# Product performance evaluation: a super-efficiency model


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**Abstract:** This study introduces the concept of product performance from the perspective of customers. Product performance is measured as a ratio of outputs that customers obtain from a product relative to inputs that customers have to spend for purchasing and using the product. The output side is modelled by a set of customer-relevant parameters such as technical performance attributes but also non-functional benefits and brand strength; the input side reflects user costs. More than 60% of the cars in this study are rated as efficient and obtain the maximum efficiency value of unity. They form the efficient frontier of the compact car market representing a reference function for performance evaluation. Using a super-efficiency model, it is possible to differentiate the efficient products that are left with a score of 100% by standard efficiency models. Our approach is relevant for companies because implications for product design and market segmentation can be derived.



**Keywords:** customer value; product marketing; Data Envelopment Analysis (DEA); super-efficiency model; market segmentation; marketing productivity.

**Reference** to this paper should be made as follows: Staat, M. and Hammerschmidt, M. (2005) 'Product performance evaluation: a super-efficiency model', *Int. J. Business Performance Management*, Vol. 7, No. 3, pp.304–319.



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## 1 Introduction

The literature on marketing performance has long advocated the use of productivity or efficiency measures. Based on a survey of more than 50 studies, Bonoma and Clark (1993) conclude that the most popular measure of marketing performance is efficiency, defined as an output-to-input ratio. Such efficiency ratios can be based on physical, non-monetary metrics (*e.g.*, sales volume per salesman-hour or orders divided by calls) or monetary metrics (*e.g.*, channel revenues to channel costs). Virtually all the marketing performance research relates to the efficiency of marketing management processes: for example selling (Mahajan, 1991), marketing channel design (Ratchford and Stoops, 1988), advertising (Luo and Donthu, 2001) and promotion (Abraham and Lodish, 1993) or – on an aggregated level – the efficiency of the overall marketing function of a firm or branch (Murthi *et al*., 1996; Hershberger *et al*., 2002). These studies focus on the assessment of the 'internal' marketing efficiency, *i.e.*, the financial return obtained from marketing initiatives.

Although products represent the tangible, market-based focus of all marketing efforts only a few studies have applied the efficiency concept to assess the performance of products. However, efficiency should not be considered a supplier-related concept only – considering the financial return on a product's manufacturing and quality costs – but first and foremost a demand-oriented one. Ultimately, creating products that fulfil the needs and expectations of customers reflects the basic idea of marketing (Doyle and Green, 1994; Parsons, 1994). Consequently, the economic value a customer obtains by purchasing a product has to be investigated and optimised. This value becomes higher if a product provides a set of demanded characteristics (outputs) for given expenditures (inputs) in an efficient manner. Offering products that create superior customer value can be seen as a prerequisite to establishing profitable customer relationships, which in turn enhance corporate value (Srivastava *et al*., 1999).

In this paper, we introduce the external, demand-side concept of marketing efficiency and investigate which return (features) a customer receives on his or her investments for purchasing and using the product. As a method to assess the productivity of business functions, Data Envelopment Analysis (DEA) is frequently applied in the literature (for an example, see Barth and Staat, 2005). We will show that the standard DEA is limited in its applicability in the context of product evaluation because it results in performance rankings where typically a large number of products tie for the top position. This is because products like cars are usually designed in order to differ from other cars sold in the same market segment. This allows them to occupy a specific position within some segment and to attract customers through reducing competition with other cars. As a result, cars are less comparable to each other than other products like batteries or car jacks, which have been assessed with DEA before (Kamakura *et al*., 1988). Therefore, using standard DEA models a large fraction of the observations become 100% efficient in their own micro corner of the market. In order to obtain a meaningful performance ranking, we apply the super-efficiency DEA model, an innovative operational research method that maintains the advantageous properties of the basic DEA model and at the same time allows to differentiate between efficient products. With the super-efficiency model, a ranking of the efficient units is possible. In addition, we demonstrate that DEA has more to offer than the detection of 'best buys'. In fact, it can be used for market segmentation, which renders it informative for both product suppliers and consumers. We apply our approach to middle class cars sold on the German market.

## 2 Product performance evaluation with Data Envelopment Analysis

### *2.1 The concept of product efficiency*

Empirical evidence shows that consumers do not search for products with either maximum quality or minimum price but try to optimise the quality-price-ratio. When selecting products, consumers consider both quality and price-related criteria within an economically oriented decision concept of "higher-order-abstraction" (Sinha and DeSarbo, 1998). In order to integrate both performance dimensions, product performance is often conceptualised as a quality-price-ratio or a performance-price-ratio (Zeithaml, 1988).

