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Sensitivity to Reinforcement Rate: The Role of Attention Problems and Frequently Co-occurring Forms of Psychopathology

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Sensitivity to Reinforcement Rate: The Role of Attention Problems and Frequently Co-occurring Forms of Psychopathology

By

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M.A. Emory University, 2016

Advisor: Jack J McDowell, Ph.D.

An abstract of
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Abstract

Sensitivity to Reinforcement Rate: The Role of Attention Problems
and Frequently Co-occurring Forms of Psychopathology

By Ryan Christopher Hackett

This study examined the assumption that attention-deficit/hyperactivity disorder is associated with a weakened response to schedules of partial reinforcement, in which only some instances of a targeted behavior are reinforced (Luman, Oosterlaan, & Sergeant, 2005; Luman, Tripp, & Scheres, 2010). We examined this assumption in a community sample of adults that varied widely in multi-informant ratings of attention problems. Participants were ages 18–38, had no major neurological conditions, and were not taking psychotropic medications. Participants were presented with two conditions that each contained five pairs of independent, concurrently available schedules of random interval reinforcement (US $0.07/reinforcement). In one condition, the overall rate of reinforcement was lean. In the other condition, the overall rate of reinforcement was rich. We computed individual differences in sensitivity to reinforcement rate under both conditions using the generalized matching law (Baum, 1974; Davison & McCarthy, 1988; Herrnstein, 1961; McDowell, 2013). We examined these individual differences in reinforcement rate sensitivity as a function of attention problems and co-occurring forms of psychopathology. Consistent with theory, we found that attention problems had a large, statistically significant, negative correlation with sensitivity to rate of reinforcement in the lean condition. This relationship disappeared in the rich condition. The same pattern of effects was found for internalizing and externalizing psychopathology, although these effects failed to reach statistical significance. These results warrant further investigation via cumulative meta-analysis.

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Chapter 1: Introduction

> Signs of the disorder may be minimal or absent when the individual is receiving frequent rewards for appropriate behavior… (American Psychiatric Association, 2013, p. 61)

Motivational accounts of attention-deficit/hyperactivity disorder (ADHD) often explain the disorder in terms of abnormal reinforcement learning (Luman et al., 2005; Luman et al., 2010; Willcutt, 2015). The exact nature of these abnormalities is contentious. However, it is virtually axiomatic that ADHD is associated with a weakened response to schedules of partial reinforcement (Luman et al., 2005; Luman et al., 2010). In a schedule of partial reinforcement, only some instances of a targeted behavior are reinforced. In contrast, all instances of a targeted behavior are reinforced in a continuous schedule of reinforcement. A corollary to this axiom asserts that a weakened response to schedules of partial reinforcement will disappear as the *rate* of reinforcement experienced approaches that of a continuous schedule of reinforcement (Catania, 2005; Sagvolden, Johansen, Aase, & Russell, 2005; Tripp & Wickens, 2008). This corollary is critical to helping parents understand how their child can have unusual difficulty sustaining attention for homework, but can spend hours with their eyes glued to the latest video game. It also has clear implications for the treatment of ADHD. Yet, these assumptions have rarely been tested at the most basic and direct level of analysis—observed behavior in response to schedules of reinforcement (Luman et al., 2005; Luman et al., 2010; Sonuga-Barke, Cortese, Fairchild, & Stringaris, 2016; Willcutt, 2015). In addition, it is unclear whether this putative under-sensitivity is independent of ADHD's complex landscape of comorbidity (Barkley, 2015; Sonuga-Barke et al., 2016).

The current study examined the relationship between an empirically-derived dimension of adult attention problems (Achenbach & Rescorla, 2003) and sensitivity to the rate of reinforcement provided by partial schedules of reinforcement. It further examined the relationship between sensitivity to rate of reinforcement and delay discounting—a popular mechanism for explaining the under-sensitivity to partial schedules of reinforcement associated with ADHD (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). In addition, the study explored bivariate relationships between sensitivity to rate of reinforcement and two broad dimensions of psychopathology that frequently co-occur with attention problems—internalizing and externalizing (Achenbach & Rescorla, 2003; Barkley, 2015; Kotov et al., 2017). To accomplish this task, the study employed the generalized matching law, a well-established experimental paradigm for quantifying behavioral sensitivity to schedules of partial reinforcement (Baum, 1974; Davison & McCarthy, 1988; Herrnstein, 1961; McDowell, 2013).

1.1. ADHD

ADHD is a neurodevelopmental disorder characterized by developmentally inappropriate and functionally impairing levels of inattentive, hyperactive, and impulsive behavior (American Psychiatric Association, 2013). When compared to healthy controls, children, adolescents, and adults with ADHD demonstrate large reductions in global and adaptive functioning; moderate-to-large reductions in academic achievement and attainment; small-to-moderate reductions in neuropsychological functioning; moderate-to-large increases in social impairments and rejection; increased odds of injury, disability, suicide, and obesity; and increased odds of concurrent or future mood, anxiety, substance use, neurodevelopmental, and impulse-control disorders (Agosti, Chen, & Levin, 2011; Cortese et al., 2008; Frazier, Youngstrom, Glutting, & Watkins, 2007; Fuemmeler, Ostbye, Yang, McClernon, & Kollins, 2011; Kessler et al., 2006; Kessler et al., 2014; Klein et al., 2012; Larson, Russ, Kahn, & Halfon, 2011; Mannuzza, Klein, Bessler, Malloy, & LaPadula, 1998; Merrill, Lyon, Baker, & Gren, 2009; Pastor & Reuben, 2006; Willcutt et al., 2012). The functional impairments associated with ADHD have generally appeared to be robust to possible confounds, such as age, sex, ethnicity, socioeconomic status, intelligence, and comorbidity (Willcutt et al., 2012). Worldwide, the disorder is estimated to affect 5% of children and adolescents (Polanczyk, de Lima, Horta, Biederman, & Rohde, 2007) and 2.5% of adults (Simon, Czobor, Balint, Meszaros, & Bitter, 2009). ADHD most often precedes its comorbid conditions, with over 70% of cumulative lifetime ADHD cases emerging between ages 4 and 6 (Kessler et al., 2012; Taurines et al., 2010).

1.2. Heterogeneity of ADHD

ADHD was defined by three nominal subtypes prior to DSM-5—inattentive, hyperactive/impulsive, and combined (American Psychiatric Association, 2013). These subtypes were defined by their patterns of elevations on the symptom dimensions of inattention and hyperactivity/impulsivity. Some theorists argued that the defining features of ADHD were subtype-specific, including reduced sensitivity to partial schedules of reinforcement (Quay, 1997; Sagvolden et al., 2005; Sonuga-Barke, 2002, 2003). By DSM-5, this typology seemed strained (Willcutt et al., 2012). The subtypes had poor longitudinal stability. They had high overlap in external correlates and etiology.

The symptom dimensions of ADHD fared better (Willcutt et al., 2012). They demonstrated evidence of rank order stability. They demonstrated reduced overlap in external correlates and etiology. Inattention appeared somewhat more associated with impairment in adaptive functioning, reduced performance on cognitive tasks, reduced academic achievement, shy and passive social skills, and emotional distress. Hyperactivity/impulsivity appeared somewhat more associated with externalizing behavior and social rejection, and was more likely to decline with age. However, these dimensions were still highly correlated (r range = 0.63–0.75) and showed no differences in response to treatment. In addition, factor analyses of an empirically-derived alternative to DSM nosology had generally placed inattentive, hyperactive-impulsive, and related symptoms on a single dimension (Achenbach & Rescorla, 2001, 2003). This dimension had evidence of cross-cultural invariance and moderate sensitivity and specificity in the prediction of ADHD diagnosis (Chang, Wang, & Tsai, 2016; Rescorla et al., 2012). Therefore, DSM-5 softened these subtypes into three patterns of symptom presentations, and a single empirically-derived dimension of attention problems can provide useful coverage of the ADHD construct (Achenbach & Rescorla, 2003; American Psychiatric Association, 2013). This single dimension has the practical advantage of reducing the number of statistical tests necessary to examine correlates of ADHD. It also maximizes the power of these tests due to its more continuous nature. This is an especially important consideration for small-sample studies.

1.3. Delay discounting

The delay discounting literature examines individual differences in the subjective value of delayed consequences (Green & Myerson, 2004; Madden & Johnson, 2010). This large and varied literature demonstrates that people show a robust preference for immediate over delayed reinforcement. Under the right combinations of reinforcement delays and magnitudes, individuals will choose a smaller–sooner over a larger–later option, even if the larger–later option provides a net benefit. In other words, they will tend to make an impulsive choice. Some are better able to hold out for a net gain than others. All of us can achieve better self-control if we are required to make an irreversible choice when the experience of both the smaller–sooner and larger–later consequences are far enough in the future (Ainslie, 1974; Mazur, 2016). This prevents the siren call of the smaller–sooner reward from pulling us off course as we pass by on our way to better things.

Individual differences in delay discounting display both state- and trait-like characteristics (Odum & Baumann, 2010). At the state level, degree of discounting appears to be associated with a variety of contextual factors, such as the magnitude and type of consequence(s); deprivation state; cognitive load; drug intoxication; mood; stress; and decision-making location (Green & Myerson, 2004; Hamilton et al., 2015; Lempert, Steinglass, Pinto, Kable, & Simpson, 2019; Moody, Tegge, & Bickel, 2017; Odum & Baumann, 2010). At the trait level, degree of discounting appears to be negatively associated with age, IQ, and socioeconomic status, and positively associated with trait impulsivity and conditions characterized by poor impulse-control (Duckworth & Kern, 2011; Green & Myerson, 2004; Hamilton et al., 2015; Lempert et al., 2019; Odum & Baumann, 2010). This includes ADHD, obesity, addiction, and borderline personality disorder (Amlung, Petker, Jackson, Balodis, & MacKillop, 2016; Gottdiener, Murawski, & Kucharski, 2008; Paret, Jennen-Steinmetz, & Schmahl, 2017; Patros et al., 2016; Pauli-Pott & Becker, 2011). Delay discounting appears moderately increased for school-age children and adolescents with ADHD relative to controls (Hedge's g =0.50, Patros et al., 2016). Preschool-age children at risk for ADHD evidence large increases in delay discounting relative to controls (Cohen's d = 0.80, Pauli-Pott & Becker, 2011). Emerging evidence suggests that delay discounting may have acceptable internal consistency, test-retest reliability, and longitudinal stability; and may be moderately heritable (Anokhin, Golosheykin, Grant, & Heath, 2011; Anokhin, Golosheykin, & Mulligan, 2015; Anokhin, Grant, Mulligan, & Heath, 2015; Hamilton et al., 2015; Isen, Sparks, & Iacono, 2014; Lempert et al., 2019;

Martínez-Loredo, Fernández-Hermida, Carballo, & Fernández-Artamendi, 2017; Nguyen, Brooks, Bruno, & Peacock, 2018; Odum & Baumann, 2010; Pauli-Pott & Becker, 2015).

Several prominent theorists have argued that increased discounting of delayed reinforcement can explain the connection between ADHD and reduced sensitivity to partial schedules of reinforcement (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). This assertion is based on several observations. First, the schedules of reinforcement that produce high rates of behavior tend to be characterized by increased rate and/or magnitude of reinforcement (Ferster & Skinner, 1957). Second, the schedules of reinforcement supporting many socially important behaviors tend to be relatively low in rate and/or magnitude. For example, a series of observational studies of 1st grade classrooms found that teachers provided verbal approval for good behavior at a rate of 0.5 approvals/minute for all pupils combined (not for each child in the class, White, 1975). This rate dropped to approximately 0.15 approvals/minute in 9th grade classrooms. Third, the rate and/or magnitude of reinforcement available for less socially important activities, such as playing the latest video game, tends to be quite high (King, Delfabbro, & Griffiths, 2009, 2010).

This unfortunate arrangement sets everyone up for some difficulty with self-control. Hence the common phrase “I’m a little ADD.” These conditions are theorized to cause more serious difficulties for individuals who significantly discount delayed reinforcement (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). These individuals might find it more difficult to initiate important tasks supported by relatively lean schedules. They might be more prone to early discontinuation of such tasks. They might be more tempted by competing activities supported by relatively rich schedules. They might find it more difficult to redirect themselves once engaged in a richer alternative. They might appear restless, impatient, and impulsive. They might find themselves chronically criticized for failure to see the big picture or follow through. Others might wonder if they are just "lazy, stupid, or crazy" (Kelly & Ramundo, 2006). Sagvolden and colleagues (2005, 2008) have argued that this captures the predicament of individuals with ADHD and gives rise to their hallmark symptoms of inattentive and hyperactive-impulsive behavior.

The most common method for estimating discounting in humans is to present participants with a series of choices between hypothetical monetary values that vary in amount and delay (Green & Myerson, 2004; Locey, 2013; Madden & Johnson, 2010; Rachlin, Raineri, & Cross, 1991). For example, participants might be asked to choose between $2,000 now and $2,000 in 1 year. Then the question would be repeated and the amount of the immediate value would be systematically decreased until a point of indifference was reached between the choices. The procedure would be repeated for a series of delays, ranging from a week to 25 years. Participants willing to sacrifice more of their maximum potential earnings in exchange for receiving some money immediately would tend to have lower indifference points. These lower indifference points would suggest steeper discounting of delayed reinforcement. By implication, this would suggest poorer self-control.

These indifference points are generally well-described by the following hyperbolic function:

$$v_{delay} = \frac{V}{1+\kappa_{delay} D}, \tag{1-1}$$

In this equation, v_{delay} is the subjective value of reinforcement after delay, V is the objective value of reinforcement, D is the objective delay to reinforcement, and k_{delay} is a constant measuring degree of delay discounting (Ainslie, 1975; Mazur, 1987). Equation 1-1 has been well-supported across species and has attractive parsimony relative to proposed hyperbola-like alternatives

(Madden & Johnson, 2010). It appears to be robust with respect to different types of consequences, including purely hypothetical, possibly real, and experienced consequences (Madden & Johnson, 2010). Individual differences in delay discounting can also be estimated using nonparametric area-under-the-curve (AUC) analysis (Myerson, Green, & Warusawitharana, 2001). This method has been recommended for studies focused on the relationship between delay discounting and other individual difference variables (Madden & Johnson, 2010). It has two advantages: (a) it makes no assumptions about the true form of the delay discounting function; and (b) it yields a single delay discounting parameter for each individual that typically falls into an approximate normal distribution.

1.4. The Generalized Matching Law

The connection between ADHD, delay discounting, and sensitivity to partial schedules of reinforcement can be rigorously examined using the generalized matching law paradigm (GML, Baum, 1974; Davison & McCarthy, 1988; McDowell, 2013). This paradigm provides a mathematical account of the relationship between behavior and its consequences when (a) individuals are free to choose how they distribute their time and efforts across available options; (b) they make these choices in a continuous manner within a dynamic environment; and (c) these choices sometimes result in positive or negative reinforcement (i.e., are governed by partial schedules of reinforcement). This account covers a very broad set of situations in the natural environment for human and nonhuman organisms. It has accrued extensive cross-species support over 60 years of development in experimental, observational, and applied settings. It allows estimation of an individual's sensitivity to fundamental features of partial reinforcement schedules using directly observed behavior. This includes sensitivity to the rate and/or magnitude of reinforcement.

The canonical GML procedure allows individuals to freely allocate their behavior between two independent, concurrently available schedules of variable- or random-interval reinforcement (VI or RI, Baum, 1974; Davison & McCarthy, 1988; McDowell, 2013). VI and RI schedules offer opportunities for reinforcement based on the end of a time delay, with the delay interval varying randomly around an average (Cheney & Pierce, 2013; Ferster & Skinner, 1957). Such schedules always produce more responses than reinforcements (i.e., partial reinforcement) and appear to be an important feature of the natural environment. Individuals are presented with a series of these pairs of schedules, with the ratio of reinforcement rates and/or magnitudes systematically varied across pairs (Baum, 1974; Davison & McCarthy, 1988; McDowell, 2013). The relationship between the ratios of response rates and the ratios of obtained reinforcement rates and/or magnitudes can be estimated for each individual once their behavior has reached a steady-state. Reinforcement sensitivity is estimated in parameters characterizing the extent to which the ratio of response rates deviates from the ratio of obtained reinforcement rates and/or magnitudes. This operationalizes sensitivity as the level of match between behavior and reinforcement history. This relationship is well-described by the following equation:

$$\log\left(\frac{B_1}{B_2}\right) = a_r \log\left(\frac{r_1}{r_2}\right) + a_m \log\left(\frac{m_1}{m_2}\right) + \log b, \tag{1-2}$$

In this equation, B_1 is the response rate for choice 1; B_2 is the response for rate choice 2; r_1 is the obtained reinforcement rate for choice 1; r_2 is the obtained reinforcement rate for choice 2; m_1 is the magnitude of reinforcements obtained from choice 1; m_2 is the magnitude of reinforcements obtained from choice 2; a_r is a constant measuring sensitivity to the rate of reinforcement; a_m is a constant measuring sensitivity to the magnitude of reinforcement; and b captures systematic bias for one choice unrelated to the rate or magnitude of reinforcement. Bias could be caused by a variety of factors, such as differences in the level of effort/cost required to respond on each option. On average, this equation explains approximately 90% of the variance in the choices made by humans and other animals in both laboratory and naturalistic settings (McDowell, 2013). The current experiment was designed to isolate the impact of manipulations in the *rate* of reinforcement (i.e., “signs of the disorder may be minimal or absent when individuals are receiving *frequent* rewards for appropriate behavior…”, American Psychiatric Association, 2013, p. 61).

1.5. Evidence using the GML paradigm

Only two published studies have made use of this paradigm to examine individual differences in response to partial schedules of reinforcement as a function of ADHD (Kollins, Lane, & Shapiro, 1997; Taylor, Lincoln, & Foster, 2010). The first study used 6 children ages 8–12 diagnosed with ADHD and 6 matched controls (Kollins, Lane, et al., 1997). The children played a computer game where they could fire “shots” at images of aliens on either side of a computer screen. The shots destroyed the aliens according to independent, concurrently available VI schedules of reinforcement (VI 3s–VI 3s; VI 6s–VI 3s; VI 3s–VI 9s; VI 15s–VI 3s; and VI 3s–VI 24s). A standard 2-second delay in reinforcement availability was imposed each time participants chose to fire at a different side (i.e., change-over-delay, or COD, which is a standard feature of laboratory-arranged concurrent schedules). Participants were exposed to one unique pair of VI schedules each day for 24–60 minutes over five days. Each time the participants killed twenty aliens, they could play two minutes of a more attractive Nintendo video game.

The results suggested a small trend towards reduced sensitivity to rate of reinforcement in children with ADHD relative to controls, but the experiment was significantly underpowered (Cohen’s $d = 0.16$, power = 0.06). In addition, the GML fit poorly to the data provided by 11 out of 12 participants in the study (i.e., r^2 values < 0.80, Horne & Lowe, 1993). This raised concerns about the reliability of the sensitivity to rate of reinforcement parameters used to make comparisons between children with ADHD and controls. These poor GML fits were suggestive of procedural errors, such as inadequately motivating reinforcements, or inadequate exposure to each pair of schedules (manuscript submitted for review, Klapes, Calvin, & McDowell, 2019).

The second published study involved 60 children ages 9–12, 30 with ADHD and 30 controls (Taylor et al., 2010). The matching task required participants to match colored shapes on a computer monitor to corresponding shapes on a keyboard. The children were given tokens and verbal praise for correct matches according to independent, concurrently available schedules of reinforcement (VI 15s; VI 35s; and VI 45s). Participants could freely switch among these schedules by pressing a change-over key. A 3-second COD was imposed for half of the participants in each group. Participants were exposed to this experimental condition for a single 45-minute session. Each individual's data was fit to the GML to obtain an estimate of their sensitivity to rate of reinforcement. A 2 group x 2 COD condition ANOVA was conducted with sensitivity to rate of reinforcement as the dependent variable. This analysis demonstrated large effects for diagnosis (Cohen's $f = 1.2$, achieved power = 1.0), COD condition (Cohen's $f = 0.96$, achieved power = 0.99), and their interaction (Cohen's $f = 0.96$, achieved power = 0.99).

