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The Metalog Distributions[1]

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The metalog distributions constitute a new system of continuous univariate probability distributions designed for flexibility, simplicity, and ease/speed of use in practice. The system is comprised of unbounded, semibounded, and bounded distributions, each of which offers nearly unlimited shape flexibility compared to previous systems of distributions. Explicit shape-flexibility comparisons are provided. Unlike other distributions that require nonlinear optimization for parameter estimation, the metalog quantile functions and probability density functions have simple closed-form expressions that are quantile parameterized linearly by cumulative-distribution-function data. Applications in fish biology and hydrology show how metalogs may aid data and distribution research by imposing fewer shape constraints than other commonly used distributions. Applications in decision analysis show how the metalog system can be specified with three assessed quantiles, how it facilities Monte Carlo simulation, and how applying it aided an actual decision that would have been made wrongly based on commonly used discrete methods.

Keywords: metalog; decision analysis; continuous probability; quantile-parameterized distributions; logistic distribution; continuous univariate distributions; Pearson distributions; Johnson distributions; flexible probability distributions; engineering design of probability distributions
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1. Introduction

In economics, business, engineering, science, and other fields, continuous uncertainties frequently arise that are not easily or well characterized by previously named continuous probability distributions. Frequently, there are data available from measurements, assessments, derivations, simulations, or other sources that characterize the range of an uncertainty. But the underlying process that generated the data is either unknown or fails to lend itself to convenient derivation of equations that appropriately characterize its probability density function (PDF), cumulative distribution function (CDF), or quantile distribution function.

Desiring a continuous probability distribution but lacking appropriate functional forms, some analysts have attempted to "fit" their data to previously named distributions, often with less-than-satisfactory results. For example, one may attempt to derive the parameters of a normal distribution from a given set of CDF data, but the resulting normal distribution will never be a satisfactory representation if the data itself is indicative of a skewed or bounded distribution, of which the normal is neither. While fitting the same data set to the parameters of a beta distribution may yield a beta distribution with appropriate skewness, the resulting beta distribution may not be satisfactory if the data itself is representative of an unbounded or semibounded distribution, which the beta is not. Moreover, such fitting involves considerable effort and complexity since such probability distributions are often nonlinear in their parameters, lack a closed-form expression, or both.

Moreover, among a set of previously named distributions that have bounds that match natural bounds of the data, it may be unclear which of many distributions to select. The choice of distribution can be important because it inherently imposes shape constraints that may or may not appropriately represent the data and the process that generated it. In such cases, one needs a distribution that has flexibility far beyond that of traditional distributions—one that enables "the data

[1] See http://www.metalogdistributions.com for Excel implementation and supporting information.

to speak for itself" in contrast to imposing unexamined and possibly inappropriate shape constraints on that data. While this need applies to a wide range of empirically generated frequency data, it can be especially acute when a probability distribution is used to represent state-of-information (or belief-based) data, as is common in decision analysis and in an increasingly wide range of other modern applications of probability.

When there are many continuous uncertainties with very different characteristics to represent, as is often the case in decision analysis, it may be simply impractical to attempt to find a continuous representation tailored to each uncertainty using traditional methods. So decision analysts often resort to using discrete (e.g., three branch) representations. These have multiple shortcomings, including that they artificially cut off the tails and introduce undue lumpiness into the analysis.

Desiring a continuous probability distribution but lacking appropriate functional forms, other analysts have resorted to sorting their data into buckets to develop histograms, which have the advantage of being able to represent the shape and location of most any continuous uncertainty. However, histogram development also involves effort and complexity, often includes an arbitrary choice of bucket limits, and inherently results in a lumpy stair-step display rather than a smooth PDF. Maximum entropy methods (Abbas 2003), which strive to add no information beyond the data, similarly result in either a stair-step or piecewise linear PDF. When knowledge of smoothness is present in addition to the data, such formulations are less than ideal.

For applications that require probabilistic (Monte Carlo) simulation, the situation of having data but not continuous distribution functions is even more challenging and complicated. Sampling directly from the data itself (discrete sampling) is not satisfactory if one believes there are gaps, lack of sufficient tail representation, or other shortcomings in the data. Sampling from bucketed data (histograms) requires programming of the buckets and is inherently lumpy. Moreover, even if an appropriate continuous distribution has been identified (e.g., by a data "fit" to its parameters), most continuous CDFs cannot be solved analytically for their inverse CDF (quantile function), which is required for simulation. So look-up tables or nonlinear programming must be employed for each sample.

The metalog family of distributions can solve all these problems, and it has been proven effective and easy to use in practice. The metalog distributions can effectively represent a wide range of continuous probability distributions—whether skewed or symmetric, bounded, semibounded, or unbounded. Scaling constants that determine shape and location are uniquely determined by a convenient linear transformation of CDF data. In contrast to other continuous distributions, there is no need for nonlinear optimization to fit parameters to the data. In addition, the metalog's simple, algebraic closed forms are easy to program, making it easy to replace lumpy, stair-step, or piecewise linear PDF displays with smooth, continuous ones.

For simulation applications, the metalog distributions enable the calculation of a sample from a uniformly distributed random number according to a simple, algebraic equation, thereby displacing any need to use look-up tables or nonlinear optimization for the calculation of each sample. Moreover, over a wide range of applications, the results of the simulation can be conveniently and accurately represented by a metalog, compressing what may otherwise require thousands of data points into a simple closed-form distributional representation.

For direct probability assessments in decision analysis and other Bayesian applications, the metalog distributions provide a convenient way to translate CDF data into smooth, continuous, closed-from distribution functions that can be used for real-time feedback to experts about the implications of their probability assessments—free from the confines of other continuous distributions that have more limited flexibility. In practice, we have found that the resulting metalog often yields a more accurate and authentic representation of expert beliefs than the data itself.

The unbounded metalog distribution is a quantile-parameterized distribution (QPD) (Keelin and Powley 2011), and might be regarded as an easier to use and more broadly applicable successor to the simple Q normal distribution introduced in that paper. Like the simple Q normal, the metalog distribution can effectively represent a wide range of unbounded continuous probability distributions. The metalog,

however, has several advantages: an unlimited number of terms rather than just four (enabling more flexible distributional representations); closed-form, smooth (continuously differentiable) quantile-function and PDF expressions, obviating any need for lookup tables; closed-form analytic expressions for its central moments; and closed-form analytic transforms that conveniently express probability distributions that are semibounded or bounded, while retaining the unbounded metalog's flexibility, smoothness, and ease-of-parameterization properties.

The remainder of this paper is organized as follows. Section 2 provides an overview of the strengths and weaknesses of existing families of flexible distributions, desiderata, engineering methods for developing new flexible distributions, and how these methods have been applied previously. Section 3 applies a novel combination of these methods to develop the unbounded metalog distribution and shows how its flexibility compares with corresponding distributions from previous distribution families, including those of Pearson (1895, 1901, 1916), Johnson (1949), and Tadikamalla and Johnson (1982). Section 4 shows how the flexibility of unbounded the metalog along with its linear quantile parameterization can be propagated into the domain of semibounded and bounded distributions. The flexibility of these semibounded and bounded metalogs is analyzed and compared with corresponding Pearson and Johnson distributions, among others. Section 5 further illustrates the flexibility of the metalog distributions by showing how well they approximate a wide range of existing distributions. Section 6 presents applications. Applications in fish biology and hydrology show how metalogs may aid data and distribution research by imposing fewer shape constraints than other commonly used distributions. Applications in decision analysis show how the metalog system can be specified with three assessed quantiles, how it facilities Monte Carlo simulation, and how applying it aided an actual decision that would have been made wrongly based on commonly used discrete methods. At the end of Section 6, we provide guidelines for distribution selection within the metalog system, using the previous applications as examples. Section 7 offers conclusions and suggested directions for future research.

2. Literature Review and Motivation

2.1. Types of Probability Distributions

For context, we divide probability distributions into three types—Type I, Type II, and Type III. Type I distributions can be derived from an underlying *probability model*, from which they gain much of their appeal and legitimacy. For example, the normal distribution was originally derived as a limiting case of the previously known binomial distribution (De Moivre 1756) and is also the limiting shape for various central limit theorems. Similarly, the exponential distribution can be derived as the probability distribution of waiting times between events governed by a Poisson process. The shape of a Type I distribution is determined largely or entirely by its underlying probability model. For example, the normal distribution has one location parameter, μ, and one scale parameter, σ, but no shape parameters. The exponential distribution has a single scale parameter, λ, but no shape parameters. Such shape restrictions make Type I distributions an excellent choice for practical use whenever the situation fits the probability model, and especially so when empirical data that would otherwise characterize the distribution are sparse or unreliable.

Type II probability distributions gain their appeal and legitimacy less from an underlying probability model and more from their ability to represent *specific* probabilistic data or processes that are not known to correspond to an existing Type I model. Most commonly they are "generalizations" of other previously identified distributions, formed by adding one or more parameters that enable a good fit to the specific (ad hoc) data under consideration. For example, Mead (1965) generalized the logit-normal distribution (proposed previously by Johnson 1949) by adding a parameter that provides flexibility to fit an empirical distribution of carrot-root diameters. Theodossiou (1998) developed a skewed version of a generalized student t distribution on the basis that it provided a better representation of financial data (e.g., log daily returns of market-traded stocks) than previously available distributions. Theodossiou's (1998) distribution is itself a generalization of a previously generalized student t distribution (McDonald and Newey 1988). By now, Type II distributions published in the literature may number in the dozens or hundreds.

Johnson et al. (1994) detail many Type I distributions and Type II generalizations.

Type III distributions gain their appeal and legitimacy from being as *broadly* applicable as possible. Unlike Type II distributions designed to match a specific class or classes of empirical data, Type III distributions would ideally match most *any* set of data. This ideal includes, but is not limited to, effectively representing data consistent with the numerous Type I and Type II distributions. Moreover, with the success and resurgence of the Bayesian revolution (McGrayne 2011) and the evolution of the theory and practice of decision analysis (Howard 1968, Howard and Abbas 2015; Raiffa 1968, Keeney and Raiffa 1993, Spetzler et al. 2016, among others), this ideal includes effectively representing Bayesian priors and other state-of-information-based (or belief-based) distributions over a very wide range of probabilistic data.

2.2. Type III Families of Distributions

Since no single, universally applicable distribution has yet been found, Type III probability distributions have typically been developed as "systems" or "families" of distributions. Within a given family, criteria are provided to enable practitioners to pick which particular distribution to use and how to estimate its parameters from data. The metalog system introduced by this paper is such a family of distributions.

In his book on families of distributions, Ord (1972, p. v) lamented that keeping track of the "wide-ranging and rapidly expanding literature [on systems of distributions] is probably a hopeless task." This is even more the case now—more than 40 years later. So, for this paper, we shall content ourselves with discussion of a few well-known systems of distributions—specifically, the Pearson (1895, 1901, 1916), Johnson (1949), and Tadikamalla and Johnson (1982) systems. We shall also discuss the general family of QPDs, Keelin and Powley (2011), because the unbounded metalog is one of these. A more complete discussion of Type III systems distributions can be found in Ord (1972) and Johnson et al. (1994).

2.3. Type III Desiderata: Flexibility, Simplicity, Ease/Speed of Use

Johnson (1949) identified several criteria for judging the desirability of any Type III system of distributions, including his own. In this view, Type I considerations are less important than practical-use considerations such as flexibility, simplicity, and ease of use. Similar criteria were adopted and employed subsequently by Mead (1965) and Johnson et al. (1994), among others.

2.3.1. Flexibility. Flexibility is the ability of the family to represent a wide range of probabilistic data, whatever their source or rationale may be. Since any distribution can be easily modified via linear transformation to accommodate changes in location and scale, shape flexibility, in contrast to location and scale, is key. To maximize shape flexibility in probability distribution design, one must eschew Type I considerations that limit flexibility. However, such Type I considerations may play useful a role for interpreting special cases of a more general and flexible distribution.

Flexibility also includes the ability to match natural bounds, if any. For example, distances, times, volumes, and other such variables often have a natural lower bound (zero) and no specific upper bound. Percentages of a population or frequencies of occurrence typically have both a lower bound (zero) and an upper bound (one). Other variables, such as bidirectional error measurements or deviations from a point, may be naturally unbounded both high and low.

2.3.2. Simplicity. Simplicity refers to the simplicity of functional form of the PDF and CDF and/or quantile function, ease of algebraic manipulation, and ease of interpretation. For example, we consider closed-form algebraic expressions to be simpler than those that include limits, integrals, statistical functions like beta and gamma, look-up tables, or implicitly defined functions that require iteration.

2.3.3. Ease/Speed of Use. Two critical components of ease of use are ease of distribution selection and ease of parameter estimation. Absent Type I considerations, the literature provides incomplete guidance for distribution selection. For example, suppose that a practitioner has a specific set of empirical data that she wishes to represent with a continuous probability distribution. She knows this her data have a natural lower bound of zero, no natural upper bound, and are right skewed "sort of like a log-normal." There are, however, many distributions that look "sort of like a log-normal." Beyond the log-normal

itself, these include the gamma, inverse gamma, chi-squared, log gamma, log Pearson Type III, log logistic, Burr, Rayleigh, and Weibull, among others. Which should she choose?

Once she has selected a potentially suitable distribution, she cannot know whether she has a good fit until she estimates the parameters of that distribution from her data and views the result. While many good parameter-estimation methods are available, there is no one method that is generally applicable and easy to use in all cases. In most cases, such methods need to be tailored to the particular mathematical form of the distribution under consideration, and even then may require a nontrivial multivariable nonlinear optimization that can be solved only by iteration within distribution-specific constraints (see, e.g., Theodossiou 1998). For this reason, a large literature has evolved to address distribution-specific parameter estimation.[2]

2.3.4. Today's Requirements. Beyond ease of distribution selection and parameter estimation, ease of use depends on purpose and context. At the time of Johnson's (1949) paper, before the advent of modern computers, ease of use included having readily available distribution tables, as had been published for the normal. Today this is much different. An easy-to-use family of distributions should be easy to program (or already be preprogrammed) within the most widely used analytic processing and charting environment.[3] Once programmed, it should be fast to input data, fast and easy to estimate parameters, fast to calculate, and fast to produce interpretable results.

Today, the requirements for flexibility, simplicity, and especially ease/speed of use are critical and can make the difference between use and nonuse in practice. Decades ago, a practitioner might have had days, weeks, or months to select an appropriate distribution and to develop an accurate fit to empirical or assessed data for that distribution. In contrast, in today's professional practice of decision analysis, once data have been assessed, a practitioner might have an hour or less to devote to developing, programming, and estimating parameters for a dozen continuous uncertainties with widely divergent shape and bounds characteristics. Distribution selection and parameter estimation must be fast, seamless, and largely without need for manual intervention over a wide range of data. Moreover, such a practitioner would need to be able to make convenient, rapid adjustments to these distributions to incorporate new information or other changes in state-of-information-based expert data and/or sensitivity analyses. Once formed, the resulting distributions need to be convenient for use in Monte Carlo simulation and ideally without the need for look-up tables or iteration.

If any of these desiderata are not met, a decision analyst might well abandon continuous distributions altogether in favor of discrete approximations, despite their limitations of artificially cutting off the tails and introducing undue lumpiness into the analysis. This particularly challenging environment with respect to flexibility, simplicity, and ease/speed of use motivated our development of the metalog family.

2.4. Engineering Design of Probability Distributions

When designing Type II or Type III probability distributions to best accomplish desiderata as described above, one faces a wide range of choices. These are summarized in a strategy table (Howard and Abbas 2015, pp. 775–776; Spetzler et al. 2016, pp. 56–59) in Table 1. The first row in each column identifies a key decision, and subsequent rows identify specific options that are available for that decision. Table 1 is not meant to cover all possible cases, but rather is intended to be illustrative of key choices that have been made by previous researchers and to provide context for understanding the metalog family. It is also intended to provide a point of reference for future researchers who wish to develop new probability distributions or systems of distributions.

As shown in this table, when designing Type II or Type III probability distributions, it is common to start with a particular form of a particular base distribution, to modify it with a particular method, to develop a method to estimate its parameters, and to provide guidance for selection of which distribution to use. Commonly used base distributions include the normal

[2] Johnson et al. (1994), Volumes 1 and 2, provide an excellent summary and extensive literature references for parameter estimation for a wide range of distributions.

[3] Today this is Excel.

Table 1 Strategy Table for Engineering Probability Distributions

Base distribution	Form modified	Modification method	Parameter estimation	Distribution selection
Normal	Probability density function	Parameter addition	Method of moments	Match moments
Logistic	Cumulative distribution function	Parameter substitution	Maximum likelihood	Match bounds
Student t	Quantile function (inverse CDF)	Transformation	Probability-weighted and L moments	…
…	Characteristic function	Series expansion	Quantile parameterization	

(Edgeworth 1896, 1907; Pearson 1895, 1901, 1916; Johnson 1949), logistic (Tadikamalla and Johnson 1982, Balakrishnan 1992), and student t (McDonald and Newey 1988, Theodossiou 1998). Commonly modified forms—any of which fully specify a probability distribution—include the probability density function (Edgeworth 1896, 1907; Pearson 1895, 1901, 1916); Tadikamalla and Johnson 1982), cumulative distribution function (Burr 1942), quantile function (Karvanen 2006, Keelin and Powley 2011), and characteristic function (Ord 1972, pp. 26–29). Commonly used modification methods include parameter addition (Mead 1965, McDonald and Newey 1988, Theodossiou 1998), parameter substitution (substituting an expression for one or more parameters; Pearson 1895, 1901, 1916), transformation (Johnson 1949, Tadikamalla and Johnson 1982, Hadlock and Bickel 2016), and series expansion (Edgeworth 1896, 1907).[4] Commonly used parameter estimation methods include the method of moments (Pearson 1895, 1901, 1916), method of maximum likelihood,[5] probability-weighted moments (Greenwood et al. 1979), L moments (Hosking 1990), and quantile parameterization (Keelin and Powley 2011, Hadlock and Bickel 2016). For distribution selection within a family, the traditional method has been to select a distribution capable of matching the moments (Pearson 1895, 1901, 1916) of frequency data. But, given sufficient flexibility to match moments, one can also select a distribution based on natural bounds or other criteria.

To provide context for the metalog family, we now show how previous researchers developed families of Type III distributions by making a coordinated set of choices across the columns of Table 1. We also cite strengths and limitations of these families.

