Chapter 10
Basic Research on the Behavioral Economics of Reinforcer Value

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10.1 Introduction

Since B. F. Skinner's seminal book, *The Behavior of Organisms* (Skinner 1938), operant conditioners have relied on reinforcement-based systems to change behavior. Central to the operant approach in psychology is the *law of effect,* premised on Thorndike's work demonstrating that contingent access to appetitive consequences strengthens behavior (Thorndike 1898). It is unsurprising, then, that positive reinforcement has been identified as the most critical component in affecting socially relevant behavior change (Skinner 1953; Skinner 1971). The ubiquity of positive reinforcement for promoting change is of particular relevance for this book given that this procedure has been identified as a core component in most evidence-based practices in autism service delivery (see Ahearn and Tiger 2013; also see Luiselli et al. 2008). The goal of this chapter is to discuss ways that the experimental analysis of behavior (EAB) has contributed to behavior analysts' (a) understanding of reinforcer efficacy and (b) identification of efficacious reinforcers for behavior change programs through behavioral economics.

This chapter expands on two foundational considerations. The first consideration underlying the research summarized in this chapter is the *law of demand* that states that the relative consumption of a commodity—for the sake of this chapter, a reinforcer—will decrease when subjected to forms of constraint (Samuelson and Nordhaus 1985). Put simply, increases in reinforcer cost (e.g., effort, delay) result

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in decreased rates of behavior. The second consideration guiding the concepts of this chapter is that the term *demand* may be defined as the extent to which an organism defends consumption of a reinforcer in the face of the aforementioned constraints (Hursh 1984; Reed et al. 2013). The ways behavior analysts study demand (i.e., demand metrics) will thereby vary as a function of the experimental question or paradigm. Despite varying approaches to demand characteristics, each demand metric provides a quantitative account regarding the extent to which an organism works to maintain consumption of the relevant reinforcer. Reinforcer demand is a multifaceted variable that entails the collective analysis of myriad components and analyses/parameters, each telling one part of the story. As such, demand may be conceptualized as a molar measure of reinforcer efficacy.

10.2 Basic Preparations for Measuring Reinforcer Value

Central to all operant approaches to behavior change is an interaction between the environment and consequences that affects a target response. Environmental stimuli may begin to exert control over behavior absent delivery of reinforcement, but only after adequate pairings between environmental context and reinforcement; this process is known as stimulus control and is discussed at length elsewhere in this volume (see Chaps. 2 and 3). Outside of stimulus control arrangements, operant approaches rely most heavily on reinforcement. A reliance on reinforcement becomes exacerbated when clients or learners have difficulty generating verbally governed rules or discriminating features of the environment that would lead to stimulus control—common behavioral deficits for individuals diagnosed with autism (Jones et al. 2013). The ubiquity of reinforcement in operant approaches to autism treatment thereby necessitates identification of the most efficacious reinforcers. The relative efficacy of a reinforcer is quantified by the *strength* of a response under its influence (see Skinner 1938; Hursh and Silberberg 2008). As such, it is no surprise that the EAB has long sought the most parsimonious measure of this construct (see Hursh and Silberberg for a comprehensive review).

Early approaches to measuring response strength entailed an analysis of operant response rate in the presence of reinforcement (Skinner 1938). As more evidence emerged that the mere scheduling of reinforcer delivery itself could drastically influence response rate patterns (i.e., the same reinforcer can produce different response rates if different schedules are used; Ferster and Skinner 1957), it became obvious that response rate, alone, was an insufficient account of reinforcer efficacy. Later approaches to response strength relied upon Herrnstein's matching law that examines choice under concurrent schedules of reinforcement (for a review, see McDowell 2013). However, the matching law approach was only relevant for relative comparisons of reinforcers in concurrent schedules and failed to account for relevant economic principles such as price and budget/income (see Hursh and Silberberg 2008). Contemporary behavior analysts and behavioral economists now recognize that the best metrics of reinforcer efficacy are those that (a) are independent of schedule arrangements, (b) can be used to quantify response strength under a single schedule, and (c) permit scaling of reinforcer value by accounting for the two aforementioned issues.

To account for the relative shortcomings of previous EAB attempts to quantify response strength and reinforcer efficacy, contemporary research focuses on two simple metrics of operant behavior: response output and reinforcer consumption. *Response output* is typically quantified as the number of responses emitted within a set of environmental constraints (i.e., conditions, contexts). For nonhuman subjects, responses may be key pecks (pigeons) or lever presses (rats). For humans, highly controlled laboratory studies may include responses such as plunger pulls or keyboard presses, while applied studies may use responses such as math problems completed (in classroom settings) or items sorted (in residential or workplace settings). The aforementioned responses in behavioral economic studies result in contingent reinforcement. The term *consumption* is used to describe reinforcer delivery to emphasize the interaction between the environment and response output as a translation of traditional economic concepts (e.g., consumption of goods in constrained markets; see Hursh 1980). For humans and nonhumans alike, consumption may include the amount of edible reinforcers consumed (in total count or in weight, depending on the experimental arrangement or research question). Human participants' level of consumption may also extend to other dimensions of reinforcement delivery, such as the number of tokens earned in a token system (assuming adequate evidence that tokens maintain behavior) or the number of praise statements provided by another person; in any case, the commodity quantified in the level of consumption must be a putative reinforcer for any analysis of reinforcer efficacy.

10.2.1 Common Design Elements in Evaluating Reinforcer Value: A Parametric Approach

Researchers in the field of behavioral economics use both behavior analytic principles and aspects from consumer demand theory to quantify reinforcer effectiveness. This interdisciplinary unification of behavior analysis and microeconomics allows for novel techniques and methods in the scientific study of behavior (Hursh and Silberberg 2008). Whereas the traditional operant analyst emphasizes the study of behavior within the context of the environment, specifically when it comes to different schedules of reinforcement, the behavioral economist, on the other hand, shifts the focus to extensively studying the reinforcer and its role within the context of consumer demand (Hursh and Silberberg 2008). This mixing pot of interdisciplinary techniques and methods allows for new questions to be asked and answered, something that neither the field of behavior analysis nor microeconomics can do quite as well on its own.

When the goal is to evaluate the properties of the reinforcer, behavioral economists typically tend to rely on the parametric design—a form of within-subject design which is useful for examining the effects of a parameter when that parameter

Fig. 10.1 A prototypical demand curve analysis indicating that there is a level of inelasticity before consumption becomes elastic using a parametric evaluation of unit prices, according to the law of demand. See text for details

is systematically manipulated (Johnston and Pennypacker 2009). By systematically manipulating the variable, the researcher not only assesses the replicability of the data but also examines the boundary conditions of the independent variable, or the points at which the variable loses its effectiveness (Branch and Pennypacker 2013). The parametric design may be interpreted as an extended comparison design (AB) where the letter designations represent the different changes in the parameter. For instance, if the behavioral economist is interested in the consumption of a reinforcer as a function of eight different prices, then the letter sequence can be construed as ranging from A through H in a comparison design. Of course, the analyst could reproduce the findings obtained at one parametric value by replicating this condition in a reversal design, but this practice is rarely used in behavioral economic studies of demand (to be described in detail later in this chapter). Systematically manipulating the price of a reinforcer, the independent variable, is useful for examining the effect it has on the consumption of that reinforcer, the dependent variable. When plotted graphically, this relation between the price of the reinforcer and its consumption is described as a *demand curve* whereby the level of consumption decreases as a function of increasing price. According to the law of demand, consumption at very low prices describes baseline (or maximum) demand for the reinforcer. As evidenced in Fig. 10.1, however, consumption decreases in a nonlinear function as prices increase. The demand curve thereby summarizes the organism's defense of baseline consumption in the context of increasing prices. The rate at which consumption changes across the demand curve constitutes *elasticity,* the primary dependent variable in demand curve analyses.