Post-hoc tests with corrections for multiple comparisons indicated that the COD manipulation created little difference in sensitivity among the two control groups, but created large and statistically significant differences in sensitivity among the ADHD groups. With the COD, differences in sensitivity between the ADHD and control group were slight. Without the COD, individuals with ADHD were much less sensitive to the rates of reinforcement they experienced on each schedule than individuals in the control group. This suggested that individuals with ADHD may be most under-sensitive to the rate of reinforcement provided by partial reinforcement schedules when there is no immediate cost for switching between available options.

Information about the quality of GML fits for each individual was not reported in this better-powered follow-up study. This is likely because Taylor and colleagues (2010) presented participants with three VI schedules of reinforcement. This left three data points per person for fitting the two-parameter GML equation. At minimum, five schedules of reinforcement have typically been required to avoid trivially perfect GML fits (Davison & McCarthy, 1988).

Furthermore, both prior studies relied on a single set of concurrent VI schedules. This excluded the possibility of examining whether individual differences in sensitivity to partial reinforcement schedules due to ADHD could be remediated by manipulating the overall rate of reinforcement presented. This left a key corollary of the partial reinforcement axiom unexamined (i.e., a weakened response to schedules of partial reinforcement will disappear as the rate of reinforcement experienced approaches that of a continuous schedule of reinforcement). Research by Alsop and Elliffe (1988) suggests that sensitivity to the rate of reinforcement provided by a set of independent, concurrent VI schedules varies with the overall rate of reinforcement characterizing the set.

These studies also sacrificed important information and statistical power by relying on a case-control design, when ADHD and related disorders appear to be dimensional in nature and highly comorbid (Kotov et al., 2017; Marcus & Barry, 2011). Finally, neither study incorporated a measure of delay discounting. This prevented exploration of the theoretical mechanism driving the relationship between ADHD and under-sensitivity to partial schedules of reinforcement.

A dissertation from our lab attempted to build on the designs of Kollins et al. (1997) and Taylor et al. (2010). This study by Popa (2013) examined the relationship between a variety of continuous measures of impulsivity, inattention, and ADHD symptoms, and sensitivity to the rate of reinforcement provided by a set of independent, concurrently available RI schedules of reinforcement (RI 0.7s–RI 0.7s; RI 2.4s–RI 1.2s; RI 2.1s–RI 1.5s; RI 1.8s–RI 1.8s; RI 1.5s–RI 2.1s; RI 1.2s–RI 2.4s). Reinforcements consisted of points on a scoreboard. The study recruited 38 undergraduates from a selective university in the southeastern U.S. The undergraduates received course credit for participation in the study.

This study produced robust estimates of GML parameters through the use of a more rigorous experimental design (Popa, 2013). Unfortunately, the results of this study were inconclusive due to lack of variability in the severity of impulsivity, inattention, and ADHD symptoms measured in the sample. The average scores for these high-achieving undergraduates were equivalent to the average scores of healthy controls in other studies of ADHD. In addition, this study presented a single set of reinforcement schedules with a high overall rate of reinforcement. These are the same conditions which should theoretically obscure the symptoms and impairments associated with ADHD. Like past studies, there was no measure of delay discounting incorporated.

1.6. Evidence outside the GML paradigm

More studies have been conducted outside of the GML paradigm, although the number of studies is still limited relative to the theoretical importance of the partial reinforcement axiom. Experimental procedures have varied and results have been mixed and difficult to interpret (for reviews, see Luman et al., 2005; Luman et al., 2010; Sonuga-Barke et al., 2016). Similar to studies within the GML paradigm, these studies have tended to rely on less powerful case-control designs and have not collected concurrent measures of delay discounting. These studies have also tended to measure sensitivity to rate of reinforcement using more indirect and limited forms of measurement.

For example, Pelham and colleagues (1986) divided 30 children ages 5–11 with ADHD into three groups that received 100%, 50%, or 0% reinforcement for correct responses on a nonsense word spelling task (Pelham, Milich, & Walker, 1986). These reinforcements were tokens that could be cashed in for desired objects at a store located within the children's summer camp. The children completed their respective version of the task once with placebo, and once following methylphenidate administration. The authors found no group differences in rates of incorrect responses due to exposure to the continuous versus partial reinforcement conditions. However, these results may have been confounded by delivery of verbal praise for correct responses on 100% of trials.

Douglas and Perry (1994) exposed 30 children with ADHD and matched controls to a simple task where a light signaled the possibility of reinforcement for pulling a lever, and reinforcement delivery progressed from 100%, to 50%, to 30%, to 0% of pulls (Douglas & Parry, 1994). They compared the groups on sustained attention (reaction time) and level of frustration (lever-pulling force). No group differences were found at 100% reinforcement. But reaction times slowed in the ADHD group at 50% and 30% reinforcement, and lever-pulling force increased in the ADHD group at 30% and 0% reinforcement.

Barber and colleagues (1996) presented 120 trials of a paired- and unpaired-associate learning task to 45 males ages 7–10 with ADHD and 45 controls (Barber, Milich, & Welsch, 1996). Each group was divided into three conditions where monetary reinforcement was delivered for 100%, 50%, or 0% of correct responses, and accuracy feedback was delivered for 100% of responses. The authors found no differences in the percentage of correct responses between ADHD children and controls due to exposure to the continuous versus partial reinforcement conditions. Again, the delivery of immediate accuracy feedback on 100% of trials (i.e., social reinforcement) may have been a confound.

Aase and Sagvolden (2006) designed a 30-minute computer task in which participants were provided intermittent reinforcement for correctly tracking the position of a box presented on a screen. Participants were rewarded for correct clicks on the box with the delivery of cartoon images and trinkets. These reinforcements were delivered according to either a VI 2s or a VI 20s schedule. The schedule in effect was always signaled by the color of the screen's background, and participants had no control over schedule switching. Twenty-eight boys ages 6–12 with ADHD and 28 controls completed this task. Boys with ADHD had a lower percentage of target responses (inattention) and greater spatial variability in responding (behavioral variability) relative to controls. These group differences increased significantly when the reinforcement schedules changed from VI 2s to VI 20s.

More recently, Alsop and colleagues (2016; 2017) presented ~250 trials of a 25–35 minute signal detection task to 97 children with ADHD and 70 controls (ages 8–13) recruited in either New Zealand or Japan. On each trial, participants were tasked with quickly and correctly identifying which of two stimuli (S_1 or S_2) they were being presented by providing the response that corresponded to that stimulus (B_1 or B_2). Correct responses were reinforced according to a 4:1 ratio across stimuli. This ratio of reinforcement was reversed and reinstated twice without warning during the session. The authors stated these schedules of reinforcement were intermittent and randomly determined. Their task appeared to provide an overall reinforcement rate of ~3 reinforcements/minute, based on the length of the sessions and a fixed number of reinforcements for each participant (60).

The children with ADHD evidenced the same response bias pattern as controls during the initial phase of this experiment, but they did not adjust their response biases to the same degree as controls during the reversal and reinstatement phases. This effect was consistent across labs and cultures. This suggested that the children with ADHD were under-sensitive to shifts in the overall ratio of obtained reinforcements. This result failed to replicate in a recent follow-up study of 32 children with ADHD and 40 controls in Brazil (Furukawa et al., 2019).

1.7. Co-occurring psychopathology

Explaining ADHD in terms of under-sensitivity to partial schedules of reinforcement offers attractive parsimony. It also seems implausible, given the failure of other single deficits to explain this highly heterogeneous and comorbid condition (Pliszka, 2015; Willcutt, 2015). The evidence summarized above provides limited insight. To complicate matters, deficits often conceptualized to be unique to ADHD (e.g., steep delay discounting) tend be found in other DSM disorders, and vice-versa (Sonuga-Barke et al., 2016; Willcutt, Sonuga-Barke, Nigg, & Sergeant, 2008; Zisner & Beauchaine, 2016). In fact, there is growing interest in examining operant learning abnormalities across a range of DSM conditions.

This complicated landscape can be greatly simplified using empirically-derived dimensional models of psychopathology. For example, much of the comorbidity associated with ADHD can be pragmatically reduced to the higher-order dimensions of internalizing and externalizing psychopathology (Achenbach & Rescorla, 2001, 2003; Kotov et al., 2017). The internalizing dimension corresponds to comorbidity among DSM-defined depressive disorders, anxiety disorders, obsessive-compulsive and related disorders, trauma- and stressor-related disorders, feeding and eating disorders, and sexual dysfunctions. The externalizing dimension corresponds to comorbidity among DSM-defined disruptive, impulse-control, and conduct disorders, substance-related and addictive disorders, cluster B personality disorders, and ADHD. ADHD has small-to-moderate correlations with internalizing and moderate-to-large correlations with externalizing (Willcutt et al., 2012). These dimensions are readily measured from well-validated and widely available multi-informant rating scales (Achenbach & Rescorla, 2001, 2003). They provide a higher degree of statistical power due to their more continuous nature and smaller number. Yet few have taken advantage of these tools to examine the partial reinforcement hypothesis across conditions. Only one prior study has combined this rigorous approach to measuring psychopathology with the GML paradigm.

This study examined the relationship between a composite measure of externalizing behavior and sensitivity to the rate of reinforcement provided by naturally occurring schedules of reinforcement in the observed conversations of 81 adolescent dyads from the Oregon Youth Study (Capaldi & Patterson, 1987; McDowell & Caron, 2010). It found a substantial correlation between sensitivity to rate of reinforcement and severity of externalizing (r= - 0.77), but it relied on secondary analyses of between-subjects data that was not designed for a within-subjects GML analysis. This makes these results difficult to interpret. Measures of attention problems, delay discounting, and internalizing were not available for these analyses. The overall rate of reinforcement presented could not be controlled.

1.8. Objective of this dissertation

It is surprising that so few studies have attempted to examine the relationship between ADHD and sensitivity to partial reinforcement schedules using the tools of quantitative behavior analysis and dimensional measurement of psychopathology. Major motivational theories of ADHD and its comorbid disorders assert the etiological role of reinforcement learning abnormalities (Luman et al., 2005; Luman et al., 2010; Sonuga-Barke et al., 2016). These theories cannot proceed without a more thorough examination of how ADHD and co-occurring psychopathology impact an individual's response to schedules of reinforcement at the most basic and direct level of analysis – observed behavior. The current study sought to contribute to this initiative by recruiting a stratified sample of adults ages 18–40 that represented the full range of possible *T* scores on the Attention Problems (AP) dimension of the multi-informant Achenbach System of Empirically Derived Assessments (ASEBA, Achenbach & Rescorla, 2003).

Participants were invited to complete a concurrent RI schedules of reinforcement task (Klapes et al., 2019; Popa, 2013; Popa & McDowell, 2016). The task had two conditions. In the first condition, the average overall rate of reinforcement was lean, characteristic of many important situations in the natural environment. In the second condition, this rate was rich, similar to many recreational situations in the natural environment. In both conditions, the scheduled ratios of reinforcement were 6:1, 3:1, 1:1, 1:3, and 1:6. Sensitivity to rate of reinforcement parameters were estimated for each individual, in each condition by fitting the GML to their concurrent-schedule data. A brief hypothetical delay discounting survey was also administered (Odum, Baumann, & Rimington, 2006; Odum & Rainaud, 2003), as well as multi-informant ratings of current internalizing and externalizing symptoms (Achenbach & Rescorla, 2003), multi-informant ratings of past and current DSM-based symptoms of ADHD (Barkley, 2011), a brief assessment of intellectual functioning (Kaufman & Kaufman, 2004), and self-reported demographics, diagnoses, and current medications.

The primary objective of the study was to examine the theoretical relationship between sensitivity to rate of reinforcement estimates in each condition, and multi-informant ratings of attention problems. Consistent with theory, we predicted there would be a strong negative monotonic relationship between attention problems (self- and informant-ratings averaged) and sensitivity to the rate of reinforcement in the lean condition (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). We predicted this relationship would be attenuated in the rich condition.

The secondary objective of the study was to examine the relationship between delay discounting and sensitivity to the rate of reinforcement in each condition. Increased delay discounting is a key theoretical mechanism of the relationship between attention problems and reduced sensitivity to partial schedules of reinforcement (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). We predicted there would be a strong negative monotonic relationship between degree of discounting and sensitivity to the rate of reinforcement in the lean condition, parallel to the pattern for attention problems. Similarly, we predicted this relationship would be attenuated in the rich condition.

The tertiary objective of the study was to examine the likely relationship between internalizing and externalizing psychopathology (self- and informant-ratings averaged) and sensitivity to the rate of reinforcement in each condition. We guessed this relationship would parallel the pattern for attention problems and delay discounting described above. This hypothesis was based on (a) evidence of moderate-to-large positive correlations between each dimension and attention problems; (b) assertions about the presence of reinforcement learning abnormalities in the etiology of a wide swath of psychopathology; and (c) the presence of other deficits claimed to be central to ADHD within frequently co-occurring disorders (Sonuga-Barke et al., 2016; Willcutt, 2015; Willcutt et al., 2012; Willcutt et al., 2008).

Finally, exploratory analyses were planned for the relationship between two potential confounds and sensitivity to rate of reinforcement—intellectual functioning and the average educational attainment of each participant's parent/guardian(s). In addition, we explored differences in the aforementioned relationships as a function of rating source (i.e., self vs. informant vs. self and informant average).

Chapter 2: Methods

2.1. Participants

Participants were recruited using community and clinic advertisements spread throughout a diverse quadrant of a major metropolitan area of the southeastern U.S. Participants were invited to join the study based on the mean of their self- and informant-rated *T*-scores on the AP dimension of ASEBA (Achenbach & Rescorla, 2003). Participants provided this information during a phone screening. The sample was stratified into four groups based on AP *T*-score composites: 50–54 (≤ 50th–65th percentile); 55–59 (69th–81st percentile); 60–64 (84th–92nd percentile); and ≥ 65 (≥ 93rd percentile). The *n* for each group was set a priori to be approximately equal, with a minimum of 8 participants in each group. These groups were collapsed together for planned analyses.

Any adult ages 18–40 was eligible to participate in the study unless they reported (a) they were currently being treated with psychotropic medication(s); (b) they had a major neurological condition; or (c) they anticipated they would not be able to complete all study requirements. Participants were placed on a waitlist if their recruitment group was full. An exception was made for stimulant medications prescribed to be taken as needed, provided that participants could be medication free starting 24 hours before their first lab visit and continuing through their last lab visit. These medications have short half-lives, are often taken as needed, and are a first-line treatment for ADHD (Connor, 2015).

2.2. Sampling procedure

The ads were posted within a 2–5 mile radius of the data collection site. This site was located in the psychology department of a private university at the heart of a large metropolitan area in the southeastern U.S. Ads were placed in areas that received heavy pedestrian traffic from a broad swath of the population. This included mass transit stations, business and financial centers, schools and universities, inpatient and outpatient medical centers, social service agencies, government buildings, religious organizations, recreational facilities, theaters, museums, libraries, and parks. Ads were preferentially placed at choke points within these areas, where foot traffic would be slowed or paused. Ads were generally positioned at eye level, on uncluttered surfaces, in high density, and in unexpected configurations intended to draw attention. Special emphasis was placed on locations that had at least some protection from the elements. The location of each ad was recorded in the My Maps feature of Google Maps. The final distribution of ads covered a triangular area of approximately 30 square-miles. Initial ads were distributed across this area as evenly as possible and as quickly as possible. Ads were regularly checked and replaced by geographic subsection throughout the remainder of the recruitment period. New ads were posted during this maintenance phase as additional locations were identified.

The ads invited adults ages 18–40 to participate in a study examining how different people learn from rewards, and how reward-learning relates to behavioral health (Appendix A). The ads specified compensation for study participation and the requirements of participation. Prospective participants were encouraged to call or email the primary investigator to determine their eligibility and to find out more about the study.

Phone screenings began with a detailed description of study participation and informed consent. Participants were told the purpose of the phone screening was to determine their level of self- and informant-rated symptoms on an unspecified dimension of behavioral health. This was the AP scale of the ASEBA Adult Self-Report For Ages 18–59 (ASR) and ASEBA Adult

Behavior Checklist For Ages 18–59 (ABCL, Achenbach & Rescorla, 2003). Participants were told their self- and informant-rated symptoms would be averaged to determine a final score. Participants were told that the study intended to recruit four equally sized groups that represented the full spectrum of possible survey scores. Participants were given the option of being on a waitlist if their study group was full. They were informed that getting off the waitlist was contingent on whether the study secured additional grant funding. They were given an estimated window of time in which this was possible.

Participants were asked to provide the following background information before completing the screening survey: age, gender, date of birth, diagnoses, current medications, and how they heard about the study. Participants were excluded if they were outside the age range, currently taking psychotropic medications, or had a major neurological condition. Excluded participants were referred to https://www.researchmatch.org/ to find alternative study opportunities.

Participants were asked to provide contact information for their current symptom informant at the end of the screening call. They were asked to notify their informant about this nomination before the primary investigator attempted to make contact. They were asked to estimate when this notification would occur. Participants were reminded that their screening results could not be determined without informant-report data. Informant calls also began with a detailed description of study participation and informed consent. Informants were given the same rationale for the phone screening as participants.

The average of the self- and informant-rated AP scale *T*-scores were used to recruit participants for each of the following groups: 50–54, 55–59, 60–64, and ≥ 65. Prospective participants were notified of their screening results via a follow-up call. Lab visits were scheduled for eligible participants during this call. The participants were also asked to provide contact information for a past symptom informant, if their current symptom informant did not know them well between ages 5 and 12. Informants were notified of screening results by phone or e-mail. All screenings were conducted by the primary investigator.

2.3. Sample size, power, and precision

Anticipating effect sizes for planned regression analyses was difficult given the limitations of prior evidence. The largest prior study to examine the relationship between GML-defined sensitivity to rate of reinforcement and ADHD reported Cohen's *f*s between 0.96 and 1.2 (Taylor et al., 2010). This translated to an expected r^2 of 0.48-0.59. The only prior study to examine the relationship between GML-defined sensitivity to rate of reinforcement and externalizing psychopathology reported a Pearson's r of - 0.77 (McDowell & Caron, 2010). This also translated to an expected r^2 of 0.59. No prior study had examined the relationship between delay discounting or internalizing psychopathology and GML-defined sensitivity to rate of reinforcement. However, given expected correlations among these variables, ADHD, and externalizing, we assumed similar effect sizes. These assumptions were consistent with the theoretical centrality of reinforcement learning abnormalities for ADHD and its comorbid conditions (Catania, 2005; Sagvolden et al., 2005; Sonuga-Barke et al., 2016; Tripp & Wickens, 2008).

