

The Demand Curve Analyzer: Behavioral economic software for applied researchers

Shawn P. Gilroy

Brent A. Kaplan

Derek D. Reed

Mikhail N. Koffarnus

Donald A. Hantula

This manuscript is not the copy of record and may not exactly replicate the final, authoritative version. The version of record is available at <https://dx.doi.org/10.1002/jeab.479>

Correspondence may be sent to:

Shawn Patrick Gilroy

sgilroy1@lsu.edu

shawnpgilroy@gmail.com

Grant Sponsor: The charity RESPECT and the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme (FP7/2007-2013)

Grant Number: PCOFUND-GA-2013-608728

Abstract

Free and open-source software for applying models of operant demand called the Demand Curve Analyzer (DCA), was developed for use in research. The software was constructed to streamline the use of recommended screening measures, prepare suitable scaling parameters, fit one of several models of operant demand, and provide publication-quality figures. The DCA allows users to easily import price and consumption data into spreadsheet-based controls and to perform statistical modeling with the aid of a graphical user interface. The results from computer simulations and re-analyses of published study data indicated that the DCA provides results consistent with commercially-available software that has been traditionally used to apply these analyses (i.e., GraphPadTM Prism). Further, the DCA provides additional functionality that other statistical packages do not include. Practical issues related to the determination of scaling parameter k , screening for non-systematic data, and the incorporation of more advanced behavioral economic methods are also discussed.

Introduction

Within an ecological approach to understanding individual choice and decision-making, empirical research has found that a range of environmental factors such as the probabilities of gains or losses (Rachlin, Raineri, & Cross, 1991), the presence of delays (Ainslie, 1974; Mazur, 1987), and the cost or levels of effort required (Hursh, Raslear, Shurtleff, Bauman, & Simmons, 1988; Tustin, 1994) influence decision-making. An ecological account of choice and decision-making has existed for some time (see Matching Law; Baum, 1974; Herrnstein, 1961), though this perspective has more recently received renewed interest following mainstream appeal of “behavioral economics” (Allison, 1983; Bickel, DeGrandpre, & Higgins, 1993; Hursh, 1980; Hursh & Roma, 2013; Rachlin, Green, Kagel, & Battalio, 1976).

Operant behavioral economics (Foxall, 2016), a subset of behavioral economics in keeping with its behavior analytic roots, was initially developed from basic experiments that evaluated the competing assumptions between behavior science and traditional economic theory (Hursh & Bauman, 1987; Hursh & Winger, 1995; Kagel, Battalio, Rachlin, & Green, 1981). Economic terms and conventions have been adapted for use in experimental procedures to evaluate the complex relationship between reinforcers and the patterns of behavior individual organisms demonstrate to access them (Hursh, 1980, 1984). Since its introduction, operant behavioral economics has expanded traditional economic conventions, such as the open and closed economies (Hursh, 1980, 1984; Imam, 1993), demand for reinforcers across varying costs (Hursh et al., 1988; Kagel et al., 1981), substitutability of reinforcers (Green & Freed, 1993; Johnson, Bickel, & Kirshenbaum, 2004; Johnson, Johnson, Rass, & Pacek, 2017; Madden, Smethells, Ewan, & Hursh, 2007a), and complements (Madden, Smethells, Ewan, & Hursh, 2007b; Spiga, Martinetti, Meisch, Cowan, & Hursh, 2005).

Continuing from research on the cost-reinforcer relationship, or the demand for reinforcers, subsequent research has expanded to include various aspects of human and nonhuman consumption. For example, this methodology has been used to analyze patterns of consumption such as those demonstrated by heavy users of cigarettes (Barlow, McKee, Reeves, Galea, & Stuckler, 2016; Johnson et al., 2004, 2017) and alcohol (Dennhardt, Yurasek, & Murphy, 2015; Kaplan & Reed, 2018; MacKillop et al., 2010; Mitchell, Fields, D'Esposito, & Boettiger, 2005; Murphy & MacKillop, 2006) as well as consumption of illegal substances, such as opiates (Karakula et al., 2016; Landes, Christensen, & Bickel, 2012), cocaine (Johnson, Johnson, Herrmann, & Sweeney, 2015; Mejía-Cruz, Green, Myerson, Morales-Chainé, & Nieto, 2016), and marijuana (Aston, Metrik, Amlung, Kahler, & MacKillop, 2016; Aston, Metrik, & MacKillop, 2015). Beyond the study of substance abuse, specifically, the behavioral economic framework has also been applied to more “everyday” patterns of consumption. For example, researchers have used these methods to evaluate food choices and diet (Appelhans et al., 2012; Wu et al., 2016), the use of indoor tanning services (Reed, Kaplan, Becirevic, Roma, & Hursh, 2016), and borrowing on credit (Meier & Sprenger, 2010). Further, many elements of this approach have also been adapted to better understand preference and choice for individuals with developmental disabilities (Gilroy, Kaplan, & Leader, 2018; Reed, Niileksela, & Kaplan, 2013). Beyond choices at the individual level, others have also applied these methods to group-level behavior to better inform development of public policy (Hursh & Roma, 2013).

Behavioral Economics and Relative Reinforcer Efficacy

In earlier studies using behavioral economics to evaluate the potency of drugs as reinforcers, the strength of these reinforcers was inferred by inspecting one or more aspects of responding as the costs to produce them varied (Katz, 1990). Among the methods used to

evaluate reinforcers over a range of costs, many studies have used some derivative of the Progressive Ratio (PR) schedule of reinforcement (Findley, 1958; Hodos, 1961). In this arrangement, the strength of a reinforcing relation can be inferred by inspecting various aspects of responding, such as the peak levels of responding, the highest schedule requirements reached (i.e., breakpoint), or some other trend in responding as costs progressively increase.

Among the methods available to assess the relative efficacy of reinforcers, the strength of the response-reinforcer relation is most often inferred from its breakpoint. Breakpoint represents some cost, or schedule of reinforcement (e.g., FR10), wherein the cost becomes insufficient to maintain the levels of responding necessary to produce access to the reinforcer¹. That is, breakpoint (BP_0) identifies a cost where the demands of the schedule of reinforcement, and theoretically any response requirements beyond it, yield levels of responding insufficient to produce access to the reinforcer. Using BP_0 as an indicator of reinforcer efficacy, stimuli with higher BP_0 are generally more efficacious up until higher costs while stimuli with a lower BP_0 are considered less efficacious and are likely to be effective only at relatively lower costs. While BP_0 is easily determined through visual inspection, inferring the strength of a reinforcing relation based on this measure alone presents with several limitations. First, BP_0 is a measure that essentially references a single schedule of reinforcement (Hursh & Silberberg, 2008). That is, BP_0 is a reference to a schedule of reinforcement where responding was insufficient to produce the reinforcer—it provides no information on how the reinforcer performed at any other cost. For example, two reinforcers may share the same BP_0 but differ significantly in levels and patterns of

¹ We note that the term ‘breakpoint’ has been used to describe the cost-reinforcer relationship in multiple ways. Whereas most have used this term to describe the schedule of reinforcement where responding no longer produces access to the reinforcer (BP_0), others have used this term to refer to the leanest schedule of reinforcement that produced some access to the reinforcer (BP_1).

responding on other schedules of reinforcement. Second, BP_0 is highly dependent on the way it is assessed. For example, a reinforcer evaluated using PR schedule A (1, 2, 4, 8, 16, 32, 64, 128) may yield a BP_0 of 64 but result in a BP_0 of 41 on PR schedule B (1, 11, 21, 31, 41, 51, 61, 71, 81, 91, 101, 111, 121). As such, BP_0 is influenced by both the number of schedules assessed and the magnitude changes between them. As a result, PR schedules that use larger progressions may result in larger BP_0 while PR schedules that use smaller progressions may result in smaller BP_0 . Due to this variability, procedural differences in how BP_0 is assessed may obscure small, but relevant, differences in relative reinforcer efficacy.

