

# Pre-Concept New Product Forecasting

By

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Revised, February 1999

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The author would like to thank participants of the workshops at University of Southern California, University of Los Angeles, McGill University and University of Florida for their many helpful suggestions. The author thanks Russell Berrie for financial assistance.

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## Abstract

This paper's goal is to provide an approach for very early predictions for new products, which includes conformance uncertainty. It makes predictions before formulating the new product concept. Although we would not expect to resolve all or most of the uncertainty at this early stage, we hope to provide significant reduction in development uncertainty. The advocated approach explains 27.8% of the outcome variance in one empirical study. By adding a measure of expected marketing effort, the approach explains 40.2% of the outcome variance. (KEYWORDS: New product models, forecasting, new product teams, motion pictures and new product design)

## Introduction

Existing new product forecasting models are extraordinarily useful for forecasting the success of new products that are close to their finished form (e.g., Silk and Urban 1978, Urban et. al., 1997), or early after market introduction (Blattberg and Golanty 1978, Xie et. al 1997). These forecasts provide important information for launching decisions (Urban and Hauser 1995) and the likely level of sales after launch. Some models help predict the flow of information after launch (Urban, Hauser, and Roberts 1990). Beyond predictions, these models provide key diagnostic information including forecasted mean category purchase rates, forecasted awareness levels, trial rates of those aware of the new product and the likely direction of word-of-mouth effects (Mahajan and Wind 1988).

When firms apply these models during a new product's development, model forecasts help improve product design, provide diagnostic analysis of the marketing plan and assist in new product introductions. With consumer data, these models can provide information about how customers might respond to changes in the product attributes (DeSarbo, Carroll, Lehmann, and O'Shaughnessy 1982, Wittink and Cattin 1989).

Despite these advances, new product developers still face very challenging problems. Many industries (e.g., pharmaceuticals, entertainment and high technology) make remarkably early and substantial commitments to new and 'really new' products (Lehmann 1994). Product development cycle times are also decreasing creating the need to make forecasts at an earlier time in the development cycle (Griffin 1997). Moreover, Urban and Hauser (1995) show that the new product development process is highly leveraged. Forecasts, made earlier in the development process, have a more dramatic impact on costs by improving the early allocation of resources.

Although useful at almost any stage of the development process, the benefits of existing pre-test market models are greatest late in the design process. At that point, these models can be as accurate as test markets for reducing market uncertainty. Specifically, these models forecast the likely success of specific designs and the impact of

possible changes in product design. Early in the process, however, development uncertainty may be as important. A firm, for example, may be as concerned about the conformance of the product to internal design objectives as the potential customer's reaction to the internal design objectives. This uncertainty is part of what is known as conformance with design specifications.

Early in the development process, conformance is critical. Implementation of the development process can be as important as the product concept itself. Consider the development of a good-tasting calorie-free beverage at a particular price. Existing models can predict the likely market share of the innovation, but it is also necessary to predict whether the new product team can successfully create such a product.

Consider the development of a more-effective medical treatment, a more durable lighter alloy or a new safety restraint system for an automobile. For these examples, effective implementation of the product concept is as important as the product concept itself. A "cure for cancer" may be a good product concept, but the market success of the cure depends on the quality of the development.

Cohen, Eliashberg, and Ho (1996) develop a decision-support system that considers the role of both performance preferences and conformance with design specifications. Their system helps manage new product development for line extensions in fast-moving consumer packaged goods industries. Using historical knowledge about the productivity of the firm's new product development process, their system helps allocate research and development resources to improve productivity.

This paper's goal is to provide an approach for making very early predictions, which include conformance predictions. The approach makes predictions of outcomes before development begins and, perhaps, before formulating the new product concept. The approach forecasts outcomes at a much earlier stage than current models. Expecting to resolve all or even most of the uncertainty, at this early stage of pre-development, is unrealistic. Current models will remain useful, when more data becomes available and conformance becomes known. However, the advocated approach might provide a

reduction in development uncertainty and early diagnostics related to ultimate success. These early diagnostics might provide guidance on early development decisions and, perhaps, initial investment in development projects.

## **A Pre-Development Model**

### ***A Team Evaluation Approach (TEA)***

This paper's goal is to provide a simple approach that yields very early forecasts before product development and, possibly, before the genesis of the product concept itself. The resulting forecast is not a substitute for later more accurate forecasts. Instead, this early forecast should provide guidance on initial decisions and, perhaps, help determine the best initial early allocation of resources. The goal is the evaluation of the expected outcome of a new product project before making any major decisions or commitments. The approach should also allow firms to perform "what if" analyses concerning selection of possible new product team members.

Start by considering the primary decision facing a firm when a project begins. At that point, the firm's primary decision concerns the composition of the central members of the new product team. These people, chosen by management, provide the best predictors of the potential success of the project. Each of these team members brings unique and, probably necessary, information and skills to the new product effort.

Indeed, current new product research focuses on the new product team and various factors influencing the project's outcome. Moorman and Miner (1997), for example, consider how the degree of consensus or shared knowledge among team members impacts the project outcome. They also consider how organizational memory impacts success through its impact on the interpretation of incoming information. Griffin (1997) examines how cross-function team characteristics can increase or decrease new product development cycle time. Wind and Mahajan (1997) consider how multi-country new product teams use differences in time zones, cost structure, and competencies. They also consider how team champions improve the likelihood of successful outcomes.

This research also suggests that team structure can vary by industry. For some industries, teams consist of a primary member supported by a staff of technicians performing specific functions. In the pharmaceutical industry, for example, the new product team often consists of a laboratory commanded by one research scientist with many assistants for specific functions such as running tests, writing reports and procuring necessary equipment. Here, the primary researcher's ability may be paramount and the abilities of the supporting staff functions may be incidental. Consequently, the focus should be on the potential, i.e. possible contribution, of the primary researcher.

In other industries, teams can consist of multi-disciplinary functions. Depending on the industry, teams can consist of functions including manufacturing (or operations), R&D, product marketing, sales, finance, systems, customer service, logistics, MIS, accounting, planning and other functions. Although each function's importance may vary, the project outcome depends on all of the functions. All functions must be adequately performed to insure a successful outcome for the project. Consider, for example, the motion picture industry where development of highly successful films depends on having resourceful production, skillful direction, great screenplays and outstanding acting (Eliashberg and Sawhney 1994; Eliashberg and Shugan 1997).

This paper advocates a team-member evaluation approach (TEA). This approach starts by considering the most relevant information available to management before developing the new product concept. That information concerns the people who may form the new product team. By considering the expected contribution of team members, the TEA model predicts the outcome. The TEA model is particularly appropriate for service industries where the people implementing an idea can be as important as the idea itself. The contribution of these people can explain substantial variance in the outcome.

### ***Steps in Implementing a Team Member Evaluation Approach***

This paper presents the TEA model as follows. The next section provides a way of linking the potential of the team to the outcome for the current project. The following

section models the current team's potential as a function of the individual team members. The next section provides a method of determining an individual's potential. The subsequent section combines team member potentials when making predictions. Next, the paper discusses the optimal team member potential based on the cost of individual team members. The next section provides the first observable implication of the entire development. The subsequent section develops some alternative measures for individual potential. The empirical section of the paper tests the different measures of potential and their ability to predict outcomes. The conclusions summarize the findings in the paper and suggest possible future directions.

### ***Predicting Current Outcomes from Individual Potentials***

This section considers the prediction of the outcome of the current project. The prediction is based on the potential of the team members. For simplicity, this section considers making a prediction based on one individual of the team. If the composition of the team does not change over time, this prediction is equivalent to the prediction based on the entire team. When the team composition does change over time, the single individual could be the team leader whose responsibilities include selecting other team members. Indeed, several studies of Japanese new product develop find that team leaders are the most important component of the outcome (Clark and Fujimoto 1990). Later sections consider prediction given multiple team members, as well as, how to determine potentials from the outcomes of past projects.

Let  $I_i$  denote the potential for individual  $i$ . Before proceeding, note that although the current discussion treats  $I_i$  as an individual characteristic, there is an another interpretation. As shown later,  $I_i$  is also a statistic summarizes information from past outcomes associated with individual  $i$ . The TEA model forecasts the current project's outcome from past outcomes.

