiency or by getting more subsidy (indirect incentives) from procurer.

The objectives of this essay are to develop a contracting model that deals with a quality control problem with the above characteristics in the supply chain using direct incentives for quality achievement and indirect incentives for technically efficient parts of quality inputs, and to illustrate the developed model using simulation in order to examine the behavior of optimal contracting parameters (incentives).

The results of this essay illustrate that incentives through contracting may make both suppliers and procurers better off and that direct incentives contribute far more to improving the performance of both suppliers and procurers. When there exists information asymmetry, procurers may not get the same profits (first best profits) as under information symmetry and it will get less profit (second best profit). These results are consistent with contract theory. The superiority of direct incentives to indirect incentives is also reasonable because it is possible to think about the objectiveness of direct incentives.

The essay starts with the literature review on contract theory. It is described how quality and quality incentives can be specified as an output flow and how technical efficiency can be involved in the model. The contracting model and empirical applications are presented.

3.1. Literature review on contract theory

This section presents a review of some literature on contracts, incentives, and the relationship between incentives and performances because this essay examines the relationship between incentives for quality improvement and performance of supplier and procurer. This review covers the general theory of the relationship between incentives and performance under contract.

The first strand of literature review in this essay is on the relationship between incentives under contract and performances of suppliers and procurer with or without any assumption of interruption of noise such as the measurability of performances and information asymmetry. Lazear (1996), Paarsch and Shearer (1996), Banker, Lee, and Potter (1996), Fernie and Metcalf (1996), McMillan, Whalley, and Zhu (1989), and Kahn and Sherer (1990) consider the effect of incentives on performance and verify that performance improves when incentives are sensitive to outputs by agents. In contrast, Foster and Rosenzweig (1994) consider the effects of incentives on inputs (efforts) rather than outputs by agents and verify more efforts under incentives sensitive to performance. However, this relationship between incentives and performance can be corrupted for various reasons. One reason is changes in actions by agents from multitasking (Prendergast, 1999). These changes in actions will give more benefits to agents but will be harmful to the agency. In this essay, agents (suppliers) can increase or decrease the amount of quality inputs used by them to get more benefits because agents can get more revenue either from a high share of quality input costs or from great use of inputs. Multitasking implies that agents change the nature of their activities in response to objective contracts in a way that is beneficial to agents but harmful to the agency (Holmstrom and Milgrom, 1991). They claim that agents are doing multiple activities and allocate the activities based on the incentive scheme given to them. Healy (1985), Asch (1990), Oyer (1998), and Courty and Marschke (1996) verified the existence of the reallocation of inputs by agents that is not obviously efficient when incentives are determined based on objective performance measures. This multitasking problem can be regarded as a kind of moral hazard problem (Chambers and Quiggin, 2000). Chambers and Quiggin (2000) claim that when there exists moral hazard due to multi-tasking, standards (fixed incentive) are optimal rather than incentive scheme. While multitasking is a problem in information symmetry, information asymmetry can corrupt the results of contracts. Because this essay uses quality production ability and technical efficiency of agents as the agent's type variables, this review focuses on adverse selection rather than moral hazard. Salanie (1996) illustrates when adverse selection exists in contracts and how it can be resolved by using a simple example of a wine quality choice problem by customers with different preferences. He claims that though when information asymmetry exists agency may not get the first best choice, incentive compatibility constraints can give the agency the second best choice. Darrough and Stoughton (1986) take an example of adverse selection in financial market. This adverse selection from agents (entrepreneurs) can make bad effect on the performance of agency (collective financial market). In this case, because many stockholders as well as agency can lose their wealth, this adverse selection can generate negative externalities. Just, Calvin, and Quiggin (1999) also present adverse selection in crop insurance. Adverse selection arises when firms with larger incentives tend to participate in insurance. Most literature suggests the design of contracts includes incentive compatibility constraints that prevent agents from lying about their types to agency.

The second strand of past literature review in this essay is on how incentives may affect the quality level in the market. Hennessy (1995) assumes that quality is measured by good and bad, not continuously, and illustrates that the increase in high quality price will lead to the increase in the level of efforts in all operations and the increase in low quality price will lead to the decrease in the level of efforts in all operations. Hennessy (1996) illustrates that the incentive to use more quality inputs decreases as quality with more quality inputs does not improve much and accuracy of quality measurement decreases. He also illustrates that if the average price of investing suppliers is greater than the average price of noninvesting suppliers then suppliers will invest. Hueth and Ligon (2002) assume that quality is perfectly observable and illustrate that contracts including quality as a performance improves the efficiency of quality production. However, literature dealing with quality contracts to manage unobservable quality is very limited.

Past works are extended by considering technical efficiency scores as well as quality achievement as the base information for the design of contracts in this essay. While the value of nonparametric and parametric estimates of firm-level technical efficiency for private goods has been well-established in the literature, the value of technical efficiency information as a basis of contract design to manage quality has not been considered.

3.2. Quality and quality incentives

This section is a modification of the contents of the papers of Weaver and Kim (2000a), Weaver and Kim (2000b), Weaver and Kim (2000c), and Weaver and Kim (2001a). A number of different types of interaction between quantity and quality exist. In the simplest case, quality is a private good and quantity-related such that the quantity flow of a product can be viewed as a set of product units, each of which can be classified by their quality, or "quality-labeled". In this case, quality has private good characteristics and is exclusively and exhaustively consumed simultaneously with the quantity. If quality measurement is costless and perfect, then quality-differentiated markets would generate a series of prices for each quality class and market coordination of quality could not be improved through contracting.

An alternative to quality for this simple case occurs when quality is not quantity-related, and it is not imperfectly observed (experience good or reputation good). Examples can be drawn from most industries and supply chain settings. Obvious examples come from the environmental impacts of production that can be interpreted as public good flows (Weaver, 1998). These environmental impacts of production such as positive externalities and negative externalities of the production process may be regarded as a not quantity-related quality. Recently, they are resolved by using the concept of the social costs of production if only the environmental impacts (quality) are observable (Spence, 1975). For example, the air pollution by emission of sulfur dioxide (Swinton, 1998) and carbon monoxide, and the water pollution of nitrogen (Piot-Lepetit and Vermersch, 1998) can be regarded as environmental effects of production. These effects are called by bad commodities (Fare and Grosskopf, 1999). On contrary, it is possible for a production process to make positive effects on environment. For example, bee-farms can help plants pollinate because their bees move over plants. These impacts will not be related to quantity of production and it is very hard to measure.

Narrowing the focus to quality relevance within the supply chain, examples would include supplier specific, though quantity independent quality attributes such as product uniformity, quality flows that contribute to the firm's reputation such as product reliability, on-time delivery, or consistency of available supply, and quality characteristics that may not have typical direct hedonic value through product consumption such as animal welfare, worker conditions, region of origin, or other characteristics of the technology of origin (Weaver, 1995; Weaver, 1996).

To proceed, the supplier technology is specified as joint in inputs producing quality flows that are not quantity-related. The quality control is limited to one stage (supplier) and focuses on how contracts can provide a solution for coordination of quality. The specification allows for a newly recognized complementary relationship between quality and quantity, e.g. Mefford (1991). He claims that inputs, practices, and efforts to improve quality contribute to increasing quantity as well as improving quality and vice versa. In fact, total quality management (TQM) is a very good example of joint quality and quantity improvement technique. See Appendix 3.2 for more detail of jointness between quality production and quantity production.

While quality cannot be controlled at the procurer level (stage 2), it incurs costs that establish an interest in its management by the procurer. The consideration is limited to performance in the supply chain, noting that extension to social implications is straightforwardly given a social preference function. Uncertainty (or noise) in quality affects supplier effort and the pool of quality available to procurers. It is assumed that suppliers are risk-neutral though relaxation to risk aversion is straightforward for a given parametric form of preferences, only functional convolution is complicated. This section is begun by presenting the supplier and procurer choice problems.

To begin with, let's start with the supplier's problem. Suppose that a vector of quality characteristics is perfectly observable by *i*th supplier. For example, if it is supposed that the production flow yields H lots of different qualities, then y_i is a Hx1 vector of quality-sorted private goods ($y_i = (y_i^1, ..., y_i^h, ..., y_i^H)$ where h is the index of quality characteristics). Under these conditions, the quality output flow is quantity-related and private good, and the private good is "quality-labeled". Given that quality is perfectly observable by both suppliers and consumers, it is assumed that each quality-labeled, private good will be priced by the market. From this perspective, the firm can be viewed as producing multiple outputs priced by a Hx1 vector p. Next, consider the case where quality is imperfectly observable. Before considering the noise in this measurement process, q_i is defined as a *K*x*1* vector of quality flows of firm *i* that are not priced by the market; call these nonmarket quality flows. It is supposed that these quality flows may include those that are not quantity-related private and quasi-public good flows as described above. In either case, the elements of q_i are interpreted as intensities of each of *K* distinguishable quality attributes. It is supposed that the market does not price these quality output flows, and a direct incentive vector for quality, l_i is the focus of contract design.

It is supposed that production occurs through the application of two vectors of variable inputs, x, as well as quality inputs, z. It is assumed that neither of these input types is allocatable to quantity or quality output flows, see Beattie and Taylor (1993) or Shumway, Pope, and Nash (1984). That is, because variable inputs and quality inputs affect both quantity and quality but it is impossible or very hard to trace the effects of variable inputs on quality and the effects of quality inputs on quantity, the production process for quality and quantity is joint in production. First, the private good production process is defined as $F(y_i, x_i, z_i) = 0$ and it is simplified to a vector of functions:

3.1) $$y_i = y(x_i, z_i)$$

Similarly, a related process that generates the vector (q_i) of quality flows is specified as $G(q_i, x_i, z_i \mid \mathbf{q}_i) = 0$ and it is simplified to a vector of functions:

3.2) $$q_i = q(x_i, z_i \mid \mathbf{q}_i)$$

where $\mathbf{q}_i$ represents the supplier type (quality ability) defined as an index that affects factor-biased productivity. In the case of quality, this can be viewed as originating from noise in a measurement process. It is assumed that supplier type is distributed by

$q_i \sim r(q_i)$. The supplier type will play an important role in our consideration of contracting.

Before proceeding, an example may be illustrative. Suppose the quality-labeled private good output (y_i) is apples, or any other product that may be contaminated, and quality control focuses on chemical residues, an element of q_i. While a particular set of apples may be quality-labeled according to size, shape, color, and sugar content, the firm may regulate the quality-labeled outputs (y_i) conditionally upon the level of chemical residues, possibly a nonmarket quantity-related (NQR) quality attribute. This quality control process focuses on defects that are not quantity-related.