Behavioral Economics and Operant Demand Curves

More recent research on the effectiveness of reinforcers has incorporated economic methods to assist in quantifying the relationship between reinforcers and the cost to produce them (Allison, 1983; Bickel et al., 1993; Foxall, Olivera-Castro, Schrezenmaier, & James, 2007; Hursh, 1984). Rather than assessing the relative efficacy of reinforcers based on a single aspect of responding (e.g., BP_0 , peak responding), the *demand* for a reinforcer can be assessed over some domain of increasing costs. In this way, the strength of a reinforcer is represented as a curve rather than a single point (e.g., BP_0 , peak responding).

In a break from assessments of relative reinforcer efficacy, where efficacy is represented by some value (e.g., breakpoint, peak responding), the demand for a reinforcer takes the form of a downward sloping curve over some domain of cost. As illustrated in Figure 1, the domain of the demand curve is characterized by two separate regions—one *inelastic* and the other *elastic*. These two regions are distinct in how changes in cost, or price, differentially affect the demand for a reinforcer. The left portion of the demand curve, the inelastic range, is characterized by relatively slight changes in demand when prices increase. In contrast, the right portion of the

demand curve, the elastic range, is characterized by increasingly substantial changes in demand as prices increase. That is, even small increases in price can substantially impact the demand for a reinforcer within the elastic range. The point at which demand switches from inelastic to elastic is termed P_{MAX} . P_{MAX} represents a point where a one-unit increase in the cost is associated with a one-unit decrease in consumption². Beyond indicating the change from inelastic to elastic demand, P_{MAX} is also strongly correlated with the breakpoint measure (Johnson & Bickel, 2006). That is, a larger P_{MAX} value would indicate that the demand for some reinforcer was not impacted significantly until *higher prices* were reached and a smaller P_{MAX} value would indicate that the demand for some reinforcer decreased significantly earlier on when increases at *lower prices* were observed.

When representing the strength of reinforcers as a curve, various aspects of the response-reinforcer relationship can be represented in a unified approach. Using *demand curve analysis*, researchers have used this approach to represent various aspects of the cost-response relationship within a single, unified approach (Bickel, Marsch, & Carroll, 2000; Johnson & Bickel, 2006). In modeling demand for a reinforcer, the form of the demand curve provides information related to the intensity of demand at a free, or low, cost (i.e., Q_0) as well as its sensitivity to changes in price (i.e., α). For this reason, among others, researchers have called for an increased use of demand methods in lieu of individual measures of relative reinforcer efficacy, such as BP_0 (Bickel & Madden, 1999; Bickel et al., 2000; Reed et al., 2009). For a broader overview of behavioral economics, especially demand curve analysis, readers are encouraged to consult Reed, Niileksela, and Kaplan (2013).

² We note that P_{MAX} refers to a point where the slope of a demand function equals -1. This can be determined using the first order derivative or the slope of a tangent line, though alternative calculations for determining this value have also been provided (Hursh & Roma, 2013).

Supporting Behavioral Economics in Applied Research Using Technology

Given that there are increased challenges associated with the cost, complexity, and accessibility of the tools necessary for applying more advanced behavioral economic analyses, such as demand curve analysis, additional supports were necessary to support the recommended use of these newer methods by a wide range of researchers. To address these challenges, a computer program was designed to perform many of the tasks required when conducting operant demand curve analyses. This program, the Demand Curve Analyzer (DCA), enables users to easily apply systematic screening measures, to select from one of several conventional methods for determining the scaling parameter k , to apply non-linear model fitting from several models of operant demand, to select from one of several optimization algorithms, and to display the resulting demand curves. The program was developed to openly-source and to function across all major platforms (i.e., Windows, macOS, Linux). The user interface was constructed using the Qt Framework (*The Qt Framework*, 2017) and the underlying computations were performed using the ALGLIB linear algebra library (Bochkanov & Bystritsky, 1999). Both tools were selected based on their maturity as stable, well-documented open-source components that functioned across multiple platforms. The entire program was written in C++ to maximize the performance, portability, and compatibility of the program on various systems and architectures.

To explore the accuracy and utility of this new software, evaluations were necessary to determine whether this novel tool provided results commensurate with existing options. That is, comparisons of the DCA and GraphPad PrismTM (GP) were drawn using computer simulation and re-analysis of existing peer-reviewed works. To evaluate this new software, the following questions were posed: 1) Does the DCA computer program perform demand curve analyses and produce results that are commensurate with existing tools (i.e., GP) for fitting the Exponential

and Exponentiated models (i.e., two contemporary models) of demand using simulated data; 2) Does the DCA computer program model operant demand and provide results that are consistent with existing tools when using data extracted from peer-reviewed studies?

Method

Statistical Programs for Quantifying Operant Demand

The DCA was constructed to address a range of barriers specific to the use of demand curve analyses in research. Specifically, the software was constructed to assist researchers in consistently determining scaling parameters (i.e., k), preparing data for analysis with demand models (e.g., handling zero values), applying one of several models of operant demand, and deriving several behavioral economic indices using a streamlined interface (e.g., P_{MAX}). A list of the models of demand featured in the DCA, as well as their structure, are provided in Table 1. The DCA was designed to mirror familiar interactions with spreadsheet software (i.e., Microsoft Excel™) and all options for modeling were provided using a guided graphical user interface (GUI; e.g., handling of zeros, optimization). The GUI of the DCA, along with the relevant fitting options, is depicted in Figure 2. A customized GUI was constructed following observations that these features improved the clarity and usability of statistical methods for behavior analysts (Fisher & Lerman, 2014; Shadish, 2014). In addition to providing a user-friendly GUI for statistical methods, the DCA was also designed to operate identically across all multiple platforms (i.e., Windows, macOS, Linux), to provide seamless updates and bug fixes, and to accommodate future releases with additional modeling options and enhancements.

Application of Criteria for Systematic Demand Data

The DCA provides methods to screen consumption data prior to applying models of demand (Stein, Koffarnus, Snider, Quisenberry, & Bickel, 2015). The Stein et al. algorithm for

determining nonsystematic responding uses three criteria to quantify several patterns of responding: 1) trend (i.e., ΔQ), 2) bounce, and 3) reversals from zero. The first criterion, trend, is calculated by dividing the difference from the first and last consumption values (i.e., levels of responding) in \log_{10} units by the difference between final and first price values (i.e., schedule requirements) in \log_{10} units. The trend criterion limit was set to 0.025 (\log_{10} units) by default and this measure was designed to identify instances where demand does not change significantly as prices increased.

The second criterion from Stein et al. (2015), bounce, was designed to check for local (i.e., sequential) fluctuations in responding as prices increase. That is, the bounce criterion provided a measure that assessed sequential decreases in responding as a function of sequential increases in price. A “bounce” was considered an instance where responding increased by 25% (or more) of the levels of responding at the lowest (or free) price point and systematic purchase data is thought to include very few, often none, of these instances. An overall bounce measure was constructed by dividing the number of bounces by the number of price increments. Consistent with the recommendations from Stein et al. (2015), individual patterns of responding with a bounce value of 0.1 or greater were flagged as non-systematic.

The third and final criterion from Stein et al. (2015) was specific to reversals from zero (i.e., BP_0). In analyses of demand, it is generally assumed that price points where there are zero rates of reported consumption should not be followed by non-zero rates of reported consumption (i.e., should not reverse from zero consumption). That is, it is atypical to demonstrate zero rates of reported consumption at some price (e.g., FR30) and then demonstrate some level of responding at a higher price (e.g., FR50). Per the Stein et al. (2015) criterion, a reversal from a

single zero was tolerable but reversals from two consecutive zeroes at consecutive prices was indicative of non-systematic responding.

