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Economic Demand and Essential Value

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The strength of a rat's eating reflex correlates with hunger level when strength is measured by the response frequency that precedes eating (B. F. Skinner, 1932a, 1932b). On the basis of this finding, Skinner argued response frequency could index reflex strength. Subsequent work documented difficulties with this notion because responding was affected not only by the strengthening properties of the reinforcer but also by the rate-shaping effects of the schedule. This article obviates this problem by measuring strength via methods from behavioral economics. This approach uses demand curves to map how reinforcer consumption changes with changes in the "price" different ratio schedules impose. An exponential equation is used to model these demand curves. The value of this exponential's rate constant is used to scale the strength or *essential value* of a reinforcer, independent of the scalar dimensions of the reinforcer. Essential value determines the consumption level to be expected at particular prices and the response level that will occur to support that consumption. This approach permits comparing reinforcers that differ in kind, contributing toward the goal of scaling reinforcer value.

Keywords: demand, value, reinforcement, reflex strength, behavioral economics

An enduring goal of learning theory has been to define a measure capable of indexing the strength or value of a reinforcer—a pursuit that may be called "hedonic scaling" (Miller, 1976). Evidence of this pursuit can be seen across the discipline (Hull, 1943; Pavlov, 1927; Skinner, 1938). Its stature may explain why it became the subject of Skinner's first research effort. Despite this focus, the goal of hedonic scaling has yet to be realized.

The purpose of the present article is to add our efforts to those of others. To anticipate some of our claims, we have adopted the language, methods, measures, and analyses of microeconomics—a discipline honed by studying human consumers in their natural setting—which may bring us closer to creating a hedonic scale than efforts heretofore. Realizing this goal requires some changes in how we do an experimental analysis of behavior. However, once this is done, an economic equation can be offered that seems capable of yielding a credible ordering of the values of different reinforcers and predicting their impact on behavior. We begin with a brief history of the pursuit of an index of strength in the experimental analysis of behavior.

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Response Rate as Strength

In reviewing the history of the concept of the reflex, Skinner (1931) argued that a single organizing principle can be discerned: From Descartes to Sherrington, the reflex has always referred to a correlation between a stimulus and a response. To demonstrate the utility of this correlation to a science of behavior, Skinner (1932a) mapped the relation between hunger drive and the eating reflex by presenting hungry rats with food pellets and measuring how the rate of food consumption changed as a function of time since beginning eating. He thought that as a superordinate proxy for the components of the eating reflex, changes in the degree of hunger would surely be reflected in orderly and continuous changes in the rate of pellet consumption. He was not disappointed: He found that for hungry rats, the rate of food consumption was a smooth, monotone-decreasing, positively accelerated function of the time spent eating.

Next, Skinner (1932b) repeated this experiment, this time with a lever press preceding initiation of the eating reflex. Despite the addition of an initial member to the reflex chain, the function relating the rate of pellet consumption to time spent eating was unchanged from his prior experiment. This meant that the rate of pellet consumption, an index of reflex strength, could itself be measured in terms of the lever press. From this observation was born the notion that response rate can measure *reflex strength* (Skinner, 1932b, 1938). Ironically, 70 years of experimental analysis return us to a conception of strength not far from Skinner's (1932a). Our only qualification to his view is that consumption must be scaled in relation to constraint.

Despite his early endorsement of rate as an index of reflex strength, Skinner devoted little space in subsequent writing to this topic, perhaps because his own research showed a strength construct to be problematic. In Ferster and Skinner (1957), multiple data sources confirmed that response rate itself can be shaped directly by reinforcement, causing, for example, ratio schedules to support higher response rates than interval schedules, even when the rates of reinforcement for these different types of schedules are the same (pp. 399–407; also see discussion of tandem schedules and differential reinforcement, pp. 415–502). The problem is clear: How can response rate index reflex strength when the value it assumes is governed not solely by the reinforcer but also by the local contingencies of reinforcement?

Relative Response Rate as Strength

Herrnstein (1970) noted that relative response rate, the measure used in choice, was more sensitive to changes in reinforcer rates than was the single-schedule approach advanced by Skinner. He noted that although Skinner's single-schedule measure can succeed when reinforcer rates are increased from low to moderate levels, response rates often do not increase when reinforcer rates are increased further (Catania & Reynolds, 1968; Hall & Lattal, 1999). In consequence, unrestricted use of the measure of response rate can, on occasion, support the improbable claim that over a range of moderate to high rates of reinforcement, strength is unchanged. Telling as this problem may be, subsequent work showed Herrnstein's critique understated the difficulties with a rate measure of strength, for under certain conditions, increases in rate of reinforcement can actually lead to reductions in responding (see Hursh, 1978, 1980, 1984, 1991).

Herrnstein proposed to remedy some of the difficulties with measuring strength by comparing reinforcers in choice. Even in the absence of experiment, the problem he noted would not be expected were moderate versus high rates of reinforcement offered in choice. But central to establishing the primacy of his choice measure was not its sensitivity to all ranges of reinforcer size. Instead, it was his demonstration of the remarkable orderliness between concurrent choice and reinforcement: Without violation, he found the proportion of choices for one of two alternatives covaried with the proportion of reinforcement that alternative obtained, a relation he called *matching* (Herrnstein, 1961).

Studies of matching relations made substantial progress in advancing what seemed a very effective measure of strength. First, with the inclusion of his so-called "equation for simple action," Herrnstein (1970) broadened his choice measure so it could incorporate both single- and concurrent-schedule effects. Second, this broadening of measures of strength was matched by a broadening of the construct of strength itself. Baum and Rachlin (1969) proposed that schedule performances be viewed as reflecting a choice between activities that differ not in strength, but in value. This reinterpretation of Skinner's and Herrnstein's conception of strength supported the subsequent claim that by using Herrnstein's measures, it is possible to scale the relative value of different types of reinforcers when those reinforcers are presented in choice (Miller, 1976).

These outcomes and applications supported Herrnstein's view that the matching equation could serve as a capable standard for scaling the strength or value of reinforcers. The key to success was to pursue not absolute value but the value of one reinforcer relative to another. However, this run of successes was soon to end, for a different approach toward operant analysis that borrowed heavily from human economic consumer theory pointed to problems with any matching-based scale of relative reinforcer value. In much of this work, the language and interpretations differ from those of traditional operant analysis, but the connectedness of this work to operant analysis cannot be denied.

To illustrate this new approach, we consider a "behavioral economic" experiment by Elsmore, Fletcher, Conrad, and Sodetz (1980). In one experiment from their study, baboons chose between food and infusions of heroin under a range of conditions: At one extreme, income was high (they had many choices to "spend" per day), and at the other, income was low (they had only a few choices per day). Under the former condition, monkeys chose more heroin than food, but under the latter condition, this preference tended to reverse. More recently, identical shifts in preference between two commodities have been shown with human subjects under conditions of increasing price (Bickel & Madden, 1999; Bickel, Marsch, & Carroll, 2000; Madden, Bickel, & Jacobs, 2000). What these results show is that any exercise in hedonic scaling must acknowledge that value is dependent on income or price (the complement of income), especially when the reinforcers being evaluated are not identical. Unfortunately, by not accommodating income/price effects, matching relations fail as a basis for scaling reinforcer value (see Hursh, 1978; Silberberg, Warren-Boulton, & Asano, 1987).

