Applications of Operant Demand to Treatment Selection II: Covariance of Evidence Strength and Treatment Consumption

Shawn P. Gilroy and Cassie Feck
Louisiana State University

This is a pre-print of an article currently in press for the Journal of the Experimental Analysis of Behavior. This may not represent the final form of this work. The readers are directed to the following link to review the definitive version of this work: http://doi.org/10.1002/jeab.735

Author Note

Shawn P. Gilroy https://orcid.org/0000-0002-1097-8366

Cassie Feck

We have no conflicts of interest to disclose. The source code necessary to reproduce this work is publicly archived at https://www.github.com/miyamot0/TreatmentDemandVaryingEvidence

Correspondence should be addressed to Shawn Gilroy, Audubon 220, Louisiana State University, Baton Rouge, LA 70806. Email: sgilroy1@lsu.edu

Abstract

Evidence-based practices (EBPs) are a critical component of effective and ethical service delivery. Clinicians in the behavioral sciences regularly advocate for the use of therapies and interventions based on the strength and breadth of scientific evidence. However, caregiver choices related to specific behavior therapies are seldom based solely on the degree (or the presence) of scientific evidence. This study applied methods from the Operant Demand Framework to characterize caregiver choices when concurrently available behavior therapies varied in terms of unit price and levels of evidence. Four Hypothetical Treatment Purchase Tasks were designed to evaluate how relative differences in scientific evidence between behavior therapies influenced the demand for, and substitutability of, EBPs. Results from 106 caregivers recruited from the Amazon Mechanical Turk (MTurk) platform indicated that low-, moderate-, and high-evidence treatment choices all functioned as substitutes for a high-evidence (i.e., well-established) behavior therapy. A main effect was observed for the level of evidence, whereby the strength of evidence appeared to moderate the degree to which respective treatments functioned as substitutes. These results extend the literature on the factors associated with treatment choices, and specifically, highlight how differences in the degree of scientific evidence influence choice when deciding between behavior therapies. These results are discussed in the context of more effectively advocating for the use of EBPs with mainstream and lay audiences.

Keywords: behavioral economics, evidence-based practices, operant demand, substitution, empirical public policy

Introduction

The American Psychological Association (APA) defines Evidence-based Practices (EBP's) as "…the integration of the best available research with clinical expertise within the context of patient characteristics, culture, and preferences" (APA Presidential Task Force on Evidence-Based Practice, 2006, p. 273). Beyond the APA and matters related to behavioral science, EBPs are a current standard for ethical practices in fields such as education (Shernoff et al., 2003; Spencer et al., 2012), allied health (American Speech-Language-Hearing Association, 2005; Kaplan et al., 2013), and medicine as well (Evidence-Based Medicine Working Group, 1992; Sackett, 1997). To this end, a variety of reviews, practice guidelines, and informational materials have been designed and disseminated to communicate the merits of EBPs to professionals across various fields.

Calls for the replacement of ineffective or otherwise questionable practices with EBPs have been particularly prominent in fields working with children diagnosed with developmental and behavioral challenges, e.g. developmental disabilities (Jacobson et al., 2015). Indeed, EBPs have been a prominent theme in practice guidelines for these types of disorders over the past several decades (Eyberg et al., 2008; Kaminski & Claussen, 2017; McDonald & DiGennaro Reed, 2018; National Autism Center, 2015). Although practice guidelines and reviews of EBPs are now plentiful and accessible to many clinicians and professionals (e.g., National Autism Center, 2015; What Works Clearinghouse, 2016), few resources are designed to be accessible to caregivers and mainstream audiences (Wong et al., 2015). This lack of accessible information related to EBPs has been noted as an issue relevant to treatment-related decision-making; specifically, some have suggested that a lack of access to credible information may contribute to caregiver pursuit of approaches that lack scientific support (McDonald & DiGennaro Reed, 2018).

Many of the current efforts to advocate for the use of EBPs, for caregivers or otherwise, focus on providing and summarizing scientific evidence (Novins et al., 2013). That is, there is a presumption that a lack of credible information, or scientific reasoning, contributes to an inaccurate appraisal of the relative merits for respective therapies (Kay, 2015; Smith, 2015). Following this logic, various groups and foundations have made commitments to supporting the field by outlining the process of determining which approaches have established credible, scientific support, which approaches have emerging support, and which are unlikely to provide meaningful benefit (Chambless et al., 1998). Using autism as one example, the National Autism Center (National Autism Center, 2015), the National Professional Development Center on ASD (https://autismpdc.fpg.unc.edu/evidence-based-practices), the Association for Science in Autism Treatment (https://www.asatonline.org), and Autism Speaks (https://www.autismspeaks.org) each synthesize the scientific literature and assist families and mainstream audiences in navigating behavioral therapies and strategies. For instance, the Autism Speaks group provides a '100-day toolkit' with videos and readings to help orient families of children with ASD to the types of supports and therapies believed to be most reliable and effective with this population (Hebert, 2014).

Behavioral Economics and Treatment-related Choice

Contemporary efforts to advocate for the use of EBPs emphasize logic and rationality in making treatment-related choices (Smith, 2015). That is, one would assume that a perfectly rational agent would favor choices more associated with larger and more probable returns (i.e., EBPs) over alternatives with lesser, or at least less probable, returns (i.e., fads, pseudoscience).

Indeed, Rational Choice Theory holds that individuals seek to maximize utility (Hantula, 2017), and in the case of behavioral therapies, should choose EBPs more often than not (Gilroy et al., In Press). However, research with human and non-human animals has found that organisms rarely behave rationally and regularly demonstrate patterns of “irrational” or “suboptimal” choice (Ainslie, 1975, 1992).

This view of individual decision-makers as rational (i.e., homo economicus) has been heavily critiqued in recent years and has been largely replaced by a behavioral economic perspective (Reed et al., 2015; Reed et al., 2013). Briefly, the behavioral economic[1] perspective integrates findings from behavioral science to better understand how human and non-human animals behave in complex and uncertain situations (Camerer & Loewenstein, 2004; Gilroy et al., 2018; Hursh, 1980, 1984). That is, findings from behavioral science have been used to characterize the situations in which organisms deviate from optimal (e.g., EBPs) to sub-optimal choices (e.g., fad therapies; Mazur, 1987; Odum, 2011). Abstracting this perspective to treatment choice, a behavioral economic approach may help characterize the situations in which caregivers deviate from optimal prospects (EBPs) and fall prey to questionable (potentially unsafe) treatment practices (Gilroy & Kaplan, 2020; Gilroy et al., In Press). For example, behavioral economic research has found treatment-related choices to be more reliably influenced by proximal environmental factors, such as delays (Call et al., 2015; Gilroy & Kaplan, 2020).