Using the three Stein et al. (2015) screening criteria, the DCA provides information relevant to any potentially nonsystematic sets of data prior to beginning demand analyses. This information was provided in this manner to make the user aware of potential issues that could complicate the application and interpretation of subsequent modeling. That is, the user is provided with information regarding the nature of the data supplied and is offered the opportunity to choose to continue with analysis or revisit the data supplied prior to interpreting results.

Determination of Scaling Parameter k

Both the Exponential and Exponentiated models of operant demand require the determination of parameter k to derive parameters Q_0 and α . This parameter generally specifies the range of consumption values in \log_{10} units and this value can be determined empirically (i.e., using data alone) or through fitting along with other parameters. Both approaches can be used at either the individual-level or grouped in aggregate (i.e., across all participants). The DCA was constructed to provide these options, supplying users with a range of potential comparisons without the need to manually determine these values for each data set³. Fitted k parameters with aggregated data performed parameter estimation using a shared k value across all individual data series (i.e., one k with many Q_0/α pairs).

³ We note that the DCA calculates the empirical parameter k using the log range method but adds a value of 0.5 to the result. This added value is provided to mitigate risks associated with modeling using a very small k value (e.g., Gentile et al., 2012).

Nonlinear Model Fitting

The ALGLIB linear algebra library was used to perform nonlinear model fitting for all included models in this study⁴ (Bochkanov & Bystritsky, 1999). The underlying Levenberg-Marquardt (LM) optimizer was used to perform gradient-based optimization of model parameters (Marquardt, 1963). Within the DCA, the LM optimizer was set to perform optimization using both the gradient and hessian. Maximum iterations for individual fittings was 1000 and change in error sum of squares to indicate convergence was set to 0.0001. The fitted Q_0 parameter had a lower bound of 0.001 and all other parameters were unbounded ($-\infty < p < +\infty$). Individual starting parameters were dynamically generated using a brute-force grid search based on a range of probable, proximal values, given the data. These settings were identical for both the Exponential (Hursh & Silberberg, 2008), Exponentiated (Koffarnus, Franck, Stein, & Bickel, 2015), and Linear (Hursh et al., 1988) models of demand—though no k value was necessary for the Linear model.

Study Aim 1: Simulation Study and Statistical Validation

A simulation study was conducted to investigate the accuracy and replicability of the DCA with respect to GP. Formal evaluation of the DCA against existing commercial products was necessary to determine whether the DCA accurately and reliably provided results consistent with current methods and practices. To explore the accuracy and reliability of the DCA 1,000 series were simulated. Simulation series were constructed using the consumption values of 1,104 participants in an Amazon Mechanical Turk (www.mturk.com) decision-making experiment

⁴ Optimization was performed using the LM algorithm, as most commercial packages employ a gradient descent-based approach to parameter estimation. The DCA also provides derivative-free optimization through the use of Genetic Algorithms for challenging datasets, though this was not compared to the results from GP.

(Kaplan & Reed, 2018). Participants in this study completed a hypothetical Alcohol Purchase Task (Murphy & MacKillop, 2006) in which they were asked how much alcohol they would consume at various prices and the specific price points included in this study were: \$0.00 (free), \$0.25, \$0.50, \$1.00, \$1.50, \$2.00, \$2.50, \$3.00, \$4.00, \$5.00, \$6.00, \$7.00, \$8.00, \$9.00, \$10.00, \$15.00, and \$20.00. From these data, the means and standard deviations of each price point were extracted and used to simulate hypothetical consumption data across various price points. Simulated data series were included if they passed all indicators of systematic demand, as measured by existing screening methods (Stein et al., 2015). To support transparency and replicability of these simulations, all data, and seed values have been open-sourced and can be found in the Appendix of this article.

Both the DCA and GP were used to fit the Exponential and Exponentiated models of demand. The k scaling parameter was determined by taking the difference between the base 10 logarithm of the highest and lowest non-zero consumption values and adding 0.5. A single k value was constructed using the log range plus 0.5 method. Model fitting was performed in GP using the programmed defaults. The DCA performed analyses for both models of demand with the LM optimizer using both the gradient and hessian. A maximum of 1000 iterations was set and the error sum of squares to indicate convergence was set to 0.0001. To address the limitations of the GP software (i.e., fitting a maximum of 255 series at once), simulation series were grouped into batches of 200 and subsequently analyzed in GraphPad Prism. The results from these analyses were later combined to provide a total of 1,000 fitted demand curves for the GP analyses.

Study Aim 2: Replicating Existing Study Results

Reported consumption was extracted from peer-reviewed publications to compare the results from the DCA to GP using real data. Three publications were selected for re-analysis to sample a range of demand-based applications. These included consumption of cigarettes among smokers with and without schizophrenia (MacKillop & Tidey, 2011) and the substitutability of nicotine products in humans (Johnson et al., 2017) and rats (Smethells, Harris, Burroughs, Hursh, & LeSage, 2018). Observed consumption data were extracted from published study figures by pairs of independent observers using the WebPlotDigitizer program (Rohatgi, 2017). Once extracted by observers, data were compared to evaluate accuracy and reliability of the data collected. Data were considered reliable if there was no more than a 5% difference in the values extracted by observers. Once considered reliable, the final extracted values were computed using the arithmetic mean of the two extracted values.

Extracted study data re-analyzed using both the DCA and GP with both the Exponential and Exponentiated models of demand. Individual k values were constructed for each series, derived from respective consumption values.

Results

Study Aim 1: Simulated Data

A simulation study was conducted to evaluate potential differences in how the two statistical packages modeled demand for the Exponential and Exponentiated models. Descriptive statistics from both software packages are listed in Table 2. Individual Wilcoxon rank sum tests were performed for the Q_0 , α , and R^2 values resulting from each of the programs for both the Exponential and Exponentiated models. For the Exponential model, individual Wilcoxon rank sum tests revealed no significant differences between the two software packages for fitted α , $W =$

4.9966×10^5 , $p = .972$, $r = .8174$, Q_0 , $W = 4.9999 \times 10^5$, $p = .9994$, $r = .75649$, or R^2 values, $W = 5.0002 \times 10^5$, $p = .9986$, $r = .81327$. The same analyses were repeated for the Exponentiated model for both software packages and no significant differences found for α , $W = 4.9967 \times 10^5$, $p = .9797$, Q_0 , $W = 4.9996 \times 10^5$, $p = .9976$, or R^2 values, $W = 4.9999 \times 10^5$, $p = .9994$, $r = .9999$.

Study Aim 2: Real Data

Published study data were extracted and re-analyzed using both GP and the DCA. The results from demand curve analyses for both software packages are presented in Table 3. With respect to the original analyses in the source work, the results of demand curve analysis with extracted data produced results that that matched closely with original results in the source works. With respect to comparisons across software packages and models, results in all combinations produced nearly identical results. As illustrated in Table 3, the results from demand curve analysis with both software packages produced results identical to the fourth decimal place across all parameters.

Discussion

Behavioral economics has provided a significant expanded framework to understand individual choice and decision-making. Despite offering robust methods for quantifying the strength of reinforcers, many researchers have yet to adopt formal demand curve analyses in lieu of individual assessments of relative reinforcer efficacy. Presumably, the increased complexity and cost of suitable tools are barriers to researchers widely adopting and using more advanced methods. The purpose of this study was to evaluate the accuracy and reliability of a free and open-source computer program that assists researchers in performing demand curve analyses. Specifically, this study sought to answer the following questions: 1) Does the DCA computer program perform demand curve analyses and produce results that are commensurate with

existing tools (i.e., GP) for fitting the Exponential and Exponentiated models of demand using simulated data; 2) Does the DCA computer program model operant demand and provide results that are consistent with existing tools when using data extracted from peer-reviewed studies? Based on the results of this study, the DCA provides results that are commensurate with those from the GP program but also offers additional functionality that supports the recommended use of demand curve analyses through a streamlined GUI.

