An Extreme-Value Model of Concept Testing

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We model concept testing in new product development as a search for the most profitable solution to a design problem. When allocating resources, developers must balance the cost of testing multiple designs against the potential profits that may result. We propose extreme-value theory as a mathematical abstraction of the concept-testing process. We investigate the trade-off between the benefits and costs of parallel concept testing and derive closed-form solutions for the case of profits that follow extreme-value distributions. We analyze the roles of the scale and tail-shape parameters of the profit distribution as well as the cost of testing in determining the optimal number of tests and total budget for the concept phase of NPD. Using an example, we illustrate how to estimate and interpret the scale and tail-shape parameters. We find that the impact of declining concept-testing costs on expected profits, the number of concepts tested, and total spending depend on the scale/cost ratio and tail-shape parameter of the profit distribution.
(*Concept Testing; Prototyping; Extreme-Value Theory; New Product Development; Parallel Testing; Concept Selection; R&D Spending*)

1. Introduction

The concept-generation, -testing and -selection phases of new product development (NPD) may be thought of as a search for the most profitable solution to a design problem. The idea generation and testing methods that comprise the "fuzzy front end" of NPD provide information to designers about the customer utility, technical feasibility, and cost of a new product. Allocating resources at this early stage poses quite a challenge considering the inherent uncertainty. In particular, uncertainty arises from imperfect information about customers and markets, undiscovered or untested product designs and technologies, and the challenges of perfectly executing and delivering even an ideal design. Concept tests help resolve this uncertainty and, in our terminology, encompass most methods used to measure the performance of new products and processes along those dimensions affecting profitability.

Methods such as voice of the customer (VOC) (Griffin and Hauser 1993), lead user analysis, conjoint analysis, Kano methods, and Pugh concept selection (cf. Dahan and Hauser 2001) clarify and focus the fuzzy front end of NPD. For example, contextual inquiry and VOC methods help identify key product attributes, and conjoint analysis (cf. Green and Srinivasan 1990) quantifies the importance of each attribute and the degree of price sensitivity, providing designers with the information to optimize attribute-level trade-offs for specific market segments. Customer-ready prototypes reveal technical problems and opportunities that might have been overlooked in the design's conceptual phase (Srinivasan et al. 1997). Product archeology (Ulrich and Pearson 1998) and design for manufacturability (Boothroyd and Dewhurst 1994) help to identify potential cost savings through product simplification and process improvement.

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Concept testing may be thought of as a search for the "best" design, positioning, pricing, and manufacturing of a new product. But how much budget should be allocated to testing new product concepts? And how many tests should be conducted? "Innovation" through multiple product concepts increases expected profit through the discovery of incrementally better designs, but because concepts are costly to generate and test, the design team must balance costs and benefits to maximize expected profits net of the cost of testing.

To place the present article in context, we divide prior research related to concept testing into three broad categories: (1) models of search, (2) the real options nature of R&D, and (3) methods of experimentation and testing.

Models from the broad literature on optimal search provide insight into the economics of concept testing. Nelson (1961) and Abernathy and Rosenbloom (1968) model product development efforts as a series of stochastic events with discrete outcomes, and demonstrate the value of conducting tests in parallel when time is of the essence. They show that the cost per test and scale of uncertainty drive the optimal number of parallel concepts to be developed. Thomke contributes the view that experimentation in NPD solves problems, uncovers bugs and reduces errors (1998a), broadens search and improves learning through parallel testing, and impacts the competitive positions (and implicitly the profits) of firms that adopt new methods of experimentation (1998c). In short, these authors pave the way for the view of NPD as search through parallel testing, an idea that motivates the present research.

Gross (1967) develops a one-period model of optimal parallel search incorporating residual uncertainty after the advertising campaigns are designed and tested. The number of parallel concepts to be tested is determined heuristically. Loch et al. (1999) also allow noisy testing outcomes and develop optimal parallel and sequential testing policies that minimize the cost and time of testing. Srinivasan et al. (1997) provide empirical evidence that parallel prototyping resolves some of the residual uncertainty remaining following the concept generation stage of product design. They show that, under reasonable assumptions, parallel prototyping is more profitable than a one-shot approach, and propose parallel development of customer-ready prototypes as an attractive method of reducing risk in the mid to late stages of NPD. One insight from previous work, quantified explicitly in this paper, is that additional tests are conducted until the marginal benefit of an additional test equals the marginal cost of conducting it.

The present analysis, recognizing that concept selection is a search for profit extremes, develops closed-form solutions for the optimal number of tests under the three extreme-value distributions. This leads to the key finding that the number of concept tests under profit uncertainty depends not only on the cost of testing and the scale of uncertainty, but also on the upper tail-shape of that uncertainty.

A second line of research suggests that multiple product concepts be viewed as *real options*. Hauser (1996) provides a comprehensive annotated bibliography on valuing R&D projects, including research on their real options nature. For example, Hauser and Zettelmeyer (1996) characterize optimal policies for managing R&D portfolios and show the value of the options provided by alternative solutions to a given problem, even if the alternatives come from R&D spillovers from outside firms. Baldwin and Clark (2000) apply an options approach to the issue of modularity in product and process design. While product concepts create real options, so does the flexibility to abandon an unprofitable NPD effort at the concept development stage. The present paper values the option of retaining NPD decision flexibility at the concept selection phase and analyzes the factors driving the value of this flexibility.

The third line of prior research proposes new forms and methods of NPD experimentation and studies their implications. This research stream suggests that experimentation requires appropriate processes, resources, and organizational structures. In a rapidly changing market environment, the concept phase must facilitate high-speed, high-performance innovation. Smith and Reinertsen (1995) emphasize the importance of speeding up new product development and suggest multiple parallel tests as one method for doing so. Leonard-Barton (1995) coins the term "failing forward" to describe experimentation in which firms learn from failures and take advantage of the creativity inherent in highly variable experimental outcomes. Wheelwright and Clark (1992) discuss the positive and negative organizational implications of having internal teams compete to design the same new product. Thomke et al. (1997) demonstrate how new technology facilitates parallel testing of solutions to technical problems. They cite, as an example, combinatorial chemistry in which pharmaceutical firms conduct large numbers of parallel tests in the search for new drugs. This body of research confirms the nonobvious notion that NPD success results as much from the many concepts that are discarded as from those few that are launched.

Further, the economics of parallel concept testing continue to improve. Combinatorial prototyping methods (Thomke et al. 1998) enable researchers to efficiently search through thousands of variations of custom-designed chemical compounds to see, for example, which metallic oxide is the best superconductor or which organic compound is the most pharmacologically active. Rapid prototyping allows computer-controlled equipment to create topologically complex physical prototypes using layering, etching, and 3-D printing techniques in place of traditional methods such as machining and casting. The economics of getting "from art to (prototyped) part" continue to improve, making high-fidelity concept testing even more affordable. In summary, the attractiveness of multiple parallel concept tests is enhanced by the steady cost decline and improved availability of new technologies.