Based on this notation for technology, the supplier's choice problem is specified using a cost function, i.e.

$$\text{3.5)} \quad \begin{aligned} &C(y_i, q_i \mid q_i) = C(y_i, q_i \mid q_i, r_x, r_z, p) \\ &\quad \equiv \min_{x_i, z_i} r_x x_i + r_z z_i \\ &\quad \text{Subject to 3.1) and 3.2).} \end{aligned}$$

Based on this cost function, profits earned from production activities by the *i*th supplier are defined as:

$$\text{3.6)} \quad p_i \equiv p y_i + l_i q_i - C(y_i, q_i \mid q_i)$$

Together, the market price and the quality incentive define a supplier-differentiated "settlement" price including a quantity independent, or fixed fee, $l_i q_i$, see e.g. Holloway (1998) or Vukina and Foster (1996). To proceed, it is assumed that the supplier is risk neutral and will choose (y_i, q_i) to maximize profits. The solution of this supplier choice problem defines the supplier's expected profit function written with superfluous notation suppressed as:

3.7) $\quad p_i(p, l \mid q_i) \equiv \max_{y_i, q_i} py_i + l_i q_i - C(y_i, q_i \mid q_i)$

It is supposed that the procurer earns profits by producing a single product, Y_p, using a vector of raw, quality-labeled products procured from suppliers, Y (=(Y^1, …,Y^H)) as well as a Jx1 vector of variable inputs, x_p. Aggregate procurement of the raw supply is defined as $Y^h = \sum_{i=1}^{n} y_i^h$, the sum of product marketed, collected across a pool of n suppliers by prior contract or on an open market. It is assumed that the procurer chooses a pool of n suppliers in a longer-term problem and by marketing agreement commits to purchase their supply. Thus, y_i is viewed as exogenous to the procurer, except when the procurer has bargaining power sufficient to determine the quality incentives on which y_i depends. Procurers implement the following technology to process the raw product produced by suppliers:

3.8) $\quad Y_p = Y_p(x_p, Y, Q)$

Here, Q[3] is defined as vector of pool-wide aggregation of the non-private good (Q=(Q^1, …, Q^K)) and $Q^k = \sum_{i=1}^{n} q_i^k$. A wide scope of specifications can be considered for Q. First, consider the nonmarket quantity-related elements of q_i. In this case, Q could be defined

3. $Q = \Xi_{i=1}^{n} q_i$ where Ξ is a general operand that can be a summation, average, or multiplication etc. because q_i is not quantity related, may not be measured, and does not have the same operating characteristic. That is, the aggregate quality of product received from suppliers by procurer cannot be defined in a unique way. It is assumed that q_i can be measured and observed by procurer after the product is delivered in this essay and the supply chain paper. On-time delivery is a good example. It is measured after the product delivered to procurer, it cannot be added up and it should be regarded as an attribute of a supplier. However, the emission of organic nitrogen can be added up. In the supply chain paper and my essay, the focus is on the NQR-quality that is measured by continuous value and can be added up. Then, the aggregate NQR-quality becomes $Q = \Sigma_{i=1}^{n} q_i$. Actually, Karmarkar and Pitbladdo (1992) point out that quality is the average performance of the product in terms of a vector of quality attributes.

as a vector of pool average quantities of quantity-related quality. Where quality is not a private good quantity-related, it is assumed that the purchase of a private good quantity from a supplier exposes the procurer to the quasi-public good flows from that supplier. As an example, the purchase of "raw" athletic shoe components from suppliers operating sweat shops with poor worker conditions exposes the athletic shoe procurer (finisher) to the reputational quality flows of the supplier. Thus, in this case, the aggregate pool-wide, non-private good quality could be defined simply as a sum of supplier quality supplies. The production function of procurer is specified as positively monotonic and concave in its arguments.

To specify the procurer's expected profit function, the procurer cost function is introduced as follows. Given $\boldsymbol{r_p}$ is a Jx1 vector of variable input prices.

3.9) $$C_p(Y_p \mid Y, Q) \equiv \min_{x_p} r_p x_p$$

subject to 3.8)

and note it satisfies $\dfrac{\partial^2 C_p}{\partial Y_p^2} > 0, \dfrac{\partial^2 C_p}{\partial Q^2} > 0, \dfrac{\partial^2 C_p}{\partial Y^2} > 0$, with nonpositive cross-derivatives. Procurer's profit is written as

3.10) $$\pi_p = P_p Y_p - \sum_{i=1}^{n} \sum_{k=1}^{K} l_i^k q_i^k - \sum_{i=1}^{n} p y_i - C_p(Y_p \mid Y, Q).$$

Alternative specifications can be imagined and may be of interest depending on the applied setting.

From this notation, it is clear that the procurer's costs and profits will be impacted by the supplier supply of quality directly through Y and Q. It is assumed that the procurer is a risk neutral and maximizes expected profits conditional on information concerning the supplier pool's set of types. The procurer's profit function is defined, and note its conditionality on l and a vector of supplier types, q, to facilitate further discussion of contract design as follows:

$$3.11)\quad p_p(P_p, l \mid q) \equiv P_p Y_p - \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k - \sum_{i=1}^{n} p y_i - C_p(Y_p \mid Y, Q)\,.$$

3.3. Quality input cost share and technical efficiency

This section is a modification of the contents of the paper of Weaver and Kim (2001b). In addition to direct incentives for quality performance, indirect incentives for quality input costs can be used to control the technical efficiency of suppliers and the quality of products produced by suppliers. In this essay, indirect incentives are to share the quality input costs of suppliers.

As noted in Weaver and Chitose (1994), where an output flow is imperfectly observable, management of this technology is problematic. For example, consider the case of reputation goods and quasi-public good output flows. Given the imperfect observability of such flows, much less the supplier's cognizance of such flows, it might be supposed that the firm manager perceives the actual technology does not involve the environmental flow, say q_i, and erroneously supposes they face a technology,

$$3.12)\quad G(y_i, x_i, z_i \mid q_i) = 0\,.$$

Suppose the true technology is that described in equation 3.13.

$$3.13)\quad F(y_i, q_i, x_i, z_i \mid q_i) = 0$$

If x_i and z_i were selected based on *G(.)*, the production plan, *(* x_i^G, z_i^G *)* would be technically inefficient with respect to the true technology given by equation 3.13.

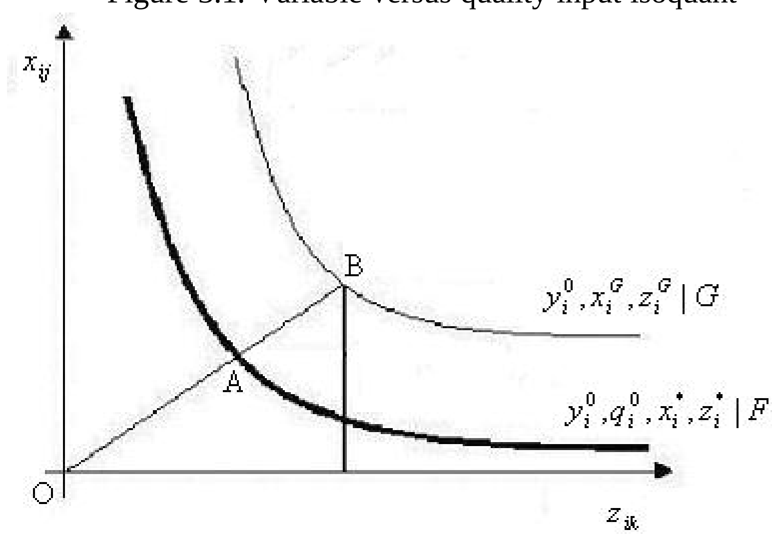
To incorporate technical inefficiency, it is clear from the above specification that where nonmarket quality flows are produced that are not priced in markets due to imperfect observability, even hedonistic profit maximizers may operate their technologies in a persistent state of technical inefficiency. To consider this possibility, suppose the true technology is represented by the thick isoquant in Figure 3.1, while the technology that is perceived by the supplier is represented by the thin isoquant. In this simple example, it is clear that although the supplier may be allocatively efficient and technically efficient with respect to the perceived technology, e.g. equation 3.12, these choices (e.g. x_i^a, z_i^a) would be technically inefficient relative to the pair (x_i^*, z_i^*). In Figure 3.1, the efficient pair (x_{ij}^*, z_{ik}^*) is contrasted with an inefficient pair (x_{ij}^a, z_{ik}^a). $d_i = z_{ik}^* / z_{ik}^a$ is defined as a measure of technical inefficiency. Without loss of generality, focus is on a radial efficiency measure: $d_i = z_{ik}^* / z_{ik}^a = x_{ij}^* / x_{ij}^a$ for all j (index for variable inputs) and k (index for quality inputs) where all inputs superscripted "*a*" are considered to follow from the supplier's choice problem that motivates the production plan. In this radial technology, it would be supposed that each input suffers from the same inefficiency. For example, in Figure 3.1, the point (x_{ij}^a, z_{ik}^a) indicates actual input use (here assumed to be technically efficient with respect to the wrong technology *G(.)* in equation 3.13), whereas the point (x_{ij}^*, z_{ik}^*) indicates efficient use of this pair with respect to the true technology. From this perspective, d_i measures the ratio of radial distance of (x_{ij}^*, z_{ik}^*) to the radial distance of (x_{ij}^a, z_{ik}^a) from the origin. This notation is readily generalized by redefinition of d_i as a vector of non-radial input-specific technical efficiency. As a simplification that retains focus on the contracting problem, this essay proceeds by viewing d_i as a scalar. It is assumed that $d_i \sim h(d_i)$.

Technical efficiency is defined as a characteristic, or attribute, of the firm (supplier) that is fixed in the short-run. While the level of technical inefficiency is conditional on firm specific attributes, this essay proceeds by viewing d_i as a measure of supplier "type", e.g. an information parameter that distinguishes each firm. Thus, there are two type variables including quality production ability and technical efficiency. Two scenarios for the principal (the procurer) are analyzed. One where the procurer has full knowledge of each supplier's d_i and q_i, information symmetry, and one where the procurer knows only the distribution of d_i and q_i, and the number of suppliers, ***n*.**

This notation is introduced into the equation 3.13 as:

3.14) $F(y_i, q_i, d_i\, x_i^a, d_i\, z_i^a) = 0$

Figure 3.1. Variable versus quality input isoquant



$A = (x_{ij}^*, z_{ik}^*) \quad B = (x_{ij}^a, z_{ik}^a) = (x_{ij}^G, z_{ik}^G)$

To proceed, defined is agent profit under contracting for technical efficiency:

$$3.15)\quad p_i = py_i - r_z z^a + g_i r_z d_i z_i^a + l_i q_i - C(y_i, q_i, z_i^a \mid d_i, q_i)$$

Intuitive interpretation of the subsidy for quality inputs or efforts is facilitated by rearrangement:

$$3.16)\quad -r_z z_i^a + g_i r_z z_i = -(1-g_i) r_z z_i - r_z (z_i^a - z_i)$$

That is, from the first term on the right-hand side, the unit cost of efficient quality inputs is subsidized proportionally below the market price. Going one step further, dependence of the subsidy on the extent of technical inefficiency is clarified by rewriting 3.16) as follows:

$$3.17)\quad -r_z z_i^a + g_i r_z z_i = -r_z (1-g_i d_i) z_i^a$$

The subsidy incentive approaches g_i as efficient quality inputs are approached. Thus, under a fixed subsidy rate, g_i, the extent of subsidy, $g_i d_i$ will increase with the extent of technical efficiency as d_i approaches unity. Through contract specification, incentives that are consistent with particular objectives for improved supply chain performance can be designed. Because the subsidy is paid for quality effort applied, it is intuitive that the procurer would seek to vary the subsidy according to the technical efficiency of the supplier. The process is specified as designing a menu of indirect incentives (g) that vary over the level of supplier technical inefficiency. In doing so, the procurer could set subsidies for quality inputs and summarizing supplier profits are defined:

$$3.18)\quad p_i = py_i - r_x x_i^a - (1-g_i d_i) r_z z_i^a + l_i q_i$$

From this notation, the motivation for and potential of quality and technical efficiency-based contracting for quality is clear. One alternative would be to introduce indirect incentives for whole quality input use. However, such an approach would subsidize technically inefficient suppliers. If the subsidy were paid on any amount of quality inputs applied, suppliers may have an incentive to expand already inefficient use of quality control. This behavior by suppliers can reduce the profits of the procurer and supply chain and, thus, be regarded as a kind of moral hazard problem because suppliers try to get more profits by producing inefficiently to gain further subsidy. To avoid this possibility, the subsidy (indirect incentives) proposed is paid based on a schedule such that the subsidy varies with technical efficiency, allowing the subsidy to encourage quality production and effort while not rewarding inefficiency. The challenge, however, is to find a way to design this subsidy such that the supplier is responsive, and such that effort is optimally supplied across a heterogeneous population of suppliers that have differing levels of technical inefficiency, d.