A behavioral economic account of treatment choice is well suited to evaluating the consumption of EBPs because these can be considered the optimal (or at least recommended)

---

[1] We note here that we refer primarily to the Operant Behavioral Economic perspective, which emphasizes ecological factors that affect choices. This contrasts with mainstream behavioral economics, which highlights cognitive biases as the basis for irrational choice. For a review of operant demand methods, see: Gilroy, S. P., Kaplan, B. A., Reed, D. D., Koffarnus, M. N., & Hantula, D. A. (2018). The Demand Curve Analyzer: Behavioral economic software for applied research. *Journal of the Experimental Analysis of Behavior, 110*(3), 553-568. https://doi.org/10.1002/jeab.479 .

choice(s) in the context of behavior therapy (Gilroy & Kaplan, 2020; Gilroy et al., In Press). Borrowing from the economic concept of demand (Hursh, 1980, 1984), hypothetical treatment choices can be evaluated under a variety of constraints (e.g., varying costs, available alternatives). Specifically, the Operant Demand Framework can be used to construct a hypothetical marketplace (see Roma et al. (2016) for a recent review and Gilroy et al. (In Press) for a representative example) in which to examine how caregivers would "spend" their limited time and resources. For example, Gilroy et al. (In Press) simulated a treatment "marketplace" to evaluate how caregivers would select behavior therapies when costs and levels of evidence varied across treatment options (for an initial demonstration of the approach, see Quisenberry et al., 2015). The findings in Gilroy et al. (In Press) indicated that caregivers would pursue unsupported behavioral therapies as functional substitutes for EBPs, even when told the unsupported approach lacked scientific evidence. That is, knowledge of evidence alone was insufficient to safeguard against the pursuit of pseudoscientific treatment alternatives. However, it warrants noting that the Gilroy et al. (In Press) study evaluated treatment choices with and without evidence and that most caregivers make choices between treatments that have *varying* degrees of scientific evidence.

The purpose of this study was to build upon and extend the findings presented in Gilroy et al. (In Press). Specifically, the focus was not on evaluating how the *absence* of scientific evidence affects caregiver choice, but rather, how *differences* in the level of scientific evidence between treatments influence caregiver choice. Several Hypothetical Treatment Marketplace Tasks (HTPTs) were developed, and in all but one, a well-established EBP was accompanied by another treatment option that varied in terms of its research support (e.g., High-, Moderate-, and Low-evidence). The specific research questions in this study were 1) whether any demographic factors appear to be significantly related to the demand for EBPs (alone-price demand) and 2) to evaluate the degree to which differences in the level of evidence correspond with the substitutability of EBPs (own-/cross-price demand).

Methods

Participants

A total of 106 caregivers were recruited using the Amazon Mechanical Turk (MTurk) framework. The MTurk framework is a resource that allows researchers to recruit “workers” to complete research tasks and compensate them for their participation in research. MTurk workers were eligible to accept the research task if they held the following qualifiers: 1) had completed at least 1,000 previous tasks, 2) maintained an overall work approval rating of 99%, 3) held the ‘parent’ qualifier as validated by MTurk, and 4) resided in the United States. These requirements are consistent with recommended practices when gathering and analyzing data collected gathered on “crowdsourced” platforms (Chandler & Shapiro, 2016).

Caregivers (i.e., workers) eligible to accept the MTurk task participated in a brief screening procedure to confirm whether they met the remaining criteria to participate in the study. This screening and all subsequent aspects of the instrument were designed using the Qualtrics Research Suite™. Several questions were designed to confirm the number of children in the household, the current level of child behavior concerns, and interest in pursuing a parent-implemented form of behavior therapy. Caregivers who indicated that they either had no children, no current child behavior concerns, or no interest in pursuing a parent-implemented form of behavior therapy were informed that they were not eligible to participate in the study. Caregivers who completed the task, or were determined ineligible to participate, were flagged in the MTurk framework so that they could not re-attempt the task. Eligible caregivers were compensated at a rate of $2.00 for an approximately 12-minute-long survey.

Procedures

Hypothetical Treatment Purchase Tasks

Eligible caregivers completed a series of four HTPTs. Each HTPT was designed to index the level of consumption for a primary treatment or a primary treatment as well as an alternative treatment. The initial HTPT (alone-price) featured a single parent-implemented behavior treatment that was supported by strong, scientific evidence. The remaining HTPTs included the primary treatment from the first HTPT (own-price) as well as an additional fixed price treatment alternative that varied in terms of scientific evidence (cross-price). Descriptions for each of the HTPTs are provided in the sections below and associated vignettes are provided in the Appendix.

Alone-Price Demand for EBPs (High Evidence). The initial HTPT was designed to evaluate the consumption of EBPs when this was the only option available to caregivers (i.e., closed economy). In this HTPT, as well as in the others that followed, Parent-Child Interaction Therapy (PCIT; Eyberg et al., 2008) was used as the primary EBP of interest. The PCIT treatment was selected due to its extensive generality and consistently high levels of evidence for improving a wide range of developmental and behavioral issues (Hembree-Kigin & McNeil, 2013).

Caregivers were provided with a hypothetical budget of up to 4,000 USD that could be spent towards up to 20 hours of parent-implemented treatment for their child in a week. Consistent with earlier HTPTs (Gilroy et al., In Press), caregivers were instructed to allocate their resources (in 0.25-hour increments) and to respond as if they could not save or direct these resources elsewhere. The price points in this task were modeled around a mean price of 200 USD per unit hour of service delivered with a standard deviation of 50 USD. This resulted in a price assay of 50, 100, 150, 200, 250, 300, and 350 USD.

Own-Price Demand for EBPs (vs. High, Moderate, and Weak Evidence). Three cross-price HTPTs were constructed to evaluate the consumption of a high-evidence EBP in the presence of alternatives that varied as a function of scientific evidence. Specifically, the base treatment option (PCIT) was accompanied by one of three fixed-price treatment alternatives (100 USD) that varied in terms of evidence in each HTPT. Each of the fixed price alternatives was also a form of parent-implemented behavior therapy that varied in terms of documented scientific evidence (i.e., High, Moderate, Weak). As such, the alternatives were all comparable forms of parent-implemented treatment that differed primarily in terms of available evidence (i.e., commensurate cost, time/effort). The price points for the primary treatment option (PCIT) were identical across both alone- and cross-price HTPTs.