Bivariate regressions were planned for the a_r parameters from the lean and rich conditions of the concurrent RI schedules of reinforcement task on each independent variable. The key family of effect sizes would be Pearson's r, r^2, and Cohen's f^2 (Cohen, 1988). Šidák-Bonferroni corrections for multiple comparisons were used to set a family-wise alpha of 0.05 for testing (a) primary hypotheses (2 tests, $p = 0.025$); (b) secondary hypotheses (4 tests, $p = 0.0127$); (c) tertiary hypotheses (4 tests, $p = 0.0127$); and (d) exploratory hypotheses (4 tests, p = 0.0127 Keppel & Wickens, 2004; Šidák, 1967). This resulted in an anticipated experiment-wide alpha of 0.20. Power was set to a minimum of 0.80 to detect the minimum expected effect size for the primary hypotheses ($r^2 = 0.48$, Cohen's $f^2 = 0.92$). These settings were entered into G*Power 3.1 for an a priori computation of required sample size for a linear multiple regression, fixed model, R^2 deviation from zero F test (Faul, Erdfelder, Buchner, & Lang, 2009). This produced a minimum required sample size of 14. The final minimum sample size was set to 32, based on the assumption that large effect sizes from initial published studies would shrink in accordance with the "winner's curse" (Young, Ioannidis, & Al-Ubaydli, 2008). This provided 0.80 power to detect a minimum Cohen's f^2 of 0.32 for the primary study hypotheses.

2.4. Measures

2.4.1. Adult Self-Report and Adult Behavior Checklist. The ASR is an empirically-derived self-report rating scale for adults ages 18–59 (Achenbach & Rescorla, 2003). The ABCL is an informant-report version of the ASR. Both rating scales contain 126 ordinal three-point problem items. The items ask about behavior over the past six months. These items measure 8 syndromes of psychopathology including anxiety, depression, somatic complaints, thought disorder, attention problems, rule-breaking, aggression, and interpersonal intrusiveness. The sum of the anxiety, depression, and somatization scales provides a broadband measure of internalizing psychopathology (32–39 items). The sum of the rule-breaking, aggression, and intrusiveness scales provides a broadband measure of externalizing psychopathology (35 items). The sum of all problem items provides a higher-order measure of general psychopathology (Kotov et al., 2017). Age-and gender-based *T*-scores constructed from a large national probability sample of nonreferred US adults indicate symptom severity on the syndrome scales

(Borderline: T = 65–69, 93rd–97th percentile; Clinical: T > 69, > 97th percentile) and higher-order scales (Borderline: T = 60–63, 84th–90th percentile; Clinical: T > 63, > 90th percentile; Achenbach & Rescorla, 2003)

The AP scale covers inattentive, hyperactive-impulsive, and related symptoms on a single dimension using 15–17 items (Achenbach & Rescorla, 2003). The Internalizing, Externalizing, and AP scales have demonstrated excellent test-retest reliability (r = 0.80–0.92), excellent internal consistency (α = 0.87–0.93), and extensive evidence of construct validity for the ASR and ABCL. Cross-informant correlations tend to be moderate (r = 0.38–0.44). ASR and ABCL *T*-scores for these dimensions were averaged together for each participant to create a composite score. These composite scores were the primary focus of analyses, to reduce the issue of multiple comparisons.

2.4.2. Barkley Adult ADHD Rating Scales-IV. The Barkley Adult ADHD Rating Scales-IV (BAARS-IV) is a DSM-based ADHD symptom checklist for adults ages 18–89 (Barkley, 2011). It covers symptoms of inattention, hyperactivity, impulsivity, and sluggish cognitive tempo. It also estimates age-of-onset and the presence of impairments in major domains of functioning. The BAARS-IV has parallel forms for self- and informant-report covering symptoms over the past six months and symptoms between ages 5–12. Each form consists of 20–30 ordinal four-point items. Age-based percentile rankings constructed from a large national probability sample representative of US adults ages 18 to 89 are available for the current and childhood self-report forms. Rankings at-or-above the 93rd percentile on the inattention, hyperactivity, impulsivity, or total symptom scales are considered clinically significant. Any adult that self-reports current symptoms at-or-above the 93rd percentile, an age-of-onset before age 16, and functional impairment in at least one domain is considered likely to have ADHD. This probability increases if these conditions are also met on the childhood self-report form. This diagnostic algorithm for the BAARS-IV was used to estimate diagnostic status within the sample using ADHD total scores.

The BAARS-IV Current and Childhood Self-Report scales have reasonable test-retest reliability (r = 0.66–0.88) and good internal consistency (α = 0.78-0.95, Barkley, 2011). In general, BAARS-IV scales have expected relationships with impairments in executive functioning, education, occupation, income, driving, health, relationships, parenting, and offspring psychopathology.

2.4.3. Kaufman Brief Intelligence Test, 2nd Edition. The Kaufman Brief Intelligence Test, Second Edition (KBIT-2) estimates verbal, nonverbal, and full-scale IQ for people ages 4–90 (Kaufman & Kaufman, 2004). It consists of two verbal subtests (Riddles, Verbal Knowledge) and one nonverbal subtest (Matrices). It takes 15–30 minutes to administer. Each participant's intellectual functioning was estimated using their IQ Composite standard score. The KBIT-2's IQ Composite has excellent test-retest reliability (r = 0.90) and internal consistency (α = .93). It is highly correlated with the Full Scale-IQ Composite on the Weschler Adult Intelligence Scale-3rd Edition (r = 0.89). standard scores for this measure were constructed from a large national probability sample representative of US children and adults ages 4–90.

2.4.4. Hypothetical delay discounting survey. A 350-item hypothetical delay discounting survey (Appendix B) was administered similar to that constructed by Odum and Rainaud (2003) and Odum et al. (2006). The task took approximately 10 minutes. In each item, participants chose between a fixed value in US dollars provided after a fixed delay (e.g., $100 in 7 days) or a variable amount provided immediately (e.g., $100, 99, 97.5, 95, 92.5, 90, 85, 80, 75, 70, 65, 60, 50, 45, 40, 35, 30, 25, 20, 15, 10, 7.5, 5, 2.5, 1). All values were hypothetical. Items were arranged in sets defined by a fixed value ($100 or $10,000) and a fixed delay (7, 14, 30, 180, 365, 1,825, or 9,125 days). Items within sets were arranged by the variable amounts delivered immediately in descending order (e.g., $100 now or $100 in 1 week, $99 now or $100 in 1 week….$1 now or $100 in 1 week). Sets were presented in ascending order by fixed delay (e.g., $100 in 7 days, $100 in 14 days….$100 in 9,125 days). The $100 fixed value sets were presented before the $10,000 fixed value sets. Points of indifference between delayed and immediate values were computed for all sets. These indifference points were equated to the last immediate value chosen for each set.

Discounting parameters for each individual were calculated using the area-under-the-curve method (AUC, Myerson et al., 2001). Separate parameters were calculated for each series of fixed value sets ($100 and 10,000). In this procedure, indifference points were normalized as proportions of the delayed payoffs associated with their fixed value set ($100 or 10,000, y-axis). Delays were normalized as a proportion of the maximum delay possible (9,125 days, x-axis). These normalized variables were plotted against each other. Straight lines connecting these points formed several trapezoids. The summed area of these trapezoids provided an AUC estimate ranging from 0.0 to 1.0 for each series of fixed value sets ($100 or 10,000). The equation for the area of a trapezoid is:

$$\mathrm{A} = (x_2 - x_1)\left[\frac{(y_1 + y_2)}{2}\right], \tag{2-1}$$

In this instance, x_1 and x_2 represented successive delays, and y_1 and y_2 represented the indifference points for these delays. Lower AUC scores indicated higher discounting.

2.4.5. Concurrent RI schedules of reinforcement task. This task was a modified version of the Procedure for Rapidly Establishing Steady-State Behavior (PRESS-B) developed by Klapes et al. (2019). In a single session of this task, participants were presented with five pairs of independent, concurrent RI schedules of reinforcement. These pairs were presented in a random order on a computer screen. A large rectangular button in the middle of the screen represented the response key (Figure 2-1). Each schedule in a pair was represented by the color of this response key (blue or yellow). Participants were free to switch back-and-forth between the schedules in a pair by changing the color of the response key. This was accomplished by pressing the control key on the keyboard, which was represented on the screen as a small rectangular button underneath the response key labeled “SWITCH.” Participants could collect reinforcements on a selected schedule by pressing the spacebar on the keyboard. This operated the response key on the screen. Reinforcements were US $0.07. A green light to left of the response key would flash and a loud “ding” would sound each time a response earned a reinforcement. The cumulative earnings for the entire experimental session were displayed on the screen in a text box above the response key.

Participants could not collect a reinforcement for the first two seconds following a change in the color of the response key. This was true even if the timer for the dormant reinforcement schedule had elapsed and a reinforcement was waiting to be collected. This is known as a change-over delay (COD). It is designed to ensure participants engage in bouts of responding on each schedule so that differences in rates of reinforcement can be experienced. It is an analogue for possible opportunity costs associated with switching between concurrently available activities.

Each pair of schedules was associated with one of five white lights at the top of the screen. The lights were arranged in a row. When a pair of schedules was active, its corresponding light would be illuminated. All other lights would be dark. The ordinal position of the illuminated light signaled the relative rate of reinforcement available from the blue and yellow response key for each pair. Further to the left indicated blue was better. Further to the right indicated yellow was better. Blue and yellow were equivalent when the light was in the middle of the row.

The task had two conditions – lean and rich (Table 2-1). In the lean condition, the five pairs of RI schedules were: RI 15s–RI 90s; RI 26.3s–RI 78.7s; RI 52.6s–RI 52.6s; RI 78.7s–RI 26.3s; RI 90s–RI 15s. In the rich condition, the five pairs of RI schedules were: RI 1.3s–RI 7.5s; RI 2.2s–6.6s; RI 4.4s–RI 4.4s; RI 6.6s–RI 2.2s; RI 7.5s–RI 1.3s. The scheduled ratios of reinforcement for the five pairs of schedules were approximately 6:1, 3:1, 1:1, 1:3, and 1:6 in both conditions. The overall rate of reinforcement governing the lean condition was approximately 3 reinforcements per minute (i.e., $0.21/min). The overall rate of reinforcement governing the rich condition was approximately 27 reinforcements per minute (i.e., $1.89/min).

The lean condition was always completed first. Each of the pairs of schedules in the lean condition were presented for 480 seconds per session. Five sessions were completed by each participant (two sessions at visit one, two sessions at visit two, and one session at visit three). Participants were encouraged to take breaks between sessions. Participants were exposed to the lean condition for a total of 200 minutes.

Each of the pairs of schedules in the rich condition were presented for 200 seconds per session. One approximately 16.7-minute session was completed by each participant at the end of visit three. Participants were allowed to complete up to two additional sessions if this was necessary to ensure that they collected at least one reinforcement from each schedule in each pair. This was sometimes required due to the short duration of exposure time and high density of reinforcement. These sessions were added to visit three or scheduled as soon as possible in a follow-up visit. This shortened overall exposure time in the rich condition was possible due to the rapid acquisition of steady state behavior that occurs when reinforcement rates are high (Klapes et al., 2019; Popa, 2013; Popa & McDowell, 2016).

All sessions were always preceded by a 60 second acquisition phase (RI 1.1s–RI 1.1s) and 60 second extinction phase (RI ∞–RI ∞). All lights at the top of the screen were illuminated during the acquisition phase. All lights at the top of the screen were dark during the extinction phase. Instructions for the task were read to the participant at each lab visit prior to starting the first session of the visit. These instructions are presented in Appendix C.

All sessions of this task were conducted in one of two blank, windowless offices, with the door closed and fluorescent overhead lights on. Participants were seated at an empty desk facing the wall with their backs to the door. The modified PRESS-B software was run on commercially purchased computers using the Windows operating system. The software was developed by O. L. Calvin using the VB.Net 2013 programming language (see Klapes et al., 2019). Summaries of responses, reinforcements, change-overs, and experimental conditions were output to spreadsheets in Microsoft Excel. A complete, millisecond-to-millisecond record of events during each session was output to XML databases. Technical specifications for each device used to run this task are available in Appendix D.

Two sensitivity to rate of reinforcement parameters were estimated separately for each participant using the GML – one from the lean condition and one from the rich condition. These a_r parameters were estimated by regressing the logarithm of their total observed response ratios on the logarithm of their total obtained reinforcement ratios for all pairs of reinforcement schedules presented in a condition using ordinary least squares regression (Equation 1-1). The a_r parameter was the slope of the line of best fit (Baum, 1974; Davison & McCarthy, 1988; McDowell, 2013). An a_r parameter of 1.0 indicated perfect matching between the ratio of obtained reinforcements and the ratio of observed responses. An a_r value below 1.0 suggested under-sensitivity to the experienced ratio of reinforcements, known as undermatching. An a_r value above 1.0 suggested a tendency towards excessive preference for the richest option within a pair of schedules, known as overmatching. The a_r value for humans has been estimated to range from 0.07 to 1.26, according to a meta-analysis of concurrent VI schedules of reinforcement experiments (Kollins, Newland, & Critchfield, 1997). The median value from this review was 0.70 (*IQR* = 0.31–1.01).

The r^2 value corresponding to each fit of the GML is used to determine whether each individual's a_r parameter should be used in analyses. It has been recommended that cases with r^2 values < 0.80 should be excluded, to ensure only reliable parameter estimates are used to draw conclusions about the nomological network of a_r (see Horne & Lowe, 1993).

2.5. Data collection

The data collection site was handicap accessible and conveniently located near public transportation and a visitor parking lot. Visits were scheduled on three consecutive days (or as close to consecutive as possible). Participants were offered early morning, evening, and weekend appointments, in addition to normal weekday hours. Parents were also offered free on-site childcare during their visits, or limited reimbursement of off-site childcare costs, as needed. In addition, participants were assisted in arranging the cheapest method possible for commuting to the lab to ensure equivalent net compensation across the sample. Visits were conducted by either the primary investigator or a trained research assistant.

At their first visit, participants completed a written informed consent (5 minutes), the ASR (15–20 minutes), the current and childhood self-report versions of the BAARS-IV (10 minutes), the KBIT-2 (15–30 minutes), the hypothetical delay discounting survey (10 minutes), and the first two sessions of the lean condition for the concurrent RI schedules of reinforcement task (90 minutes). Participants returned to complete their remaining schedules of reinforcement task sessions across visits two and three. Participants were compensated for study participation through their efforts in the schedules of reinforcement task. They received their earnings immediately in cash at the end of each visit. This generally resulted in total earnings between $70 and $90. Participants were guaranteed to receive a minimum of $70.

Participants were given the option of scheduling a debriefing following the end of their participation. This debriefing covered the purpose of the study and an optional review of their assessment results, excluding the KBIT-2. Participants with concerns about their behavioral health were provided with appropriate referrals and education. Prior to the debriefing, participants were asked about their general experience of the study, their hypotheses about the purpose of the study, and their approach to the schedules of reinforcement task.

The current symptom informant was asked to complete and return the following: a written informed consent document (5 minutes), the ABCL (15–20 minutes), and the BAARS-IV (5 minutes). The childhood symptom informant was asked to complete and return the following: a written informed consent document (5 minutes) and the BAARS-IV (5 minutes). Each informant received $5.00 for their efforts, in the form of cash or gift card.

2.6. Quality of measurements

A team of 7 research assistants (RAs) was recruited in the fall of 2017 and trained over the spring of 2018. RAs learned to administer the assessment battery for each lab visit, to conduct informed consent discussions, to maintain a detailed ledger of participant compensations, to securely store sensitive study materials, and to report any issues to the team in a timely manner. The bulk of this training involved learning to administer the KBIT-2 through repeated rehearsals with colleagues under the supervision of the primary investigator (PI). All KBIT-2 administrations during data collection were subject to score checking prior to data entry. All data was verified via double entry. Staff met weekly as a team at the start of the study to allow troubleshooting. As the team demonstrated competence these weekly meetings were faded and replaced with regular individual or small group advising meetings with the PI. RAs also completed an online training in the ethical conduct of research prior to starting data collection, as required by the Emory Institutional Review Board (https://about.citiprogram.org/en/homepage/).

Team norms and values were established collaboratively at the outset of the project to ensure all members understood the mission, understood key behaviors that would increase the probability of achieving that mission, and understood how desirable behavior would be proactively identified and positively reinforced. A major target behavior of this system was the timely disclosure of concerns or errors to the PI. RAs were informed that any future recommendations on their behalf would only include specific examples of effective behavior. Hence, an RA concerned about their performance need only worry about a very short list of good behaviors that could be lengthened at any moment in collaboration with the PI, rather than a long list of mistakes that could never be undone. A major goal of this system was to empower RAs to exercise disciplined initiative within their understanding of the PI's intent, and to maintain open lines of communication.

RAs were also provided strategies to enhance their executive functioning at the start of the project during team meetings, and then provided follow-up training during individual or small group meetings, as needed. These strategies were drawn from two evidence-based treatment manuals for adults with ADHD (Safren, Spirch, Perlman, & Otto, 2005; Solanto, 2011). This was a proactive measure to increase the probability that RAs would be available to run participants on a consistent basis without becoming overwhelmed by competing demands. It also served as an active learning exercise for team members interested in behavioral interventions for ADHD.

Team members were informed of each participant's level of reported attention problems prior to visits. This was designed to signal which participants might require extra supports (within the bounds of the experiment's standard operating procedures) to make it through participation. It was hoped this would increase the probability of sampling the high end of the AP dimension.

2.7. Data diagnostics

Participants were contacted to clarify apparent omission and commission errors in their survey data by the primary investigator. Accidental omissions or commissions were corrected as much as possible. Any remaining minor instances of missing data were resolved using the imputation methods detailed in Section 3.2. Cases were dropped from relevant analyses if a particular scale was completely missing.

Participants were invited to complete up to two additional sessions of the rich condition in the concurrent RI schedules of reinforcement task if they emitted zero responses or earned zero reinforcements on at least one of the options within a pair of reinforcement schedules. Cases that continued to have this issue were resolved via imputation. Otherwise, this data could not be fit to the GML (can't have zero in the denominator of a ratio). First, the number of responses per reinforcement was calculated for each pair of schedules for each participant in (a) the lean condition and (b) the rich condition. Second, we calculated the median number of responses per reinforcement for each pair of schedules in each condition. Third, we added a single reinforcement to the totals for each option, in each pair, in each condition, for all participants.

Finally, we added the corresponding median responses to the totals for each option, pair, and condition for all participants.

This method was designed to shift the entire sample to the right on the number line, to eliminate zeros without changing the structure of the data. This method was founded on the assumption that given sufficient exposure to a schedule pair with missing data, all participants would eventually emit some responses on the neglected option and earn a reinforcement. This assumption is well-supported in research focused on understanding exclusive preference in the context of concurrent schedules (e.g., Herrnstein & Loveland, 1975). The method used data from the entire sample to infer the number of responses that would have been emitted before a reinforcement was earned, for each set of experimental conditions.

2.8. Analytic strategy

All analyses were conducted in Microsoft Excel 2016. Sampling groups were collapsed together for all analyses. All tests throughout the experiment were two-tailed. Family-wise error was set to an alpha of 0.05 for each set of hypotheses using the Šidák-Bonferroni correction (Keppel & Wickens, 2004; Šidák, 1967). Self- and informant-ratings (*T*-scores) were averaged together to create composite scores for each individual for analyses involving the AP, Internalizing, and Externalizing scales. These analyses were repeated using single informants to allow for the exploration of rater effects. Interested readers will find scatterplots of these relationships reported in Appendix E.

2.8.1. Primary hypotheses. Bivariate linear regressions were used to examine the relationships between AP *T*-score composites and the a_r parameters from (a) the lean condition and (b) the rich condition. We used the subset of the sample with complete data in both conditions to estimate the significance of observed differences in sensitivity to rate of reinforcement across conditions as a function of attention problems. We relied on a comparison of dependent correlations with a common index for this analysis (Faul et al., 2009). The per comparison alpha was set to 0.017.

2.8.2. Secondary hypotheses. Bivariate linear regressions were used to examine the relationship between AUC from the \$100 and \$10,000 conditions of the hypothetical delay discounting survey and the a_r parameters from (a) the lean condition and (b) the rich condition. Where possible differences across (a) and (b) were identified, the significance of these differences were examined using a comparison of dependent correlations with a common index (Faul et al., 2009). The per comparison alpha was set to 0.009.