Ratio Breakpoint as Strength

An obvious solution to this problem is to use an alternate assay of strength. One likely candidate was proposed by Hodos (1961). In his progressive-ratio (PR) schedule, animals are, at first, reinforced according to a small fixed ratio (FR), the size of which is increased in steps across successive reinforcers. The measure of strength is the ratio size at which the animal quits responding—the so-called breakpoint. Hodos found that the breakpoint-ratio size increased with decreases in body weight and increases in reinforcer size. In other words, the breakpoint covaried in orderly and sensible ways with manipulations that alter the value of the reinforcer.

With these results in hand, the argument could be made that PR schedules should serve as our measure of the strength of a reinforcer. Indeed, many behavioral pharmacologists seem to have that view as evidenced by their frequent use of PR schedules to compare the reinforcing efficacy of different drugs (see Stafford, LeSage, & Glowa, 1998, for a review). Nevertheless, the popularity of this measure among students of drug effects has not been matched among operant analysts who lack a pharmacological focus. Part of the problem is that this measure, unlike, say, response rate or choice, is discontinuous: The mere specification of the breakpoint tells us little about behavior at costs other than the breakpoint. Moreover, this measure has problems unique to its method of construction. In some cases, the breakpoint-ratio size has an unfortunate tendency to vary with the FR step size (e.g., Hodos & Kalman, 1963; see, however, Stafford & Branch, 1998) and to be dependent on the duration of the interval defining the terminal ratio size (Stafford & Branch, 1998).

Despite these problems, we wish not to protest much, for we consider breakpoint analysis to be a credible, if not optimal, approach to the scaling of strength. Among its virtues is its apparent face validity: It makes the sensible assumption that one way to measure the value of a reinforcer is by how much work an animal is willing to do in order to earn it. As we show, this assumption is central to the methods this article proposes regarding how to assess a reinforcer's strength.

Behavioral Momentum as Strength

A recent analogic addition to the mix of measures of strength has been offered by Nevin (1992; also see Nevin & Grace, 2000). In their scheme, response rate is an analogue of the velocity of a moving body, and the resistance of this measure to change from, say, extinction or satiation, is akin to inertial mass. Called behavioral momentum, this construct is typically evaluated in a multiple variable-interval schedule in which components differ only in some dimension of reinforcement, such as rate or amount. When responding was disrupted by some experimental manipulation (e.g., undergoing extinction, providing response-independent reinforcement, or reducing an animal's motivation level), Nevin and his colleagues found that response rate in the schedule that provided the higher rate or amount of reinforcement was more resistant to change than the alternate schedule.

This covariation between apparent schedule value and resistance to change supports the use of the behavioral-momentum construct in scaling the strength of a reinforcer. However, more work may be needed. The theory underlying behavioral momentum requires that resistance to change be independent of the response-rate differences various types of schedules naturally create and be solely dependent on the reinforcer rates or amounts these components provide. In two conditions of Experiment 2 of their study, Nevin, Grace, Holland, and McLean (2001) tested this thesis by using a multiple variable-interval, variable-ratio schedule that provided approximately equal rates of reinforcement. They found that variable-interval responding was more resistant to change by disrupters than variable-ratio responding, an outcome that weakens the utility of behavioral momentum as a measure of strength or value of a reinforcer.

Demand as Strength

This gives closure on the major, operant-based accounts of strength that have been advanced to date, save the one that is the target of this paper: a scaling of strength on the basis of the economics of demand. To us, it seems no small irony that a goal that has proved elusive for operant analysts—measuring the value of a reinforcer—is a process we engage in every day whenever we make consumer decisions in the human economy. So, for this reason, it is surprising that only recently have learning theorists entertained the idea that microeconomics, the discipline that documents the decision processes in the human economy, might be useful in scaling reinforcer value (Allison, 1983; Hursh, 1980, 1984; Lea, 1978).

Called behavioral economics, this new approach has led some students of operant behavior to change their language, methods, and predictions in ways that are consonant with the discipline of microeconomics they have adopted. Subjects now are often viewed as animal workers, and their behavior is no longer strengthened by reinforcement. Instead, they earn goods in exchange for labor, with the price they pay defined in terms of the response-reinforcer feedback function. Although at one time plots of response rate as a function of reinforcer rate prevailed, one now sees plots of how consumption of a good changes as a function of the amount of work required to produce it. Often, this means plotting the number of reinforcers earned per day as a function of price, with price defined as the number of responses an animal must make under an FR schedule in order to produce a reinforcer. When microeconomists plot consumption as a function of price, they call that function a *demand curve*. In their approximations to microeconomics, behavioral economists use the same language.

To ensure the integrity of its links to microeconomics, demand analysis by the behavioral economist requires procedural changes in the traditional operant methods illustrated above. Other factors equal, demand analysis favors use of ratio schedules over others because they simplify the definition of price as responses per reinforcer. And since the price the worker pays is viewed as a behavioral adjustment to meet consumptive need, demand analysis is more tractable if all goods are earned, and none given—an arrangement called a *closed economy* (Hursh, 1980, 1984). When food is the reinforcer, a closed economy provides all food within the experimental arrangement and eliminates postsession feeding. Finally, the economic perspective encourages the evaluation of reinforcers that differ in kind, not just in rate of occurrence. Studies have evaluated demand for different essential commodities, such as food, water, and sucrose (Bauman, Raslear, Hursh, Shurtleff, & Simmons, 1996; Hursh, 1980, 1984; Lea, 1978; Madden, Dake, Mauel, & Rowe, 2005; Tsunematsu, 2000), and inessential reinforcers, such as drugs, saccharin-sweetened water, brain stimulation, TV time, nesting material, and money (Dawkins, 1983; Gunnarsson, Mathews, Foster, & Keeling, 2000; Harris, Briand, Orth, & Galbicka, 1999; Hursh, 1991; Hursh, Galuska, Winger, & Woods, 2005; Hursh & Natelson, 1981; Hursh & Winger, 1995; Jacobs & Bickel, 1999; Johnson & Bickel, 2006; Matthews & Ladewig, 1985; Rowlett, 2000).

In sum, a demand analysis changes the questions we ask, the methods we use, and the measures of our work. More likely than not, comparisons among schedules that differ in type will not be a primary concern, nor will measures of response rate and the near-exclusive use of food as a reinforcer. In their stead, the behavioral economist will typically favor use of ratio over interval schedules and will create curves of demand (instead of response rate) for reinforcers that are earned and seldom freely given (cf. Bauman, 1991).

These differences in approach reflect between-discipline differences in goals. The operant analyst scales the effects of different types of schedules on the strength of behavior. In most of these comparisons, behavior is maintained by the same reinforcer and the datum measuring between-schedule differences is the rate of response. The behavioral economist, on the other hand, typically scales consumer demand for different goods on the same schedule. The measure reflecting between-good differences is the demand curve itself, the function relating quantity consumed to the work required to produce it.

The complementarity between the goals of the operant analyst and the behavioral economist ensures the continued development of both approaches. Indeed, a given researcher is likely to switch approaches depending on which element of the response-reinforcer relationship is of primary interest. When comparisons among schedules are desired, traditional operant methods often seem more advantageous. Alternatively, when attention turns from the response-reinforcer feedback function to evaluating the properties of the reinforcer itself, a demand-based analysis is likely to prove more useful.