The three treatments selected to serve as alternatives to the base service (PCIT) consisted of the Incredible Years Basic Parenting Program (IY; Webster-Stratton, 2001), the Rational Positive Parenting Program (RPP; David & DiGiuseppe, 2016), and Collaborative and Proactive Solutions (CPS; Greene, 1998). The Incredible Years (IY) program was designated as the 'high evidence' alternative to PCIT based on its widely demonstrated generality and documented effectiveness in the literature (Thomas et al., 2017). The IY program is well-researched with evidence of effectiveness demonstrated across multiple teams, multiple settings, and multiple randomized-controlled trials (RCTs). The Rational Positive Parenting (RPP) program was considered to be the 'moderate evidence' alternative because the effectiveness of this approach was not as broadly and widely demonstrated as PCIT (David, 2014). That is, evidence of efficacy and effectiveness was demonstrated but to a lesser degree than what was currently observed for

PCIT and IY (e.g., fewer teams evaluating the program). The Collaborative and Proactive Solutions program approach was considered the relatively ‘weak evidence’ alternative because this approach had few trials demonstrating efficacy, was less extensively researched, and relatively few research teams had been involved in its evaluation (Ollendick et al., 2016).

Systematic Purchase Task Data

The quality and consistency of hypothetical purchase task data were evaluated in several ways. First, a total of five several attention checks were included in the survey to assess engagement with the task. Second, data were inspected to determine whether they conformed to the prototypical trends expected in systematic (i.e., orderly) purchase task data. Specifically, purchase task data were evaluated for the three indicators of systematic consumption outlined in Stein et al. (2015) and this was performed using the *beezdemand* R package (Kaplan et al., 2019). A total of 96 (90.56%) caregivers provided data that met all indicators of systematic responding (i.e., global trend, bounce, reversals from zero) and 73 (68.87%) failed no more than one of the five attention checks. In each of the analyses, both the full and screened data sets were analyzed using a multilevel modeling approach (Kaplan et al., 2021). Study analyses were performed with both the full and screened data set (i.e., passing all data quality indicators) and the final analyses used the full data set if both the full and screened data sets supported the same conclusions.

Analytical Plan

Alone- and Own-Price Demand for EBPs. The consumption of EBPs was modeled using the Zero Bounded Exponential (ZBE) model of operant demand (Gilroy et al., 2021). The ZBE model extends the framework presented in Hursh and Silberberg (2008) by replacing the log scale with a log-like alternative (Inverse Hyperbolic Sine). Among several differences, the log-like scale used in this model supports a true lower bound at zero (for a discussion of this issue, see Gilroy, 2021), if necessary, and multiple implementations of this model exist (see Eq. 1-3). Each form of the ZBE model represents changes in consumption on the same scale and may be evaluated using traditional model selection procedures (e.g., F-test). That is, both Eq. 2 and Eq. 3 were considered restricted forms of Eq. 1.

Model performance was evaluated before performing each of the final analyses for both alone- and own-price demand for EBPs. The price elasticity of demand (i.e., the relationship between relative changes in price and relative changes in consumption) was evaluated by examining peak expenditure (O_{MAX}) on the natural scale (Gilroy et al., 2021)[2] _ENREF_10. This value was then used as a reference point to identify the price (P_{MAX}) at which peak expenditure on EBPs occurred (O_{MAX}).

$$IHS(Q) = IHS(Q_0) + k\,(e^{-\alpha Q_0 P} - 1) \quad 1)$$

$$IHS(Q) = IHS(Q_0) * e^{-\frac{\alpha}{IHS(Q_0)} Q_0 P} \quad 2)$$

$$IHS(Q) = IHS(Q_0) \quad 3)$$

Cross-price Demand for Treatment Alternatives. The cross-price demand for treatment alternatives (i.e., High, Moderate, Weak Evidence) was evaluated using a Generalized Estimating Equation (GEE). In contrast to methods that have previously been applied to cross-price experiments, e.g. Hursh and Roma (2013), the GEE approach is preferable to traditional methods for several reasons. Specifically, this approach allows for the evaluation of covariates (e.g., cost, evidence, demographics) within a single-stage analysis, supports model evaluations to

[2] Further description of the concept of elasticity and its interpretation in the Operant Demand Framework is provided in Gilroy, S. P., Kaplan, B. A., & Reed, D. D. (2020). Interpretation(s) of elasticity in operant demand. *Journal of the Experimental Analysis of Behavior, 114*(1), 106-115. https://doi.org/10.1002/jeab.610

address risks associated with under or overfitting, and more reliably converges in situations where earlier methods may encounter difficulty (Gilroy et al., In Press).

The GEE in this study was applied using the *geeglm* method included in the *geepack* R package (Halekoh et al., 2006) and model comparisons were performed using the QIC metric included in the *MuMin* R package (Barton, 2015). The QIC metric is functionally similar to the Akaike Information Criterion (AIC; Akaike, 1974), but modified to support comparisons that do not rely on Maximum Likelihood Estimation (Pan, 2001).

Results

Alone-Price Demand for EBPs

The demographics of the 106 caregivers included in the study are listed in Table 1. The alone-price demand for EBPs (High Evidence) was evaluated using aggregated consumption values with each of the ZBE models before proceeding with the final analysis using individual-level consumption values. Using generalized nonlinear least squares, Sum of Squares F-Tests with the full (3-parameter) and simplified (2-parameter) ZBE models revealed that a separate span parameter was not supported ($F[1, 739] = 0.1212$, $p = .7278$). Similarly, the 2-parameter model better characterized the data than the intercept-only (1-parameter) model ($F[1, 740] = 39.156$, $p = 0$).

The 2-parameter form of the ZBE model was used to estimate Q_0 and α across reported levels of education, gender, and family size using a mixed-effects modeling approach with individual-level consumption data (Kaplan et al., 2021). No separate span parameter was estimated in the model. The results of this regression are listed in Table 2 and illustrated in Figure 1. Model fits indicated a main effect for Gender, whereby fathers demonstrated lower baseline levels of EBP consumption than mothers (Q_0 [Male] = -4.681, $T = -3.224$, $p < .01$). No other factors were significantly associated with demand for EBPs. Population-level predictions revealed a peak expenditure (O_{MAX}) of 2,364.23 USD towards EBPs, which occurred at a price (P_{MAX}) of 812.54 USD per unit hour of therapy.