As the potential for an individual increases, the expected outcome of the project also increases. When a Nobel laureate becomes the head of a pharmaceutical project, for

example, the project's expected outcome becomes more favorable. When a famous director, such as George Lucas, becomes the director of a film project, the expected outcome increases. As shown later, the team or individual potential can vary over time. For simplicity at this point, however, consider the potential to be time invariant.

Individuals, however, may fail to achieve their full potentials. Outcomes depend on factors beyond  $I_i$ . One factor is the environment. Unfavorable environmental factors, beyond the control of the team, may cause the contributions of team members to be less than their full potential.

Consider, for example, a research scientist with the potential of developing a very effective drug for fighting cancer. However, environmental conditions work against the scientist. The scientist's laboratory may be inadequately equipped. The scientist may have poorly trained staff and insufficient access to recently published findings relevant to the research. In addition, the employer may restrict the actions of the scientist, with for example, bureaucratic requirements or unreasonable time constraints. This hostile environment may prevent productive avenues for research. The result may be a less effective or, possibly, ineffective drug. Hence, both individual potential, as well as the environment, ultimately determines the outcome.

To be more precise, define the environment for project  $h$  as  $v_h$ . A value of  $v_h = 1$  represents a perfect environment and a value of  $v_h = 0$  represents the worst environment. Given a perfect environment of  $v_h = 1$ , the individual achieves their full potential and the project outcome is  $I_i$ , where  $I_i$  is the potential for individual  $i$ . In the case of the worst environment of  $v_h = 0$ , the project generates an outcome of zero.

It follows that, given individual potential  $I_i$  and environment  $v_h$ , the expected project outcome is  $I_i v_h$ . Consider, for example, an individual who has a potential of \$12 million. With a project environment of  $\frac{1}{2}$ , the expected project outcome is \$6 million. Hence, the potential for an individual is the predicted outcome that we would expect given a perfect environment and only information about individual  $i$ .



## ***Determining Individual Potentials***

The TEA model, in the last section, can both predict an outcome from the potentials as well as infer individual potentials. Past project outcomes for an individual provide information about that individual's potential. For past project  $h$ , the outcome  $S_h$  equals  $I_i v_h$ . Therefore, observing past outcome  $S_h$ , for an individual, implies the individual's potential is  $S_h / v_h$ .

Hence, we can infer each individual potential  $I_i$  for all potential team members from the outcomes of past projects using the formula  $S_h / v_h$ . However, the individual potential depends on both the past project outcome  $S_h$  and the past environment  $v_h$ . Although firms can observe past outcomes, they often lack objective data on past environments. Therefore, allow the environment for the past project  $h$  to be a random variable. The random variable  $v_h$ , with density function  $f(v_h)$ , is the environmental effect that varies from zero, for a very hostile environment, to one, for a friendly environment. When little information concerning past environmental conditions are available,  $f(v_h)$  follows a uniform distribution between zero and one. When information is available,  $f(v_h)$  assumes the form of the appropriate Bayesian prior distribution reflecting that information.

Given the distribution  $f(v_h)$ , we can determine an individual's potential from the past outcomes of past teams in which the individual participated<sup>1</sup>. Let  $M(i, t)$  be the subset of all past projects prior to time  $t$  in which individual  $i$  was a member. Let  $N(M(i, t))$  be the number of past projects for the individual prior to time  $t$ , denoted  $N_i$  for short.

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<sup>1</sup> The empirical section estimates different potentials when an individual assumes different functions. For example, the potential contribution of an individual acting as a team leader is different than the potential contribution of the same individual acting as a media planner.

Consider a series of  $N_{it}$  observed outcomes  $S_h$  where  $h \in M(i, t)$  associated with the past outcomes of teams in which individual  $i$  was a member. These outcomes occurred prior to the current time period  $t$ . Let  $I_{it}^{\max}$  be the maximum likelihood estimator of the individual potential  $i$  at time  $t$ , then equation (1) provides the maximum likelihood function.

$$I_{it}^{\max} = \max_I \prod_{j \in M(i, t)} \left( \frac{S_j}{I} \right) \quad (1)$$

The maximization is subject to the constraint that  $0 \leq v_i \frac{S_j}{I} \leq 1$  for all observations  $j$ , because the percent of potential achieved must be in the range between 0 and 100 percent. Hence, the maximum-likelihood estimator for an individual's potential is maximized at the point when  $I = v_i S_j$  where  $S_j \geq S_i$  for all  $i$ . Denote the maximum past outcome (MPO) measure<sup>2</sup> of the potential contribution by  $I_{it}^{\max}$ .

The MPO measure takes an individual's best past outcome as the most likely measure of the individual's potential. This result is consistent with the hiring practices of many employers. These employers often evaluate people based on their best past accomplishments. Consider, for example, a person who achieves a major accomplishment such as being elected to a high office, achieving an advanced degree, winning a Nobel price, developing a breakthrough technology, inventing a widely successful innovation or winning a Olympic medal. These accomplishments would overshadow lesser accomplishments. Indeed, résumés are records of best accomplishments rather than either a random sample of past outcomes or a compilation of summary statistics on all past outcomes.

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<sup>2</sup> Note that when the observed outcome is the sum of the individual contribution and some unknown constant, say,  $\mathbf{w}$ , the maximum likelihood estimator for  $\mathbf{w}$  is the minimum observed  $S_h$  for all projects where the individual served in the specified function.

## ***Combining Individual Potentials***

The last section discussed prediction given a single team member with the model  $I_i v_h$ . This model also predicts outcomes when team composition is invariant from project to project. In that case, interpret the potential  $I_i$  as the potential of team  $i$  rather than the potential of an individual. However, team composition can vary across projects.

This section considers predicting the outcome of a team when the team consists of several members who may not have worked together on past projects. Here, the team consists of multiple individuals who take well-defined functions such as marketing, operations and engineering. For a football team predicting the outcome of a game, the team's functions would include the coach, wide receiver, defensive back, the quarterback and so on. For another example, consider the entertainment industry where team functions include the producer, the director, the screenwriter and so on. Each of these team members performs some function. The outcome of the team depends on the potential of the members doing each function.

Note that a team member's potential  $I_i$  now depends on the team member's function. An individual, for example, may have a greater potential performing the function of the systems analyst than in the function of the development manager or the project leader. For notational simplicity, however, consider individuals as performing the same function across projects. The empirical section of this paper, however, does estimate different potentials for individuals for each function performed. For example, we allow William Shatner to have a different potential as a director than as a lead actor.

Note also that, with multiple team members, different functions can contribute differently to the project outcome. The TEA model predicts the outcome of a new product development project based on the potentials of the current team members, the importance of each team member's function and the environment in which the team exists. The procedure is the same regardless of the number and type of critical functions on the team. The expected outcome of the current project is the weighted sum of the

team member potentials. Let  $S_h$  represent the expected success of a new product project  $h$  at time  $t$ . Let  $F$  denote the number of functions on the team. Then equation (2) provides the expected outcome for the project.

$$S_h = \sum_{f=1}^F v_h \mathbf{b}_f \mathbf{I}_{i(f,h)} \quad (2)$$

Here,  $\mathbf{I}_{i(f,h)}$  represents the potential of the individual serving in function  $f$  for project  $h$  at the time of the project. The constant  $\mathbf{b}_f$  denotes the importance of function  $f$  or the weight associated with that function toward predicting the project outcome. For example,  $\mathbf{b}_f$  may be the importance of the systems programmer for a software company, a coach for a football team or a director for a motion picture.

Note that the constants  $\mathbf{b}_f$  will depend on the team functions included in the model. For example, were we to have no other information than an unbiased estimate of  $\mathbf{I}_1$  for the team leader at time  $t$ , the TEA model predicts the outcome  $\mathbf{b}_1 \mathbf{I}_1 v_h$  and, for consistency,  $\mathbf{b}_1 = 1$ . With two team members, the TEA model predicts the outcome  $v_h \mathbf{b}_1 \mathbf{I}_1 + v_h \mathbf{b}_2 \mathbf{I}_2$  and, for consistency,  $\mathbf{b}_1 + \mathbf{b}_2 = 1$ , in theory. However, using biased measures of potential would result in values for  $\mathbf{b}_f$  which do not sum to one.