To move toward the definition of the contracting problem, consider the procurer's profit. In the current setting, the procurer is defined as a downstream procurer. The procurer procures products produced by suppliers and produces final products by processing them using additional inputs. The quality of final products is affected by the average quality of products procured from suppliers. Thus, the production function of procurer is expressed as follows: $F^p(Y_p, x_p, Y, Q) = 0$. Note, in the absence of the procurer agency that would allow enforcement of a contract to manage quality effort, Y would be exogenous to the procurer. With the agency, the procurer designs the quality effort incentive, allowing for control of quality and affecting Y. Thus, with agency, the procurer is viewed as facing uncertainty with respect to Y. The cost function,

$C(Y_p \mid r_p, p)$, is defined as $\underset{x_p, l_i^k}{Min}\, r_p x_p + pY + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k$ subject to $F^p(Y_p, x_p, Y, Q) = 0$

for all *i* and *k*. The procurer's profit is defined as

$$
\text{3.19)} \quad
\begin{aligned}
p_p &= P_p Y_p - r_p x_p - pY - \sum_{i=1}^{n} g_i\, r_z d_i z_i^a - \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \\
&= P_p Y_p - C_p(Y_p \mid r_p, p) - \sum_{i=1}^{n} g_i\, r_z d_i\, z_i^a
\end{aligned}
$$

3.4. Contracting model

From the above specification, the contracting problem is defined by adding further constraints to ensure 1) truth-telling (IC) and 2) participation by the agents (IR). Truth-telling constraints (IC) are not needed because all information on types is known to procurer. The contract design problem under symmetric information can be written:

$$
\text{3.20)} \quad \underset{x_p, g_i, l_i^k}{Max}\, p_p = P_p y_p - r_p x_p - pY - \sum_{i=1}^{n} g_i r_z (d_i z_i^a) - \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k
$$

s.t.

$$
py_i - r_x x_i^* - (1-g_i) r_z (d_i z_i^*) - (1-d_i) r_z z_i^* + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \geq R_{NO\,Contract} \quad \text{(IR)}
$$

for all *i* and *k*, where

$$
\begin{aligned}
&(x_i^*, z_i^*) = \underset{x_i^a, z_i^a}{\arg\max}\, p_i^c = py_i - r_x x_i^a - (1-g_i) r_z (d_i z_i^a) - (1-d_i) r_z z_i^a + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \\
&R_{NO\,Contract} = \underset{x_i^a, z_i^a}{Max}\, py_i - r_x x_i^a - r_z z_i^a
\end{aligned}
$$

In contrast, when it is assumed that asymmetric information between procurers and suppliers exists, then the procurer can be misled by suppliers that report about the production ability and the use of quality inputs and type untruthfully. In order to eliminate this possibility, an incentive compatibility constraint can be added to the contract design. The contracting scheme would then be derived from:

$$3.21)\quad \underset{x_p, g_i, l_i^k}{Max}\, E(p_p) = \int_0^1 [P_p Y_p - r_p x_p - pY - \sum_{i=1}^{n} g_i r_z (d_i z_i^a) - \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k] g(q_i, d_i) dq_i dd_i$$

s.t.

$$py_i - r_x x_i^* - (1-g_i) r_z (d_i z_i^*) - (1-d_i) r_z z_i^* + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \geq R_{NO\,Contract} \qquad \text{(IR)}$$

for all i and k,

$$\begin{aligned} & py_i - r_x x_i^* - (1-g_i) r_z (d_i z_i^*) - (1-d_i) r_z z_i^* + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \geq \\ & py_i - r_x x_i^{'} - (1-g_i^{'}) r_z (d_i^{'} z_i^{'}) - (1-d_i^{'}) r_z z_i^{'} + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k \end{aligned} \qquad \text{(IC)}$$

for all i and k where

$$(x_i^*, z_i^*) = \underset{x_i^a, z_i^a}{\arg\max}\, p_i^c = py_i - r_x x_i^a - (1-g_i) r_z (d_i z_i^a) - (1-d_i) r_z z_i^a + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k$$

$$(x_i^{'}, z_i^{'}) = \underset{x_i^a, z_i^a}{\arg\max}\, p_i^c = py_i - r_x x_i^a - (1-g_i^{'}) r_z (d_i z_i^a) - (1-d_i) r_z z_i^a + \sum_{i=1}^{n}\sum_{k=1}^{K} l_i^k q_i^k$$

Here, $g(q_i, d_i)$ is a joint distribution of two type variables (q_i, d_i) in order to make the model simplifier though distribution function of q_i and the distribution of d_i were defined separately in section 3.2 and section 3.3. Incentive compatibility constraints ensure that incentives are designed such that the choices by agents that are untruthful, i.e. they announce type as *d'* and *q'* though true type is *d* and *q*, will lead to reduced expected profits.

In Equation 3.20 and Equation 3.21, the two control targets (quality achievement and technical efficiency) in this essay may look like interdependent, which implies that only one incentive (direct or indirect) can control both targets. This interdependence may come from the fact that direct incentives lead suppliers to produce the quality optimally and technical inefficiency from the imperfect observability of quality can be resolved by the survey implemented by procurer or the fact that indirect incentives lead suppliers to produce the quality technically efficiently and more use of quality inputs by indirect incentives can also improve the quality. In the first fact, since suppliers hope to produce the quality technically efficiently, suppliers can respond to survey questions frankly and procurer can has the perfect information on technical efficiency of suppliers. However, if procurer there does not exist indirect incentives, procurer does not have any motivation to implement the survey for the measurement of technical efficiency because it does not need to have the information on technical efficiency of suppliers any more. As a result, the persistent technical inefficiency exists. Thus, the use of indirect incentives is needed to manage technical efficiency as well as direct incentives. In the second fact, while indirect incentives can improve technical efficiency and quality level, they may not optimize the quality production allocatively. Thus, direct incentives are needed.

3.5. Empirical analysis

This section illustrates a numerical illustration of theoretical contents in the above sections using a simulation method to analyze the behavior of optimal direct and indirect incentives against supplier type variables, and to compare the effect of direct incentives to that of indirect incentives on performance. The reason why the empirical application approach is a simulation though equation 3.20 and 3.21 are optimization models is that the objective function and constraints are simulated and calculated for a variety of the combinations of the decision variables of contracting models (contract parameters: l , g) and types of suppliers (q , d) instead of optimizing the models to find the optimal contract parameters. Strictly speaking, because the empirical application approach in this essay is neither a 'pure' simulation nor a 'pure' optimization, it can look a mixture of optimization and simulation. Based on the above theoretical models, an imaginary but could-be-realistic situation is modeled and analyzed. For the simulation, as illustrated in equation 3.20 and 3.21, the information on factor prices (r_x, r_z, r_p), product prices (p, P_p), production functions (y_i, q_i, Y_p) or cost functions (C_i, C_p), the joint distribution function of q_i, d_i ($=g(q_i, d_i)$) the number of suppliers (n), and the number of quality characteristics (K). Of course, while theoretic models can be analyzed by comparative statics, a simulation method is chosen in this essay because differentiation can be very complex. Moreover, in order to examine the ranges of parameters where there exist optimal contract solutions, a sensitivity analysis is also implemented.

In fact, it is not easy to find literature on the empirical application of contract models such as simulation and estimation of contract parameters. For simulation, it is possible to take Vukina and Foster (1995) and Bogetoft and Olesen (2000), and for estimation of contract parameters with data, it is possible to take Hueth and Ligon (2002) and Ferrall and Shearer (1999). Vukina and Foster (1995) simulated the behavior of output, utility inputs, average settlement cost of groups, total revenue, internal cost, and profit of broiler farms in North Carolina. They estimated the cost function of farms with data using 3SLS (3 step least square) method and simulated the behavior by changing contract parameters such as base price and bonus, separately. Moreover, they considered only the behavior of suppliers' profit and cost not the behavior of processor's profit and costs under information symmetry (That is, they do not use the Principal-agent model). The approach in this essay is the same as theirs in that it simulates the behavior of performances of firms by changing contract parameters. However, the approach in this essay is different from them in that it does not estimate production function but select a functional form and parameters that satisfy the principles of neoclassical economics and, in that it uses the principal-agent model to consider the individual rationality constraints and incentive compatibility under both information symmetry and information asymmetry. Bogetoft and Olesen (2000) use a simulation method to illustrate the effect of competitive regimes on the level of investment. Their approach is the same as the approach in this essay in that they compute the level of investment by setting a value for each parameter. However, they do not consider the incentives under contract scheme but incentives for investments.

This illustration is meaningful in that it can illustrate how the above contracting scheme works and illustrate those who have real data on a supply chain how to apply the contract scheme to the industry. This illustration can also examine the following things: there exists the different optimal direct and indirect incentive menu for different types of suppliers under a reasonable contract setting and a reasonable set of parameters, the incentives affect the performance, and the direct incentives have more effect than the indirect incentives. Moreover, the behavior of optimal incentives against supplier type variables is examined.

The simulation is implemented based on particular parameterizations of the supplier and procurer production functions, the joint distribution of the quality type and technical efficiency type of suppliers, and a set of prices including product prices and factor prices (see Appendix 3.1). Here, simple classical forms are chosen though, in general, functional forms would be derived econometrically or nonparametrically from case data of interest. Chosen is a joint distribution for quality type and efficiency type for suppliers.

After the determination of functional forms and parameters, the first step of simulation is the calculation of reservation profits of suppliers that they can get when they do not participate in contracts. These reservation profits should be calculated for each supplier type (q) but not (d) because technical efficiency of suppliers is not included in suppliers' profit model under independent operations. To calculate the reservation profits for suppliers, the first order conditions of the suppliers' profit function with respect to their decision variables (x, z) should be obtained. From the first order conditions, $x^* = x^*(q)$ and $z^* = z^*(q)$ are obtained and each value of q generates the reservation profit for each type of suppliers. Under my simulation specification, the reservation profits are in Table 3.1.

Table 3.1. Reservation profits of suppliers and procurer for each type of suppliers

Type (q)	0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
Suppliers	328.25	352.14	376.67	401.83	427.60	453.92	481.08	507.84	534.99	561.64
Procurer	46.159	143.02	208.57	260.11	303.53	341.6	375.98	407.02	435.69	461.94

Reservation profits of suppliers are increasing in supplier type. In order to encourage each type of supplier to participate in contracts, procurers should guarantee at least the profits in Table 3.1 to suppliers. The procurer's reservation profits are not necessary under procurer agency case. However, because the procurer can eliminate types of suppliers who give procurer profits less than reservation profits in contract pool, procurer's reservation profits can be used as a criterion for the determination of contract pool.

Next, the suppliers' profit function should be optimized conditioned on the contract parameters (incentive menus) that are determined by the procurer. The profit function is differentiated with respect to suppliers' decision variables (x, z) and as a result,

$x^* = x^*(q, d, l, g)$ and $z^* = z^*(q, d, l, g)$ are calculated. During this step, since it is intractable to solve simultaneous equations symbolically, for fixed values of prices including product prices and factor prices, optimal supplier choices as agents are simulated over a discrete range for two supplier type variables ($q = 0.0, 0.2, \ldots, 2.0$, $d = 0.0, 0.1, \ldots, 1.0$) and two incentive values ($l = 0.00, 0.05, \ldots, 1.00$, $g = 0.00, 0.05, \ldots, 1.00$). A numerical approximation method (Broyden's method) is used to calculate the optimal values of choice variables (x, z). Through the above processes, the optimal values for each combination of supplier types (l, g) of suppliers are calculated, that is, x^* and z^* are calculated for each combination of (l, g) for each type of suppliers (q, d). Because optimal quantity output (y^*), optimal quality output (q^*), and optimal expected profit (p^*) for suppliers are determined by x^* and z^*, the optimal quantity, the optimal output, and the optimal expected profit for each type of suppliers (q, d) under each incentive menu (l, g) are also calculated easily. Table 3.2 illustrates some examples of the above processes.