We contend that a demand analysis brings added value to an operant theorist when his or her focus shifts from feedback functions to the reinforcers they arrange. To illustrate the comparative advantage that a demand analysis brings to comparisons among reinforcers, we return to the Elsmore et al. (1980) study discussed earlier. To remind the reader, in one experiment from that report, baboons chose between infusions of heroin and food under a range of income conditions: when they had many choices per day and the price of both goods was low to when they had few choices and the price of both goods was high. In the former case, the subjects preferred heroin to food, but in the latter case, one baboon preferred food to heroin. Although this change in preference obviates scaling reinforcer value in terms of any preference test, matters differ when these data are viewed from the perspective of a demand analysis. The very feature that compromises use of a preference test—that choice is price dependent—defines the functions that generate a demand curve. When the quantity of each good consumed is plotted as a function of price, the curve for heroin decreases more rapidly than does the curve for food. Clearly, these subjects preferred heroin to food when the price of each was low but tended to reverse this preference when the price was high. These results were subsequently replicated in a second experiment by Elsmore et al. (reported in Hursh, 1991) with rhesus monkeys working under FR schedules. Consistent with their baboon-based choice data, consumption of heroin was more sensitive to increases in the FR than was consumption of food.

The price dependency of between-good preference suggests that Miller (1976) erred in creating a matching-based scale for ranking the value of goods because his model assumed that value could be assessed independently of price and income. What Elsmore et al.'s (1980) demand curves made clear was that the assessment of the comparative value of two goods must include not only a comparison of consumption level between two goods but also each good's price point. In terms of how the word is commonly used, a good's "value" is a joint function of hedonically positive and negative characteristics. The positive characteristics in value are all the appetitive attributes the good has, such as its positive biological effects on the consumer. The negative characteristics in value are all features of the price charged in its purchase. For example, it could be the time or responses that must be paid for each good.

Microeconomists call sensitivity to the cost-benefit ratio "elasticity of demand." It indexes the degree to which consumption is insensitive to the effects of price increases. Unfortunately, scaling reinforcer value, using Elsmore et al.'s (1980) model, on the basis of comparative elasticity of demand for food and heroin is problematic because the demand "lines" of this study almost certainly misrepresent the curvilinear form that a demand curve would draw were demand assessed at more price points. For this reason, the negative slopes of these functions have limited quantitative resolution.

A way to improve predictive resolution is to mimic the added predictive power that Herrnstein's (1961) choice procedure lends to a simple preference test. By collecting several data points in choice and modeling the slope of preference change across them with the matching equation, he provided a basis for not just rank ordering the value of two goods but also scaling the distance in value between them. To follow his approach, we need at least two, well-defined, multiple-point demand curves and a mathematical equation that accommodates them.

For this reason we now turn to a more suitable data set—one provided by Hursh (1991). In this study, two monkeys earned their daily ration of food and saccharin-sweetened water by responding under FR schedules, the sizes of which were manipulated across sessions. The top panel of Figure 1 presents the demand data in logarithmic coordinates for these two goods averaged across both monkeys. Lines connect successive data points so as to define two curves.

Two features of these curves are noteworthy: Both curves are downward sloping, and the curve for saccharin water drops more rapidly than the curve for food. This multipoint presentation of demand has the important advantage over the Elsmore et al. (1980) data set of delineating the true form of demand curves—that they are not only downward sloping but also that the negative slope often accelerates with increasing price. Further, we can see the problem inherent with using elasticity of demand alone as an index of value: Not only does elasticity change continuously with changes in price for each good but the rate of change differs between goods at each price point also. In any between-good comparison, it is not possible to pick a price point at which "value" resides, a weakness of the behavioral economic approach noted by Killeen (1995). Although his simple linear demand equation is not an adequate resolution to the problem, a general solution is offered here that addresses the spirit of his concern.

The approach we favor is to scale "value"—what we call *essential value*—in terms of the rate of change in elasticity of demand. Given the curvilinear appearance of most multipoint demand curves, how does one select a single number that represents a good's elasticity of demand that can serve as our measure of essential value? The answer is to use a model that has a parameter for the rate of change in elasticity. If the model accommodates the curvature of most demand curves with a single parameter that specifies the rate of change in elasticity, then we have in the value of that parameter a simple index of a good's essential value. It is to the definition of such a single-parameter model that we now turn.

Demand Equations

Linear-Elasticity Equation

Prior to the present article, there was only one model for behavioral-economic demand curves—Hursh, Raslear, Bauman, and Black's (1989) linear-elasticity equation. When their equation is applied to demand curves plotted in logarithmic coordinates, it states that

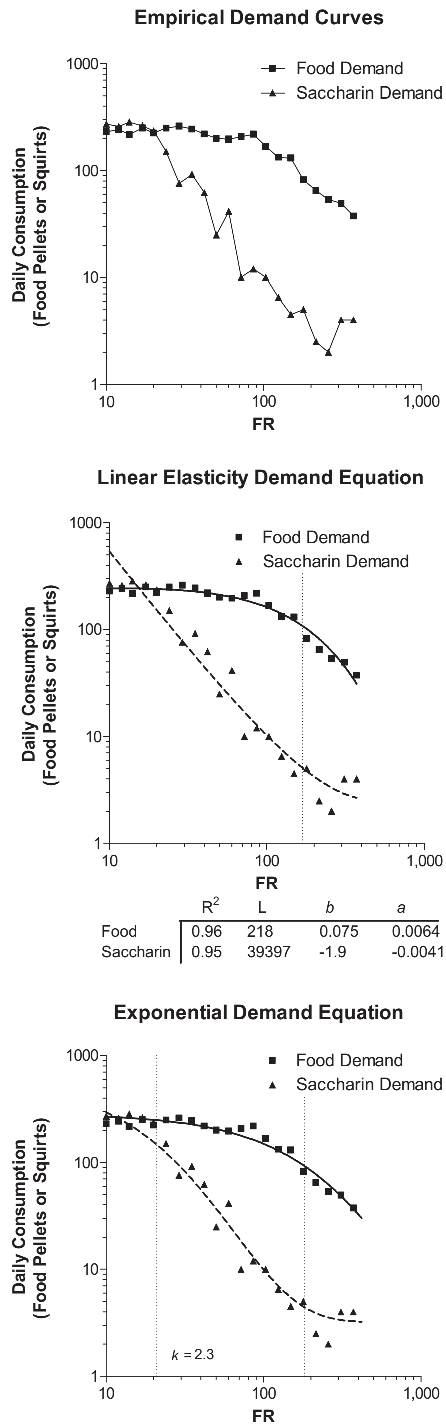
$$\ln Q = \ln L + b \ln P - aP, \tag{1}$$

where Q is the quantity consumed, price (P) is set by the FR schedule, L is the level of consumption as P approaches zero, b is the slope of the demand curve after an infinitesimally small increase from a zero-level price, and a is a coefficient.

In this equation, the value of L is determined empirically. For example, in assessing demand for food, L could be defined as the amount consumed under unrestricted access. The value of b is expected to be near zero. This expectation is based on the assumption that an imperceptibly small increase in price should, by virtue of its imperceptibility, leave consumption levels unchanged.