More recently, Internet-based tests that enable low-cost, high-speed market testing of new product concepts have emerged. Dahan and Srinivasan (2000) compare static and animated methods of Web-based visual depiction against traditional paper-and-pencil conjoint methods and physical, customer-ready prototypes. Their results show that Web-based methods are fast, effective in measuring market potential, and 1 low in cost. Dahan and Hauser (2001) describe methods of adaptive-conjoint questioning and interactive user design of new product concepts that portends highly efficient market research uniquely tailored to each respondent. And Chan et al. (2000) employ Securities Trading of Concepts (STOC), a stock-trading game in which securities represent competing product ideas, to assess market preferences for multiple concepts. In summary, the emergence of the Internet should profoundly affect concept testing by virtue of application of the three Cs of Web-based market research: communication, computation, and conceptualization.

Of course, the Web may also lower the cost of conducting concept tests. Declining testing costs improve the economics of NPD, not only because of potential R&D savings, but also because of the ability to innovate more by testing a larger number of potential product solutions. Virtual and rapid prototyping techniques portend dramatic declines in the cost per concept test and allow designs to be evaluated without the expense and time requirements of physical prototyping.

When distributed over the World Wide Web using formats such as VRML (Virtual Reality Markup Language), MetaStream, or streaming video, virtual prototypes allow potential customers to experience the "look and feel" of multiple designs before physical versions are built (cf. Dahan and Srinivasan 2000). Consumer preference, price sensitivity, and demand data may be collected cost-effectively in this way at the earliest stages of NPD.

How will more efficient methods of concept generation and testing affect R&D budgets and allocations to concept testing during NPD? The present analysis yields the insight that the optimal response to improved concept testing varies greatly based not only upon traditional measures of profit uncertainty such as variance, but also upon the upper tail-shape of that uncertainty. Consider two potential benefits of declining testing costs: savings on total development expense, or incremental profit deriving from additional concept tests. Importantly, the research suggests that "fatter" tails in the profit distribution shift the optimal emphasis away from savings and towards additional testing. How might managers measure the "fatness" of upside profit uncertainty? The paper suggests several sources of data to inform the analysis and illustrates, through an example, an estimation approach using XTREMES software.

In summary, the present research contributes to the existing literature by demonstrating the relevance of extreme-value theory to the concept phase of NPD, identifying and estimating a new class of decision-relevant data (namely the tail-shape of profit uncertainty), and optimizing concept testing based on the theory. The key concepts are illustrated through an example in which a firm develops several new products.

The remainder of the paper proceeds as follows. Section 2 employs an example to illustrate decisions managers face during the fuzzy front end of NPD and suggests estimation procedures decision makers might utilize to characterize profit uncertainty. Section 3 lays out a model of optimal concept generation and testing, and §4 discusses the resource-allocation results derived from the model. Section 5 concludes and summarizes key managerial implications.

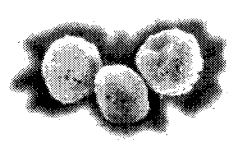
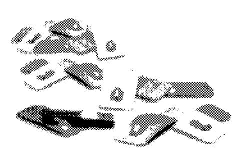
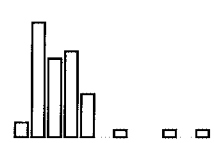
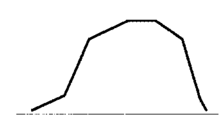
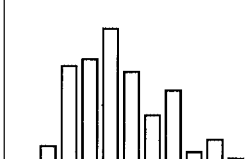
2. Example: Inhale Therapeutic Systems, Inc.

To highlight the problem of allocating testing resources under various forms of upside profit uncertainty, consider Inhale Therapeutic Systems, Inc. (http://www.inhale.com), which was founded in 1990 to commercialize a new system of delivering protein- and peptide-based drugs, such as insulin, to the deep lung. A significant amount of venture capital was raised, primarily to fund the extensive R&D and testing that would be required to gain FDA approval and demonstrate the medical benefits and feasibility of new drug delivery systems. Allocating concept-testing resources optimally across NPD projects posed a challenge to the firm's management. Because of time-to-market pressures, Inhale's management was open to the idea of testing multiple product concepts in parallel.

Delivering drugs to the deep lung through inhalation provides an attractive alternative to subcutaneous or intravenous injection for protein-based drugs that cannot be taken orally since they would be broken down by the digestive system before entering the blood stream. The market for inhalable protein-based medicines represents a multibillion dollar opportunity.

As Table 1 illustrates, deep-lung drug delivery for each drug requires three parallel product develop-

Table 1 Inhale's Systems Comprise Three NPD Efforts

Product	Formulation and Excipient (Drug A)	Powder Processing and Packaging (Drug B)	Delivery Device (Drug C)
Illustration			
Factors influencing profitability	Success depends on consistently generating 1-5 micron dry powder particles and finding an excipient that is compatible with the drug macromolecule.	Profits derive from a process with low unit cost, precise dosing and high-yields. The easy-flowing powder is packaged in individual blister packs.	A good design must deliver dosages consistently across a wide range of patients, dosing levels, and delivery conditions. Cost should also be minimized to encourage rapid adoption.
Data Source	Historical profits	Quantile estimates	Market Simulations
Probability Distribution (or Histogram) of Profits			

ment efforts: (1) dry powder formulation, including the choice of excipient to be combined with the drug molecule to make it inhalable, (2) processing and packaging of the powder to deliver the proper dosage at low cost, and (3) design of the delivery device to be used by patients to inhale the powder cloud.

For each pharmaceutical, Inhale could choose to develop one, two, or all three components of the drug-delivery system. Depending on relative expertise and competencies among its partner drug firms, it could make more sense for Inhale to delegate development of some components to an outside group. Our example assumes that inhalable drug-delivery components are being developed for multiple drugs, i.e., the excipient/formulation is being developed is for Drug A, packaging for Drug B, and the device for Drug C.

Based on historical profit data, management estimates about costs, and simulations of device adoption, profit uncertainty is summarized in Appendix A. To estimate the shape and scale of profit uncertainty based on the data, we employ the software package XTREMES (see http://www.xtremes.math.uni-siegen.de), which uses numerical optimization to find the Maximum Likelihood Estimates (MLE) for the tail-shape, mean, and scale parameters of an extreme-value distribution. For each data set, we perform likelihood ratio tests for the null hypothesis that the data comes from the Gumbel distribution, versus the alternative hypothesis that the data are distributed according to some other extreme-value distribution. The resulting estimates reveal that the expected profits for excipient concepts are estimated to be distributed according to the Frechet (fat-tailed) distribution, those for processing and packing conform to a Weibull distribution, and those for the device correspond to a Gumbel distribution.

Inhale's management seeks to maximize expected profitability by deciding how many concepts to generate and test for each of the three system components. In this example, three simplifying assumptions are justified: (1) the profitability of each of the three subsystems is assumed to be independent, (2) all concepts are tested in parallel (i.e., there is no cross-learning) because of the time constraint, and (3) the total cost of testing is linear in the number of concepts tested. Clearly, Inhale's situation is far more complex, but as our focus is on the relationship between concept testing and the shape of profit uncertainty, these simplifications are appropriate. Section 3 now proposes a model of parallel testing that offers insight into the testing decision.