Table 3.2. Samples of simulated optimal profits of suppliers against types and incentive menus

Supplier type		Incentive menu		Optimal inputs		Optimal output		Optimal profit
Quality	Efficiency	Quality	Efficiency	x^*	z^*	Quantity	Quality	
0.20	0.10	0.05	0.85	839.46	152.93	466.04	8.02	279.19
0.40	0.10	0.05	0.10	776.54	130.86	431.10	14.49	258.39
0.60	0.90	0.65	0.25	1104.67	241.17	601.90	32.50	348.35
0.80	0.40	0.10	0.50	1004.44	208.58	552.24	39.34	322.49
1.00	0.50	1.00	1.00	2100.91	730.20	1104.72	112.28	595.35
1.20	1.00	0.70	0.05	1004.36	181.63	537.15	54.31	300.00
1.40	0.30	0.30	0.90	1185.05	275.07	644.54	82.64	371.77
1.60	0.70	0.05	0.50	1196.97	308.62	663.52	101.29	397.46
1.80	0.50	0.10	0.85	1406.52	411.05	774.08	137.54	456.78
2.00	0.30	0.15	0.60	1002.08	206.76	550.50	97.81	325.00

Next, the optimal procurer's inputs (x_p) and the optimal profit of procurer for each type of suppliers and each menu of incentives ($\boldsymbol{p}_p$) are calculated. While the optimal profits of suppliers are not affected by whether there is information asymmetry between suppliers and procurer or not, procurer's profit is affected by it. For information symmetry, the profit of procurers is simulated against supplier type factors and incentive factors like the profits of suppliers. For the information asymmetry case, the expected profit with respect to the joint distribution of quality type and efficiency type of suppliers should be calculated because the procurer does not know the type of suppliers but knows the distribution of it. Thus, the optimal expected profit of the procurer is simulated against only incentive menus. Table 3.3 illustrates some examples of the optimal profit of procurers under information symmetry and Table 3.4 illustrates some examples of the optimal expected profit of procurers under asymmetric information.

Table 3.3. Samples of simulated optimal profits of procurer against supplier types and incentive menus under information symmetry

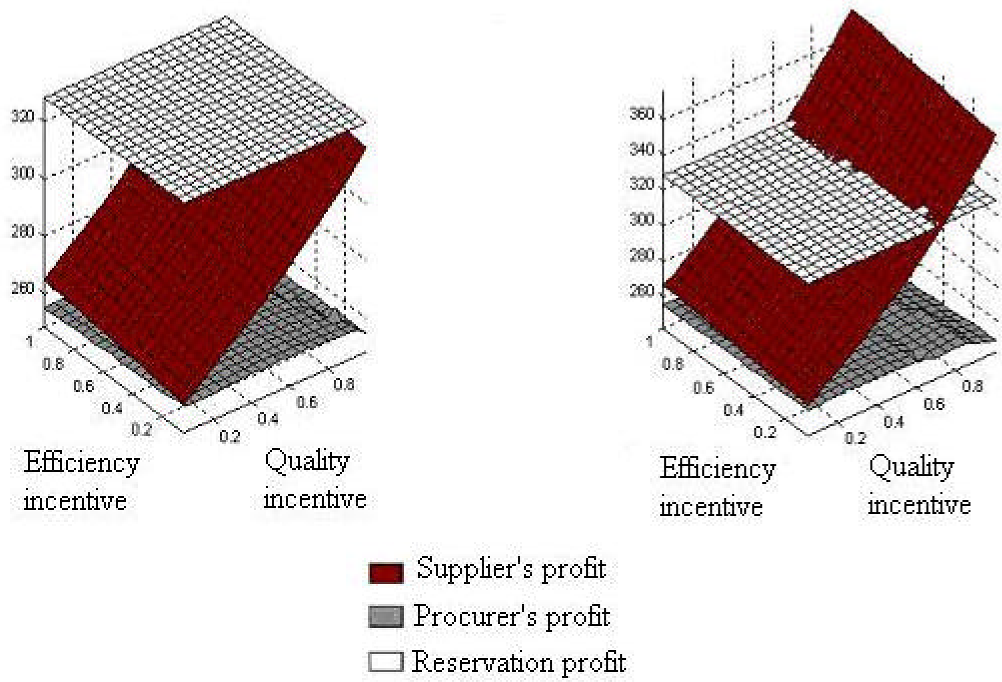
Supplier type		Incentive menu		Procurer's optimal profit
Quality	Efficiency	Quality	Efficiency	
0.20	0.10	0.05	0.85	258.11
0.40	0.10	0.05	0.10	370.27
0.60	0.90	0.65	0.25	482.87
0.80	0.40	0.10	0.50	547.06
1.00	0.50	1.00	1.00	641.72
1.20	1.00	0.70	0.05	629.18
1.40	0.30	0.30	0.90	727.31
1.60	0.70	0.05	0.50	786.98
1.80	0.50	0.10	0.85	866.81
2.00	0.30	0.15	0.60	792.38

Table 3.4. Sample of simulated expected optimal profits of procurer against incentive menus under information asymmetry

Incentive menu		Procurer's optimal profit
Quality	Efficiency	
0.05	0.10	552.59
0.10	0.50	610.80
0.20	0.60	603.35
0.25	0.50	617.64
0.35	0.70	609.05
0.40	0.05	561.63
0.55	0.90	290.86
0.70	0.50	610.22
0.85	0.85	133.86
0.95	0.60	561.24

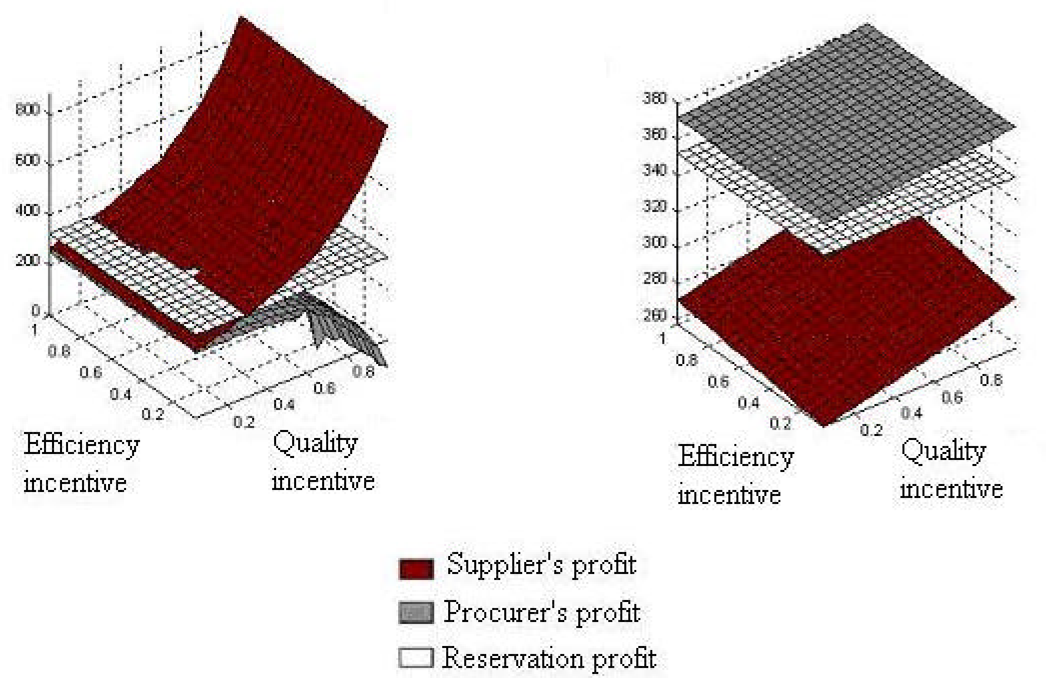
Thus, the optimal profits of suppliers and procurers are available for each combination of supplier types and incentive menus. With the optimal profits of suppliers and procurers, the optimal incentive menu (l^*, g^*) for each type of suppliers should be determined under the case of information symmetry, which maximizes the profits of the procurer guaranteeing the reservation profits of suppliers. In order to illustrate how the optimal incentive menu for each type of suppliers is determined and the optimal incentive menu for each type of suppliers under information symmetry, some representative sample graphs including the profits functions and reservation profit are illustrated and the optimal incentive tables are illustrated.

Figure 3.2. Profits when $q = 0.2, d = 0.2$ and $q = 0.2, d = 0.3$



The first figure in Figure 3.2 illustrates that suppliers with quality type of 0.2 and efficiency type of 0.2 will not participate in contracting because the incentive menu of procurers does not guarantee the reservation profits to them, though their profit is increasing in both quality incentive and efficiency incentive. The width of increase in profit against quality type is far greater than that against efficiency type. Meanwhile, suppliers with quality type of 0.2 and efficiency type of 0.3 will participate in contracting if a quality incentive of more than 0.65 is given to them without regard to an efficiency incentive. One notable thing is that though the supplier’s profit is increasing and the minimum quality incentive is decreasing in efficiency type, the effect is not quite large in current specification of parameters. This phenomenon is common in all supplier types, which implies that direct incentives have far more effect on suppliers’ profit than indirect incentives in this simulation. The increase in direct incentives increases the suppliers’ profit by far more than the increase in indirect incentive. The procurer will make an effort to find quality incentives and efficiency incentives to maximize its profit. Table 3.5 and 3.6 illustrate that the optimal incentive menu for suppliers of quality type of 0.2 and efficiency type of 0.3 (l^*, g^*) is 0.85 and 0.05, respectively. The reason why the optimal incentive menu is greater than the minimum incentive menu is that the profit function of the procurer is not monotonously increasing or decreasing but is fluctuating. The small value for the optimal efficiency incentive implies that the profit function of the procurer is decreasing in efficiency incentives for this type of suppliers and the optimal quality incentive level.

Figure 3.3. Profits when $q = 0.2, d = 0.7$ and $q = 0.4, d = 0.1$



The second figure of Figure 3.3 illustrates the same situation as the first figure of Figure 3.2. There is no contract because suppliers of the type do not get the reservation profit from contracting. This occurs due to the fact that because the efficiency type of the suppliers is too small, their production cost is too high. The comparison between the first figure of Figure 3.3 and the second figure of Figure 3.2 that have the same quality type but different efficiency type illustrates that the increase of efficient type gives suppliers more profit and reduces the minimum value of contractible quality incentives. While the minimum quality incentive in the second figure of Figure 3.2 is about 0.65, in the first figure of Figure 3.3 is about 0.45. This implies that because suppliers of high efficiency type get more subsidy for their quality input costs in each level of efficiency incentive, they can get more profit in each quality incentive level than suppliers of low efficiency type. Table 3.5 and 3.6 illustrate that the optimal incentive menu for suppliers of quality type of 0.2 and efficiency type of 0.7 (l^*, g^*) is 0.65 and 0.85, respectively. Moreover, Table 3.5 and 3.6 also illustrate that the optimal incentive menu is not increasing in efficiency type, though there are some exceptions.

Figure 3.4 and 3.5 are related to the first figure of Figure 3.3 in that fixing efficiency type to quality type of 0.7 is being changed (0.4, 0.6, 1.6 and 1.8). One notable thing is that as the quality type of suppliers becomes better, the profit of suppliers increases. In fact, the profit of suppliers in the first figure of Figure 3.3 is far less than that in the first figure of Figure 3.4. This implies that because the procurer can get high quality at low cost from the contract with suppliers of high quality type, procurer get more profit. These are samples to examine the behavior of incentive menus when the quality type of suppliers is different under a fixed efficiency type.