2.8.3. Tertiary hypotheses. Bivariate linear regressions were used to examine the relationship between Internalizing and Externalizing *T*-score composites and the a_r parameters from (a) the lean condition and (b) the rich condition. Where possible differences across (a) and (b) were identified, the significance of these differences were examined using a comparison of dependent correlations with a common index (Faul et al., 2009). The per comparison alpha was set to 0.009.

2.8.4. Exploratory analyses. Bivariate linear regressions were used to explore the relationship between KBIT-2 IQ Composite standard scores and parent/guardian educational attainment composite scores and the a_r parameters from (a) the lean condition and (b) the rich condition. Where possible differences across (a) and (b) were identified, the significance of these differences were examined using a comparison of dependent correlations with a common index (Faul et al., 2009). The per comparison alpha was set to 0.009.

2.8.5. Regression diagnostics. Violations of regression assumptions and the presence of influential outliers were examined for all analyses using residual plots indexed by independent variables, normal q-q plots of residuals, locally weighted scatterplot smoothing lines (lowess), and Cook's D statistics, (Cleveland, 1979; Cohen, Cohen, West, & Aiken, 2003; Cook, 1977). All lowess lines employed the same smoothing alpha ($\alpha = 0.50$). Cook's D statistics initiated scrutiny of influential outliers if the value for any case within a test reached the critical value of the F distribution at a cumulative probability of 0.50, with degrees of freedom ($k + 1$, $n - k - 1$, see Cohen et al., 2003). Results of regression diagnostics are displayed in Appendix F.

Chapter 3: Results

3.1. Recruitment and data collection

Participants were recruited over a 10-month period from 4/5/18 to 2/19/19 (Figure 3-1). A total of 217 individuals contacted the study to express interest in participation. Seventy-three of these individuals were lost to follow-up. The remaining one hundred and forty-four individuals were assessed for study eligibility via phone.

Seventy-five of these individuals were excluded due to at least one of the following reasons: declined participation (n = 25); age ≥ 41 (n = 25); taking psychotropic medications (n = 16); major neurological condition (n = 9); could not produce required informants (n = 3); and did not finish screening (n = 2). Five prospective participants met more than one of these exclusion criteria. A detailed list of conditions and medications that resulted in exclusions is included in Figure 3-1. Twenty participants were placed on a waitlist because their recruitment group was full. All of these participants had average AP scale *T*-scores in the 50–54 range (self- and informant-rated). The 49 remaining participants were invited to join the study.

Five participants joined the study but dropped out prior to their first lab visit. The average AP scale *T*-scores of those who left the study early were as follows: 50–54 (n = 0); 55–59 (n = 4); 60–64 (n = 0); ≥ 65 (n = 0). One participant left the study before any formal scale scores could be collected. This participant had a self- and informant-reported history of severe ADHD and externalizing behavior.

Forty-four participants completed the study. These participants had the following average AP scale *T*-scores: group 1, T = 50–54 (n = 11); group 2, 55–59 (n = 9); group 3, 60–64 (n = 17); and group 4, ≥ 65 (n = 7).

3.2. Missing data

Overall, missing data were minimal. Only 6 participants (13.6%) had any missing data. Two cases accounted for the majority of missing data cells because their informants did not complete ABCLs. These cases were deleted from analyses involving the internalizing and externalizing dimensions. Missing data for the paper-and-pencil version of the ABCL AP scale could be imputed from the phone screening for these two cases. Similarly, two participants omitted their parent/guardian(s) highest level of education. These cases were dropped from analyses involving this variable.

Only six cells had missing data on the ASR Internalizing scale. Only three cells had missing data on the ASR Externalizing scale. These cells were imputed with 0s, the modal response for each item in the original norming sample of nonreferred US adults (Achenbach & Rescorla, 2003). The only exception was item 22—"Worries about future"—which had a high endorsement rate in the norming sample. This item was imputed with a 1. No missing data affected the ASR AP scale, KBIT-2, hypothetical delay discounting survey, or BAARS-IV diagnostic algorithm.

Seventeen participants (39%) were eligible for extra sessions of the rich condition of the concurrent RI schedules of reinforcement task. These participants were eligible for extra sessions after emitting zero responses or earning zero reinforcements on at least one of the options within one of the five pairs of reinforcement schedules. Fifty-three percent of these participants had missing data within a single pair, (24%) within two pairs, (12%) within three pairs, and (12%) within five pairs. This missing data nearly always reflected a tendency towards exclusive preference for the richer option within a schedule pair. This missing data was resolved for (65%)

of these cases with one additional rich session, and (9%) of these cases with two additional rich sessions.

Missing data could not be resolved by collecting more data for five participants. Three completed one extra rich session and two were unavailable for extra rich sessions. This missing data was resolved via the imputation method described in Chapter 2 (see Section 2.7). Table 3-1 presents the values used for imputation (i.e., median responses per reinforcement for the entire sample in each pair of schedules within each condition). In the lean condition, these median values ranged from 82.31 to 147.82 responses per reinforcement. In the rich condition, these median values ranged from 13.57 to 31.03 responses per reinforcement. Paired sample t-tests failed to find a significant difference in GML regression parameters before and after imputation, including a_r and r^2 (a_r, $t(38) = 0.26$, $p = 0.80$, Cohen's $d = 0.04$; r^2, $t(38) = 1.08$, $p = 0.29$, Cohen's $d = 0.17$). This method maximized the number of cases available for analyses without evidence of bias.

3.3. Sample characteristics: Demographics

The sample consisted of 44 adults ages 18 to 38 with an average age of 25 ($SD = 5.7$) and a median age of 23 (Table 3-2). Twenty-one participants identified as male, and 23 participants identified as female. The race/ethnicity of the sample was: African American (30%), LatinX (14%), Asian (9%), Native American (0%), Pacific Islander (0%), White, non-Hispanic (39%), and two or more (9%). The marital status of the sample was: never married (84%), married (11%), separated (0%), divorced (2%), and widowed (0%). Twenty-nine percent of participants reported living with a spouse or partner at some point in the past six months. The educational attainment of the sample ranged from high school to doctoral or law degree, with a median education between some college and associate's degree. The educational attainment of the parent/guardian(s) of each participant were averaged to provide (limited) information about their socioeconomic background. These educational attainment composite scores ranged from General Equivalency Diploma (GED) to doctoral or law degree, with a median of bachelor's degree or registered nurse (RN).

Table 3-3 compares the demographics of the sample to the demographics of 18 to 40 year-olds in the Metropolitan Statistical Area (MSA) where participants were recruited (U.S. Census Bureau, 2017). The distribution of age within the sample was skewed towards youth (77% under age 30). In contrast, the distribution of age within the MSA was approximately uniform (54% under age 30). The sample also reported far less experience with marriage (11%) than its MSA (32%), consistent with its more youthful composition. In addition, the sample reported significantly higher educational attainment than its MSA (i.e., 2% high school, GED, or less vs. 36% high school, GED, or less, respectively). There was no difference in the percentage of females between the sample (52%) and the MSA (51%). The racial/ethnic identity of the sample was also equivalent to that of the MSA: African American (30% vs. 36%), LatinX (14% vs. 12%), Asian (9% vs. 7%), Native American (0% vs. 0.1%), Pacific Islander (0% vs. 0.5%), White, non-Hispanic (39% vs. 42%), and two or more (9% vs. 3%). This suggested the sample was representative at the level of sex and race/ethnicity, but younger and better educated than expected based on age and catchment area.

3.4. Sample characteristics: Variables of interest

3.4.1. Attention problems. Table 3-4 presents the characteristics of all independent variables earmarked for analyses. AP *T*-score composites ranged from 50 to 77.5 with a mean of 60 (SD = 6.4). These scales had fair-to-excellent internal consistency: ASR AP (α = 0.78); ABCL AP (α = 0.88). Cross-informant Pearson correlations were moderate (r = 0.41). Average scores reported in the non-referred norming sample were: ASR (*M* = 54.2, *SD* = 5.9); ABCL (*M* = 54.2, *SD* = 6.0, Achenbach & Rescorla, 2003).

3.4.2. Internalizing. Internalizing *T*-score composites ranged from to 39 to 77 with a mean of 56.5 (*SD* = 9.4). These scales had fair-to-excellent internal consistency: ASR Internalizing (α = 0.91); ABCL Internalizing (α = 0.91). Cross-informant Pearson correlations were moderate (*r* = 0.37). Average scores reported in the non-referred norming sample were: ASR (*M* = 50.2, *SD* = 9.8); ABCL (*M* = 50.2, *SD* = 9.9, Achenbach & Rescorla, 2003).

3.4.3. Externalizing. Externalizing *T*-score composites ranged from to 41 to 70.5 with a mean of 55.3 (*SD* = 7.7). These scales had fair-to-excellent internal consistency: ASR Externalizing (α = 0.87); ABCL Externalizing (α = 0.93). Cross-informant Pearson correlations were moderate (*r* = 0.37). Average scores reported in the non-referred norming sample were: ASR (*M* = 50.1, *SD* = 9.9); ABCL (*M* = 50.2, *SD* = 9.9, Achenbach & Rescorla, 2003).

3.3.4. Intellectual functioning. KBIT-2 IQ Composite Scores ranged from 78 to 142 with a mean of 109 (*SD* = 14.4]). This is similar to the mean IQ Composite Score reported for ages 16-45 in the norming sample (*M* = 104, *SD* = 13.4).

3.4.5. Delay discounting. The surveys constructed by Odum and Rainaud (2003) and Odum et al. (2006) are not similar enough to the survey constructed for this study to allow meaningful comparison of descriptive statistics across samples. In this sample, internal consistencies of the AUC $100 scale (α = 0.31) and AUC $10,000 scale (α = 0.26) were poor. No internal consistency measures were calculated in Odum and Rainaud (2003) and Odum et al. (2006). Other studies of hypothetical delay discounting surveys have found good internal consistency (e.g., Lempert et al., 2019; McCarthy et al., 2016). These surveys may have been more reliable due to reliance on automated titration with more sophisticated safeguards against inconsistent or careless responding (e.g., McCarthy et al., 2016), although the Monetary Choice Questionnaire developed by Kirby, Petry, and Bickel (1999) appears to have good psychometric properties (e.g., Nguyen et al., 2018).

We hypothesized that this poor internal consistency was due to the presence of nonsystematic discounting data (i.e., divergence from monotonically decreasing indifference points with delay). We identified and removed cases with such data using the widely accepted algorithm recommended by Johnson and Bickel (2008). This algorithm removes cases that meet either or both of the following criteria: (a) any indifference point is greater than the preceding indifference point by more than 20% of the delayed payoff; (b) the first indifference point was higher than the last indifference point by less-than-or-equal-to 10% of the delayed payoff. This method assumes that these response patterns are due to measurement error (e.g., participant did not understand the task; experimental conditions elicited inattentive, careless, or socially desirable response style; participant responded idiosyncratically; etc.).

Application of the algorithm resulted in the removal of four cases from the AUC \$100 scale (3 cases based on criterion (b), 1 case based on both criteria). Eight cases were removed from the AUC \$10,000 scale based on criterion (b), including three of the cases removed from the AUC \$100 scale. Fifty percent of cases removed from the AUC \$100 scale had AP *T*-score composites within normal limits (i.e., < 84^{th} percentile). Only twenty-five percent of cases removed from the AUC \$10,000 scale had AP *T*-score composites within normal limits. This suggested that measurement error later in the survey was related to attention problems. Participants with higher attention problems appeared more likely to adopt exclusive preference for one response, perhaps in order to end the survey quickly. Removal of these cases did not improve internal consistency: AUC \$100 scale ($\alpha = 0.33$); AUC \$10,000 scale ($\alpha = 0.28$).

Despite this systematic error related to attention problems, removal of these cases did not result in a restriction of range in AP *T*-score composites (see side-by-side boxplots in Appendix F, Figure F-11). In addition, the correlation between the AUC $100 and AUC $10,000 scales was high ($n = 35$, Pearson's $r = 0.66$, $SE = 0.13$, $p < 0.001$). Planned analyses involving hypothetical delay discounting should be interpreted with caution, due to this high level of measurement error.

Following the removal of cases with nonsystematic discounting data, the AUC $100 scale ranged from 0.01 to 1 with a mean of 0.38 ($SD = 0.28$). AUC for the $10,000 condition ranged from 0.01 to 1 with a mean of 0.64 ($SD = 0.23$). This reduction in discounting across conditions was large and statistically significant according to a paired two sample *t*-test: $t(34) = -7.67$, $p < 0.001$, Cohen's $dz = 1.3$. This replicated the well-validated magnitude effect (Green & Myerson, 2004), in which discounting decreases over identical delays as the size of the larger-later option increases.

3.4.6. ADHD diagnosis. Past and present ADHD diagnostic status was estimated for each participant using the diagnostic algorithm recommended for the Current and Childhood Self-Report Symptoms scales of the BAARS-IV (see Section 2.4.2., Barkley, 2011). A total of 16 participants (36.4%) met this threshold for probable ADHD. Four participants met this threshold at present only, 6 participants met this threshold during childhood only, and 6 participants met this threshold during both time periods. The Current Self-Report ADHD total score had a mean of 31.7 ($SD = 9.3$). The Childhood Self-Report ADHD total score had a mean of 36.4 ($SD = 11.6$). These mean scores are higher than those reported for ages 18–39 in the population-based norming sample: Current ($M = 25.8$, $SD = 8.6$); Childhood ($M = 27.6$, $SD = 10.5$). The internal consistency of these scales was excellent: Current ($\alpha = 0.90$); Childhood ($\alpha = 0.92$).

3.4.7. Sensitivity to rate of reinforcement. In the total sample, a_r estimates in the rich condition ranged from 0.01 to 0.85 with a mean of 0.54 (*SD* = 0.21). The a_r estimates in the lean condition ranged from - 0.17 to 0.44 with a mean of 0.12 (*SD* = 0.14). After cases with r^2s < 0.80 were excluded, a_r estimates in the rich condition (*n* = 39) ranged from 0.11 to 0.85 with a mean of 0.58 (*SD* = 0.17). This subset of a_r values in the lean condition (*n* = 19) ranged from - 0.17 to 0.44, with a mean of 0.20 (*SD* = 0.17).

Table 3-4 presents the characteristics of these subsets alongside the characteristics for the total sample. Descriptive statistics were generally equivalent across subsets. In Table 3-5, the sample was split into two groups based on a participant's r^2 value from the lean condition (i.e., r^2 < 0.80 vs. $r^2 \geq 0.80$). Independent samples t-tests were used to examine differences in independent variables as a function of group membership. No significant differences were observed. This suggested that excluding cases with r^2s < 0.80 from analyses did not result in throwing out meaningful variance in the independent variables.

3.5. Primary hypotheses

Scatterplots of all planned comparisons are displayed in Figures 3-2 through 3-8. Results for all regressions are summarized in Table 3-6. Pearson correlations among all independent and dependent variables are presented in Table 3-7. Regression diagnostics for all analyses are presented in Appendix F.

3.5.1. Attention problems in the lean condition. As predicted, AP *T*-score composites had a large negative correlation with sensitivity to rate of reinforcement in the lean condition (*n* = 19, Pearson's *r* = - 0.58, *SE* = 0.20, 98.3% CI [- 1.0, - 0.06]). This association reached statistical significance (*p* = 0.009).

3.5.2. Attention problems in the rich condition. The relationship between AP *T*-score composites and sensitivity to rate of reinforcement was highly attenuated in the rich condition, as predicted (*n* = 39, Pearson's *r* = - 0.14, *SE* = 0.16, 98.3% CI [- .55, 0.26], *p* = 0.38).

3.5.3. Attention problems across conditions. We failed to observe a statistically significant difference in the relationships between AP *T*-score composites and sensitivity to rate of reinforcement across conditions, despite a moderate effect size (*n* = 15, *t*(12) = 1.6, *p* = 0.13, Cohen's *q* = 0.41). In the subsample available for this analysis, correlations between attention problems and sensitivity to rate of reinforcement were: lean condition (Pearson's *r* = - 0.61, *SE* = 0.22, 98.3% CI [- 1.0, - 0.01], *p* = 0.02); rich condition (Pearson's *r* = - 0.29, *SE* = 0.27, 98.3% CI [- 1.0, 0.44], *p* = 0.30). In this subsample, the correlation between sensitivity to rate of reinforcement in the lean and rich condition was high (Pearson's *r* = 0.63, *SE* = 0.22, 98.3% CI [0.04, 1.0], *p* = 0.01).

3.6. Secondary hypotheses

3.6.1. Delay discounting in the lean condition. AUC values from the $100 condition of the delay discounting survey had a small, negative, nonsignificant correlation with sensitivity to rate of reinforcement in the lean condition (*n* = 18, Pearson's *r* = - 0.24, *SE* = 0.24, 99.1% CI [- 0.96, 0.48], *p* = 0.33). This association was small and positive for the $10,000 condition of the hypothetical delay discounting survey (*n* = 14, Pearson's *r* = 0.14, *SE* = 0.29, 99.1% CI [- 0.74, 1.0], *p* = 0.62). This lack of large, significant, and consistently positive associations violated expectations.

3.6.2. Delay discounting in the rich condition. As predicted, AUC values from both conditions had small and insignificant associations with sensitivity to rate of reinforcement in the rich condition (AUC \$100: n = 35, Pearson's r = 0.02, SE = 0.17, 99.1% CI [- 0.46, 0.51], p = 0.89; AUC \$10,000: n = 33, Pearson's r = - 0.01, SE = 0.18, 99.1% CI [- 0.51, 0.49], p = 0.96).

3.7. Tertiary hypotheses

3.7.1. Internalizing in the lean condition. Internalizing *T*-score composites had a large negative association with sensitivity to rate of reinforcement in the lean condition, consistent with prediction (n = 18, Pearson's r = - 0.52, SE = 0.21, 99.1% CI [- 1.0, 0.11]). Contrary to prediction, this association was nonsignificant (p = 0.03)

3.7.2. Internalizing in the rich condition. As predicted, the relationship between Internalizing *T*-score composites and sensitivity to rate of reinforcement was attenuated in the rich condition (n = 37, Pearson's r = - 0.11, SE = 0.17, 99.1% CI [- 0.58, 0.35], p = 0.51).

3.7.3. Externalizing in the lean condition. Externalizing *T*-score composites had a moderate negative correlation with sensitivity to rate of reinforcement in the lean condition, as hypothesized (Pearson's r = - 0.47, SE = 0.22, 99.1% CI [- 1.0, 0.19], p = 0.05). However, this association was not statistically significant.

3.7.4. Externalizing in the rich condition. Externalizing *T*-score composites had a small negative correlation with sensitivity to rate of reinforcement in the rich condition that was statistically insignificant (n = 37, Pearson's r = - 0.07, SE = 0.17, 99.1% CI [- .54, 0.40], p = 0.69). This was consistent with expectations.

3.8. Exploratory analyses

3.8.1. Intellectual functioning in the lean condition. IQ Composite standard scores had a small positive association with sensitivity to rate of reinforcement in the lean condition that did not reach statistical significance (n = 18, Pearson's r = 0.22, SE = 0.24, 99.1% CI [- 0.48, 0.92], p = 0.37).

3.8.2. Intellectual functioning in the rich condition. IQ Composite standard scores had a small positive association with sensitivity to rate of reinforcement in the rich condition (*n* = 39, Pearson's *r* = 0.07, *SE* = 0.16, 95% CI [- 0.39, 0.52], *p* = 0.68). This association was not statistically significant.

3.8.3. Parent/guardian educational attainment in the lean condition. Parent/guardian educational attainment composites had a moderate positive correlation with sensitivity to rate of reinforcement in the lean condition (*n* = 18, Pearson's *r* = 0.47, *SE* = 0.22, 99.1% CI [- 0.19, 1.0]). This association was nonsignificant.