Several authors emphasise that product performance should not merely be interpreted as a quality-price trade-off but in a more general sense as customer value in terms of value for money (Sinha and DeSarbo, 1998; Despotis *et al.*, 2001; Staat *et al.*, 2002). They view value as a construct that is more complex and in which all 'get' and 'give' components of a product should be embedded. In line with this multifaceted conceptualisation we measure product performance (*i.e.*, the customer value (*CV)* of a product) as an efficiency value:

$$CV = \frac{f\left(\text{Outputs}\right)}{g\left(\text{Inputs}\right)} = \frac{\sum_{r}^{R} u_r y_r}{\sum_{i}^{I} v_i x_i} \tag{1}$$

where inputs $x$ and respective weights $v$ are indexed by $i$. They represent the customer's 'investments' to be made in order to obtain and use a good. Outputs $y$ and respective weights $u$ are indexed by $r$ and represent 'outcomes' of a product, *i.e.*, performance attributes from which utility is derived (*e.g.*, reliability, safety). The *CV* concept models the consumer's trade-off between all received outputs and all inputs for the entire process of purchasing and using the good. Thus, a multitude of single output-input ratios has to be transformed into a single value measure. In order to determine a function for the aggregation of the inputs and outputs, a weighting scheme is necessary. Frequently, a fixed weighting scheme is applied (Norman and Stoker, 1991). For instance, the largest German association of car drivers (ADAC) regularly ranks new cars in this way. A differentiated ranking results; only one product is ranked first and is therefore classified as the 'best buy' in the market. If the weights for all products are exogenously fixed the individual concepts of product design, which result in specific strengths and weaknesses to serve particular consumer segments, may not be reflected adequately when product efficiency is determined.

An alternative to product evaluation with a fixed weighting scheme is DEA, a nonparametric method to determine the relative efficiency of multiple input – multiple output structures. Several studies that have dealt with product efficiency analysis use DEA. Most of them focus exclusively on *technical aspects* (Doyle and Green, 1991; Doyle and Green, 1994; Khouja, 1995; Odeck and Hjalmarsson, 1996; Papagapiou *et al.*, 1997; Papahristodoulou, 1997; Despotis *et al.*, 2001; Bulla *et al.*, 2000). They measure efficiency based on technical parameters only and neglect the fact that non-technical attributes also – and in some product categories predominantly – affect consumer choice. These studies do not assess product efficiency within a comprehensive marketing perspective.

To assure a realistic product evaluation all characteristics from which utility is derived and which determine product choice need to be considered. Hence, product efficiency in the sense of customer value consists of a multitude of purchase-relevant components, including qualitative attributes (Zeithaml, 1988; Fernandez-Castro and Smith, 2002). Only a few empirical attempts have been made to make such a broader construct of product efficiency operational (Staat *et al*., 2002; Fernandez-Castro and Smith, 2002; Bauer *et al*., 2003).

In the sequel, the standard DEA model will be discussed rather briefly because this basic model is used only as the starting point. We then develop an extended approach for product evaluation in more detail drawing on the customer-oriented efficiency perspective introduced above.

## *2.2 DEA as a method of product efficiency analysis*

DEA is a non-parametric method to measure the relative efficiency of observations (in our case: products or product managements) by comparing it to a piecewise linear efficient frontier made up of observed best practice units (Cooper *et al*., 2000). The use of DEA for the purpose of product evaluation is consistent with the characteristics approach to consumer theory widely established in the literature (Fernandez-Castro and Smith, 2002; Hjorth-Andersen, 1984). Goods are not considered as desirable by themselves (*i.e.*, as 'entities') but as bundles of qualitative and quantitative characteristics, which generate utility for the consumer. Accordingly, we specify products as bundles of output and input parameters and argue that product efficiency analyses should be based on these. This is essentially a problem of Multicriteria Decision-Making (MCDM). Products have to be assessed considering a diversity of input and output attributes; weightings for the attributes are required in order to obtain a rating system that successfully integrates all the criteria into a single measure (Doyle and Green, 1994). Up to now, such problems have been dealt with using typical MCDM tools like multiattribute utility models or analytic hierarchy processes. These methods tend to be normative as they aim to generate an ideal alternative, which somehow stands out.

DEA integrates multiple input and output attributes while calculating a single efficiency score. No *a priori* specification of a preference function in form of input and output weights is required. Thus, DEA avoids the problem that a product may perform best on one parameter and be inefficient in terms of another; in such a case only the choice of the weights determines how the product is rated. The relevance of DEA results from the fact that it achieves product evaluation by assigning the best possible weights to all parameters for each product individually (see Equation 1 as well as the discussion below). DEA chooses a set of weights that maximises the efficiency rating of each observation. Thus, different products can be rated as efficient; these products represent the efficient frontier.