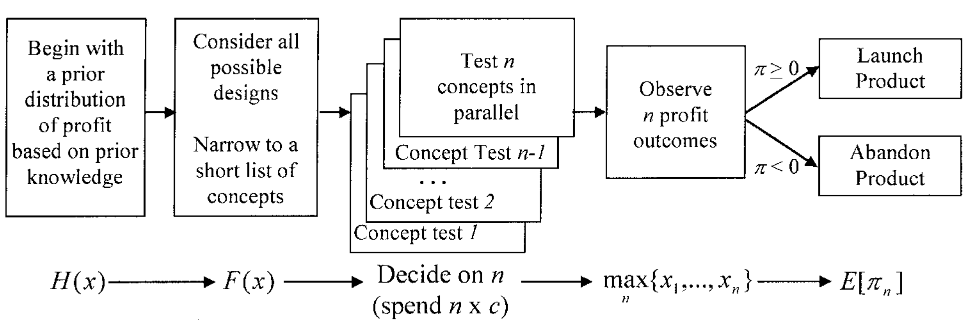
3. Model of Parallel Concept Testing

Our model of parallel concept testing, depicted in Figure 1, rests on the following assumptions:

Expected Profits From Concepts Are i.i.d. New product concepts yield expected profits that are independently and identically distributed. This is justified by the idea that profit is an outcome that depends on independently distributed underlying random variables, each representing some form of technical, marketing, or managerial uncertainty, and that concepts are generated and tested independently.

Best Subconcepts Are Considered Before Being Proposed. For any particular new product concept,

Figure 1 **Model of Parallel Concept Testing.**



design decisions for that concept are made so as to maximize profitability before being proposed for testing. Thus, each proposed concept is the most profitable, or "best" of a possible set of subconcepts.

Distribution Parameters Are Unique to Firm and Product Category. The parameters of the profit probability distribution depend upon the particular firm and product category under consideration and also upon firm-specific assets such as concept-testing capability.

Cost per Concept Is Constant. Each concept costs c to develop and test. The model applies to situations in which multiple concepts are tested similarly, such as through repeated customer or technical tests. Testing costs that are independent of the number of concepts tested are not included in c, but rather are subsumed in the location parameter of the profit distribution, x_0.

The Number of Concepts Is Decided Up Front. The design team determines how many concepts to test independently of observed outcomes, consistent with situations in which resources are allocated before test results are observed.

The Most Profitable Concept Is Launched. The expected profit realized is the expected highest draw from the profit distribution.

3.1. General Model of Parallel Concept Testing

We model the concept phase of NPD as uncertain search informed by test outcomes. A concept test consists of specifying the details of a product or process, measuring its performance (testing) on one or more dimensions, and translating that measurement into an expected profit outcome. Concept tests can be characterized by three parameters:

- the cost per test (c),
- the scale of potential profit uncertainty (b), a measure of variance, and
- the "fatness" of the upper tail of profit uncertainty (α).

Consider a simple model of concept testing in which a finite number, n, of concepts are tested in parallel, and the best outcome is chosen (Srinivasan et al. 1997). Let each test cost c and have independent profit outcomes, denoted by $x_i, i = 1, \ldots, n$, that are observed at the conclusion of each test. The x_is are i.i.d. random variables distributed as a random variable X with probability distribution $F(x)$, that captures expected profits (e.g., because of aesthetics, ease-of-use, performance, unit cost); the values of the x_is are revealed at the conclusion of the n parallel concept tests. A potential extension to this model would allow for outcomes that cannot be observed deterministically, as in Gross (1967) and Loch et al. (1999). The assumption that tests provide perfect information about design-specific outcomes may be relaxed by noting that if x_i represents the *expected value* of profit for design i, our analysis still holds. The value of x_i reflects the net present value of incremental gross profits resulting from launching design i, net of all costs other than those of testing. Hence, X captures the variability of potential design-specific market or technology outcomes. The parameters of the distribution of X derive from uncertainty about profit and are specific to the firm and product category. The choices made by the firm are shown in Figure 1. In this simplified model, testing offers one key benefit: The expected value of the highest observed profit, $E[\pi_n]$, increases as additional concepts are explored.

A firm has to decide on n^*, the optimal number of concepts to generate and test so as to maximize its expected net profit. As concepts cost c each, deducting the total cost, $n \times c$, from gross profit determines net profit. After the expected profitability of each of the n concepts is revealed, the firm develops the one with the highest expected profit. We treat the number of parallel concept tests, n, as a continuous decision variable (even though it would be integer-valued in actuality).

The cumulative distribution function of the maximum outcome of n independent tests is $[F(x)]^n$, and the corresponding density function is $n \cdot f(x) \cdot [F(x)]^{n-1}$. The expected profit from testing n concepts (assuming that the best outcome is ultimately launched), is given by

$$E[\pi_n] = n \int_{-\infty}^{\infty} x \cdot [F(x)]^{n-1} \cdot f(x)\, dx - c \cdot n. \tag{1}$$

When the objective Function (1) is strictly concave in n, the globally optimal number of concept tests, n^*, is determined by differentiating $E[\pi_n]$ with respect to n

and solving the first-order condition,

$$\int_{-\infty}^{\infty} [n \cdot \ln \ F(x)+1] \cdot x \cdot [F(x)]^{n-1} \cdot f(x)\, dx = c, \qquad (2)$$

which equates the marginal benefit of the nth draw with its marginal cost. We note that the solution to Equation (2) depends on the ratio between c and the scale of X, hence n^* does not change when X and c are both scaled by a constant.

The optimality condition implies:

$$\frac{\partial E[\pi_{n^*}(n^*(c), c)]}{\partial c} = \frac{\partial E[\pi_{n^*}(n^*(c))]}{\partial n} \cdot \frac{\partial n^*(c)}{\partial c} + \frac{\partial E[\pi_{n^*}(c)]}{\partial c} = -n^*, \qquad (3)$$

since $((\partial E[\pi_{n^*}(n^*(c))])/\partial n) = 0$ at n^*. Since $n^* > 0$ for any test worth running, $((\partial E[\pi_{n^*}])/\partial c) < 0$, so Equation (3) demonstrates that a (small) reduction in unit testing cost impacts profit by n^*, the number of tests. That is, if the cost for each test is cut by one dollar, and if n^* remains (approximately) the same, the overall cost reduction will be n^*.

3.2. Real Option

When the option to abandon product launch is not available, Equations (1) and (2) apply. However, if the profit distribution $F(x)$ allows negative outcomes (i.e., losses), then even the best of n^* draws may be negative, an event that occurs with probability $F(0)^{n^*}$. In that instance, the firm benefits from retaining the option to abandon product launch at the concept-selection phase. The option to abandon may not be available if: (a) the firm is contractually obligated to deliver, (b) the product is a required component of a larger system, or (c) the firm preannounced the launch, thus creating an implicit contract with its customers. Also, personal incentives on the part of individual decision-makers may preclude the abandonment option from being exercised, even when that choice might be optimal for the firm. In cases where potential losses are small or unlikely, the option to abandon is virtually worthless, in which case early commitment to launch may provide a strategic advantage.