3.8.4. Parent/guardian educational attainment in the rich condition. Parent/guardian educational attainment composites had a small positive correlation with sensitivity to rate of reinforcement in the rich condition that was nonsignificant (*n* = 37, Pearson's *r* = 0.12, *SE* = 0.17, 99.1% CI [- 0.34, 0.59]).

3.9. Regression diagnostics

The assumptions of homoscedasticity of residuals across values of x and normally distributed residuals appeared to be reasonably satisfied for most regression models (Appendix F). In addition, Cook's D statistics identified only a single influential outlier (i.e., at-or-above the critical value of ~0.7). This case was only an outlier in the regression of sensitivity to rate of reinforcement in the lean condition on the AUC $10,000 delay discounting scale. This case was dropped from this regression. Lowess lines supported a linear X-Y relationship for the following regressions: (a) sensitivity to rate of reinforcement in the lean condition on AP *T*-score composites; (b) sensitivity to rate of reinforcement in the rich condition on the AUC $10,000 scale of the delay discounting survey; (c) sensitivity to rate of reinforcement in the lean condition on KBIT-2 IQ Composite standard scores; and (d) sensitivity to rate of reinforcement in the rich condition on parent/guardian education composite scores. All other X-Y relationships examined appeared non-linear (see Figures 3-2 through 3-8).

Chapter 4: Discussion

4.1. Support of original hypotheses

It is virtually axiomatic that ADHD is associated with reduced sensitivity to schedules of partial reinforcement, despite the small number of studies that have sought to rigorously examine this phenomenon (American Psychiatric Association, 2013; Luman et al., 2005; Luman et al., 2010). A key corollary of this axiom asserts that a weakened response to schedules of partial reinforcement will disappear as the *rate* of reinforcement experienced approaches that of a continuous schedule of reinforcement (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). Thus, we predicted there would be a strong negative relationship between attention problems averaged across informants and sensitivity to the rate of reinforcement in the lean condition. We predicted this relationship would be attenuated in the rich condition. Consistent with theory, we found a large and statistically significant negative correlation between attention problems composite scores and sensitivity to the rate of reinforcement in the lean condition (Pearson's $r = -0.58$). This relationship virtually disappeared in the rich condition (Pearson's $r = -0.14$). Despite this moderate effect size (Cohen's $q = 0.41$), this difference failed to reach statistical significance. This may have been due to the low statistical power for this planned comparison ($n = 15$, $1-\beta = 0.22$). Further investigation via cumulative meta-analysis will be necessary to draw accurate conclusions about the size, direction, and significance of these effects (Braver, Thoemmes, & Rosenthal, 2014). Such an investment is warranted, since (a) the partial reinforcement axiom and its corollary offer a compelling and parsimonious account for observed variability in ADHD symptoms and impairments across settings; and (b) this account has important implications for the treatment of ADHD (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008).

We predicted the pattern for ADHD would be repeated in the relationship between delay discounting and sensitivity to rate of reinforcement. Delay discounting is a key theoretical mechanism for explaining the reduced sensitivity to partial schedules of reinforcement associated with ADHD (Catania, 2005; Sagvolden et al., 2005; Tripp & Wickens, 2008). Furthermore, meta-analytic results have supported the link between ADHD and steepened discounting of delayed reinforcement (Patros et al., 2016; Pauli-Pott & Becker, 2011). We failed to find this expected relationship. Effect sizes for delay discounting were small, statistically insignificant, and lacked a consistent direction. These results should be interpreted with caution, given the poor reliability of the delay discounting survey. In bivariate regression, poor reliability in the independent variable always causes underestimation of effect size (Cohen et al., 2003). Automated surveys that use titration to safeguard against inconsistent responding and shorten administration time (e.g., Richards, Zhang, Mitchell, & de Wit, 1999), or brief surveys that infer levels of discounting based on response patterns (Kirby et al., 1999), may provide better reliability (Nguyen et al., 2018). However, it is possible that hypothetical delay discounting surveys simply tap into a different aspect of impulsive choice than experiential discounting procedures (i.e., self-reported choice in hypothetical situations that span periods of days, weeks, months, and years vs. observed choices captured on a moment-to-moment time scale; Duckworth & Kern, 2011; Nguyen et al., 2018). If this is the case, it should be no surprise that GML-based measures of sensitivity to rate of reinforcement failed to have strong associations with a measure of hypothetical delay discounting. The two procedures examine choice in relation to delayed/infrequent reinforcement via different methods (self-report vs. behavioral observation) and in reference to different time scales (days–years vs. seconds–minutes) and reinforcement magnitudes (hundreds and tens vs. dollars and cents). Consistent with this perspective, a recent head-to-head comparison of experiential vs. hypothetical delay discounting procedures reported that only the experiential procedure succeeded in measuring steepened discounting as a function of ADHD (Yu & Sonuga-Barke, 2016). A recent study found this same pattern for identifying steepened discounting of delayed reinforcement in patients with schizophrenia relative to controls (Horan, Johnson, & Green, 2017). Future studies should compare the relationship between both forms of discounting procedures and classic GML-based measures of reinforcement rate sensitivity.

We guessed the pattern for ADHD would also be repeated in the relationships between internalizing and externalizing psychopathology and sensitivity to rate of reinforcement. This hypothesis was based on (a) evidence of moderate-to-large positive correlations between each dimension and attention problems; (b) assertions about the presence of reinforcement learning abnormalities in the etiology of a wide swath of psychopathology; and (c) the presence of other deficits claimed to be central to ADHD within frequently co-occurring disorders (Sonuga-Barke et al., 2016; Willcutt, 2015; Willcutt et al., 2012; Willcutt et al., 2008; Zisner & Beauchaine, 2016). This hypothesis was partially supported. We found moderate-to-large negative correlations between sensitivity to rate of reinforcement in the lean condition and (a) internalizing (Pearson's r = - 0.52); (b) externalizing (Pearson's r = - 0.47). These relationships were greatly attenuated in the rich condition: internalizing (Pearson's r = - 0.11); externalizing (Pearson's r = - 0.07). None of these effects reached statistical significance. This was true at both the family-wise error rate set for these tertiary comparisons and the family-wise error rate set for primary comparisons. These effects would have reached statistical significance at the conventional per-comparison alpha of 0.05. These effects also warrant further investigation via cumulative meta-analysis (Braver et al., 2014).

Finally, exploratory analyses were planned for the relationship between two potential confounds and sensitivity to rate of reinforcement–intellectual functioning and the averaged educational attainment of each participant's parent/guardian(s). In addition, we reported the results of single-informant analyses for readers curious about rater effects in Appendix E. It was important to examine these confounds. ADHD is associated with slightly lower average IQ (Willcutt et al., 2012). Parent/guardian education composite scores can provide (limited) insight into background socioeconomic status (SES), and differences in SES in this diverse sample could have resulted in differences in motivation to engage in the reinforcement task. Such deprivation states are tightly controlled in animal studies using the GML paradigm (Kollins, Newland, et al., 1997). Informants may rate levels of ADHD and externalizing behavior more accurately than participants, and vice-versa for internalizing symptoms, though the incremental validity of multi-informant assessment is in need of greater study (De Los Reyes et al., 2015). Less measurement error in independent variables would be expected to result in larger estimated effect sizes.

These analyses suggested small and statistically insignificant positive correlations between IQ and sensitivity to rate of reinforcement across conditions. The direction of this effect was consistent with the small negative association between ADHD and IQ. Parent/guardian education composites had a moderate positive correlation with sensitivity to rate of reinforcement in the lean condition. The direction of this effect suggested that potential SES-related deprivation states did not enhance engagement in the task. This effect also failed to reach statistical significance. This relationship was small and statistically insignificant in the rich condition. Finally, we failed to observe statistically significant rater effects, although the direction and magnitude of these effects support the need further investigation (see Appendix E).

4.2. Similarity to past findings and significance

These results make a small, incremental contribution to our understanding of how individuals with attention problems, internalizing psychopathology, and externalizing psychopathology respond to schedules of reinforcement. Like some previous authors, we found a reduced match between behavior allocation and reinforcement history in individuals with elevated attention problems (Aase & Sagvolden, 2006; Alsop et al., 2016; Douglas & Parry, 1994; Furukawa et al., 2017; Kollins, Lane, et al., 1997; Taylor et al., 2010). We extended these findings by manipulating the overall rate of reinforcement across two conditions, similar to Aase and Sagvolden (2006) and Douglas and Parry (1994). This allowed for a more direct test of the partial reinforcement axiom and its corollary. It also addressed concerns that effects could be masked by especially rich schedules of reinforcement in a single condition (Popa, 2013) or inadvertent continuous reinforcement across conditions (e.g., Barber et al., 1996; Pelham et al., 1986).

We extended this work further by measuring sensitivity to rate of reinforcement using a rigorous experimental paradigm from the quantitative analysis of behavior (Baum, 1974; Davison & McCarthy, 1988; Herrnstein, 1961; Klapes et al., 2019; McDowell, 2013; Popa, 2013; Popa & McDowell, 2016). This paradigm allowed us to estimate sensitivity to reinforcement using directly observed, precisely measured, free-operant behavior captured over extended time (≥ 217 minutes/participant, ~163 hours total, 141 lab visits). It yielded sensitivity to rate of reinforcement estimates for each individual at the continuous level of measurement. This enhanced our statistical power and precision. We further enhanced statistical power and precision using an empirically-derived, multi-informant, dimensional approach to the measurement of attention problems and psychopathology (Kotov et al., 2017).

Finally, we based our estimates on a fairly representative sample collected from a diverse quadrant of a major metropolitan area that was stratified based on self- and informant-rated attention problems. We took great care to address obstacles to participation based on either demographic or clinical characteristics. Use of a diverse group likely produced some additional noise in our analyses, but it was consistent with the ethical principle of justice (i.e., equal access to the benefits of research participation, American Psychological Association, 2002). This noise can become useful information via a cumulative meta-analytic approach (Braver et al., 2014). This noise also allowed us to examine attention problems in its natural state of high co-morbidity (Barkley, 2015; Kessler et al., 2006; Willcutt et al., 2012). This co-morbidity allowed us to test the unlikely hypothesis that reduced sensitivity to rate of reinforcement is unique to ADHD (e.g., Sagvolden et al., 2005). Although observed effects for internalizing and externalizing psychopathology did not reach family-wise significance, they were large and consistent with the pattern observed for attention problems in this sample. Therefore, it is important to withhold judgement of the "significance" of these point estimates until confidence intervals begin to narrow with accumulating data. It is possible that reduced sensitivity to reinforcement schedules is a transdiagnostic risk factor for psychopathology (e.g., LaFreniere & Newman, 2019; Sonuga-Barke et al., 2016; Zisner & Beauchaine, 2016). Of course, these effects could also be due to the high correlations between these dimensions and attention problems.

4.3. Limitations

This study was limited in its ability to examine the role of delay discounting in the aforementioned relationships due to the poor reliability of our hypothetical delay discounting survey and lack of an experiential discounting procedure. Similarly, this study relied on a single method to assess sensitivity to rate of reinforcement. The GML approach is well-established and has high internal validity, but it may not capture all relevant aspects of sensitivity to rate of reinforcement. In addition, this study elected to reduce the issue of multiple comparisons by relying on multi-informant composite scores of attention problems and psychopathology. It would be valuable to compare results using these composite scores to results derived from single informant analyses, and results derived from DSM-based symptom dimensions of ADHD. We were unable to thoroughly examine these potentially important nuances.

This study was also limited by the difficulty of obtaining useable data in the lean condition of our GML task. Even though poor fits to the GML in the lean condition did not appear related to our independent variables, they effectively cut our statistical power in half. We hypothesize that this high frequency of poor fits was due to the low overall reinforcement rate in our lean condition. Under such conditions, it may take longer for each individual's behavior to reach a steady-state equilibrium (Klapes et al., 2019). It is possible that cases excluded from analyses due to poor GML fits needed even more exposure to the schedules (although our participants will tell you that 200 minutes was plenty!). Future studies should consider using a slightly faster overall reinforcement rate in the lean condition. This will have the added benefit of cutting down on experiment time and may even make room for an additional overall reinforcement rate condition. Dose-response relationships could begin to be examined with the addition of just one more condition.

Greater precision of measurement could have also been obtained by customizing schedule exposure time to each individual using quantitative measurement of steady-state behavior. This measurement process could have been programmed into task software, and might have ensured that the response patterns of all participants reached steady-state and remained there for a roughly equal amount of time. This might have also eliminated the need for imputation due to zeros in the behavior and/or reinforcement column for one option within a schedule.

If the need for imputation cannot be eliminated from GML studies using such procedural modifications, then the methods used in this study should be further investigated and refined via simulation (e.g., Brown & White, 2005). The approach used was defensible and did not appear to produce any bias in GML parameter estimates. But any use of imputation is novel (if not anathema) within the quantitative behavior analytic tradition.

Another limitation has to do with generalizability. This sample was diverse, but it was not completely representative of its catchment area in terms of age distribution and educational attainment. More work needs to be done to recruit these missing community members. Authors should take this into account when interpreting these findings.

4.4. Future directions

Priority should be given to continued data collection using these procedures to provide better statistical power and precision. This will require a difficult decision about whether to (a) keep the current lean condition as is, to allow direct accumulation of effects; (b) to change the criteria for ending the lean condition to ensure steady state behavior is achieved; or (c) to revise the RI values of the lean condition to see if the main effects reported above hold with a slightly higher overall reinforcement rate. Priority should also be given to analyzing the moment-to-moment dynamics of behavior allocation recorded in this and other samples. The current analysis focused only on steady-state behavior patterns. It is important to understand whether similarities in steady-state effects mask differences in underlying behavior dynamics that differentially relate to our variables of interest. Finally, multimethod and multisource assessment of our independent and dependent variables should be incorporated into future work.