While this study found that the DCA provides results that are consistent with GP, the DCA software offers several notable advantages. First and foremost, the DCA is a free and open-source statistical program. This program will run free-of-charge on all modern versions of Windows (95+), MacOS (10.6+), and Linux. The program source code has been openly-shared and affords the possibility of being expanded as advances in demand curve modeling are proposed and evaluated. The DCA includes several demand models (as shown in Table 1) but can be expanded to accommodate newer models as they are developed. Second, the DCA facilitates the a priori use of data inspection methods using recommended screening criteria (Stein et al., 2015). Historically, this type of procedure would have to be designed by the user with separate spreadsheet software or programming. As such, users traditionally required multiple tools in addition to the GP templates to perform this recommended step. Third, the DCA supports several recommended methods for determining the parameter k . Through the DCA, users can determine a k value based on several options commonly observed in the literature. Previously, k would have to be determined a priori before modeling or fitted along with other parameters. Like the application screening criteria, attempts to determine parameter k a priori without the DCA would require the use of separate spreadsheet software or programming. Through providing options for dynamically determining k , the DCA may limit the degree to

which novice users inaccurately prepare this parameter or defer to some existing or arbitrary default. Fourth, the DCA provides functionality that supports a broader range of demand applications. The GP program has known limits that may be a barrier to performing certain analyses. For example, users of the DCA can fit a shared, global regression k parameter to data sets of any size while GP is limited by the number of data sets that can be fitted in this way (i.e., 255). Presently, GP does not offer the possibility to lift this restriction and no workaround has yet been presented. For example, Kaplan & Reed (2018) conducted a study with more than 1000 participant datasets and the DCA software would allow for the fitting of a global regression k while the GP templates would not. As such, the DCA may prove to be a tool that supports a wider range of experiments and demand curve analyses. Lastly, the DCA provides additional functionality while also simplifying the modeling of demand. That is, the DCA displays information using spreadsheet-based controls and provides options for modeling using a simplified GUI. Through supporting a range of modeling options in an easily accessible format, the DCA and tools like it may encourage users to consider using more advanced and contemporary analyses rather than defaulting to simpler methods, such as those in assessments of relative reinforcer efficacy). In this way, user-focused tools such as the DCA may further support a growing movement towards increasing the use of modern statistics and quantitative techniques in behavior analytic research (Fisher & Lerman, 2014; Gilroy, Franck, & Hantula, 2017; Kaplan, 2018; Young, 2017).

Limitations

While the results from the DCA mirror those obtained from existing commercial products and support the use of a wide range of demand curve analyses, these new possibilities are not without risks of improper use. For example, researchers using assessments of relative reinforcer

efficacy have traditionally used methods that did not require mathematical modeling or statistical consultation. Tools such as the DCA and others like it are not a replacement for formal training in statistics or proper consultation with trained statisticians. Rather, the DCA should be viewed as one means to support the use of the use of modern statistics while encouraging the use of recommended screening criteria, handling of parameter k , and calculations of demand elasticity.

While the DCA performs most of the quantitative methods that are used in contemporary studies of operant demand, there are some advanced techniques that it does not yet perform. For example, the DCA does not provide some of more complex calculations referenced in the literature. For example, the DCA has yet to include methods such as the Extra Sum-of-Squares F-test (Roma, Hursh, & Hudja, 2016), analyses of substitutability (Hursh & Roma, 2013), and mixed-effects demand curve modeling (Zhao et al., 2016). As such, the DCA will require ongoing development and expansion to ensure that researchers with a range of backgrounds can reliably and accurately perform modern demand curve analyses. Future developments in the study of operant demand should capitalize on the open-source nature of this project and researchers are encouraged to evaluate the source code and methods, as well as propose enhancements using the source repository identified in the Appendix of this work.

Conclusions

The DCA is free and open source software (FOSS) to analyze data from operant behavioral economic studies of demand. Its performance matches that of commercial products, and it provides additional analyses that are not provided in these other packages. The software is GUI-based and user friendly. Marr (2017) identified a lack of quantitative expertise and application as a major impediment to further development in behavior analysis and behavior science. As quantitative methods become more complex, the response cost and economic cost

associated with their use rises commensurately. With the introduction of the DCA and other behaviorally relevant FOSS applications such as BDataPro (Bullock, Fisher, & Hagopian, 2017) and Discounting Model Selector (Gilroy et al., 2017), perhaps barriers may be lessened and quantitative tools may be more readily used in basic, translational and applied research.

More quantitatively sophisticated research in operant behavioral economics has great promise to break new ground in areas in diverse areas including effort-based choice (Salamone, Correa, Yang, Rotolo, & Presby, 2018), consumer behavior analysis (Foxall, Wells, Chang, & Oliveira-Castro, 2010; Oliveira-Castro & Foxall, 2016; Oliveira-Castro, Foxall, & Wells, 2010; Wells & Foxall, 2011), and interventions for individuals with disabilities (Gilroy et al., 2018). Perhaps some of the most important are those related to health behavior change (Bickel, Moody, & Higgins, 2016). Indeed, enduring challenges such as alcohol use and sexual risk (Lemley, Fleming, & Jarmolowicz, 2017; MacKillop et al., 2015), food choice and obesity (Epstein, Stein, Paluch, MacKillop, & Bickel, 2018; Rasmussen, Robertson, & Rodriguez, 2016), including applications to nutrition education (Guthrie, 2017) and improving the USA SNAP program (Ammerman, Hartman, & DeMarco, 2017) may be informed by such work. Further, innovative practical and policy approaches for emerging health issues such as nonmedical use of prescription drugs (Pickover, Messina, Correia, Garza, & Murphy, 2016), indoor tanning (Reed et al., 2016), cannabis use (Strickland, Lile, & Stoops, 2017), and substitution between conventional cigarettes and e-cigarettes (Snider, Cummings, & Bickel, 2017) may well arise from this work.

References

- Ainslie, G. (1974). Impulse control in pigeons. *Journal of the Experimental Analysis of Behavior*, 21(3), 485–489. <https://doi.org/10.1901/jeab.1974.21-485>
- Allison, J. W. (1983). *Behavioral economics*. Praeger Publishers.
- Ammerman, A. S., Hartman, T., & DeMarco, M. M. (2017). Behavioral Economics and the Supplemental Nutrition Assistance Program:: Making the Healthy Choice the Easy Choice. *American Journal of Preventive Medicine*, 52(2S2), S145–S150. <https://doi.org/10.1016/j.amepre.2016.08.017>
- Appelhans, B. M., Waring, M. E., Schneider, K. L., Pagoto, S. L., DeBiasse, M. A., Whited, M. C., & Lynch, E. B. (2012). Delay discounting and intake of ready-to-eat and away-from-home foods in overweight and obese women. *Appetite*, 59(2), 576–584. <https://doi.org/10.1016/j.appet.2012.07.009>
- Aston, E. R., Metrik, J., Amlung, M. T., Kahler, C. W., & MacKillop, J. (2016). Interrelationships between Marijuana Demand and Discounting of Delayed Rewards: Convergence in Behavioral Economic Methods. *Drug and Alcohol Dependence*, 169, 141–147. <https://doi.org/10.1016/j.drugalcdep.2016.10.014>
- Aston, E. R., Metrik, J., & MacKillop, J. (2015). Further Validation of a Marijuana Purchase Task. *Drug and Alcohol Dependence*, 152, 32–38. <https://doi.org/10.1016/j.drugalcdep.2015.04.025>
- Barlow, P., McKee, M., Reeves, A., Galea, G., & Stuckler, D. (2016). Time-discounting and tobacco smoking: a systematic review and network analysis. *International Journal of Epidemiology*, dyw233. <https://doi.org/10.1093/ije/dyw233>