The parametric approach to reinforcement entails the three elements of baseline logic as described by Cooper et al. (2007): prediction, verification, and replication. Prediction refers to the notion that similar levels of responding are to be expected if the baseline were held constant (Cooper et al. 2007). Thus, the element of prediction is applied to evaluating demand curves when little or no change in consumption is expected as a result of confining the price of the reinforcer to a single value *(inelasticity)*. For example, if the price of a reinforcer is zero, then its consumption is expected to persist at a relatively similar level after repeated trials as long as the price remains the same. However, it is noteworthy to mention that the consumption of a freely available reinforcer may be affected by factors such as the organisms' level of deprivation as well as by the magnitude of reinforcement (Hursh 1984). In nonhuman experiments, for example, it has been shown that pigeons tend to maintain a stable free-feeding weight when the food is freely available. It is expected that levels in consumption will remain unchanged as long as the price of obtaining that reinforcer remains unchanged.

The second element of baseline logic, verification, is also applicable and pertinent to the parametric experiment, specifically the demand curves analysis. The operant behavior analyst attempts verification only after demonstrating stability in responding prior to implementing the independent variable (Johnston and Pennypacker 2009). Observing a change in responding after the independent variable is introduced reveals a correlation between the independent and dependent variable. Similarly, the withdrawal of the independent variable is expected to bring upon changes in the dependent variable. If, after the withdrawal of the independent variable, the levels of responding revert to similar levels as in the baseline phase, then a functional relation between the independent and dependent variable appears more likely, and thus, the verification has decreased the likelihood of extraneous variables affecting levels of responding (Cooper et al. 2007). The behavioral economist uses the element of verification in a similar manner by observing that a change in consumption coincides with a change in the price of the reinforcer. At this point, the behavioral economist has three options: (1) to maintain the current price of the reinforcer, (2) to revert to a previous price, or (3) to increase the price. Manipulating the price of the reinforcer and observing a change in consumption will decrease the likelihood that extraneous variables coincided with changes in the dependent variable. Systematically manipulating the price several times provides further support for a functional relation between the two variables. There is, however, yet another way to bolster the confidence between changes in price and changes in consumption. The behavioral economist might, for example, manipulate the price of a reinforcer for several subjects at different times in the experiment. In doing so, it is reasonable to expect that the levels of consumption will remain relatively stable for each subject until the price is changed in some way. Observing that the change in consumption coincides with the change in price helps verify a relation between the two. The logic for this attempt at verification is identical to that of the multiple baseline across subjects design within the framework of single subject methodology.

The third element of baseline logic, replication, deserves greater consideration and a sufficient understanding of reliability. According to Sidman (1960), "when we ask whether data are reliable, we usually mean: 'will the experiment, if repeated, yield the same results?'" (p. 43). A study bears little importance if the findings are irreproducible. This concept of reliability deserves great consideration for any scientific discipline, and especially for the field of behavioral economics in which the goal may be to guide public policy. Fortunately, a parametric design is beneficial for demonstrating the reliability of the results. As mentioned previously, a replication is demonstrated when consumption reverts to previous levels following a decrease in the price of the reinforcer. This is similar to the reversal design, or ABA design, within the single subject framework. Furthermore, the behavioral economist may demonstrate replicability of results by systematically changing the price of the reinforcer in an ascending or descending sequence and observing changes in consumption, a technique that has similarly been used in behavior analysis, specifically when performing a direct replication (Sidman 1960). The third technique for demonstrating replication relies on the multiple baseline across subject design that was previously introduced. The key point with all of these techniques is that the confidence in the relation between price and consumption is increased "each time a behavior changes when, and only when, the independent variable is introduced" (Cooper et al. 2007, p. 203).

Finally, this three-step strategy facilitates a form of inductive logic known as affirmation of the consequent. According to Cooper et al. (2007), affirmation of the consequent is an "if–then" statement that consists of the premise and the conclusion. The relation between the premise and the conclusion is interpreted in the following way: if the independent variable is a controlling factor, then changes in responding will coincide with the independent variable. Indeed, it is observed that the behavior changes after the independent variable is introduced. Therefore, there is an increased likelihood that the independent variable is responsible for changes in the behavior. Nevertheless, there is always the possibility that extraneous factors are somehow involved in the observed behavior change. Replication is the most important tool for decreasing the likelihood that extraneous factors are affecting the dependent variable (Sidman 1960). Each time the independent variable is implemented and removed, and a change in behavior is observed, it becomes less and less likely that the change is due to extraneous factors (Cooper et al. 2007; Sidman 1960).

10.2.2 Preparations that Render Demand Curves

10.2.2.1 Progressive-Ratio Schedules and Breakpoint

Early approaches to understanding the efficacy of a reinforcer was by measuring the strength of responding via the analysis of response rates in the presence of some disruption (cf. behavior momentum; see Chaps. 12 and 13 of this volume). Disruptions could be the change in stimulus conditions, imposing a punisher, or extinction. A response that persisted in the face of this behavioral adversity is thereby considered stronger than one that more quickly extinguishes. In 1961, Hodos noted that many disruptions—especially electric shock—would generate high variability in responding, complicating across condition comparisons (Hodos 1961). To arrive at a more pure measure of response strength, Hodos proposed the use of progressive-ratio (PR) schedules in which the price of each reinforcer (the number of responses necessary to earn one unit of reinforcement; termed *unit price*) increases upon the completion of each response requirement (i.e., the delivery of a reinforcer) until reinforcer consumption ceases; the first unit price at which schedule requirements are no longer met is known as the *breakpoint;* as described by Jarmolowicz and Lattal (2010), breakpoint

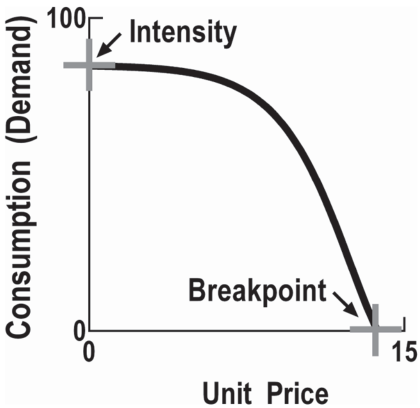

Fig. 10.2 A prototypical demand curve analysis indicating intensity of demand (*gray crosshair* indicating maximum consumption at unit price of zero) and breakpoint (*gray cross* at consumption level of zero to indicate the unit price at which responding (and thereby reinforcer consumption) ceases)

constitutes the "point at which schedule-specified contingencies no longer provide sufficient reinforcement to maintain responding" (p. 121). Initial consumption at the lowest unit price may thereby be considered a measure of demand intensity, or maximum demand (see Fig. 10.2 for a visual depiction of demand intensity and breakpoint). Hodos supported this proposal with the inclusion of data from rats earning access to primary reinforcers (small amounts of milk). Rats were presented with initially low unit prices to document demand intensity. Upon completion of the response requirement, a small amount of reinforcement was provided which then activated the next response requirement that consisted of two additional responses (amount of reinforcement was carefully selected to best circumvent a confound of satiation). Thus, with the unit price requiring two responses, completion of the ratio requirement (termed the *ratio run*) resulted in the next unit price requirement of four responses, and so on. Ratio requirement increased within session until demonstration of a breakpoint. This procedure was implemented across three conditions: (a) decreasing concentrations of milk (diluted with water; that is, a reinforcer magnitude manipulation), (b) stable concentrations of milk but under different amounts of food restriction (i.e., a deprivation manipulation to evoke motivating operations for the reinforcer), and (c) increasing concentrations of milk under different amounts of food restriction. Each condition yielded orderly breakpoint data suggesting that the PR schedule was sensitive to predicted differences in reinforcer efficacy. These data nicely illustrate the advantages of using the breakpoint as a metric of reinforcer efficacy. The advancements provided by PR schedules in the analysis of reinforcer efficacy resulted in this arrangement becoming the gold standard in behavioral pharmacology research, evidenced by an exponential increase of its use in peer reviewed studies over the subsequent decades (Jarmolowicz and Lattal 2010).