The expected profit from n tests given the option to abandon, $E[\pi_n^{option}]$, is given by:

$$E[\pi_n^{option}] = E[\max(0, X_1, \ldots, X_{n^*})] - c \cdot n = n \cdot \int_0^{\infty} x \cdot [F(x)]^{n-1} \cdot f(x) dx - c \cdot n. \qquad (4)$$

An assumption here is that testing costs are sunk at the time outcomes are observed. Note that $E[\pi_n^{option}]$ could be negative for all n, in which case the firm should abandon product development *before* concept generation. Given that the firm conducts n tests, the value of the abandonment option is given by the difference between (1) and (4),

$$E[\pi_n^{option}] - E[\pi_n] = -\int_{-\infty}^{0} x \cdot n \cdot [F(x)]^{n-1} \cdot f(x)\, dx, \qquad (5)$$

which is the mean minimum loss, given that all n outcomes are negative, weighted by the corresponding probability of that event, i.e., the probability-weighted loss that is being avoided.

Clearly, the option value at the optimum requires a comparison of $E[\pi_{n^{**}}^{option}]$ and $E[\pi_{n^*}]$, where n^{**} maximizes (4). The difference between the two is higher than in Expression (5) with $n = n^*$ since n^* maximizes (1), but is only a feasible solution to (4). Hence, $E(\pi_{n^*}) \le E(\pi_{n^*}^{option}) \le E(\pi_{n^{**}}^{option})$.

3.3. Extreme-Value Theory Model of Concept Testing

This section applies the statistical theory of extreme values to new product concept testing. The distribution $F(x)$, which characterizes the design-specific profit uncertainty, is determined by the process depicted in the first two boxes of Figure 1. As described in Chapter 6 of Ulrich and Eppinger (2000, p. 108), "an effective development team will generate hundreds of concepts, of which 5 to 20 will merit serious consideration during the concept selection activity." Hence, we model $F(x)$ as a distribution over product concepts, each of which is the maximum of a larger subset of product possibilities drawn from a general underlying profit distribution, $H(x)$. In our model, the profit of the product concept chosen for launch is the maximum of the sample profits. When the maximum is taken over a large number of i.i.d. random variables, its asymptotic distribution is given by extreme-value theory (cf. Gumbel 1958, Galambos 1978). The following theorem summarizes the pertinent results.

Theorem 1 (Galambos 1978). *Let $H(x)$ be a distribution function from which m independent draws are taken. Then $\lim_{m\to\infty} H^m(x)$, the limiting distribution of the maximum of m draws from $H(x)$, converges to one of three distributions (with properly chosen a_m and b_m) or to none at all*:

$$F_I^m(x) = e^{-\left(\frac{x-x_0}{b_m}\right)^{-\alpha}} \quad \text{iff} \lim_{t\to\infty} \frac{1-H(tx)}{1-H(t)} = x^{-\alpha} \quad \textit{for some } \alpha \in (0,\infty), \tag{6}$$

$$F_{II}^m(x) = e^{-\left(\frac{x_0-x}{b_m}\right)^{\alpha}} \quad \text{iff} \lim_{t\to 0} \frac{1-H(x_0-tx)}{1-H(x_0-t)} = x^{\alpha} \quad \textit{for some } \alpha \in (0,\infty), \textit{ or} \tag{7}$$

$$F_{III}^m(x) = e^{-e^{-\frac{x-a_m}{b_m}}} \quad \text{iff} \lim_{t\to\infty} \frac{1-H(t+xR(t))}{1-H(t)} = e^{-x}, \quad \textit{where } R(t) = \frac{1}{1-H(t)} \int_t^\infty 1-H(x)\,dx. \tag{8}$$

We assume that $H(x)$, the underlying profit distribution for the universe of possible concepts, satisfies one of the limits in (6)–(8). Appendix B summarizes the three extreme-value distributions, provides their means and variances, and demonstrates their closedness under maximization, meaning that the highest of n draws from $F_i(x)$, $i = I, II, III$ is also distributed $F_i(x)$ with modified parameters. Since product ideas that are good enough to make it onto Figure 1's "short list" are each a maximum from a large sample of subconcepts drawn from $H(x)$, $F(x)$ also takes the form of one of the three extreme-value distributions. Appendix C summarizes the appropriate limit tests and distribution parameters connecting a given underlying distribution to its limiting extreme-value distribution.

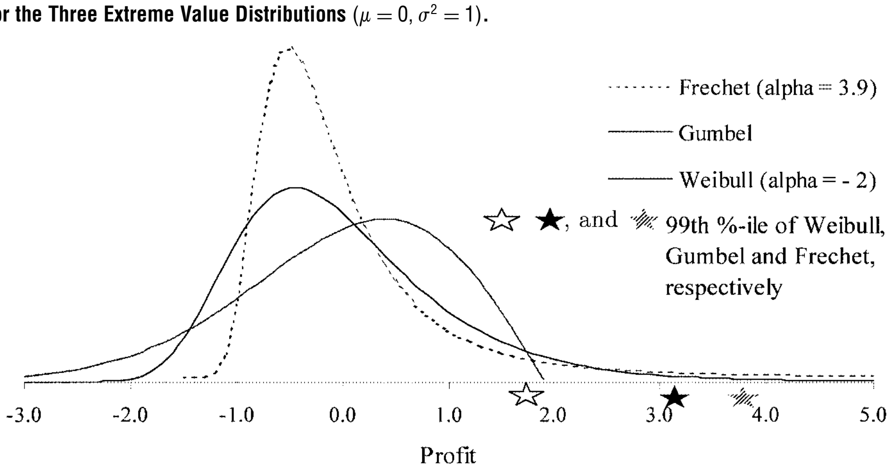
The three extreme-value distributions can be unified under a single continuous model (von Mises 1936)

$$F(x) = e^{-(1+\frac{x}{\alpha})^{-\alpha}}, \tag{9}$$

where the distribution is Frechet if $\alpha > 0$, Weibull if $\alpha < 0$, and Gumbel as $|\alpha| \to \infty$. This last fact suggests that for sufficiently large $|\alpha|$, the optimal parallel testing results for the Gumbel distribution apply broadly. The parameter α captures the "fatness" of the upper tail of the profit distribution. Our analysis reveals that lower absolute values of α lead to widely different optimal policies, but the convergence, for sufficiently large $|\alpha|$, of all extreme-value distributions to the Gumbel distribution suggests that it merits special attention.

The three extreme-value distributions, normalized to zero mean and unit variance, are shown in Figure 2 and interpreted in the context of NPD below. We note the pronounced variation in the upper quantiles of the three distributions, as exemplified by the 99th-percentile stars in Figure 2.

Figure 2 Densities for the Three Extreme Value Distributions ($\mu = 0, \sigma^2 = 1$).



Frechet. Consider a product category with great upside uncertainty such as a new pharmaceutical or paradigm-shifting consumer durable. In such cases, products may become "mega-hits," accounting for the vast majority of the firm's profits. This may be due to network externality and dominant-design effects, resulting in random variables that may be highly correlated in their effect on profit. In the Inhale example, the choice of excipient and drug formulation is characterized by "fat-tailed" profit uncertainty because it determines medical effectiveness and the number of candidate drugs that are compatible with the Inhale system. When the gross profit distribution has a fat tail (e.g., when $F(x)$ declines as $x^{-\alpha}$), the Frechet distribution applies with higher values of α denoting "thinner" upper tails. The gross profits from each test are then distributed over an interval $[x_0, \infty]$. As shown in Appendix C, the Frechet distribution has infinite mean when $0 < \alpha \leq 1$. Hence, we assume throughout that $\alpha > 1$.