Consider, for example, a team of two individuals who have potentials of \$12 million and \$16 million, respectively, at time  $t$ . Suppose the project environment is  $\frac{1}{2}$ . With only information about the first individual so that  $\mathbf{b} = 1$ , the TEA model predicts an outcome of \$6 million. With only information about the second individual, the TEA model predicts an outcome of \$8 million. With information about both individuals, and weighting equally each of the two members ( $\mathbf{b} = \frac{1}{2}$ ), the expected project outcome is half of the average potential, i.e.,  $(\$12 + \$16)/4$  or \$7 million. Hence, the potentials continue to reflect the outcome given information about only one team member, but equation (2) combines these potentials to create an overall prediction based on information about all team members.

Hence, we can interpret the individual potentials as summary statistics providing information about past projects for each individual on the team. Each summary statistic can be more or less influential in the forecast depending on the team function. For a motion picture, for example, past successful projects for the producer may be more or less important than past successful projects for the director.

Two comments are in order. It is possible to use equation (2) to predict outcomes despite some bias in the measure of individual potential. For example, suppose that the expected potential  $\mathbf{I}_{i(f,h)}$  for individual  $i$  were only a linear function of the true potential, so that  $\mathbf{I}_{i(f,h)} = \mathbf{a} + \mathbf{b}_f \mathbf{I}_{i(f,h)}^T$ . In that case, the predicted outcome remains a linear function of the true potentials, i.e.,  $\mathbf{a}_h + \sum_{f=1}^F v_h \mathbf{b}_f^2 \mathbf{I}_{i(f,h)}^T$ .

Second, note it is also possible to consider the impact of higher level interactions among team members. Some researchers refer to these interaction effects of the team members as chemistry. Here, certain team members may work well together while others do not. Let, for example, the constants  $\mathbf{y}_*$  represent the interaction effects of the team members. The presence of interaction effects yields the following equation for the predicted outcome.

$$S_h = \left( \sum_{f=1}^F \mathbf{b}_f u_h \mathbf{I}_{i(f,h)} + \sum_{f=1}^F \sum_{g1 \neq f}^F \mathbf{y}_{1f} u_h \mathbf{I}_{i(f,h)} \mathbf{I}_{i(g1,h)} + \sum_{f=1}^F \sum_{g1 \neq f}^F \sum_{g2 \neq f, g1}^F \mathbf{y}_{2fjk} u_h \mathbf{I}_{i(f,h)} \mathbf{I}_{i(g1,h)} \mathbf{I}_{i(g2,h)} + \dots \right)$$

Although the modeling of interaction effects may provide interesting insights, it adds both unnecessary analytical complexity and much greater demands on data availability. Therefore, that modeling is left to future research.

### **Choosing Team Members**

Having considered how each individual's potential impacts the project outcome, consider now how to choose team members. When choosing individuals for the team, a firm must consider both the potential of each individual as well as the cost of putting that

individual on the team. That cost could be a direct out-of-pocket cost when the individual is an independent contractor who is employed only for the project. That cost could also be an opportunity cost when the individual is a company employee and the company could deploy the employee on other projects.

Let  $v_0$  be the non-random environment for the current project. Let  $\bar{I}_f$  be the expected value of the potential for the individual in function  $f$ . Let  $a\bar{I}_f^k$  be the cost function for hiring an individual with expected potential  $\bar{I}_f$  where  $a, k$  are positive constants. Then, Equation (3) is the expected profit function given  $\bar{I}_f$ .

$$E\mathbf{p} = \sum_{f=1}^F (\mathbf{b}_f v_0 \bar{I}_f - a\bar{I}_f^k) \quad (3)$$

Maximizing equation (3), with respect to team member potential, suggests hiring an individual with optimal expected potential given by equation (4).

$$\mathbf{I}_f^* = \left[ \frac{\mathbf{b}_f v_0}{ak} \right]^{\frac{1}{k-1}} \quad (4)$$

Examination of equation (4) yields intuitive results. Consider the organization of a new product development team. Equation (4) suggests that when providing a more favorable environment for the team  $v_0$ , the firm should hire individuals with greater potential. Moreover, as the importance of a team member in a particular function,  $\mathbf{b}_f$ , increases, the optimal potential for that function increases.

To consider precisely how increases in  $\mathbf{b}_f$  impact the optimal level of potential, take the derivative of equation (4) with respect to  $\mathbf{b}_f$ . Equation (5) results.

$$\frac{\partial \mathbf{I}_f^*}{\partial \mathbf{b}_f} = \left[ \frac{\mathbf{b}_f v_0}{ak} \right]^{\frac{1}{k-1}} \frac{1}{(k-1)\mathbf{b}_f} \quad (5)$$

Equation (5) illustrates that, although the firm seeks to hire individuals with greater potential as the importance of their position increases, that effect decreases dramatically when the marginal cost of hiring, i.e.,  $k$ , increases. Moreover, this effect decreases in magnitude as the importance, i.e.,  $\mathbf{b}_f$ , of the team member becomes still larger.

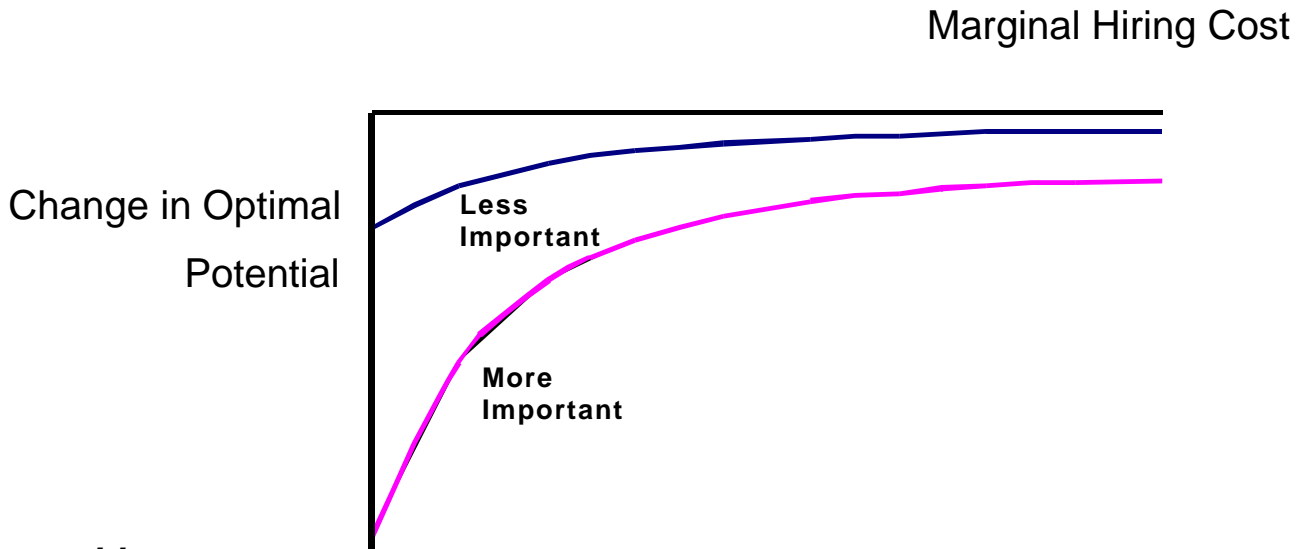
Finally, consider how the marginal cost of hiring impacts the optimal level of potential. Taking the derivative of equation (4) with respect to  $k$  yields equation (6).

$$\frac{\partial \mathbf{I}_f^*}{\partial k} = - \left[ \frac{\mathbf{b}_f v_0}{\mathbf{a} k} \right]^{\frac{1}{k-1}} \frac{\ln \left( \frac{\mathbf{b}_f v_0}{\mathbf{a} k} \right) k + k - 1}{(k-1)^2 k} \quad (6)$$

The mathematical result appears somewhat complex. However, graphing equation (6) yields the simple relationship shown in figure 1. Figure 1 shows the derivative of the optimal potential with respect to the marginal cost of hiring  $k$ , i.e.,  $\frac{\partial \mathbf{I}_f^*}{\partial k}$ . The upper curve shows the change in this derivative for a less important team member functions, i.e., a smaller  $\mathbf{b}_f$ . The lower curve shows the change in this derivative for a more important team member, i.e., a larger  $\mathbf{b}_f$ . For both cases, the curves are in the negative domain.