Underlying the prototypical PR schedule arrangement are three specific contingencies that influence operant performance (see Jarmolowicz and Lattal 2010). In the first contingency, a reinforcer is delivered when the active ratio requirement is satisfied via the target response (e.g., the 20th response on a fixed-ratio (FR)

20 schedule is consequated with access to a reinforcer). After the organism consumes the reinforcer, the second contingency becomes activated wherein there is a change in the response requirement for the next unit of reinforcer (i.e., increased or decreased; most studies, however, feature increases in the response requirement). Regardless of the increasing/decreasing direction of the PR progression, each organism's response activates the third contingency of advancing the total session duration.

While the majority of PR schedule work has used the design components detailed in the above paragraph, the past several decades have seen a gradual increase in the number of studies modifying the traditional PR approach. As described by Jarmolowicz and Lattal (2010), the bulk of such studies can be summarized into two broad categories: (1) between-sessions schedule progression or (2) intermittent PR schedules. Limitations exist within both PR alternatives, however, which complicate between-studies comparisons. Between-sessions PR progressions program the PR step size to be constituted at the start of the next session. In this approach, the active FR requirement is in place for one session and remains in place until the organism completes the requirement that thereby terminates the session. This deviates from typical PR arrangements in that the organism no longer controls the duration of the session and there is no immediate change in contingency. Such preparations may render demand curves that are topographically similar to those generated by standard PR arrangements, but there is ample evidence to suggest that the response rates and breakpoints observed between such procedures are actually disparate (see review by Jarmolowicz and Lattal 2010; also see Foster et al. 1997). The intermittent alternative to PR arrangement entails the ratio requirement being in effect for a repeated number of blocks concluding with reinforcer deliveries. For example, an organism may earn three reinforcers under three consecutive FR 10 requirements, after which the requirement increases to FR 15 for the next three reinforcement opportunities (all within session). While more similar to the standard PR arrangement, such intermittent approaches extend the duration of the session and make responding less sensitive to ratio strain. This approach complicates comparisons between standard PR arrangements because organisms tend to complete a larger number of ratio requirements but may also generate lower breakpoints (again, see review by Jarmolowicz and Lattal; also see Li et al. 2003; Stafford et al. 1999).

Consider the following bridge study by Reed et al. (2009) that investigated the degree to which standard preference assessments (paired stimulus, multiple stimulus without replacement, and free operant) predicted relative reinforcing efficacy of edibles for an adult diagnosed with pervasive developmental delays. In this study, the researchers used a standard single-operant within-session PR arrangement to evaluate reinforcer efficacy. The operant task in this study was pressing a large push-button switch. Programmed ratio requirements resulted in the delivery of an auditory tone when the requirement was met, prompting the participant's therapist to deliver one edible. As depicted in Fig. 10.3, four possible reinforcers (Gushers, Doritos, Pringles, and Sour Patch Kids) featured equal demand intensity, suggesting relatively equivalent preference, given that preference assessments typically entail an FR 1 selection criterion (i.e., participant points to the preferred edible). However,

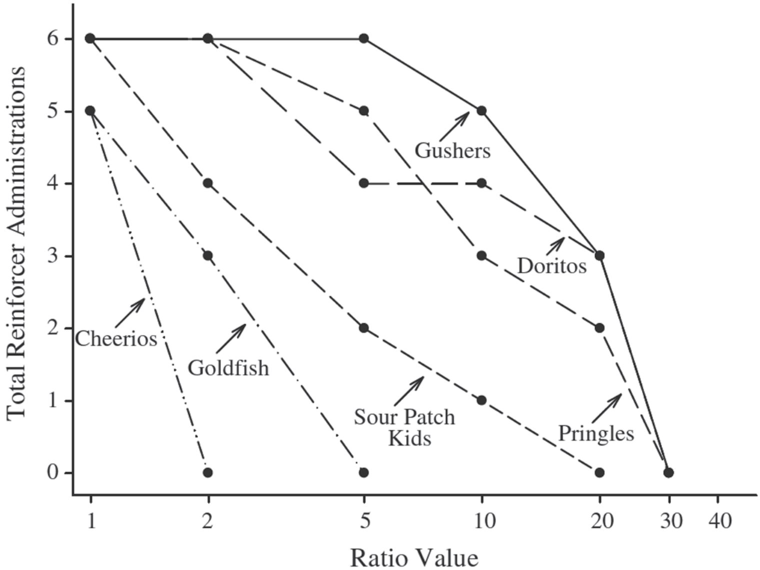

Fig. 10.3 Independent consumption of six different edibles as a function of ratio value by an adult with developmental disabilities, as assessed by standard single-operant within-session PR arrangement in Reed et al. 2009. Printed with permission granted under the author copyright permission agreement to the first author

the elasticity of demand across the entire range of ratio values was quite disparate, highlighting the importance of supplementing preference assessments with some form of demand assay. Notwithstanding the contributions of the PR assessment in understanding relative reinforcer efficacy beyond simple preference assessments, Fig. 10.3 also underscores two important limitations in the use of PR breakpoints without formal quantitative analysis of demand elasticity (see Sect. 10.3 below). First, the absence of a quantitative model prohibits an objective description of demand elasticity. This limitation is amplified when many potential reinforcers share equal demand intensity and breakpoints, but clearly differ in demand elasticity, as is the case for Gushers, Doritos, and Pringles in Fig. 10.3. Second, PR breakpoints may mask meaningful boundaries in reinforcer demand that could inform clinical service delivery (e.g., selecting a particular unit price for use in programming reinforcers in actual behavior change interventions based on demand performance). In the case of Fig. 10.3, three reinforcers shared a PR breakpoint of 30, which seemingly suggests that using the next lowest ratio value (FR 20) would be an efficient means of programming reinforcement. However, ratio values of 21–29 were not assessed in the PR schedule, posing a major limitation in the identification of the reinforcer demand boundaries (perhaps, Gushers would actually have a breakpoint of 21, while Doritos would have a breakpoint of 29). In sum, PR breakpoints are only as useful as the thoughtfulness of the prices tested. If the PR step sizes are too large, they become relatively meaningless as they bypass many potential breakpoints. This limitation necessitates investigation of changes between each step size which is best analyzed via nonlinear regression using formal quantitative models of demand elasticity (discussed in detail in Sect. 10.3).

10.2.2.2 FR Schedules and Rapid Demand Assays

As described in detail by Hursh (1980, 1984), early operant studies on organisms' demand for reinforcement that employed FR schedules in lieu of PR schedules relied on data stabilization to guide decisions on when FR values were manipulated (using the parametric design elements described above). However, these procedures often resulted in experiments of very long durations, especially considering that organisms often worked for food across 24 h per day. Such procedures would result in up to 6 months of data collection to render just one demand curve (see Hursh 1984). If multiple levels of an independent variable were manipulated (e.g., magnitude of the reinforcer), it was common for one subject to take over a year to complete a study. Such onerous and lengthy experiments may have exercised extremely rigorous levels of control, but such precision and control become obsolete when behavioral science is necessary to answer critical questions regarding drug trials or potential reinforcers that could be translated to application for the betterment of society are needed in short order.