The first family of continuous distributions was developed by Karl Pearson (1895, 1901, 1916). In Pearson's time, more and more people, Pearson among them, were recognizing that the normal distribution was not the universal "end-all" of continuous probability distributions. Specifically, it had become increasingly evident that many probabilistic data sets, survival data, for example, exhibited skewness and kurtosis characteristics that the normal distribution could neither explain nor represent. So Pearson set out to develop a system of continuous distributions with variable skewness and kurtosis characteristics.

In terms of Table 1, he selected the normal as his base distribution, the differential equation that characterizes the normal density function as the form to modify, and parameter substitution as his modification method. Specifically, he substituted a quadratic function of the random variable X for the otherwise constant variance (σ^2) in the denominator of this differential equation. This substitution effectively introduced variable skewness and kurtosis parameters into his system. Depending on the values of these parameters, Pearson's generalized-normal-density differential equation has a dozen solutions (Ord 1972).

[4] Johnson et al. (1994) and Ord (1972) provide perspectives on Gram–Charlier, Edgeworth, and other series expansions.

[5] Aldrich (1997) chronicles the development of maximum likelihood by R. A. Fisher during 1912–1921.

These include the normal, beta, uniform, exponential, gamma, chi-square, F, student t, and Cauchy distributions, among others.

As shown in Figure 1,[6] Pearson's system was the first to collectively cover the entire accessible[7] space of combinations of third and fourth central moments. Zero-flexibility distributions show up as points in this diagram. These include the normal, uniform, logistic, Gumbel, and exponential. The flexibility range of triangular distributions is limited to a short line segment as shown. In contrast, bounded Pearson distributions (the beta) are sufficiently flexible to cover the entire accessible area above the Pearson 3 line.[8] Unbounded Pearson distributions (Pearson 4 and student t) cover the area below the Pearson 5 line. Because they are symmetrical, t distributions with various degrees of freedom (df) show up as points on the vertical axis. The area between the Pearson 3 and 5 lines and inclusive of them is the flexibility range for semibounded Pearson distributions (gamma, chi-square, F, inverse gamma, and inverse chi-square).

So while there is at least one Pearson distribution available for each point in Figure 1, Pearson's system offers zero flexibility for choosing boundedness at a given point. For example, if a practitioner needs a semibounded distribution with a combination of skewness and kurtosis that is either above the Pearson 3 line or below the Pearson 5 line, there is no Pearson distribution that satisfies this need. Moreover, given a particular combination of skewness and kurtosis, the Pearson system has zero flexibility to match higher-order moments. This follows from observing that Pearson introduced only two additional parameters into the normal distribution. Finally, Pearson's skewed unbounded distribution (the Pearson 4) is so difficult to use that now, a century later, researchers are still looking for practical ways to do so (Nagahara 1999, Cheng 2011).

The Johnson (1949) and Tadikamalla and Johnson (1982) families of distributions have similar limitations. In terms of Table 1, Johnson (1949) selected the normal as his base distribution and transformed it using log, logit, and hyperbolic-sine transformations to produce his "S" family of distributions that, like Pearson's family, covers the entire accessible space of Figure 1. However, the only semibounded distribution within that family is the log-normal, which is limited to the log-normal line. All S distributions above that line are bounded, and all below it are unbounded. Tadikamalla and Johnson's (1982) "L" family is similar except that it takes the logistic in place of the normal as its base distribution. Semibounded distributions within the L family are limited to the log-logistic line, while all L distributions above it are bounded and below it are unbounded. Moreover, all distributions within both of these families have two or fewer shape parameters, implying that, like Pearson's family, these families have no flexibility to match higher-order moments.

Other noteworthy families of distributions are based on series expansion. Best known are the Edgeworth and Gram–Charlier series expansions of the normal density function. While in theory these expansions have flexibility to match higher-order moments, they tend to be limited to modest areas in the $\beta_1 - \beta_2$ plane by difficulty of parameter estimation and other practical considerations.[4]

In contrast, as presented below, the metalog family provides a choice of boundedness for a wide range of combinations of skewness and kurtosis, flexibility to match higher-order moments, and a straightforward method for parameter estimation.

3. The Unbounded Metalog Distribution

3.1. A Generalized Logistic Distribution

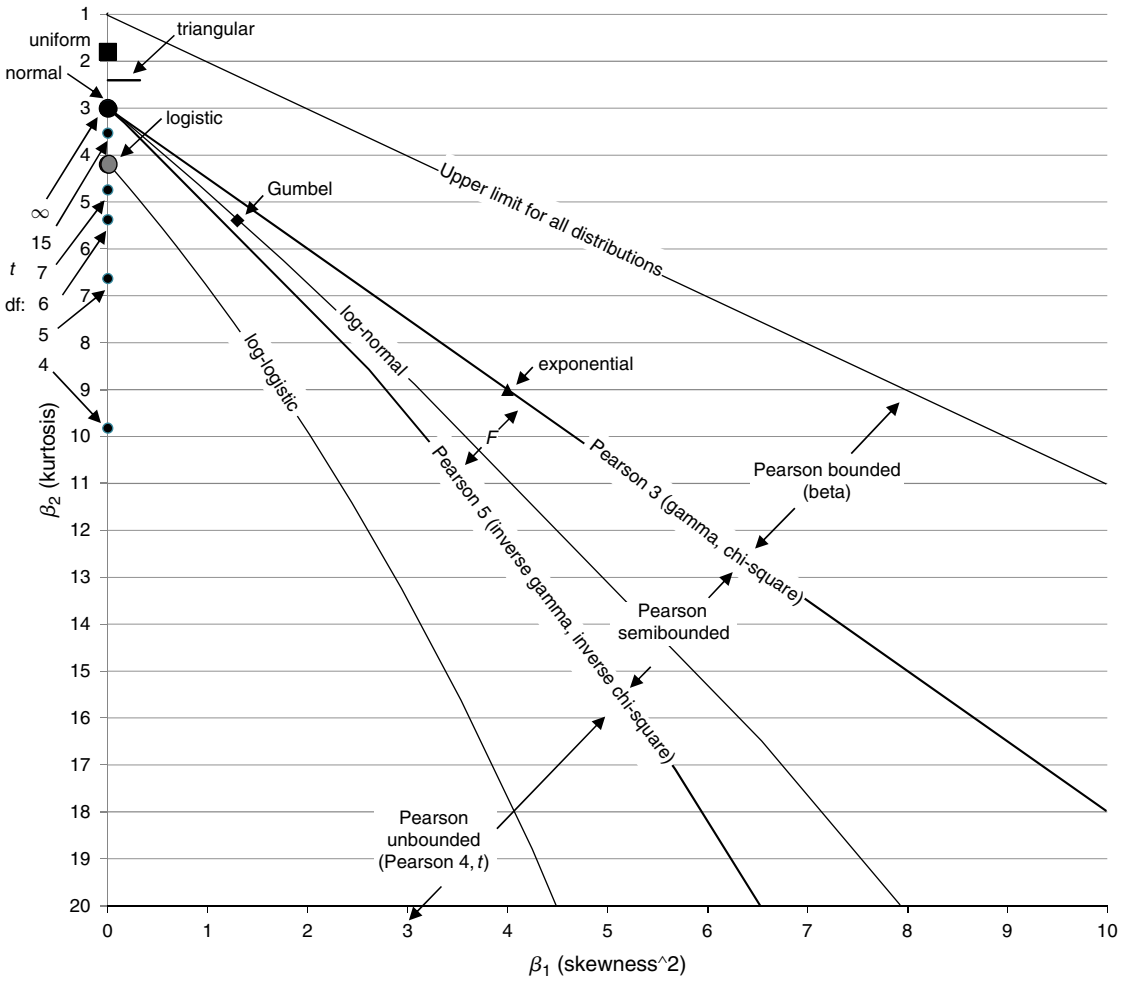
In terms of Table 1, our development of the metalog family starts with the logistic as a base distribution, introduces modifications to its quantile function,

[6] Figure 1 is the format traditionally used to display the flexibility of families of continuous distributions. See Ord (1972), Johnson (1949), Johnson et al. (1994), and Tadikamalla and Johnson (1982), among others. The horizontal axis measures skewness in terms of the square of the standardized skewness, while the vertical axis is standardized kurtosis. This standardization ensures that β_1 and β_2 are location and scale independent. See Section 3.4 below for precise definitions.

[7] "Accessible" in this context refers to the area below the "upper limit for all distributions" line in Figure 1.

[8] "Pearson 3," "Pearson 4," etc., are synonymous with the terms "Pearson Type III," "Pearson Type IV," etc., as commonly used elsewhere in the literature.

Figure 1 **Flexibility and Bounds Limitations of Pearson Distributions**



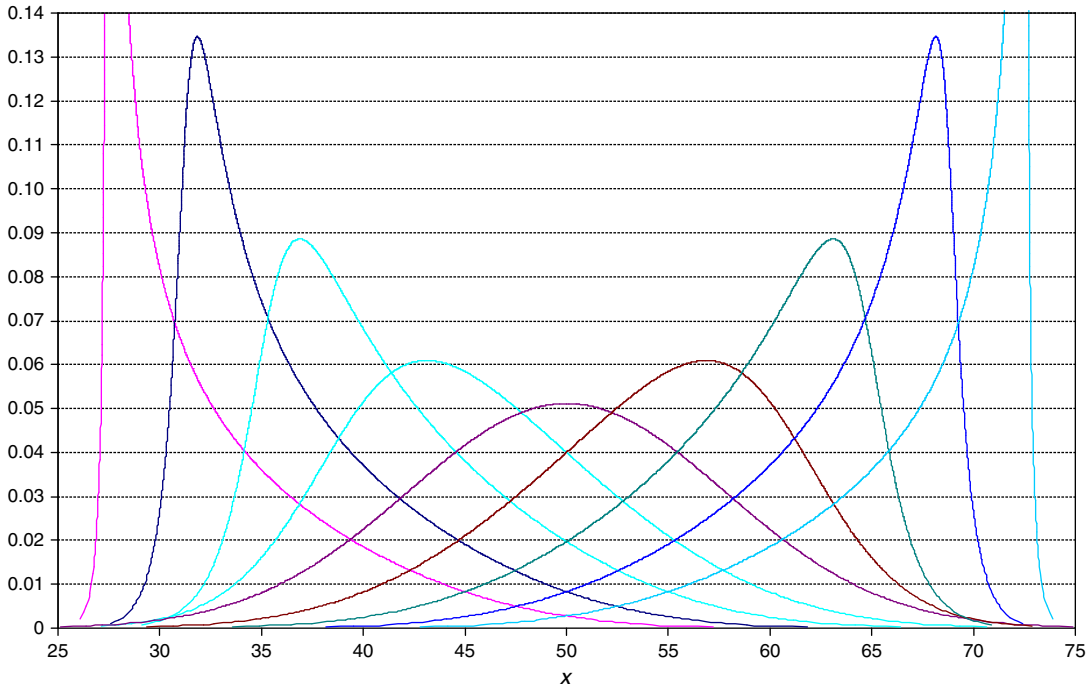
and uses three of the Table 1 modification methods—parameter substitution, transformation, and series expansion.

Among its Type I interpretations, the logistic is the limiting distribution of the midrange sample (average of largest and smallest random samples) as sample size approaches infinity. We chose it as a base distribution, however, not because of its Type I interpretations, but because of its simple closed-form expressions for PDF, CDF, and quantile functions; smoothness and symmetry; infinite differentiability in closed form; tail behavior that is "in between" the lighter-tailed beta and normal distributions and the heavier-tailed student t distributions; and its wide range of fully investigated and well-known properties (Balakrishnan 1992).

In terms of which form to modify, we have chosen the quantile function. Like Burr (1942), we prefer to start with a closed-form CDF or quantile function because, assuming differentiability, either one can be easily differentiated to find the PDF. In contrast, starting with the PDF often leads to a form that cannot be conveniently integrated to find the CDF or quantile function. We have chosen to modify the quantile function in particular because, in contrast to the CDF, it expresses the value x of a random variable as a function of probability y, thereby having the simplicity of being scale independent of x and also guaranteeing ease of use in Monte Carlo simulation.[9] Moreover, the

[9] In Monte Carlo simulation via the inverse transform method, uniformly distributed random samples of y can simply be inserted

Figure 2 **(Color online) Skewed Distributions Produced by Systematically Varying the Standard Deviation Parameter of a Logistic Distribution**



logistic quantile function in particular is linear in its parameters, and thus is already a QPD[10] prior to any modification. The logistic quantile function is

$$\mu + s \ln \frac{y}{1-y} \quad \text{for } 0 < y < 1, \tag{1}$$

where μ is the mean, median, and mode, and s is proportional to standard deviation $\sigma = s\pi/\sqrt{3}$.

For modification method, we use a combination of parameter substitution (following Pearson's lead) and series expansion, where a_i's are real constants:

$$\mu = a_1 + a_4(y-0.5) + a_5(y-0.5)^2 + a_7(y-0.5)^3 + a_9(y-0.5)^4 + \cdots, \tag{2}$$

$$s = a_2 + a_3(y-0.5) + a_6(y-0.5)^2 + a_8(y-0.5)^3 + a_{10}(y-0.5)^4 + \cdots. \tag{3}$$

Substituting these series expansions for the parameters μ and s is easily interpreted. Note that the unmodified logistic distribution (1) is smooth, symmetric, unimodal, and unbounded. Imagine how its shape might change if the otherwise-constant μ and s were to change systematically. For example, given a systematically increasing standard deviation parameter as one moves from left to right it, is natural to visualize that a right skewed distribution would result. Alternatively, if the standard deviation parameter decreases when moving from left to right, one might visualize that a left skewed distribution would result. A range of such distributions is shown in Figure 2.

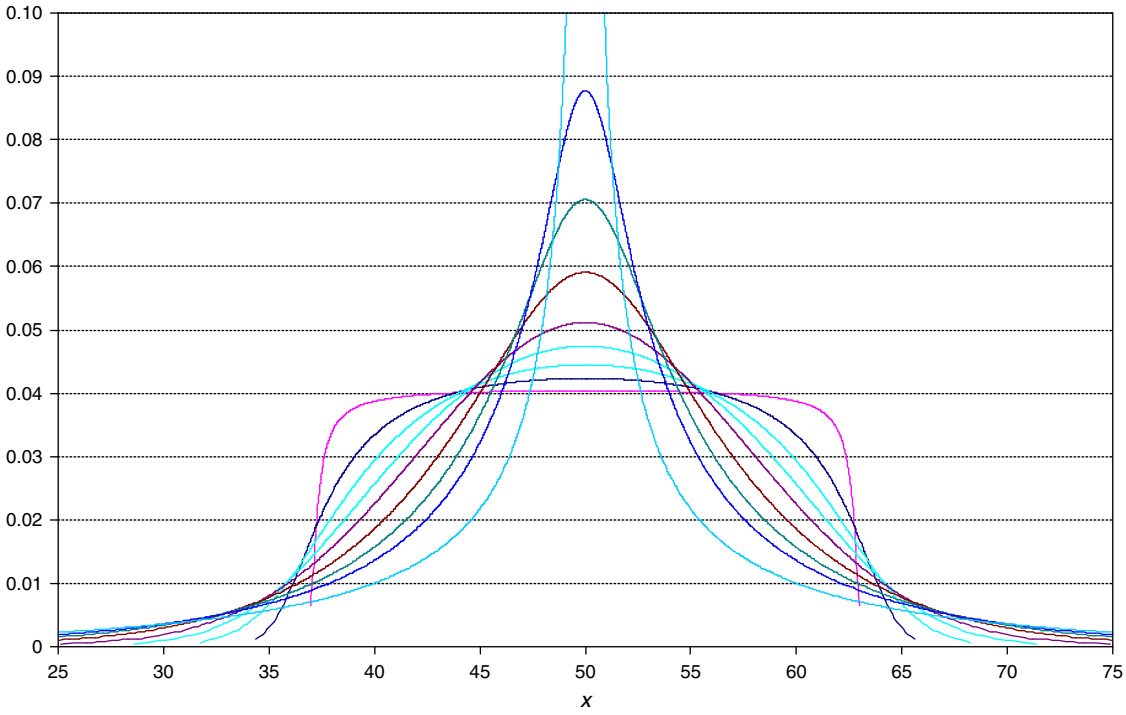
Similarly, one can envision that increasing μ from left to right would make a distribution fatter in the middle and therefore have lighter tails. And by systematically decreasing it as one moves from left to right, the distribution would become thinner (or spikier) in the middle with correspondingly heavier tails. A range of such distributions is shown in Figure 3.

Regarding (2) and (3), our choice of an unlimited number of series-expansion terms for modifying μ

into a closed-form quantile function to yield corresponding samples of x. This is trivially simple for closed-form quantile functions in contrast to the nonlinear optimization or look-up tables typically required otherwise.

[10] Keelin and Powley (2011) provide definitions, moments derivation, linear parameter estimation, and other QPD properties that we further build upon in this paper.

Figure 3 **(Color online) Symmetric Distributions Produced by Systematically Varying the Mean Parameter of a Logistic Distribution**



and s might be envisioned to provide nearly unlimited shape flexibility, the specifics of which we explore in Section 3.5.

Substituting (2) and (3) into the logistic quantile function (1) yields a generalized logistic quantile function, where n is the total number of series terms in use:

$$M_n(y) = a_1 + a_2 \ln \frac{y}{1-y} + a_3(y-0.5) \ln \frac{y}{1-y} + a_4(y-0.5) + \cdots . \quad (4)$$

For $M_n(y)$ to be a valid quantile function of a continuous distribution, it must be strictly increasing as a function of y; that is, $d[M_n(y)]/dy > 0$ for all $y \in (0, 1)$. Applying this requirement to (4) leads to a feasibility condition on the constants a_i:

$$\frac{a_2}{y(1-y)} + a_3\left(\frac{y-0.5}{y(1-y)} + \ln \frac{y}{1-y}\right) + a_4 + \cdots > 0 \quad \text{for all } y \in (0, 1). \quad (5)$$

For example, if $a_i = 0$ for all $i \geq 3$, then a_2 must be positive for this condition to hold. Since (4) reduces to (1) in this case, the requirement that a_2 be positive is equivalent to requiring that the standard deviation be positive, which must be true for any probability distribution. Equation (5) is the generalization of this requirement that corresponds to the generalized quantile function (4). Any set of constants $\boldsymbol{a} = (a_1, \ldots, a_n)$ that satisfies (5) we shall henceforth call *feasible*.