Each of the efficient benchmark products reflects a distinct optimisation strategy for a product and, therefore, a separate product submarket. At a specific scale level, it demands the lowest inputs for given output characteristics compared to all other observed units and, therefore, creates a maximum customer value. Out of this set of efficient products DEA assigns customised benchmarks to each inefficient product adjusted to its specific characteristics mix. This type of evaluation is in line with consumers choosing the good from which they receive the highest *relative* performance, *i.e.*, a maximum value in relation to the comparable alternatives and corresponds with the major tenet in marketing: that alternative value-creating product concepts (parameter-mixes) exist to serve consumer segments with corresponding preferences. This is the greatest strength and, at the same time, the greatest weakness of DEA when employed for product evaluation. Flexible weights make it possible to assess distinct products but often lead to many efficient observations which all get the same performance score of unity.

Clearly, DEA provides an objective ‘hands-off’ assessment of the alternatives; this is achieved by looking at the available alternatives from different perspectives (*i.e.*, weighting schemes of the parameters). Thus, the aim is not to select a single ideal from the product set. Instead, the best units for each segment are identified allowing the evaluation of alternative products in the best possible way. It is then for the user to decide which segment (weighting scheme) closely matches his or her preferences over attributes.

The *CV* of a particular product (indexed with subscript ‘0’) is estimated by maximising the ratio of the weighted outputs to weighted inputs (1) under the restriction that no other product attains a score greater than one with these weights (2b). This results in the following fractional programming problem (Staat *et al*., 2002; Cooper *et al*., 2000):

$$\max_{u_{r0}, v_{i0}} CV_0 = \frac{\sum_{r=1}^{R} u_{r0} y_{r0}}{\sum_{i=1}^{I} v_{i0} x_{i0}} \tag{2a}$$

$$s.t. \quad \frac{\sum_{r=1}^{R} u_{r0} y_{rj}}{\sum_{i=1}^{I} v_{i0} x_{ij}} \le 1, \qquad \forall j = 1, ..., J \tag{2b}$$

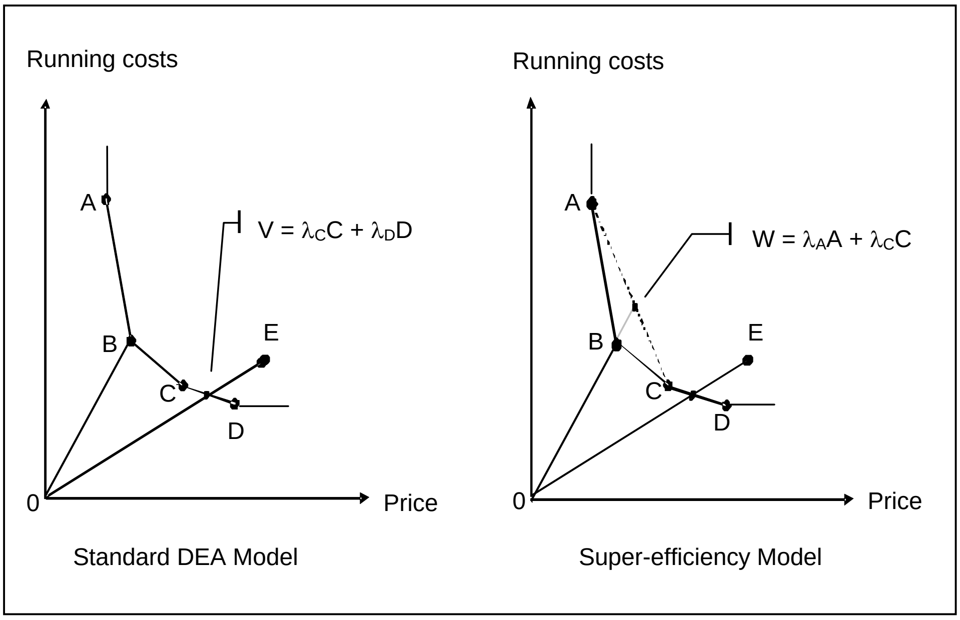
$$u_r, v_i > 0, r = 1, ..., R, i = 1, ..., I$$

where $R$ is the number of outputs $y_{rj}$, $I$ is the number of inputs $x_{ij}$, $J$ is the number of products in the data set.