In an effort to refine the practicality of demand curve studies, Raslear et al. (1988) conducted a series of studies aimed at the development of a rapid demand assay to quickly render demand curves without sacrificing the validity of the procedure with respect to demonstrating relative demand for reinforcement. In study 1 of their experiment, the researchers exposed six rats to four sequences of seven FR values, with each FR value in effect for 24 h. Each rat thereby worked continuously for food in an operant chamber across 28 days. The researchers evaluated numerous aspects of demand in an effort to detect potential limitations with the rapid progression. After accounting for the rats' change in weight, neither replication of the FR values nor the sequence of the FR values substantively accounted for the change in food consumption; the FR values themselves were the strongest predictors of demand. Moreover, the FR values followed the law of demand in that higher values were associated less food consumption. Most importantly, however, was that the shape of the demand function was curvilinear and appeared similar to those obtained in previous studies (e.g., Hursh 1984) that employed long experimental durations relying on data stabilization—rather than temporal sequencing—to advance the ascending FR progression. These findings prompted the researchers to then consider whether the rapid ascending sequence produced data similar to those in a random FR sequence. In study 2, Raslear and colleagues exposed two groups of rats to the same procedures as study 1 (with exception of only 14 days of exposure); the progression was ascending for six rats, and random for another six rats. At the conclusion of study 2, the demand curves between the two groups were nearly indiscriminable, suggesting that rapid ascending progressions do not bias responding in any way that differs from demand curves generated using random FR sequences. Finally, in study 3, the researchers examined whether the rapid ascending sequence yielded differential demand when different FR price densities were used. In this study, the researchers used identical procedures between two groups of rats, with exception of FR values. For one group, the FR values were 1, 1, 3, 9, 27, 81, and 243. For the other group, the FR values were 1, 1, 15, 45, 90, 180, and 360. Neither group experienced an FR value equal to the other group, with exception of FR 1. When plotted on the same figure, the two groups' demand curves were nearly indistinguishable, suggesting that the demand for the reinforcer was equivalent regardless of how the FR prices were presented in the rapid ascending sequence. Note also that the findings from study 3 diminish concerns regarding the ascending progression of the parametric design used in demand curve assays, given that the results do not differ from those presented in a multielement fashion using randomization. Collectively, the three studies of Raslear and colleagues' experiment demonstrate the robust ability of rapid demand assays in describing reinforcer demand using a parametric design. The Raslear et al. rapid demand assay has thereby become the gold standard in reinforcer demand studies using *actual* reinforcer delivery, including those conducted with human adults (e.g., Johnson and Bickel 2006) and children (e.g., Delmendo et al. 2009). Note that human reinforcer self-administration and purchase task studies have replicated the effects of the Raslear et al. experiment, in that PR and random FR sequences do not result in differential demand outcomes (e.g., Giordano et al. 2001), and that different price densities in the price progressions yield similar findings between groups (Reed et al. 2014; Roma et al. 2015).

As an example of the applicability of the rapid demand assay, consider its application in a translational context using children by Delmendo et al. (2009). In the Delmendo et al. study, the researchers were interested in evaluating whether preference assessments accurately described reinforcer demand for four typically developing children in ascending unit prices. The researchers used within-subject comparisons when the FR requirement or magnitude (i.e., number of reinforcers) was manipulated but yoked to the same unit price. Unit price progressed in an ascending sequence and concluded when either 3 min of no responding was observed or the participant vocally indicated being done. Each unit price was conducted across five or more sessions, constituting a slight deviation from the rapid demand assay, but still within the general premise of its design. The demand curves generated for these children were similar to those obtained with nonhumans in highly controlled laboratory settings, suggesting cross-species utility and implications for practice.

10.2.2.3 Hypothetical Purchase Tasks

Notwithstanding the great success of the demand curve assessment in identifying relative reinforcer efficacy, even the rapid demand assay carries the limitation of the necessity of repeated sessions over time. Moreover, repeated sessions with repeated consumption can become costly when the reinforcer is highly valued, if not dangerous when the reinforcer is an illicit or controlled substance, or perhaps harmful if consumed in large quantities in one session (e.g., alcohol, sugar), especially when the unit price is low (e.g., FR 1). Given the growing interest in behavioral economic considerations of drug addiction, the repeated administration of actual commodities may be unethical, especially when assessing abuse liability with nonaddicts. Finally, the rapid demand assay may be especially challenging when the outcomes are impractically (or, perhaps, impossibly) manipulated, as is the case in studies of public policy interventions where repeated administration is infeasible, costly, or likely to produce social unrest (see Hursh and Roma 2013). Consider, for example, what would happen if behavioral scientists manipulated fuel prices to understand motor vehicle users' demand for driving gasoline-powered vehicles; such a manipulation would be not only unethical but may result in adverse side effects (e.g., outrage/aggression from drivers). To circumvent these issues, behavioral economists have recently begun to rely on hypothetical purchase tasks (HPTs) to quickly and safely assess consumers' demand for a given commodity.

The seminal article on the use of HPTs was authored by Jacobs and Bickel (1999) who were interested in evaluating the number of cigarettes or amount of heroin consumed by opioid-dependent participants. However, rather than exposing these participants to actual consumption of cigarettes and heroin—a time- and resource-intensive endeavor—the authors sought to examine whether self-reports of purchases/consumption at various prices would mimic demand curves obtained using the rapid demand assay approach in other studies (e.g., Bickel et al. 1992; Hursh and Winger 1995). Toward this end, Jacobs and Bickel asked participants to imagine they were not receiving any drug abstinence treatment, that they had no other means of acquiring cigarettes or heroin, and that any cigarettes or heroin purchased had to be used by them alone (they could not be shared) within 24 h with no fear of consequences associated with the heroin use. The unit prices (per cigarette or bag of heroin) were presented on a questionnaire, beginning with US$0.01 and progressing across 15 prices to US$1120. Participants were asked to simply report the number of cigarettes or bags of heroin they would hypothetically purchase at the price. The resultant demand curves appeared similar to those obtained using real consequences in extended laboratory arrangements. Similar to what would be expected using real consequences with this population, demand for heroin was much stronger than demand for cigarettes, lending further confidence to the validity of the data. Note also that these data conformed to the expectations of a parametric design, supporting the use of an ascending sequence of unit price (akin to the findings by Raslear et al. 1988).

Perhaps the most compelling case for the importance and utility of HPTs is from Murphy and MacKillop's (2006) extension of Jacobs and Bickel's (1999) HPT. Murphy and MacKillop were interested in modeling undergraduate students' purchases of alcohol across differing prices. Their sample was composed of 267 college student drinkers, which would have been difficult to manage using extended laboratory tasks using actual operant procedures. Moreover, selling alcohol to the undergraduates—with and without alcohol-related problems—and asking them to consume their purchases may present ethical concerns at such a large scale. Data obtained from the demand analysis indicated general conformance with previously established studies with nonhumans in operant arrangements (referenced above), as well as humans in operant arrangements or HPTs (both described above). Specifically, students' demand for alcohol became more elastic as prices progressed well past what college students would typically pay for access to alcohol (conforming to the law of demand). Importantly, students who self-reported heavy drinking exhibited relative inelasticity and greater demand using quantitative analyses. Murphy and MacKillop's procedure has led to extensions wherein university policies such as class meeting times can be evaluated as a possible means of deterring late-night binging without the need for actually manipulating university policies or requiring that students actually binge drink on nights preceding courses (e.g., Gentile et al. 2012).