The slope of the Equation 1 draws in log-log space defines elasticity of demand. That is,

$$\text{Elasticity} = b - aP. \quad (2)$$



	R^2	L	b	a
Food	0.96	218	0.075	0.0064
Saccharin	0.95	39397	-1.9	-0.0041

	R^2	α	Q_0
Food	0.96	4.6e-006	288
Saccharin	0.97	2.4e-005	628

Figure 1. Three renditions of demand for food and saccharin-sweetened water from Hursh (1984). The top panel connects data points for the mean of two monkeys. The middle panel shows the same data with curves fit using the linear-elasticity model. The bottom panel presents the same data with curves fit using the exponential-demand equation (Equation 4). Vertical dashed lines indicate the calculated point of unit elasticity from each model; for the linear-elasticity model, the slope of saccharin demand is more negative than −1 starting from the origin. The variance accounted for (R^2) and parameter values of each equation are shown in the tables below the middle and bottom panels. In the linear-elasticity equation, L and b, respectively, signify level of consumption at the lowest price and the slope of the demand curve after a small price increase from a price of zero. In the exponential-demand equation, α defines the rate of change in the exponential; Q_0 specifies the highest level of demand; and k is a constant that specifies the range of the dependent variable with price increases. FR = fixed-ratio.

Because a and b are fixed in value for each demand curve, elasticity changes as a linear function of P.

By setting elasticity equal to −1 and solving for P, we arrive at the price point economists call *unit elasticity*, in which a 1% increase in price results in a 1% decrease in consumption. The limb of the curve to the left of this point shows *inelastic demand* (where a 1% increase in price results in a <1% decrease in consumption), but the limb to the right of this point shows *elastic demand* (where a 1% increase in price results in a >1% decrease in consumption). This is also the point of maximal responding or expenditure, previously defined as $P_{\max}$ (see Hursh and Winger, 1995). The price at unit elasticity for food is denoted by a dashed line in the middle panel of Figure 1. This panel presents the same demand data as the top panel. However, now they are fitted by the best-fit function defined by the linear-elasticity model, and the price at unit elasticity is defined by solving Equation 2.

In terms of its predictive adequacy, the linear-elasticity equation does quite well. The R^2 for the food- and saccharin-demand curves are .96 and .95, respectively. Impressive as these accommodation statistics may be, they do not speak to the goal of defining a single parameter for indexing the rate of change in elasticity of demand. Therefore, in terms of our goal of defining essential value, this equation fails because it models demand curves in terms of two parameters, a and b.

A psychologically plausible solution to this problem would be to eliminate the b parameter by setting it to zero, its theoretical value. We would then realize our goal of having a single number representing changes in elasticity for a complete demand curve. Regrettably, the price paid for this constraint is high: Although it does no damage to the predictive adequacy of Equation 1 when applied to demand for food (R^2 = .95), it causes the linear-elasticity equation to fail in fitting the saccharin-demand curve (R^2 = .7).

Our goal of using an equation's parameter to index a good's essential value has, for the moment, been cut short. What is needed is a new equation that maintains the predictive successes of the linear-elasticity equation but addresses the need of having a single parameter defining changes in elasticity of demand. The presentation of such an equation is a primary purpose of the present article.

Exponential-Demand Equation

The economics literature provides little guidance on how to define a demand curve for behavioral-economic data. The problem is that microeconomists define demand in terms of large numbers of consumers, creating market-demand curves, but behavioral economists study demand at the level of the individual consumer. This difference in aggregation is unsurprising. For behavioral economists, the demand curve remains part of a functional analysis, and for this reason, they remain intent on characterizing the relation between price and consumption for a single consumer. For microeconomists, on the other hand, there is little concern with modeling a psychological process. Instead, they focus on predicting how the relation between price and consumption will play out in the marketplace. This prediction requires a market-demand function and results in a literature populated by many equations, none of which needs to relate to individual consumption. Microeconomists' predilections for market-demand curves make it difficult to uncover examples of demand data for individual consumers in the economics literature.

Nevertheless, a strategy Allen (1962) has suggested for mapping market demand can be readily applied to demand curves based on individual consumption. He noted that the core feature of a demand curve is that it is downward sloping in price-consumption space. He proposed eight types of equations that provided possibly appropriate functional forms. On the basis of a serial application of these and other equations to extant behavioral-economic data sets, the one that appears most promising for our purposes is an exponentially based demand equation. When plotted in logarithmic coordinates, it takes the following form:

$$\log Q = k(e^{-\alpha P}) + minimum. \tag{3}$$

This exponential equation is a general model; k specifies the range of the dependent variable in logarithmic units, α specifies that rate of change in the exponential, and *minimum* specifies the asymptotic level of logarithmic consumption at infinite price.[1]

The maximum of the exponential in Equation 3 is the logarithm of consumption at zero price, log Q_0, and is calculated as k plus minimum. Q_0 is comparable to the L parameter of Equation 1 and specifies the highest level of demand. Because level of demand, Q_0, is more important conceptually than minimum, we can rewrite Equation 3 as follows:

$$\log Q = \log Q_0 + k(e^{-\alpha P} - 1). \tag{4}$$

The rate constant, α, determines the rate of decline in relative consumption (log consumption) with increases in price. The value of k is generally set to a common constant across comparisons because it merely specifies the range of the data. The slope of the demand curve, elasticity, is jointly determined by k and α, but because k is a constant, changes in elasticity are determined by the rate constant, α.

Compared to the linear-elasticity equation it replaces, the exponential equation is clearly advantaged. This point is illustrated by comparing the bottom panel of Figure 1, which shows the fit of the exponential equation to the saccharin-water and food demand curves, with the predictions of the linear-elasticity model shown in the middle panel. First, it is descriptively as adequate even though it has one less free parameter than the linear-elasticity equation. Second, the values its parameters assume seem more plausible. In particular, the linear-elasticity equation's values of L (the initial level of consumption at a low price) for saccharin and b for food are, in the former case, too high (consumption is 39,397) and, in the latter case, positive instead of equaling zero or being negative as expected (for normal goods, economists assume consumption never increases with price; yet a positive b value predicts this outcome). Third, only the exponential equation correctly describes the initial range of saccharin consumption as a positively accelerating function of price with a slope between 0 and -1 (see dashed lines for unit elasticity in the bottom panel of Figure 1). Finally, the exponential equation fulfills the goal of having a single parameter (α) to scale elasticity of demand, our basis for defining essential value given a constant range of consumption (k).

Standardized Price

Although it should now be possible to make cross-good comparisons in terms of the rate constant of the exponential-demand curve, an important problem remains: The form a demand curve assumes may be critically dependent on the dimensions of the good purchased. In a study by Hursh, Raslear, Shurtleff, Bauman, and Simmons (1988), two groups of rats earned their daily food ration by responding under FR schedules ranging in size from 1 to 360. For one group, the reinforcer size was one food pellet; for the other, it was two. Although the only difference between groups was the size of their food reinforcer, the demand curves that were generated differed in slope (see Figure 2). How can one scale the essential value of different goods when the elasticity of demand of a unitary good is dependent on its scalar properties?

Hursh and Winger (1995) proposed a way to eliminate scalar differences by expressing price in terms of the number of responses per 1% of maximal consumption, what we call Q_0 (see also Peden and Timberlake, 1984). Here we take an equivalent approach by standardizing price as the total cost required to defend Q_0 at each schedule requirement (i.e., $Q_0 \times C$), where C represents the varying cost of each reinforcer, such as the number of responses or amount of time required to earn a good. Stated another way, when commodities differ in size, differences in the exponent of the exponential are due to two factors—differences in the true cost required to defend the level of demand at Q_0 and differences in the essential value of the good. By standardizing price in relation to Q_0, we can isolate that component of elasticity due entirely to differences in essential value, α:

$$P_s = Q_0 \times C, \tag{5}$$

with P_s defined as the standardized price, Q_0 defined as a parameter representing consumption at a price of zero, and C defined as the cost of each reinforcer—the independent variable usually set as a certain number of responses per reinforcer (FR schedule). Substituting into Equation 4, we have the following:

$$\log Q = \log Q_0 + k(e^{-\alpha Q_0 C} - 1), \tag{6}$$

[1] The value of α is unaffected by the base of the logarithm used to scale Q. However, when taking the first derivative of Equation 3 to solve for unit elasticity (slope $= -1$), k must be in $\log_e$ units of Q.