The order of the terms in (2), (3), and (4) is somewhat arbitrary and could be changed without loss of generality. We chose the order such that the first term would be the median, the second term would be a base shape (the logistic) that subsequent terms modify, the third term would primarily modify skewness, the fourth term would primarily modify kurtosis, and subsequent terms would alternate in further refining the s and μ parameters in (3) and (2), respectively. The third and fourth terms could be reversed if one wanted, for example, the third term to modify kurtosis and the fourth term to modify skewness. This would be useful in a situation where $n = 3$ and it is known from a priori considerations that a symmetric distribution with variable kurtosis properties is appropriate.

Since (4) is linear in the constants $\boldsymbol{a} = (a_1, \ldots, a_n)$, so can be the parameter estimation of these constants.

Given a set of m distinct CDF data points $(\mathbf{x}, \mathbf{y})$ where $\mathbf{x} = (x_1, \ldots, x_m)$, $\mathbf{y} = (y_1, \ldots, y_m)$, the constants are related to the data by a set of linear equations:

$$\begin{aligned}
x_1 &= a_1 + a_2 \ln\frac{y_1}{1-y_1} + a_3(y_1 - 0.5)\ln\frac{y_1}{1-y_1} \\
&\quad + a_4(y_1 - 0.5) + \cdots, \\
x_2 &= a_1 + a_2 \ln\frac{y_2}{1-y_2} + a_3(y_2 - 0.5)\ln\frac{y_2}{1-y_2} \\
&\quad + a_4(y_2 - 0.5) + \cdots, \\
&\vdots \\
x_m &= a_1 + a_2 \ln\frac{y_m}{1-y_m} + a_3(y_m - 0.5)\ln\frac{y_m}{1-y_m} \\
&\quad + a_4(y_m - 0.5) + \cdots.
\end{aligned}$$

Equivalently, $\mathbf{x} = \mathbf{Y}\boldsymbol{a}$, where $\mathbf{x}$ and $\boldsymbol{a}$ are column vectors, and $\mathbf{Y}$ is the $m \times n$ matrix

$$\mathbf{Y} = \begin{bmatrix} 1 & \ln\frac{y_1}{1-y_1} & (y_1-0.5)\ln\frac{y_1}{1-y_1} & (y_1-0.5) & \cdots \\ & & \vdots & & \\ 1 & \ln\frac{y_m}{1-y_m} & (y_m-0.5)\ln\frac{y_m}{1-y_m} & (y_m-0.5) & \cdots \end{bmatrix}.$$

If $m = n$ and $\mathbf{Y}$ is invertible, then $\boldsymbol{a}$ is uniquely determined by $\boldsymbol{a} = \mathbf{Y}^{-1}\mathbf{x}$. If $m \geq n$ and $\mathbf{Y}$ has rank of at least n, then $\boldsymbol{a}$ is can be conveniently estimated using the familiar linear least squares equation $\boldsymbol{a} = [\mathbf{Y}^T\mathbf{Y}]^{-1}\mathbf{Y}^T\mathbf{x}$, which reduces to $\boldsymbol{a} = \mathbf{Y}^{-1}\mathbf{x}$ when $m = n$.[11] As such, this parameter estimation method can be interpreted as the maximum likelihood estimator if a Gaussian noise model is assumed. Note that it scales directly with n, the number of series terms in use. The size of the matrix to be inverted is $n \times n$ regardless of the number of data points m.

These observations give rise to the following definitions and formalizations.

3.2. Metadistributions

We use the term "metadistribution" to reference the class of a probability distributions that generalize a base distribution by substituting for one or more of its parameters an unlimited number of shape parameters. In doing so, the shape of a metadistribution "goes beyond" the shape of the base distribution with considerable added flexibility. To be useful, a metadistribution must also be associated with a practical method for estimating its parameters.

The generalized logistic distribution above is one specific example of a metadistribution, which we formally define below as the "metalog" distribution. The term "metalog" is short for "metalogistic."

Whenever the functional form of a base distribution is linear in its parameters, as is true for the quantile function of the logistic distribution, one can employ the same theoretical development method as above to create a new metadistribution. For example, a meta-normal distribution can be developed by replacing (1) with the normal quantile function

$$\mu + \sigma\Phi^{-1}(y),$$

where Φ is standard normal CDF, and $0 < y < 1$. If one then substitutes series expansions like (2) and (3) for μ and σ, the "meta-normal" follows from the same subsequent development as in Section 3.1. Similarly, one could develop meta-Gumbel and meta-exponential distributions—since these too possess quantile functions that are linear in their parameters.

Such metadistributions defined with respect to quantile functions, including the metalog, are generally quantile parameterized distributions as defined by Keelin and Powley (2011). The simple Q normal distribution used for illustration in that paper is akin to the first several terms of the meta-normal.

Our initial explorations of the meta-normal distribution show that its flexibility properties are similar to those of the metalog, which we discuss below. For this paper, we have chosen to develop the metalog rather than the meta-normal because of its simple closed-form expression and greater ease of use compared to the meta-normal, which requires non-closed-form look-up tables. For many practical applications, either would suffice.

3.3. The Metalog Distribution

We define the metalog distribution by formalizing the generalized logistic distribution of Section 3.1. Note that we have subsumed the linear-least-squares solution for $\boldsymbol{a}$ within the following definition to express the metalog, consistent with practical needs, as a function of its quantile parameters $(\mathbf{x}, \mathbf{y})$.

[11] Keelin and Powley (2011) also includes a weighted least squares formulation as an option for providing additional shape flexibility.

Definition 1 (Metalog Quantile Function). The metalog quantile function with n terms is

$$
\begin{aligned}
&M_n(y;\mathbf{x},\mathbf{y}) = \\
&a_1 + a_2 \ln\frac{y}{1-y} \quad \text{for } n=2, \\
&a_1 + a_2 \ln\frac{y}{1-y} + a_3(y-0.5)\ln\frac{y}{1-y} \quad \text{for } n=3, \\
&a_1 + a_2 \ln\frac{y}{1-y} + a_3(y-0.5)\ln\frac{y}{1-y} \\
&\qquad + a_4(y-0.5) \quad \text{for } n=4, \\
&M_{n-1} + a_n(y-0.5)^{(n-1)/2} \quad \text{for odd } n \geq 5, \\
&M_{n-1} + a_n(y-0.5)^{n/2-1}\ln\frac{y}{1-y} \quad \text{for even } n \geq 6, \qquad (6)
\end{aligned}
$$

where y is cumulative probability, $0 < y < 1$. Given $\mathbf{x} = (x_1, \ldots, x_m)$ and $\mathbf{y} = (y_1, \ldots, y_m)$ of length $m >= n$ consisting of the x and y coordinates of CDF data, $0 < y_i < 1$ for each y_i, and at least n of the y_i's are distinct, the column vector of scaling constants $\boldsymbol{a} = (a_1, \ldots, a_n)$ is given by

$$\boldsymbol{a} = [\mathbf{Y}_n^T \mathbf{Y}_n]^{-1} \mathbf{Y}_n^T \mathbf{x}, \qquad (7)$$

where $\mathbf{Y}_n^T$ is the transpose of $\mathbf{Y}_n$, and the $m \times n$ matrix $\mathbf{Y}_n$ is

$$
\begin{aligned}
&\mathbf{Y}_n = \\
&\begin{bmatrix} 1 & \ln\frac{y_1}{1-y_1} \\ & \vdots \\ 1 & \ln\frac{y_m}{1-y_m} \end{bmatrix} \quad \text{for } n=2, \\
&\begin{bmatrix} 1 & \ln\frac{y_1}{1-y_1} & (y_1-0.5)\ln\frac{y_1}{1-y_1} \\ & \vdots & \\ 1 & \ln\frac{y_m}{1-y_m} & (y_m-0.5)\ln\frac{y_m}{1-y_m} \end{bmatrix} \quad \text{for } n=3, \\
&\begin{bmatrix} 1 & \ln\frac{y_1}{1-y_1} & (y_1-0.5)\ln\frac{y_1}{1-y_1} & y_1-0.5 \\ & \vdots & & \\ 1 & \ln\frac{y_m}{1-y_m} & (y_m-0.5)\ln\frac{y_m}{1-y_m} & y_m-0.5 \end{bmatrix} \quad \text{for } n=4, \\
&\left[\begin{array}{c|c} \mathbf{Y}_{n-1} & \begin{matrix}(y_1-0.5)^{(n-1)/2} \\ \vdots \\ (y_m-0.5)^{(n-1)/2}\end{matrix} \end{array}\right] \quad \text{for odd } n \geq 5, \\
&\left[\begin{array}{c|c} \mathbf{Y}_{n-1} & \begin{matrix}(y_1-0.5)^{n/2-1}\ln(y_1/(1-y_1)) \\ \vdots \\ (y_m-0.5)^{n/2-1}\ln(y_m/(1-y_m))\end{matrix} \end{array}\right] \\
&\qquad \text{for even } n \geq 6. \qquad (8)
\end{aligned}
$$

In the special case of $m = n$, (7) reduces to $\boldsymbol{a} = \mathbf{Y}_n^{-1}\mathbf{x}$.

Definition 2 (Metalog PDF). Differentiating (6) with respect to y and inverting the result yields the metalog PDF:[12]

$$
\begin{aligned}
&m_n(y) = \\
&\frac{y(1-y)}{a_2} \quad \text{for } n=2, \\
&\frac{1}{\frac{a_2}{y(1-y)} + a_3\left(\frac{y-0.5}{y(1-y)} + \ln\frac{y}{1-y}\right)} \quad \text{for } n=3, \\
&\frac{1}{\frac{a_2}{y(1-y)} + a_3\left(\frac{y-0.5}{y(1-y)} + \ln\frac{y}{1-y}\right) + a_4} \quad \text{for } n=4, \\
&\left[\frac{1}{m_{n-1}(y)} + a_n\frac{n-1}{2}(y-0.5)^{(n-3)/2}\right]^{-1} \quad \text{for odd } n \geq 5, \\
&\left[\frac{1}{m_{n-1}(y)} + a_n\left(\frac{(y-0.5)^{n/2-1}}{y(1-y)} + \left(\frac{n}{2}-1\right)\right.\right. \\
&\qquad \left.\left. \cdot (y-0.5)^{n/2-2}\ln\frac{y}{1-y}\right)\right]^{-1} \quad \text{for even } n \geq 6. \qquad (9)
\end{aligned}
$$

Note that the PDF $m_n(y)$ is expressed as a function of cumulative probability y. To plot this PDF as is customary, with values of random variable X on the horizontal axis, use $M_n(y)$ on the horizontal axis and $m_n(y)$ on the vertical axis, and vary $y \in (0, 1)$ to produce the corresponding values on both axes.

For (6) and (9) to be a valid probability distribution, the matrix $\mathbf{Y}_n^T\mathbf{Y}_n$ must be invertible, and the constants $\boldsymbol{a}$ must be feasible. Since (6) is a QPD, invertibility is guaranteed in all but pathological cases.[13]

[12] For proof that this method yields the PDF, see Keelin and Powley (2011).

[13] "If such a [pathological] case were to occur, a small perturbation would solve the problem. In practical applications, we have never encountered a case where… [the matrix that needs to be inverted] is singular" (Keelin and Powley 2011, p. 212).

Regarding feasibility, note that $m_n(y)$ is the reciprocal of the feasibility expression on the left-hand side of (5). Since this expression is positive if and only if its reciprocal is positive, it follows that the feasibility condition (5) can be restated stated as

$$m_n(y) > 0 \quad \text{for all } y \in (0, 1); \tag{10}$$

that is, $\boldsymbol{a}$ is feasible if and only if $m_n(y)$ is everywhere positive, and for any feasible $\boldsymbol{a}$, $m_n(y)$ is the probability density function that corresponds to (6).

Note that we have placed no constraints on the data $(\mathbf{x}, \mathbf{y})$. As such, there is no guarantee that any particular data set will lead to feasibility. Indeed, many data sets will not. If in doubt, feasibility must be checked according to (5) or (10). In practice, this means computing or plotting $m_n(y)$ and ensuring that the result is positive over all $y \in (0, 1)$. If so, then $\boldsymbol{a}$ is feasible and $m_n(y)$ is a valid probability density function. Later in this paper, we provide closed-form constraints on the data $(\mathbf{x}, \mathbf{y})$ that ensure feasibility for the case of $n = 3$. Any data set $(\mathbf{x}, \mathbf{y})$ that yields feasible constants $\boldsymbol{a}$ we shall henceforth call feasible.

Given feasibility, certain special cases of these constants can be readily interpreted. In all cases, a_1 is the median, as is evident from observing that all subsequent terms are zero when $y = 0.5$. Constants a_i for $i \geq 2$ determine shape. When $a_2 > 0$ and $a_i = 0$ for all $i \geq 3$, (6) is a logistic distribution exactly, with a_2 being directly proportional to the standard deviation, as is obvious by comparison with (1). When $a_i = 0$ for $i \geq 4$, a_3 primarily controls skewness. Increasing a_3 from zero results in an increasingly right-skewed distribution, while increasingly negative values of a_3 result in an increasingly left-skewed distribution. When $a_4 > 0$ and $a_2 = 0$, $a_3 = 0$, and $a_i = 0$ for $i \geq 5$, (6) reduces to a linear function of y, which means that it is a uniform distribution exactly. More generally, when $a_2 > 0$, $a_3 = 0$, and $a_i = 0$ for $i \geq 5$, a_4 determines kurtosis. Increasing a_4 from zero reduces kurtosis, resulting in a symmetric distribution that is fatter than a logistic in its midrange with correspondingly lighter tails (e.g., more like a normal or symmetric beta distribution than a logistic). Reducing a_4 from zero into increasingly negative values increases kurtosis, producing a distribution that is narrower than a logistic in its midrange with correspondingly heavier tails (e.g., more like a student t distribution with eight or fewer degrees of freedom).

Generally, the metalog, like the logistic, is unbounded. However, it is bounded in the special case that $a_i = 0$ for all $i \in \{2, 3, \textit{all even numbers} \geq 6\}$. This is evident from observing that this is the particular set of a_i's that multiplies the unbounded expression $\ln(y/(1-y))$ in (6). If all these a_i's are zero, then only bounded terms remain. Table 2 summarizes the above interpretations.

3.4. Metalog Moments

We use traditional notation for moments of the n-term metalog distribution M_n:

- $\mu'_{k,n}$ kth moment;
- $\mu_{k,n}$ kth central moment;
- σ_n standard deviation $= \mu_{2,n}^{1/2}$;
- β_1 square of standardized skewness $= (\mu_{3,n}/\sigma_n^3)^2$ (horizontal axes of Figures 1, 4, 6, and 7); and
- β_2 standardized kurtosis $= \mu_{4,n}/\sigma_n^4$ (vertical axes of Figures 1, 4, 6, and 7).

Since the metalog is a QPD, then, as shown by Keelin and Powley (2011), its kth moment is given simply by the integral of the kth power of the quantile function

$$\mu'_{k,n} = \int_{y=0}^{1} [M_n(y; \mathbf{x}, \mathbf{y})]^k \, dy.$$

For $n = 5$ terms, this integral yields an explicit expression in closed form for the mean

$$\mu'_{1,5} = a_1 + \frac{a_3}{2} + \frac{a_5}{12} \quad \text{(mean)},$$

from which it follows that the kth central moment for the 5-term metalog is given by

$$\mu_{k,5} = \int_{y=0}^{1} \left[M_5(y; \mathbf{x}, \mathbf{y}) - \left(a_1 + \frac{a_3}{2} + \frac{a_5}{12} \right) \right]^k dy.$$

Though tedious to solve by hand, this integral can be shown to yield the following central moments of M_5 as closed-form polynomial expressions of the a_i's:

$$\mu_{2,5} = \frac{1}{3}\pi^2 a_2^2 + \left(\frac{1}{12} + \frac{\pi^2}{36} \right) a_3^2 + a_2 a_4 + \frac{a_4^2}{12} + \frac{a_3 a_5}{12} + \frac{a_5^2}{180}, \quad \text{(variance)};$$

Table 2 Interpreting Metalog Constants

Constants	Interpretations
a_1	Location, median
$k^*\{a_i$ for all $i \geq 2\}$, where $k > 0$	k is a scale parameter
a_i for all $i \geq 2$	Shape
$a_2 > 0$, $a_i = 0$ for all $i \geq 3$	M_n is a logistic distribution
$a_4 > 0$, $a_i = 0$ for all $i \in \{2, 3, \text{integers} > 4\}$	M_n is a uniform distribution
$a_2 > 0$, $a_4 > 0$, and $a_i = 0$ for $i \in \{3, \text{integers} \geq 5\}$; a_2 and a_4 need not sum to 1	M_n is a mixture of logistic and uniform distributions, where a_1 is the mean and median of both. M_n is unimodal and symmetric. In Figure 4, M_n plots to the vertical line segment from (0, 1.8) to (0, 4.2).
$a_2 > 0$, $a_4 < 0$, $a_4/a_2 \geq -4$, and $a_i = 0$ for all $i \in \{3, \text{integers} \geq 5\}$	M_n is unimodal and symmetric. In Figure 4, M_n plots to the vertical line segment from (0, 4.2) to (0, 17.2).
$a_2 > 0$, $-1.67 < a_3/a_2 < 1.67$, and $a_i = 0$ for all $i \geq 4$	M_n is unimodal and right skewed if $a_3 > 0$, unimodal and left skewed if $a_3 < 0$. In Figure 4, M_n plots to the "3-term metalog" line segment from (0, 4.2) to (4.29, 8.58).
$a_i = 0$ for all $i \in \{2, 3, \text{all even numbers} \geq 6\}$	M_n is bounded
$a_i \neq 0$ for any $i \in \{2, 3, \text{all even numbers} \geq 6\}$	M_n is unbounded

$$\begin{aligned}\mu_{3,5} = {} & \pi^2 a_2^2 a_3 + \frac{1}{24}\pi^2 a_3^3 + \frac{1}{2}a_2 a_3 a_4 + \frac{1}{6}\pi^2 a_2 a_3 a_4 + \frac{1}{8}a_3 a_4^2 \\ & + a_2^2 a_5 + \frac{1}{24}a_3^2 a_5 + \frac{1}{180}\pi^2 a_3^2 a_5 + \frac{1}{4}a_2 a_4 a_5 \\ & + \frac{1}{60}a_4^2 a_5 + \frac{1}{120}a_3 a_5^2 + \frac{a_5^3}{3{,}780}, \quad \text{(skewness);}\end{aligned}$$

$$\begin{aligned}\mu_{4,5} = {} & \frac{7}{15}\pi^4 a_2^4 + \frac{3}{2}\pi^2 a_2^2 a_3^2 + \frac{7}{30}\pi^4 a_2^2 a_3^2 + \frac{a_3^4}{80} + \frac{1}{24}\pi^2 a_3^4 \\ & + \frac{7\pi^4 a_3^4}{1{,}200} + 2\pi^2 a_2^3 a_4 + \frac{1}{2}a_2 a_3^2 a_4 + \frac{2}{3}\pi^2 a_2 a_3^2 a_4 \\ & + 2a_2^2 a_4^2 + \frac{1}{6}\pi^2 a_2^2 a_4^2 + \frac{1}{8}a_3^2 a_4^2 + \frac{1}{40}\pi^2 a_3^2 a_4^2 + \frac{1}{3}a_2 a_4^3 \\ & + \frac{a_4^4}{80} + a_2^2 a_3 a_5 + \frac{1}{2}\pi^2 a_2^2 a_3 a_5 + \frac{1}{24}a_3^3 a_5 + \frac{1}{40}\pi^2 a_3^3 a_5 \\ & + \frac{5}{6}a_2 a_3 a_4 a_5 + \frac{2}{45}\pi^2 a_2 a_3 a_4 a_5 + \frac{3}{40}a_3 a_4^2 a_5 + \frac{1}{6}a_2^2 a_5^2 \\ & + \frac{1}{90}\pi^2 a_2^2 a_5^2 + \frac{1}{45}a_3^2 a_5^2 + \frac{11\pi^2 a_3^2 a_5^2}{7{,}560} + \frac{1}{15}a_2 a_4 a_5^2 \\ & + \frac{11 a_4^2 a_5^2}{2{,}520} + \frac{1}{420}a_3 a_5^3 + \frac{a_5^4}{15{,}120}, \quad \text{(kurtosis).}\end{aligned}$$

As k and n increase, the number of polynomial terms increases, but within a pattern that continues with the kth central moment of the n-term metalog being a closed-form kth order polynomial of the a_i's. For example, the ninth central moment of the 5-term metalog $\mu_{9,5}$ has a closed-form expression that consists of a ninth-order polynomial in the a_i's with 297 terms. The fourth central moment of the 10-term metalog $\mu_{4,10}$ has 474 terms. These central moments are available at http://www.metalogdistributions.com. For all such central moments $\mu_{k,n}$, the central moments of $\mu_{k,j}$ where $j < n$ can be calculated from $\mu_{k,n}$ simply by setting $a_i = 0$ for all $i > j$.