Maximum weights are attached to parameters on which a product compares favourably and minimum (zero) weights to those on which it compares unfavourably. Thus, the weights contain important information about the efficiency contributions of the parameters and therefore indicate the efficiency drivers (*i.e.*, strengths) of a product.

Figure 1 shows how DEA compares observations to their reference points on the frontier. Inefficient products are compared to the efficient units on the frontier located next to them, *i.e.*, to their efficient peers. For example, the inefficient observation *E* is located closest to the efficient peers *C* and *D*; therefore, a virtual reference unit *V* is constructed as a weighted average of observations *C* and *D*. In this way, only observations with like input mix are compared and the inefficiency (the distance to the frontier) is minimised. Thus, DEA allows the detection of ‘natural’ market partitions by identifying different benchmarks as well as similar inefficient products. Each product, whose efficiency is estimated through the same set of efficient peers, must offer a comparable mix of characteristics (input-output-structure).

**Figure 1** Standard DEA vs. Super-efficiency model




The fractional programming problem (2) is transformed into a linear programming equivalent (3) by dividing the denominator and the numerator of the objective function and the constraints (2b) by the aggregated inputs of product$_0$ (Charnes *et al.*, 1978):

$$\begin{aligned} &\max_{\mu_{r0},\nu_{i0}} h_0 = \sum_{r=1}^{R} \mu_{r0} y_{r0} \\ &s.t. \quad \sum_{r=1}^{R} \mu_{r0} y_{rj} - \sum_{i=1}^{I} \nu_{i0} x_{ij} \le 0 \qquad \forall j = 1,\dots,J, \\ &\qquad \sum_{i=1}^{I} \nu_{i0} x_{i0} = 1, \\ &\qquad \mu_{r0} \ge 0,\ \nu_{i0} \ge 0 \end{aligned} \tag{3}$$

where $h_0$ is the efficiency score corresponding to *CV* in (2), $\nu_i$ are input weights corresponding to $v_i$ in (2) and $\mu_r$ are output weights corresponding to $u_r$ in (2).

Because programme (3) estimates the multipliers $\nu_i$ and $\mu_r$ that can be interpreted as the shadow prices of the respective inputs and outputs it is referred to as the *multiplier form.* The following dual minimisation problem (4) is the so-called *envelopment form* because it identifies the products that form the efficient frontier that envelops the observations (Cooper *et al.*, 2000):

$$
\begin{aligned}
&\min_{\lambda_j, s_r^+, s_i^-} \theta_0 - \varepsilon\left(\sum_{r=1}^{R} s_r^+ + \sum_{i=1}^{I} s_i^-\right) \\
&s.t. \quad \sum_{j=1}^{J} \lambda_j y_{rj} - s_r^+ = y_{r0} \qquad \forall r = 1,\dots,R, \\
&\qquad -\theta_o x_{i0} + \sum_{j=1}^{J} \lambda_j x_{ij} + s_i^- = 0 \quad \forall i = 1,\dots,I, \\
&\qquad \sum_{j=1}^{J} \lambda_j = 1, \\
&\qquad \lambda_j, s_r^+, s_r^- \geq 0, j = 1,\dots,J.
\end{aligned} \tag{4}
$$

where $\lambda_j$ denote the weights of an observation $j$ in the reference unit of $\text{product}_0$ and $\varepsilon$ denotes a very small positive number which ensures that no segment of the frontier has a zero or infinite slope. In (4), the efficiency score $\theta$ indicates the proportional reduction that could be achieved simultaneously in all inputs without decreasing actual outputs. Because efficiency is defined through the potential reduction of inputs this model is of the input-oriented type (Cooper *et al.*, 2000). The proportional reduction projects the observed input onto the isoquant. The efficiency score in the envelopment LP (4) is determined by comparing actual parameter values of the product that is evaluated, $x_0$ for inputs and $y_0$ for outputs, with the corresponding values of the reference unit. This unit consists of a linear combination of efficient peers in the market offering the highest observed amounts of each characteristic $\sum_{j=1}^{J} \lambda_j y_{rj}$ (equal to or greater than $y_0$) at the lowest inputs $\sum_{j=1}^{J} \lambda_j x_{ij}$ (equal to or less than $x_0$). The factors $\lambda$ describe the importance of the efficient peers in the reference product, *i.e.*, the importance of the efficient peers for the benchmarking of the product being evaluated. Nonzero values of the slack variables ($s^-$ and $s^+$) indicate weak efficiency, *i.e.*, that the proportional reduction $\theta$ does not suffice for the respective parameters to reach the frontier (Cooper *et al.*, 2000).