Weibull. Some firms face predictably finite bounds on the upside profit potential of a new product due to limited market potential, price ceilings, or fixed-price contracts. Such might be the case for a product that serves a small market, upgrades an existing user base, conforms to a fixed-price contract, or is capacity-constrained. In the Inhale example, the cost containment aspect of packaging and process exemplifies bounded upside profit. When the gross profit is *upper-bounded*, the Weibull distribution applies. The gross profits from each test are distributed over an interval $[-\infty, x_0]$, where $x_0 > 0$.

Gumbel. In many industries, there are no specific limits on the gross profit potential from a new product, but profit outcomes outside of a central range are extremely unlikely. Established products such as automobiles, food staples, or commodities are only partially constrained by production capacity or market potential limits, but nevertheless tend towards profit performance with central tendency. The Inhale device represents such uncertainty because profit outcomes for any particular concept depend on multiple random outcomes each of which is normally distributed. When gross profit is *unbounded* from above, but with exponentially declining probability density, an extreme-value distribution with exponential tails is appropriate. The Gumbel distribution is the asymptotic distribution for the maximum of multiple draws from exponential-tailed distributions such as the normal.

We next evaluate (1)–(5) and obtain closed-form solutions for n^* for the three extreme-value distributions.

4. Results and Analysis

4.1. Optimal Number of Tests

In this section, we derive closed-form solutions to §3's model for the Frechet, Weibull, and Gumbel distributions, and then apply these to Inhale therapeutic systems example of §2.

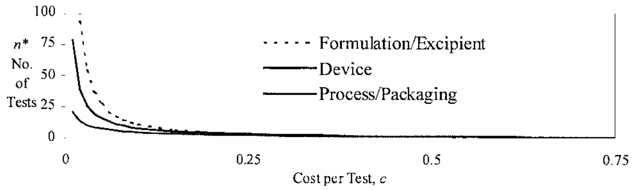
The key results for the Frechet, Weibull, and Gumbel distributions are summarized in Table 2. In the table, x_0 is the location parameter of the distribution, b is its scale parameter which varies monotonically with variance, and α is the tail-shape parameter. As before, c is the unit cost per concept test and x is the random variable for expected profit outcomes. It is easily shown that the objective functions are strictly concave, i.e., $(\delta^2 E[\pi_n]/\delta n^2) < 0$, for all three extreme-value distributions (here we use the assumption made earlier that $\alpha > 1$ for the Frechet) so that the n^*s shown in the table are globally optimal.

The first row of the table simply applies (1) using the three distribution functions to calculate the expected value of the most profitable of n concepts, net of the total cost of testing. In the second row, the optimal number of concepts is calculated. Under the Gumbel distribution, the remarkably simple expression,

$$n^* = \frac{b}{c} \tag{10}$$

is intuitively appealing, in that either greater profit uncertainty or lower testing costs drive increased concept testing. We note that the optimal number of concepts for all of three distributions are a function of b/c, the ratio of the scale of profit uncertainty to the cost per concept and are independent of x_0, the location parameter of the distribution. Therefore, as pointed out in §3, shifting the profit distribution or

Figure 3 **Inhale's Optimal Number of Concepts as Unit Testing Costs Decrease.**



Note. Distributions have zero mean and unit variance.

scaling b and c by a constant does not change the results. The n^*th concept has an expected marginal benefit exactly equal to the cost of that concept, c. As the cost per concept test, c, declines, profit increases, $((\partial E[\pi_{n^*}])/\partial c) = -n^* < 0$, consistent with (3) and the optimal number of tests increases, $\partial n^*/\partial c < 0$, as common sense dictates. Also, $\partial n^*/\partial \alpha < 0$ (not applicable in the Gumbel case) since a higher value of α implies a "thinner" tail for the Frechet distribution and a tighter upper bound for the Weibull.

Returning to the Inhale example, we can now calculate the optimal number of tests for excipient, packaging, and device based on the three standardized (zero mean, unit variance) profit distributions we estimated earlier.

Figure 3 applies the results in the second row of Table 2 and depicts the optimal number of concepts to be tested as unit testing cost varies. Here the units for the x-axis are dollars per concept test, so that, for example, if the unit cost were 0.1, the optimal number of concept tests would be 11, 8, and 5 for excipient, device, and process, respectively. For testing costs above $c = 0.5$, all three components of the Inhale system should have only a single concept tested, but below $c = 0.25$ the optimal number of concepts increases and diverges greatly.

4.2. Effect of Unit Testing Costs on Total Spending

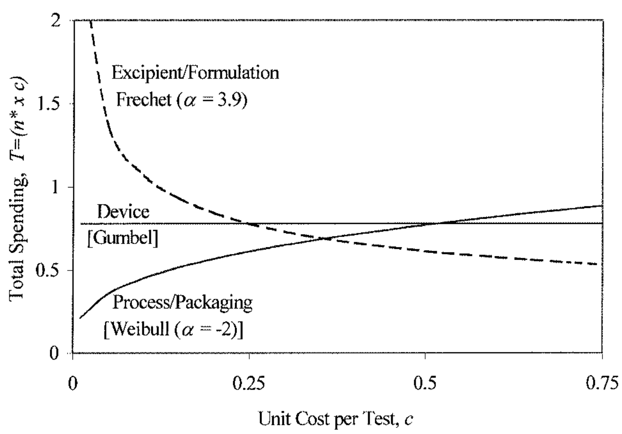
Figure 4 shows the effect of declining unit testing costs on total concept test spending, using the same x-axis units as in Figure 3, for the three components of Inhale's system.. As shown in Figure 4, holding mean and variance constant, total spending depends on the tail-shape α of the distribution of X, not just on the cost per test, c. We note the reversal of total spending rankings when $c \le 0.25$ against those for $c \ge 0.5$. This reversal in total spending highlights the interaction between tail-shape, α, and unit testing cost, c, in determining total spending on concept testing.

Clearly, the cost per concept may decline over time as a result of technological innovations such as the use of Web-based concept tests and combinatorial methods. Firms can take advantage of declines in unit testing costs either by increasing the number of concepts tested or by reducing total testing expense. The choice of which path to follow depends directly on the tail-shape parameter, α, of the distribution, i.e., on the nature of upside profit uncertainty.