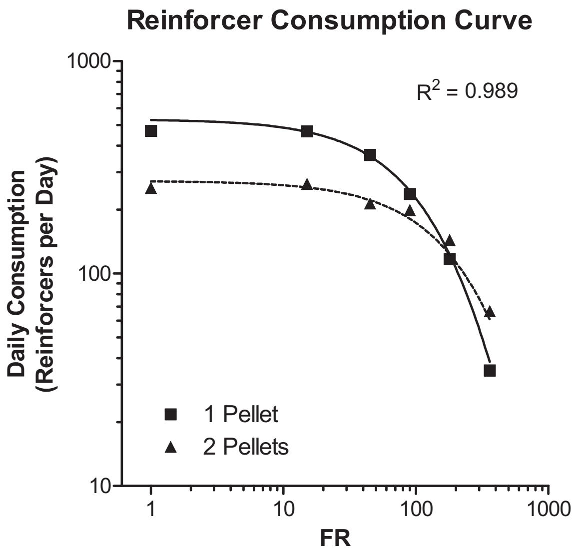


Figure 2. Mean consumption of food reinforcers per day by rats as a function of fixed-ratio (FR) schedule size. Squares and triangles present data based on one and two food pellets, respectively. The curve through each set of data points is a best-fit function based on the exponential-demand equation. Variance accounted for (R^2) across conditions is shown in the panel and the parameter values of the equation for each condition are shown in Table 1. (Data from Hursh et al., 1988.)

with α remaining as the measure of essential value, the parameter that controls the rate of decline in consumption with changes in standardized price.[2]

To illustrate this approach, we applied Equation 6 to the data in Figure 2, with a constant value of *k*. Table 1 summarizes the results of the analysis. As is clear from the figure, Q_0 was higher for the one-pellet reinforcer than for the two-pellet reinforcer (i.e., it took more of the former to satisfy the subject at a price of zero). Taking that difference into account in the representation of price, we found that the rate constant, α, was equivalent for the two demand curves, as it should be if α reflects the essential value of food as a reinforcer.

Tests of Model Veracity

The claim that α represents the essential value of a reinforcer can be validated by demonstrating that the value of the parameter changes in expected ways with manipulations that alter a good's essential value. Figure 3 presents a data set from Hursh (1991) that is appropriate for such an evaluation. In one condition of this experiment, each of three monkeys earned its daily food ration under FR schedules in 12-hr sessions ("earned only" in Figure 3). Two other conditions were the same except monkeys received one third and two thirds of their ration at session's end on a response-independent basis ("one-third free" and "two-thirds free" in Figure 3). In a final condition, four 65-min sessions were conducted in a single day, during the last 5 min of which monkeys earned food pellets for every response ("5-min CRF" in Figure 3).

Three features of the data in Figure 3 are noteworthy. First, the exponential-demand model presented as Equation 6 does a good job of accommodating data variance, with the values of R^2 equaling at least .95 in all individual curves and a global fit of .986. Second, the manipulations that should decrease essential value (reflected in an increase in the α parameter) did so: As shown in Table 2, increases in the availability of a temporally removed, "cheap" food (the delivery of one third vs. two thirds of the daily food ration after 12 hr of work), and of temporally proximal, "cheap" food (5 min of continuous reinforcement following a 1-hr work session) produced the expected increases in the value of the α parameter. In other words, Equation 6 does an acceptable job not only in mirroring the functional form of the demand curve but also in scaling the essentiality of earned food.

Figure 4 illustrates three additional successful applications of the exponential-demand model to different data sets found in the literature. The top panel of the figure presents a pigeon's food consumption (grams consumed) as a function of response requirement expressed as pecks/gram when the animal's daily food ration was earned within the experimental session (see Figure 7 from Peden & Timberlake, 1984). The graph, anchored by a baseline condition of free consumption, shows data for three reinforcer sizes (3, 9, and 15 s of access to grain) under an increasing series of FR schedules. As a second illustration, the middle panel of Figure 4 presents the average consumption of eight cigarette smokers when the delivery of a three-puff reinforcer was contingent on completing one of nine different FR or PR schedules (see Figure 1 from Giordano, Bickel, Shahan, & Badger, 2001). The highest "per-puff" price was 8,000 (24,000 responses for a three-puff reinforcer). Finally, a third example is shown in the bottom panel of Figure 4 which was based on data from a study by Jacobs and Bickel (1999). In this study, human subjects simulated a demand curve by responding to a questionnaire indicating how much of a commodity, either cigarettes or heroin, they would purchase over a range of unit prices. As might be expected, demand for cigarettes had a rate constant, α, about 10 times larger than that for heroin. This example is important because it demonstrates that the form of the demand curve and sensible comparisons between reinforcers do not depend on actual consumption or variations in motivation throughout the course of a test session.

As is apparent from the three panels of Figure 4, Equation 6 does a good job of modeling variations in consumption, whether the data were based on pigeons pecking a key for varying amounts of grain, humans smoking cigarettes, or humans reporting simulated purchasing decisions. Interestingly, Jacobs and Bickel (1999) applied the demand model of Equation 1 to the data from the 17 human subjects, each asked to assess two demand curves for each commodity. Of the 68 demand curves evaluated by that older model, 21 yielded positive initial slopes (*b*) at the hypothetical price of zero, a predictive error that could not happen with the exponential demand model in Equation 6.

The modeling exercise begun in Figure 4 is consistent with our claim that Equation 6 often does a good job in accommodating data variation in a wide variety of behavioral-economic demand curves. Although we could offer additional examples to strengthen this claim, it would invite concern that the target data sets may have been selected less for their representativeness of model

[2] A calculator for determining approximate parameter values of Equation 6 is available on the Institutes for Behavior Resources website: http://www.ibrinc.org/ibr/centers/bec/BEC_demand.html

Table 1
Parameter Values of Exponential-Demand Model for Fits to Two Demand Curves for Food Reinforcers by Rats

Parameter	Reinforcer: 1 pellet	2 pellets
Q_0	533	273
k	3.00	3.00
α	2.5×10^{-06}	2.5×10^{-06}

Note. Q_0 specifies the highest level of demand; k represents the range of the dependent variable in logarithmic units; α specifies the rate of change in the exponential.

adequacy than for their felicity of fit. One way of deflecting such criticism is to model all demand curves from a single review article where those curves were selected by that article's author for reasons other than their prospects of fitting Equation 6. Toward this end, we have applied Equation 6 to the 15 demand curves in Figure 1 from Lea (1978) that are composed of five or more data points. These curves are presented in Figure 5. The letter code in each panel matches that used by Lea. The reader is referred to Lea for references and discussion of these studies. The values of α and R^2 are shown in each panel; the span of the exponential (k) was constrained to the best value between 1 and 4 log units. Generally speaking, Equation 6 does an acceptable job of characterizing the data in this figure. This conclusion is supported by noting that across the 15 data sets in the figure, the median proportion of the