- Baum, W. M. (1974). On two types of deviation from the matching law: Bias and undermatching. *Journal of the Experimental Analysis of Behavior*, 22(1), 231–242. <https://doi.org/10.1901/jeab.1974.22-231>
- Bickel, W. K., DeGrandpre, R. J., & Higgins, S. T. (1993). Behavioral economics: A novel experimental approach to the study of drug dependence. *Drug and Alcohol Dependence*, 33(2), 173–192. [https://doi.org/10.1016/0376-8716\(93\)90059-Y](https://doi.org/10.1016/0376-8716(93)90059-Y)
- Bickel, W. K., & Madden, G. J. (1999). A comparison of measures of relative reinforcing efficacy and behavioral economics: cigarettes and money in smokers: *Behavioural Pharmacology*, 10(6), 627–638. <https://doi.org/10.1097/00008877-199911000-00009>
- Bickel, W. K., Marsch, L. A., & Carroll, M. E. (2000). Deconstructing relative reinforcing efficacy and situating the measures of pharmacological reinforcement with behavioral economics: a theoretical proposal. *Psychopharmacology*, 153(1), 44–56.
- Bickel, W. K., Moody, L., & Higgins, S. T. (2016). Some current dimensions of the behavioral economics of health-related behavior change. *Preventive Medicine*, 92, 16–23. <https://doi.org/10.1016/j.ypped.2016.06.002>
- Bochkanov, S., & Bystritsky, V. (1999). *ALGLIB*. Retrieved from <http://www.alglib.net>
- Bullock, C. E., Fisher, W. W., & Hagopian, L. P. (2017). Description and validation of a computerized behavioral data program: “BDataPro.” *The Behavior Analyst*, 1–11. <https://doi.org/10.1007/s40614-016-0079-0>
- Dennhardt, A. A., Yurasek, A. M., & Murphy, J. G. (2015). Change in delay discounting and substance reward value following a brief alcohol and drug use intervention: Delay Discounting and Substance Reward Value. *Journal of the Experimental Analysis of Behavior*, 103(1), 125–140. <https://doi.org/10.1002/jeab.121>

- Epstein, L. H., Stein, J. S., Paluch, R. A., MacKillop, J., & Bickel, W. K. (2018). Binary components of food reinforcement: Amplitude and persistence. *Appetite, 120*, 67–74. <https://doi.org/10.1016/j.appet.2017.08.023>
- Findley, J. D. (1958). Preference and switching under concurrent scheduling. *Journal of the Experimental Analysis of Behavior, 1*(2), 123–144. <https://doi.org/10.1901/jeab.1958.1-123>
- Fisher, W., & Lerman, D. C. (2014). It has been said that, “There are three degrees of falsehoods: Lies, damn lies, and statistics.” *Journal of School Psychology, 52*(2), 243–248. <https://doi.org/10.1016/j.jsp.2014.01.001>
- Foxall, G. (2016). Operant Behavioral Economics. *Managerial and Decision Economics, 37*(4–5), 215–223. <https://doi.org/10.1002/mde.2712>
- Foxall, G., Olivera-Castro, J., Schrezenmaier, T., & James, V. (2007). *The Behavioral Economics of Brand Choice*. Springer.
- Foxall, G., Wells, V. K., Chang, S. W., & Oliveira-Castro, J. M. (2010). Substitutability and Independence: Matching Analyses of Brands and Products. *Journal of Organizational Behavior Management, 30*(2), 145–160. <https://doi.org/10.1080/01608061003756414>
- Gentile, N. D., Librizzi, E. H., & Martinetti, M. P. (2012). Academic constraints on alcohol consumption in college students: A behavioral economic analysis. *Experimental and Clinical Psychopharmacology, 20*(5), 390–399. <https://doi.org/10.1037/a0029665>
- Gilroy, S. P., Franck, C. T., & Hantula, D. A. (2017). The discounting model selector: Statistical software for delay discounting applications. *Journal of the Experimental Analysis of Behavior, 107*(3), 388–401. <https://doi.org/10.1002/jeab.257>

- Gilroy, S. P., Kaplan, B. A., & Leader, G. (2018). A systematic review of applied behavioral economics in assessments and treatments for individuals with developmental disabilities. *Review Journal of Autism and Developmental Disorders*. <https://doi.org/10.1007/s40489-018-0136-6>
- Green, L., & Freed, D. E. (1993). The substitutability of reinforcers. *Journal of the Experimental Analysis of Behavior*, *60*(1), 141–158. <https://doi.org/10.1901/jeab.1993.60-141>
- Guthrie, J. F. (2017). Integrating Behavioral Economics into Nutrition Education Research and Practice. *Journal of Nutrition Education and Behavior*, *49*(8), 700-705.e1. <https://doi.org/10.1016/j.jneb.2016.09.006>
- Herrnstein, R. J. (1961). Relative and absolute strength of response as a function of frequency of reinforcement. *Journal of the Experimental Analysis of Behavior*, *4*(3), 267–272. <https://doi.org/10.1901/jeab.1961.4-267>
- Hodos, W. (1961). Progressive ratio as a measure of reward strength. *Science (New York, N.Y.)*, *134*(3483), 943–944. <https://doi.org/10.1126/science.134.3483.943>
- Hursh, S. R. (1980). Economic concepts for the analysis of behavior. *Journal of the Experimental Analysis of Behavior*, *34*(2), 219–238. <https://doi.org/10.1901/jeab.1980.34-219>
- Hursh, S. R. (1984). Behavioral economics. *Journal of the Experimental Analysis of Behavior*, *42*(3), 435–452. <https://doi.org/10.1901/jeab.1984.42-435>
- Hursh, S. R., & Bauman, R. A. (1987). The behavioral analysis of demand. In L. Green & J. H. Kagel (Eds.), *Advances in behavioral economics* (Vol. 1, pp. 117–165). Norwood, New Jersey: Ablex Publishing Corporation.

- Hursh, S. R., Raslear, T. G., Shurtleff, D., Bauman, R., & Simmons, L. (1988). A cost-benefit analysis of demand for food. *Journal of the Experimental Analysis of Behavior*, *50*(3), 419–440. <https://doi.org/10.1901/jeab.1988.50-419>
- Hursh, S. R., & Roma, P. G. (2013). Behavioral economics and empirical public policy: Empirical public policy. *Journal of the Experimental Analysis of Behavior*, *99*(1), 98–124. <https://doi.org/10.1002/jeab.7>
- Hursh, S. R., & Silberberg, A. (2008). Economic demand and essential value. *Psychological Review*, *115*(1), 186–198. <https://doi.org/10.1037/0033-295X.115.1.186>
- Hursh, S. R., & Winger, G. (1995). Normalized demand for drugs and other reinforcers. *Journal of the Experimental Analysis of Behavior*, *64*(3), 373–384. <https://doi.org/10.1901/jeab.1995.64-373>
- Imam, A. A. (1993). Response-reinforcer independence and the economic continuum. *Journal of the Experimental Analysis of Behavior*, *59*, 231–243. <https://doi.org/10.1901/jeab.1993.59-231>
- Johnson, M. W., & Bickel, W. K. (2006). Replacing relative reinforcing efficacy with behavioral economic demand curves. *Journal of the Experimental Analysis of Behavior*, *85*(1), 73–93. <https://doi.org/10.1901/jeab.2006.102-04>
- Johnson, M. W., Bickel, W. K., & Kirshenbaum, A. P. (2004). Substitutes for tobacco smoking: a behavioral economic analysis of nicotine gum, denicotinized cigarettes, and nicotine-containing cigarettes. *Drug and Alcohol Dependence*, *74*(3), 253–264. <https://doi.org/10.1016/j.drugalcdep.2003.12.012>
- Johnson, M. W., Johnson, P. S., Herrmann, E. S., & Sweeney, M. M. (2015). Delay and Probability Discounting of Sexual and Monetary Outcomes in Individuals with Cocaine

Use Disorders and Matched Controls. *PLOS ONE*, *10*(5), e0128641.