Table 2 **Summary of Results for the Three Extreme-Value Distributions**

	Frechet	Weibull	Gumbel
Objective Function: $E[\pi_n]$	$\frac{n\alpha}{b}\int_{x_0}^{\infty} x\cdot\left(\frac{x-x_0}{b}\right)^{-\alpha-1} e^{-n\left(\frac{x-x_0}{b}\right)^{-\alpha}}dx - n\cdot c$	$\frac{n\alpha}{b}\int_{-\infty}^{x_0} x\cdot\left(\frac{x_0-x}{b}\right)^{-\alpha-1} e^{-n\left(\frac{x_0-x}{b}\right)^{-\alpha}}dx - n\cdot c$	$x_0 + b\ln n + b\gamma - n\cdot c$
Optimal # of Concepts: n^*	$\left[\frac{b}{c\alpha}\Gamma\left(\frac{\alpha-1}{\alpha}\right)\right]^{(\alpha/(\alpha-1))}$	$\left[\frac{b}{c\alpha}\Gamma\left(\frac{\alpha+1}{\alpha}\right)\right]^{\frac{\alpha}{\alpha+1}}$	$\frac{b}{c}$
Effect of lower c on spending $T = n^* \times c$	Convex increasing	Concave decreasing	Constant
Option Value	$-x_0 e^{-n(-x_0/b)^{-\alpha}} - bn^{1/\alpha}\Gamma\left(\frac{\alpha-1}{\alpha}, n\cdot\left(\frac{-x_0}{b}\right)^{-\alpha}\right)$	$-x_0 e^{-n(x_0/b)^{\alpha}} + bn^{-1/\alpha}\Gamma\left(\frac{\alpha+1}{\alpha}, n\cdot\left(\frac{x_0}{b}\right)^{\alpha}\right)$	$\left[-b\cdot \mathrm{Ei}\left(-ne^{x_0/b}\right)\right]$

Figure 4 Total Cost of Concept Testing as Testing Costs Decrease.



Note. Distributions have zero mean and unit variance.

Let $T = n^* \times c$, the optimal total spending on concept tests. In the Frechet case, reducing the unit testing cost *increases* optimal total expenditures, $\partial T/\partial c < 0$ when $\alpha > 1$ (which is consistent with our earlier assumption of finite mean), in a convex fashion, i.e., $\partial^2 T/\partial c^2 > 0$. In other words, the firm's demand for testing is elastic when profits follow a Frechet distribution.

This behavior contrasts with total expenditures for the Weibull and Gumbel profit distributions as depicted in Figure 4. In the Weibull case, the induced demand for testing is inelastic, as declining unit testing costs concavely reduce optimal total expenditures, that is, $\partial T/\partial c > 0$ and $\partial^2 T/\partial c^2 < 0$. Intuitively, since Weibull-regime firms are constrained in their upside profit potential, the marginal benefits of additional tests are small, hence total spending declines as testing costs drop.

In the Gumbel case, reducing the unit testing cost has no effect on total spending ($\partial T/\partial c = 0$) since total spending stays constant at b, the scale parameter of the distribution. Thus, the induced demand for testing has *unit elasticity* in the Gumbel case.

Importantly, firms that fix R&D spending during a regime of high testing costs (e.g., when $c > 0.5$) may be caught with suboptimal testing capacity when those costs decline, especially if upside uncertainty is fat-tailed.

As the absolute value of the tail-shape parameter, α, increases, the Frechet and Weibull distributions converge to the Gumbel, consistent with the discussion of Equation (9). Thus, the optimal number of parallel tests and the expected profits resulting from running them also converge to the Gumbel result as $|\alpha|$ increases. For lower values of $|\alpha|$, however, the three distributions diverge greatly in their profit implications and in their optimal number of tests, particularly when testing costs are low. Holding mean and variance constant, lower $|\alpha|$ values imply fatter tails in the case of the Frechet distribution and tighter upper bounds in the Weibull case. Thus, the upper tail-shape of the profit distribution, as parameterized by α, plays a pivotal role in determining the optimal testing policy and the expected profit that results from following that policy.

The ratio of profit uncertainty to cost per test and the tail-shape of the distribution underlying *innovative* uncertainty are key drivers. As shown in Figure 3, lower testing costs convexly increase the optimal number of tests. The degree of this effect hinges on the upper-tail parameter, with Frechet distribution scenarios benefiting the most from unit cost reductions. The dramatic differences between the number of Frechet, Gumbel, and Weibull tests, especially when the cost per test is low, illustrate the importance of estimating α, the tail-shape parameter.

4.3. Option Value Results

Deriving the objective function as in (4), with the option to abandon, yields the results in the last row of Table 2. Obviously, the option to abandon is only relevant when the lower bound in the Frechet distribution is negative ($x_0 < 0$) because otherwise losses could never arise, or when the upper bound is positive under the Weibull distribution, that is, when $x_0 > 0$, because only then are profits even possible and concept tests worth running. The option values shown can be interpreted as the probability-weighted loss that would be avoided given that the option to abandon needed to be exercised. In particular, as the downside risk increases (i.e., as x_0 decreases and losses become more likely), the option values increase. In the Gumbel case, including the option to abandon if the best of n concepts loses money, yields:

$$E\left[\pi_n^{opt}\right] = x_0 + b\ln n + b\gamma - cn + \left[-b\cdot \mathrm{Ei}\left(-ne^{x_0/b}\right)\right], \qquad (11)$$

where $\mathrm{Ei}(y)$ is the exponential integral function, $-\mathrm{Ei}(y) = \int_{-\infty}^{y} (e^{-y}/y)\,dy$. Given that n tests are conducted, the value of the option to abandon is $[-b \cdot \mathrm{Ei}(-ne^{x_0/b})]$, which can be interpreted as follows. For negative values of y, $-\mathrm{Ei}(y)$ is always positive and decreases in $|y|$. Thus, as $ne^{x_0/b}$ increases, $[-b \cdot \mathrm{Ei}(-ne^{x_0/b})]$ stays positive, but decreases in magnitude. Indeed, the option to abandon has the greatest value when only a few tests are conducted (low n), when uncertainty is very high (high b), or when mean profit is low (low x_0). When many tests are run (high n), and high profits (high x_0) are relatively certain (low b), the option value approaches zero, as one might expect.

Comparative statics on the option value fit our intuition. As profit variability, b, increases, so does the optimal number of tests, since the possibility of at least one very high outcome increases and we must remember that only the highest outcome matters. As the location parameter of the distribution, x_0, increases so does the optimal number of tests because downside costs are less likely. Without the option, upward or downward shifts in the distribution (i.e., changes to x_0) have no effect on n^*.

5. Concluding Remarks

We have quantified the costs and expected benefits of conducting parallel concept tests at the fuzzy front end of NPD. Our contributions include calculating the optimal number of parallel concept tests, valuing the real option to abandon launch, highlighting the varying impact of lower testing costs on total spending, and identifying the pivotal role played by the tail-shape parameter. Our model applies the statistical theory of extreme values to quantify the effects of optimal testing policies. We demonstrate the profoundly differing implications of exploring new product concepts under Frechet-, Gumbel- and Weibull-distributed profits. Holding means, variances, and costs constant, we show that the upper tail-shape of the distribution drives the number of tests, the allocation of total spending, and the resulting expected profit.

The tail-shape parameter α can be estimated using the methods of Reiss and Thomas (1997), who fit observed maxima to the three extreme-value distributions, just as we did for Drug A's excipient and formulation in the Inhale example. Another approach would be to simulate data on the potential profit outcomes from the underlying profit distribution, $H(x)$, as we did for Drug C's device in the Inhale example. Alternatively, given that the choice of a family of distributions determines the qualitative results, managers can subjectively classify the uncertainty about potential upside outcomes for different product types based on prior experience and specific knowledge using, for example, quantile estimates as was the case for Inhale's process and packaging of Drug B.