The self-report nature of the HPT may seem counter to the kind of data typically collected in behavior analysis. In the seminal article on the dimensions of applied behavior analysis, Baer et al. (1968) provide the following recommendation for how to handle self-report information: "a subject's verbal description of his own nonverbal behavior usually would not be accepted as a measure of his actual behavior unless it were independently substantiated (p. 93)." Fortunately, the psychometric evaluation of HPTs has become a focus of research in contemporary behavioral economics. For instance, MacKillop and Murphy (2007) measured hypothetical demand for alcohol using an HPT and demonstrated predictive validity by indicating that hypothetical demand significantly predicted post-intervention alcohol use and frequency of heavy drinking in college students. A similar finding was reported by Madden and Kalman (2010) who demonstrated that cigarette smokers' hypothetical demand for cigarettes following bupropion treatment predicted long-term smoking cessation. Beyond predictive validity, the HPT demonstrates excellent construct validity in that the elasticity of demand reported by participants completing HPTs is sensitive to environmental cues (e.g., cue-elicited craving) for both alcohol drinkers (MacKillop et al. 2010) and tobacco users (MacKillop et al. 2012). Concurrent and convergent validity has also been indicated through studies demonstrating that individuals' hypothetical demand is related to other established scales or accurately predicts categorical differences (MacKillop et al. 2008; Murphy and MacKillop 2006; Murphy et al. 2011). The most compelling evidence regarding validity, however, comes from HPT studies showing that self-reports predict actual consumption of the same commodities within-subjects, as is the case of Amlung and colleagues' study of alcohol consumption with heavy-drinking adults (Amlung and MacKillop 2012; Amlung et al. 2012). Finally, procedural studies on the sequencing and price densities of HPTs have reproduced the general findings from studies 2 and 3 of Raslear et al. (1988) seminal paper on rapid demand assays (in which Raslear et al. used rats in highly controlled operant arrangements) in that demand elasticity from HPTs appears to be a robust measure that is unaffected by random/sequential price sequences (see Amlung and MacKillop 2012) or differential price densities (see Reed et al. 2014; Roma et al. 2015).

Collectively, the extant research on the psychometrics and procedural variations of the HPT suggest that demand elasticity is a higher-order intervening variable that is highly compatible with Skinnerian operant psychology (cf. discounting in Odum 2011). For example, demand elasticity within an HPT appears to be sensitive to cues, as would be expected in actual operant arrangements (MacKillop et al. 2010, 2012).

Moreover, test–retest analyses (Few et al. 2011, 2012; Murphy et al. 2009) suggest that data obtained from HPTs describe stable valuation of a hypothetical consequence over time, likely due to the participants' personal reinforcement histories with these commodities. In this sense, participants are describing hypothetical choice in the context of experienced boundaries of prices and cues that have personally encountered in the past. As eloquently described by Odum (2011) regarding delay discounting, "The choice is not hypothetical, only the rewards (p. 430)"; that is to say that reporting consumptive behavior in an HPT *is* a behavior in its own right, it is just directed at a hypothetical consequence of which the participant has direct personal experience in at least some capacity, even when the consequence is novel yet similar to something personally consumed in the past. In sum, the extant HPT literature clearly indicates that demand metrics obtained using self-report pass the field's standards of evidence concerning data adequacy and does not violate the tenets of behavior analysis. Such conclusive and well-documented evidence clearly substantiates the self-report nature of data obtained by the HPT, which should please even the most ardent proponents of applied behavior analysis (e.g., Baer et al. 1968). Note, however, that HPTs have been exclusively employed in adult populations. It remains unknown whether the verbal capacity of children or individuals with intellectual or developmental disabilities could render psychometrically sound hypothetical demand curves; this constitutes a ripe and long overdue area of research. Given demonstrations that children have the capacity to reliably self-report hypothetical intertemporal choices (e.g., Reed and Martens 2011) or provide self-report of preferences and behavioral functions (e.g., Kern et al. 1994), we are optimistic that child-based HPT innovations could be fruitful. Modifications for high-functioning learners with limited verbal capacities would be necessary, however.

10.3 Quantitative Analysis of Reinforcer Value

Despite reliance on the single subject in behavior analysis (Skinner 1938), the field has become increasingly enriched by formalized quantitative models that describe unique environment–behavior–consequence relations (Marr 1989; Nevin 2008; Shull 1991). For example, formalized models of matching (see Chap. 6 of this volume; also, Herrnstein 1961; McDowell 2013), momentum (see Chap. 12 of this volume; also Nevin and Grace 2000; Nevin and Shahan 2011), and discounting (see Chap. 14 of this volume; also, Madden and Bickel 2010; Mazur 1987) have provided a level of insight into these behavioral phenomena that could not be achieved by strictly relying on single-case design elements. In the cases of matching, momentum, and discounting, formal quantitative relations provide researchers with additional tools and analyses that promote more meaningful application to clients suffering from a host of disorders (for more on this, see Critchfield and Reed 2009; Jacobs et al. 2013; Waltz and Follette 2009). The evaluation of reinforcer efficacy is no exception. As described above, there are many limitations in evaluating demand using visual inspection alone;

breakpoint analyses are limited by the step sizes used, reinforcers with similar intensity and breakpoint may feature different elasticity, etc. In this section, we will provide a brief primer on quantifying reinforcer demand. A comprehensive review on the topic is beyond the scope of this chapter; as such, readers are encouraged to consult the citations provided in this section for more detail and articulation.

The curious reader may appropriately question the relevance of mathematical descriptions of behavior. To this reader, we summarize the points articulated by Critchfield and Reed (2009). First, quantitative models provide "parsimonious shorthand," meaning that the models summarize complex behavior–environment–consequence relations into one succinct equation. These equations often result in several lines of text when deconstructed and explained in narrative terms. Mathematics, being the language of science, provides a quick account of the relations in highly objective and scientific forms. Second, quantitative models can describe higher-order relations that factor individual differences (from nuanced learning histories or stimulus contexts) into the environment–behavior–consequence interaction in a way that would be difficult to achieve using narrative forms alone. Specifically, fitted parameters are within models to describe how environment–behavior–consequence interactions can modulate the core relation in the model; these fitted parameters thereby serve as descriptors of individual differences to describe the higher-order relations. These higher-order relations involve four components that we will use to describe the quantitative model of demand: behavior predictions (explanation of the dependent variable), description of predictor variables (explanation of the variables that influence behavior), core functional relations (how predictor variables mathematically influence responding), and modulating effects (how fitter parameters modulate the environment–behavior–consequence relations).

10.3.1 The Use of Logarithmic Scales in Demand Curves

The relation between the price of the reinforcer and the consumption of the reinforcer is known as a demand curve where price and consumption are graphed on the x- and y-axes, respectively (see Figs. 10.1 and 10.2, described earlier in this chapter). These two variables are inversely related, as the price of a reinforcer increases, the consumption of that reinforcer decreases, and this relation is presented in the form of a demand curve. Hursh et al. (2013) explain that demand curves are typically graphed on logarithmic axes because doing so allows for an easier visual inspection of the proportional changes in the relation between price and consumption. Logarithmic scales are useful for presenting data that appear to be skewed or compressed, as well as for transforming data that appear curvilinear into data that are linear (Bourret and Pietras 2012).

When presented in log–log coordinates, demand curves allow the researcher to quickly see the degree of unit elasticity. Recall that the law of demand dictates that consumption should be highest at the lowest price. As prices increase, consumption *should* only decrease; thus, one expects that any slope in the demand curve should be negative. In the log–log coordinates, a one unit change in price that is

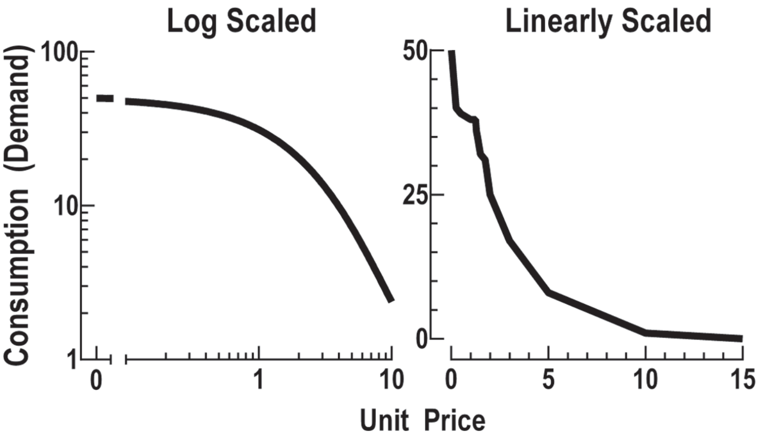

Fig. 10.4 *Left panel* depicts a dataset plotted in log *x*- and log *y*-axes to illustrate the convenience of log-scaled demand curves. The *right panel* presents the same demand curve data in linearly scaled axes to demonstrate the loss in clarity regarding elasticity of demand. See text for details