The identification of reference points in terms of benchmark product(s) has valuable implications for product management. It reveals meaningful and realistic targets, quantifies performance gaps, identifies which attributes render them inefficient and provides managerial implications on the extent of improvements of every attribute in order to provide maximum customer value.

## 2.3 *Limitations and extension of standard DEA*

In all previous studies on product efficiency analysis the original DEA model discussed so far is applied. In this model, a considerable proportion of observations is typically characterised as efficient. This holds especially in cases where the number of observations is small relative to the number of inputs and outputs. As outlined above, especially in the case of product performance measurement, the problem of ‘specialisation’ occurs and a large number of units is rated efficient only because these products exhibit extreme values for a single parameter or unique parameter combinations (Andersen and Petersen, 1993). For the efficient products, a differentiated efficiency analysis is impossible, because standard DEA leaves all efficient units with a score of 1.0. In 13 empirical investigations on product efficiency using standard DEA (see the studies cited in Section 2.1) we found that the median percentage of efficient products was 40%. This amount renders basic DEA less useful for a comprehensive investigation of a complete product market. Leading products, *i.e.*, products that push out the frontier among the group of efficient products cannot be identified. Consequently, the degree of competitive superiority of the efficient products themselves cannot be estimated.

In the remainder of this section we will introduce the super-efficiency model as a DEA approach particularly useful for product evaluation. We suggest that its discriminatory power provide insights that cannot be gained with standard DEA. To our knowledge no study exists that employs the super-efficiency model for product evaluation.

We recur to Figure 1 showing a simple example with five fictitious products (*A* – *E*) that can be described by two inputs (price, running costs) and one output (quality). To allow a two-dimensional depiction the inputs are standardised on the output. As products *A, B*, *C* and *D* are not dominated (efficient) they are assigned an identical efficiency score of 1.0 (100%) when the standard DEA approach is employed.

In our example, only product *E* is dominated (inefficient). The reference product indicates how an inefficient product would have to perform in order to be considered one of the 'best buys'. The score of *E* is calculated as $0V/0E < 1$.

For inefficient products, the results obtained with the super-efficiency are the same as the results obtained with the standard DEA model. The difference between both approaches is the treatment of efficient units as demonstrated in the right part of Figure 1. Consider the evaluation of product *B*. With the standard model, the reference point of observation *B* is *B* itself; the efficiency score is $0B/0B = 1.0$. The degree of super-efficiency of product *B* can be determined, however, by excluding *B* from the reference set. Product *B* is compared to the input frontier spanned by the remaining set of efficient observations (in our case *A, C* and *D*). Figure 1 shows that the reference point of *B* is *W*, a linear combination of *A* and *C*. Thus, *B* is assigned a super-efficiency index of approximately 1.25 ($0W/0B$). The score reflects the maximum proportional increase in inputs preserving efficiency (Andersen and Petersen, 1993). The super-efficiency score of 1.25 for product *B* implies that even if consumers had to pay 25% more to buy and use product *B* it would remain efficient for them. By using the super-efficiency procedure a ranking of the entire set of products is possible. Consequently, influential units that push out the frontier can be identified and the competitive edge of efficient products can be assessed.

The mathematical formulation of the super-efficiency model requires a slight modification of the linear programme (4) presented in the previous section where the restriction $\lambda_0 = 0$ has to be added (Andersen and Petersen, 1993).

## 3 Empirical application

### *3.1 Data*

The DEA approach of product evaluation is now applied to data on the German middle class car market. Our analysis includes 48 variants of the 17 bestselling models. According to the industry news service AAA, the brands considered in this study represent a combined market share of 73.5% for 2002.

Automobiles are infrequently purchased items bearing a significant financial risk. Therefore, a substantial fraction of consumers is likely to show high cognitive involvement and technical and cost parameters will be important choice criteria (Papahristodoulou, 1997). For this reason, most related studies use ‘objective’ technical output parameters only while the input side is modelled exclusively by using price information (Doyle and Green, 1991; 1994; Papagapiou *et al*., 1997; Papahristodoulou, 1997; Despotis *et al*., 2001; Fernandez-Castro and Smith, 2002) and other costs that are relevant for the purchase decision, *e.g.*, running costs, are ignored. In addition to technical features, non-technical parameters have to be considered on the output side in order to meet the requirements of a comprehensive performance evaluation. Undoubtedly, affective elements play an important role for a car purchase decision (Lancaster, 1966; ADAC, 2001) as well. Consequently, the value of middle class cars arises to a significant extent from psychoemotional or social attributes like brand image (Bearden and Etzel, 1982).