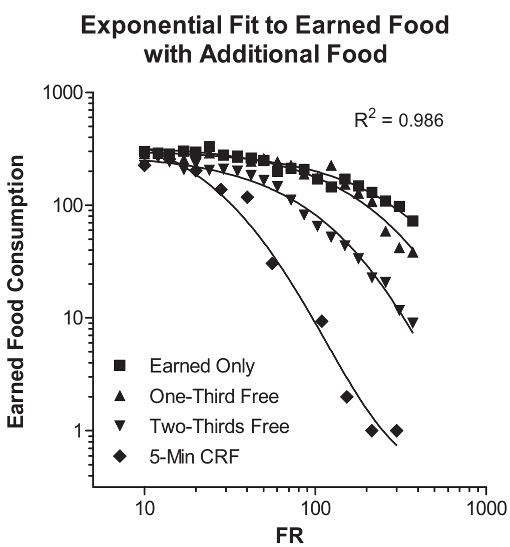


Figure 3. Food reinforcers earned per day by monkeys working for food, mean of three subjects. The squares are from baseline with no free food. The triangles are from conditions in which one third (peak up) or two thirds (peak down) of baseline consumption was given freely at the end of the 12-hr work period. The diamonds are from a condition in which the subjects worked in four 1-hr sessions and received food under a fixed ratio (FR) 1 for 5 min following each 1-hr session. Variance accounted for (R^2) across all curves is shown in the panel and the parameter values of the equation for each condition are shown in Table 2. (Data from Hursh, 1991.) CRF = continuous reinforcement.

Table 2
Parameter Values of Equation 6 for Fits to Four Demand Curves for Earned Food With Varying Amounts of Free Food After the Work Session With Monkeys

Parameter	Condition: No free	1/3 free	2/3 free	5-min CRF
Q_0	305	336	285	588
k	3.13	3.13	3.13	3.13
α	1.99×10^{-06}	2.78×10^{-06}	6.67×10^{-06}	1.47×10^{-05}

Note. No free denotes that all food had to be earned in the experimental session; 1/3 free and 2/3 free indicate the portion of the daily ration given after the session ended; 5-min continuous reinforcement (CRF) signifies that for 5 min at session's end, every response was reinforced. Q_0 specifies the highest level of demand; k represents the range of the dependent variable in logarithmic units; α specifies the rate of change in the exponential.

data variance accommodated by Equation 6 was 0.94 and the interquartile range of these proportions was 0.92 to 0.985.

Finally, our claim that Equation 6 adequately adjusts for differences in Q_0 is illustrated in Figure 6. Hursh and Winger (1995) proposed to normalize demand curves in terms of the size of the reinforcer relative to baseline consumption, Q_0. This approach has been demonstrated as a useful way to isolate the strength of demand for drugs that differ in dose and potency (Hursh et al., 2005; Ko, Terner, Hursh, Woods, & Winger, 2002; Winger, Hursh, Casey, & Woods, 2002; Winger, Woods, & Hursh, 1996).

This normalization process is inherent in Equation 6. Normalization of price is accommodated by the inclusion of Q_0 in the exponential rate constant, and normalization of consumption is accommodated by a logarithmic transformation of consumption. Scalar variations in the price that result from varying amounts of reinforcement under each response requirement are reflected in the standardized price as the amount of responding that would be required to defend the highest level of consumption, Q_0 (see Equation 5). Scalar differences in consumption resulting, for example, from changes in dose (a multiplicative operation on consumption) become additive shifts in logarithmic consumption and have no effect on slope or elasticity of demand. The adequacy of these transforms is verified in the top panel of Figure 6, which shows different demand curves for four doses of alfentanil, a powerful opiate reinforcer (see Ko et al., 2002). Shown for a group of monkeys are mean numbers of drug infusions per day obtained as a function of the prevailing FR schedule. Although the demand curves in the top panel of the figure appear to differ dramatically in slope, these differences disappear when subjected to analysis with the exponential-demand model (see bottom panel of the figure and Table 3). As is apparent, all scalar differences in slope are accommodated by variations in Q_0 such that α is constant across the four doses of the drug. To illustrate this conclusion graphically, we have rescaled the top panel to adjust for differences in Q_0, shown in the bottom panel of Figure 6. All FR values were converted to the standardized price for each dose ($FR_n \times Q_0$), and all consumptions were rescaled as proportions of Q_0 for that dose (Q_n/Q_0). The four demand curves in the top panel converge to a single standardized demand curve for alfentanil with a singular α of 1.41×10^{-5}.

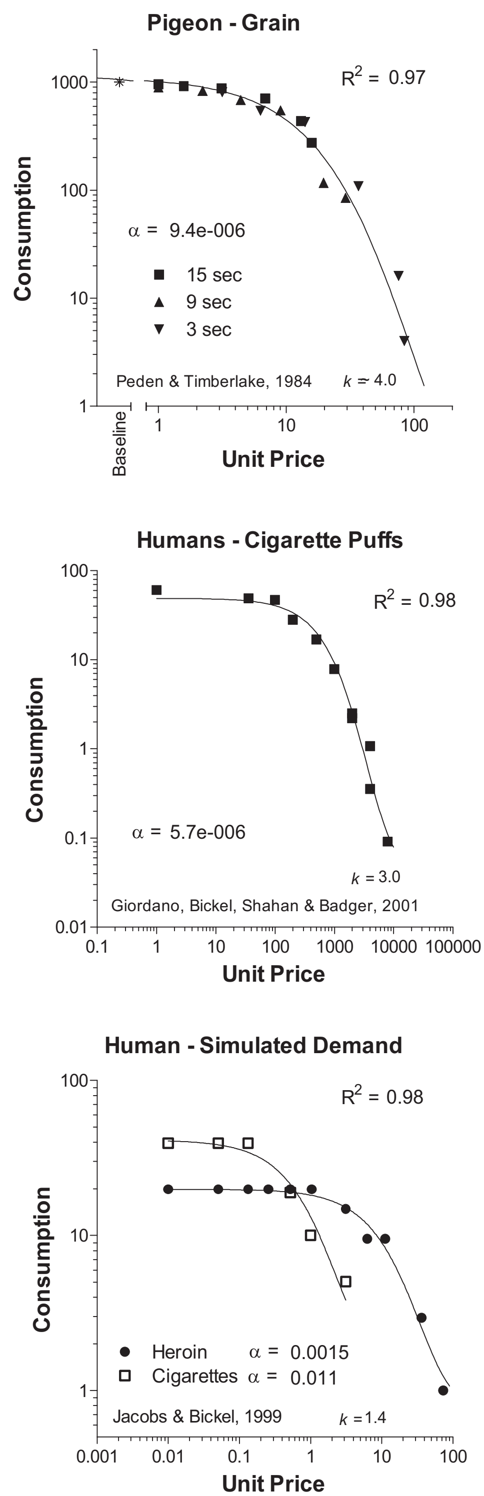


Figure 4. The fit of the exponential-demand equation to three data sets from pigeons and humans. Data sets are from the references cited in each panel. Variance accounted for (R^2) and the value of α for each commodity are shown in each panel.