associated with a less than one unit change in consumption will result in a slope less than −1.00. Visually, this manifests as a line that appears relatively flat due to the log axes. See Fig. 10.4 for a comparison between a log and linearly scaled graph, depicting the same data. The log-scaled graph presents a very clear representation of the effect of price on consumption. Recall that the interaction of price and consumption is known as elasticity. Elasticity is a measure of the relative change in consumption as a function of unit price. The left panel of Fig. 10.4 depicts a log scale that standardizes relative changes in consumption and price to account for the relative nature of the elasticity metric. While one could perform mathematical computations to derive the same information from the linearly scaled data (right panel of Fig. 10.4), the log-scaled depiction provides a visual account that quickly describes elasticity in the same way as a quantitative description: there is a period of inelasticity where a one unit change in price results in less than one unit decrease in consumption, but when prices become high enough, the function results in a slope that negatively accelerates at rate greater than −1.00 (in accordance with the law of demand). This articulation cannot be performed on raw, linearly scaled depictions. As such, researchers and clinicians alike can quickly glean information from the log scale to efficiently identify unit prices associated with relative inelasticity and elasticity.

10.3.2 The Linear-Elasticity Model and Its Limitations

The previous (and now defunct) quantitative model of demand was the 1989 linear-elasticity model proposed and popularized by Hursh, Raslear, Bauman, and Black. The reader should note that this model is no longer of utility given the existence of a superior model (Hursh and Silberberg 2008) proposed with the sole purpose of refining and correcting for the limitations of the linear-elasticity model. Our presentation of the linear-elasticity model is merely for posterity, and to provide a foundation for the exponential model described in the next section.

As described throughout this chapter, demand curves are best visualized in log units and described mathematically to account for the limitations of visual inspection of intensity and breakpoint alone. The Hursh et al. (1989) linear-elasticity model was the first formal demand equation to describe elasticity. The model states:

$$\ln Q = \ln L + b \ln P - aP, \tag{10.1}$$

where Q represents the level of consumption that serves as the dependent variable in the demand curve analysis, L represents the level of consumption as price *(P)* approaches zero, b represents the slope of the demand curve at initial price, and a represents a coefficient used in calculating elasticity. In this model, the elasticity of the curve is computed as:

$$\text{Elasticity} = b - aP, \tag{10.2}$$

where parameters a and b are fixed based on nonlinear regression curve fitting of Eq. 10.1 using observed levels of consumption *(Q)* at the manipulated prices *(P)* in the experiment. Elasticity thereby changes linearly with increases in P. Given that behavioral economists need an account of elasticity to better describe the demand function above and beyond the simple intensity and breakpoint metrics, solving Eq. 10.2 for P with elasticity set to -1.00 (-1.00 on the left side of the equation) allows the investigator to determine the price associated with perfect unit elasticity; that is the price associated with a change of elasticity of -1.00, suggesting that this price describes the moment in the curve where a one-unit increase in price is perfectly met with a one-unit decrease in consumption (i.e., unit elasticity). This point is referred to as P_{max} and represents the point in the curve where inelasticity shifts to elasticity (see example in Fig. 10.5). This metric is useful since it permits a more precise measure of demand boundaries than breakpoint, as P_{max} can be calculated at prices not directly manipulated in the study. Note that P_{max} has been found to significantly correlate with breakpoint in both human operant self-administration studies with adults (Johnson and Bickel 2006), as well as in clinical evaluations validating preference assessments with individuals with autism (Reed et al. 2009).

In addition to providing P_{max}, the linear-elasticity model can be used to describe the work function associated with demand. In many cases, the investigator (researcher or practitioner) may find it useful to know the effect of unit price on response output (i.e., the amount of the target behavior emitted at each price). For example, consider a situation in which a practitioner wants to program a token economy in the classroom and needs to know the boundary on how many responses may be emitted/expected at given token production or exchange requirements (unit prices themselves) to prevent a learner/client from experiencing ratio strain or extinction. Understanding P_{max} provides insight into the price at which consumption becomes

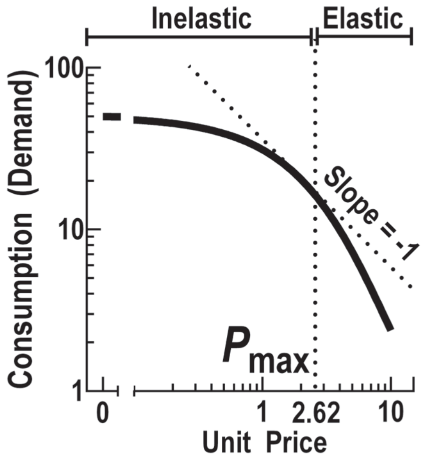

Fig. 10.5 Visual depiction of P_{max} as the point at which unit elasticity is observed (slope = −1.00 in the demand function), representing the shift in inelasticity to elasticity of demand

elastic, which can be reinterpreted to understand total response output. Multiplying $P_{\max}$ by the number of reinforcers consumed at $P_{\max}$ (which can be calculated by solving for Q using the obtained a- and b-fitted parameters and substituting $P_{\max}$ for P in Eq. 10.1) thereby quantifies predicted peak response output, which is termed $O_{\max}$. A complete work function can be plotted by using this same calculation across a range of desired prices. When plotted together as in Fig. 10.6, the investigator can visualize the relation between the demand and work functions, especially in regards to how responding and consumption interact around the point of unit elasticity ($P_{\max}$). With respect to the investigator interested in the token economy, $O_{\max}$ could indicate the cap on an effective token production schedule, with $P_{\max}$ indicating the necessary magnitude of reinforcement (i.e., number of tokens or quality of the backup reinforcer associated with one token) to render the maximally effective unit price before consumption/responding becomes elastic. For further discussion on demand curves in practice, see the next chapter or consult (Reed et al. 2013).

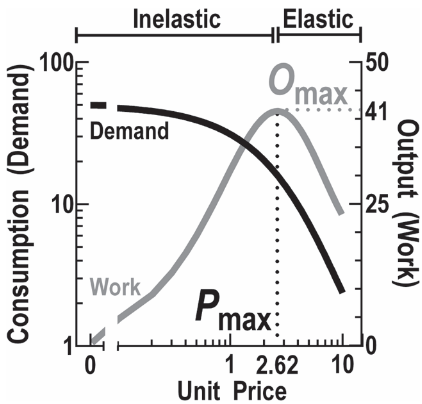

Fig. 10.6 Visual representation of the demand (plotted on the *left y-axis*) and work (plotted on the *right y-axis*) functions in behavioral economic analyses of reinforcer efficacy. See text for details

Despite that the linear-elasticity model revolutionized the field's understanding of demand and work in evaluating reinforcer efficacy/value, a major limitation was inherent in the inclusion of two fitted parameters in Eq. 10.1. As in any regression model, multiple fitted parameters complicate the interpretation of the fitted parameters when values in all parameters differ between subjects or studies. For example, if two subjects differ in both the *a* and *b* parameters of Eq. 10.1, the investigator cannot discern whether the difference is due to the initial slope or the subjects' elasticity; the best one can deduce from this finding is that the subjects differ in the entire model. In many cases, investigators will want to understand the specific effects of reinforcer efficacy on demand—in short, how does the reinforcer differ in *value* between particular contexts or populations? With two fitted parameters, Eq. 10.1 does not permit quantification of reinforcer value that is of use to either the scientist or practitioner, posing a serious limitation in its applicability. One could certainly constrain one fitted parameter to be identical between two sets of observations, but such constraint comes at the cost of model precision in explaining the variance in data. To circumvent this mathematical limitation of Eq. 10.1, Hursh and Silberberg (2008) proposed the exponential model of demand that contains only one fitted parameter. The exponential model is the focus of the next section. The reader should note that the advent of the exponential model renders the linear-elasticity model obsolete and inferior; as such, readers are strongly encouraged to use the exponential model when quantifying demand elasticity.