Own-Price Demand for EBPs

The own-price demand for EBPs (High Evidence) was evaluated using aggregated consumption values with each of the ZBE models before proceeding with the final analysis. Comparisons between the full and simplified ZBE models revealed that the 2-parameter model better characterized own-price consumption of EBPs ($F[1, 2223] = 258.23$, $p = 1$). Similarly, the 2-parameter model better characterized the data than the intercept-only model ($F[1, 2224] = 89.21$, $p = 0$). The results from cross-price HTPTs using the 2-parameter model are listed in Table 2 and the fits to levels of consumption are illustrated in Figure 2.

The 2-parameter form of the ZBE model was used to estimate Q_0 and α across reported levels of evidence using individual-level consumption data in a multilevel modeling approach. Using the weak comparison level as a reference, results indicated an effect for the level of Evidence on demand intensity for both the moderate, Q_0 [Moderate Evidence] = -1.5233, $T = -2.479$, $p < .05$), and the strong levels, Q_0 [Strong Evidence] = -3.576, $T = -3.866$, $p < .001$). That is, the own-price demand for the primary treatment option decreased as the differences in levels of evidence shrank or the levels of evidence became identical (i.e., less difference in levels of evidence was associated with higher degrees of substitution). Pairwise comparisons of demand intensity using the *emmeans* package (Lenth, 2018) with the remaining contrasts indicated significant and orderly differences in demand intensity for the Moderate vs. High tasks (*estimate* = 2.05, $df = 2115$, $p < .05$). Similarly, using the weak comparison level as a reference, results indicated an effect for Evidence on rates of change in elasticity for both the moderate, α

[Moderate Evidence] = 0.00002, $T = -2.2334$, $p < .05$), and the strong levels, α [Strong Evidence] = 0.00003, $T = 2.9431$, $p < .01$). Overall, the rates of change in elasticity increased as the level of evidence for the alternative approached those of the primary service. Pairwise comparisons of α with the remaining contrasts indicated orderly but nonsignificant differences for the Moderate vs. High tasks (*estimate* = -.000012, $df = 2115$, $p = .6426$).

Cross-Price Demand for Treatment Alternatives

The consumption of the various treatment alternatives was evaluated using GEE with an exchangeable correlation structure. The factors included in the full GEE model included Price, level of Evidence (Weak, Moderate, High), Gender (Male, Female), Family Size (Single, Multiple Children), and Education (i.e., Less than Bachelors, Bachelors or Higher) and all possible interactions. Model selection using QIC favored the model with Price (β [*Price]* = 0.00321, $W = 20.96$, $p < .0001$) and Evidence as the sole factors. The results from this analysis are illustrated in Figure 2.

Across all HTPTs, all treatment alternatives (Weak, Moderate, High) functioned as substitutes to a high-evidence EBP regardless of the level of evidence (β [*Price]* = 0.0032, $W = 20.96$, $p < .0001$). Using the high evidence alternative as the contrast, there was a significant difference in the level of consumption for the Moderate (β [*Moderate]* = -2.3557, $W = 23.38$, $p < .0001$) and the Weak alternatives (β [*Weak]* = -3.3504, $W = 58.2$, $p < .0001$). That is, there was an orderly relationship observed between the level of evidence and the level of consumption for the treatment alternative. Estimated marginal means were calculated to further explore these levels and results indicated a significant difference between the levels of alternative treatment consumption in the Moderate and Weak HTPTs (*estimate* = 0.99, $Z = 2.48$, $p < .01$). Results overall indicated that caregivers would consume each of the alternatives as a substitute for EBPs but that there was a significant main effect for the level of evidence on the levels of consumption for treatment alternatives.

Discussion

Clinicians and researchers regularly advocate for the adoption and use of methods that are supported by credible, scientific research (Kaminski & Claussen, 2017; Smith, 2013). Efforts have been made to increase the visibility of scientific evidence, often by compiling this information into databases and other resources accessible to practitioners and lay audiences alike (APA Presidential Task Force on Evidence-Based Practice, 2006; What Works Clearinghouse, 2016). Although such resources provide an effective means of making scientific evidence more visible to non-researchers, this approach implicitly assumes that a lack of scientific information is the main (or at least a major) factor in treatment choice. Most classical economic and cognitive approaches to characterizing choice are based on the assumption that decision-makers behave rationally unless otherwise influenced by some internal cause (e.g., bias, heuristic; Hantula, 2017; Kahneman et al., 1982); however, basic and applied research with human and non-human animals regularly reveals deviations from these predictions and such assumptions seldom hold (Mazur, 1987; Reed et al., 2013). Revisiting treatment choice, it stands to reason that expecting caregivers to make perfectly rational treatment choices is untenable (i.e., what we *should* do as opposed to what we *actually* do).

The purpose of this study was to extend the operant behavioral economic approach to characterizing treatment choice. Specifically, this study evaluated how caregivers would allocate resources when treatment options varied in terms of evidence and unit price. Similar to the results from Gilroy et al. (In Press), the caregivers in this study overwhelming endorsed the consumption of any treatment option as a substitute to EBPs. That is, caregivers consumed any alternative to EBPs as a substitute regardless of its level of evidence. These results correspond with earlier work in this area and further question the assumption of rationality in choices related to behavior therapies.

The results of this replication and extension advance the understanding of treatment-related choices in three practical and meaningful ways. The first is related to relationships between concurrently available therapies. Both in this study and the prior demonstration (Gilroy et al., In Press), caregivers substituted high-evidence treatments (EBPs) regardless of the level of evidence for the treatment alternative. As such, this study replicates the earlier trend of EBP substitutability and provides converging support that the relationship between evidence-based and non- (or somewhat) evidence-based treatments is more complex than originally presumed. Second, this study parametrically evaluated how *differences* in the levels of evidence influence caregiver choice. Given that a range of child behavior therapies is concurrently available to caregivers, each with varying levels of evidence, this is a more representative context in which to evaluate treatment-related choices. This parametric evaluation revealed a main effect for the level of evidence, whereby the treatment alternatives with greater evidence were consumed as substitutes at higher levels. That is, all alternatives (i.e., low, moderate, high evidence) functioned as substitutes for highly efficacious treatment, but the degree of substitution tracked with levels of evidence. This finding corresponds with the earlier point that scientific evidence is a factor in treatment choice, but is unlikely to be the sole or primary factor influencing treatment-related choices. Third, and building from the second point, this study provides converging support for the use of HTPTs as a vehicle for elucidating the factors that influence treatment-related choices. Indeed, the Operant Demand Framework could be expanded to explore treatment-related factors beyond scientific evidence. Further exploration of other ecological factors may reveal meaningful contingencies related to treatment choices (e.g., indirect contingencies of treatment choice).