In line with this reasoning, we use comfort, safety features and engine power (HP) as technical outputs. Comfort and safety are evaluated, *i.e.*, by standardised crash tests, and are rated on a scale from zero to five and zero to one, respectively. As an important safety feature, the number of airbags is specified as a separate output. Non-technical outputs include special equipment (which to a certain degree are symbolic attributes that express status and prestige), hedonic attributes (attributes that provide emotional experiences like enjoyment) and brand strength. According to the brand equity evaluation model employed by the ADAC (2001), brand strength is measured as an index of brand awareness, recognition, image and sympathy. Price and running costs (exclusive of depreciation) serve as inputs. We use the street price of the cars charged by reimport retailers, which we believe is more realistic than the fictitious list price of authorised dealers. All data were taken from car tests provided by the leading German automobile magazine, and the 2002 driver survey conducted by the ADAC. Table 1 contains some descriptive statistics on our data.

**Table 1** Descriptive statistics for input and output parameters

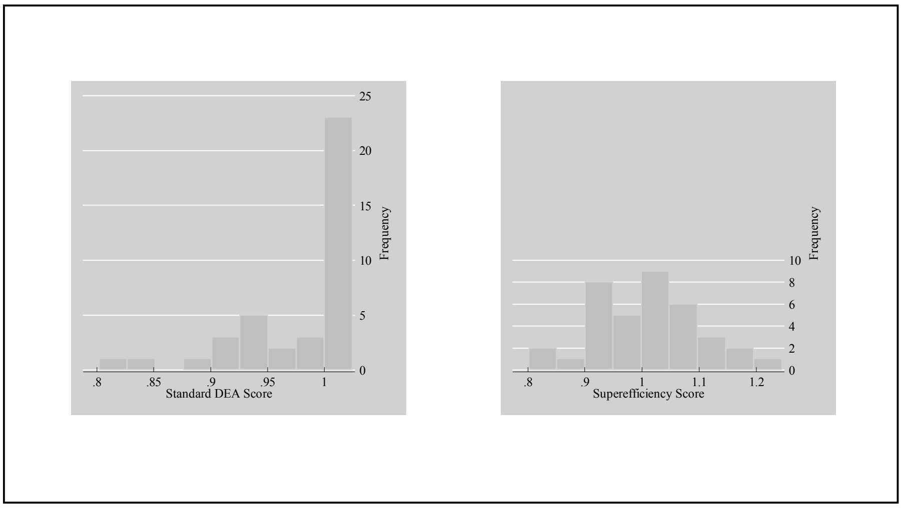
| | *Price €* | *Running costs €* | *Comfort* | *Airbags* | *Safety* | *Engine power* | *Special equipment* | *Hedonic attributes* | *Brand strength* |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 16,045 | 287.85 | 2.33 | 4.71 | 0.52 | 106.04 | 1.42 | 2.79 | 3.03 |
| Std. dev. | 4,129 | 30.53 | 0.79 | 0.97 | 0.50 | 26.09 | 0.54 | 0.94 | 0.73 |
| Max. | 27,027 | 364.00 | 3.00 | 6.00 | 1.00 | 172.00 | 2.00 | 5.00 | 4.55 |
| Min. | 9,694 | 246.00 | 0.00 | 4.00 | 0.00 | 74.00 | 0.00 | 1.00 | 2.13 |

Compared to previous studies on car efficiency the multitude of employed parameters conceptualises the customer value of cars in a more adequate way. The inputs and outputs selected are deemed by most automotive sales statistics and consumer reports to be the purchasing-relevant characteristics of middle class cars (Staat *et al*., 2002; Papahristodoulou, 1997; Despotis *et al*., 2001; Fernandez-Castro and Smith, 2002; ADAC, 2001).

### *3.2 Results*

The distribution of efficiency scores for both DEA models is shown in Figure 2. Applying the standard model results in a distribution with a positive probability mass at unity (see the histogram to the left in Figure 2). With the standard DEA model, 66.7% (32/48) of the cars are left with a score of unity, which is obviously not helpful for assessing the competitive position (relative performance) of the efficient cars themselves. For the majority of the investigated products only limited marketing implications and little support for consumer decision making can be derived. In contrast, the super-efficiency model provides a more differentiated ranking of all cars, including the efficient ones (see the histogram to the left of Figure 2). Of the 32 efficient cars 27 are super-efficient.