As the marginal cost of hiring  $k$  increases, the optimal potential for hiring individuals decreases. The rate of decrease is larger for environments that are more favorable and functions that are more important. Finally, as the marginal cost increases, the optimal potential decreases at a decreasing rate.

**Figure 1**  
**Change in Optimal Potential as a Function of**  
**Marginal Hiring Cost**



**Observable**  
**Implications**

It is now possible to derive the first observable implication of the TEA model. The TEA model assumptions allow the prediction of the distribution of observed new product development outcomes. Substituting equation (4) into equation (2) yields equation (7).

$$S_h = \sum_{f=1}^F (\mathbf{a}k)^{\frac{1}{1-k}} \mathbf{b}_f^{\frac{k}{k-1}} v_h^{\frac{k}{k-1}} \quad (7)$$

Since  $v_h$  is uniformly distributed, equation (8) provides the cumulative distribution,  $\Pr(S \leq s)$ , function for  $S$ .

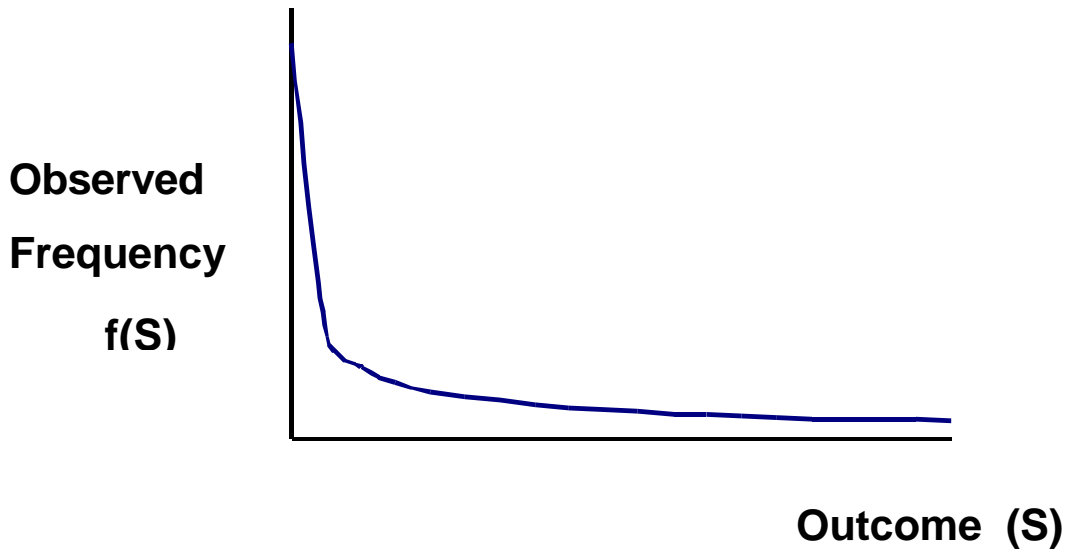
$$\Pr(S_h \leq s) = \frac{\sum_{f=1}^F \mathbf{b}_f^{\frac{k}{k-1}} s^{\frac{k-1}{k}}}{(\mathbf{a}k)^{\frac{1}{1-k}}} \quad (8)$$

Taking the derivative with respect to  $S$  provides the density function for  $S$  shown in equation **Error! Reference source not found.**



$$f(S_h) = \frac{k-1}{k} \left( \frac{\sum_{f=1}^F \mathbf{b}_f^{\frac{k}{1-k}} \left( \frac{1}{S_h} \right)^{\frac{1}{k}}}{(\mathbf{a}k)^{\frac{1}{1-k}}} \right) \quad (9)$$

**Figure 2**  
**Predicted Frequency of Expected Outcomes**  
**(Proposed Model)**



Note that  $S_h$  is bounded between 0 and  $\sum_{f=1}^F (\mathbf{a}k)^{\frac{1}{1-k}} \mathbf{b}_f^{\frac{k}{k-1}}$ . Figure 2 shows the distribution of outcomes described by equation **Error! Reference source not found.**. The rate of decline increases with increases in  $k$ .

Figure 2 shows that the frequency of an outcome, i.e.,  $f(S_h)$ , should decrease exponentially with the magnitude of the outcome,  $S_h$ . In other words, the frequency of successful projects should decrease exponentially with the magnitude of the success. We

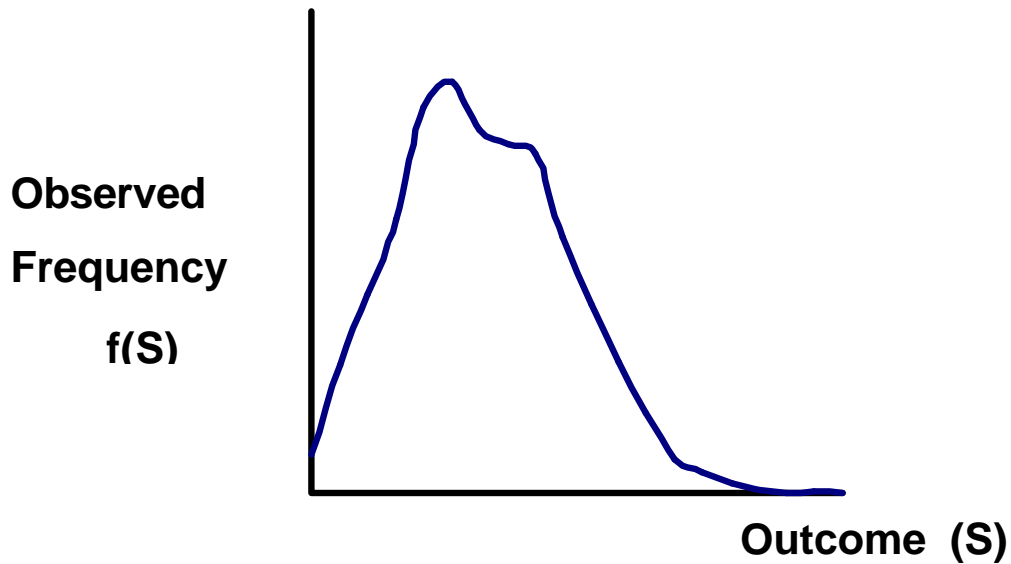
see that a uniform distribution for the environment does not necessarily lead to an aggregate uniform distribution of outcomes.

Given that the team-member evaluation theory is correct and that firms are, on average, correctly hiring, then equation **Error! Reference source not found.** and figure 5 provide specific predictions regarding the distribution of outcomes that we should anticipate observing in the market. Note that this distribution is specific. Other assumptions would usually lead to different predictions for the distribution of observed outcomes. As an alternative model to equation (5), for example, we might argue that outcomes are the sum of random variables. We might argue, for example, that the same project might create different independent environments for different individuals. Here, the environmental variables vary across individual team members, so that, a good environment for one team member may be a bad environment for other team members. In the case of statistically independent environments, equation (7) changes to the outcomes generated by equation (10) where  $\mathbf{n}_f$  is the individual-specific environment for function  $f$ .

$$S' = \sum_{f=1}^F (\mathbf{a}k)^{\frac{1}{1-k}} \mathbf{b}_f^{\frac{k}{k-1}} v_f^{\frac{k}{k-1}} \quad (10)$$