Figure 3.4. Profits when $q = 0.4, d = 0.7$ and $q = 0.6, d = 0.7$

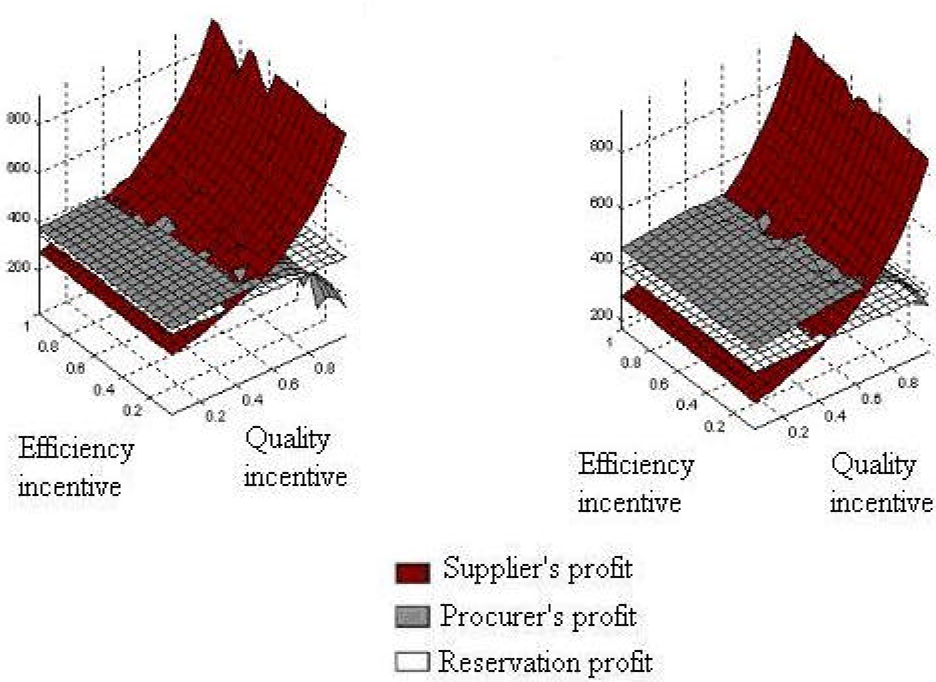
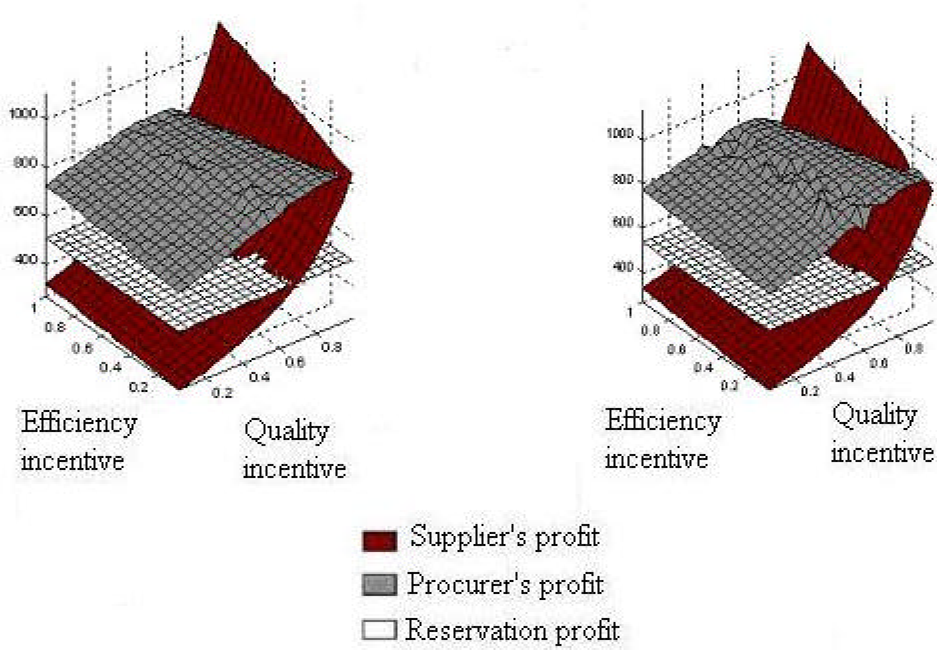


Figure 3.5. Profits when $q = 1.6, d = 0.7$ and $q = 1.8, d = 0.7$



As quality type is getting better, profits for both suppliers and procurers increase. This implies that suppliers with high quality type can get more quality incentive from procurers and procurers can get more profit from selling final products made with higher quality products though it pays more incentive to suppliers. As illustrated in the figures, the minimum quality incentive value is increasing in quality type because reservation profits for suppliers are increasing in quality type of them. Table 3.6 indicates that the optimal quality incentive is not decreasing and the optimal efficiency incentive is not increasing in quality type though there are some exceptions.

Figure 3.6. Profits when $q = 1.0, d = 0.4$ and $q = 1.0, d = 0.5$

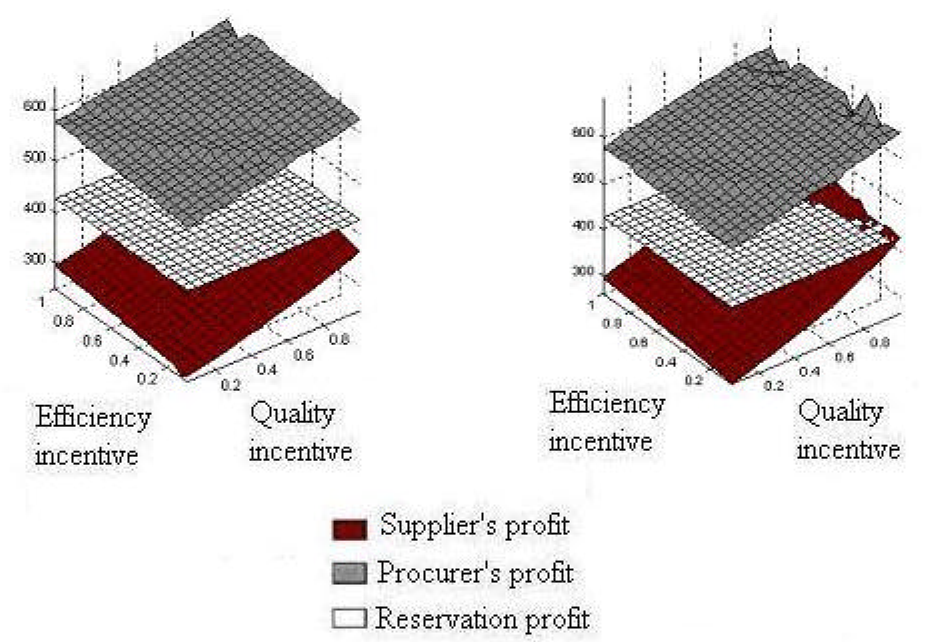


Figure 3.6 is similar to Figure 3.2 in that quality type is fixed (1.0) and efficiency type is changed. With the same logic as Figure 3, they can be interpreted. One notable thing is that the procurer's profit dominates the suppliers' profit because procurers may

get high quality from suppliers. However, as efficiency type grows, the difference between them is reduced.

Figure 3.7. Profits when $q = 1.0, d = 0.6$ and $q = 2.0, d = 0.2$

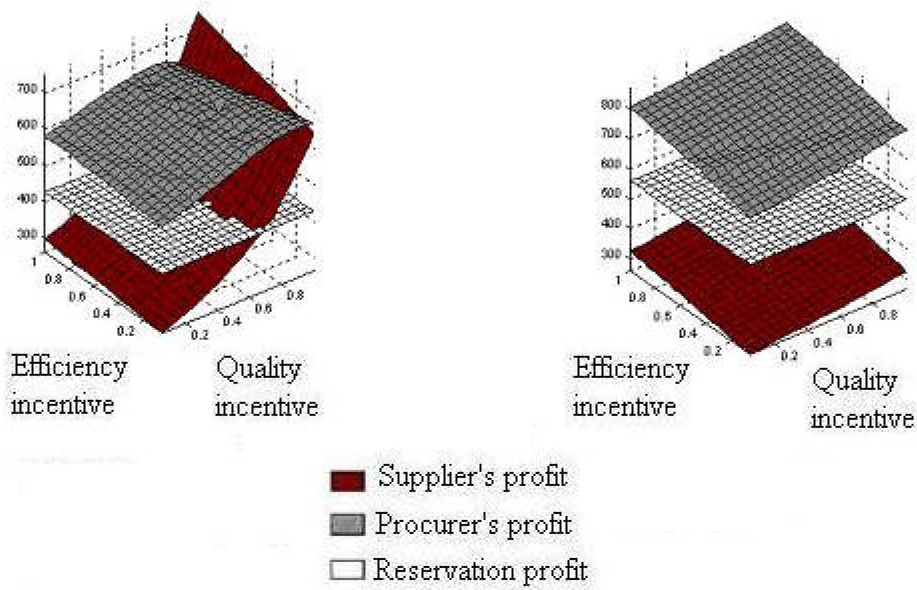


Figure 3.7 illustrates the figures with some other types. One notable thing is that when efficiency type is very low like 0.1 and 0.2, suppliers do not participate in contracts in many cases. There are two cases: suppliers do not participate in contracting because they do not get the reservation profit or procurers rule out suppliers because they get very low profit from the contract with them. The first figure of Figure 3.2 illustrates the former and the second figure of Figure 3.7. That is, the current incentive menu system determines the type of suppliers that participate in contracts. This result can be related to endogenous contract pool setting.

Table 3.5. Optimal quality incentives under information symmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	1.00	0.85	0.80	0.75	0.70	0.65	0.55	0.40	0.25
0.4	0.00	0.00	1.00	0.90	0.75	0.75	0.65	0.45	0.40	0.35
0.6	0.00	0.00	1.00	1.00	0.75	0.75	0.65	0.55	0.50	0.45
0.8	0.00	0.00	1.00	1.00	0.85	0.85	0.70	0.60	0.55	0.50
1.0	0.00	0.00	0.00	1.00	0.90	0.90	0.75	0.65	0.60	0.55
1.2	0.00	0.00	0.00	1.00	0.90	0.85	0.80	0.70	0.65	0.55
1.4	0.00	0.00	0.00	1.00	0.95	0.90	0.85	0.75	0.65	0.60
1.6	0.00	0.00	0.00	1.00	1.00	1.00	0.85	0.75	0.65	0.60
1.8	0.00	0.00	0.00	1.00	1.00	1.00	0.90	0.80	0.70	0.60
2.0	0.00	0.00	0.00	0.00	1.00	1.00	0.90	0.80	0.70	0.65

Table 3.5 illustrates that optimal quality incentive is nondecreasing in quality type and is non-increasing in efficiency type. The first result implies that because high quality type suppliers can give more added-value to procurers, procurers should give more quality incentive to high type suppliers. By giving more incentives to high type suppliers, procurers encourage high type suppliers to participate in contracting and to produce better quality products, and procurers can get more profit from selling high quality final products. The second result implies that because high efficiency type suppliers will have low input costs, relatively low quality incentive can attract them to contract. The zero incentives that are in low efficiency type indicate no contract between suppliers and procurers because either procurers or suppliers cannot get their reservation profit.

Table 3.6. Optimal efficiency incentives under information symmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	1.00	1.00	0.95	0.95	0.90	0.85	0.60	0.45	0.05
0.4	0.00	0.00	1.00	0.95	0.90	0.85	0.75	0.15	0.15	0.05
0.6	0.00	0.00	1.00	0.90	0.85	0.75	0.75	0.05	0.05	0.05
0.8	0.00	0.00	1.00	0.90	0.75	0.05	0.05	0.05	0.05	0.05
1.0	0.00	0.00	0.00	0.75	0.65	0.05	0.05	0.05	0.05	0.05
1.2	0.00	0.00	0.00	0.65	0.45	0.05	0.05	0.05	0.05	0.05
1.4	0.00	0.00	0.00	0.50	0.40	0.05	0.05	0.05	0.05	0.05
1.6	0.00	0.00	0.00	0.40	0.35	0.05	0.05	0.05	0.00	0.00
1.8	0.00	0.00	0.00	0.40	0.30	0.05	0.05	0.05	0.00	0.00
2.0	0.00	0.00	0.00	0.00	0.15	0.05	0.05	0.00	0.00	0.00

Table 3.6 illustrates that optimal efficiency incentive is non-increasing in both quality type and efficiency type. The first result implies that because high quality type suppliers give more quality incentive as illustrated in Table 3.5, they will participate in contract with relatively low efficiency incentives. That is, though getting low efficiency incentive, high quality type suppliers can get at least reservation profit from high quality incentives. The second result implies that because high efficiency type suppliers will have low input costs, relatively low quality incentives can attract them to contract. The zero incentives that are in low efficiency type indicate no contract between suppliers and procurers because either procurers or suppliers cannot get their reservation profit. However, the zero incentives that are in high efficiency type indicate just zero incentive though there are contracts between suppliers and procurer.

The next step is to determine the optimal contract scheme under the information asymmetry case. One different thing from the information symmetry case is that the procurer's profit will be the expected profit with respect to the joint distribution function of quality type and efficiency type of suppliers. As noted in Table 3.4, the procurer's expected profit is calculated for all types of suppliers just against the incentive menu.