**Figure 2** Distributions of efficiency scores




To conserve space, we only list the five most efficient and the five most inefficient cars of our ranking in Table 2. The super-efficiency results show considerable differences concerning the extent of value creation to customers. The Renault Laguna provides maximum customer value and represents the 'best buy' in the middle class market. These are distinct product concepts which all obtain a score of unity. While the Hyundai is efficient because it is a fully equipped middle class car at a very reasonable price the BMWs are much more expensive and yet, due to their enormous brand strength, efficient as well. The Renault, fully equipped, certainly more expensive and technically somewhat more advanced than the Hyundai and at the same time cheaper than the BMW but offering less in terms of brand is in between these two concepts. While the Renault is part of the reference technology of 17 other cars, the BMW 316 TI Compact occupies a niche and is not part of any reference product.

**Table 2** The five most efficient and most inefficient cars

| *Rank* | *Model* | *Score (frequency in reference set)* |
|---|---|---|
| 1 | Renault Laguna 1.8 16V Dyn. | 1.31 (17) |
| 2 | BMW 318 I | 1.22 (1) |
| 3 | BMW 330 I | 1.15 (11) |
| 4 | Hyundai Elantra 2.0 GLS | 1.15 (4) |
| 5 | BMW 316 TI Compact | 1.14 (0) |
| . | | |
| . | | |
| . | | |
| 44 | Rover 75 Connoisseur | 0.89 |
| 45 | Alfa Romeo156 | 0.87 |
| 46 | Mazda 626 1.8 CC Comfort | 0.86 |
| 47 | Rover 75 Club | 0.78 |
| 48 | Rover 75 Classic | 0.77 |

At the other end of the *CV*-distribution, the Rover 75 variants provide poorest value in the market and are the 'worst buys'. When buying the reference cars of Rover's models customers would receive the same outputs for less than 80% of the respective inputs. Thus, customers could improve their purchase efficiency significantly by not buying a Rover 75.

DEA results provide further useful information for product marketing in form of the variables generated by the two linear programmes. First, we consider the virtual multipliers (parameter weights) given by the primal solution (see Equation 3). The product-specific multipliers indicate the parameters on which the product performs well relative to its immediate competitors, *i.e.*, the parameters with the highest contribution to the product's efficiency. Thus, the multiplier pattern provides information about the particular product strategy (parameter mix) employed in order to create customer value. The features with high weights are the ones to be played up in advertising. In contrast, the features with low or zero weights need significant improvements in order to position the product on the efficient frontier.

For a detailed interpretation of the results we focus on a few cars (see Table 3). First, by looking at the multipliers of the efficient cars (which serve as targets for the inefficient cars) successful product strategies can be identified. The Mitsubishi Carisma and the Toyota Avensis are efficient, even though they do not rank among the top five cars. They follow a strategy of offering a nearly well balanced mix of outputs – lacking only in brand strength as well as safety features and airbags as indicated by the zero values in the respective columns of the 'multiplier' panel of Table 3 – at a very competitive price. This implies that these cars will appeal to those customers who value, *i.e.*, special equipment and hedonic attributes, more than other aspects of a car.

**Table 3** Data and super-efficiency results for selected models

| *Data* | *Score* | *λ-Weights* | *Price, €* | *Running cost, €* | *Comfort* | *Airbags* | *Safety* | *Engine power* | *Special equipment* | *Hedonic attributes* | *Brand strength* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mazda 626 2.0 S | 0.93 | | 12,788 | 283 | 0 | 4 | 0 | 85 | 2 | 3 | 2.5 |
| Targets | | | 11,924 | 264 | 2.06 | 4 | 0 | 85 | 2 | 3 | 2.63 |
| Mitsubishi Carisma | 1.11 | 0.53 | 11,617 | 266 | 3.00 | 4.00 | 0.00 | 76 | 2.00 | 3.00 | 2.50 |
| Toyota Avensis | 1.06 | 0.47 | 12,269 | 261 | 1.00 | 4.00 | 0.00 | 95 | 2.00 | 3.00 | 2.78 |
| Multipliers | | | | | | | | | | | |
| Mazda 626 2.0 S | | | 1.00 | 0.00 | 0.00 | 0.28 | 0.00 | 0.24 | 0.00 | 0.02 | 0.34 |
| Mitsubishi Carisma | | | 1.00 | 0.00 | 0.43 | 0.00 | 0.00 | 0.00 | 0.54 | 0.02 | 0.00 |
| Toyota Avensis | | | 0.53 | 0.47 | 0.00 | 0.00 | 0.00 | 0.39 | 0.60 | 0.07 | 0.00 |
| Slacks | | | | | | | | | | | |
| Mazda 626 2.0 S | | | 0.00 | 0.00 | 2.06 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.13 |