Given central moments in closed form, corresponding closed-form cumulants can also be calculated. Thus, the cumulants of the sum of independent (irrelevant, according to Howard and Abbas 2015) metalog-distributed random variables can be expressed in closed form as the sum of the cumulants of these random variables.

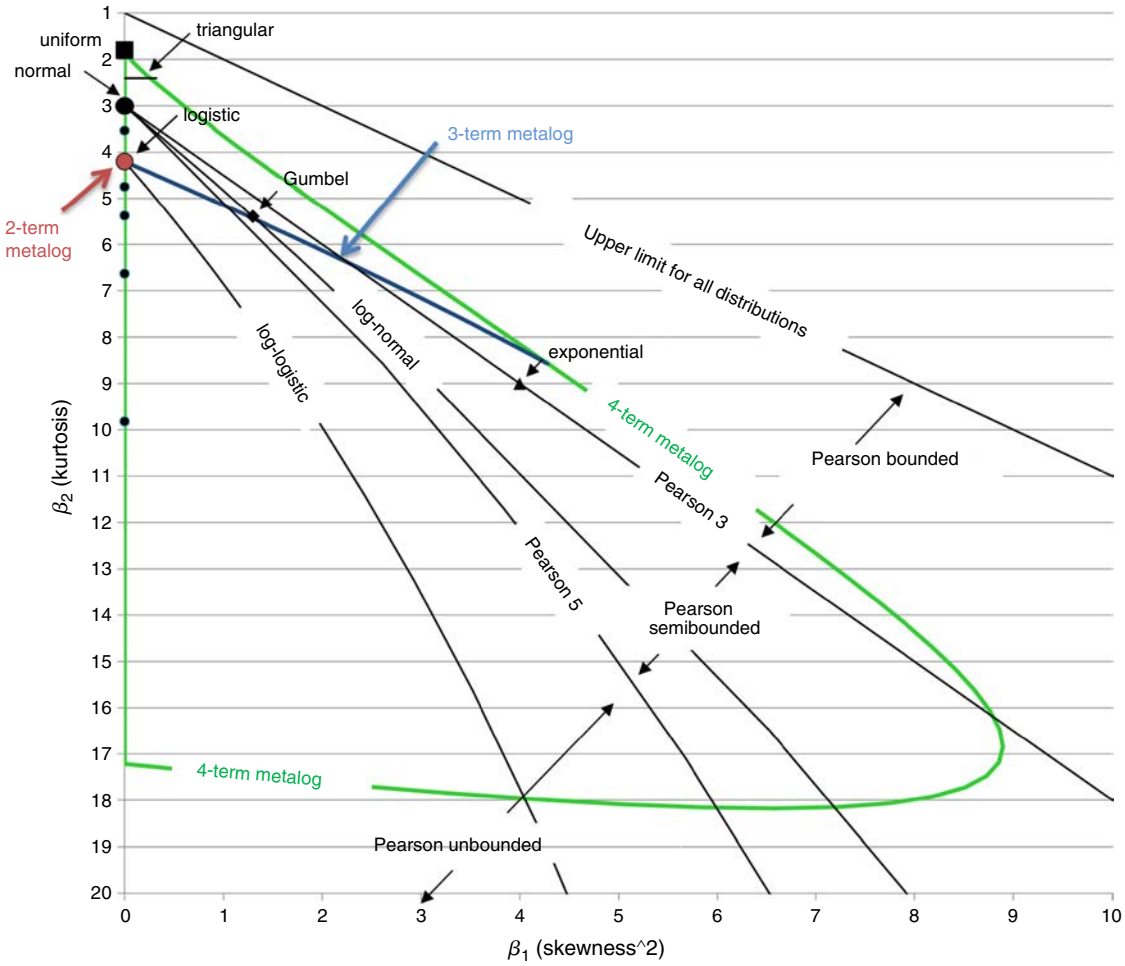
3.5. Metalog Shape Flexibility

The shape flexibility of the metalog expands with the number of terms in use. As shown in Figure 4, for $n = 2$, the metalog reduces to a logistic distribution and thus to the single point (0, 4.2). For $n = 3$, metalog shape flexibility expands from a point to a line segment as shown. This line segment contains the full range of shapes shown in Figure 5.

For $n = 4$, the metalog shape flexibility further expands to include all of area within "4-term metalog" envelope.[14] This area encompasses many common distributions including normal, uniform, triangular,

[14] Since the metalog is parameterized by data rather than moments, we derived the metalog flexibility limits in Figure 4 by varying $\boldsymbol{a} = (a_1, \ldots, a_n)$ over its feasible range and deriving the corresponding (β_1, β_2) feasible range from the moments expressions in Section 3.4. This process was enhanced by Keelin and Powley's (2011) proof that the set of feasible $\boldsymbol{a} = (a_1, \ldots, a_n)$ is convex.

Figure 4 **(Color online) Shape Flexibility for Two- to Four-Term Metalog Distributions**



logistic, exponential, Gumbel, and student t distributions with four or more degrees of freedom. Within the 4-term metalog envelope, the Pearson family offers unbounded distributions only below the Pearson 5 line. In contrast, the 4-term metalog offers unbounded distributions for a significant portion of the Pearson semibounded area and a significant portion (primarily unimodal) of the Pearson bounded area. Similarly, the 4-term metalog offers substantial additional unbounded flexibility compared to the areas below the log-normal and log-logistic lines, which are the upper limits respectively for unbounded Johnson S and L distributions.

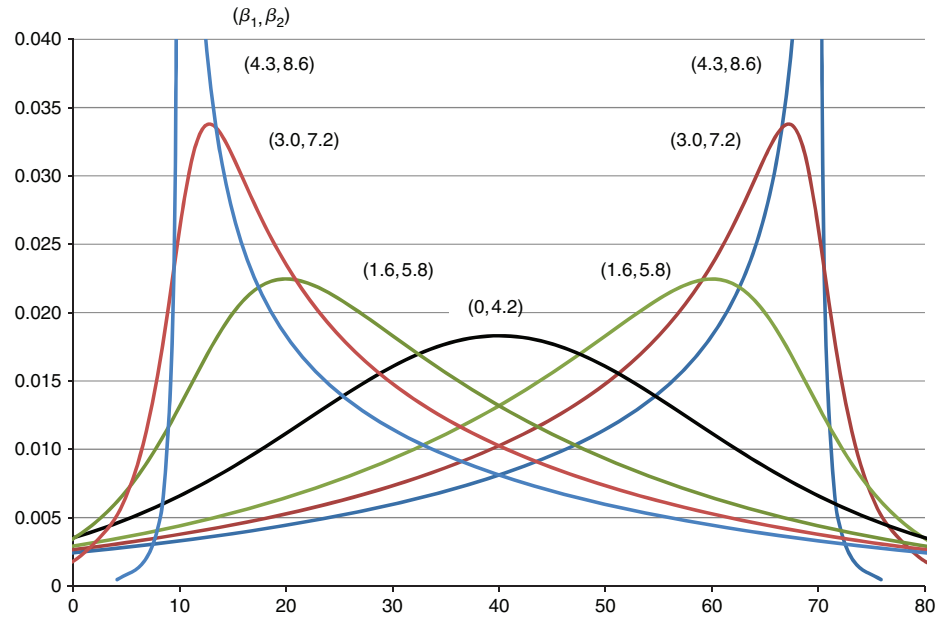
There are certain relatively extreme skewness-kurtosis combinations that unbounded members of these other Type III families can represent that the 4-term metalog cannot. These include student t distributions with three or fewer degrees of freedom, and other distributions outside of the envelope.

However, with 5 or more terms, the metalog can represent multimodal shapes and fifth- or higher-order moments. In addition, the metalog's (β_1, β_2) coverage expands further. For example, with 10 terms, the metalog can reasonably represent student t distributions with three or two degrees of freedom. The metalog cannot effectively represent the Cauchy distribution (student t with one degree of freedom), all the moments of which are infinite.

4. Bounded and Semibounded Metalogs

In many cases, one knows from a priori considerations that a distribution of interest is either semibounded or bounded. For example, uncertainties

Figure 5 **(Color online) Range of Shapes for the Three-Term Metalog**



involving sizes, weights, and distances might naturally have a lower bound of zero and no definite upper bound. Uncertainties that involve fractions of a population are typically are bounded between zero and 100%. For such cases, it is desirable to have flexible, simple, easy-to-use distributions with bounds that can be specified a priori.

We now develop such distributions. In terms of Table 1, we use the metalog quantile function (6) as a base distribution and modify it using the method of transformation. This approach effectively propagates metalog shape flexibility forward into the domain of semibounded and bounded distributions. It also preserves the closed-form simplicity of (6) as well as the ease of use associated with linear quantile parameterization.

Specifically, we use log and logit transformations, respectively, to produce semibounded and bounded members of the metalog family. These well-known transformations have been used previously for a similar purpose by Johnson (1949) and Tadikamalla and Johnson (1982).

4.1. Log Metalog (Semibounded Metalog) Distribution

Suppose that $z = \ln(x - b_l)$ is metalog distributed according to (6), where b_l is a known lower bound for x. Setting $\ln(x - b_l)$ equal to (6) and solving for x yields the log metalog quantile function with n terms:

$$M_n^{\log}(y; \mathbf{x}, \mathbf{y}, b_l) = b_l + e^{M_n(y)} \quad \text{for } 0 < y < 1,$$
$$= b_l \quad \text{for } y = 0, \tag{11}$$

where $\mathbf{x} = (x_1, \ldots, x_m)$, $m \geq n$; each $x_i > b_l$, $\mathbf{y} = (y_1, \ldots, y_m)$, $0 < y_i < 1$ for each y_i; at least n of the y_i's are distinct; $\mathbf{z} = (\ln(x_1 - b_l), \ldots, \ln(x_m - b_l))$ is a column vector; $\mathbf{Y}_n$ is (8); and

$$\boldsymbol{a} = [\mathbf{Y}_n^T \mathbf{Y}_n]^{-1} \mathbf{Y}_n^T \mathbf{z}. \tag{12}$$

Differentiating (11) with respect to y and inverting the result yields the log metalog PDF:

$$m_n^{\log}(y) = m_n(y) e^{-M_n(y)} \quad \text{for } 0 < y < 1,$$
$$= 0 \quad \text{for } y = 0, \tag{13}$$

where $m_n(y)$ is (9) and $M_n(y)$ is (6). The log metalog feasibility condition is $m_n^{\log}(y) > 0$ for all $y \in (0, 1)$. Since the quantity $e^{-M_n(y)}$ is always positive, this condition is equivalent to (10). Some interpretations of log metalog constants are provided in Table 3.

Similarly, for representations that have a known upper bound b_u and no lower bound, the transform

Table 3 Interpreting Log Metalog Constants

Constants	Interpretations
b_l	Location, lower bound
a_1	Scale
a_i, for all $i \geq 2$	Shape
$a_2 > 0$, $a_i = 0$, for all $i \geq 3$	$M_n^{\log}$ is a log-logistic distribution, also known in economics as the Fisk distribution
$a_4 > 0$, $a_i = 0$, for all $i \in \{2, 3,$ integers $> 4\}$	$M_n^{\log}$ is a log-uniform distribution (i.e., $\ln(x - b_l)$ is uniformly distributed)

$z = -\ln(b_u - x)$ yields a corresponding negative-log (nlog) quantile function and PDF

$$M_n^{\text{nlog}}(y; \mathbf{x}, \mathbf{y}, b_u) = b_u - e^{-M_n(y)} \quad \text{for } 0 < y < 1,$$
$$= b_u \quad \text{for } y = 1,$$
$$m_n^{\text{nlog}}(y) = m_n(y)e^{M_n(y)} \quad \text{for } 0 < y < 1,$$
$$= 0 \quad \text{for } y = 1,$$

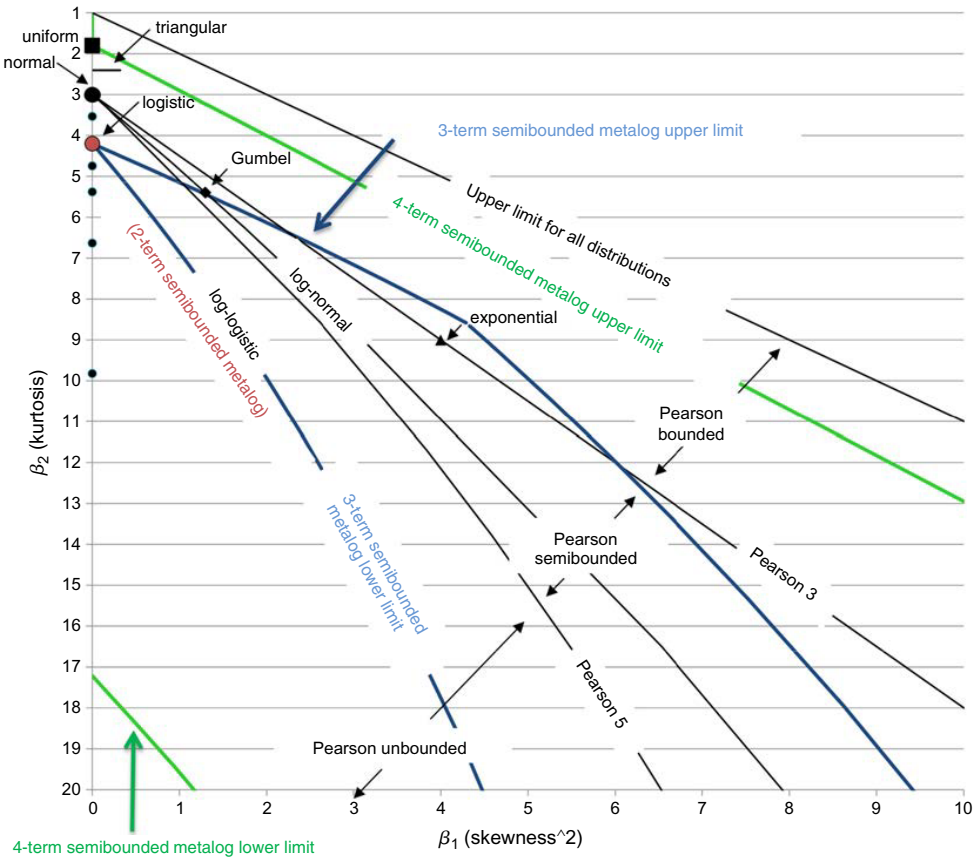
where $\mathbf{x} = (x_1, \ldots, x_m)$, each $x_i < b_u$, $\mathbf{z} = (-\ln(b_u - x_1), \ldots, -\ln(b_u - x_m))$, $\mathbf{y} = (y_1, \ldots, y_m), 0 < y_i < 1$ for each y_i, and (12) determines $\boldsymbol{a}$.

4.2. Log Metalog Shape Flexibility

Like the metalog, log metalog shape flexibility expands with the number of terms in use. However, the addition of a lower bound parameter b_l increases the shape dimensionality by one for each value of n. For example, the 2-term metalog is a point in the (β_1, β_2) plot, and the 3-term metalog is a line segment. In contrast, the 2-term log metalog is a line in the (β_1, β_2) plot, and the 3-term log metalog is an area. Effectively, this means that for any given number of terms n, the log metalog is more flexible than the metalog.

As shown in Figure 6, flexibility of the 2-term log metalog is simply that of the log-logistic line. Equivalently, this is the flexibility of the Fisk distribution in economics, which has been used in to represent

Figure 6 (Color online) Shape Flexibility for Two- to Four-Term Semibounded Metalog Distributions



survival data. The 3-term metalog increases this flexibility to cover the area between the upper and lower limits shown. The 4-term log metalog covers the expanded limits between the upper and lower 4-term lines shown. Unlike the "4-term metalog envelope" in Figure 4, these upper and lower limits extend indefinitely down and to the right corresponding to indefinitely larger values for β_1 and β_2. From Figure 6, it is evident that this 4-term semibounded metalog offers far more flexibility than the Pearson (1895, 1901, 1916) semibounded distributions. In addition, it offers far more flexibility than the semibounded Johnson S and L distributions (Johnson 1949, Tadikamalla and Johnson 1982, respectively), which are limited to the log-normal and log-logistic lines, respectively.

With five or more terms, the log metalog's (β_1, β_2) coverage expands further, providing a compelling option for representing a wide range of semibounded distributions. In addition, additional terms provide additional flexibility to match fifth- and higher-order moments.