Findings from this study prompt further reflection on how researchers and clinicians should advocate for the use of EBPs by caregivers. For instance, we now ask ourselves, if evidence is not the most critical factor in advocating for optimal treatment, then what must we do differently to advocate against dubious and potentially unsafe treatment alternatives? Given that rationality is not a reliable presumption in treatment-related choice, greater emphasis must then be placed on other factors that may contribute to this pattern of decision-making. To wit, the application of Consumer Behavior Analysis appears to be the next logical step towards better characterizing the contingencies that contribute to consumer (i.e., caregiver) treatment choices. Choices related to therapy are likely driven jointly by a combination of direct (i.e., treatment efficacy and evidence thereof) as well as other indirect contingencies resulting from treatment choice. For instance, in the case of popular ‘fad’ treatments, the choice to consume these alternatives to EBPs is likely to be less influenced by direct contingencies (i.e., limited to no effect on behavior) but more influenced by the indirect contingencies of such choices (e.g., social signaling to the verbal community). Conversely, the choice to consume EBPs may be less likely because there are indirect contingencies that discourage such choices (e.g., social disapproval from the verbal community).

Applied behavior analysts are keenly aware of issues related to the public perception of behavior analytic treatment. Indeed, mainstream views of behavior analytic intervention regularly evoke unjustified fears associated with punishment and other aversive events (Freedman, 2015). As such, choices related to treatment (e.g., pursue ABA intervention or not) are often influenced by contingencies that are not directly related to the treatment received. In a

Consumer Behavior Analytic approach, Foxall (2016) distinguished between direct (i.e., Utilitarian) and indirect (i.e., Informational) sources of reinforcement. Viewing fads therapies as an example, such choices are likely maintained by favorable indirect contingencies (i.e., social approval, popularity) despite negligible or absent direct contingencies (i.e., no effect on behavior). Conversely, behavior analytic intervention may produce favorable direct contingencies (i.e., behavior reliably improves) but have highly unfavorable indirect contingencies (e.g., family members or community inaccurately viewing caregivers as ‘harming’ their child). Future attempts to explore caregiver choices related to treatment choice would benefit from exploring both direct (i.e., Utilitarian) and indirect (i.e., Informational) contingencies related to treatment choice.

Limitations and Future Directions

Although the results of this study correspond with earlier investigations of EBPs using the Operant Demand Framework, several limitations must be discussed. First, the primary research question was specific to the effect of varying levels of evidence, and this test and methodology were sufficiently powered to answer this broad question. However, the relatively modest sample size included in this study warrants consideration when interpreting effects associated with participant demographics. Indeed, the present sample was comprised predominantly of White/Caucasian, higher-educated, and married caregivers. As such, larger and more representative samples are necessary to better characterize how demographic factors may contribute to differential patterns of treatment choice. Second, the range of treatments included in the HTPTs presented here are idealized and focus on discrete pairs of treatments differing in terms of evidence. Real-world caregiver choices are likely to consider a much wider range of available treatments and varying degrees of evidence. Future expansions upon this approach will need to develop the methodology to include a larger and more targeted range of treatments, as well as prices, that more closely correspond with the resources available to most consumers. Third, the comparisons performed in this study focused solely on the direct consequences of treatments (i.e., degree of efficacy) and did not explore how other indirect contingencies may contribute to direction types of choices. Viewing treatment choice through a Consumer Behavior Analytic lens, it is likely that current attempts to advocate for EBPs overemphasize direct contingencies (i.e., highlighting evidence) and underemphasize indirect contingencies. Future research in this area should explore the role that these types of contingencies play in caregiver choices related to behavior therapy.

Appendix

Vignette for Primary Treatment (Parent-Child Interaction Therapy)

In the following questions, you will be asked to allocate time and resources to a treatment recommended by your healthcare provider for problem behavior.

The recommended treatment, Parent-Child Interaction Therapy (PCIT), teaches parents skills that will help them improve their children's challenging behavior. This treatment teaches play skills in order to help make the child-caregiver bond stronger. It also promotes positive social behaviors, then teaches discipline skills to help parents increase compliant behavior. Some examples of specific skills taught in PCIT are praising children for good behavior and using rewards and consequences for increasing compliance.

PCIT is has been shown in research to be an effective treatment. This is called a well-established evidence-based treatment. Because it is an evidence-based treatment, PCIT is considered an effective intervention for decreasing problem behaviors in children. It has been shown to be as good as other treatments that have been proven effective in treating problem behavior. It is highly recommended by professionals in the field, and better outcomes are correlated with more, higher-quality treatment.

Vignette for Alternative Treatment (Incredible Years Basic Parenting Program)

Another recommended treatment, Incredible Years Basic Parenting Program is an intervention that teaches parents about child behavior and how to manage it. Incredible Years uses video models and roleplay of effective and ineffective parenting strategies. It also includes discussions, collaborations, and self-reflection to learn more about child development and effective parenting skills. Incredible Years helps the child's academic, social and emotional development by using specific praise and rewards.

Incredible Years has been shown in research to be an effective treatment. This is called a Well-Established evidence-based treatment for improving problem behavior in children. It has been shown to be as good or better than other treatments for decreasing problem behaviors in children. It is highly recommended by professionals in the field, and better outcomes are correlated with more, higher-quality treatment.

Vignette for Alternative Treatment (Rational Positive Parenting Program)

The Rational Positive Parenting program (RPP) is a treatment that uses a combined cognitive and behavioral approach to teach parents skills to manage their child's problem behaviors. The cognitive portion of the program teaches caregivers how to improve emotion regulation for themselves and their kids. First, the program focuses on improving the emotional problems of caregivers and helps them build positive emotions. This helps caregivers understand their child's problem behaviors, and learn discipline strategies to manage them better. RPP uses behavioral techniques such as coaching, modeling, and consequences. This helps build better communication skills, social skills, and problem-solving skills with the child.

RPP has not been shown in all research to be effective. Because of this, it is considered a Possibly Efficacious treatment, because there is not a lot of research supporting it. At least one good research study showed the treatment to work, but it lacks other studies showing that it works to reduce problem behavior in kids. It is not considered a well-established treatment and needs more research to know if it is actually an effective treatment.

