

A MODEL OF TECHNOLOGY SELECTION BY COST MINIMIZING PRODUCERS*

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A set of microeconomic assumptions are presented that lead to a model of the technology choices made by producers of a homogenous energy product. Under these assumptions it is possible to model the technology selection decision as being made solely to minimize product cost. Since the cost of producing energy using a particular technology will be different for different producers, a number of technologies will be adopted in the market rather than a single, "least-cost" technology.

(MARKET SHARE; ENERGY MODELING)

1. Introduction

This paper presents a set of assumptions that lead to a model of the share of an energy product market served by each technology of a set of competing technologies. Many energy product markets can be thought of as having a homogenous product that can be produced by a variety of technologies. In this situation, the choice of technology is strictly a producer decision, as the consumer is unable to distinguish among products from different sources. The producer will seek to minimize costs and the technology selection decision can be modeled as being made solely to minimize product cost.¹

The market share model developed using the minimum cost criterion is similar to the familiar logit model [3], [10]. However, rather than market share being based on a maximization of utility as in the logit model, market share is based on a minimization of cost. In fact, it has been shown elsewhere that the logit model is inappropriate when applied to cost minimization [14]. A model similar to that discussed here is presented formally in [12], [13] and [15]. This paper derives the model from basic microeconomic assumptions. Thus the paper provides a fundamental justification for a model that is useful in a wide variety of market penetration analyses. Specifically, it is useful in those situations in which the cost minimizing assumption is a reasonable approximation [1], [2], [5], [7], [9], [11], [16], [17]. In other words, when all the factors affecting the choice of a technology such as capital cost, capital charge rate, fuel cost, efficiency, operating and maintenance cost, and so on can be combined into one overall measure of cost, such as the levelized cost of producing energy, then the model is a useful approximation. However, in some contexts, particularly those involving consumer choices, models that depend on more variables, similar in spirit to those in [8], might be more useful.

2. Background

There are three types of variables affecting the cost of producing energy with a particular technology:

1. Global Variables—factors that affect the energy system as a whole, such as inflation.

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¹ The model applies to any other market with similar characteristics such as minerals, chemicals, or forest products. We use the energy context since this is where most applications have occurred.

2. Technology Specific Variables—variables that affect only a specific technology, such as its cost and performance characteristics.

3. Producer Specific Variables—factors describing technology users, such as site characteristics, local wage rates, operating and maintenance experience, and so on.

In many analyses that involve estimating the penetration of a technology it is convenient to consider similar producers as a group rather than model each separately. In these analyses, illustrated in Figure 1, a market share function models the effects of varying producer characteristics, while the effects of global and technology variables are considered explicitly. Thus, the role of the market share function is to represent the fact that even in a deterministic world, where the cost and performance characteristics of each technology are known, the technology that is the least costly for one producer to use may not be the least costly for the next producer to use. In this paper we derive a market share function appropriate for this role.

3. Market Model Description

The technologies competing in a particular market can be described in varying levels of detail, depending on the decision being analyzed. For example, in an analysis of electric utility storage options each technology might be defined in general terms as advanced battery storage, underground pumped hydro, compressed air energy storage, and so on. However, in an analysis of R&D funding for advanced batteries, we would use more specific technology descriptions for each of the alternatives such as sodium-sulfur, zinc-chlorine, and so on. In general, we assume that the technologies considered for selection in the market analysis are described at equivalent levels of detail. We call these technologies generic technologies since each represents a set of more specific designs, or specific technologies. Each specific technology has a cost c_{ij} , the cost of producing an energy output using the specific technology where i denotes the generic technology and j denotes the specific technology.

To develop the market share function we will look at these specific technology costs from two points of view: that of the producer and that of the market modeler. To the producer the cost of producing a product using a specific technology is deterministic, given a set of assumptions about global and technology specific variables. Differences between producers represented by variations in producer specific parameters leads to a distribution of costs which can be represented by a histogram such as that in Figure 2. To the modeler the product costs experienced by the producers are uncertain and the histogram constructed in Figure 2 is the conditional probability density function describing the modeler's uncertainty about the product costs conditional upon the global and technology specific variables. We will assume that such a conditional probability density function characterizes each specific technology in each generic class under consideration.

We have been careful to condition the distribution of the c_{ij} on global and technology specific variables, because in general, the unconditional product costs for each member of a particular generic class will *not* be independent random variables. For example, technologies that use the same feedstocks will have probabilistically dependent product costs. However, in analyses structured as outlined in Figure 1 product costs will be conditionally independent. For example, it may be reasonable to assume product costs are independent if the feedstock cost is known. Assuming that we use such structuring, then the cost of producing energy with technology j in generic class i is conditionally independent of the cost of producing energy with technology k in generic class i for all j not equal to k .