With the expected profits of procurers and the profits of suppliers, the optimal incentive menu for each type of suppliers will be determined. Unlike information symmetry, information asymmetry requires the contract to be designed in order to prevent suppliers from lying about their type. Thus, as noted, incentive compatibility constraints are included in the model. The optimal contract scheme is illustrated in Table 3.7 and 3.8.

Table 3.7. Optimal quality incentives under information asymmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.4	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.6	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
0.8	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.0	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.2	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.4	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.6	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
1.8	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00
2.0	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00

Table 3.7 illustrates that all quality incentives are one. This result is consistent with the fact that the profit functions of all types of suppliers are increasing in quality incentive. Therefore, in order to prevent suppliers from lying about their quality type, procurers should give all types of suppliers the maximum quality incentive that is one, as illustrated in Table 3.5. This comes from the current specification of profit function of suppliers. If the curvature of the profit function of suppliers is changed into normal distribution type curves, Table 3.7 will have different numbers. Moreover, if one quality incentive does not give procurers their reservation profits, there will be no contract. For example, while suppliers of quality type of 0.2 and efficiency type of 0.2 get a positive

quality incentive under information symmetry, procurers will not make contracts with them under information asymmetry because they get less than reservation profit.

Table 3.8. Optimal efficiency incentives under information asymmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	0.00	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
0.4	0.00	0.00	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85
0.6	0.00	0.00	0.85	0.85	0.85	0.85	0.85	0.60	0.60	0.60
0.8	0.00	0.00	0.85	0.85	0.85	0.85	0.85	0.60	0.60	0.60
1.0	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60	0.60
1.2	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60	0.60
1.4	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60	0.60
1.6	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60	0.60
1.8	0.00	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60
2.0	0.00	0.00	0.00	0.00	0.60	0.60	0.60	0.60	0.60	0.60

Table 3.8 illustrates that all efficiency incentives consist of two numbers (0.60 and 0.85) and are non-increasing in both quality type and efficiency type. This result implies that the profit function of suppliers is not monotonously decreasing or increasing in efficiency incentive. Therefore, in order to prevent suppliers from lying their quality type, procurers should give all types of suppliers the maximum quality incentive that is 0.60 or 0.85, as illustrated in Table 3.6. This comes from the current specification of the profit function of suppliers. If the curvature of the profit function of suppliers is changed into normal distribution type curves, Table 3.8 will have different numbers.

As noted, there exists the optimal incentive menu for each type of suppliers under an imaginary but reasonable contract setting. For optimal quality incentives, those under information symmetry are less than or equal to those under information asymmetry. This is natural because suppliers can use their exclusive information to get more incentives under information asymmetry. In fact, suppliers get more profit under information asymmetry than under information symmetry. Tables for profits of suppliers and procurers are in the appendix. However, for optimal efficiency incentives there does not exist a definite relationship between under information symmetry and information asymmetry because the profit function for suppliers is not monotonously increasing or decreasing.

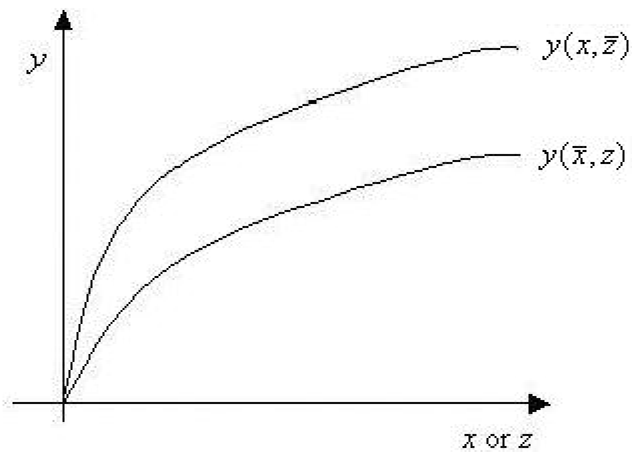
The result that direct incentives affect the profits of suppliers and procurer much more than indirect incentives seems to come from the selection of parameters in simulation process rather than the interdependence between two control targets because, as noted in section 3.4, only one scheme of incentives (direct or indirect) may not control both targets fully and as the result, there does not exist the interdependence. To verify this claim, a sensitivity analysis scheme is proposed in section 3.6.

3.6. Sensitivity analysis of empirical application

This section discusses the sensitivity of the above empirical application results to functional forms, factor prices, and product prices in order to illustrate the robustness of the current empirical application results. In this essay, because simulation method for empirical analysis is used with a set of specific functional forms and parameters including factor prices and product prices, unless the results of empirical analysis are robust and consistent when the setting is changed the results are useless. Therefore, it is meaningful to illustrate what conditions should be satisfied for the simulation results to be similar to the results of this essay.

All production functions including suppliers' production function, quality production function, and procurer's production function are Cobb-Douglas form with decreasing returns to scale, which implies concavely increasing in production factors having different slope for each production factor. That is,

Figure 3.8. Functional form of supplier's quantity output



$\bar{x}$: a fixed level of x and $\bar{z}$: a fixed level of z

Figure 3.8 illustrates that $\partial y/\partial x > \partial y/\partial z > 0$ and $\partial^2 y/\partial x^2 < 0, \partial^2 y/\partial z^2 < 0, \partial^2 y/\partial x\partial z > 0$. These properties are applied to quality production function and procurer's production function. That is, $\partial q/\partial z > \partial q/\partial x > 0$ and $\partial^2 q/\partial x^2 < 0, \partial^2 q/\partial z^2 < 0, \partial^2 q/\partial x\partial z > 0$ and $\partial Y_p/\partial y > \partial Y_p/\partial Q > \partial Y_p/\partial x_p > 0$, and $\partial^2 Y_p/\partial y^2 < 0, \partial^2 Y_p/\partial Q^2 < 0, \partial^2 Y_p/\partial x_p^2 < 0$. In order to satisfy the above conditions, in suppliers' production function, $y = a_0 x^{a_1} z^{a_2}$, it should be that $a_0 > 0, a_1 > 0, a_2 > 0, a_1 + a_2 < 1, a_1 < a_2$. In other production functions, the same thing is true. Because these properties come from the neoclassical production function, these functional settings are reasonable. These properties of production functions make the profit functions for suppliers and procurer have a maximum value at a combination of decision variables (the amount of inputs). If other returns to scale such as increasing returns to scale and constant returns to scale are used, the profit functions for procurer and suppliers may not have any optimal solutions for decision variables because profits will increase unboundedly in the decision variables. Moreover, it is possible to use some other functional forms such as a quadratic form rather than Cobb-Douglas form for production functions. In that case, it is more difficult to set parameters for production function to have the concavity characteristic and the difference in the slope between different inputs.

The other analysis is to examine the effects of changes in parameters in production functions and prices on the simulation results. That is, the problems are in what range of parameters the optimal solutions for procurer and suppliers can exist and how the solutions will move against the change in parameters. In the simulation of this essay, because x_i^* and z_i^* for suppliers are also plugged into procurer's profit function to calculate the optimal profit of procurer and the optimal incentives for procurer and suppliers, if it is possible to obtain x_i^* and z_i^* for each combination of parameters, it is also possible to calculate the optimal profits for suppliers and procurer, and the optimal incentives. Therefore, the most important point of this sensitivity analysis is to find in what range of parameters the optimal solutions (x_i^* and z_i^*) for suppliers. In order to do that, the following steps should be followed.

Step 1. Differentiate the profit function of suppliers with respect to *x* and *z*. So,

$\frac{\partial p}{\partial x} = p_x(x, z \mid p, r_x, r_x, a_0, a_1, a_2, b_1, b_2, l, g, q, d) = 0$ and

$\frac{\partial p}{\partial z} = p_z(x, z \mid p, r_x, r_x, a_0, a_1, a_2, b_1, b_2, l, g, q, d) = 0$.

Step 2. Make a matrix whose columns consist of product price (p), factor prices (r_x, r_z), parameters for supplier's production function (a_0, a_1, a_2 of $a_0 x^{a_1} z^{a_2}$), and parameters of supplier's quality production function (b_1, b_2 of $qx^{b_1} z^{b_2}$). Thus, the matrix should be (p, r_x, r_z, a_0, a_1, a_2, b_1, b_2). The first rows of the matrix are ($\underline{p} \le p \le \overline{p}$, r_x, r_z, a_0, a_1, a_2, b_1, b_2), the second rows are (p, $\underline{r_x} \le r_x \le \overline{r_x}$, r_z, a_0, a_1, a_2, b_1, b_2), …, and the final rows are (p, r_x, r_z, a_0, a_1, a_2, b_1, $\underline{b_2} \le b_2 \le \overline{b_2}$) where $\underline{\ }$ is the lower bound of variables and $\overline{\ }$ is the upper bound of variables.

Step 3. Make a matrix whose columns consist of incentives (l , g) and supplier's types (q , d). Thus, the matrix should be (l , g , q , d). The first rows of the matrix are ($\underline{l} \le l \le \overline{l}$, g , q , d), the second rows are (l , $\underline{g} \le g \le \overline{g}$, q , d), …, and the final rows are (l , g , q , $\underline{d} \le d \le \overline{d}$).

Step 4. Plug each row of parameter matrix and incentive-type matrix into the simultaneous equations of $\frac{\partial p}{\partial x} = p_x(x, z \mid p, r_x, r_x, a_0, a_1, a_2, b_1, b_2, l, g, q, d) = 0$ and $\frac{\partial p}{\partial z} = p_z(x, z \mid p, r_x, r_x, a_0, a_1, a_2, b_1, b_2, l, g, q, d) = 0$. Solve them for each combination of parameter vector and incentive-type vector to find x^* and z^*.

Step 5. Examine the interval for each parameter where x^* and z^* exist.

The results of the sensitivity analysis for the contract model in this essay are summarized in Table 3.9. When product price is between 3 and 5 assuming other parameters are fixed, the optimal solution (x^*, z^*) can be calculated. When the factor price of variable input is only 1, assuming other parameters are fixed, the optimal solution (x^*, z^*) can be calculated. Other parameters can be interpreted in the same way.

Table 3.9. The sensitivity analysis results for suppliers

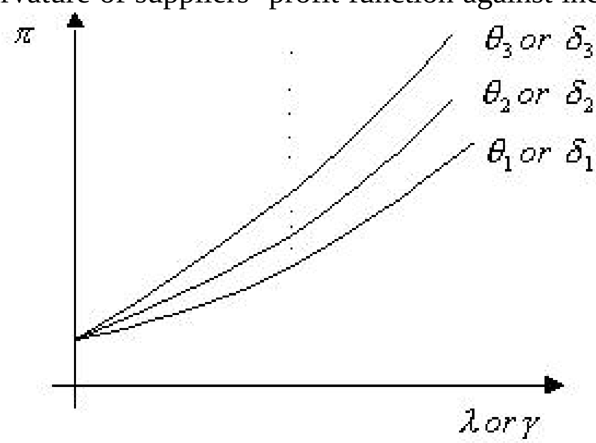
Parameter	Test range	Test Unit	Interval where x^*, z^* exist
p	1 ~ 10	1	3 ~ 5
r_x	1 ~ 10	1	1
r_z	1 ~ 10	1	2 ~ 3
a_0	1 ~ 10	1	3 ~ 5
a_1	0.1 ~ 1.0	0.1	0.6
a_2	0.1 ~ 1.0	0.1	0.2
b_1	0.1 ~ 1.0	0.1	0.1 ~ 0.5
b_2	0.1 ~ 1.0	0.1	0.1 ~ 0.8

When parameters are included in the range of Table 3.9, it is possible to find the optimal incentives and profits for procurer and each type of suppliers.

One more important thing is whether the contract model in this essay satisfies the Spence-Mirrless condition that is an important condition in the analysis of the case that there are different types of agents (Salanie, 1998). Its economic significance is that at any given level of decision variable, the higher types of agents are willingness to perform better than the lower agents for the same increase in the incentives. In this essay, it can be rephrased that at any given quality incentive level or efficiency incentive level, the suppliers with higher type in quality or efficiency are willing to achieve better quality than the suppliers with lower type for the same increase in incentive. Therefore, the profit function of high type suppliers has the steeper slope than that of low type suppliers.