<https://doi.org/10.1371/journal.pone.0128641>

Johnson, M. W., Johnson, P. S., Rass, O., & Pacek, L. R. (2017). Behavioral economic substitutability of e-cigarettes, tobacco cigarettes, and nicotine gum. *Journal of Psychopharmacology (Oxford, England)*, *31*(7), 851–860.

<https://doi.org/10.1177/0269881117711921>

Kagel, J. H., Battalio, R. C., Rachlin, H., & Green, L. (1981). Demand curves for animal consumers. *The Quarterly Journal of Economics*, *96*(1), 1–15.

<https://doi.org/10.2307/2936137>

Kaplan, B. A. (2018). *beezdemand: R package containing functions to help aid in analyzing behavioral economic demand curve data*. Retrieved from

<https://github.com/brentkaplan/beezdemand>

Kaplan, B. A., & Reed, D. D. (2018). Happy hour drink specials in the alcohol purchase task. *Experimental and Clinical Psychopharmacology*.

Karakula, S. L., Weiss, R. D., Griffin, M. L., Borges, A. M., Bailey, A. J., & McHugh, R. K. (2016). Delay discounting in opioid use disorder: Differences between heroin and prescription opioid users. *Drug and Alcohol Dependence*, *169*, 68–72.

<https://doi.org/10.1016/j.drugaldep.2016.10.009>

Katz, J. L. (1990). Models of relative reinforcing efficacy of drugs and their predictive utility. *Behavioural Pharmacology*, *1*(4), 283–301.

Koffarnus, M. N., Franck, C. T., Stein, J. S., & Bickel, W. K. (2015). A modified exponential behavioral economic demand model to better describe consumption data. *Experimental and Clinical Psychopharmacology*, *23*(6), 504–512. <https://doi.org/10.1037/pha0000045>

- Landes, R. D., Christensen, D. R., & Bickel, W. K. (2012). Delay Discounting Decreases in Those Completing Treatment for Opioid Dependence. *Experimental and Clinical Psychopharmacology*, *20*(4), 302–309. <https://doi.org/10.1037/a0027391>
- Lemley, S. M., Fleming, W. A., & Jarmolowicz, D. P. (2017). Behavioral Economic Predictors of Alcohol and Sexual Risk Behavior in College Drinkers. *The Psychological Record*, *67*(2), 197–211. <https://doi.org/10.1007/s40732-017-0239-y>
- MacKillop, J., Celio, M. A., Mastroleo, N. R., Kahler, C. W., Operario, D., Colby, S. M., ... Monti, P. M. (2015). Behavioral economic decision making and alcohol-related sexual risk behavior. *AIDS and Behavior*, *19*(3), 450–458. <https://doi.org/10.1007/s10461-014-0909-6>
- MacKillop, J., Miranda, R., Monti, P. M., Ray, L. A., Murphy, J. G., Rohsenow, D. J., ... Gwaltney, C. J. (2010). Alcohol Demand, Delayed Reward Discounting, and Craving in relation to Drinking and Alcohol Use Disorders. *Journal of Abnormal Psychology*, *119*(1), 106–114. <https://doi.org/10.1037/a0017513>
- MacKillop, J., & Tidey, J. W. (2011). Cigarette demand and delayed reward discounting in nicotine-dependent individuals with schizophrenia and controls: an initial study. *Psychopharmacology*, *216*(1), 91–99. <https://doi.org/10.1007/s00213-011-2185-8>
- Madden, G. J., Smethells, J., Ewan, E. E., & Hursh, S. R. (2007a). Tests of behavioral economic assessments of relative reinforcer efficacy: Economic substitutes. *Journal of the Experimental Analysis of Behavior*, *87*, 219–240. <https://doi.org/10.1901/jeab.2007.80-06>
- Madden, G. J., Smethells, J., Ewan, E. E., & Hursh, S. R. (2007b). Tests of behavioral economic assessments of relative reinforcer efficacy II: Economic complements. *Journal of the*

- Experimental Analysis of Behavior*, 88, 355–367. <https://doi.org/10.1901/jeab.2007.88-355>
- Marquardt, D. (1963). An Algorithm for Least-Squares Estimation of Nonlinear Parameters. *Journal of the Society for Industrial and Applied Mathematics*, 11(2), 431–441. <https://doi.org/10.1137/0111030>
- Marr, M. J. (2017). The Future of Behavior Analysis: Foxes and Hedgehogs Revisited. *The Behavior Analyst*, 40(1), 197–207. <https://doi.org/10.1007/s40614-017-0107-8>
- Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In *Quantitative analysis of behavior: Vol. 5. The effect of delay and intervening events on reinforcement value* (pp. 55–73). Hillsdale, NJ: Erlbaum.
- Meier, S., & Sprenger, C. (2010). Present-Biased Preferences and Credit Card Borrowing. *American Economic Journal: Applied Economics*, 2(1), 193–210.
- Mejía-Cruz, D., Green, L., Myerson, J., Morales-Chainé, S., & Nieto, J. (2016). Delay and probability discounting by drug-dependent cocaine and marijuana users. *Psychopharmacology*, 233(14), 2705–2714. <https://doi.org/10.1007/s00213-016-4316-8>
- Mitchell, J. M., Fields, H. L., D’Esposito, M., & Boettiger, C. A. (2005). Impulsive Responding in Alcoholics. *Alcoholism: Clinical and Experimental Research*, 29(12), 2158–2169. <https://doi.org/10.1097/01.alc.0000191755.63639.4a>
- Murphy, J. G., & MacKillop, J. (2006). Relative reinforcing efficacy of alcohol among college student drinkers. *Experimental and Clinical Psychopharmacology*, 14(2), 219–227. <https://doi.org/10.1037/1064-1297.14.2.219>

- Oliveira-Castro, J. M., & Foxall, G. (2016). Dimensions of demand elasticity. In G. Foxall (Ed.), *The Routledge companion to consumer behavior analysis* (pp. 121–137). London/New York: Routledge.
- Oliveira-Castro, J. M., Foxall, G., & Wells, V. K. (2010). Consumer Brand Choice: Money Allocation as a Function of Brand Reinforcing Attributes. *Journal of Organizational Behavior Management*, *30*(2), 161–175. <https://doi.org/10.1080/01608061003756455>
- Pickover, A. M., Messina, B. G., Correia, C. J., Garza, K. B., & Murphy, J. G. (2016). A behavioral economic analysis of the nonmedical use of prescription drugs among young adults. *Experimental and Clinical Psychopharmacology*, *24*(1), 38–47. <https://doi.org/10.1037/pha0000052>
- Rachlin, H., Green, L., Kagel, J. H., & Battalio, R. C. (1976). Economic demand theory and psychological studies of choice. *Psychology of Learning and Motivation*, *10*, 129–154. [https://doi.org/10.1016/S0079-7421\(08\)60466-1](https://doi.org/10.1016/S0079-7421(08)60466-1)
- Rachlin, H., Raineri, A., & Cross, D. (1991). Subjective Probability and Delay. *Journal of the Experimental Analysis of Behavior*, *55*(2), 233–244. <https://doi.org/10.1901/jeab.1991.55-233>
- Rasmussen, E. B., Robertson, S. H., & Rodriguez, L. R. (2016). The utility of behavioral economics in expanding the free-feed model of obesity. *Behavioural Processes*, *127*, 25–34. <https://doi.org/10.1016/j.beproc.2016.02.014>
- Reed, D. D., Kaplan, B. A., Becirevic, A., Roma, P. G., & Hursh, S. R. (2016). Toward quantifying the abuse liability of ultraviolet tanning: A behavioral economic approach to tanning addiction. *Journal of the Experimental Analysis of Behavior*, *106*(1), 93–106. <https://doi.org/10.1002/jeab.216>