Now consider the generic technology. For a cost-minimizing producer, the generic or representative technology is the least-cost technology, so the product cost for the

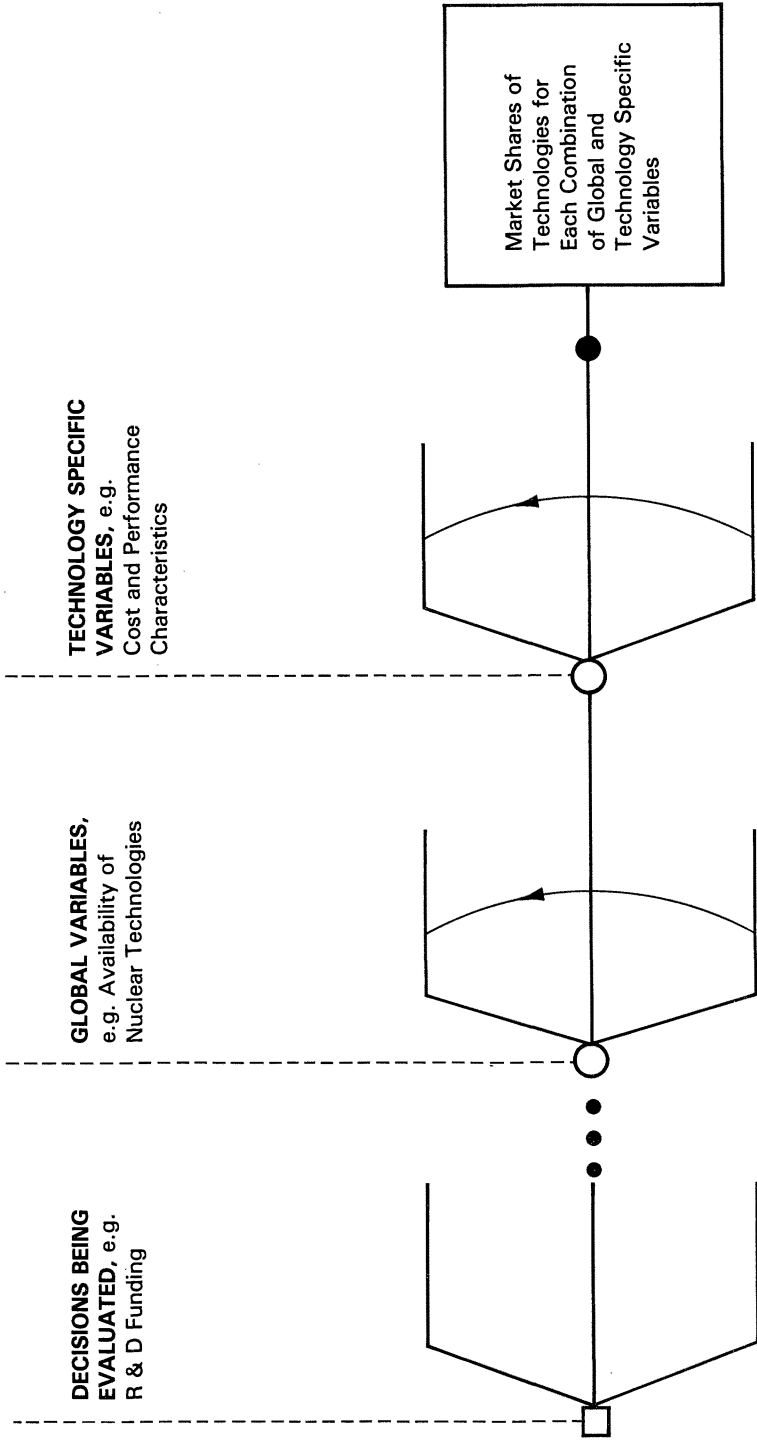


FIGURE 1. Context for Application of Market Share Model.