4.3. Logit Metalog (Bounded Metalog) Distribution

The logit metalog distribution is useful for representations that have known lower and upper bounds, b_l and b_u, respectively, where $b_u > b_l$. The logit metalog distribution is the metalog transform that corresponds to $z = \text{logit}(x) = \ln((x-b_l)/(b_u-x))$ being metalog distributed. Setting $\ln((x-b_l)/(b_u-x))$ equal to (6) and solving for x yields the logit metalog quantile function with n terms:

$$M_n^{\text{logit}}(y; \mathbf{x}, \mathbf{y}, b_l, b_u) = \frac{b_l + b_u e^{M_n(y)}}{1 + e^{M_n(y)}} \quad \text{for } 0 < y < 1,$$
$$= b_l \quad \text{for } y = 0,$$
$$= b_u \quad \text{for } y = 1, \tag{14}$$

where $\mathbf{x} = (x_1, \ldots, x_m)$, $b_l < x_i < b_u$ for each x_i; $\mathbf{y} = (y_1, \ldots, y_m)$, $0 < y_i < 1$ for each y_i; $\mathbf{z} = (\ln((x_1 - b_l)/(b_u - x_1)), \ldots, \ln((x_m - b_l)/(b_u - x_m)))$; and (12) determines $\boldsymbol{a}$. Differentiating (14) with respect to y and inverting the result yields the logit metalog PDF:

$$m_n^{\text{logit}}(y) = m_n(y) \frac{(1 + e^{M_n(y)})^2}{(b_u - b_l)e^{M_n(y)}} \quad \text{for } 0 < y < 1,$$
$$= 0 \quad \text{for } y = 0 \quad \text{or} \quad y = 1, \tag{15}$$

where $m_n(y)$ is (9) and $M_n(y)$ is (6). The logit metalog feasibility condition is $m_n^{\text{logit}}(y) > 0$ for all $y \in (0, 1)$. Since the quantity $(1 + e^{M_n(y)})^2/((b_u - b_l)e^{M_n(y)})$ is always positive, this condition is equivalent to (10). Some interpretations of logit metalog constants are provided in Table 4.

Table 4 Interpreting Logit Metalog Constants

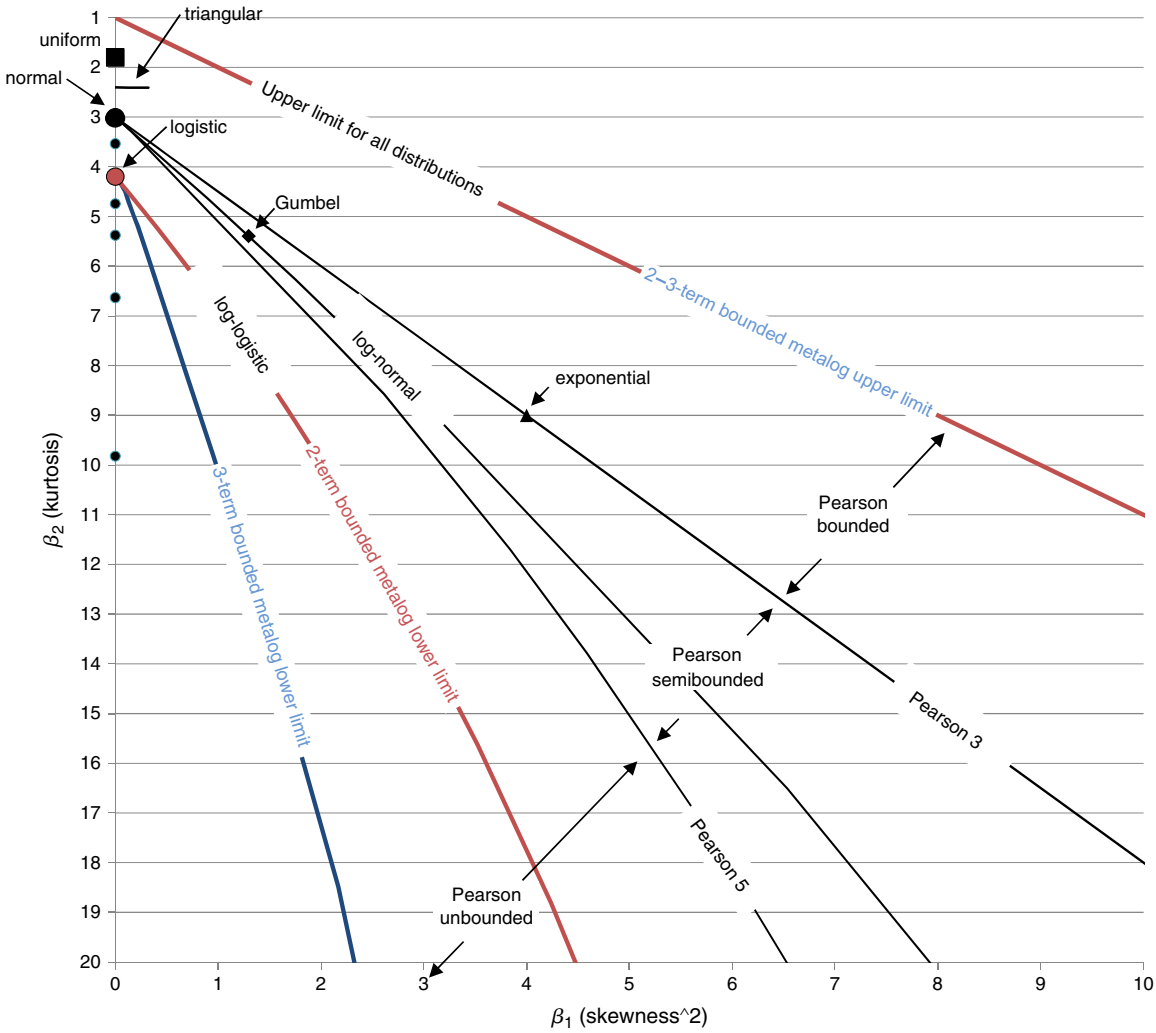
b_l and b_u	Location, lower and upper bound
$b_u - b_l$ where $b_u > b_l$	Scale
a_i, for all $i \geq 1$	Shape
$a_2 > 0$, $a_i = 0$, for all $i \geq 3$	M_n^{logit} is a logit-logistic distribution (Wang and Rennolls 2005), also known as the Tadikamalla and Johnson LB distribution (Tadikamalla and Johnson 1982, Balakrishnan 1992)
$a_1 = 0$, $0 < a_2 < 1$, $a_i = 0$, for all $i \geq 3$	M_n^{logit} is a unimodal logit-logistic distribution
$a_1 = 0$, $a_2 = 1$, $a_i = 0$, for all $i \geq 3$	M_n^{logit} is a uniform distribution
$a_1 = 0$, $a_2 > 1$, $a_i = 0$, for all $i \geq 3$	M_n^{logit} is a U-shaped, symmetric logit-logistic distribution

4.4. Logit Metalog Shape Flexibility

Like the metalog and log metalog, logit metalog shape flexibility expands with the number of terms in use. However, the presence of an upper bound parameter in addition to a lower bound parameter increases the shape dimensionality for any value of n by two relative to the metalog and by one relative to the log metalog. For example, the two-term metalog is a point in the (β_1, β_2) plot and the three-term metalog is a line segment. In contrast, the two-term logit metalog is a area in the (β_1, β_2) plot and the three-term logit metalog is a broader area plus flexibility to match a fifth moment. Effectively, this means that for any given number of terms n, the logit metalog is more flexible than either the metalog or log metalog.

As shown in Table 4, the two-term logit metalog is also known as the Tadikamalla and Johnson LB distribution. As shown in Figure 7, the flexibility of this distribution is the entire accessible area down to and including the log-logistic line. The three-term logit metalog increases this flexibility to cover the entire accessible area down to and including the "3-term bounded metalog lower limit." The four-term logit metalog covers the entire accessible display area shown in Figure 7. Its lower limit includes the following points that are below that display area: (0, 21), (0.1, 29), (0.4, 40), (1, 52), (1.8, 70), (3.05, 95), (4.8, 135), and (10.5,330).

Figure 7 (Color online) Shape Flexibility for Two- and Three-Term Bounded Metalog Distributions



Like the upper and lower limits in Figure 6, the upper and lower limits in Figure 7 extend indefinitely down and to the right.

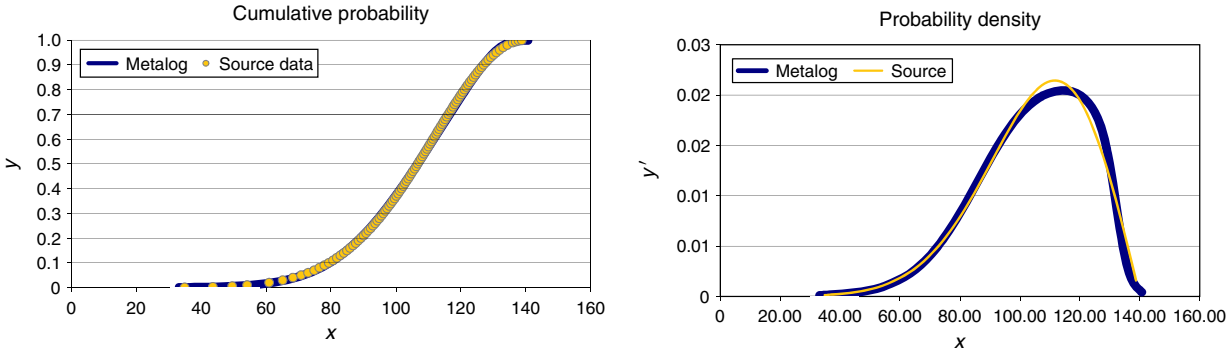
Thus, it is evident that the four-term bounded metalog offers far more flexibility than the Pearson bounded distributions. In addition, it offers far more flexibility than the Johnson S and L bounded distributions, which are limited to the areas above the log-normal and log-logistic lines, respectively.

With five or more terms, the logit metalog's (β_1, β_2) coverage expands further, providing a compelling option for representing a wide range of bounded distributions. In addition, additional terms provide additional flexibility to match fifth- and higher-order moments.

5. Metalog vs. Alternative Representations of Traditional Distributions

When the CDF data (x, y) are from a known source distribution, there would ordinarily be no need to represent these CDF data with a metalog. However, metalog representations of CDF data from previously named source distributions may provide insight about the range of effectiveness and limitations of

Figure 8 (Color online) M_5 Representation of an Extreme Value Distribution



Note. Source is the extreme value ($\mu = 100$, $\sigma = 20$, $\eta = -0.5$).

metalog representations and about metalog performance compared to alternatives. The alternatives we consider include a three-branch discrete approximation with 30%, 40%, and 30% probabilities assigned to the 10%, 50%, and 90% quantiles. They also include a range of QPDs, including the normal, the simple Q normal (Keelin and Powley 2011), the logistic, and metalog distributions with various numbers of terms.

The figures and tables below compare these alternatives based on CDF data taken from a wide range of source distributions. In each case, we use 105 points from the CDF of the source distribution to parameterize the metalog and alternative representations. These 105 points correspond to $y = (1/1{,}000, 3/1{,}000, 6/1{,}000, 10/1{,}000, 20/1{,}000, \ldots, 980/1{,}000, 990/1{,}000, 994/1{,}000, 997/1{,}000, 999/1{,}000)$. For each y_i, the corresponding x_i is the inverse CDF of the source distribution. For source distributions with known upper and/or lower bounds, we use the corresponding log or logit metalog.

5.1. Unbounded Source Distributions

For example, Figure 8 illustrates how M_5 approximates a particular extreme value distribution ($\mu = 100$, $\sigma = 20$, $\eta = -0.5$). Visually, the metalog CDF is virtually indistinct from that of the extreme value source distribution, and the PDFs are very similar. To measure the accuracy of this approximation, we use the Kolmogorov–Smirnoff (K–S) distance (maximum cumulative-probability deviation on the CDFs). For convenience, we measure this as the maximum over the 105 points defined above. In this case, the K–S distance is 0.009, which means that the difference between the source-distribution and M_5 CDFs is everywhere less than 1% probability.

Table 5 shows this K–S distance for a range of unbounded source distributions and approximation methods. Based on the rankings at the bottom of this table, M_4 and M_5 are better that the other approximation methods, and M_5 is best overall.

5.2. Semibounded Source Distributions

For a range of semibounded source distributions, we similarly compare the log metalog to other approximation methods. Table 6 shows the results. The log metalog approximations with three to five terms generally rank better than the other methods. In addition, the log metalog approximations have the same bounds as the source distributions, whereas the other approximation methods (discrete, normal, simple Q normal, and logistic) do not.

5.3. Bounded Source Distributions

For a range of bounded source distributions, we similarly compare the logit metalog to other approximation methods. Table 7 shows the results. The logit metalog approximations with three to five terms generally rank better than the other methods. In addition, the logit metalog approximations have the same high and low bounds as the source distributions, whereas the other approximation methods do not.

While most of the source distributions in Table 3 are unimodal, note that Beta ($\alpha = 0.8$, $\beta = 0.9$) and Beta ($\alpha = 0.9$, $\beta = 0.9$) are bimodal (U shaped) and are represented by the logit metalog with a high degree of

Table 5 Accuracy of Various Approximations for Unbounded Source Distributions

	K–S distance							
	Approximation method							
		QPD						
	Discrete[a]				Metalog			
Source distribution	p: 30–40–30 q: 10–50–90	Normal	Simple Q normal	Logistic	M_2	M_3	M_4	M_5
Normal ($\mu = 50$, $\sigma = 15$)	0.200	0.000	0.000	0.035	0.035	0.035	0.006	0.006
Logistic ($\mu = 40$, $s = 4.6$)	0.200	0.032	0.009	0.000	0.000	0.000	0.000	0.000
Student t (df = 6)	0.200	0.043	0.019	0.012	0.012	0.012	0.008	0.008
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.5$)	0.200	0.064	0.020	0.093	0.093	0.070	0.017	0.009
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.2$)	0.200	0.027	0.004	0.056	0.056	0.047	0.008	0.008
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.025$)	0.200	0.102	0.039	0.111	0.111	0.036	0.028	0.006
Maximum	0.200	0.102	0.039	0.111	0.111	0.070	0.028	0.009
Average	0.200	0.045	0.015	0.051	0.051	0.033	0.011	0.006
Rank based on lowest maximum	8	5	3	6	6	4	2	1
Rank based on lowest average	8	5	3	6	6	4	2	1

[a]Approximation is bounded, whereas source distribution is unbounded.

Table 6 Accuracy of Various Approximations for Semibounded Source Distributions

	K–S distance							
	Approximation method							
		QPD						
	Discrete[a]				Log metalog			
Source distribution	p: 30–40–30 q: 10–50–90	Normal[b]	Simple Q normal[b]	Logistic[b]	$M_2^{\log}$	$M_3^{\log}$	$M_4^{\log}$	$M_5^{\log}$
Log-normal ($\mu = 0$, $\sigma = 0.5$)	0.200	0.130	0.068	0.140	0.035	0.035	0.006	0.006
Log-normal ($\mu = 0$, $\sigma = 0.3$)	0.200	0.078	0.026	0.092	0.035	0.035	0.006	0.006
Log-normal ($\mu = 0$, $\sigma = 0.15$)	0.200	0.039	0.012	0.060	0.035	0.035	0.006	0.006
Weibull ($\lambda = 3$, $\kappa = 3$)	0.200	0.023	0.009	0.058	0.103	0.037	0.022	0.006
Weibull ($\lambda = 7$, $\kappa = 7$)	0.200	0.044	0.009	0.066	0.103	0.037	0.022	0.006
Gamma ($\kappa = 4$, $\theta = 2$)	0.200	0.088	0.029	0.106	0.062	0.038	0.011	0.006
Gamma ($\kappa = 2$, $\theta = 2$)	0.200	0.124	0.056	0.142	0.078	0.038	0.015	0.006
Inverse gamma ($\alpha = 3$, $\beta = 1$)	0.200	0.240	*	0.245	0.068	0.038	0.012	0.006
Inverse gamma ($\alpha = 5$, $\beta = 0.5$)	0.200	0.174	0.149	0.179	0.059	0.038	0.010	0.006
Exponential ($\alpha = 0.5$)	0.200	0.174	0.130	0.193	0.103	0.037	0.022	0.006
Chi-squared (df = 3)	0.200	0.143	0.077	0.161	0.087	0.038	0.017	0.006
Chi-squared (df = 6)	0.200	0.101	0.038	0.119	0.068	0.038	0.012	0.006
Inverse chi-squared (df = 3)	0.200	0.388	*	0.394	0.087	0.038	0.017	0.006
Inverse chi-squared (df = 6)	0.200	0.240	*	0.245	0.068	0.038	0.012	0.006
F (df1 = 1, df2 = 1)	0.200	0.621	*	0.623	0.020	0.020	0.001	0.001
F (df1 = 15, df2 = 30)	0.200	0.106	0.045	0.118	0.039	0.033	0.007	0.006
Maximum	0.200	0.621	0.149	0.623	0.103	0.038	0.022	0.006
Average	0.200	0.170	0.054	0.184	0.066	0.036	0.013	0.006
Rank based on lowest maximum	6	7	5	8	4	3	2	1
Rank based on lowest average	8	6	4	7	5	3	2	1

[a]Approximation is bounded, whereas source distribution is semibounded. In addition, the low bound of approximation does not correspond to the low bound of source distribution.

[b]Approximation is unbounded, whereas source distribution is semibounded.

*The approximation method does not yield a valid probability distribution.