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FIGURES AND TABLES

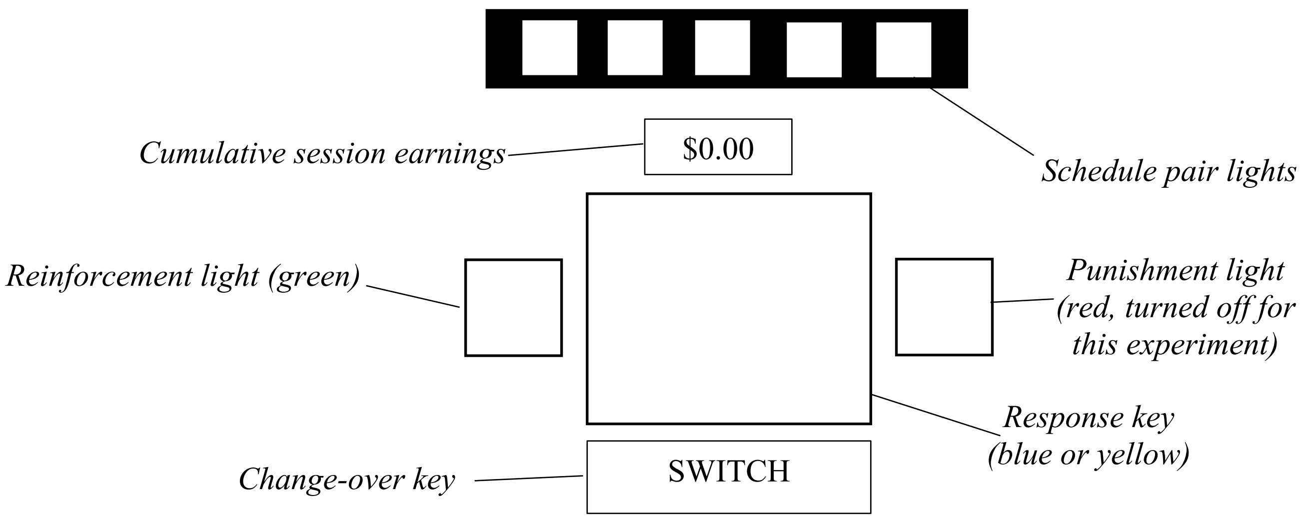

Figure 2-1. PRESS-B user interface

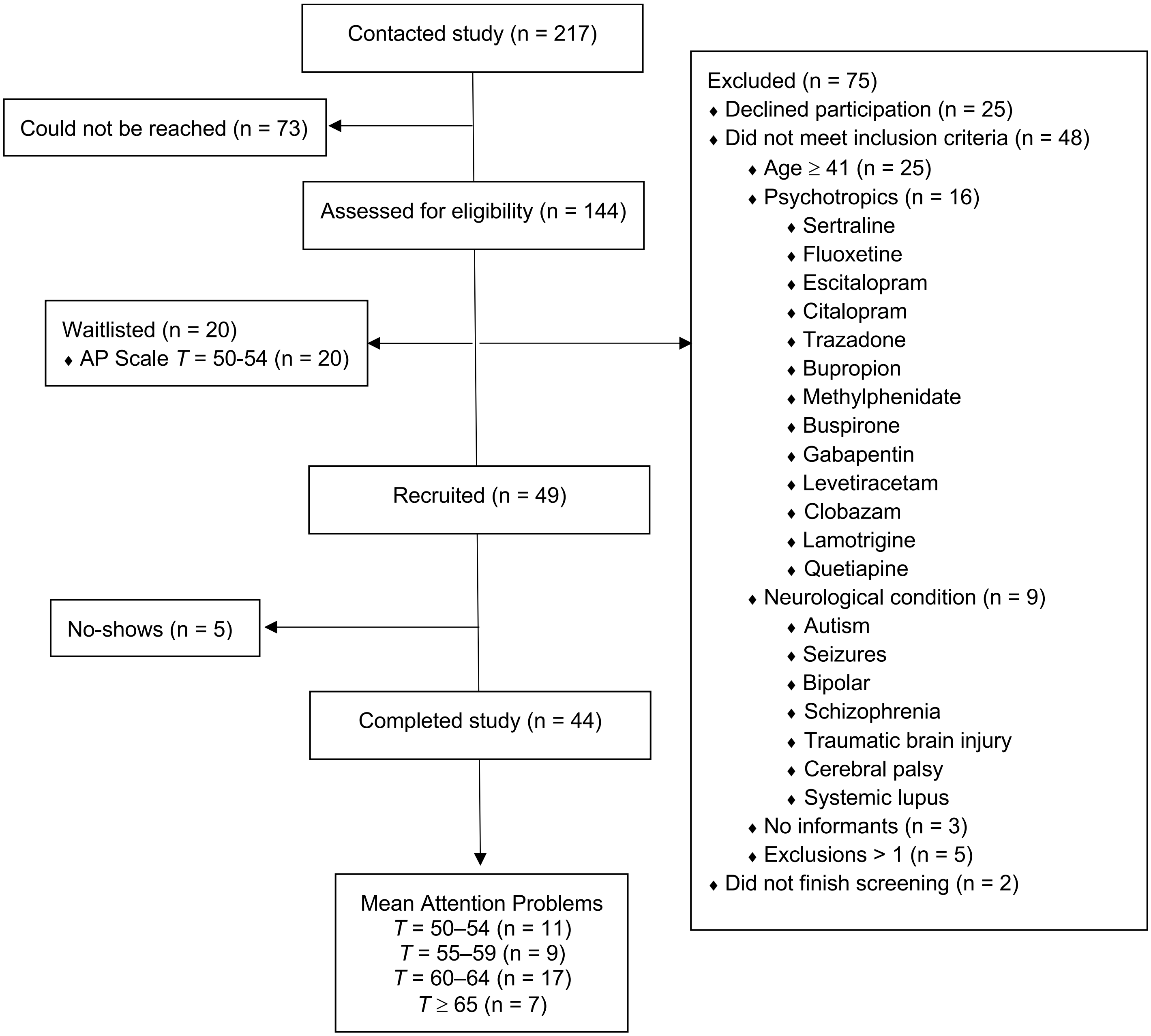

Figure 3-1. Recruitment flow diagram

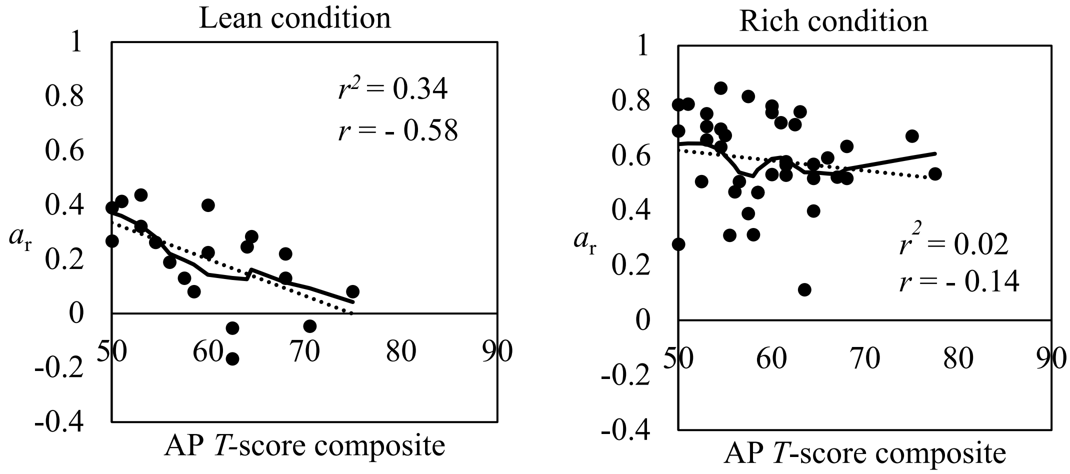

Figure 3-2. Regression: a_r lean and a_r rich on AP *T*-score composites

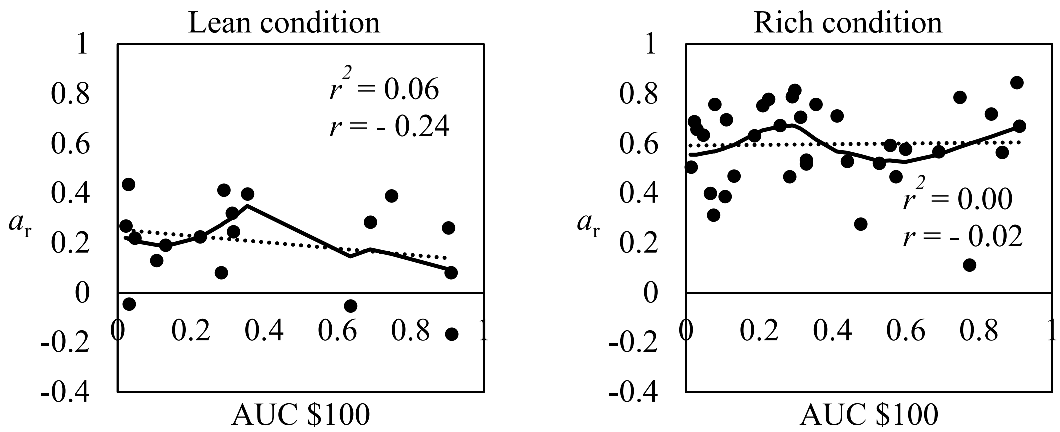

Figure 3-3. Regression: a_r lean and a_r rich on AUC $100

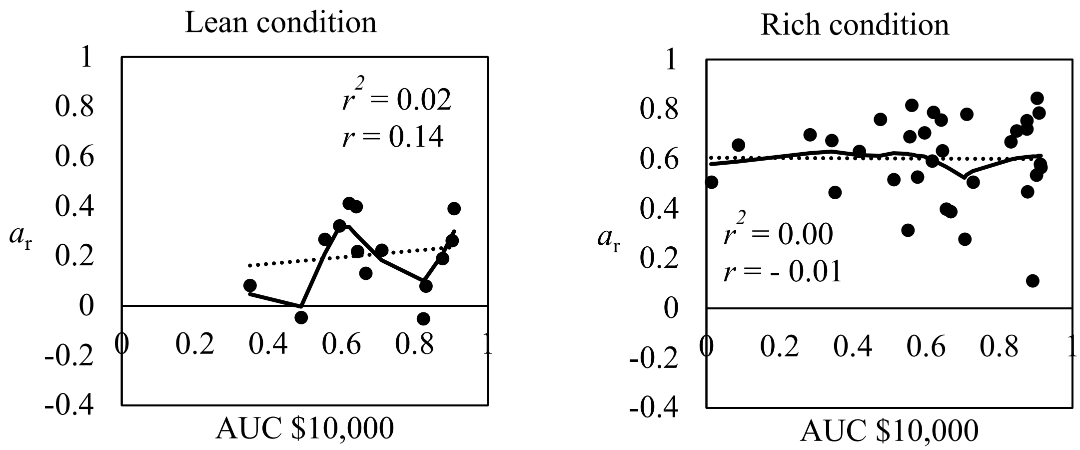

Figure 3-4. Regression: a_r lean and a_r rich on AUC $10,000

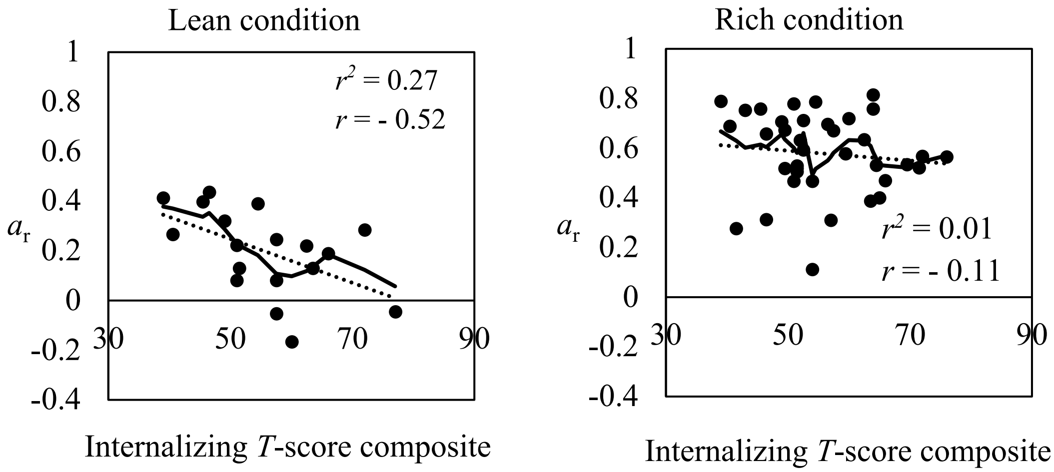

Figure 3-5. Regression: a_r lean and a_r rich on Internalizing *T*-scores composites

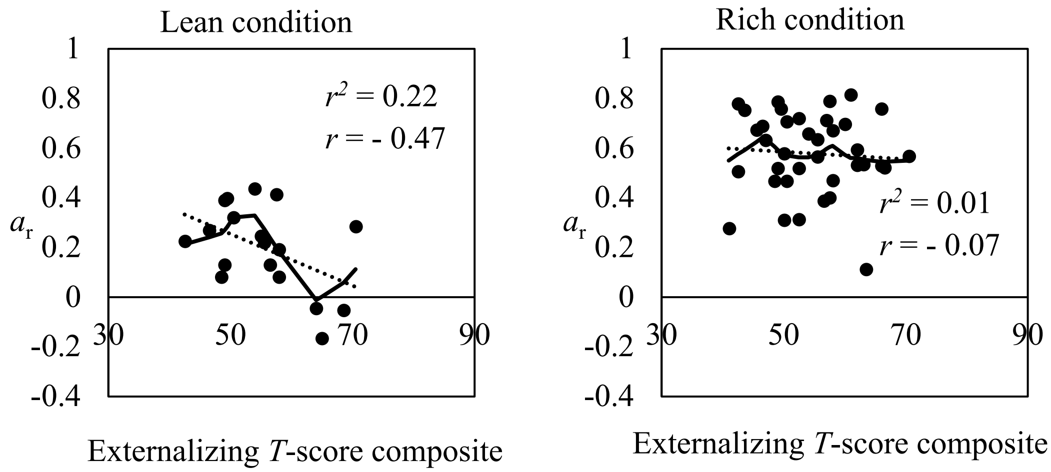

Figure 3-6. Regression: a_r lean and a_r rich on Externalizing T-score composites

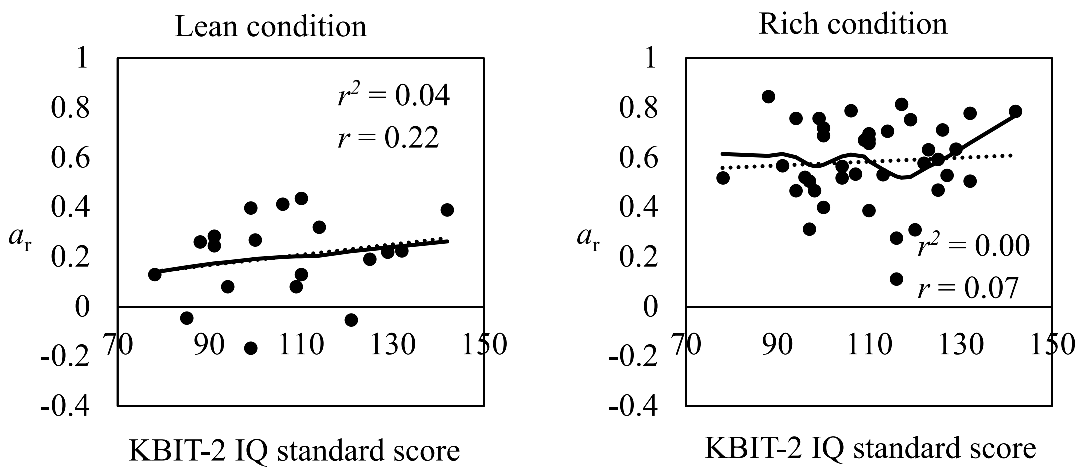

Figure 3-7. Regression: a_r lean and a_r rich on KBIT-2 IQ standard scores

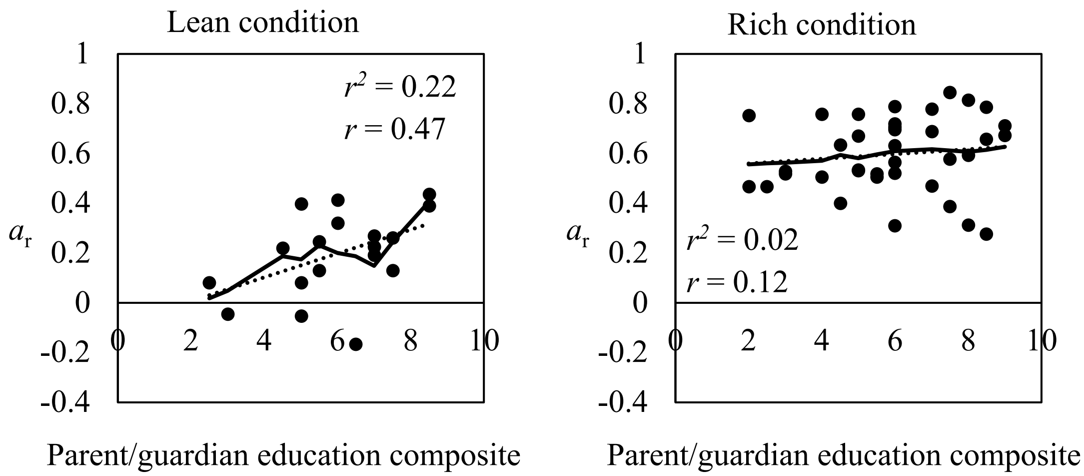

Figure 3-8. Regression: a_r lean and a_r rich on parent/guardian education composites

Table 2-1. Experimental conditions

Slow condition					
	RI values				
Schedule pair	Blue key	Yellow key	Duration (s)	Interval ratios	# of sessions
Acquisition	1.1	1.1	60	1:1	5
1	15	90	480	1:6	5
2	26.3	78.7	480	1:3	5
3	52.6	52.6	480	1:1	5
4	78.7	26.3	480	3:1	5
5	90	15	480	6:1	5
Extinction	∞	∞	60	1:1	5
Fast condition					
	RI values				
Schedule pair	Blue key	Yellow key	Duration (s)	Interval ratios	# of sessions
Acquisition	1.1	1.1	60	1:1	1-3
1	1.3	7.5	200	1:6	1-3
2	2.2	6.6	200	1:3	1-3
3	4.4	4.4	200	1:1	1-3
4	6.6	2.2	200	3:1	1-3
5	7.5	1.3	200	6:1	1-3
Extinction	∞	∞	60	1:1	1-3

Table 3-1. Median responses per reinforcement

Lean condition			
	RI values		
Schedule pair	Blue key	Yellow key	Responses / reinforcement: *Mdn*
1	15	90	82.31
2	26.3	78.7	108.17
3	52.6	52.6	147.82
4	78.7	26.3	108.25
5	90	15	82.99
Rich condition			
	RI values		
Schedule pair	Blue key	Yellow key	Responses / reinforcement: *Mdn*
1	1.3	7.5	13.57
2	2.2	6.6	21.81
3	4.4	4.4	31.03
4	6.6	2.2	21.47
5	7.5	1.3	13.50

Table 3-2. Sample demographics

Demographics	Sample
N	44
Male/female	21/23
Age in years: *M* (*SD*)	25 (5.7)
Race/ethnicity: *n* (%)	
African American	13 (30)
LatinX	6 (14)
Asian	4 (9)
Native American	0 (0)
Pacific Islander	0 (0)
White, non-Hispanic	17 (39)
Multiple	4 (9)
Marital status: *n* (%)	
Never married	37 (84)
Married	5 (11)
Separated	0 (0)
Divorced	1 (2)
Widowed	0 (0)
Lived with spouse or partner in past 6 months: *n* (%)	13 (29)
Education: *n* (%)	
No high school, no GED	0 (0)
General Equivalency Diploma (GED)	0 (0)
High school	1 (2)
Some college	21 (48)
Associate’s	7 (16)
Bachelor’s or registered nurse (RN)[4]	10 (23)
Some graduate school	2 (5)
Master’s	2 (5)
Doctoral or law	1 (2)
Parent/guardian education composite: *n*	42
Min	GED
25th	Some college/associate’s
Mdn	Bachelor’s or RN
75th	Some graduate school/master’s
Max	Doctoral or law
Mode	Bachelor’s or RN

Table 3-3. Sample demographics relative to Metropolitan Statistical Area by age

Demographic	Sample	MSA[1]
N	44	1,796,356
Female: (%)	52	51
Age in years: (%)		
18 to 24	59	30
25 to 29	18	24
30 to 34	16	22
35 to 39	7	24
Race/ethnicity: (%)		
African American	30	36
LatinX	14	12
Asian	9	7
Native American	0	0.1
Pacific Islander	0	0.5
White, non-Hispanic	39	42
Multiple	9	3
Marital status: (%)		
Never married	84	62
Married	11	32
Separated	0	2
Divorced	2	4
Widowed	0	0.1
Education: (%)		
No high school, no GED	0	11
High school or GED	2	25
Some college	48	23
Associate's	16	7
Bachelor's or RN	28	22
Graduate or professional	7	11

[1]MSA = Metropolitan Statistical Area.

Table 3-4. Sample characteristics: Variables of interest

Characteristic	All participants	$r^2 \geq 0.80$ Rich Condition	$r^2 \geq 0.80$ Lean Condition
n	44	39	19
AP[1,2] *T*: *M* (*SD*)	60 (6.4)	59.4 (6.5)	59.9 (7.3)
AUC $100[3]: *M* (*SD*)	0.38 (0.28)	0.38 (0.27)	0.41 (0.32)
AUC $10,000[3]: *M* (*SD*)	0.64 (0.23)	0.64 (0.24)	0.65 (0.22)
Internalizing[2] *T*: *M* (*SD*)	56.5 (9.4)	55.6 (9.2)	55.7 (10.2)
Externalizing[2] *T*: *M* (*SD*)	55.3 (7.7)	54.4 (7.6)	55.4 (7.7)
IQ standard scores: *M* (*SD*)	109 (14.4)	110.3 (14.1)	106.5 (17.4)
Parent/guardian education composite: *Mdn*	Bachelor's or RN	Bachelor's or RN	Bachelor's or RN
a_r rich condition[4]: *M* (*SD*)	0.54 (0.21)	0.58 (0.17)	0.56 (0.24)
a_r lean condition[4]: *M* (*SD*)	0.12 (0.14)	0.13 (0.13)	0.20 (0.17)
ADHD probable[5]: *n* (*%*)			
Never	28 (64)	27 (69)	13 (68)
Childhood only	6 (14)	5 (13)	2 (11)
Current only	4 (9)	3 (8)	1 (5)
Both	6 (14)	4 (10)	3 (16)

[1]AP = Attention Problems. [2]Self- and informant-ratings averaged to construct score. [3]Area-under-the-curve estimates from discounting survey. [4]Sensitivity to rate of reinforcement parameters. [5]Algorithm: (1) ≥ 93rd %ile ADHD total score on BAARS-IV Self-Report Current or Childhood Symptoms scales; (2) onset ≤ age 16; and (3) impairment in ≥ 1 domain.

Table 3-5. Variables of interest stratified by r^2 in the lean condition

Characteristic	$r^2 \geq 0.80$ Slow Condition	$r^2 < 0.80$ Slow Condition	Test	*p*	*d*
n	19	25			
AP[1,2] *T*: *M* (*SD*)	59.9 (7.3)	60.1 (5.8)	$t(42) = 0.07$	0.94	0.02
AUC $100[3]: *M* (*SD*)	0.41 (0.32)	0.37 (0.26)	$t(38) = 0.48$	0.63	0.15
AUC $10,000[3]: *M* (*SD*)	0.65 (0.22)	0.63 (0.24)	$t(34) = 0.24$	0.81	0.08
Internalizing[2] *T*: *M* (*SD*)	55.7 (10.2)	57.2 (9.0)	$t(40) = 0.51$	0.61	0.16
Externalizing[2] *T*: *M* (*SD*)	55.4 (7.7)	55.3 (7.9)	$t(40) = 0.08$	0.94	0.02
IQ standard scores: *M* (*SD*)	106.5 (17.4)	110.9 (11.5)	$t(42) = 0.96$	0.34	0.31
Parent/guardian education composite: *M* (*SD*)	6.0 (1.7)	5.65 (2.13)	$t(40) = 0.54$	0.59	0.17

[1]AP = Attention Problems. [2]Self- and informant-ratings averaged to construct score. [3]Area-under-the-curve for $100 and $10,000 conditions of delay discounting survey.