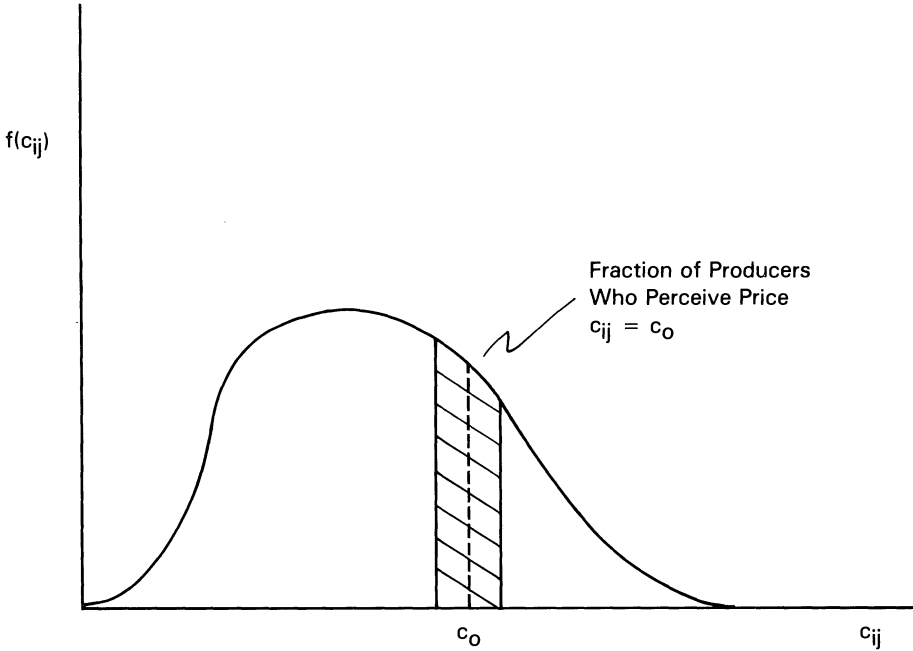


FIGURE 2. Histogram of Production Costs Using a Specific Technology.

generic technology is

$$c_i = \min_j (c_{ij}).$$

Thus, the distribution of generic technology costs can be derived from distributions on the specific technology costs. For a large class of possible cost distributions it can be shown [4], [6] that the limiting distribution for the minimum cost is a Weibull or third asymptotic distribution. For this reason, we assume that uncertainty in the cost, c_i , of a product produced by generic technology i from a diversity of producers has the Weibull distribution:

$$f_i(c_i) = \left(\frac{b_i}{a_i}\right) \left(\frac{c_i}{a_i}\right)^{b_i-1} \exp\left[-\left(\frac{c_i}{a_i}\right)^{b_i}\right] \tag{1}$$

where a_i , b_i , and c_i are all greater than zero. The mean and variance of product cost are

$$\bar{c}_i = a_i \Gamma(1 + b_i^{-1}), \tag{2}$$

$$\check{c}_i = a_i^2 [\Gamma(1 + 2b_i^{-1}) - \Gamma^2(1 + b_i^{-1})], \tag{3}$$

where a_i is a scale parameter and b_i determines the shape of the distribution. Notice that this is *not* the distribution referred to as the Weibull in some discussions. In particular, the distribution identified as the Weibull in [3], [10] is more commonly called the Gumbel or first asymptotic distribution [6]. In the present context, the Weibull has the useful characteristic that the minimum of a set of independent Weibull random variables also has a Weibull distribution. Similarly, the maximum of a set of independent Gumbel random variables has a Gumbel distribution.

There are two important observations to make about our characterization of a generic technology. First, recall that the uncertainty represented in each of the generic

product cost probability density functions arises from the differing characteristics among producers and the aggregated characteristics of the generic technology. Since the potential producers are the same for any generic technology serving the market and the generic technologies are defined at equivalent levels of aggregation, we assume that the shape of the probability density functions describing each generic technology product cost is the same. Technically this means that the shape parameter b_i is the same for all technologies. The differing characteristics of the various generic technologies are reflected in different values of the scale parameter a_i . Second, notice that the generic technology can be defined at whatever level of detail is appropriate. For example, the generic technology could be coal-gasification in general, a particular generation of coal-gasification such as first or second generation, or a particular gasification process such as the Lurgi process. In each case, the variation in costs among producers as represented in equation (1) remains, although the parameter values change.

4. Market Share Function Derivation

Our problem now is to compute the shares of a particular energy market captured by competing generic technologies the product costs of which are uncertain and have Weibull distributions. Since a technology is only selected by a particular producer because its product cost is less than the product costs from all other technologies, the share of the market that a technology serves is equal to the probability that it has the least product cost. The market share to technology i can be found by computing for a particular product cost which the i th technology can take, the probability that all other technologies will experience a greater product cost. Figure 3 illustrates in simplified form this calculation for two technologies. Next, this probability is weighted by the probability that technology i will have the particular cost. This weighted probability is summed over all possible costs that the i th technology can take. Since the product costs for the generic technologies are conditionally independent as discussed in the