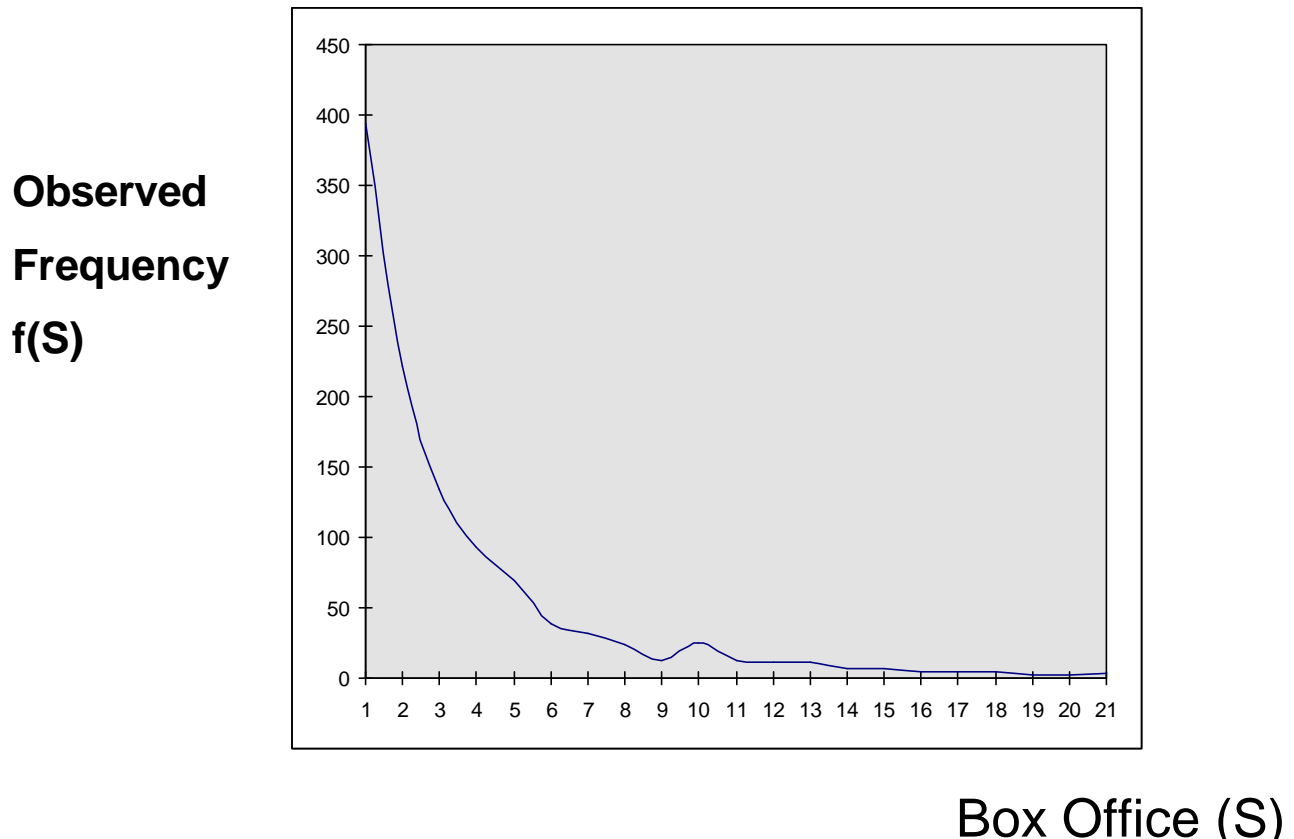
Equations (7) and (10) suggest very different distributions of outcomes. Equation (7) suggests that project outcomes be distributed with the exponential-like distribution shown in figure 2. As the number of team members increase, the distribution associated with equation (10) approaches a normal distribution. For example, when the environments in Equation (10) follow independent uniform distributions and there are four team members, the expected distribution of outcomes is shown in figure 3.

**Figure 2**  
**Predicted Frequency of Expected Outcomes**  
**(Alternate Model)**



For any particular firm or industry, we can compare these distributions with the actual distribution of outcomes. Suppose, for example, we measure project success in terms of sales. In that case, figure 4 shows the actual distribution of box office sales for the motion picture industry (2019 films). We see that the distribution of outcomes is closer to the distribution in figure 2 than the distribution in figure 3. Although figure 4 is hardly conclusive support for equation (7), it does provide more consistency with equation (7) than equation (10), for the entertainment industry.

**Figure 3**  
**Distribution of Box Office for**  
**the Motion Picture Industry (2019 films)**



### ***Alternative Measures***

The prior sections hypothesized that the MPO measure is the best measure of individual potential. However, several shortcomings of this measure suggest examining alternative measures. First, for example, the MPO measure is biased downward; it favors team members with longer or more complete histories. A second shortcoming of the MPO measure is that individuals may receive unique assistance on a particular project that inflates their apparent potential. Two managers, for example, may share the execution of the production manager position on the team, although only one gets official credit. A third shortcoming occurs when individual potentials decrease over time. The

MPO measure captures upward changes but fails to capture changes in a downward direction.

These shortcomings suggest different measures of past performance. The best measure is an empirical question because different measures suggest different testable implications. The empirical section tests the amount of variance explained by the difference measures of past performance. Note that the best measure is the measure that is most correlated with the actual project outcome.

The first, most obvious measure is the average or mean past outcome given by equation (11).

$$\mathbf{I}_{it}^{mean} = \frac{\sum_{h \in M(i,t)} S_h}{N(M(i,t))} \quad (11)$$

The symbol  $\mathbf{I}_{it}^{mean}$  denotes the mean measure of potential for individual  $i$  at time  $t$ . Equation (11) presents a pure average where all past outcomes contribute equally to evaluating an individual's potential.

Equation (1) only considers the best of all past outcomes. Equation (11) equally weights all past outcomes. An intermediate approach is also possible. One compromise is to assign a large weight to the maximum past observation while still assigning non-zero weights to other past observations. See equation (12).

$$\mathbf{I}_{it}^{mean\ square} = \frac{\sum_{h \in M(i,t)} S_h^2}{N(M(i,t))} \quad (12)$$

Equation (12) computes the mean squared past outcome for individual  $i$  at time  $t$ . The squared measure weights larger observations more than smaller observations. Hence, individuals participating in relatively successful past outcomes get full credit. When past projects fail, participating individuals get partial blame.

Finally, the empirical analysis in this paper uses another simple benchmark measure of potential. That measure is the experience of the individual or number of past projects. See Equation (13).

$$\mathbf{I}_{it}^{number} = N(M(i, t)) \quad (13)$$

Note that all previous measures of potential may vary over time. An individual, for example, may have a different estimated potential in 1/1997 than in 1/1998 because of the projects occurring during 1997. For example, a project leader with a successful project in 1997 might show greater potential in 1998 than was shown in 1996.

It is now possible to evaluate the four measures. The TEA model suggests the following steps.

1. Start with a database consisting of project outcomes and the team composition for those projects.
2. Consider each project and each individual in each function for that project.
3. For each project, search the database of all past projects involving each individual serving in each function.
4. Use each of the four measures, i.e., equations (1), (11), (12) and (13), to predict the project outcome. Use the weight  $\mathbf{b}_f$  that maximizes the correlation between  $\mathbf{b}_f \mathbf{I}_{iht}$  and  $S_{iht}$  where  $\mathbf{I}_{iht}$  is determined from projects in earlier periods only.
5. Compare the predicted project outcome to the actual project outcome to determine the best measure of potential.

### ***Multiple Individuals in a Function***

Before presenting an empirical test of the TEA model, one last complication remains. Sometimes, several individuals on a team perform the same function. For example, a project may have several programmers or multiple actors. In that case, the potential for that function may depend on potential for all of the individuals performing that function.

The preceding arguments suggest two methods of combining individual potentials when multiple individuals serve the same function. First, average the individual potentials so that the predicted outcome is a function of the average of the individuals doing the function. Second, take the maximum potential of all the individuals performing the function. This second method takes the best individual to determine the outcome. Here, all individuals performing a function rise to the best individual performing the function.

The empirical section uses the measure that past predicts future outcomes.

## **Empirical Analysis**

The TEA model should interest firms with proprietary records containing information about their own past team outcomes. This section, however, seeks to explore the applicability of the TEA model with publicly available data. With that purpose, the motion picture industry provides an ideal application area for several reasons. First, within this industry, many new product development projects (i.e., films) are well defined and data about them are publicly available (Monaco 1992). Second, like other industries, film studios often make important commitments, both financial and to personnel, well before product development begins or before the product concept (i.e., the final script) is entirely developed. Third, the composition of the new product team is mostly unambiguous and identities are publicly available. Fourth, measures of the past outcomes (i.e., box office performance) for prior teams are objective and publicly available (e.g., Krider and Weinberg 1988, Sackett 1996).