This Spence-Mirrlees condition is also called by single-crossing condition because if the condition is satisfied, then the profit function of different types can only cross once. Since the profit function of suppliers with the parameter values in Table 3.9 has the curvature of graphs in Figure 3.9, which implies that the profit function of different types cross once, the contract model in this essay can be said to satisfy the Spence-Mirrless condition.

Figure 3.9. The curvature of suppliers' profit function against incentives in this essay



The previous sensitivity analysis is to examine the ranges of parameters where the optimal contracting parameters (l^*, g^*) exist and the profit functions of suppliers and procurer satisfy the Spence-Mirrless condition. Moreover, the sensitivity analysis that might be needed in this essay is to examine whether the pattern of simulation results in section 3.5 that direct (quality) incentives affect the profits of suppliers and procurer much more than indirect (efficiency) incentives can be changed by the change in parameters. In other words, when parameters in factor prices, product prices, and functional forms are changed, may indirect incentives affect the profits of suppliers and procurer more than direct incentives?, may the optimal direct incentives decrease in quality type and increase in efficient type of suppliers?, and may the optimal indirect incentives increase in quality type and increase in efficient type of suppliers?

In order to do above things, it is necessary to implement all simulation steps described in section 3.5 for each set of parameters. The simulation steps are summarized as follows.

Step 1. Choose a set of parameters for factor prices (r_x, r_z), product prices (p, P_p), and production functions. A notable thing is that the parameters should belong to the ranges that are identified in Table 3.9.

Step 2. Calculate the reservation profits of suppliers and procurer for each type of suppliers.

Step 3. Calculate the optimal inputs (x^*, z^*), outputs (y, q), and profit of each type of suppliers on given direct incentives and indirect incentives.

Step 4. Calculate the optimal profit of procurer in the contract with each type of suppliers on given direct incentives and indirect incentives under information symmetry and information asymmetry.

Step 5. Plot the profits on direct incentives and indirect incentives like Figure 3.2 and determine the optimal direct incentives and indirect incentives like Table 3.7 and Table 3.8.

Step 6. Review the figures plotted in Step 5 and the pattern of optimal incentives determined in Step 5 to examine whether they have the different pattern from the results in section 3.5.

Step 7. Repeat from step 1 to step 6 until all sets of parameters are considered.

Through the above steps, it is possible to examine whether the results in section 3.5 come from the interdependence between two control targets, quality achievement and technical efficiency. If the different pattern in results between different sets of parameters is found, the results in section 3.5 may not be said to come from the interdependence but from the selection of parameters. This essay does not include the implementation of this sensitivity analysis but it will be a topic for other paper.

3.7. Conclusion

Quality may be imperfectly observed by suppliers and procurers in supply chain. This imperfect observability of quality leads the quality market to fail to price the quality and leads suppliers to produce quality technically inefficiently because suppliers cannot perceive true quality production technology. The problem in essay three is to determine how a supply chain might be coordinated to manage the imperfectly observable quality and to improve technical efficiency in quality production of suppliers. An alternative coordination method is vertical integration. However, the vertical integration cannot guarantee the increase of social welfare when the vertical integration is to resolve the market failure generated from the imperfect information on products. Therefore, contracts between suppliers and procurer are taken to deal with the problem of this essay. The objectives of this essay are to develop a contract model to control the quality and technical efficiency of suppliers and to illustrate the behavior and effect of optimal incentives on performance of suppliers and procurer using a simulation method.

The past literature on the relationship between incentives and performance of suppliers and procurers is available. Lazear (1996), Paarsch and Shearer (1996), Banker, Lee, and Potter (1996), Fernie and Metcalf (1996), McMillan, Whalley, and Zhu (1989), and Kahn and Sherer (1990) consider the effect of incentives on outputs and verify that outputs improve when incentives are sensitive to outputs by agents. In contrast, Foster and Rosenzweig (1994) consider the effects of incentives on inputs (efforts) rather than outputs by agents and verify more efforts under incentives sensitive to performance. However, this relationship between incentives and performance can be corrupted for various reasons. One reason is changes in actions by agents from multitasking (Prendergast, 1999). Multitasking implies that agents change the nature of their activities in response to objective contracts in a way that is beneficial to agents but harmful to the agency (Holmstrom and Milgrom, 1991). Healy (1985), Asch (1990), Oyer (1998), and Courty and Marschke (1996) verified the existence of the reallocation of inputs by agents that is not obviously efficient when incentives are determined based on objective performance measures. While multitasking is a problem in information symmetry, information asymmetry can also corrupt the results of contracts. Salanie (1996) illustrates when adverse selection exists in contracts and how it can be resolved by using a simple example of a wine quality choice problem by customers with different preferences. It is not easy to find literature on the empirical application of contract models such as simulation and estimation of contract parameters. For simulation, it is possible to take Vukina and Foster (1995) and Bogetoft and Olesen (2000), and for estimation of contract parameters with data, it is possible to take Hueth and Ligon (2002) and Ferrall and Shearer (1999). Vukina and Foster (1995) simulated the behavior of output, utility inputs, average settlement cost of groups, settlement cost, total revenue, internal cost, and profit of broiler farms in North Carolina. They estimated the cost function of farms with data using 3SLS (3 step least square) method and simulate the behavior by changing contract parameters such as base price and bonus, separately. Moreover, they considered only the behavior of suppliers' profit and cost not the behavior of processor's profit ad costs under information symmetry (That is, they do not use the Principal-agent model). Bogetoft and Olesen (2000) use a simulation method to illustrate the effect of competitive regimes on the level of investment. Their approach is the same as the approach in this essay in that they compute the level of investment by setting a value for each parameter. However, they do not consider the incentives under contract scheme but incentives for investments.

In this essay, contracting between procurers and suppliers are examined with two incentives: direct incentives for the quality achievement and indirect incentives for the technically efficient part of quality input use. The basic story of the contract is that suppliers produce a product to supply to procurers (quality is imperfectly observable to suppliers and procurer), procurer purchases the product from suppliers, procurer measures the quality of product after the product arrived (quality is known to both suppliers and procurer), procurer determines the direct incentives for quality achievement (still persistent technical inefficiency exists in suppliers), and procurer gives the indirect incentives for the technically efficient part of quality input use to improve the quality level and technical efficiency. In these processes, the information asymmetry on the types of suppliers (quality production ability and technical efficiency) can be inserted. If information symmetry on suppliers' types is assumed, contracting has only to set direct incentive for quality to resolve the quality market failure and to set indirect incentive to improve technical efficiency only guaranteeing the reservation profits to suppliers (individual rationality constraints). However, if information asymmetry exists between procurers and suppliers, the incentives should be constrained by incentive compatibility constraints as well as individual rationality constraints to prevent suppliers from lying about their types. To illustrate these contracting schemes empirically, a simulation method is used. Unlike the above literature, the simulation in this essay is not based on the estimation of production/cost function but is based on an arbitrary selection of functional forms and parameters. Therefore, a sensitivity analysis is implemented to examine in what ranges of parameters the optimal incentives exist.

The results from simulation illustrate that the optimal incentive schemes can be determined for each type of suppliers, the incentives improve the performance of suppliers and procurer, and the direct incentive has more effect on performance than the indirect incentive. Three kinds of contributions of this essay can be summarized below. The first contribution is the contribution to contracting specification. In this essay, the model has two type variables for suppliers and includes technical efficiency as well as quality performance as base information for contracting by giving direct incentives and indirect incentives. The second contribution is that the simulation method is used for empirical application instead of theoretical comparative statics. This simulation method helps us reduce the complexity of analysis as well as gives us good insights into the behavior of contracting models. The third contribution is the finding that incentives affect quality performance and the use of quality inputs, direct incentives have more effect on quality performance and the use of quality inputs than indirect incentives.

Appendix 3.1. Simulation scheme

There is equation 3.20 as the profit function for procurers and suppliers. As noted, these profit functions consist of some parameters such as factor prices for suppliers and procurers, product prices for suppliers and procurers, some decision variables such as the amount of variable inputs, the amount of quality inputs, and contracting parameters, some sun-functions such as production function for quantity and quality, dumping function, and stochastic quality event distribution function. Thus the very first step of the approach is to determine the functional forms, parameters of functions, and other parameters. The functional form for quantity production and quality production is a kind of Cobb-Douglas form that is usually taken for production function. The parameters involved in the production functions are determined for them to satisfy concavity and to enable profit function to satisfy the Spence-Mirrlees condition. The functional forms and parameters are as follows:

Table A3.1. Functional forms and parameters

Description	Function
Supplier market good technology	$y(x,z) = 3x^{0.6}z^{0.2}$
Non-market quality technology	$q(x,z \mid e) = q \times x^{0.1}z^{0.6}$
The processing function for procurers	$Y_p(x_p, Y, Q) = 3Y^{0.4}x_p{}^{0.1}Q^{0.2}$
Joint distribution of quality type and efficiency type	$g(q,d) = \dfrac{(-\lvert q - 1.05\rvert^{1.3} \times \lvert d - 0.75\rvert + 1)}{87.40}$

Also, the other parameters involved in profit functions are as follows:

Table A3.2. Product prices and factor prices

Price	Description	Value
p	Price for product by suppliers	3
P_p	Price for the final product by procurer	5
r_x	Factor price of x	1
r_z	Factor price of z	2
r_p	Factor price of x_p	1

Moreover, the quality type ranges from 0.2 to two and the efficiency type d ranges from 0.1 and one uniformly. In this paper, q has 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8, 2.0 and d has 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1.0 for simulation.

The above specification can be expressed in the profit function as follows: $p_i^c(x_i^a, z_i^a \mid q_i, d_i, g_i, l_i, b_i)$ and $p_p(x_p, g, l \mid q, d, a)$ where b_i includes all parameters related to suppliers such as parameters in the supplier's production function for quantity and quality, dumping function, quality event distribution function, and factor prices, and a includes all parameters related to procurer. Since individual rationality constraints and incentive compatibility constraints require the optimal expected profits, the first order condition of the expected profit function of profit with respect to x_i^a and z_i^a is generated, and they are solved to get the optimal decision variables as a function of parameters ($x_i^a* = x_i^a*(q_i, d_i, g_i, l_i, b_i^s)$ and $z_i^a* = z_i^a*(q_i, d_i, g_i, l_i, b_i^s)$) using Broyden's method. By plugging them into $Ep_i^c(x_i^a, z_i^a \mid q_i, d_i, g_i, l_i, b_i)$ and $p_p(x_p, g, l \mid q, d, a)$, there is $Ep_i^c(q_i, d_i, g_i, l_i, b_i^s)$ and $p_p(x_p, g, l \mid q, d, a, b_i^s)$. Finally, it is possible to run non-linear constrained optimization processes as follows (asymmetric information): $\underset{g, x_p, g}{Max}\, E_q p_p(x_p, g, l \mid q, d, a, b_i^s)$ subject to $Ep_i^c(q_i, d_i, g_i, l_i, b_i^s) \geq p_i^r$ (IR) and $Ep_i^c(q_i, d_i, g_i, l_i, b_i^s) \geq Ep_i^c(q_i, d_i, g_j, l_i, b_i^s)$ (IC). For the symmetric information case, it is possible to run the program without incentive compatibility constraints. Here, because the objective function is the expected profit of the procurer with respect to supplier type it is not necessary to do integration.

Appendix 3.2. The properties of production function of quality and quantity

From Mefford's paper (1991) and literature review on quality production function, is suggested the following type of implicit production functions for quantity (F^y) and quality (F^Q): $F^y(y,x,z,w)=0$ and $F^Q(q,z,y,t)=\underline{q}$ where y is a vector of quality-sorted private goods, q is a vector of quality flows that are not priced by the market, $\underline{q}$ is a vector of the basic quality flows that is produced without any quality inputs, x is a vector of variable inputs, z is the vector of quality inputs, w is the technique for quantity production, and t is the technique for quality production.