Practical Applications of Essential Value

The economic-demand model has immediate application for assessment of drug abuse liability and animal welfare. For human consumers, pharmaceuticals are often evaluated for potential to serve as reinforcers and support drug abuse. Currently, no standard method has been adopted by the industry to evaluate abuse liability even though studies with humans and nonhuman primates have demonstrated the validity of a behavioral-economic approach (see reviews by Hursh et al., 2005; Rowlett, 2000; also see Bickel, Madden, & Petry, 1998; Bickel et al., 2000; Bickel, Warren, & DeGrandpre, 1996; Hursh, 1991; Jacobs & Bickel, 1999; Spiga, Martinetti, Meisch, Cowan, & Hursh, 2004). The model described here advances that approach by providing a quantitative solution to the problem of scaling abuse liability.

In designing habitats for confined animals or for agricultural purposes, ethical concerns have been raised concerning the quality of life for the animals. One of the first questions that must be answered is what features of the environment or what kinds of consumables are of greatest importance to animals. Scientific methods, behavior analysis, and economic theory have been proposed to address this question (Dawkins, 1983, 1990; Gunnarsson et al., 2000; Harris et al., 1999; Matthews & Ladewig, 1985; Sumpter, Foster, & Temple, 1995; Sumpter, Temple, & Foster, 1999), and the approach detailed here seems to provide one clear answer: Essential value based on differences in exponential demand provides a metric that indirectly reflects the animal's priorities of need.

Essential Value and Choice

We have argued for a standard of value that is based on demand-curve analysis. However credible our arguments seem, they face a remaining hurdle: the face validity of the preference test as an index of value. After all, given an item is chosen, why should one question that it is the most valued among alternatives? Do we really need to generate demand curves to define the value of a good?

An answer to these questions can be found by example in the diamond-water paradox that is often presented to students of economics: The preference the reader may have for a diamond over water while reading this article would readily reverse were you given this choice while thirsty in the desert. What this example shows is that relative reinforcer strength or value as measured in choice fails because it is not independent of income and price. As a corollary of this conclusion, there is no direct relationship between essential value and the outcome of a preference test. The results of Elsmore et al. (1980) cited earlier illustrate the effects of an income variable on choice.

Choice is a complex derivation from underlying demand relationships, but because consumption at a particular price is dependent on the prices of alternatives and possible interactions with other available substitutes and complements (Hursh, 1978, 1980, 1984), the outcome of a particular choice test is not reliably related to a simple comparison of essential values. On the other hand, comparative demand curves for commodities that do not interact (i.e., they are neither substitutes nor complements) should predict choice under conditions of equal price (see Bickel & Madden, 1999; Bickel et al., 2000; Madden et al., 2000). Although it is

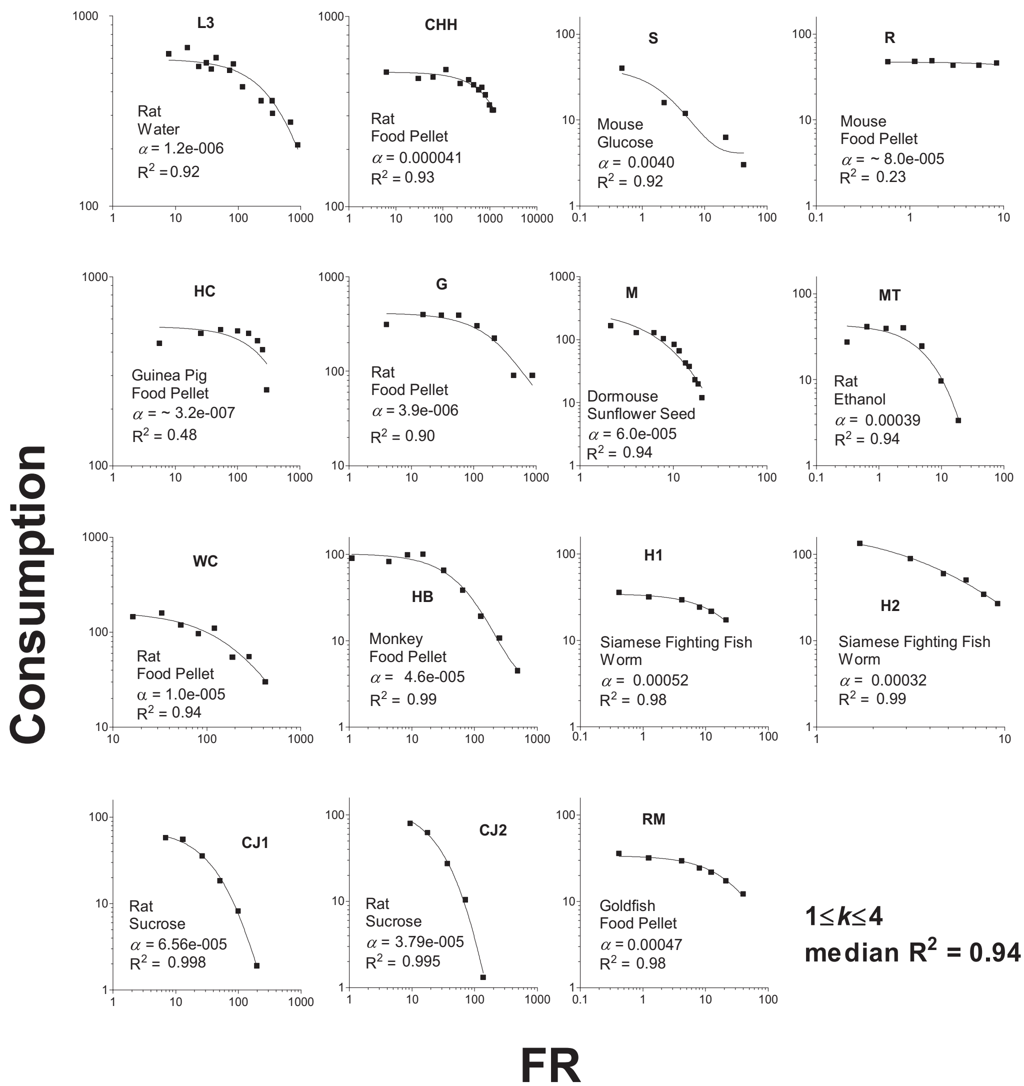


Figure 5. Data from fifteen studies reviewed by Lea (1978) and shown in his Figure 1. These data were extracted from the figures and reanalyzed here using the exponential-demand model. Each graph is labeled with a key that indicates the species, reinforcer, the value of the α parameter, and the R^2 for the exponential-demand equation. The letter code in each panel matches that used by Lea in his study.

beyond the scope of this article to elaborate on how this might be accommodated within the context of exponential demand, our analysis of demand-curve data from two-commodity situations indicates that the consumption of one of two reinforcers is the weighted sum of two exponentials. One exponential is related to the price of the target commodity, and the second is related to the price of the alternative commodity. The sign of the weighting factor determines whether the two reinforcers interact as substitutes or complements. If the constant has a negative sign, then consumption of one subtracts from consumption of the other and the two commodities are defined as substitutes. The degree of substitution is determined by the size of the weighting factor. Alternatively, if the weighting factor is zero, then demand for one of the reinforcers is independent of the price of the other.

From the perspective of a demand analysis, preference is a derived outcome of comparative levels of consumption, and the underlying demand curves of the goods chosen describe the more general impact of different reinforcers on behavior across the full spectrum of constraint. For this reason, we contend that essential value, and not preference, is the superior approach for defining reinforcer strength or value.