Similar to other industries, motion picture studios may have inaccurate or no record of the past contributions of an individual to past projects. The studios do have, however, considerable information about the success of teams in which the individual served. Hence, to evaluate an individual's potential contribution to the project at hand, studios need only examine the past outcomes associated with past teams.

Moreover, like many other industries, early forecasting techniques could be very valuable. Executives make early funding decisions with little information. “Funding decisions are normally highly subjective, and mistakes are often made: promising projects are rejected or aborted, and whimsical ones accepted” (Vogel 1998, p.66.). It is also difficult to do marketing research during film development, making early forecasting more important. Directors seldom shoot scenes in the final scripted sequence because of cost considerations (Bridges 1992). It is common, for example, to sequence production schedules to minimize the number of consecutive days involving expensive cast members, expensive equipment or shooting in a remote location. After shooting begins, tight timetables limit the ability to conduct timely marketing research and implement any findings. The necessarily tight development schedules provide little time to conduct or complete market research. Note, it is also difficult, or impossible, to test scenes until final editing occurs which adds essential elements such as sound effects, music and context (Lazarus 1992, p. 134). Until the production process nears completion, there is very little of the actual product to test. It is analogous to trying to test a partially built automobile or a half-baked pizza. Unfortunately, once the film is complete, most design decisions are irrevocable, unlike some consumer non-durables, which can be re-designed repeatedly. Team members, such as cast members, leave for other projects. Given these limitations, the only remaining options for films are often minor editing and re-positioning through advertising. The primary design decisions remain outside the scope of traditional marketing research.

The motion picture industry, therefore, seems to be a good area for early forecasting using the TEA model. Obviously, predicting the box office outcome of a film before shooting the film is a risky task and one would not expect extraordinary accuracy. The final box office outcome of the film must depend on changes made to the script during shooting, random factors (e.g., public events, the weather during the release), the success in the editing process and the advertising of the film. Never the less, obtaining a ball-park forecast, at a very early point, can be extremely valuable because the forecast can influence a large number of decisions before major commitments and the finalizing



of financing. Moreover, early forecasting can help in the process of selecting among a myriad of possible production projects.

Motion picture industry wisdom suggests that forecasting at a very early stage in a film's life is almost impossible. Many trade publications suggest that, not only is forecasting box office outcomes very difficult before production begins, it remains very difficult until after production is complete. Many industry observers, for example, believe that the true success of a film is only apparent when it actually appears in the theaters.

This belief in the inability to forecast box office outcomes is, perhaps, somewhat self-serving. As Sherman (1990, p. 109) notes: "because of the fear of ... losing their magic, producers, distributors and exhibitors would sooner risk millions of dollars on a production than figure out the correct survey to find out what a potential film audience member would really like to see." Avoiding marketing research also helps justify bad production decisions. Arguing that outcomes are unpredictable supports the view that movie-making is an art and, unlike other expensive new product developments, movie-making should remain unaccountable to demand forecasts. "Film, more than any other business, has an almost paranoid view of marketing research. It is almost as though industry leaders fear learning that something can be known and understood about audience tastes. This is one of those areas where the art/business dichotomy crosses over (Sherman 1990, p. 110)." As Lazarus (1992, p. 154) notes: "the marketer is called in well after the fact and given the assignment of selling an already finished product."

To be fair, however, motion pictures are like many other services because their successful development is very dependent on the people or team making the film. Determining the optimal mix of attributes in the concept may be less important than the potential ability of the team to execute the concept. Hence, the initial film concept, i.e., the script synopsis, may be far less important than the quality of the director. Therefore, team-evaluation approach seems appropriate.

The TEA model forecasts the outcome for a film project from the potentials of the current team members and the outcomes of their past films. The team members include the cast, the screenwriter, the producer and the director. The history includes the box office outcomes of past films made by each team member. Ultimate cumulative box office data allows the estimation of the potential of each team. For illustrative purposes only, consider Table 1.

Table 1's second column provides films directed by Mr. Barry Levinson since 1985. Table 2's second column provides the respective cumulative box office outcomes. As shown, Levinson has 12 past films. The mean and mean-squared outcomes were \$53,548,752 and  $5.130 \times 10^{15}$ , respectively. Levinson's maximum outcome was for film 6 "Rain Man", grossing \$171,188,895. Levinson's minimum outcome was film 5, "Jimmy Hollywood", grossing \$3,241,815.

Obviously, the enormous success of the film "Rain Man" indicates a very favorable environment allowing team members (cast and crew) to achieve their potential. The film demonstrates Barry Levinson's tremendous potential as a director. With a favorable environment, Levinson is able to create a very successful motion picture.

In contrast, the outcome of the film "Jimmy Hollywood" appears far less favorable. The MPO hypothesis suggests that this poor outcome fails to capture Levinson's potential as a director because of conditions beyond the director's control. The MPO hypothesis implies that the environment limited Levinson's direction. For example, the property, on which the film was based, may have been a poor choice (which, unfortunate for Levinson, was written by Levinson). Maybe Levinson has less potential in other functions or multiple serving in multiple functions, i.e., director, coproducer and screenwriter, created a poor environment that stretched Levinson's capabilities. That explanation is consistent with the poor outcome of the next worst outcomes, film 1 (Avalon) and film 10 (Toys), which Levinson also produced, wrote and directed.

**Table 1**  
**PAST PROJECTS OF POTENTIAL TEAM MEMBERS**

Film No.	Barry Levinson	Sandra Bullock	Demi Moore	Julia Roberts	Meg Ryan
1	Avalon	Demolition Man	About Last Night	Conspiracy Theory	Addicted to Love
2	Bugsy	Hope Floats	Butcher's Wife, The	Dying Young	Anastasia
3	Disclosure	In Love and War	Deconstructing Harry	Everyone Says I Love You	Armed and Dangerous
4	Good Morning, Vietnam	Love Potion No. 9	Disclosure	Flatliners	City of Angels
5	Jimmy Hollywood	Net, The	Few Good Men, A	Hook	Courage Under Fire
6	Rain Man	Speed	G. I. Jane	I Love Trouble	D. O. A.
7	Sleepers	Speed 2: Cruise Control	Ghost	Mary Reilly	Doors, The
8	Sphere	Thing Called Love, The	Hunchback of Notre Dame, The	Michael Collins	Flesh and Bone
9	Tin Men	Vanishing, The	Indecent Proposal	My Best Friend's Wedding	French Kiss
10	Toys	Time to Kill, A	Juror, The	Mystic Pizza	I.Q.
11	Wag the Dog	Two if by Sea	Mortal Thoughts	Pelican Brief, The	Innerspace
12	Young Sherlock Holmes	While You Were Sleeping	Nothing But Trouble	Player, The	Joe Versus the Volcano
13	.	Wrestling Ernest Hemingway	Now and Then	Pretty Woman	Prelude to a Kiss
14	.	.	One Crazy Summer	Ready to Wear	Presidio, The
15	.	.	Scarlet Letter, The	Satisfaction	Promised Land
16	.	.	Seventh Sign, The	Sleeping with the Enemy	Restoration
17	.	.	Striptease	Something to Talk About	Sleepless in Seattle
18	.	.	We're No Angels	Steel Magnolias	When a Man Loves a Woman
19	.	.	Wisdom	.	When Harry Met Sally