The following assumptions are made with regard to F^y and F^Q. 1) Both F^y and F^Q are continuous, twice differentiable, convex and closed in output and inputs, 2) Both are strictly increasing in y and q, respectively and strictly decreasing in x and z, 3) y is finite for all finite x and z. One notable thing is that quality inputs are not allocable (allocatable) to y and q because quality inputs are used to improve the quality rather than quantity and as a byproduct, they affect the quantity. By allocability, it means that the amount of an input used in producing a product can be distinguished from the amount of the input used in producing the other product (Beattie and Taylor, 1993; Shumway, Pope, and Nash, 1984). If z is allocable then the total amount of z used would be $z = z_q + z_y$ where z_q is the amount of z used to produce quality (q) and z_y is the amount of z used to produce quantity (y). On the other hand, a non-allocable input is one for that it is not possible to distinguish between units used in producing different products (Beattie and Taylor, 1993). In steel factory, iron and coke are produced simultaneously using iron ores and coking coals. However, it is not possible to distinguish the amount of iron ores and coking coals used to produce iron and that used to produce coke. There exist two outputs such as quantity and quality, and two types of inputs such as variable inputs and quality inputs that are used to improve the quality of product. Thus the corresponding profit function of firm is $p = p(x, z; p, l, r_x, r_z, w, t) = py + l\,q - r_x x - r_z z - m_1 F^y(y, x, z) - m_2 F^Q(q, y, z)$ (A.1) where p is the price of a product, l is the price of quality per unit quantity, r_x is the vector of prices for variable inputs, and r_z is the vector of prices for quality inputs.

The normalized profit function (Lau, 1976) is $p^n(p, l, r_x, r_z) = Max\,p = py^* + l\,q^* - r_x x^* - r_z z^*$ (A.2) where the * represents the optimized value. From equation (A.1) and duality condition, $\frac{\partial p^n}{\partial p} = y^*$, $\frac{\partial p^n}{\partial l} = q^*$, $\frac{\partial p^n}{\partial r_x} = -x^*$, and $\frac{\partial p^n}{\partial r_z} = -z^*$ (A.3). From the optimality conditions of equation, $p + l = m_1^* \frac{\partial F^y}{\partial y} + m_2^* \frac{\partial F^Q}{\partial y}$, $\frac{\partial F^Q}{\partial q} = \frac{l}{m_2^*}$, $\frac{\partial F^y}{\partial x} = \frac{-r_x}{m_1^*}$, and $-r_z = m_1^* \frac{\partial F^y}{\partial z} + m_2^* \frac{\partial F^Q}{\partial z}$ (A.4). The normalized profit function is characterized by the following properties from the above properties of production functions: 1) p^n is continuous, twice differentiable, convex and closed in $p, l, r_x,$ and r_z, 2) p^n is strictly increasing in output prices and strictly decreasing in factor prices, 3) p^n is finite for all finite p and l. The profit function in this essay is not homogeneous of degree one in $p, l, r_x,$ and r_z unlike the normalized profit function in the paper of Lau (1972a) from equation (A.3). That is, $\dfrac{\partial F^y}{\partial x}\Big/\dfrac{\partial F^y}{\partial z} = \dfrac{-r_x}{m_2 \dfrac{\partial F^Q}{\partial z} - r_z}$ and $\dfrac{\partial F^y}{\partial y}\Big/\dfrac{\partial F^y}{\partial x} = \dfrac{p + l - m_2 \dfrac{\partial F^Q}{\partial y}}{-r_x}$ (A.5), and this implies that the value of equation (A.4) is dependent on the multiplier of inputs or outputs. Because most of properties of homogeneity in the paper of Lau (1972a) are based on this theorem, my normalized profit function and production functions do not satisfy the properties.

For separability of inputs from outputs of my production functions, $F^y(y,x,z) = G^y(y) - H^y(x,z) = 0$ and $F^Q(q,x,z) = G^Q(q) - H^Q(x,z) = 0$ means the separability of inputs from outputs. However, since my production function for quality is expressed by $F^Q(q,y,z) = G^Q(q) - H^Q(y,z) = 0$, intuitively, the production process is not separable between inputs and outputs. If the production function for quality is expressed by $F^Q(q,x,z) = G^Q(q) - H^Q(x,z) = 0$, the production process can be separable between inputs and outputs as follows. Profit maximization in separable case leads to the following necessary conditions:

$$\begin{aligned}
&\frac{\partial p}{\partial y} = p + l - m_1 \frac{\partial G^y}{\partial y} = 0, \frac{\partial p}{\partial q} = l\,y - m_2 \frac{\partial G^Q}{\partial q} = 0,\\
&\frac{\partial p}{\partial x} = -r_x - m_1 \frac{\partial H^y}{\partial x} - m_2 \frac{\partial H^Q}{\partial x} = 0, \frac{\partial p}{\partial z} = -r_z - m_1 \frac{\partial H^y}{\partial z} - m_2 \frac{\partial H^Q}{\partial z} = 0,\\
&\frac{\partial p}{\partial m_1} = G^y(y) - H^y(x,z) = 0, \frac{\partial p}{\partial m_2} = G^Q(q) - H^Q(x,z) = 0
\end{aligned}$$

(A.6). It is possible to solve (A.3) to get $\begin{matrix} y = g^y(p, l, q, m_1), q = g^Q(p, l, y, m_2), \\ x = h^x(r_x, r_z, m_1, m_2), z = h^q(r_x, r_z, m_1, m_2) \end{matrix}$ (A.7). The normalized profit

function is given by
$$\begin{aligned}p^n &= pg^y(p,l,q,m_1) + l\,g^Q(p,l,y,m_2)g^y(p,l,q,m_1)\\ &-r_x h^x(r_x,r_z,m_1,m_2) - r_z h^q(r_x,r_z,m_1,m_2) = G^*(p,l,q,y,m_1,m_2)\\ &-H^*(r_x,r_z,m_1,m_2)\end{aligned}$$
(A.8).

Equation (A.7) illustrates production function is separable between inputs and outputs only if G* and H* are both homogeneous of degree one in their respective arguments.

In order to see whether my production function is non-joint or not, let's see the cost minimization problem when producing $\overline{y}$ and $\overline{q}$. The Lagrangian problem is $L = r_x x + r_z z + g_1[\overline{y} - y(x,z)] + g_2[\overline{q} - q(z,y)]$ (A.9). The first order conditions of equation (A.8) are $\frac{\partial L}{\partial x} = r_x - g_1\frac{\partial y}{\partial x} - g_2\frac{\partial q}{\partial y}\frac{\partial y}{\partial x} = 0$ (A.10), $\frac{\partial L}{\partial z} = r_z - g_1\frac{\partial y}{\partial z} - g_2\frac{\partial q}{\partial z} = 0$ (A.11), $\frac{\partial L}{\partial g_1} = \overline{y} - y(x,z) = 0$ (A.12), and $\frac{\partial L}{\partial g_2} = \overline{q} - q(z,y) = 0$ (A.13). From equations (A.9) and (A.10), it is possible to get $g_1 = \left. r_x - \frac{r_x y_z - r_z y_x}{q_y y_z - q_z} \middle/ y_x \right.$, $g_2 = \frac{r_x y_z - r_z y_x}{y_x(q_y y_z - q_z)}$ (A.14) where $y_x = \frac{\partial y}{\partial x}$, $y_z = \frac{\partial y}{\partial z}$, $q_y = \frac{\partial q}{\partial y}$, and $Q_z = \frac{\partial q}{\partial z}$. The conditional factor demand functions are $x^c = x^c(r_x, r_z, \overline{y}, \overline{q})$ (A.15) and $q^c = q^c(r_x, r_z, \overline{y}, \overline{q})$ (A.16), and the minimized cost function is
$$\begin{aligned}VC &= r_x x + r_z z = r_x x^c(r_x, r_z, \overline{y}, \overline{q}) + r_z q^c(r_x, r_z, \overline{y}, \overline{q})\\ &= C(r_x, r_z, \overline{y}, \overline{q}) \neq C^y(\overline{y}, r_x, r_z) + C^Q(\overline{q}, r_x, r_z)\end{aligned}$$
where $C^y()$ is individual cost function for quantity and $C^Q()$ is individual cost function for quality. The fact illustrates that the minimized cost function is not additively separable for each output (at least, cost function cannot be written for each product) and production function is not nonjoint.

Here, based on the fact in cost function, it is possible see how to express the profit function. If it is assumes that general outputs are y and q rather than $\overline{y}$ and $\overline{q}$, the output side profit maximization problem is $p = py + l\,q - VC = py + l\,y - C(y, q, r_x, r_z)$ (A.17)

where $VC = r_x x + r_z z = r_x x^c(r_x, r_z, y, q) + r_z q^c(r_x, r_z, y, q) = C(r_x, r_z, y, q)$ $\neq C^y(y, r_x, r_z) + C^Q(q, r_x, r_z)$ that implies that the cost function is not additively separable. Therefore, the production function and profit function in this essay are joint in production.

The following origin properties will be assumed as follows. When x = 0 and $z \neq 0$, both y and q are also zero because no quantity implies no quality. That is, $y(x = 0, z, w) = 0$ and $q(z, y; y = 0, t) = 0$. However, when $x \neq 0$ and z = 0, both y and q can be greater than zero because z is not essential to produce a quantity but also complementary and the product has a basic quality ($\underline{q}$) without z. That is, $y(x, z = 0, w) > 0$ and $q(z = 0, y; y > 0, t) \geq 0$. When $x \neq 0$ and $z \neq 0$, both y and q are greater than zero and specially, q becomes greater than $\underline{q}$ (Beattie and Taylor, 1993).

Appendix 3.3. Optimal profits for suppliers and procurer

Table A3.3. The optimal profits of suppliers under information symmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	328.44	342.83	377.04	380.72	386.71	390.39	403.03	419.97	420.64
0.4	0.00	0.00	365.55	387.76	410.26	427.88	430.20	435.76	437.76	445.40
0.6	0.00	0.00	377.95	419.30	447.90	456.54	474.89	485.45	490.41	501.41
0.8	0.00	0.00	407.97	430.68	513.69	524.19	533.61	544.89	550.05	563.69
1.0	0.00	0.00	0.00	458.97	524.56	559.43	561.72	566.06	569.43	571.90
1.2	0.00	0.00	0.00	474.53	539.92	569.63	575.96	585.96	621.38	632.90
1.4	0.00	0.00	0.00	501.83	541.70	595.92	617.92	635.92	642.49	645.92
1.6	0.00	0.00	0.00	533.18	558.67	607.09	629.07	647.09	663.61	677.09
1.8	0.00	0.00	0.00	536.91	572.14	648.26	681.10	700.66	711.10	728.26

2.0	0.00	0.00	0.00	0.00	587.13	679.42	702.39	722.00	732.39	742.74

Table A3.4. The optimal profits of suppliers under information asymmetry

Quality type	Efficiency type									
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.2	0.00	0.00	374.01	436.97	525.04	657.58	877.89	1204.80	1745.67	2084.24
0.4	0.00	0.00	383.53	448.35	539.79	677.24	880.80	1242.57	1773.86	2421.83
0.6	0.00	0.00	392.91	451.94	554.40	696.68	920.34	1363.48	1917.88	2652.04
0.8	0.00	0.00	412.42	462.12	568.78	715.89	954.03	1416.80	2117.88	2728.35
1.0	0.00	0.00	0.00	466.83	570.02	716.88	969.63	1444.95	2296.02	2829.62
1.2	0.00	0.00	0.00	475.70	572.14	720.37	971.07	1477.64	2410.07	3027.51
1.4	0.00	0.00	0.00	512.68	582.16	733.71	995.23	1500.82	2529.61	3115.18
1.6	0.00	0.00	0.00	546.30	592.07	746.90	1008.6	1531.98	2535.71	3208.65
1.8	0.00	0.00	0.00	0.00	601.86	759.93	1027.3	1593.36	2678.89	3274.27
2.0	0.00	0.00	0.00	0.00	611.54	772.79	1045.5	1633.89	3191.99	3293.99

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