Table 7 Accuracy of Various Approximations for Bounded Source Distributions

	K–S distance							
	Approximation method							
		QPD						
	Discrete[a]				Log metalog			
Source distribution	p: 30–40–30 q: 10–50–90	Normal[b]	Simple Q normal[b]	Logistic[b]	M_2^{logit}	M_3^{logit}	M_4^{logit}	M_5^{logit}
Beta ($\alpha = 3.5$, $\beta = 3.5$)	0.200	0.029	0.005	0.066	0.024	0.024	0.004	0.004
Beta ($\alpha = 9$, $\beta = 3.5$)	0.200	0.054	0.012	0.084	0.044	0.031	0.008	0.005
Beta ($\alpha = 0.8$, $\beta = 0.9$)	0.200	0.106	*	0.146	0.013	0.005	0.002	0.001
Beta ($\alpha = 60$, $\beta = 1.5$)	0.200	0.138	0.069	0.157	0.085	0.037	0.017	0.006
Beta ($\alpha = 1.2$, $\beta = 1.2$)	0.200	0.076	0.004	0.115	0.005	0.005	0.001	0.001
Beta ($\alpha = 0.9$, $\beta = 0.9$)	0.200	0.095	*	0.135	0.003	0.003	0.000	0.000
Uniform ($A = 1$, $B = 1$)	0.200	0.088	0.000	0.127	0.000	0.000	0.000	0.000
Triangular ($A = 5$, $B = 20$, $C = 25$)	0.200	0.077	0.016	0.112	0.033	0.019	0.009	0.003
Maximum	0.200	0.138	0.069	0.157	0.085	0.037	0.017	0.006
Average	0.200	0.083	0.018	0.118	0.026	0.016	0.005	0.002
Rank based on lowest maximum	8	6	4	7	5	3	2	1
Rank based on lowest average	8	6	4	7	5	3	2	1

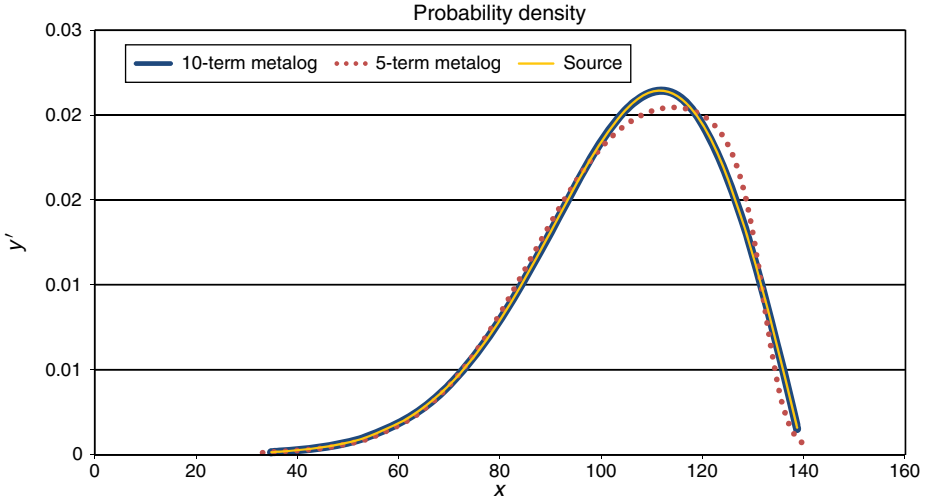
[a]Bounds of approximation do not correspond to bounds of source distribution.
[b]Approximation is unbounded, whereas source distribution is bounded.
*The approximation method does not yield a valid probability distribution.

accuracy (K–S distance ≤ 0.001). In addition, note that nonsmooth PDFs (uniform and triangular) are well represented (K–S distance ≤ 0.003).

5.4. Increased Accuracy with Higher-Order Terms

Increasing the number of terms beyond 5 further increases accuracy. For example, Figure 9 shows how the 5-term metalog approximation of the extreme value distribution in Figure 8 becomes nearly exact when using 10 terms. Similar increased accuracy can be observed across the entire range of source distributions considered previously. Specifically, Table 8

Figure 9 (Color online) How 10 Terms Increases Accuracy Compared to 5



Note. Source is the extreme value ($\mu = 100$, $\sigma = 20$, $\eta = -0.5$).

Table 8 How Additional Terms Increase Accuracy

Unbounded Source distributions	K–S distance: Metalog M_5	M_6	M_7	M_8	M_9	M_{10}
Normal ($\mu = 50$, $\sigma = 15$)	0.006	0.002	0.001	0.001	0.001	0.000
Logistic ($\mu = 40$, $s = 4.6$)	0.000	0.000	0.000	0.000	0.000	0.000
Student t (df = 6)	0.008	0.004	0.002	0.002	0.002	0.001
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.5$)	0.009	0.002	0.001	0.001	0.001	0.000
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.2$)	0.008	0.003	0.002	0.001	0.001	0.000
Extreme value ($\mu = 100$, $\sigma = 20$, $\varepsilon = -0.025$)	0.006	0.005	0.005	0.001	0.000	0.000
Maximum	0.009	0.005	0.005	0.002	0.002	0.001
Average	0.006	0.003	0.002	0.001	0.001	0.000
Rank based on lowest maximum	6	4	5	3	2	1
Rank based on lowest average	6	5	4	3	2	1
Semibounded Source distributions	**Log metalog $M_5^{\log}$**	**$M_6^{\log}$**	**$M_7^{\log}$**	**$M_8^{\log}$**	**$M_9^{\log}$**	**$M_{10}^{\log}$**
Log-normal ($\mu = 0$, $\sigma = 0.5$)	0.006	0.002	0.001	0.001	0.001	0.000
Log-normal ($\mu = 0$, $\sigma = 0.3$)	0.006	0.002	0.001	0.001	0.001	0.000
Log-normal ($\mu = 0$, $\sigma = 0.15$)	0.006	0.002	0.001	0.001	0.001	0.000
Weibull ($\lambda = 3$, $\kappa = 3$)	0.006	0.004	0.003	0.001	0.000	0.000
Weibull ($\lambda = 7$, $\kappa = 7$)	0.006	0.004	0.003	0.001	0.000	0.000
Gamma ($\kappa = 4$, $\theta = 2$)	0.006	0.002	0.002	0.001	0.000	0.000
Gamma ($\kappa = 2$, $\theta = 2$)	0.006	0.003	0.002	0.001	0.000	0.000
Inverse gamma ($\alpha = 3$, $\beta = 1$)	0.006	0.002	0.002	0.001	0.000	0.000
Inverse gamma ($\alpha = 5$, $\beta = 0.5$)	0.006	0.002	0.001	0.001	0.000	0.000
Exponential ($\lambda = 0.5$)	0.006	0.004	0.003	0.001	0.000	0.000
Chi-squared (df = 3)	0.006	0.003	0.003	0.001	0.000	0.000
Chi-squared (df = 6)	0.006	0.002	0.002	0.001	0.000	0.000
Inverse chi-squared (df = 3)	0.006	0.003	0.003	0.001	0.000	0.000
Inverse chi-squared (df = 6)	0.006	0.002	0.002	0.001	0.000	0.000
F (df1 = 1, df2 = 1)	0.001	0.000	0.000	0.000	0.000	0.000
F (df1 = 15, df2 = 30)	0.006	0.002	0.001	0.000	0.000	0.000
Maximum	0.006	0.004	0.003	0.001	0.001	0.000
Average	0.006	0.002	0.002	0.001	0.000	0.000
Rank based on lowest maximum	6	5	4	3	2	1
Rank based on lowest average	6	5	4	3	2	1
Bounded Source distributions	**Logit metalog M_5^{logit}**	**M_6^{logit}**	**M_7^{logit}**	**M_8^{logit}**	**M_9^{logit}**	**M_{10}^{logit}**
Beta ($\alpha = 3.5$, $\beta = 3.5$)	0.004	0.001	0.000	0.000	0.000	0.000
Beta ($\alpha = 9$, $\beta = 3.5$)	0.005	0.002	0.001	0.000	0.000	0.000
Beta ($\alpha = 0.8$, $\beta = 0.9$)	0.001	0.000	0.000	0.000	0.000	0.000
Beta ($\alpha = 60$, $\beta = 1.5$)	0.006	0.003	0.003	0.001	0.000	0.000
Beta ($\alpha = 1.2$, $\beta = 1.2$)	0.001	0.000	0.000	0.000	0.000	0.000
Beta ($\alpha = 0.9$, $\beta = 0.9$)	0.000	0.000	0.000	0.000	0.000	0.000
Uniform ($A = 1$, $B = 1$)	0.000	0.000	0.000	0.000	0.000	0.000
Triangular ($A = 5$, $B = 20$, $C = 25$)	0.003	0.003	0.002	0.002	0.001	0.001
Maximum	0.006	0.003	0.003	0.002	0.001	0.001
Average	0.002	0.001	0.001	0.000	0.000	0.000
Rank based on lowest maximum	6	5	4	3	2	1
Rank based on lowest average	6	5	4	3	2	1

shows how accuracy increases with each additional term as the number of terms increases from 5 to 10.

Based on Tables 5–8, we observe that the metalog distributions are capable of closely approximating a wide range of traditional distributions, and typically do so with greater accuracy than other practical alternatives.

6. Applications

We now turn to two applications. The first illustrates how the metalog system can produce insight about frequency data that would not be possible using traditional distributions, thereby providing evidence that the metalog system offers a new vehicle for data and distribution research. The second example, decision analysis, shows an actual decision that would have been made wrongly if the decision makers had relied on three-branch discrete approximations (as commonly used in decision analysis) instead of metalog-based continuous representations. As part of the decision analysis application, we develop simplified expressions in terms of assessed quantiles for the metalog system for the special case of $n = 3$.

6.1. Application 1: Data and Distribution Research

Our data and distributions research examples are based on real data from the disparate fields of fish biology and hydrology. Both show how metalog flexibility can aid data and distribution research by generating insight that might not otherwise emerge.

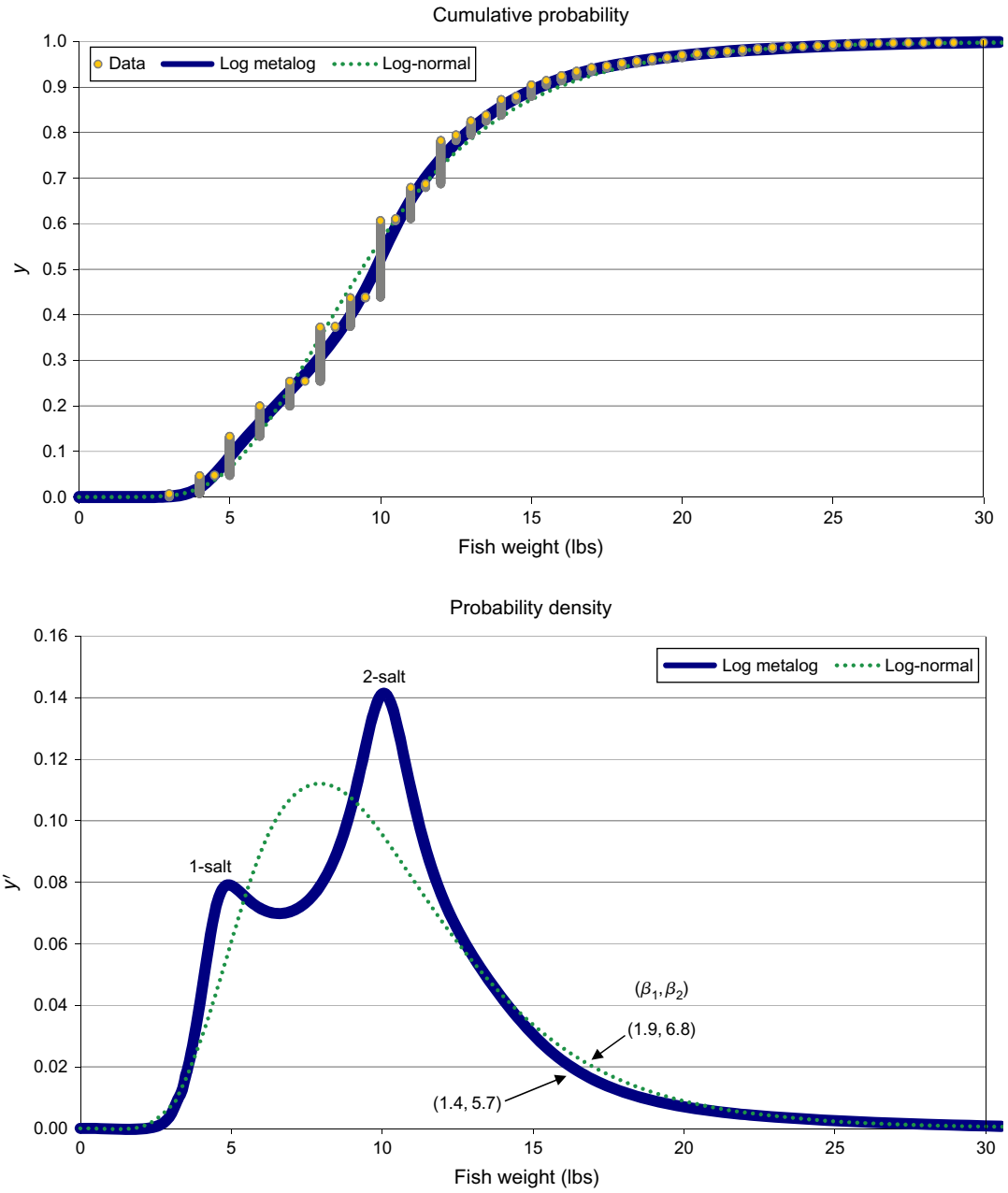
6.1.1. Fish Biology. Metalog distributions can mold themselves to the data with fewer unexamined shape constraints compared to other distributions. To illustrate, we consider the weight distribution of steelhead trout in the Babine River in northern British Columbia. A fly fishing lodge on that river has kept meticulous records of the weight of every fish landed by clients or staff over many years. Specifically, during 2006–2010, 3,474 steelhead trout were caught and released. The recorded data for the weights of these fish are plotted in Figure 10. This plot also shows two alternative distributions that could be used to represent that data. One is the log-normal, a shape that is representative of multiple other one-to-two-shape-parameter distributions (such as the log-logistic, gamma, log Pearson 3, and F) that might typically be used in such a case. The other is a the 10-term log metalog $M_{10}^{\log}$ with $b_l = 0$. Note that both CDFs appear to reasonably approximate the CDF data. However, the corresponding log metalog PDF shows a clear bimodal pattern in the data, which the log-normal and other similar distributions lack the flexibility to represent.

The population of steelhead in the river when this lodge is open, during the fall of each year, consists of fish that are returning upriver to spawn after having lived in salt water. Those fish returning from salt water to spawn for the first time are called "1-salt" fish. After spawning, these fish typically return to salt water, gain additional weight in ocean-rich feeding grounds, and then come back up the river some years later to spawn for a second time, becoming "2-salt" fish. A few very-large steelhead are "3-salt" or "4-salt" fish. One might reasonably consider that the modes of the log metalog PDF in Figure 10 may be respectively indicative of the 1-salt and 2-salt fish populations. Both the relative population sizes and weight differences between 1-salt and 2-salt fish are unsolved research questions in fish biology. It is apparent that the log metalog representation may shed some light on both questions. More broadly, by telling a more nuanced story about the data than alternative distributions, the metalog system may open new avenues for data and distribution research.

6.1.2. Hydrology. When a Type I interpretation of data is available, it is natural to use a corresponding Type I distribution. The advantage of this approach is that it constrains the shape to one consistent with the Type I model, and relatively few data are needed to parameterize that model. A disadvantage is that the data may have been generated by a process that does not exactly correspond to the assumptions of the model, and therefore may have a legitimately different shape than the model predicts. If Type I shape constraints go unexamined, erroneous conclusions might result. In contrast, the flexibility of the metalog system allows "the data to speak for itself" with fewer unexamined shape constraints compared to other distribution families. Thus, it can be compared to various Type I representations of the same data.

In hydrology, for example, it is common to compute maximum annual river stream flows and gauge heights for each year as the maximum of the 365 daily

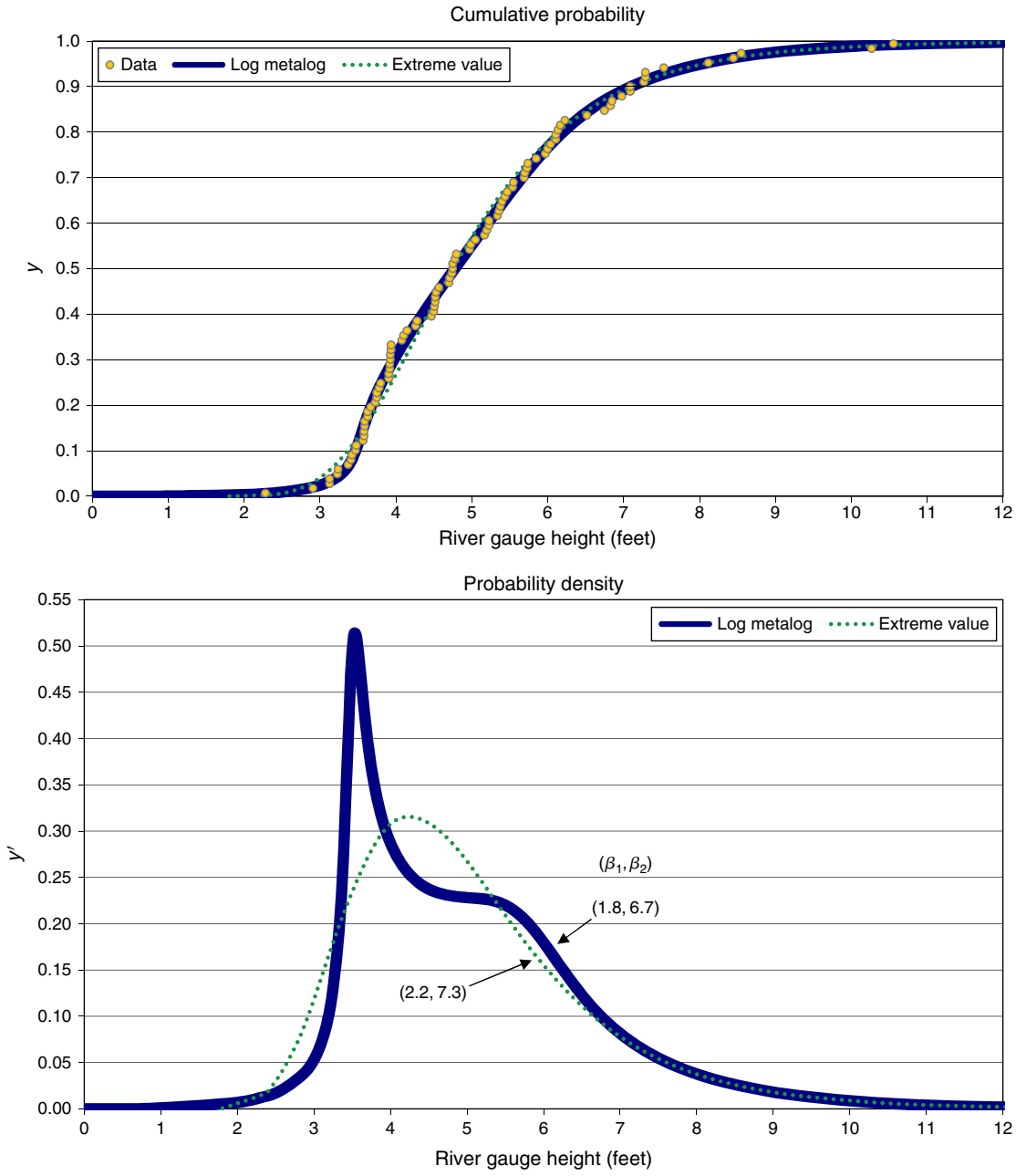
Figure 10 (Color online) How the Metalog System Can Aid Data and Distribution Research



observations for that year. These measures are important for decisions such as bridge design, high-water mitigation, and river regulations. Even though there is typically autocorrelation among such observations, one might nevertheless try an extreme value distribution to represent such data given that this distribution has a simple Type I interpretation as the limiting distribution of a large number of independent and identically distributed samples. In Figure 11, we consider 95 years (1920–2014) of maximum annual gauge-height data as reported by the U.S. Geological Survey for the Williamson River (below its confluence with the Sprague River) near Chiloquin, Oregon.[15]

[15] This data is available from U.S. Geological Survey website and also from http://www.metalogdistributions.com.