- Reed, D. D., Luiselli, J. K., Magnuson, J. D., Fillers, S., Vieira, S., & Rue, H. C. (2009). A comparison between traditional economical and demand curve analyses of relative reinforcer efficacy in the validation of preference assessment predictions. *Developmental Neurorehabilitation, 12*(3), 164–169. <https://doi.org/10.1080/17518420902858983>
- Reed, D. D., Niileksela, C. R., & Kaplan, B. A. (2013). Behavioral economics. *Behavior Analysis in Practice, 6*(1), 34–54. <https://doi.org/10.1007/BF03391790>
- Rohatgi, A. (2017). WebPlotDigitizer (Version 3.12). Austin, TX. Retrieved from <http://arohatgi.info/WebPlotDigitizer>
- Roma, P. G., Hursh, S. R., & Hudja, S. (2016). Hypothetical Purchase Task Questionnaires for Behavioral Economic Assessments of Value and Motivation. *Managerial and Decision Economics, 37*(4–5), 306–323. <https://doi.org/10.1002/mde.2718>
- Salamone, J. D., Correa, M., Yang, J.-H., Rotolo, R., & Presby, R. (2018). Dopamine, Effort-Based Choice, and Behavioral Economics: Basic and Translational Research. *Frontiers in Behavioral Neuroscience, 12*. <https://doi.org/10.3389/fnbeh.2018.00052>
- Shadish, W. R. (2014). Analysis and meta-analysis of single-case designs: An introduction. *Journal of School Psychology, 52*(2), 109–122. <https://doi.org/10.1016/j.jsp.2013.11.009>
- Smethells, J. R., Harris, A. C., Burroughs, D., Hursh, S. R., & LeSage, M. G. (2018). Substitutability of nicotine alone and an electronic cigarette liquid using a concurrent choice assay in rats: A behavioral economic analysis. *Drug and Alcohol Dependence, 185*, 58–66. <https://doi.org/10.1016/j.drugalcdep.2017.12.008>
- Snider, S. E., Cummings, K. M., & Bickel, W. K. (2017). Behavioral economic substitution between conventional cigarettes and e-cigarettes differs as a function of the frequency of

- e-cigarette use. *Drug and Alcohol Dependence*, *177*, 14–22.
<https://doi.org/10.1016/j.drugalcdep.2017.03.017>
- Spiga, R., Martinetti, M. P., Meisch, R. A., Cowan, K., & Hursh, S. (2005). Methadone and nicotine self-administration in humans: a behavioral economic analysis. *Psychopharmacology*, *178*(2–3), 223–231. <https://doi.org/10.1007/s00213-004-2020-6>
- Stein, J. S., Koffarnus, M. N., Snider, S. E., Quisenberry, A. J., & Bickel, W. K. (2015). Identification and management of nonsystematic purchase task data: Toward best practice. *Experimental and Clinical Psychopharmacology*, *23*(5), 377–386.
<https://doi.org/10.1037/pha0000020>
- Strickland, J. C., Lile, J. A., & Stoops, W. W. (2017). Unique prediction of cannabis use severity and behaviors by delay discounting and behavioral economic demand. *Behavioural Processes*, *140*, 33–40. <https://doi.org/10.1016/j.beproc.2017.03.017>
- The Qt Framework*. (2017). The Qt Company Ltd. Retrieved from <http://www.qt.io/qt-framework/>
- Tustin, R. D. (1994). Preference for reinforcers under varying schedule arrangements: A behavioral economic analysis. *Journal of Applied Behavior Analysis*, *27*(4), 597–606.
<https://doi.org/10.1901/jaba.1994.27-597>
- Wells, V. K., & Foxall, G. (2011). Special issue: Consumer behaviour analysis and services. *The Service Industries Journal*, *31*(15), 2507–2513.
<https://doi.org/10.1080/02642069.2011.531122>
- Wu, M., Brockmeyer, T., Hartmann, M., Skunde, M., Herzog, W., & Friederich, H.-C. (2016). Reward-related decision making in eating and weight disorders: A systematic review and meta-analysis of the evidence from neuropsychological studies. *Neuroscience &*

Biobehavioral Reviews, 61(Supplement C), 177–196.

<https://doi.org/10.1016/j.neubiorev.2015.11.017>

Young, M. E. (2017). Discounting: A practical guide to multilevel analysis of indifference data:

Multilevel Analysis of Indifference Data. *Journal of the Experimental Analysis of*

Behavior, 108(1), 97–112. <https://doi.org/10.1002/jeab.265>

Zhao, T., Luo, X., Chu, H., Le, C. T., Epstein, L. H., & Thomas, J. L. (2016). A two-part mixed

effects model for cigarette purchase task data. *Journal of the Experimental Analysis of*

Behavior, 106(3), 242–253. <https://doi.org/10.1002/jeab.228>

Appendix

The source code necessary to simulate and systematically compare the accuracy of the Demand Curve Analyzer to other statistical tools has been open-sourced and publicly shared. Both the code to simulate data, as well as the raw data used in the study, is publicly available on the corresponding author's Github page. Installation files for the program can be obtained from <http://www.smallnstats.com/downloads/>. All simulation methods and analyses were conducted using the R computer program and all R scripts and supplemental files can be found on the corresponding author's public Git, located in the repository named "DemandSimulations."

Table 1

Behavioral Economic Models of Operant Demand Included in the DCA

Model	Form	Source
Linear-Elasticity	$\log C = \log L + b(\log P) - a P$	Hursh et al. (1988)
Exponential	$\log_{10} C = \log_{10} Q_0 + k(e^{-\alpha Q_0 P} - 1)$	Hursh & Silberberg (2008)
Exponentiated	$C = Q_0 * 10^{k(e^{-\alpha P} - 1)}$	Koffarnus et al. (2015)

Table 2

Results of Simulation Study

Model	GraphPad			Demand Curve Analyzer		
	Mean α (Q1-Q3)	Mean Q_0 (Q1-Q3)	Mean R-Squared (Q1-Q3)	Mean α (Q1-Q3)	Mean Q_0 (Q1-Q3)	Mean R-Squared (Q1-Q3)
Exponential	0.0026 (0.0022-0.0029)	5.866 (5.028-6.536)	0.686 (0.592-0.796)	0.0026 (0.0022-0.0029)	5.866 (5.028-6.536)	0.686 (0.592-0.796)
Exponentiated	0.0026 (0.0022-0.0029)	6.637 (5.899-7.319)	0.726 (0.660-0.809)	0.0026 (0.0022-0.0029)	6.637 (5.899-7.319)	0.726 (0.661-0.809)

Note: An overall k value was determined by the aggregate log range plus 0.5 method, resulting in a k value of 5.312 that was used in both approaches and with both modeling options. Parameter estimation was performed using the Levenberg-Marquardt algorithm.