In the context of our example, we will briefly discuss how markets can be segmented using DEA. For this purpose, we will look at one inefficient car that is dominated by the Mitsubishi and the Toyota (like observation *E* in Figure 1 was dominated by observations *C* and *D*). As the λ-weights from the dual solution – see LP (4) – show, the Mitsubishi and the Toyota form the virtual reference car for the inefficient Mazda 626 and serve as its individual target position for efficiency improvements. The relevance of both peers for assessing the relative efficiency of the Mazda is nearly the same (with $\lambda_{Mitsubishi} = 0.53$ and $\lambda_{Toyota} = 0.47$). Both peers deliver the same or higher outputs than the Mazda and yet are considerably cheaper. The relatively good brand strength of the Mazda is not enough to justify its price. The efficiency score of 0.93 estimated for the Mazda implies that only 93% of the inputs can be justified in terms of the outputs offered. Consequently, the Mazda could reach the target by reducing price and running costs by 7%. The slacks given by the dual solution, *e.g.* for running costs and comfort (see Table 3) indicate possible improvements beyond the proportional reduction. The slacks and the efficiency scores jointly indicate the extent by which parameter must change in order to reach the target values (provided in Table 3), which is necessary to create an efficient offer.

The efficient models Mitsubishi Carisma and Toyota Avensis appear in the reference set of five other cars apart from Mazda as they tend to offer a well-balanced output mix; they can therefore be characterised as ‘all-round cars’ which are comparable with a number of other cars. They are positioned in the centre of the market-space, *i.e.*, in a highly competitive submarket that is occupied by several other middle class cars.

From the results of the two LPs we can infer the following: the efficient peers Mitsubishi and Toyota represent the benchmarks for that submarket of cars that position themselves by offering a balanced mix of functional outputs at a very reasonable price, but are weak in providing brand strength and hedonic features. They demand lowest inputs from customers relative to the alternatives in that segment and their specific mix of product characteristics. Interestingly, this market partition which is derived endogenously by the DEA corresponds with the ‘typical’ classification of cars based on the country of origin criterion (‘Japanese segment’).

## 4 Conclusion

Several studies have been devoted to the development of efficiency measures for products using DEA. The methodology proved to be a valuable tool for product performance assessment in a marketing context, as it views available product information in a flexible way. For different patterns of input and output weightings, reflecting certain preferences for the product attributes, a segment of corresponding products can be identified including best buys for consumers. The main weakness of standard DEA in the context of product evaluation is that it leaves the efficient units of the product set undifferentiated with respect to their *CV*. Thus the implications of these studies for the supplier’s product management are limited.

Drawing on previous studies in the field we have extended a model of product evaluation that maintains the desirable properties of the original DEA model but adds more information allowing a ranking of the total set of observations. Thus, further insights into the efficiency properties of the products that span the frontier can be derived. Now differences in the superiority of the efficient units can be identified. At the same time, the DEA results can be used for endogenous market segmentation.

We evaluate the efficiency of the 48 bestselling cars of the German middle class market. In contrast to other studies in this field, we conceptualise the efficiency value not merely as a technical measure but from the customer's perspective. On the output side we integrate a multitude of customer relevant attributes such as non-functional benefits (status attributes, brand equity) which go beyond the pure technical features. The parameters employed conceptualise the customer value in a comprehensive way. We interpret the product efficiency score as a measure of customer value, *i.e.*, as a ratio of outputs that customers obtain from a product relative to inputs (price, running costs) that customers have to invest.

The super-efficiency analysis demonstrates that efficient cars show significant differences in their degrees of super-efficiency and allows for the identification of leading cars among the efficient ones, *i.e.*, cars that push out the frontier and have a high competitive ledge. Such cars could demand a considerable increase in customer inputs while still creating maximum customer value in relation to alternative offers. By identifying clusters of cars that employ a similar product strategy market segments can be derived. We provided examples that underscore the intuitive appeal of our approach and were able to demonstrate the potential of DEA as a tool for marketing decisions that has not been fully exploited in previous studies.

The implications for product management, which can be derived from these results, can be summarised as follows: Products are identified as either being efficient or inefficient. For inefficient products, targets are derived, which point out possible improvements that would render them efficient. Inefficient products and their peers are products with like input and output mix. Therefore, they can be grouped into product markets segments allowing the assessment of competitive relationships between products. Finally, the degree of super-efficiency of efficient products can be assessed. Management can then judge whether an efficient product needs further improvement to maintain its competitive edge or whether the degree of super-efficiency is such that the product is virtually without competition within its market segment.

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