When the parameters of the profit distributions are unknown, the outcomes of the experiments could be used to update those parameters, leading to a multi-arm bandit-type problem. Future research could examine the optimal joint determination of the parameters and the testing policy.

Managers' knowledge of the upper tail-shape of the profit distribution should guide their response to declining testing costs. Lower unit testing costs under a bounded profit distribution lead to reductions in total spending; the firm takes the money and runs. In contrast, declining unit testing costs under a fat-tailed profit distribution may lead to increases in total spending on concept tests. The fact that, holding mean and variance constant, optimal concept test spending diverges significantly based on the tail-shape parameter (cf. Figure 4) highlights the importance of carefully managing NPD projects based on the nature of the uncertainty they resolve. Our results show that two key drivers determine the optimal level of parallel concept testing:

The Ratio of Profit Uncertainty to Cost per Test (b/c): Higher profit uncertainty and lower testing costs increase the number of concept tests and expected profit. Product categories with fat upper tails benefit most from unit cost reductions due to their higher probability of generating breakthrough profits, suggesting that firms focus cost reduction efforts on methods that explore innovative, higher-risk products and processes.

The "Fatness" of the Upper Tail of *Innovative* Uncertainty (α): Dramatic differences between the optimal number of Frechet, Gumbel, and Weibull tests underscore the importance of the tail-shape parameter. These differences become more apparent under a low testing cost regime. Declining testing costs should result in increased testing of product concepts with so-called "fat-tailed" profit uncertainty.

Our results have several implications for improving NPD practice. Firms should: (1) evaluate a new product opportunity not only in terms of its expected profit and variance, but also based on the *shape* of its upside uncertainty, (2) seek out new methods of NPD testing that lower the cost of exploring many high-risk, high-profit designs, (3) wisely exploit declining costs of concept testing by spending more total dollars on high-risk, high-upside NPD product categories while lowering expenditures on categories with bounded upside potential, (4) retain the option to abandon product launch when downside risks outweigh the benefits of early commitment, (5) increase internal testing capacity through parallel testing, higher investment in R&D, or improved efficiency and effectiveness, and (6) expand external testing capacity by outsourcing, engaging suppliers, or facilitating user design by customers. The issue of increased internal and external concept testing capacity suggests the need for further research regarding implementation and execution.

Most importantly, firms should keep a close eye on the dramatic technological changes that improve the cost efficiency of concept testing. Even when testing methods experience the same proportional decline in costs, their relative attractiveness shifts dramatically depending on the upside profit opportunities they measure. Considering that concept tests are relatively cheap, but have high leverage on later, much more expensive phases of product development, it becomes especially important for firms to seek out the most effective, low-cost methods to enhance innovation.

The trend towards lower unit costs per test is fueled by investment in technologies such as virtual design, rapid experimentation, combinatorial methods, and automated processing. Lower unit costs may also derive from economies of scale inherent in parallel concept testing itself, since some costs may be fixed. Recent work by Dahan and Srinivasan (2000) demonstrates that virtual prototypes on the Web result in market share predictions that are nearly identical to those for costlier physical prototypes. Virtual concept tests and other Web-based methods (e.g., Dahan et al. 2000 and Chen et al. 2000) portend widespread growth in parallel concept testing driven by the desire to develop the most profitable products.

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Appendix A. Inhale Illustration

NPD Effort	Formulation and Excipient (Drug A)	Powder Processing and Packaging (Drug B)	Delivery Device (Drug C)
Potential data sources for tail-shape estimation	Data on profits realized on (50) competitive drug formulations, converted into Inhale profits	Management's quantile estimates of process yields and packaging costs, converted into profit impact	(100) Outcomes of detailed simulations of patient response and device performance, converted into profit impact
Estimated profit distribution function	Frechet: $F_I(x) = e^{-(\frac{x+2.3}{1.8})^{-3.9}}$	Weibull: $F_{II}(x) - e^{-\left(\frac{1.9-x}{2.2}\right)^{2.0}}$	Gumbel: $F_{III}(x) = e^{-e^{-\left(\frac{x+0.45}{0.78}\right)}}$

Appendix B. Summary of Frechet, Weibull, and Gumbel Distributions

Cumulative Distribution and Probability Density	Mean and Variance	Closedness Under Maximization (for n draws)
Frechet (Type-I) $F_I(x) = e^{-\left(\frac{x-x_0}{b}\right)^{-\alpha}}$ $f_{I(x_0,b,\alpha)}(x) = \frac{\alpha}{b}\left(\frac{x-x_0}{b}\right)^{-\alpha-1} e^{-\left(\frac{x-x_0}{b}\right)^{-\alpha}}$	$E[x] = x_0 + b\cdot\Gamma\left(\frac{\alpha-1}{\alpha}\right)$ where $\Gamma(t)$ is the Gamma function $\mathrm{Var}[x] = b^2\Gamma\left(\frac{\alpha-2}{\alpha}\right) - \left[b\Gamma\left(\frac{\alpha-1}{\alpha}\right)\right]^2$	$[F_{I(x_0,b,\alpha)}(x)]^n = e^{-n\left(\frac{x-x_0}{b}\right)^{-\alpha}}$ $= e^{-\left(\frac{x-x_0}{bn^{\frac{1}{\alpha}}}\right)^{-\alpha}} = F_{I(x_0,\, b\cdot n^{\frac{1}{\alpha}},\, \alpha)}(x)$
Weibull (Type-II) $F_{II}(x) = e^{-\left(\frac{x_0-x}{b}\right)^{\alpha}}$ $f_{II(x_0,b,\alpha)}(x) = \frac{\alpha}{b}\left(\frac{a-x}{b}\right)^{\alpha-1} e^{-\left(\frac{a-x}{b}\right)^{\alpha}}$	$E[x] = x_0 - b\cdot\Gamma\left(\frac{\alpha+1}{\alpha}\right)$ $\mathrm{Var}[x] = b^2\Gamma\left(\frac{\alpha+2}{\alpha}\right) - \left[b\Gamma\left(\frac{\alpha+1}{\alpha}\right)\right]^2$	$[F_{II(x_0,b,\alpha)}(x)]^n = e^{-n\left(\frac{x_0-x}{b}\right)^{\alpha}}$ $= e^{-\left(\frac{x_0-x}{bn^{-\frac{1}{\alpha}}}\right)^{\alpha}} = F_{II(x_0,\, b\cdot n^{-\frac{1}{\alpha}},\, \alpha)}(x)$
Gumbel (Type-III) $F_{III}(x) = e^{-e^{-\frac{x-x_0}{b}}}$ $f_{III(x_0,b)}(x) = \frac{1}{b} e^{-\left(\frac{x-x_0}{b}\right)} e^{-e^{-\left(\frac{x-x_0}{b}\right)}}$	$E[x] = x_0 + b\cdot\gamma$ where $\gamma \cong 0.57722$ is Euler's constant $\mathrm{Var}[x] = b^2\frac{\pi^2}{6}$	$[F_{III}(x)]^n = e^{-n\cdot e^{-\frac{x-x_0}{b}}}$ $= e^{-e^{-\frac{x-(x_0+b\ln n)}{b}}}$ $= F_{III(x_0+b\ln n,\, b)}(x)$