Figure 11 **(Color online) How the Metalog System Can Illuminate Unexamined Shape Constraints**



Comparing log metalog (with $b_l = 0$) and extreme value representations of the data, we observe that the CDFs are similar. In addition, the extreme value PDF shows a shape that would commonly be attributed to these data, not only by the extreme value distribution, but also by the log-normal, log Pearson 3, log-logistic, and other distributions commonly used to represent such data in hydrology. But by molding itself more closely to the data than possible with such other distributions, the log metalog PDF tells a somewhat different story: a lower mode and a "flat region" of equally likely values above that mode. To a knowledgeable expert, this deviation of the data from typically assumed shapes might suggest systematic

interpretations that would otherwise be masked by assuming a Type I model that may not appropriately apply.

6.2. Application 2: Decision Analysis

For decision analysis applications, it is common to use three assessed quantiles that correspond, for example, to probabilities of 0.1, 0.5, and 0.9. In this section, we show how the metalog system simplifies for such special cases. Then we apply it within an actual decision analysis.

6.2.1. SPT Parameterization of the Metalog System.

Definition 3 (Symmetric-Percentile Triplet).[16] Metalog parameters $(\mathbf{x}, \mathbf{y})$ are a symmetric-percentile triplet (SPT) when they can be expressed as $\mathbf{y} = (\alpha, 0.5, 1-\alpha)$ and $\mathbf{x} = (q_\alpha, q_{0.5}, q_{1-\alpha})$ for some $\alpha \in (0, 0.5)$ and $q_\alpha < q_{0.5} < q_{1-\alpha}$.

This is often the case in decision analysis when, for example, 10–50–90 quantiles $(q_{0.1}, q_{0.5}, q_{0.9})$ are encoded from an expert and correspond to the 0.1, 0.5, and 0.9 probabilities on the CDF. We begin with the SPT-parameterized metalog distribution (SPT metalog) and then extend the results to develop the SPT-parameterized log and logit metalogs.

Proposition 1 (SPT Metalog Constants). *Given that random variable X is metalog distributed and given a feasible SPT $\mathbf{x} = (q_\alpha, q_{0.5}, q_{1-\alpha})$, the metalog constants $\boldsymbol{a} = (a_1, a_2, a_3)$ can be expressed directly as*

$$a_1 = q_{0.5},$$

$$a_2 = \frac{1}{2}\left[\ln\left(\frac{1-\alpha}{\alpha}\right)\right]^{-1}(q_{1-\alpha} - q_\alpha), \tag{16}$$

$$a_3 = \left[(1-2\alpha)\ln\left(\frac{1-\alpha}{\alpha}\right)\right]^{-1}(1-2r)(q_{1-\alpha} - q_\alpha),$$

$$\text{where } r = \frac{q_{0.5} - q_\alpha}{q_{1-\alpha} - q_\alpha}. \tag{17}$$

Proof. For $m = n = 3$, (7) reduces to $\boldsymbol{a} = \mathbf{Y}_3^{-1}\mathbf{x}$. Given that the second element of $\mathbf{y}$ is 0.5, the second row of $\mathbf{Y}_3$ reduces to (1, 0, 0). Inverting $\mathbf{Y}_3$ under this condition, postmultiplying by column vector $\mathbf{x}$, and substituting in the definition of r in (17) yields the above expressions. □

The SPT-metalog quantile function and PDF are (6) and (9), respectively, for the special case of $n = 3$. The importance of Proposition 1 is that (7), the expression for the constants, is greatly simplified. The the metalog constants $\boldsymbol{a}$ can be expressed directly in terms of the quantile assessments $(q_\alpha, q_{0.5}, q_{1-\alpha})$. Constant a_1 is simply the median, as is true for all metalog distributions. Constant a_2 is proportional to the $q_{1-\alpha} - q_\alpha$ quantile range. For example when $\alpha = 0.1$, a_2 is $1/(2\ln 9) = 0.23$ times the 10–90 quantile range. Constant a_3, which controls skewness, is also proportional to the $q_{1-\alpha} - q_\alpha$ quantile range. We define r to mark the location of the median within this $q_{1-\alpha} - q_\alpha$ range. If the median is the midpoint of this range, then $r = \frac{1}{2}$, $a_3 = 0$, and the three-term metalog reduces to a symmetric logistic distribution. If the median is closer to q_α, then $r < \frac{1}{2}$, a_3 is positive, and the distribution is right skewed accordingly. If the median is closer to $q_{1-\alpha}$, then a_3 is negative, and the distribution is left skewed.

There is a feasibility limit as to how much skewness and kurtosis can be represented with an SPT-parameterized metalog. Since there is a one-to-one correspondence between $\boldsymbol{a}$ and $\mathbf{x}$ in Proposition 1, this limit is just the "three-term metalog" line segment shown in Figure 4, and the range of feasible shapes for SPT metalogs is as shown in Figure 5. Intuitively, the three-term metalog, whether SPT-parameterized or more generally, can represent any shape from symmetric to roughly the skewness of the exponential distribution.[17] Quantitatively, this limit is determined in closed form for the SPT metalog by the following proposition.

Proposition 2 (SPT Metalog Feasibility). *Any given SPT $\mathbf{x} = (q_\alpha, q_{0.5}, q_{1-\alpha})$ is a feasible parameterization of the metalog distribution if and only if*

$$k_\alpha < r < 1 - k_\alpha, \quad \text{where } r = \frac{q_{0.5} - q_\alpha}{q_{1-\alpha} - q_\alpha}$$

$$\text{and} \quad k_\alpha = \tfrac{1}{2}\left[1 - 1.66711\left(\tfrac{1}{2} - \alpha\right)\right]. \tag{18}$$

[16] Hadlock and Bickel (2016) defined SPTs to parameterize Johnson quantile-parameterized distributions (J-QPDs). Our definition of SPT is the same, and we use it to simplify parameterization of the metalog system for the special case of $n = m = 3$. See Hadlock and Bickel (2016) for a J-QPD alternative to the SPT-parameterized metalog system presented in this section.

[17] Note that in Figure 4 the exponential distribution with $(\beta_1, \beta_2) = (4.0, 9.0)$ is very close to the end of the three-term metalog line segment (4.3, 8.6). So conceptually we can use the exponential distribution as a close proxy for the three-term metalog skewness limit.

For 10–50–90 quantiles ($\alpha = 0.1$), a close approximation to this expression is

$$\tfrac{1}{6} \le r \le \tfrac{5}{6}. \tag{19}$$

Proof. For $n = 3$, the feasibility condition (5) reduces to

$$\frac{a_2}{y(1-y)} + a_3\left(\frac{y-0.5}{y(1-y)} + \ln\frac{y}{1-y}\right) > 0, \quad \text{for all } y \in (0,1). \tag{20}$$

Consider three cases: $y \in (0, 0.5)$, $y = 0.5$, and $y \in (0.5, 1.0)$. The feasibility condition is satisfied if and only if it is satisfied for all three cases. For $y = 0.5$, the second case, (20) reduces to $a_2 > 0$, which is obviously true by (16) since, by definition, $q_\alpha < q_{1-\alpha}$ and $0 < \alpha < 0.5$. Given $a_2 > 0$, then, for the first case, (20) can be expressed as

$$\frac{a_3}{a_2 C(y)} < 1, \quad \text{for all } y \in (0, 0.5),$$
$$\text{where } C(y) = -\frac{1}{y - 0.5 + y(1-y)\ln(y/(1-y))}.$$

Since $C(y) > 0$ everywhere in this interval, the feasibility condition for this case becomes

$$\frac{a_3}{a_2} < k_0, \quad \text{where } k_0 = \min_{y \in (0,\, 0.5)} C(y) = 1.66711.$$

Similarly, the feasibility condition for the third case is

$$\frac{a_3}{a_2} > k_1, \quad \text{where } k_1 = \max_{y \in (0.5,\, 1.0)} C(y) = -1.66711 = -k_0.$$

Thus, (18) is satisfied if and only if $-k_0 < a_3/a_2 < k_0$. Substituting (16) and (17) for a_2 and a_3 in this expression, defining $k_\alpha = \frac{1}{2}[1 - 1.66711(\frac{1}{2} - \alpha)]$, and simplifying yields (18). Applying (18) for $\alpha = 0.1$ yields $0.166578 \le r \le 0.833442$, of which (19) is a close approximation. □

The importance of Proposition 2 is that the feasibility of the SPT $\mathbf{x} = (q_\alpha, q_{0.5}, q_{1-\alpha})$ can readily be checked prior to any further calculations. If (18) or (19) is satisfied, then $\mathbf{x}$ is feasible, as it will always be over the range of shapes shown in Figure 5. If $\mathbf{x}$ is not feasible, then adding one or more data points ($n = m \ge 4$) would provide greater flexibility, as shown in Figure 4.

Proposition 3 (SPT Log Metalog). *Given that $\ln(x - b_l)$ is metalog distributed and given a feasible SPT $\mathbf{x} = (q_\alpha, q_{50}, q_\alpha)$ with known lower bound b_l, the log metalog constants $\boldsymbol{a} = (a_1, a_2, a_3)$ can be expressed directly as*

$$a_1 = \ln(\gamma_{0.5}),$$
$$a_2 = \frac{1}{2}\left[\ln\frac{1-\alpha}{\alpha}\right]^{-1} \ln\frac{\gamma_{1-\alpha}}{\gamma_\alpha},$$
$$a_3 = \left[(1-2\alpha)\ln\frac{1-\alpha}{\alpha}\right]^{-1} \ln\frac{\gamma_{1-\alpha}\gamma_\alpha}{\gamma_{0.5}^2},$$

where $\gamma_\alpha = q_\alpha - b_l$, $\gamma_{0.5} = q_{0.5} - b_l$, $\gamma_{1-\alpha} = q_{1-\alpha} - b_l$. Moreover, $\mathbf{x}$ is feasible if and only if

$$b_l + \gamma_\alpha^{1-k_\alpha}\gamma_{1-\alpha}^{k_\alpha} < q_{0.5} < b_l + \gamma_\alpha^{k_\alpha}\gamma_{1-\alpha}^{1-k_\alpha},$$

where k_α is as in (18).

Proof. For the log metalog, $\ln(x - b_l)$ is metalog distributed. In Proposition 1, substitute $\ln(\gamma_\alpha)$, $\ln(\gamma_{0.5})$, and $\ln(\gamma_{1-\alpha})$, for q_α, $q_{0.5}$, and $q_{1-\alpha}$, respectively. The above expressions for the log metalog constants follow from algebraic simplification. In (18), substitute $\ln(\gamma_\alpha)$, $\ln(q_{0.5} - b_l)$, and $\ln(\gamma_{1-\alpha})$ for q_α, $q_{0.5}$, and $q_{1-\alpha}$, respectively. The above expression for the log metalog feasibility condition follows from solving the resulting equation for $q_{0.5}$. □

The SPT-log-metalog quantile function and PDF are (11) and (13), respectively, for the special case of $n = 3$. The importance of Proposition 3 is that (12) and (5), the expressions for constants and feasibility, respectively, are greatly simplified. The log metalog constants and feasibility condition can be expressed directly in terms of the quantile assessments $(q_\alpha, q_{0.5}, q_{1-\alpha})$ and lower bound b_l. The feasible range of flexibility for the log metalog parameterized by an SPT is same as the "three-term semibounded metalog" region in Figure 6, which also extends beyond the plot indefinitely down and to the right. Thus, the shape flexibility of an SPT-parameterized log metalog is inclusive of that of the SPT-parameterized metalog, but includes significant additional area as well.

Proposition 4 (SPT Logit Metalog). *Given that $\ln((x - b_l)/(b_u - x))$ is metalog distributed and given a feasible SPT $\mathbf{x} = (q_\alpha, q_{50}, q_{1-\alpha})$ with known lower and upper bounds b_l and b_u, the logit metalog constants $\boldsymbol{a} = (a_1, a_2, a_3)$ can be expressed directly as*

$$a_1 = \ln(\gamma_{0.5}),$$
$$a_2 = \frac{1}{2}\left[\ln\frac{1-\alpha}{\alpha}\right]^{-1} \ln\frac{\gamma_{1-\alpha}}{\gamma_\alpha},$$

$$a_3 = \left[(1-2\alpha)\ln\frac{1-\alpha}{\alpha}\right]^{-1} \ln\frac{\gamma_{1-\alpha}\gamma_\alpha}{\gamma_{0.5}^2},$$

where

$$\gamma_\alpha = \frac{q_\alpha - b_l}{b_u - q_\alpha}, \qquad \gamma_{0.5} = \frac{q_{0.5} - b_l}{b_u - q_{0.5}}, \qquad \gamma_{1-\alpha} = \frac{q_{1-\alpha} - b_l}{b_u - q_{1-\alpha}}.$$

Moreover, $\mathbf{x}$ *is feasible if and only if*

$$\frac{b_l + b_u\gamma_\alpha^{1-k_\alpha}\gamma_{1-\alpha}^{k_\alpha}}{1+\gamma_\alpha^{1-k_\alpha}\gamma_{1-\alpha}^{k_\alpha}} < q_{0.5} < \frac{b_l + b_u\gamma_\alpha^{k_\alpha}\gamma_{1-\alpha}^{1-k_\alpha}}{1+\gamma_\alpha^{k_\alpha}\gamma_{1-\alpha}^{1-k_\alpha}},$$

where k_α *is as in* (18).

Proof. For the logit metalog, $z = \ln((x - b_l)/(b_u - x))$ is metalog distributed. In Proposition 1, substitute $\ln(\gamma_\alpha)$, $\ln(\gamma_{50})$, and $\ln(\gamma_{1-\alpha})$ for q_α, $q_{0.5}$, and $q_{1-\alpha}$, respectively. The resulting equations are identical those in Proposition 3, so the logit metalog constants follow from the same algebraic simplification as in the proof of Proposition 3. To prove the logit metalog feasibility condition, substitute $\ln(\gamma_\alpha)$, $\ln((q_{0.5} - b_l)/(b_u - q_{0.5}))$, and $\ln(\gamma_{1-\alpha})$ for q_α, $q_{0.5}$, and $q_{1-\alpha}$ in (18). The above logit metalog feasibility condition follows from solving the resulting expression for $q_{0.5}$. □

The SPT-logit-metalog quantile function and PDF are (14) and (15), respectively, for the special case of $n = 3$. The importance of Proposition 4 is that (12) and (5), the expressions for constants and feasibility, respectively, are greatly simplified. The logit metalog constants and feasibility condition can be expressed directly in terms of the quantile assessments (q_α, $q_{0.5}$, $q_{1-\alpha}$) and lower and upper bounds b_l and b_u. The feasible range of flexibility for the SPT-parameterized logit metalog is same as the "three-term bounded metalog" region in Figure 7, which also extends beyond the plot indefinitely down and to the right. Comparing the feasible "three-term" ranges in Figures 4, 6, and 7, it is apparent that the shape flexibility of the SPT-parameterized logit metalog is far greater than that of the SPT-parameterized metalog and log metalog distributions.

6.2.2. Bidding Decision Example. As one illustration of the value of SPT parameterization of the metalog family of distributions, we offer an example of an actual decision analysis in which a wrong decision would have been made if the decision makers had relied on a commonly used three-branch discrete representation of continuous uncertainties instead of a metalog-system continuous representation.

The decision was how much to bid for a portfolio of 259 troubled real estate assets, which a financial institution had offered for sale via public auction. These assets were of different geographies, sizes, and types, including single family, multifamily, commercial, and land. To varying degrees, the value of each asset involved considerable uncertainty and complexity concerning current and future real estate values, occupancy and leases, potential tenant negotiations, local regulations, and, in some cases, bankruptcy or other litigation.

To help determine how much to bid for the portfolio and how one might monetize its various assets, a potential bidder wished to see a probability distribution over the value of the portfolio, which would be the sum of the values of the 259 individual assets. So he engaged a team of experts to assess the value of each asset. Their assignment included visiting each property, discussing comparables with local real estate agents and other knowledgeable parties, and undertaking independent research concerning any issues that would affect that asset's current or future value. As an overall summary of their conclusions, the potential bidder requested a probabilistic range of low, median, and high scenarios for each asset. For each scenario, the team assessed a projected cash flow over time and translated this cash flow into a net present value (NPV). The low scenario was defined as the NPV such that, from the experts' perspective, there was a 10% chance that the ultimate realized NPV would be lower than this amount. The high NPV was defined such that there was a 90% chance that the ultimate realized NPV would be lower than this amount and a 10% chance that it would exceed it. The median scenario was defined such that it was equally likely that the actual realized NPV would be higher or lower than this amount. The expert's analyses and assessments resulted in the range of values for each asset as shown in Table 9.

It was apparent from this data that some assets were worth far more than others. Some asset distributions were narrow, while others were wide. Some asset distributions were symmetric, while others were skewed left and still others were skewed right. In addition, while some of the asset-level uncertainty was probabilistically independent of (irrelevant to; see Howard and Abbas 2015) that of other assets, the team judged

that there was a degree of positive correlation among these assets due to their common dependence on the future economy and, in particular, on the future health of global and local real estate markets.

To calculate a probability distribution over the value of the portfolio, the team used a modified form of Monte Carlo simulation in which they had induced what they believed was an appropriate level of positive correlation across assets. For many of the assets, the team judged the correlation coefficient with the market to be about 80%. For other assets, especially those in litigation, the team believed the correlation with the market to be negligible. The value of the portfolio for each simulation trial was the sum of the (appropriately correlated with market) simulated values for each asset for that trial.