10.3.2 The Exponential Model

The exponential model (Eq. 10.3 below) proposed by Hursh and Silberberg (2008) describes demand similarly to the linear-elasticity model (Eq. 10.1), but does so by offering the advantage of a single fitted parameter *(α)* describing the rate of change in elasticity across the demand curve. The single fitted parameter is made possible by standardizing the demand function in terms of its log range of consumption values *(k)* and standardizing the function by the level of maximum demand (i.e., demand intensity [Q_0]; cf. Hursh and Winger 1995). Specifically, the exponential model states:

$$\log Q = \log Q_0 + k(\mathrm{e}^{-\alpha Q_0 C} - 1), \qquad (10.3)$$

where Q represents consumption (similar to Q in the linear-elasticity model), C represents the cost of the reinforcer (equivalent to P in the linear-elasticity model), and Q_0, k, and α are as described in the above paragraph. The exponent includes a product of Q_0 and C that standardizes prices in order to isolate α as the sole fitted parameter to describe demand elasticity. As such, different magnitudes of the same reinforcer will render equivalent α values in the same subject, providing researchers a valid tool in describing reinforcer value. We present Fig. 10.7 as an additional narrative on how Eq. 10.3 is a beneficial quantitative model of behavior, as per our discussion in the opening paragraph of this section (in this figure we substitute

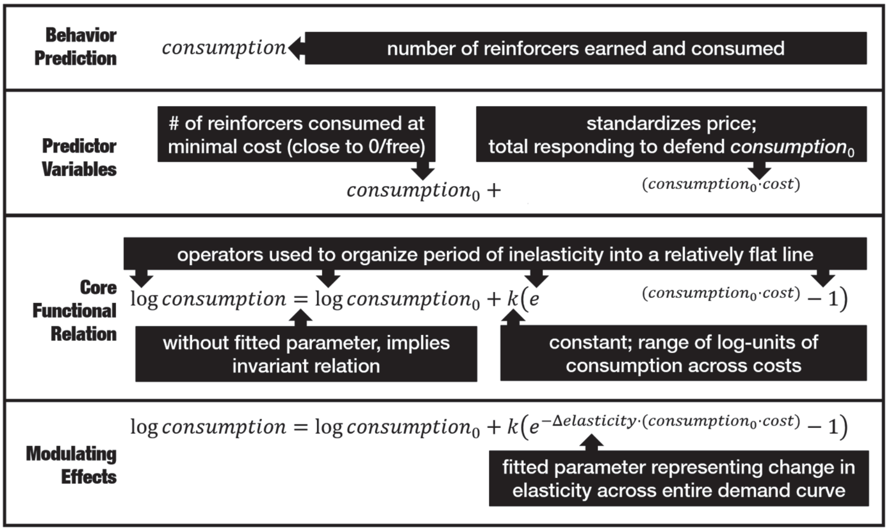

Fig. 10.7 Description of how Eq. 10.3 provides parsimonious shorthand of the higher-order relations within the exponential model demand

everyday language for the parameters in Eq. 10.3). Researchers interested in using the exponential model can download a GraphPad Prism template of the model (developed by Peter Roma and Steven Hursh at Institutes for Behavior Resources, Inc.) at http://ibrinc.org/index.php?id=181.

Similar to the linear-elasticity model, the exponential model of demand can be used to generate P_{max} and O_{max} as additional metrics of reinforcer efficacy and demand boundaries. The exact value of P_{max} can be computed using the following equation

$$P_{max} = \frac{(0.083k + 0.65)}{(Q_0 \alpha k^{1.5})}, \tag{10.4}$$

where all parameters on the right side of the equation are equivalent to those in Eq. 10.3 (see Hursh 2014). The work function for the exponential demand model may be solved for using the same process described for the linear-elasticity model above, where P_{max} and all other prices/costs of interest are substituted into Eq. 10.4, with the resulting Q multiplied by the price to derive response output levels.

A final advancement of the exponential model is its ability to describe the *essential value* (EV) of different reinforcers between any study regardless of reinforcer quality/quantity, prices, operant tasks, or species/context employed in the experiment. The EV of a reinforcer is inversely related to price sensitivity *(α)* and describes the degree to which an organism will work to defend consumption of that reinforcer. EV (Hursh 2014) may be calculated as:

$$\text{EV} = \frac{1}{(100 \alpha k^{1.5})}, \tag{10.5}$$

where all parameters on the right side of the equation are those used in Eq. 10.3. The elegance and advantage of this EV equation is that any study can be analyzed post hoc to determine the EV of the reinforcers used (assumed the relevant demand metrics are adequately described in the results) to permit comparisons across research studies since the use of Eqs. 10.3 and 10.5 collectively account for scalar differences in consumption. Researchers interested in calculating P_{max}, O_{max}, and/or EV can download an Excel-based tool (developed by Brent Kaplan and Derek Reed at the University of Kansas) at http://kuscholarworks.ku.edu/dspace/handle/1808/14934.

10.4 Factors Modulating Reinforcer Value

Several factors influence the degree to which a reinforcer will be efficacious in maintaining behavior. Among these include whether reinforcer access is restricted within the experimental session or is available elsewhere and the presence of concurrently available reinforcers. In autism service delivery, it is our experience that clinicians often isolate preferred items for use in clinical programming to render it more effective. Likewise, classroom and clinical settings are bound to include numerous concurrent reinforcers that may be used in behavior support plans or academic lesson plans to aid learners or clients diagnosed with autism. This section explores the basic research on how such factors interact with demand elasticity to modulate the relative efficacy of reinforcement. This topic is explored in greater detail in the next chapter, as well as in Reed et al. 2013.

10.4.1 Open Versus Closed Economies

The type of economy, whether open or closed, is one of the most important variables to consider when assessing demand for a reinforcer. The degree to which a reinforcer is available outside of the experimental session characterizes the difference between the two economy types. Put simply, a *closed economy* refers to an experimental arrangement in which the reinforcer is available only within the experimental session. Usually these sessions are lengthy, often 12 h or longer, such that the organism has the opportunity to respond (i.e., work) and consume enough of a reinforcer at various schedule requirements. On the other hand, an *open economy* is one where the reinforcer is available outside of the experimental session (e.g., post-session feeding). In these cases, session duration is usually shorter, but need not be, so long as there is an alternative source of reinforcement outside of the session. Of interest here, is the effect of economy type on the EV of the reinforcer.

Typically in closed economies, increases in price will result in corresponding increases in expenditure (Hursh 1980, 1984) because the reinforcer is never free—it is always earned. Thus, as the price of the reinforcer increases, the organism will increase its total responding in an attempt to maintain a stable level of consumption (i.e., inelastic demand). In an open economy, however, only a fraction of the total reinforcement is earned within the experimental session so the organism does not have to defend a certain level of consumption to survive. Alternative sources of reinforcement may be provided at another time, for example during post-session feeding. Open economies generally do not maintain as high of levels of responding due in part to the alternative sources of reinforcement. It is not necessarily in the organism's best interest to expend energy (i.e., responses) for more "expensive" reinforcers during an experimental session if there have been "cheaper" reinforcers available outside the experimental session in the past. Important to note is that demand curve analyses are more easily interpreted within a closed economy as differences in consumption and responding are directly related to the price of the reinforcer (Hursh and Silberberg 2008). Although demand is often assessed using closed economies in controlled laboratory studies, this is not a necessary condition so long as alternative sources and types of reinforcement are held relatively constant.