**Table 2**  
**OUTCOMES OF PAST PROJECTS**  
**OF POTENTIAL TEAM MEMBERS**

Film No.	Barry Levinson	Sandra Bullock	Demi Moore	Julia Roberts	Meg Ryan
1	\$14,874,434	\$58,055,768	\$38,561,529	\$76,043,654	\$34,673,095
2	\$48,165,109	\$60,053,195	\$8,946,819	\$32,280,097	\$58,366,896
3	\$82,816,737	\$14,481,231	\$10,670,032	\$9,725,847	\$15,368,023
4	\$123,922,370	\$710,329	\$82,816,737	\$58,699,450	\$78,731,676
5	\$3,515,260	\$50,621,733	\$141,352,000	\$116,347,538	\$59,003,384
6	\$171,188,895	\$121,226,560	\$48,169,156	\$30,687,955	\$12,653,462
7	\$53,311,285	\$48,076,583	\$214,288,325	\$5,627,323	\$32,723,461
8	\$37,020,277	\$872,417	\$100,128,227	\$11,063,149	\$9,488,998
9	\$25,302,048	\$13,441,821	\$106,035,860	\$126,813,153	\$38,863,798
10	\$21,326,485	\$108,706,165	\$22,730,924	\$12,784,088	\$26,265,119
11	\$43,035,585	\$10,552,633	\$17,264,325	\$100,768,056	\$25,893,810
12	\$18,106,539	\$81,033,805	\$7,494,426	\$21,702,768	\$39,146,273
13	.	\$235,828	\$27,067,247	\$178,396,916	\$19,343,600
14	.	.	\$13,431,806	\$11,203,670	\$18,855,038
15	.	.	\$10,330,685	\$7,878,504	\$66,022
16	.	.	\$16,484,164	\$100,294,830	\$3,713,485
17	.	.	\$32,773,011	\$50,865,589	\$126,103,186
18	.	.	\$10,009,890	\$79,426,749	\$50,021,959
19	.	.	\$5,715,174	.	\$90,351,322
Number of Films	12	13	19	18	19
Mean	\$53,548,752	\$43,697,544	\$48,119,491	\$57,256,074	\$38,928,032
Mean Squared (000,000,000)	\$5,130,167	\$3,245,231	\$5,336,750	\$5,713,092	\$1,515,392
Maximum	\$171,188,895	\$121,226,560	\$214,288,325	\$178,396,916	\$126,103,186

Perhaps, Levinson is better at the director function than the producer function. He might be better at creating a successful picture than making the business decisions. A more successful production may require an environment with more checks and balances by having the production function overseen by a different producer.

The MPO hypothesis is that the best past outcome is a better measure of future outcomes than other possible measures, including the mean past outcome. In the case of Barry Levinson, as director, the outcome \$171,188,895 for “Rain Man” could be a better measure of Levinson’s potential than his mean outcome of \$53,548,752.

The MPO hypothesis for the cast is still more compelling because each cast member has less control over the production's environment. Unlike directors, each cast member has little influence over the artistic decisions beyond their own contribution. With a few exceptions, such as Kevin Costner in *Waterworld*, actors must live with director's decisions. Hence, cast members may often be unable to achieve their full potential.

Consider the next four columns in Table 1. These columns provide outcomes (since 1985) for the actresses: Sandra Bullock, Demi Moore, Julia Roberts and Meg Ryan. Their number of past projects are 13, 19, 18 and 19, respectively. Table 2 shows that for the four actresses, Julia Roberts has the highest mean box office outcome (\$57,256,074), followed by Demi Moore (\$48,119,491), Sandra Bullock (\$43,697,544) and Meg Ryan (\$38,928,032), in that order. Note that Table 2 excludes films where the actresses played very minor roles (i.e., not billed as one the first 10 cast members) or films that never went into wide distribution.

Despite the mean measures, Demi Moore has had the most successful film. Her film 7 "Ghost" had a box office outcome of \$214,288,325. That outcome indicates an extraordinary potential for Actress Moore given the best environment. That maximum outcome also exceeds the maximum outcomes for Actress Julia Roberts' film best film, "Pretty Woman", despite Robert's higher mean box office outcome. Note also that the MPO measure suggests Meg Ryan enjoys a greater potential than Sandra Bullock. Her best film showed a slightly better box office outcome than Sandra Bullock's best film, despite a slightly lower mean box office outcome for Meg Ryan. Here, the maximum and mean past outcome provide different implications.

For example, on a mean measure, Roberts has only 83% of Moore's potential, i.e.,  $178396916/214288325$ . On a maximum measure, Roberts has 119% of Moore's potential i.e.  $57256074/48119491$ . The mean square measure considers both the mean and the large values to conclude that Roberts has 107% of Moore's potential. Of course, the best measure is an empirical question, which we now consider.

Our hypothesis is that the MPO measure better predicts team member potential and contribution than the mean outcome. However, as noted earlier, the maximum outcome measure does ignore less successful outcomes. The mean squared outcome may be a good compromise measure of potential. This measure has the property of weighting successful outcomes more but still providing some penalty for being associated with an unsuccessful outcome. For completeness, the analysis also includes total number of past projects measure for the team member<sup>3</sup>.

To test the ability of the team evaluation approach to predict project success and test the MPO hypothesis, we require a history of the past outcomes for past team members. For example, to evaluate the potential of a director at a particular point in time, we need to determine all past films by that director and the box office outcomes of each of those films.

The database contains information from different sources. Archival film records from Baseline, Microsoft and several reference books provided team composition for the 20759 films. Baseline, EDI, Variety Magazine's CD and several reference books provided box office data. The compilation required careful matching because films, and sometimes actors, can assume very different names in different sources. This problem is prevalent for films with long titles and for sequels. For example, "Jason Goes to Hell", "The Final Friday", "Friday the 13<sup>th</sup> Part 9", "Friday the Thirteenth 9", and "Friday the 13: Jason Goes to Hell" are all titles for the same film. Moreover, different films appear with the same name. For example, six films have the title "Beauty and the Beast" and five films have the title "Captive". Of the 20759 films, 568 films had the same name as another film.

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<sup>3</sup> This number includes past projections in the same position. For example, it includes the past projects of the current cast members when they served as cast members rather than when they served exclusively in other roles, such as directors or producers.

**Table 3**  
**DESCRIPTION OF DATABASE**

Number of Observations	Variable
75989	cast members
7841	Directors
7601	Producers
8609	Screenwriters
20759	total films
3688	films with reported cumulative box office as follows:
85	year 1980 w/box office
79	year 1981 w/box office
121	year 1982 w/box office
122	year 1983 w/box office
141	year 1984 w/box office
204	year 1985 w/box office
241	year 1986 w/box office
298	year 1987 w/box office
305	year 1988 w/box office
303	year 1989 w/box office
244	year 1990 w/box office
276	year 1991 w/box office
265	year 1992 w/box office
260	year 1993 w/box office
311	year 1994 w/box office
274	year 1995 w/box office
159	year 1996 w/box office
2608	l films with reported opening box office

This paper uses a database described by Table 3. The database contains some data for 20,759 films so it is possible to identify past projects for most team members. For those projects, the database contains outcomes for 3,688 films released between 1980 to 1996, inclusive.

When predicting outcomes for early films, however, team members' histories are usually incomplete. For films made in 1980, for example, all team members have no histories because the data begins in 1980. For films made in 1981, the database contains outcomes for only 85 past films made before 1981. These films may or may not involve the team members making films in 1981. Hence, it is better to analyze only films appearing later in the database but use the entire database for constructing team member histories<sup>4</sup>. The empirical analysis predicts outcomes for films made after 1992. There are 1004 films of these films with known outcomes.

Hence, when computing measures of potential for a film at a particular date the analysis computes the past outcome measures using all films released prior to that date. For example, the computation of the number of prior films made uses all of the possible 20759 films made prior to that date. The computation of maximum, mean and mean-squared measures of potential prior to a particular date uses all of the possible 3,688 films made prior to that date.

Using these data, the analysis computes the variance explained by each of the measures of team member potential: the MPO, the mean past outcome, the mean-squared past outcome and the number of prior outcomes. Table 4 provides the results. The hypothesis that the MPO is the best measure suggests the highest correlation for this measure with observed outcomes.

#### **Table 4**

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<sup>4</sup> There is an issue regarding whether forecasts for films in one year should include information from subsequent years. The question becomes, when testing the model, should the forecast for a 1987 film include only data for all prior to 1987 or all data including films after 1987. The more conservative approach is to only include data prior to 1987 because that best mirrors the actual forecasting problem done in current time. Subsequent analyses, therefore, re-computed each measure each year for each individual.