Table 3-6. Regression results

			a_r[3] lean				
Independent variables	*n*	fwise α	Test	*p*	*r* (*SE*)	r^2	1-β
AP[1,2] *T*	19	.017	*F*(1, 17) = 8.6	.009	- .58 (.20)	.34	.68
AUC $100[4]	18	.009	*F*(1, 16) = .99	.334	- .24 (.24)	.06	.05
AUC $10,000[4]	14	.009	*F*(1, 12) = .26	.621	.14 (.29)	.14	.10
Internalizing[2] *T*	18	.009	*F*(1, 16) = 6.1	.026	- .52 (.21)	.27	.38
Externalizing[2] *T*	18	.009	*F*(1, 16) = 4.5	.049	- .47 (.22)	.22	.28
IQ standard scores	19	.009	*F*(1, 17) = .84	.371	.22 (.24)	.05	.04
Parent/guardian education composite	18	.009	*F*(1, 16) = 4.4	.052	.47 (.22)	.22	.28
			a_r[3] rich				
Independent variables	*n*	fwise α	Test	*p*	*r* (*SE*)	r^2	1-β
AP[1,2] *T*	39	.017	*F*(1, 37) = .79	.380	- .14 (.16)	.02	.06
AUC $100[4]	35	.009	*F*(1, 33) = .02	.893	.02 (.17)	.00	.04
AUC $10,000[4]	33	.009	*F*(1, 31) = .00	.964	- 0.01 (.18)	.00	.01
Internalizing[2] *T*	37	.009	*F*(1, 35) = .45	.506	- .11 (.17)	.01	.02
Externalizing[2] *T*	37	.009	*F*(1, 35) = .17	.685	- .07 (.17)	.005	.02
IQ standard scores	39	.009	*F*(1, 37) = .17	.684	.07 (.16)	.005	.02
Parent/guardian education composite	37	.009	*F*(1, 35) = .55	.465	.12 (.17)	.02	.04

[1]AP = Attention Problems. [2]Self- and informant-ratings averaged to construct score. [3]Sensitivity to rate of reinforcement parameter. [4]Area-under-the-curve for $100 and $10,000 conditions of delay discounting survey.

Table 3-7. Correlation matrix

Variable	1	2	3	4	5	6	7	8	9
1. AP[1,2] *T*									
2. AUC $100	.20								
3. AUC $10,000	.21	.66***							
4. Internalizing[2] *T*	.58***	.19	.24						
5. Externalizing[2] *T*	.55***	.22	.03	.61***					
6. IQ standard scores	- .28	.02	.30	- .22	- .23				
7. Parent/guardian education composite	- .33*	.11	.12	- .18	- .16	.31*			
8. a_r[4] lean	- .58**	- .24	.14	- .52*	- .47*	.22	.47		
9. a_r[4] rich	- .14	.02	- .01	- .11	- .07	.07	.12	.63*	

[1]AP = Attention Problems. [2]Self- and informant-ratings averaged to construct score. . [3]Area-under-the-curve for $100 and $10,000 conditions of delay discounting survey. [3]Sensitivity to rate of reinforcement parameter. *p < .05, **p < .01, ***p < .001

APPENDICES

Appendix A: Recruitment Ad

How do YOU learn from REWARD?

The Emory Behavior Analysis Laboratory is interested in understanding how different people learn from rewards, and how reward-learning relates to behavioral health.

EMORY

EMORY

Earn $70-$80 for 5 hours of your time

3 easy steps:

1. Call and complete a 10-minute phone screening.

2. Provide contact information for someone who knows you well to complete 5-15-minute survey about your health. They will receive $5 for their efforts.

3. Attend three lab visits ranging from 1-2.5 hrs to complete surveys and tasks in which you will earn money.

We are seeking adults aged 18-40.

Contact: emory.rewards.study@gmail.com or (814) 433-0307
to find out if you're eligible

Appendix B: Delay Discounting Survey

“This survey asks you to make decisions about which of two rewards you prefer. You will not receive the rewards that you choose, but I want you to make your decisions as though you were really going to receive these rewards.”

“The possible rewards are shown in a series of tables (slide finger down first table, flip pages to show examples of other tables). The columns on the left of the tables display rewards (slide finger down left column in first table) that you can get today (point at “Now”). The columns on the right of the tables (slide finger down right column) display rewards that you can get after specified amounts of time (point to “1 Week,” flip page to show that there are other delays). You will be asked to choose between rewards delivered immediately versus rewards delivered after delays. The choices you make are completely up to you. Please select the option that you prefer, not what you think I want you to prefer. I do not expect you to choose one particular reward over the other. Just choose the one you really want.”

“Let’s do the first item together. Which would you prefer, $100 now, or $100 in 1 week? Circle your preference. Good!

Do the rest like this. Please complete the items in order and do not skip any. Let me know when you are finished."

Now	**1 Week**
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	2 Weeks
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	1 Month
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	6 Months
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	1 Year
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	5 Years
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	25 Years
$100.00	$100.00
$99.00	$100.00
$97.50	$100.00
$95.00	$100.00
$92.50	$100.00
$90.00	$100.00
$85.00	$100.00
$80.00	$100.00
$75.00	$100.00
$70.00	$100.00
$65.00	$100.00
$60.00	$100.00
$50.00	$100.00
$45.00	$100.00
$40.00	$100.00
$35.00	$100.00
$30.00	$100.00
$25.00	$100.00
$20.00	$100.00
$15.00	$100.00
$10.00	$100.00
$7.50	$100.00
$5.00	$100.00
$2.50	$100.00
$1.00	$100.00

Now	1 Week
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	2 Weeks
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	1 Month
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	6 Months
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	**1 Year**
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	5 Years
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Now	25 Years
$10,000.00	$10,000.00
$9,900.00	$10,000.00
$9,750.00	$10,000.00
$9,500.00	$10,000.00
$9,250.00	$10,000.00
$9,000.00	$10,000.00
$8,500.00	$10,000.00
$8,000.00	$10,000.00
$7,500.00	$10,000.00
$7,000.00	$10,000.00
$6,500.00	$10,000.00
$6,000.00	$10,000.00
$5,000.00	$10,000.00
$4,500.00	$10,000.00
$4,000.00	$10,000.00
$3,500.00	$10,000.00
$3,000.00	$10,000.00
$2,500.00	$10,000.00
$2,000.00	$10,000.00
$1,500.00	$10,000.00
$1,000.00	$10,000.00
$750.00	$10,000.00
$500.00	$10,000.00
$250.00	$10,000.00
$100.00	$10,000.00

Appendix C: Instructions for the Concurrent RI Schedules of Reinforcement Task

“Thank you again for choosing to participate in this study. This task investigates how people behave in changing environments. Your goal is to earn as much money as possible. You can earn money by pressing the ‘space’ bar on the keyboard (point). The center button that says ‘START’ on it is grey (point). It will change to blue or yellow when the experiment begins. You can switch between blue and yellow at any time by pressing the ‘ctrl’ button on the keyboard (point). Each color will provide opportunities to earn money for pressing the space bar. These opportunities will change during the task. Pay attention to the row of lights at the top of the screen (point across row). This will provide information about changes in the opportunities provided by blue and yellow. Both colors will always provide at least some opportunities to earn money for pressing the space bar.”

“Your mission is to figure out how to earn as much money as possible. You are guaranteed to earn at least $70 by the end of your last lab visit. If you earn more than the guaranteed minimum payment through your focused efforts on this task, you will be paid the higher amount. Visual and auditory cues will help you with this task. Every time that you earn money, the green light to the left of the center button will flash and a ‘ding’ will sound. Your earnings will be displayed above the center button (point). You will be paid at the end of each study visit in cash or check.”

“You will complete five 40-minute sessions and one 18-minute session for this task. You will complete two 40-minute sessions at the first lab session, and two 40-minute sessions at the second lab session. You will complete one 40-minute session and one 18-minute session during the last lab visit. You will be encouraged to take breaks between sessions.

During these breaks, you may exit the laboratory. There is water, coffee and tea to the right. There is a restroom to your left at the end of the hall on the left-hand side. Tell the experimenter when you are finished with your break. They will set up your next session."

"Please focus on the task and refrain from other activities, such as using your phone, during each session. Please let the experimenter know when you finish each session."

"Do you have any questions?"[1]

"When you are ready, press the 'space' bar to begin."

[1] Task administrators were allowed to repeat/clarify instructions as needed. They were instructed to ensure that participants understood the task before starting.

Appendix D: Technical Specifications of all Computers Used to Run the Concurrent RI Schedules of Reinforcement Task

<u>Laptop # 1</u>

Operating System: Windows 7 (64-bit)

Processor: dual-core 2.53 Ghz processor with 6 GB of RAM

Screen Size: 15.6”

Screen Resolution: 1600 x 900 pixels (widescreen display)

<u>Laptop # 2</u>

Operating System: Windows 8 (64-bit)

Processor: quad-core 2.40 Ghz processor with 8 GB of RAM

Screen Size: 17.0”

Screen Resolution: 1280 x 1024 pixels (full-screen display)

<u>Desktop # 1</u>

Operating System: Windows 10 Home (32-bit)

Processor: dual-core 2.70 Ghz processor with 4 GB of RAM

Screen Size: 14.0”

Screen Resolution: 1280 x 1024 pixels (full-screen display)

<u>Desktop # 2</u>

Operating System: Windows 7 Enterprise (32-bit)

Processor: dual-core 2.60 Ghz processor with 4 GB of RAM

Screen Size: 14.0”

Screen Resolution: 1280 x 1024 pixels (full-screen display)

Desktop # 3

Operating System: Windows 10 Enterprise (64-bit)

Processor: quad-core 3.00 Ghz processor with 8 GB of RAM

Screen Size: 23.0”

Screen Resolution: 1920 x 1080 pixels (widescreen display)

Desktop # 4

Operating System: Windows 10 Enterprise (64-bit)

Processor: quad-core 3.00 Ghz processor with 4 GB of RAM

Screen Size: 23.0”

Screen Resolution: 1920 x 1080 pixels (widescreen display)

Appendix E: Single Informant Analyses

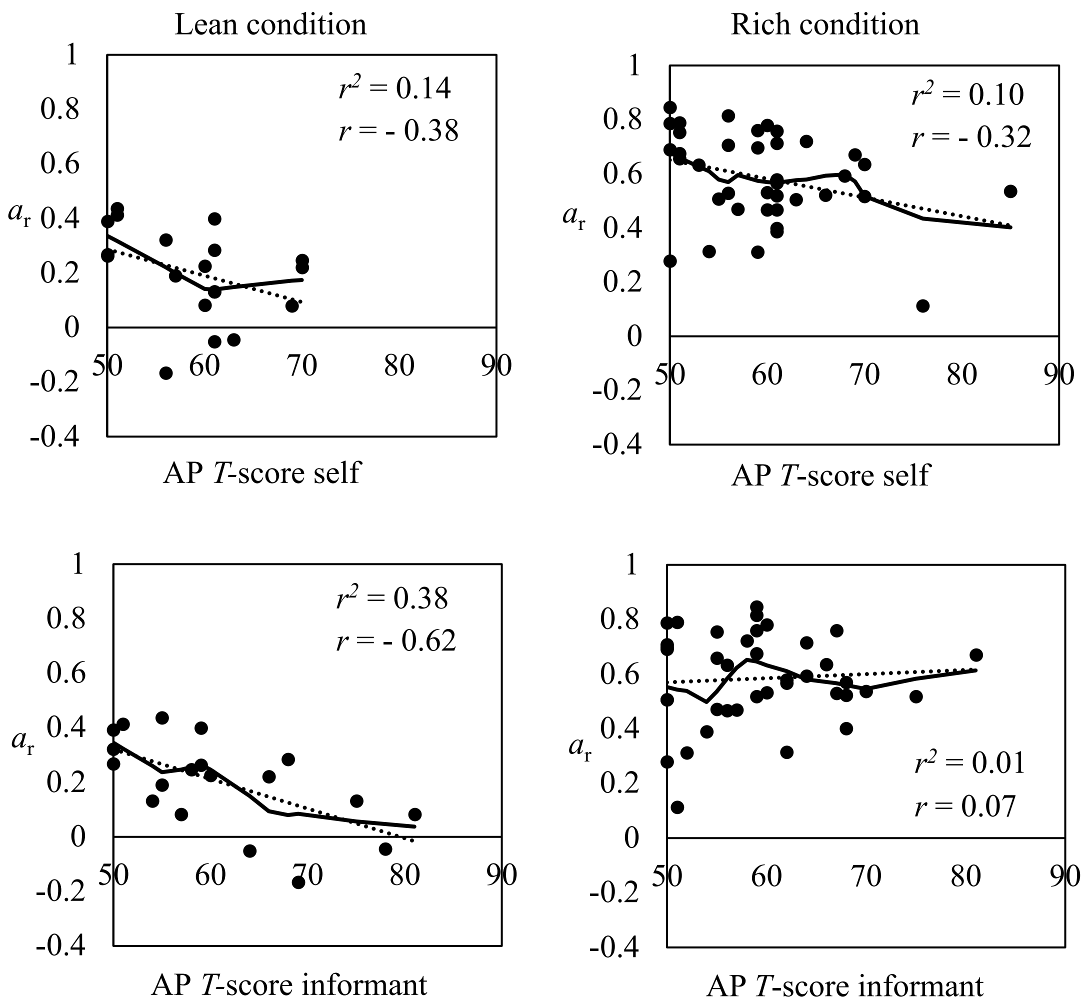

Figure E-1. Regression: a_r lean and a_r rich on single informant AP T-scores

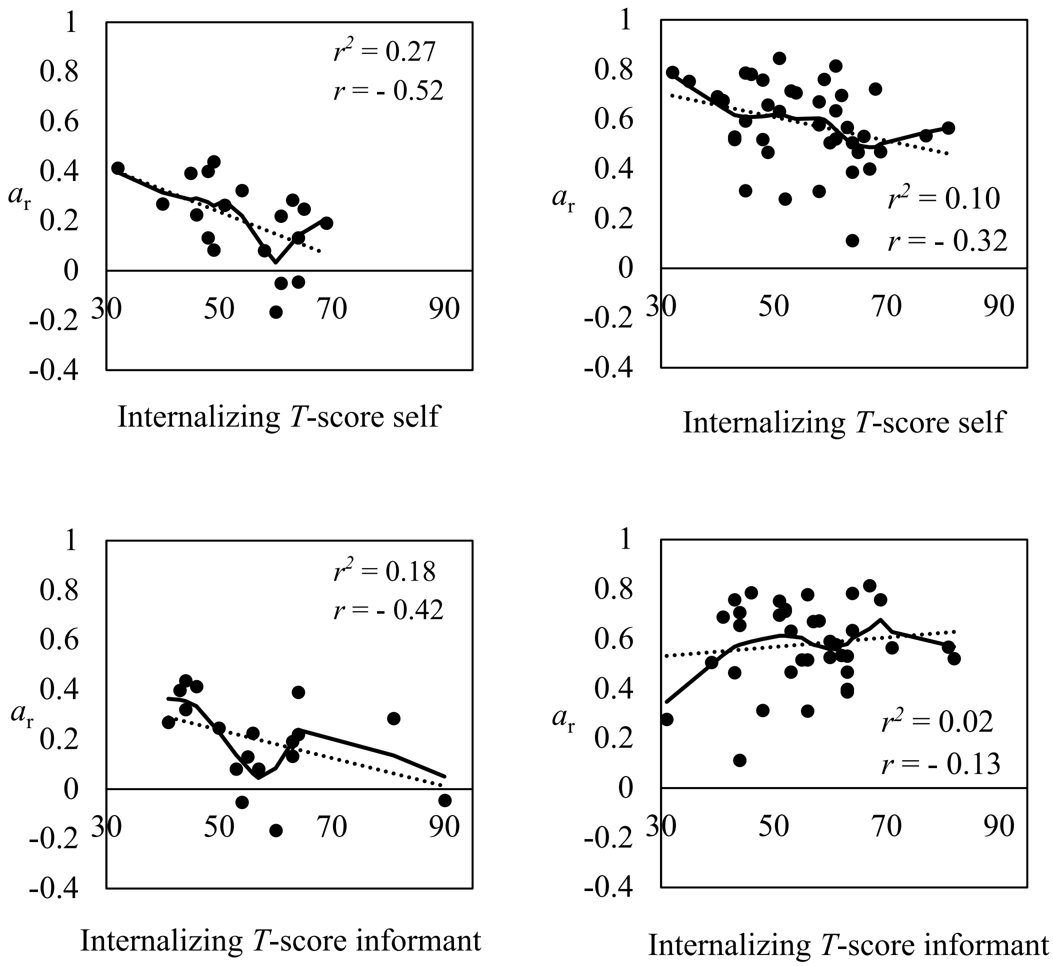

Figure E-2. Regression: a_r lean and a_r rich on single informant Internalizing T-scores

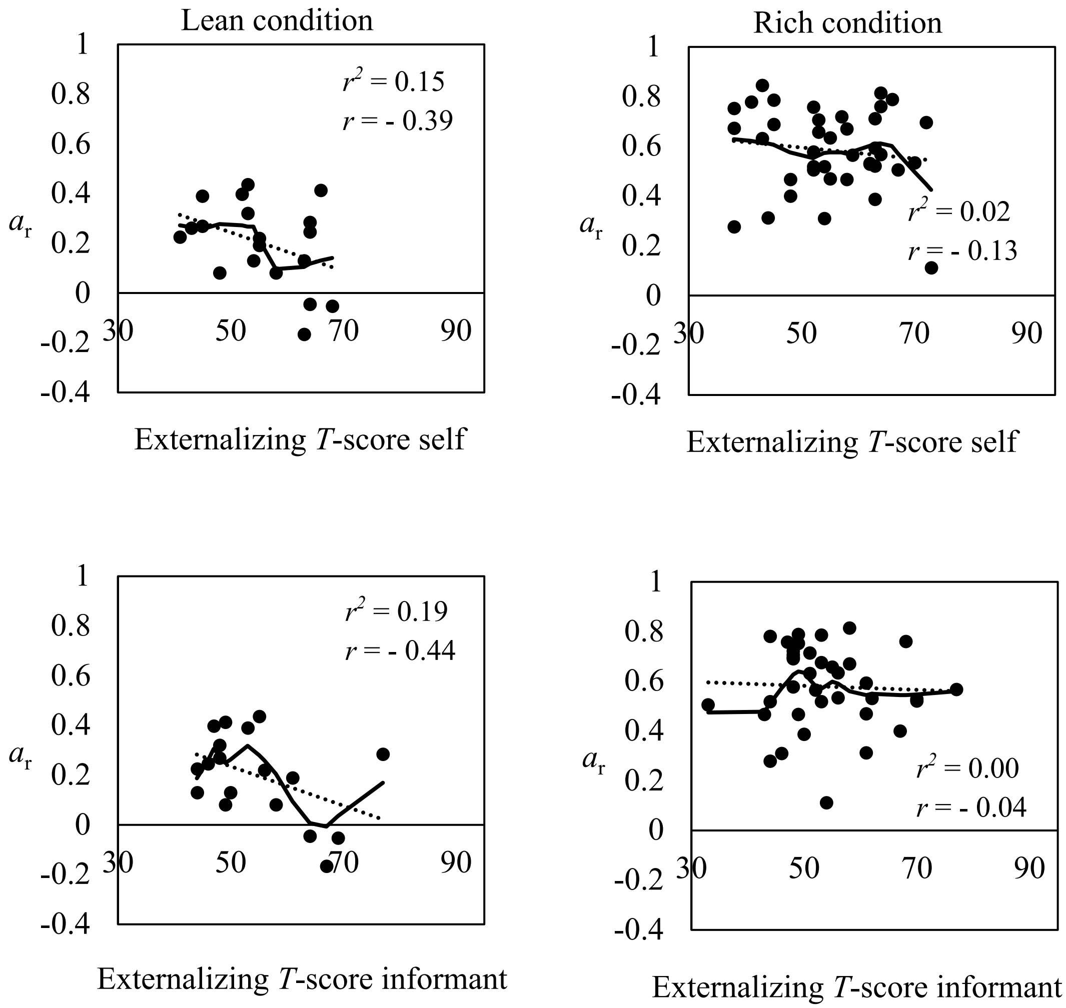

Figure E-3. Regression: a_r lean and a_r rich on single informant Externalizing *T*-scores