Vignette for Alternative Treatment (Collaborative and Proactive Solutions)

An experimental treatment, Collaborative and Proactive Solutions (CPS), is an intervention based on the idea that children with challenging behavior have skill deficits. CPS focuses on teaching parents and children to work together and proactively solve problems that contribute to challenging behavior. Some examples of specific skills taught in CPS are how to prioritize problems and how to create plans to solve problems before they occur.

CPS is not supported yet among experts as an effective intervention for reducing problem behavior in children with disruptive behavior disorders. Because there is no support from experts, this treatment is considered an Experimental treatment. It has not been evaluated in a good research study, which is important to determine if the treatment actually works to reduce problem behaviors. There is no good evidence supporting the use of this treatment because it is still experimental.

References:

Ainslie, G. W. (1975). Specious reward: a behavioral theory of impulsiveness and impulse control. *Psychological Bulletin, 82*(4), 463-496. https://doi.org/10.1037/h0076860

Ainslie, G. W. (1992). *Picoeconomics: The strategic interaction of successive motivational states within the person*. Cambridge University Press.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control, 19*(6), 716-723. https://doi.org/10.1109/tac.1974.1100705

American Speech-Language-Hearing Association. (2005). Evidence-based practice in communication disorders [Position Statement]. https://doi.org/10.1044/policy.PS2005-00221

APA Presidential Task Force on Evidence-Based Practice. (2006). Evidence-based practice in psychology. *The American Psychologist, 61*(4), 271. https://doi.org/10.1037/0003-066X.61.4.271

Barton, K. (2015). *R Package 'MuMIn'.* In https://cran.r-project.org/web/packages/MuMIn/index.html

Call, N. A., Reavis, A. R., McCracken, C. E., Gillespie, S. E., & Scheithauer, M. C. (2015). The impact of delays on parents' perceptions of treatments for problem behavior. *Journal of*

Autism and Developmental Disorders, *45*(4), 1013-1025. https://doi.org/10.1007/s10803-014-2257-9

Camerer, C., & Loewenstein, G. (2004). Behavioral Economics: Past, Present, Future. In *Advances in Behavioral Economics*. Princeton University Press.

Chambless, D. L., Baker, M. J., Baucom, D. H., Beutler, L. E., Calhoun, K. S., Crits-Christoph, P., Daiuto, A., DeRubeis, R., Detweiler, J., & Haaga, D. A. (1998). Update on empirically validated therapies, II. *The clinical psychologist*, *51*(1), 3-16. https://doi.org/https://doi.org/10.1037/e619622010-001

Chandler, J., & Shapiro, D. (2016). Conducting Clinical Research Using Crowdsourced Convenience Samples. *Annual Review of Clinical Psychology*, *12*(1), 53-81. https://doi.org/10.1146/annurev-clinpsy-021815-093623

David, O. A. (2014). The rational positive parenting program for child externalizing behavior: mechanisms of change analysis. *Journal of Evidence-Based Psychotherapies*, *14*(1).

David, O. A., & DiGiuseppe, R. (2016). The rational positive parenting program. In *The rational positive parenting program* (pp. 15-48). Springer. https://doi.org/10.1007/978-3-319-22339-1_3

Evidence-Based Medicine Working Group. (1992). Evidence-based medicine. A new approach to teaching the practice of medicine. *Journal of the American Medical Association, 268*(17), 2420. https://doi.org/10.1001/jama.1992.03490170092032

Eyberg, S. M., Nelson, M. M., & Boggs, S. R. (2008). Evidence-based psychosocial treatments for children and adolescents with disruptive behavior. *Journal of Clinical Child & Adolescent Psychology, 37*(1), 215-237. https://doi.org/10.1080/15374410701820117

Foxall, G. R. (2016). Operant Behavioral Economics. *Managerial and Decision Economics, 37*(4-5), 215-223. https://doi.org/10.1002/mde.2712

Freedman, D. H. (2015). Improving Public Perception of Behavior Analysis. *The Behavior Analyst, 39*(1), 89-95. https://doi.org/10.1007/s40614-015-0045-2

Gilroy, S. P. (2021). Hidden equivalence in the operant demand framework: A review and evaluation of multiple methods for evaluating nonconsumption. *Journal of the Experimental Analysis of Behavior*. https://doi.org/10.1002/jeab.724

Gilroy, S. P., & Kaplan, B. A. (2020). Modeling Treatment-Related Decision-Making Using Applied Behavioral Economics: Caregiver Perspectives in Temporally-Extended Behavioral Treatments. *Journal of Abnormal Child Psychology, 48*(5), 607-618. https://doi.org/10.1007/s10802-020-00619-6

Gilroy, S. P., Kaplan, B. A., & Reed, D. D. (2020). Interpretation(s) of elasticity in operant demand. *Journal of the Experimental Analysis of Behavior*, *114*(1), 106-115. https://doi.org/10.1002/jeab.610

Gilroy, S. P., Kaplan, B. A., Reed, D. D., Koffarnus, M. N., & Hantula, D. A. (2018). The Demand Curve Analyzer: Behavioral economic software for applied research. *Journal of the Experimental Analysis of Behavior*, *110*(3), 553-568. https://doi.org/10.1002/jeab.479

Gilroy, S. P., Kaplan, B. A., Schwartz, L., Reed, D. D., & Hursh, S. R. (2021). A Zero-Bounded Model of Operant Demand. *Journal of the Experimental Analysis of Behavior*, *115*(3), 729-746. https://doi.org/10.1002/jeab.679

Gilroy, S. P., Waits, J. A., & Kaplan, B. A. (In Press). Applications of Operant Demand to Treatment Selection I: Characterizing Demand for Evidence-based Practices. *Journal of the Experimental Analysis of Behavior*.

Greene, R. W. (1998). *The explosive child: A new approach for understanding and parenting easily frustrated," chronically inflexible" children*. HarperCollins Publishers.

Halekoh, U., Højsgaard, S., & Yan, J. (2006). The R package geepack for generalized estimating equations. *Journal of Statistical Software*, *15*(2), 1-11. https://doi.org/10.18637/jss.v015.i02

Hantula, D. A. (2017). Editorial: Retrospections, Prospections and New Paths for Behavioral Science. *The Behavior Analyst, 40*(2), 291-295. https://doi.org/10.1007/s40614-017-0130-9

Hebert, E. B. (2014). Factors Affecting Parental Decision-Making Regarding Interventions for Their Child with Autism. *Focus on Autism and Other Developmental Disabilities*, *29*(2), 111-124. https://doi.org/10.1177/1088357614522291

Hembree-Kigin, T. L., & McNeil, C. B. (2013). *Parent—child interaction therapy*. Springer Science & Business Media.