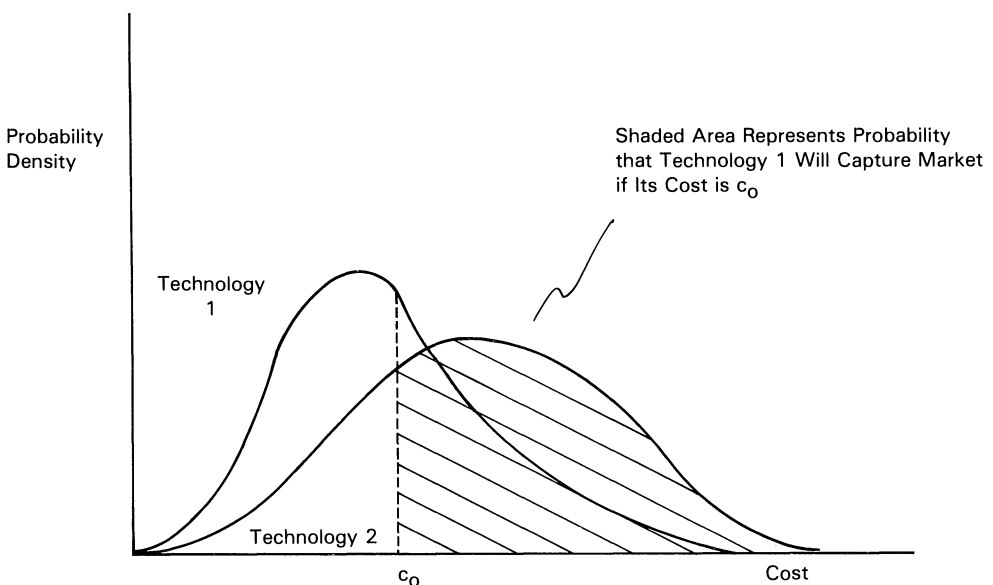


FIGURE 3. Illustration of the First Step in Calculating Market Share for the Case of Two Technologies.

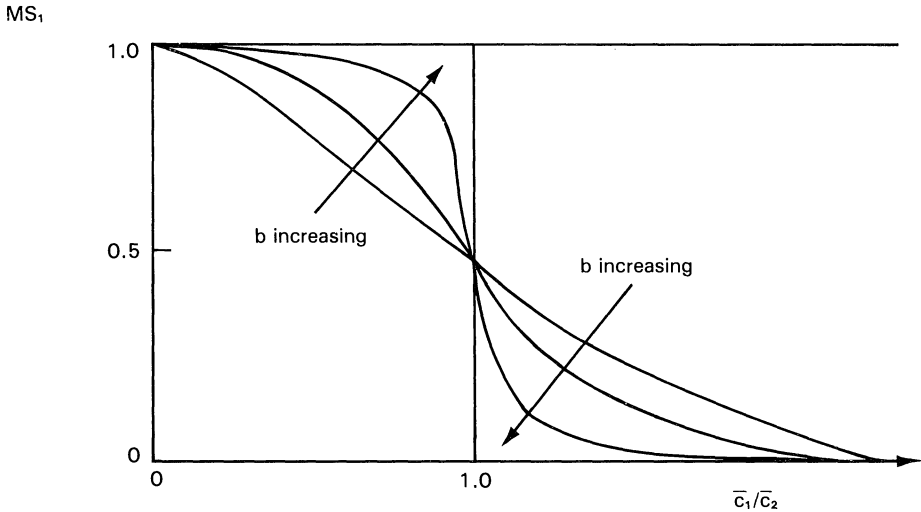


FIGURE 4. Market Share Curve for Two Technologies.

previous section, the market share calculation can be expressed mathematically as:

$$MS_i = \int_0^\infty f_i(x_i) \prod_{j \neq i} \int_{x_i}^\infty f_j(x_j) dx_j dx_i \tag{4}$$

where n is the number of generic technologies.

Now this general formula can be applied to the case of product costs that have Weibull distributions by substituting (1) into (4) and solving to yield:

$$MS_i = \frac{\bar{a}_i^{-b}}{\sum_{j=1}^n \bar{a}_j^{-b}} .$$

Substituting the mean values of the distributions, \bar{c}_j , as determined by (2), we have

$$MS_i = \frac{\bar{c}_i^{-b}}{\sum_{j=1}^n \bar{c}_j^{-b}} . \tag{5}$$

Thus, the market share depends only on the relative average costs of the product produced using each generic technology. The market share for a market with two technologies has the familiar S-shaped behavior shown in Figure 4.

5. Average Product Cost

The distribution of product costs actually incurred by producers is determined by the technology selection process described above. The mean of this distribution is the average product cost for all producers. The distribution of production costs experienced by the users of a particular technology is also affected by the technology selection process, since not every producer who considers technology i will find that it produces the least-cost product. Since the minimum of a set of independent random variables with Weibull distributions also has a Weibull distribution, it is easy to calculate the interesting result that the average cost incurred by the users of any

particular technology is equal to the average cost incurred by users of all technologies and is given by

$$\bar{c} = \left[\sum_{i=1}^n (\bar{c}_i)^{-b} \right]^{-1/b} \quad (6)$$

(5) and (6) can be used directly to calculate the impact of introducing a new technology into the market.

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