Conclusions

A simple classroom exercise can be used to explain the notion of operant strength: Imagine a student is told there is \$10 in the top drawer of the teacher's office desk. The door to the office is unlocked, and the student may take the money whenever it is convenient. As matters unfold, the student picks up the money 3 days later, the student's next occasion for visiting that area of the campus. Next, the teacher repeats this experiment, but this time the amount in the desk drawer is \$10,000. To no one's surprise, the

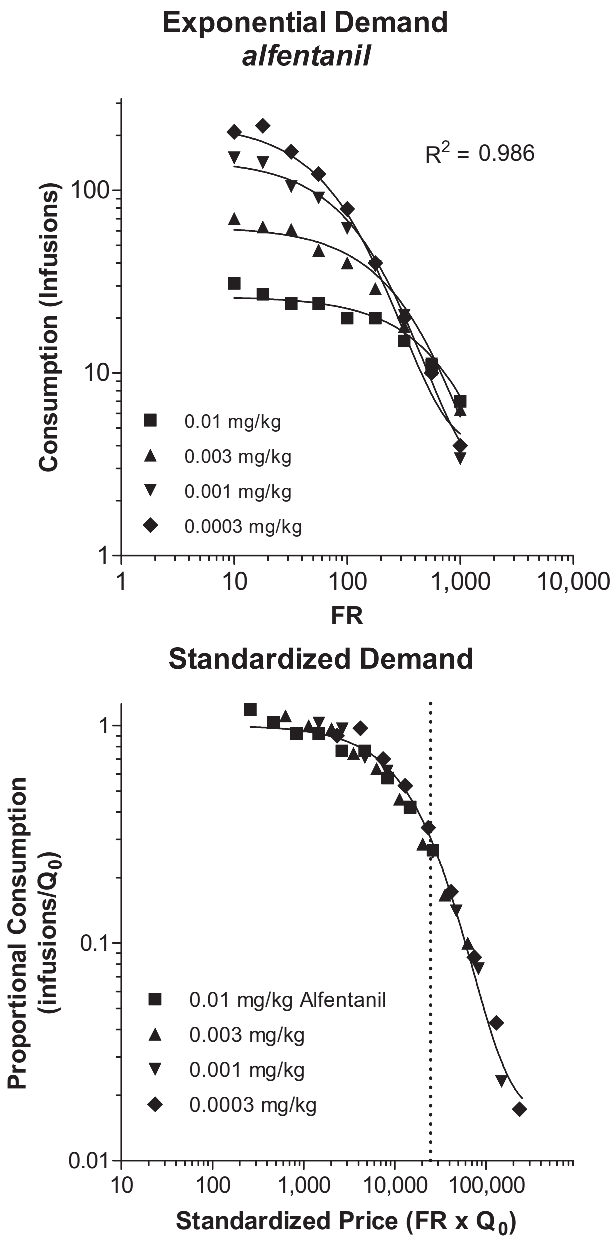


Figure 6. For four doses of alfentanil self-administered by monkeys, exponential-demand (Equation 6) fit to consumption data and standardized demand are shown, respectively, in the top and bottom panels. Variance accounted for (R^2) across all curves is shown in the top panel and the parameter values of the equation for each condition are shown in Table 3. In the bottom panel, the point of unit elasticity is indicated with a dashed vertical line. Data are from Ko et al., 2002. FR = fixed ratio; Q_0 = highest level of demand.

student bolts from the classroom and picks up the money 5 min later.

In this example, behavior indexed the strength of the reinforcer, whether measured in terms of its vigor or its speed. Ironically, showing a similar effect through the use of schedules of reinforcement proves more difficult. To illustrate, imagine a rat completes an FR 50 more rapidly for two food pellets than for one. Despite the superficial similarity to the money experiment presented above, the training history necessary to illustrate this effect complicates the analysis, as, by responding more rapidly for two pellets than for one, two things now vary: the amount of reinforcement and the rate of reinforcement. To what degree is the increased vigor of responding due to the increase in the amount of food rather than the increased density of reinforcement that increased response rate produces?

Much of the problem with making a schedule-based assessment of strength is inherent in how schedules are arranged. In the pursuit of steady-state behavior, operant analysts typically give many repetitions of a schedule per session. Although this experience enables animals to learn a schedule's properties, it raises the concern that any dependent variable used to assess strength might be a consequence not just of the reinforcer used but also of the rate-shaping properties of the schedule by which it is presented.

A major virtue of a behavioral-economic approach is that its use of schedules is holistic—the focus is on the relation between behavioral output and consumption and not on rates of response, rates of reinforcement, or the specific response–reinforcer relations that produce these measures. The question is as follows: Just how hard is an animal willing to work to produce the goods it consumes? In this regard, a behavioral-economic approach to assessing strength has a face validity that is hard to reproduce when the underlying schedule of reinforcement is an important property of the assessment.

To the extent this argument is accepted, students interested in assessing the strength/value of a reinforcer/good will move naturally toward the use of ratio schedules over others and will scale these variables in terms of consumption constrained by price. Sessions will end not after an arbitrary number of reinforcers but when the subject has "had enough" at the price the investigator is "charging." In our view, a demand curve constructed in this way has embedded within it the true measure of value.

Where in that curve does true value reside? One need only measure the rate at which consumption diminishes with price. Considered alone, such a measure of value is problematic because value changes continuously with the price charged. The solution this paper proposes is to use the exponential model of demand based on standard units of price. Its virtue is that it can largely reproduce this continuously changing demand curve in terms of an equation that has a single free parameter that determines slope. It is the value that parameter attains that scales a good's essential value.

Table 3
Parameter Values of Equation 6 for Fits to Daily Self-Administered Infusions of Four Doses of Alfentanil by Monkeys

	Dose (mg/kg)			
Parameter	0.01	0.003	0.001	0.0003
Q_0	26	63	147	232
k	1.76	1.76	1.76	1.76
α	1.41×10^{-05}	1.41×10^{-05}	1.41×10^{-05}	1.41×10^{-05}

Note. Q_0 specifies the highest level of demand; k represents the range of the dependent variable in logarithmic units; α specifies the rate of change in the exponential.

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Correction to Sedlmeier and Kılınç (2004)

On p. 772 (*Real Data* section) of the article 'The Hazards of Underspecified Models: The Case of Symmetry in Everyday Predictions," by Peter Sedlmeier and Berna Kılınç (*Psychological Review*, 2004, Vol. 111, No. 3, pp. 770–780), some numbers were listed incorrectly. The correct numbers are as follows:

For soccer world championships (1930–1978), number of games in which a given team both won and led at halftime = 151, number of games in which a team won the game = 243, number of games in which a team led at halftime = 196, $P(\text{WinMid}|\text{WinEnd}) = .62$, and $\boldsymbol{P}(\text{WinEnd}|\text{WinMid}) = .77$.

For the German Bundesliga (1994–1995), number of games in which a given team both won and led at halftime = 132, number of games in which a team won the game = 223, number of games in which a team led at halftime = 174, $P(\text{WinMid}|\text{WinEnd}) = .59$, and $P(\text{WinEnd}|\text{WinMid}) = .76$. The conditional probabilities are referred to again on p. 778. There, it should read 'These quotients correspond to $P(\text{WinMid}|\text{WinEnd})/P(\text{WinEnd/WinMid})$, the empirical values of which were found to be .81 and .78 (.62/.77 and .59/.76, see above)."

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