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., & Roma, P. G. (2013). Behavioral economics and 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

Jacobson, J. W., Kryszak, E., & Mulick, J. A. (2015). Developmental disabilities and the paranormal. In R. M. Foxx & J. A. Mulick (Eds.), *Controversial Therapies for Autism and Intellectual Disabilities: Fad, Fashion, and Science in Professional Practice* (2nd ed., pp. 116-140). Routledge.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge University Press.

Kaminski, J. W., & Claussen, A. H. (2017). Evidence Base Update for Psychosocial Treatments for Disruptive Behaviors in Children. *Journal of Clinical Child and Adolescent Psychology, 46*(4), 477-499. https://doi.org/10.1080/15374416.2017.1310044

Kaplan, B. A., Franck, C. T., McKee, K., Gilroy, S. P., & Koffarnus, M. N. (2021). Applying Mixed-Effects Modeling to Behavioral Economic Demand: An Introduction. *Perspectives on Behavior Science, 44*, 333-358. https://doi.org/10.1007/s40614-021-00299-7

Kaplan, B. A., Gilroy, S. P., Reed, D. D., Koffarnus, M. N., & Hursh, S. R. (2019). The R package beezdemand: Behavioral Economic Easy Demand. *Perspectives on Behavior Science, 42*(1), 163-180. https://doi.org/10.1007/s40614-018-00187-7

Kaplan, S. L., Coulter, C., & Fetters, L. (2013). Developing evidence-based physical therapy clinical practice guidelines. *Pediatric Physical Therapy*, *25*(3), 257-270. https://doi.org/10.1097/PEP.0b013e31829491c5

Kay, S. (2015). Helping parents separate the wheat from the chaff: Putting autism treatments to the test. In R. M. Foxx & J. A. Mulick (Eds.), *Controversial Therapies for Autism and Intellectual Disabilities* (2nd ed., pp. 216-228). Routledge.

Lenth, R. (2018). Emmeans: Estimated marginal means. *Aka Least-squares Means, R*.

Mazur, J. E. (1987). An adjusting procedure for studying delayed reinforcement. In M. L. Common & J. E. Mazur (Eds.), *Quantitative analysis of behavior: Vol. 5. The effect of delay and intervening events on reinforcement value* (pp. 55-73). Erlbaum.

McDonald, M. E., & DiGennaro Reed, F. D. (2018). Distinguishing science and pseudoscience in the assessment and treatment of autism spectrum disorder. In S. Ozonoff & S. Goldstein (Eds.), *Assessment of autism spectrum disorder* (2nd ed., pp. 415-441).

National Autism Center. (2015). Findings and conclusions: National standards project, Phase 2. https://www.nationalautismcenter.org/national-standards-project/phase-2/

Novins, D. K., Green, A. E., Legha, R. K., & Aarons, G. A. (2013). Dissemination and implementation of evidence-based practices for child and adolescent mental health: A systematic review. *Journal of the American Academy of Child & Adolescent Psychiatry, 52*(10), 1009-1025. https://doi.org/10.1016/j.jaac.2013.07.012

Odum, A. L. (2011). Delay discounting: I'm a k, you're a k. *Journal of the Experimental Analysis of Behavior*, *96*(3), 427-439. https://doi.org/10.1901/jeab.2011.96-423

Ollendick, T. H., Greene, R. W., Austin, K. E., Fraire, M. G., Halldorsdottir, T., Allen, K. B., Jarrett, M. A., Lewis, K. M., Whitmore Smith, M., & Cunningham, N. R. (2016). Parent management training and collaborative & proactive solutions: A randomized control trial for oppositional youth. *Journal of Clinical Child & Adolescent Psychology, 45*(5), 591-604. https://doi.org/10.1080/15374416.2015.1004681

Pan, W. (2001). Akaike's information criterion in generalized estimating equations. *Biometrics, 57*(1), 120-125. https://doi.org/10.1111/j.0006-341X.2001.00120.x

Quisenberry, A. J., Koffarnus, M. N., Hatz, L. E., Epstein, L. H., & Bickel, W. K. (2015). The experimental tobacco marketplace I: Substitutability as a function of the price of conventional cigarettes. *Nicotine & Tobacco Research*, *18*(7), 1642-1648.

Reed, D. D., Kaplan, B. A., & Becirevic, A. (2015). Basic research on the behavioral economics of reinforcer value. In F. D. DiGennaro-Reed & D. D. Reed (Eds.), *Autism Service Delivery* (pp. 279-306). Springer New York. https://doi.org/10.1007/978-1-4939-2656-5_10

Reed, D. D., Niileksela, C. R., & Kaplan, B. A. (2013). Behavioral economics: a tutorial for behavior analysts in practice. *Behavior Analysis in Practice, 6*(1), 34-54. https://doi.org/10.1007/BF03391790

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

Sackett, D. L. (1997). Evidence-based medicine. Seminars in perinatology,

Shernoff, E. S., Kratochwill, T. R., & Stoiber, K. C. (2003). Training in evidence-based interventions (EBIs): What are school psychology programs teaching? *Journal of School Psychology, 41*(6), 467-483. https://doi.org/10.1016/j.jsp.2003.07.002

Smith, T. (2013). What is evidence-based behavior analysis? *The Behavior Analyst, 36*(1), 7-33. https://doi.org/10.1007/BF03392290

Smith, T. (2015). The appeal of unvalidated treatments. In R. M. Foxx & J. A. Mulick (Eds.), *Controversial therapies for autism and intellectual disabilities* (2nd ed., pp. 49-62). Routledge. https://doi.org/10.4324/9781315754345-10

Spencer, T. D., Detrich, R., & Slocum, T. A. (2012). Evidence-based practice: A framework for making effective decisions. *Education and Treatment of Children, 35*(2), 127-151. https://doi.org/10.1353/etc.2012.0013

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

Thomas, R., Abell, B., Webb, H. J., Avdagic, E., & Zimmer-Gembeck, M. J. (2017). Parent-child interaction therapy: a meta-analysis. *Pediatrics*, *140*(3). https://doi.org/10.1542/peds.2017-0352

Webster-Stratton, C. (2001). The incredible years: Parents, teachers, and children training series. *Residential treatment for children & youth, 18*(3), 31-45. https://doi.org/10.1300/J007v18n03_04

What Works Clearinghouse. (2016). U.S. Department of Education.