Hursh (1980) was among the first to coin the terms *open* and *closed economy*. By reanalyzing Felton and Lyon (1966) and Collier et al.'s (1972) work with pigeons and rats responding under a range of schedule values, he surmised that differences in the rate of responding were partly due to the structure of the environment. Pulling from a representative pigeon's data (Felton and Lyon), Hursh found the response rate increased as a function of schedule requirement until about FR 50 where he then found the response rate decreased. Interestingly, he found the response rates of two rats (Collier et al.) to increase well above FR 50, nearly plateauing around FR 250. The pigeons in Felton and Lyon's study were maintained at 80 % of their free-feeding weight and were given supplementary food post-session to maintain that ratio, whereas the rats in Collier et al.'s study obtained their daily food in the operant chamber working 24 h a day. Thus, Hursh coined the term closed economy for an environment in which access to the daily allotment of reinforcement depends on working in the setting—no free reinforcement is provided—whereas in an open economy, supplemental reinforcement is provided outside of the experimental session. Conceptually, then, open and closed economies lie at opposite ends of a continuum where at one end consumption is a direct result of response requirements (i.e., closed economy) and at the other a result of a multitude of other factors (i.e., open economy; e.g., delay to and quality of post-session feeding; Cassidy and Dallery 2012; Hursh 1984).

Hursh and Silberberg (2008) demonstrated effects of economy type on EV by reanalyzing data from Hursh (1991) where, across a series of conditions, monkeys either earned all of their food in a 12-h experimental session or received one third and two thirds of their daily ration after the session. In a final condition, the monkeys earned food on a continuous reinforcement schedule for the last 5 min of a session. Hursh and Silberberg found EV varied in orderly and predictable ways as a function of economy type. That is, EV was highest when all food was earned within the experimental session but lower in the one third free condition and lowest in the two thirds free condition.

As discussed above (Sect. 10.3 above), EV derived from the exponential demand equation, accounts for differences in scalar value but will vary with levels of deprivation. Therefore, economy type—open or closed—should modulate EV, whereas differences in scalar value should not (at least in the closed economy). In the first of two experiments testing this prediction, Cassidy and Dallery (2012) evaluated the effects of economy type with two different amounts of a food reinforcer in Long Evans rats. In the open economy, sessions lasting 130 min (with supplemental feeding) and the closed economy sessions lasting 23 h (with no supplemental feeding), rats worked on increasing FR schedules for either one or two food pellets. The researchers fit the data using Hursh and Silberberg's (2008) demand equation and found significant differences in EV across the two reinforcer magnitudes in the open economy, but not in the closed economy. In the open economy, EV for the larger reinforcer magnitude was lower across all four rats. These differences in EV found in the open economy may have been due to satiation effects. That is, because the food pellets were relatively larger, the value of the reinforcer decreased during the course of the session as the rats consumed more food. Thus, when evaluating the EV of a reinforcer in an applied setting, it would be beneficial to determine to what degree the reinforcer is available within or outside the session (i.e., closed vs. open economy) and estimate the degree of deprivation present in the client. If the client has not had access to the reinforcer being used in the intervention for quite some time, then deprivation should be relatively higher resulting in relatively higher demand. On the other hand, if the client has had access to the reinforcer recently, then demand should be relatively low. Another important factor to consider when conducting demand assessments is the presence or absence of concurrently available sources of reinforcement as this variable will affect the degree of elasticity of target reinforcer.

10.4.2 Substitutability and Complementarity

Apart from more traditional nonhuman operant studies, organisms are rarely faced with only one reinforcer alternative. Typically more than one reinforcer is available to earn and more often than not, the price of each reinforcer will vary. Alternative sources of reinforcement will generally influence demand for other concurrently available reinforcers. The degree to which reinforcer alternatives affect demand varies and as with economy type, the relation between the alternative and target reinforcers may be conceptualized as a continuum. On one end of the continuum, two reinforcers are considered *complementary* when one reinforcer, combined with another, enhances the value of the other reinforcer (Hursh 2014). This type of interaction occurs when changes in price for one reinforcer affect demand for both reinforcers in the same way. For example, if the price of tortilla chips increases, demand for both tortilla chips and salsa might decrease. However, if the price of tortilla chips decreases, demand for tortilla chips and salsa might increase. Simply put, complementary reinforcers "go together."

Likewise, on the other end of the continuum when the price of one reinforcer increases (and subsequently decreases demand for that reinforcer), demand will increase for the alternative reinforcer. This is a *substitutable* relation. When the two alternatives are identical, both are perfect substitutes for each other. On the other hand, these alternatives become partial substitutes when they become less similar. For example, if the price of 1 % milk was to increase, consumption of skim or 2 % milk might increase because skim or 2 % milk might share similar characteristics to that of 1 % milk. Many commodities partially substitute for one another, especially pharmacological drugs (Spiga et al. 2005).

Finally, when the alternative reinforcer does not influence demand for the target commodity, the alternative reinforcer is labeled as *independent*. For example, if the price of salsa were to change (e.g., increase or decrease), consumption for another food, such as cereal, would not change. That is to say, these two types of food are independent of one another because a change in price for one does not affect consumption for the other. It is often the case that there are no similar or complementary characteristics of the reinforcers.

Two caveats should be noted with respect to the aforementioned interactions. First, two reinforcers might act as complements for one individual but not another. The same notion goes for substitutes and independents. Interactions between reinforcers are only classified based on changes in demand relative to the price of each. The results of the demand curve analysis will indicate the relation between two reinforcers. Second, substitutable and complementary relations need not be symmetrical. Just because commodity A substitutes for commodity B does not mean commodity B will necessarily substitute for commodity A. For example, Allison and Mack (1982) found that when *food* intake was suppressed below baseline levels, rats consumed higher levels of concurrently available water relative to baseline levels. However, when *water* was restricted below baseline levels, food intake decreased. Thus, water appeared to substitute for food but food was not substitutable for water.

In a fascinating study examining the interaction between cocaine and food, Christensen et al. (2008) had rats respond to obtain either cocaine alone, food alone, or both. In their first experiment, the researchers found food to be a relatively higher efficacious (i.e., higher EV) reinforcer than cocaine when both could be obtained within the same session. However, they hypothesized this may have been due to either within-session satiation effects/changing body weight or drug sensitivity. In their next experiment, Christenson et al. kept body weights constant and assessed demand with cocaine alone and found a decrease in EV for cocaine leading them to speculate an interaction effect. In a final experiment, demand for food alone was assessed, and EV was higher than when both reinforcers were assessed together.

Christensen et al.'s (2008) study has several key implications for assessing demand. First, when the goal is to determine the extent to which a reinforcer can be classified as either strong or weak, demand for the reinforcer should be assessed across the entire range of prices. In addition, it is important to compare both demand for a reinforcer alone and while in the presence of other reinforcers, especially at differing prices, to determine the extent to which EV differs. As we have seen, the EV of one reinforcer might differ depending on other concurrently available reinforcers. That is, the substitutable/complementary/independent relations present should be accounted for, or at the very least considered, when determining the extent to which a reinforcer will maintain behavior. Researchers interested in quantifying degrees of complementarity, independence, and/or substitutability of reinforcers are encouraged to use Hursh's cross-price elasticity model (2014), derived from the exponential model described in Sect. 10.3 above.

10.5 Conclusion

Reinforcer value is a complex and multifaceted concept necessitating numerous levels of analyses and integration of both visual and quantitative approaches. This chapter summarized the seminal basic operant laboratory work with both humans and nonhumans on this topic. In doing so, we provide the reader with numerous references and examples for prototypical approaches to the assessment and measurement of reinforcer demand and efficacy. The current state of this science is ripe for application. Novel preparations (e.g., rapid demand assays, hypothetical tasks) continue to be developed, suggesting a healthy interest by researchers. Nevertheless, this contemporary literature remains relatively mute on the extension of these preparations and analyses to application in autism service delivery. The advancement of behavioral economics in applied contexts—described in the next chapter—allows for speculation that the next decade of applied behavioral economics should result in direct translation to the needs and interests of researchers/caregivers working in the developmental disabilities sector.

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