### UNIVARIATE ANALYSIS

Variable	t-statistic	Prob. for t	Multiple R	F-ratio	Prob. for F
Screenwriter	.	.	.	.	.
Maximum	11.480	0.000	0.341	131.788	0.000
Mean	10.582	0.000	0.317	111.976	0.000
Mean Squared	9.344	0.000	0.283	87.308	0.000
Number Past	3.600	0.000	0.113	12.958	0.000
Cast	.	.	.	.	.
Maximum	10.579	0.000	0.317	111.920	0.000
Mean	10.309	0.000	0.310	106.268	0.000
Mean Squared	7.174	0.000	0.221	51.466	0.000
Number Past	3.059	0.002	0.096	9.358	0.002
Director	.	.	.	.	.
Maximum	15.887	0.000	0.449	252.407	0.000
Mean	15.618	0.000	0.442	243.931	0.000
Mean Squared	11.522	0.000	0.342	132.748	0.000
Number Past	3.359	0.001	0.106	11.281	0.001
Producer	.	.	.	.	.
Maximum	13.578	0.000	0.394	184.363	0.000
Mean	13.713	0.000	0.398	188.045	0.000
Mean Squared	11.251	0.000	0.335	126.594	0.000
Number Past	3.974	0.000	0.125	15.790	0.000
N=1004	Year>1992	.	.	.	.

Table 4 shows the results of testing the MPO hypothesis. It shows the results of each measures of potential, i.e., the maximum, mean, mean-squared and number-of-past projects, and each team member, i.e., screenwriter, cast, director and producer. The table shows the results for the univariate regressions for each member for each measure on the project outcomes.

The results generally show the maximum outcome measure correlates best with project outcomes. The results of the univariate regressions for the screenwriter show that the maximum measure of potential provides the largest t-statistic (11.480) and F-ratio (131.788). However, the t-statistics for all four measures are statistically significant. The multiple R, for the screenwriter, is .341 for the maximum measure. Hence, knowing the best past outcome of the screenwriter alone explains .3412 or 11.6 % of the variance of the

final project's box office outcome before making the film. That percentage increases when the analysis includes other members of the team.

Simultaneously regressing the two most significant measures, i.e., the maximum and mean past outcomes, on the current outcome, provides similar results (not shown in the table). The t-statistic for the maximum outcome remains significant ( $t = 4.625$ ) while the mean outcome measure becomes statistically insignificant ( $t = .061$ ). Similar findings result from other bivariate analyses that combine the MPO measure with other measures.

The results for the cast members are also consistent with the hypothesis that the maximum outcome measure is best. The univariate regressions for the cast members show that the maximum measure of potential provides the largest t-statistic (10.579) and F-ratio (111.920). However, the t-statistics for all four measures again are significant. The multiple R is .317 for the maximum measure.

Analysis of the director provides qualitatively similar findings. The results again are consistent with the hypothesis that the MPO measure is best. The results of the univariate regressions for the directors show that the maximum measure of potential provides the largest t-statistic (15.887) and F-ratio (252.407). The director explains the highest amount of variance. The multiple R is .449 for the maximum measure for the director. Hence, knowing the best past outcome of the director alone explains .4492 or 20.2% of the variance of the final project's box office outcome before making the film.

Unlike the other team members, the producer analysis is inconsistent with hypothesis that the maximum outcome measure is best. The results of the univariate regressions for the producer show that the mean measure of potential provides the largest t-statistic (4.786) and F-ratio (283.309). However, the t-statistics for MPO measure is significant at less than the 0.001 level. The multiple R is .398 and .394 for the mean and MPO measure, respectively.

Here, the mean measure of past outcomes explains slightly more variance than the maximum measure of past outcomes. This finding is consistent with the explanation that the producer helps create the film's environment. The producer, in theory, has the most

control over the film and, in theory, is ultimately responsible for the film's success. Hence, a producer should get credit for favorable outcomes and blame for negative outcomes. Therefore, producers with some poor past outcomes are expected to have less favorable future outcomes.

**Table 5**  
**FOUR-VARIABLE ANALYSIS**

Variable	t-statistic	Prob. for t	Multiple R	F-ratio	Prob. For F
Maximum Past Outcome	.	.	.	.	.
Screenwriter	4.66462	0.0000	0.527	96.102	0.0000
Cast	2.92504	0.0035	"	"	"
Director	9.11633	0.0000	"	"	"
Producer	5.90530	0.0000	"	"	"
.	.	.	.	.	.
N=1004	Year>1992	.	.	.	.

Table 5 shows the results of using the MPO measure for all team members (i.e., the screenwriter, the cast, the director and the producer). The table shows the results of regressing all four variables on the box office outcomes. The four variables combine to explain about .527<sup>2</sup> or 27.8% of the variance of the project outcomes. Hence, it is possible to explain about 28% of the outcomes from only observing the best past outcomes for four of the team members.

**Table 6**  
**FIVE-VARIABLE ANALYSIS**

Variable	t-statistic	Prob. for t	Multiple R	F-ratio	Prob. For F
Maximum Past Outcome	.	.	.	.	.
Screenwriter	2.0826	0.0375	0.634	134.455	0.0000
Cast	-1.3289	0.1842	"	"	"
Director	7.5843	0.0000	"	"	"
Producer	2.3898	0.0170	"	"	"
Effort (screens)	14.4276	0.0000	"	"	"
.	.	.	.	.	.
N=1004	Year>1992	.	.	.	.

Finally, it is desirable to add a measure of marketing resources to the analysis for two reasons. First, in most cases, the forecaster would know the expected resources to be devoted to the project. Adding marketing effort adds this information to the forecast. Marketing effort can “critically affect the income-generating potential of a film...” (De Vany and Walls 1996) and improve forecasting accuracy. Second, team member histories may be correlated with marketing resources because, as noted earlier, projects with greater resources should involve team members with better histories. Adding marketing effort helps control for that bias giving better estimates for team member contributions.

Table 6 provides the results with marketing effort. The number opening of theaters measures that effort because marketing effort (e.g., advertising, promotion, contractual incentives, tie-in agreements, etc.) is highly correlated with exhibitor participation (Sherman 1990).

Table six shows that including marketing effort improves forecasting accuracy. The multiple R increases to .634 and the variance explained increases to about  $.634^2$  or 40.2%. Hence, it is possible to explain approximately 40.2% of the variance from a partial history of the team members' past projects and a measure of marketing effort devoted to the current project. Further improvements to the forecasting accuracy are possible by adding other covariates such as film genre and MPAA rating. These later covariates should be included when they are known at the very early stages of the product development process.

## Conclusions

This paper investigated the problem of very early forecasting for new products. The objective was to forecast the potential of new products before the concept development phase. This research adopted a team evaluation approach (TEA). The TEA model makes early predictions from information about the past performance of the current new product team members. Those predictions might help in the evaluation and selection of team members. The TEA model provides a method for early forecasting based on attributes about the people making the new product rather than the attributes of the new product itself.

This paper examined four measures of individual potential based on past outcomes. The first measure was the mean past outcome, i.e., the mean outcome of all past projects for an individual. The second measure was the MPO, i.e., the outcome of the best past project for an individual. The third was the mean squared past outcome, i.e., the mean squared outcome of all past projects for an individual. The fourth and last measure was the number of past projects.

The empirical analysis was inspired by the problem of new product development in the motion picture industry where data is publicly available. For this industry, the TEA model can, to some accuracy, predict the success of new films before production begins. By evaluating the team, rather than the film itself, it is possible to make predictions at a very early stage before major commitments and financing have been finalized. Moreover, early forecasting can help in the process of selecting among a myriad of possible production projects.

The empirical analysis, for this industry, uses the past outcomes for the important members of a new product development team and a measure of the resources devoted to the team. The analysis reveals that it is possible to explain about 27.8% of the variance in the project outcome with only team member histories (i.e., four variables). By including a

measure of marketing effort, the analysis reveals that it is possible to explain about 40.2% of the variance in the project outcome. Hence, the TEA model provides considerable promise for providing forecasts at a very early stage that may be very helpful for making decisions early in the new product development process.

These findings could, hopefully, stimulate additional research on both the very early forecasting for new products and the challenge of forecasting outcomes for motion pictures. In particular, future research might examine still other measures of past team performance and the environment of the team. This research might help improve very early decisions in the new product development process.

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