Wong, C., Odom, S. L., Hume, K. A., Cox, A. W., Fettig, A., Kucharczyk, S., Brock, M. E., Plavnick, J. B., Fleury, V. P., & Schultz, T. R. (2015). Evidence-based practices for children, youth, and young adults with autism spectrum disorder: A comprehensive review. *Journal of Autism and Developmental Disorders, 45*(7), 1951-1966. https://doi.org/10.1007/s10803-014-2351-z

Figure Captions

Figure 1. This figure illustrates the Alone-Price demand for Evidence-based Practices across reported gender, reported number of children in the household, and level of reported education. The darker lines illustrate group-level estimates and the lighter lines reflect individual-level responding.

Figure 2. This plot illustrates the Cross-Price demand for Evidence-based Practices and respective alternatives. Demand for the primary service and alternatives from each of the three purchase tasks are presented. The darker lines illustrate group-level estimates related to the consumption of the treatment alternative and the lighter lines reflect individual-level responding related to the consumption of Evidence-based Practices.

Table 1

Participant Demographics

Participant Demographics (n = 106)			
Age (years)		**Number of Children**	
Mean (SD)	39.2 (8.77)	Mean (SD)	2.13 (0.97)
Median (Q1-Q3)	32.2-44.8	Median (Q1-Q3)	2-2
Sex		**Education**	
Male	41(38.7%)	Less than High School	3 (2.83%)
Female	65 (61.3%)	High School graduate	4 (3.77%)
Income		Some college but no degree	18 (17.0%)
Q1	45000	Associate degree	9 (8.49%)
Median	64500	Bachelor's degree	59 (55.7%)
Q3	88825	Master's degree	13 (12.3%)
Behavior Concern		**Race/Ethnicity**	
A little	23 (21.7%)	Black/African-American	7 (6.6%)
A moderate amount	44 (41.5%)	Asian	5 (4.72%)
A lot	29 (27.4%)	Other	1 (0.94%)
A great deal	10 (9.43%)	White/Caucasian	85 (80.2%)
Marital Status		Native American	7 (6.6%)
Single	9 (8.49%)	Other	1 (0.94%)
Married	91 (85.8%)		
Divorced	5 (4.72%)		
Other	1 (0.94%)		

Table 2

Alone- and Own-Price Demand for Evidence-based Practices

	Alone-Price Demand for EBPs			
	Estimate	*Std. Err*	*T-value* (SE)	*p*
Q_0 [Intercept]	14.3145	1.1208	12.7716	.0000***
Q_0 [Education < Bachelors]	1.7289	1.5473	1.1173	.2643
Q_0 [Male]	-4.6810	1.4519	-3.2242	.0013**
Q_0 [Single]	-1.3020	1.6489	-0.7896	.4301
α [Intercept]	0.000066	0.0000	3.2494	.0000***
α [Education < Bachelors]	0.000004	0.0000	0.1481	.8823
α [Male]	0.000007	0.0000	0.2378	.8121
α [Single]	0.000037	0.0000	1.2179	.2237

	Cross-Price Demand for EBPs			
	Estimate	*Std. Err*	*T-value* (SE)	*P*
Q_0 [Intercept; Weak Evidence]	13.0563	0.8116	16.0876	0.0000***
Q_0 [Moderate Evidence]	-1.5233	0.6144	-2.4794	0.013*
Q_0 [Strong Evidence]	-3.5767	0.9251	-3.8663	0.0001***
α [Intercept; Weak Evidence]	0.00008	0.00001	5.6674	0.0000***
α [Moderate Evidence]	0.00002	0.00001	2.2334	0.0256*
α [Strong Evidence]	0.00003	0.00001	2.9431	0.0033**

Note: * $p < .05$, ** $p < .01$, ** $p < .001$

Figure 1. Alone-Price Demand for EBPs

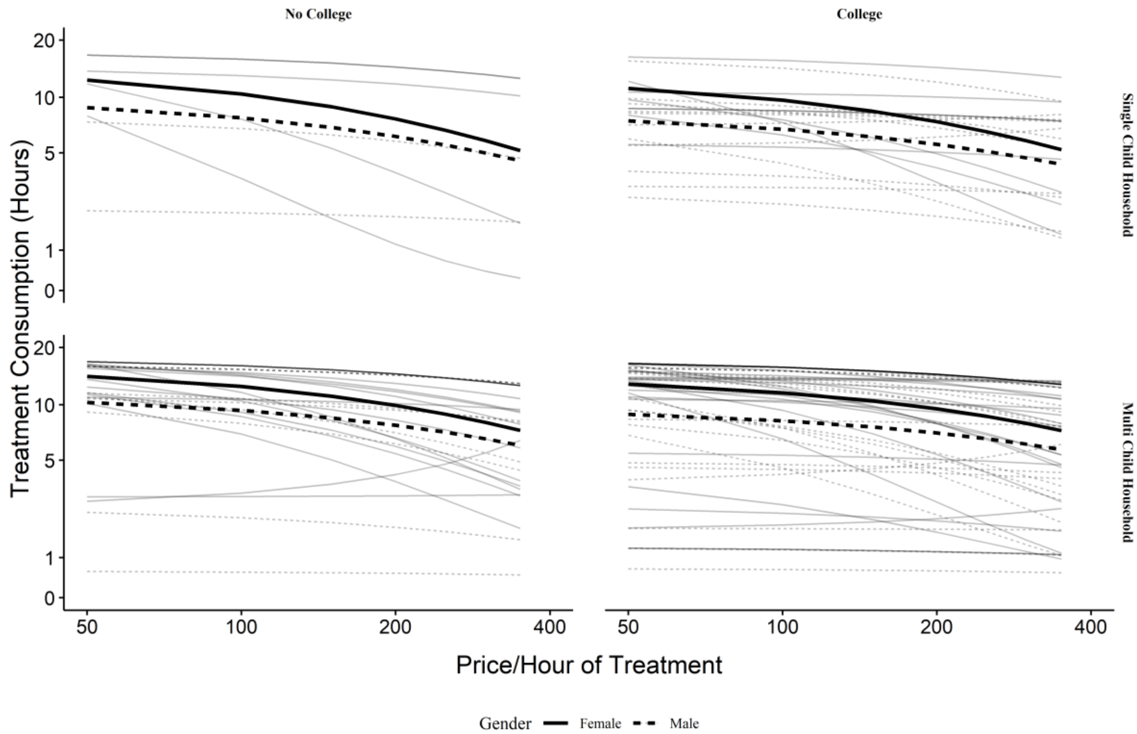

Figure 2. Treatment Consumption as a Function of Relative Evidence