When performing the simulation, the team initially performed a discrete simulation, using only the discrete values in Table 9 for each asset. They followed a commonly used decision analysis approach of assigning probabilities of 30%, 40%, and 30%, respectively, to the low, median, and high discrete scenarios for each asset (see Bickel et al. 2011) and summing the results across assets for each simulation trial. Doing this for 1,000 simulation trials resulted in the CDF data labeled "discrete simulation data" in Figure 12. To gain further insight into this distribution, they calculated the corresponding metalog distribution M_5 parameterized by these data and plotted the results. The results are labeled "discrete simulation metalog" in Figures 12 and 13.

Table 9 Range of Uncertainty in Asset Value ($000s)

Asset	10%	50%	90%
	Probability that realized value is less than …		
1	$18,150	$21,133	$22,625
2	$10,465	$11,362	$12,408
3	$15,781	$16,908	$18,260
4	$4,234	$4,422	$4,610
5	$2,629	$2,979	$3,295
6	$13,945	$14,875	$16,176
⋮	⋮	⋮	⋮
259	$3,500	$4,000	$4,500
Total		$185,348	

Considering Figure 13, the team felt that the discrete simulation tails were too narrow—even though this simulation had taken correlation into account. While the median portfolio value of about $185,000,000 seemed to make sense, the near-zero probability that realized portfolio value would be less than $170,000,000 did not. They felt, based on their experience, that the low end of the distribution should be lower. Similarly, they felt that the high end should be higher.

The team then ran the same simulation using metalog (continuous) representations of the data in Table 9.

Figure 12 (Color online) Cumulative Distribution Functions Over Portfolio Value

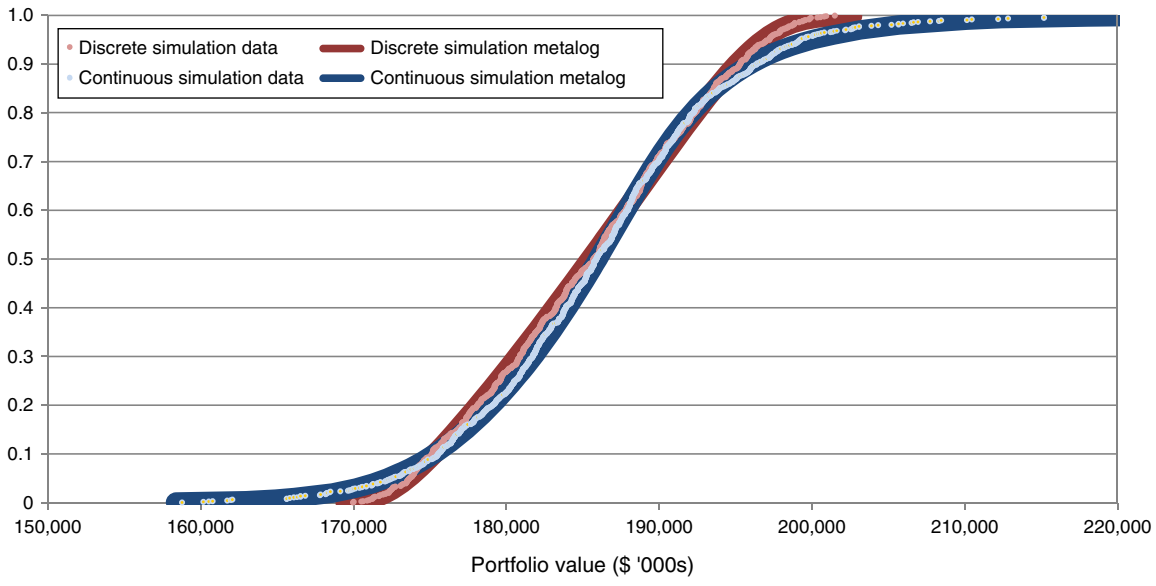


Figure 13 (Color online) Probability Density Functions Over Portfolio Value

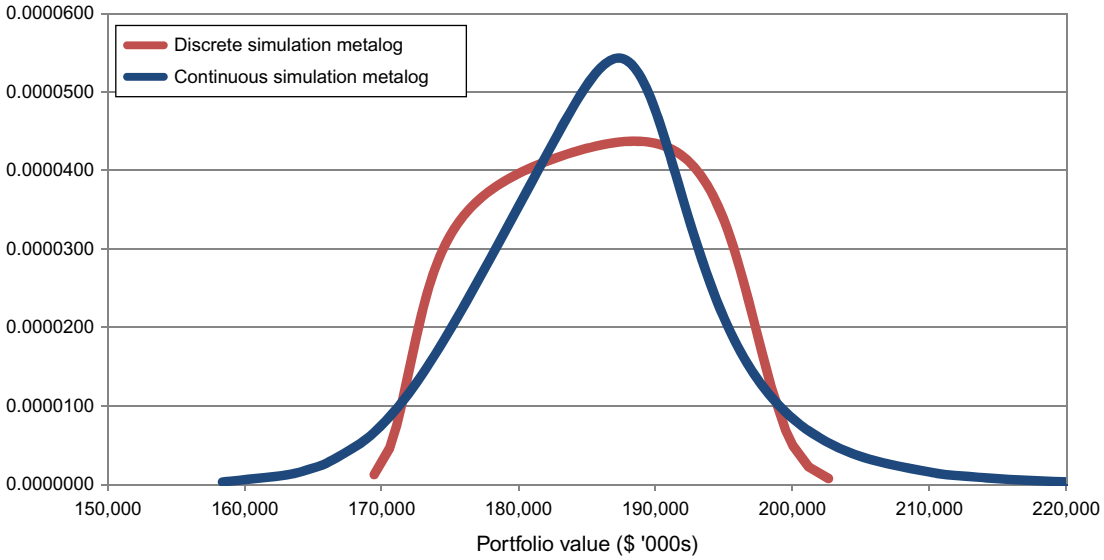
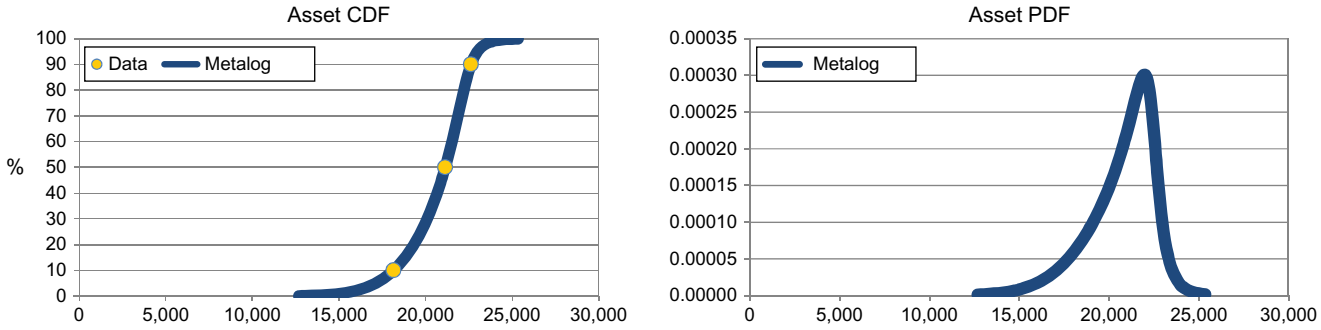


Figure 14 (Color online) Metalog Distribution for Asset 1



Using the SPT assessments in Table 9, the team parameterized the three-term metalog accordingly for each asset. Figure 14 shows the result of this calculation for Asset 1 in Table 9. When reviewing such asset-level distributions prior to simulation, they noted that the 10–50–90 quantiles for each distribution corresponded exactly to the 10–50–90 value assessments in Table 9, and that these distributions appeared to have appropriate right or left skewness. They further noted that the low, median, and high values appeared reasonable. Intuitively, they felt these asset-level continuous distributions were a more accurate representation of asset-level uncertainty than the three discrete scenarios.

They further observed that none of the 259 assessed 10–50–90 ranges violated feasibility conditions in Proposition 2. Rerunning the (similarly correlated) portfolio simulation based on continuous (metalog represented) asset-level uncertainties yielded the "continuous simulation data" shown in Figure 12 and the corresponding "continuous simulation metalog" in Figures 12 and 13. The continuous simulation showed wider tails and a narrower midrange. The lower end of the distribution visibly extended below $160,000,000, which made sense to the team.

Similarly, the high end now extending above $210,000,000 also made sense. After further reflection and analysis, the team concluded that the continuous simulation was a more accurate and authentic representation of the uncertainty in portfolio value than the discrete simulation. The discrete simulation, they reasoned, arbitrarily cut off the tails of the asset-level distributions prior to simulation (no values outside

the low-high range were considered), so it was not surprising that the sum over 259 assets had resulted in artificially short tails as well.

Based on clarity and confidence gained through such analysis, the decision makers chose to submit a bid for this portfolio of assets and subsequently won the auction. Had they relied only on the discrete representation in Figures 12 and 13, they would have overbid. The portfolio value ultimately realized several years later was about $180,000,000—just slightly less than their prior median.

To date, professional decision analysts have used metalog distributions to represent thousands of uncertainties over dozens of applications across many fields, including life science asset valuations, loan asset valuations, real estate asset valuations, environmental studies of fish migration and river stream flows, and a wide range of portfolios of such items. Like the team valuing the portfolio of troubled real estate assets in the above example, such teams have generally concluded that treating continuous uncertainties as continuous and discrete uncertainties as discrete yields more authentic probabilistic results than discretizing all uncertainties from the outset. The metalog system enables practitioners to do this easily and conveniently.

6.3. Distribution Selection within the Metalog System

Given input data $(\mathbf{x}, \mathbf{y})$ that one wishes to represent with a continuous probability distribution, which metalog should one select, and how many terms should one use for that selection? As with any distribution selection that is not purely Type 1 driven, this is ultimately a matter of judgment. We now offer several guidelines and tools to help aid this judgment.

With respect to choosing among unbounded, semibounded, and bounded distributions, the traditional basis of choice for the Pearson (1895, 1901, 1916), Johnson (1949), and Tadikamalla and Johnson (1982) systems is to match third and fourth central moments of the data with a corresponding distribution from Figure 1. However, given a moments-based selection within the Pearson and Johnson systems, this approach has the disadvantage that it offers no choice of boundedness. In contrast, as shown in Figures 4–7, the metalog family offers a wide range of flexibility for each of its unbounded, semibounded, and bounded options. So as a starting point, per Table 1, we suggest selecting the metalog, log metalog, or logit metalog according to whether the distribution of interest is naturally unbounded, semibounded, or bounded.

Additional considerations include closed-form moments and flexibility. While all three options are highly flexible, the logit metalog is the most flexible for any given number of terms. However, moments of the metalog are available in closed form, as detailed in Section 3.4, whereas moments of the log and logit metalogs must be calculated numerically. Thus, if maximizing flexibility for a given number of terms is critical, one may opt for the logit metalog. If the availability of closed-form moments is critical, one may opt for the metalog.

How many terms to use depends significantly on purpose and context. For example, in decision analysis applications with three assessed data points ($m = 3$), it is natural to use three terms ($n = 3$). In this case, for any feasible data, the metalog CDF will pass through these data points exactly as illustrated in Figure 14. More generally, the metalog distributions will pass through the data exactly whenever $n = m$ and the data is feasible, so it makes sense to start with $n = m$ when this result is desired.

In the case of tens or even thousands of data points (e.g., of empirical- or simulation-frequency data), an exact fit is generally neither desired nor practical. In such cases, one may wish to use (A) relatively few terms (e.g., $n = 3$–6) if a smooth representation is desired, (B) a larger number of terms (e.g., $n = 7$–15) if one is engaged in data or distribution research, or (C) the n that maximizes some closeness-of-fit criterion such as K–S distance. In the case of (B) or (C), one must take care not to overfit[18] the data, as is potentially possible with any linear least squares application with a variable number of terms.

To aid such considerations, we have found the "metalog panel" to be a useful tool. As shown in Figures 15 and 16, the metalog panel arrays density functions for a range of n for a given set of data parameters $(\mathbf{x}, \mathbf{y})$.

Figure 15 shows the array of log metalog density functions for $n = 2$ to $n = 16$ that correspond to fish

[18] Among others, Hawkins (2004) and Draper and Smith (1998) provide perspectives on overfitting and rules of thumb for dealing with it.

Figure 15 **(Color online) Metalog Panel for Fish Biology Data**

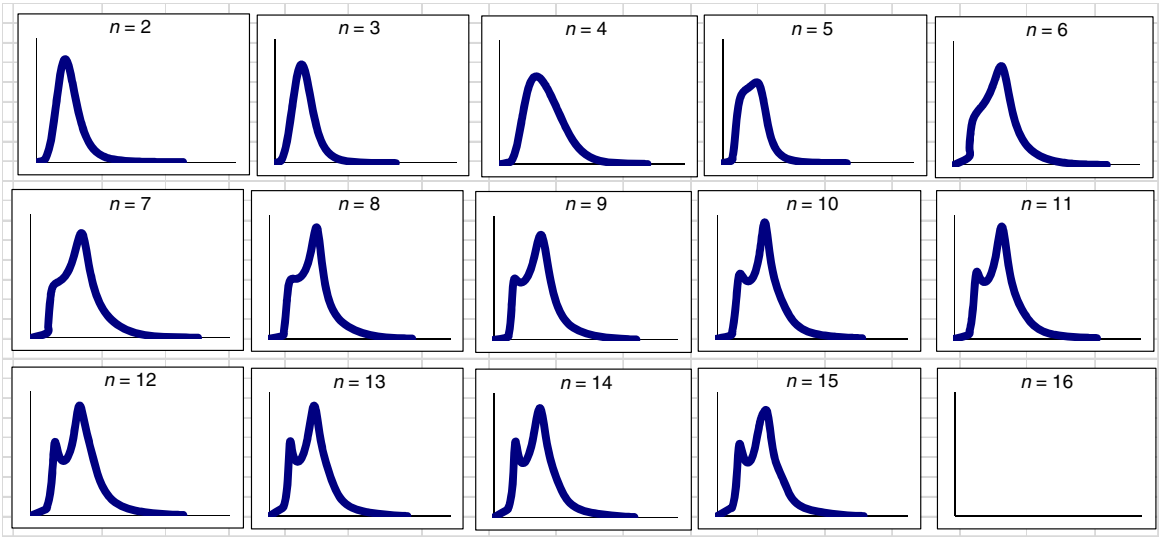
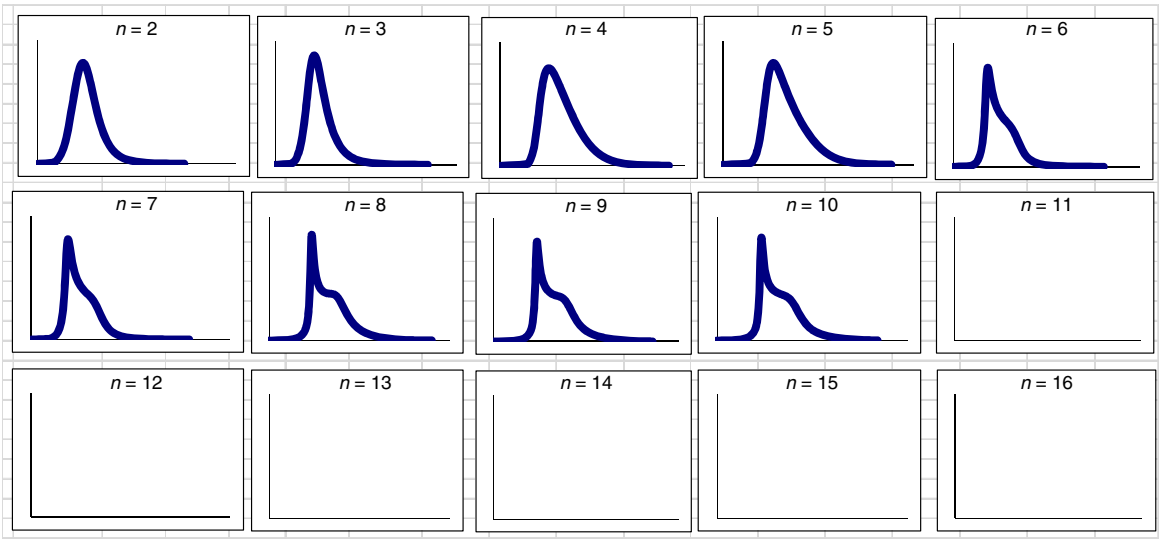


Figure 16 **(Color online) Metalog Panel for Hydrology Data**



biology data in Figure 10. Figure 16 is a similar representation for the hydrology data in Figure 11. In both Figures 15 and 16, it is evident how the log metalog increasingly molds itself to the shape of the data and eventually stabilizes its shape as n increases. Blank cells in these figures correspond to the data being infeasible for that choice of n.

From a Bayesian perspective, the choice of n ultimately corresponds to a declaration of "yes, that's what I mean" by a decision maker or expert; that is, the resulting distribution authentically represents his beliefs.

7. Conclusions

This paper introduces the metalog distributions, a system of continuous univariate probability distributions designed for flexibility, simplicity, and ease/speed of use in practice. While the metalog system offers unbounded, semibounded, and bounded distributions that broadly achieve these goals and that compare

favorably with previous systems, it also suggests several areas for further research.

First, one can envision various improvements to the metalog system. These include, for example, characterizing the full range of metalog-system flexibility, including for five or more terms in the β_1–β_2 plane and for the ability to match fifth and higher-order moments. In addition, it might be useful to extend to four or more terms an expression of the constants and feasibility conditions that we developed for up to three terms in Section 6.2.1.

Second, as suggested in Section 3.2, other "meta" distributions can be developed by applying the methodology of Section 3.1 to other base distributions such as the normal, Gumbel, and exponential. While this research appears to be straightforward, it has not been done yet, and it may well yield new systems of quantile-parameterized distributions that have certain advantages relative to the metalog.

Third, and more broadly, there is a need for new distribution systems that may result from a different combination of choices or the addition of new choices to Table 1. These might include quantile-parameterized systems without feasibility conditions, with additional flexibility for given levels of feasibility, or with flexibility to represent infinite-moments distributions like the Cauchy.

Future research contributions notwithstanding, we believe the metalog system as presented in this paper is ready for use in practice[19]—for any situation in which CDF data is known and a flexible, simple, and easy-to-use continuous probability distribution is needed to represent that data.

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[19] Downloadable Excel workbooks that implement the metalog system, data underlying the examples in this paper, and other aids for use in practice are available at http://www.metalogdistributions.com.

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