Appendix C. Summary of Extreme-Value Theory Limiting Distributions

Required Limit for the Underlying Distribution	Limiting Distribution (parent examples)	a_m and b_m
$\lim_{t\to\infty}\frac{1-H(tx)}{1-H(t)} = x^{-\alpha}$ Requires: $x_0 \le x \le \infty$ and $\alpha > 1$ for finite mean Note: $\lim_{x\to\infty}\frac{xh(x)}{1-H(x)} = \alpha$	Frechet (Type-I) $F_I^m(x) = e^{-\left(\frac{x-x_0}{b_m}\right)^{-\alpha}}$ (e.g. Pareto $H(x) = 1-\frac{1}{x^{\alpha}}$)	$b_m = \inf\left\{x : 1-H(x) \le \frac{1}{m}\right\}$
$\lim_{t\to 0}\frac{1-H(x_0-tx)}{1-H(x_0-t)} = x^{\alpha}$ Requires: $-\infty < x \le x_0$ and $\alpha > 0$	Weibull (Type-II) $F_{II}^m(x) = e^{-\left(\frac{x_0-x}{b_m}\right)^{\alpha}}$ Upper bounded parent	$b_m = x_0 - \inf\left\{x : 1-H(x) \le \frac{1}{m}\right\}$
$\lim_{t\to\infty}\frac{1-H(t+xR(t))}{1-H(t)} = e^{-x}$ where $R(t) = \frac{1}{1-F(t)}\int_t^{\infty} 1-F(x)\,dx$	Gumbel (Type-III) $F_{III}^m(x) = e^{-e^{-\frac{x-a_m}{b_m}}}$ (e.g. Normal or Exponential parent such as $H(x) = 1-e^{-x}$)	$a_m = \inf\left\{x : 1-F(x) \le \frac{1}{m}\right\}$ and $b_m = R(a_m) = m\int_{a_m}^{\infty} 1-F(x)\,dx$

References

Abernathy, W., Rosenbloom. 1968. Parallel and sequential R&D strategies: Application of a simple model. *IEEE Trans. Engrg. Management* **EM-15** (1).

Baldwin, Carliss Y., Kim B. Clark. 2000. *Design Rules: The Power of Modularity*. MIT Press, Cambridge, MA.

Boothroyd, Geoffrey, Peter Dewhurst, Winston Knight. 1994. *Product Design for Manufacturability and Assembly*. Marcel Dekker, New York.

Chan, Nicholas, Ely Dahan, Andrew Lo, Tomaso Poggio. 2000. Securities trading of concepts (STOC).

Chess, Robert. 2000. Inhale Therapeutic Systems, Inc., Personal conversations held from January to April.

Dahan, Ely. 1998. Listening to the customer. Teaching note.

———, John R. Hauser. The virtual customer: Communication, conceptualization, and computation. Submitted to *J. Product Innovation.*

———, V. Srinivasan. 2000. The predictive power of Internet-based product concept testing using visual depiction and animation. *J. Product Innovation Management* (March).

Galambos, Janos. 1978. *The Asymptotic Theory of Extreme Order Statistics*. John Wiley & Sons.

Green, Paul E., V. Srinivasan. 1990. Conjoint analysis in marketing: New developments with implications for research and practice. *J. Marketing* (October) 3–19.

Griffin, Abbie, John R. Hauser. 1993. The voice of the customer. *Marketing Sci.* **12**.

Gross, Irwin. 1967. An analytical approach to the creative aspects of advertising operations. Unpublished Ph.D. thesis, Case Institute of Technology, Cleveland, OH.

Gumbel, E. J. 1958. *Statistics of Extremes*. Columbia University Press, New York.

Hauser, John R. 1996. Metrics to value R&D: An annotated bibliography. Working paper, International Center for Research on the Management of Technology, MIT Sloan School, Cambridge, MA.

———, Florian Zettelmeyer. 1996. Metrics to evaluate R,D&E. *Res.-Tech. Management* **40**(4) 32–38.

Lai, T. L., Herbert Robbins. 1976. Maximally dependent random variables. *Proc. National Acad. Sci.* **73**(2) 286–288.

Leonard-Barton, Dorothy. 1995. *Wellsprings of Knowledge*. Harvard Business School Press, Boston, MA.

Loch, Christoph, Christian Terwiesch, Stefan Thomke. 1999. Parallel and sequential testing of design alternatives. Working paper 00-024, Harvard Business School, Boston, MA.

Mendelson, Haim, Ravi Pillai. 1999. Industry clockspeed: Measurement and operational implications. *Manufacturing and Ser. Oper. Management* **1**(1) 1–20.

Montgomery, D. 1991. *Design and Analysis of Experiments.* Wiley, New York.

Nelson, Richard R. 1961. Uncertainty, learning, and the economics of parallel search and development efforts. *Rev. Econom. and Statist.* **43** 351–364.

Pratt, John W., Howard Raiffa, Robert Schlaifer. 1995. *Introduction to Statistical Decision Theory*. The MIT Press, Cambridge, MA. 382–384.

Pugh, Stuart. 1996. *Creating Innovative Products Using Total Design: The Living Legacy of Stuart Pugh*, Don Clausing and Ron Andrade, eds. Addison-Wesley.

Reiss, Rolf-Dieter, Michael Thomas. 1997. *Statistical Analysis of Extreme Values*. Birkhauser Verlag, 52–58.

Roberts, K., M. Weitzman. 1981. Funding criteria for research, development, and exploration projects. *Econometrica* **49**(5) 1261–1288.

Shoolery, Mark. 1996. Shoolery Designs, Personal conversations from September to October.

Smith, Preston G., Donald G. Reinertsen. 1995. *Developing Products in Half the Time*. Van Nostrand Reinhold.

Srinivasan, V., William S. Lovejoy, David Beach. 1997. Integrated product design for marketability and manufacturing. *J. Marketing Res.* **34** (February) 154–163.

Thomke, Stefan H. 1998a. Managing experimentation in the design of new products. *Management Sci.* **44**(6) 743–762.

———. 1998b. Simulation, learning and R&D performance: Evidence from automotive development. *Res. Policy* 27 55–74.

———. 1997. The role of flexibility in the development of new products: An empirical study. *Res. Policy* **26** 105–119.

———, Eric A. von Hippel, Roland R. Franke. 1998. Modes of experimentation: An innovation process—and competitive—Variable. *Res. Policy* **27** 315–332.

Ulrich, Karl T., Scott Pearson. 1998. Assessing the importance of design through product archaeology. *Management Sci.* **44**(3) 352–369.

———, Steven D. Eppinger. 2000. *Product Design and Development*. McGraw-Hill, 107–180.

von Mises, R. 1936. La distribution de la plus grande de n valuers. *Rev, Math, Union Interbalcanique* **1** 141–160; Reproduced in "Selected Papers of Richard von Mises," *Amer. Math. Soc.* **2** 271–294.

Wheelwright, Steven C., Kim B. Clark. 1992. *Revolutionizing Product Development*. The Free Press, New York.

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