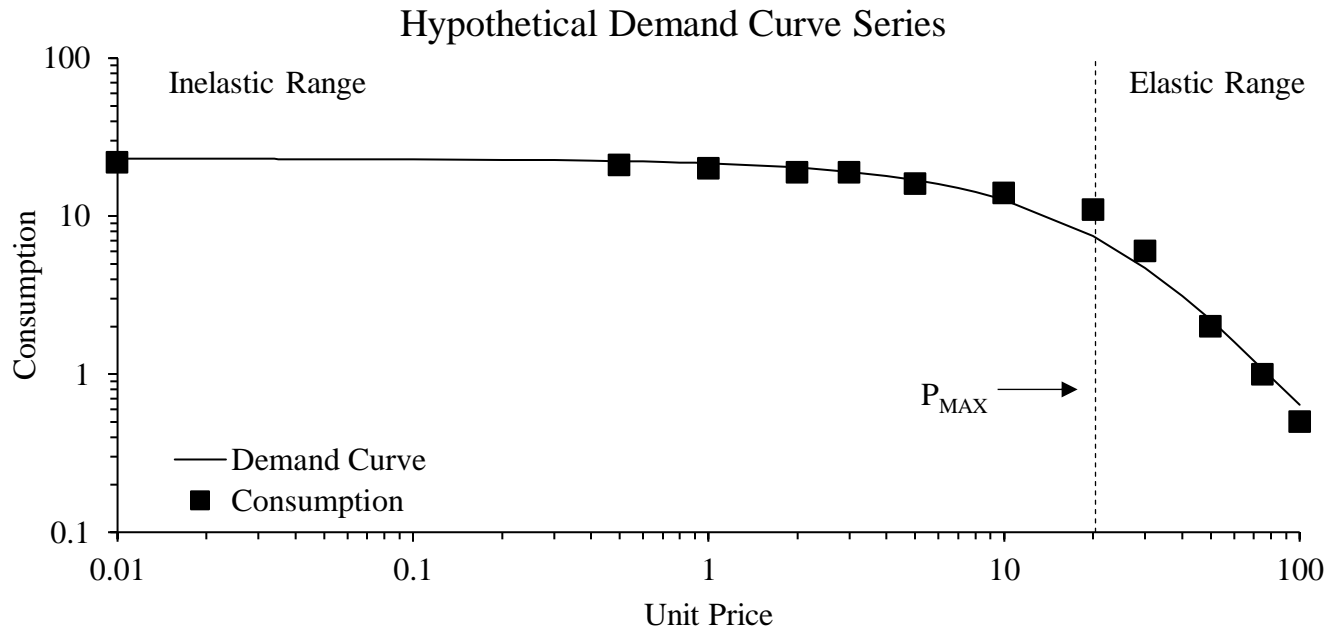
Table 3

Fitting Comparisons with Extracted Data

	<i>k</i>	GraphPad Prism		Demand Curve Analyzer	
		<i>Q0</i>	α	<i>Q0</i>	α
Hursh & Silberburg Model (2008) – Exponential					
Smethells et al. (2018) – Electronic Cigarette Liquid	2.90292	2.5759	0.0004	2.5759	0.0004
Smethells et al. (2018) – Nicotine Liquid	2.83988	4.1812	0.0005	4.1812	0.0005
Johnson et al. (2017) – Tobacco Cigarettes	4.50478	52.449	0.0118	52.449	0.0118
Johnson et al. (2017) – Electronic Cigarettes	4.50120	76.173	0.0068	76.173	0.0068
MacKillop & Tidey (2011) – Schizoaffective Smokers	4.09596	67.539	0.0015	67.539	0.0015
MacKillop & Tidey (2011) – Control Smokers	3.90741	35.847	0.0025	35.847	0.0025
Koffarnus et al. (2015) Model – Exponentiated					
Smethells et al. (2018) – Electronic Cigarette Liquid	2.90292	2.6020	0.0004	2.6020	0.0004
Smethells et al. (2018) – Nicotine Liquid	2.83988	2.6717	0.0008	2.6717	0.0008
Johnson et al. (2017) – Tobacco Cigarettes	4.50478	148.97	0.0275	148.93	0.0275
Johnson et al. (2017) – Electronic Cigarettes	4.50120	110.26	0.0120	110.26	0.0120
MacKillop & Tidey (2011) - Schizoaffective Smokers	4.09596	37.208	0.0033	37.208	0.0033
MacKillop & Tidey (2011) - Control Smokers	3.90741	25.279	0.0060	25.279	0.0060

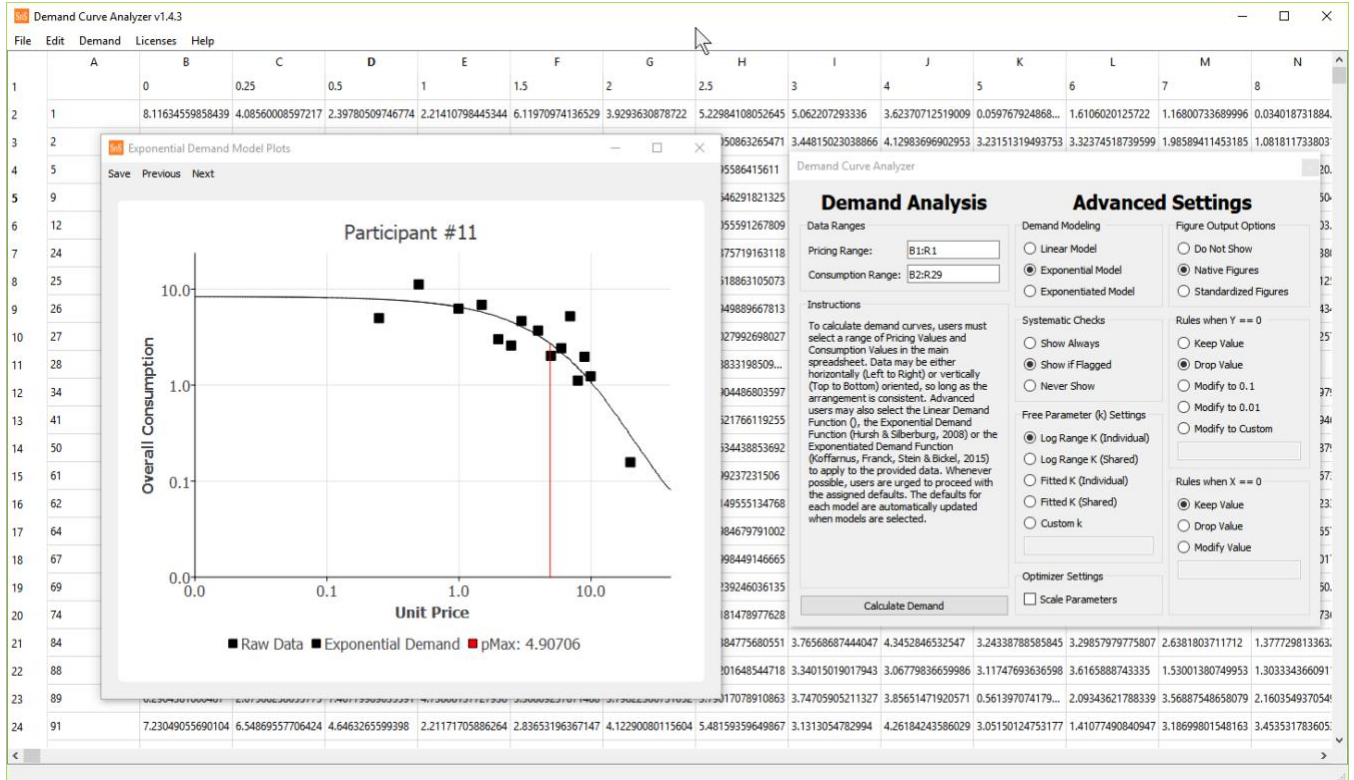
Note: An overall *k* value was determined by the aggregate log range plus 0.5 method. Given that *k* was derived empirically, the same *k* value was retained across both modeling options.

Figure 1. Prototypical Demand Curve



The figure above illustrates the form and composition of the demand curve. The inelastic range represents a portion of the demand curve characterized by relatively slight changes in consumption as price increases. In contrast, the elastic range is characterized by larger changes in consumption as prices increase.

Figure 2. Graphical User Interface of DCA



This figure depicts the GUI of the DCA and associated options. Among the options for fitting, the DCA assists users in performing screening criteria, fitting one of several models of demand, handling scaling parameters, and managing data options (i.e., handling zero values). In this way, the DCA supports the application of demand curve modeling while providing functionality that no other software currently performs (e.g., scaling parameter k , handling zero values, screening data).