Appendix F: Regression diagnostics

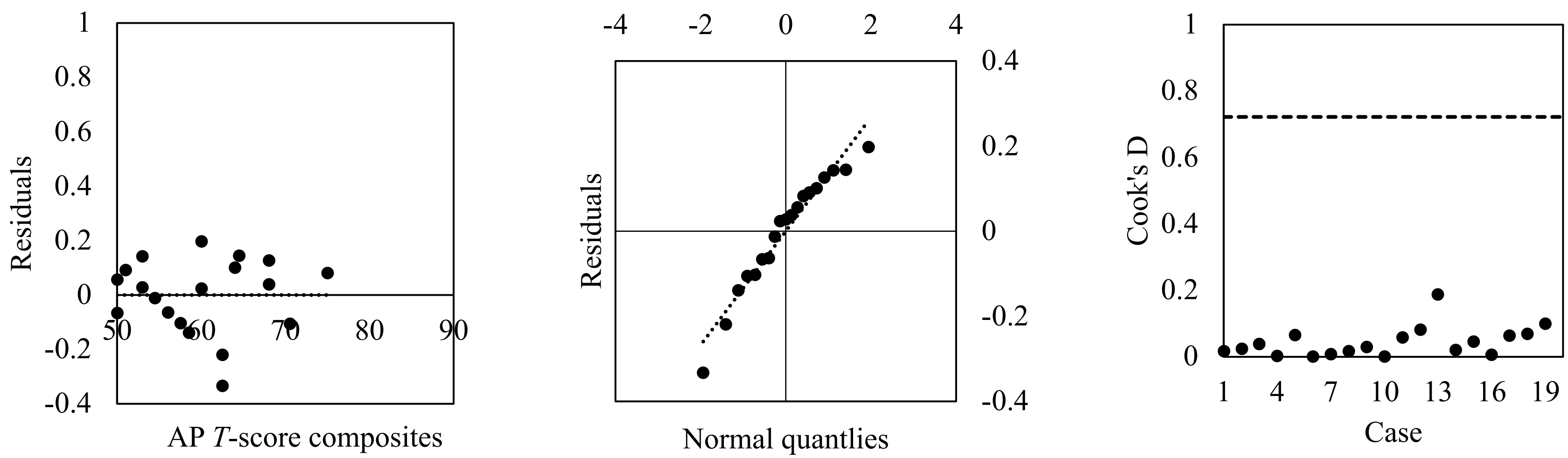

Figure F-1. Regression diagnostics: a_r lean on AP *T*-score composites

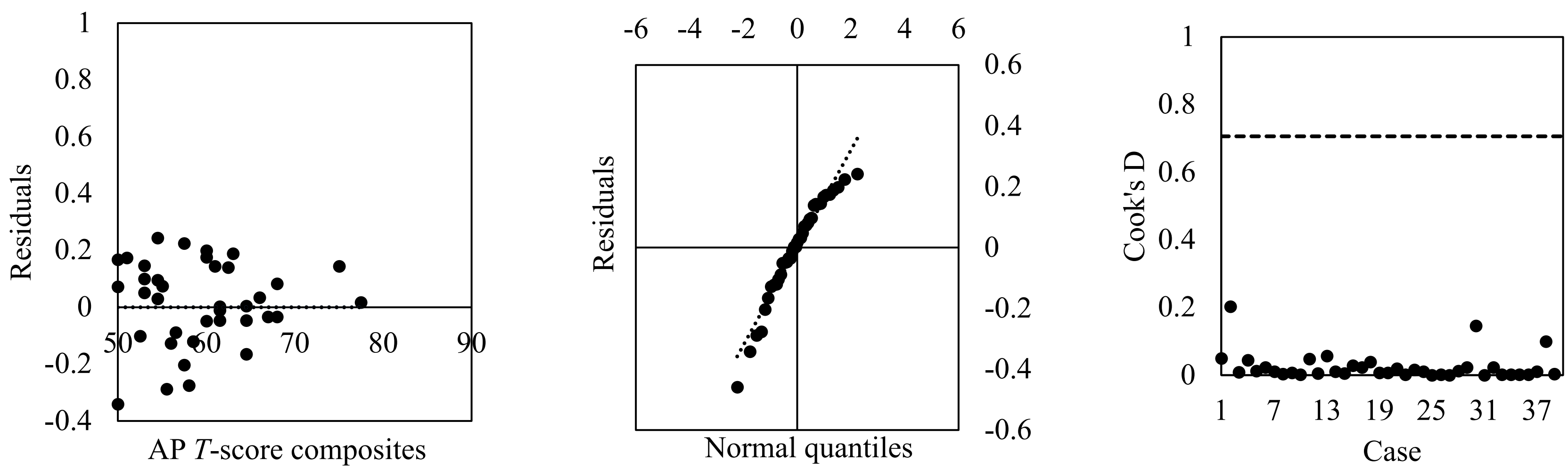

Figure F-2. Regression diagnostics: a_r rich on AP *T*-score composites

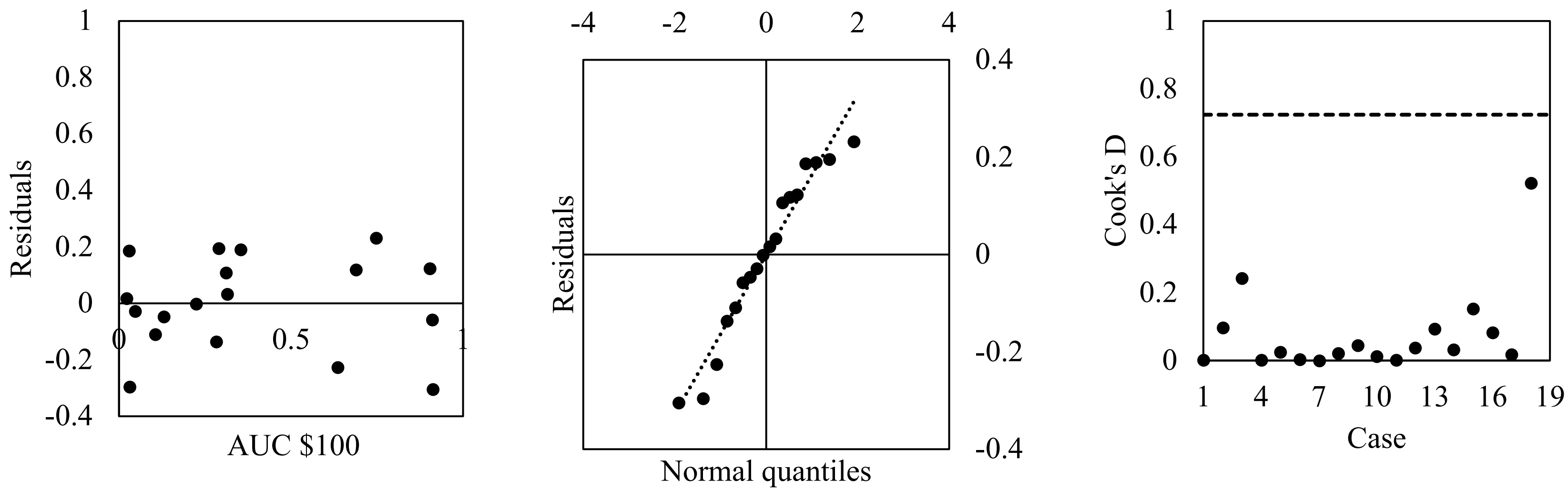

Figure F-3. Regression diagnostics: a_r lean on AUC $100

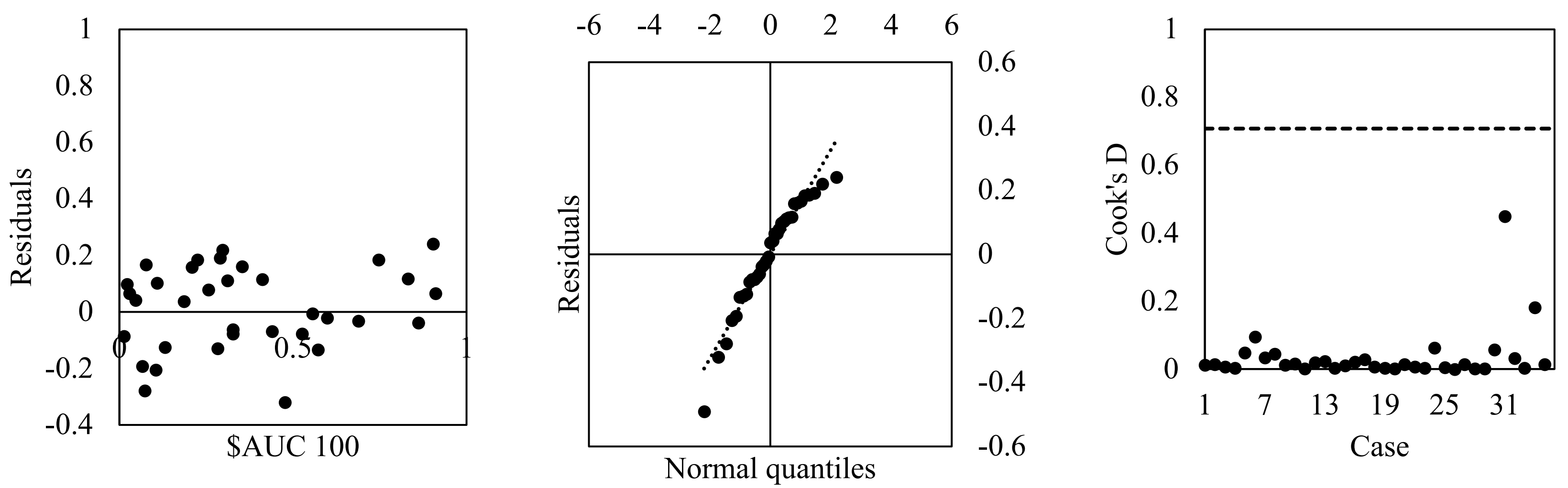

Figure F-4. Regression diagnostics: a_r rich on AUC $100

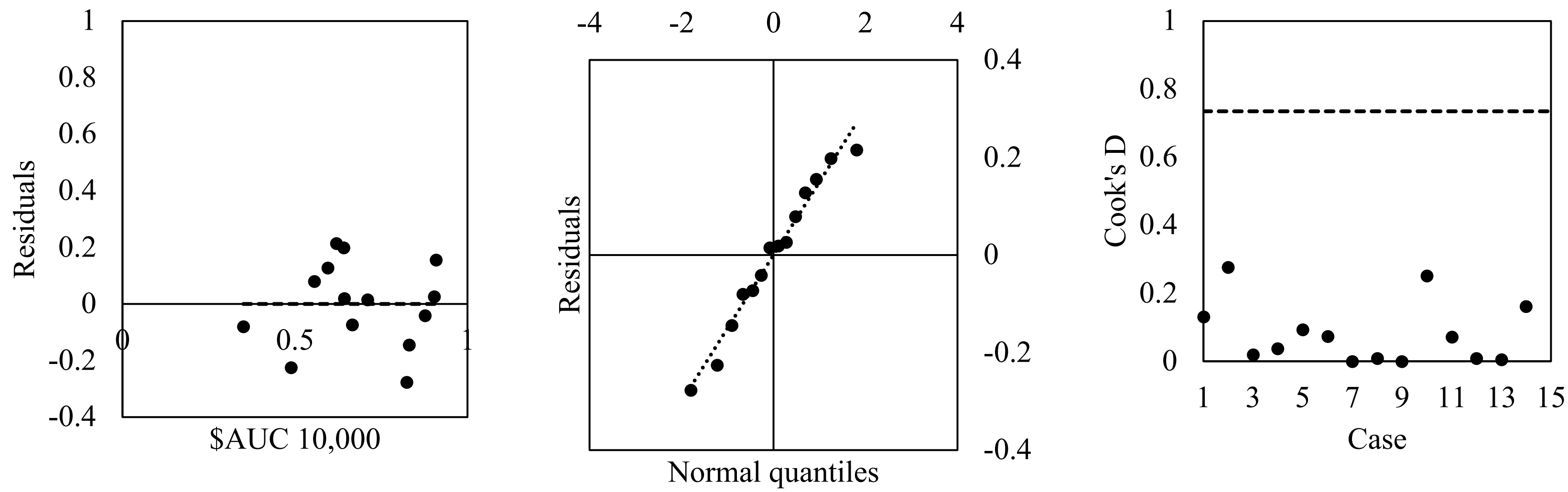

Figure F-5. Regression diagnostics: a_r lean AUC $10,000

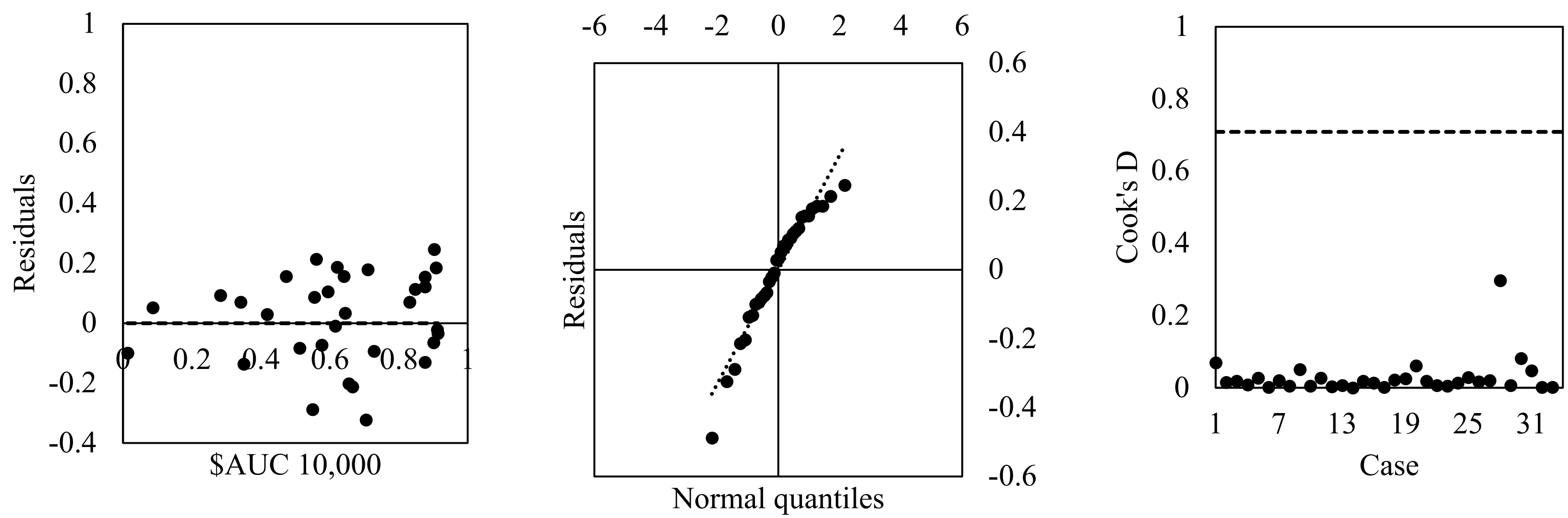

Figure F-6. Regression diagnostics: a_r rich AUC $10,000

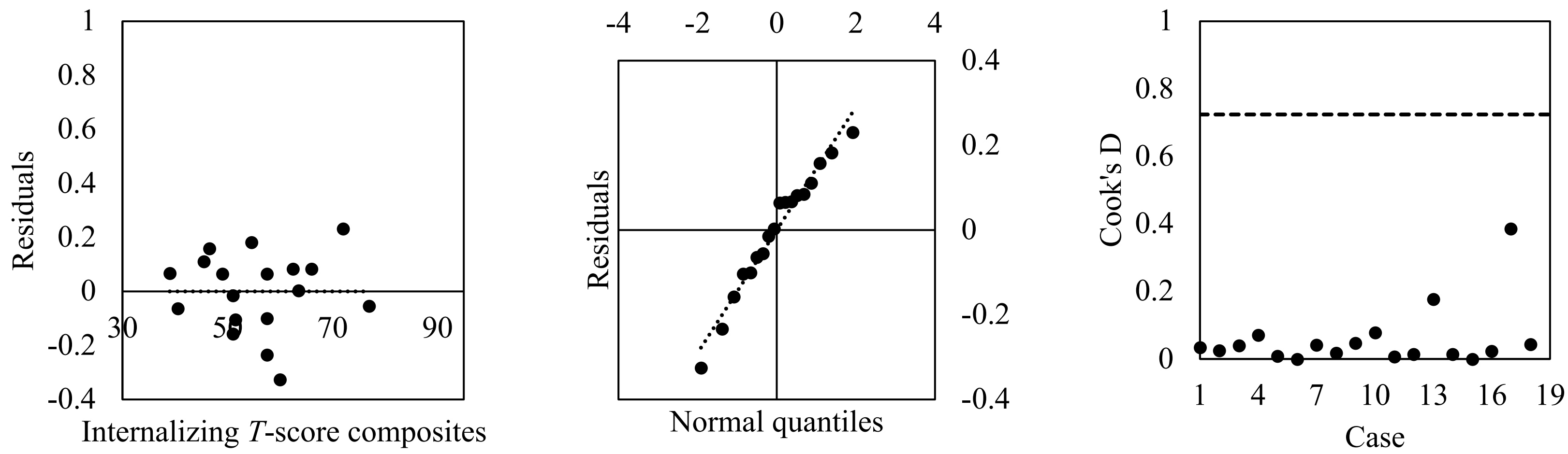

Figure F-7. Regression diagnostics: a_r lean on Internalizing *T*-score composites

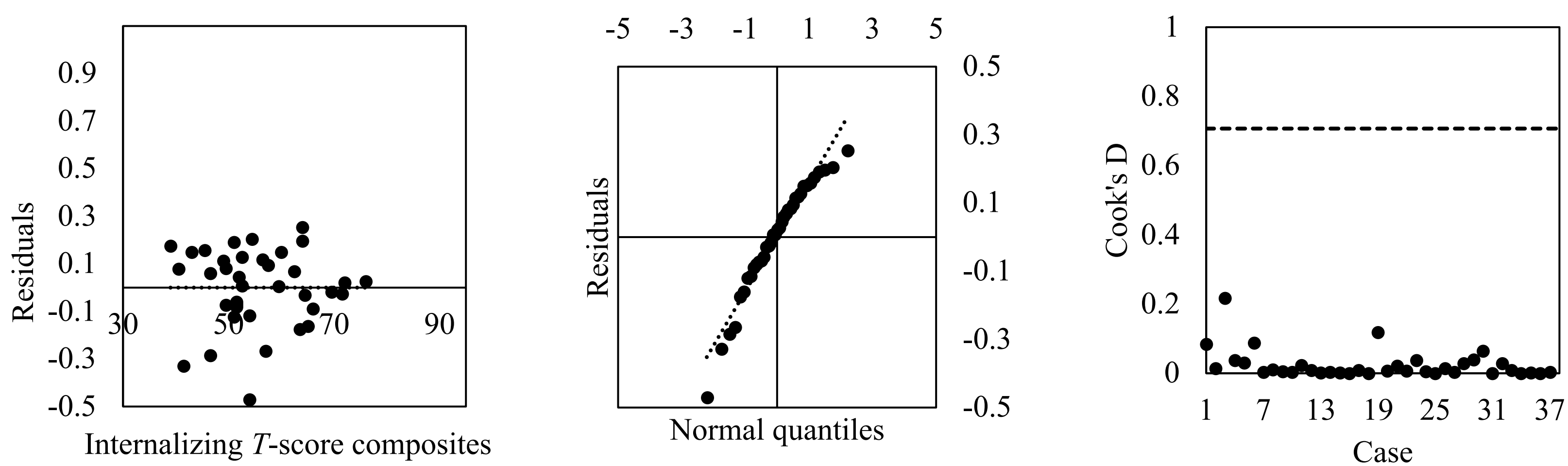

Figure F-8. Regression diagnostics: a_r rich on Internalizing *T*-score composites

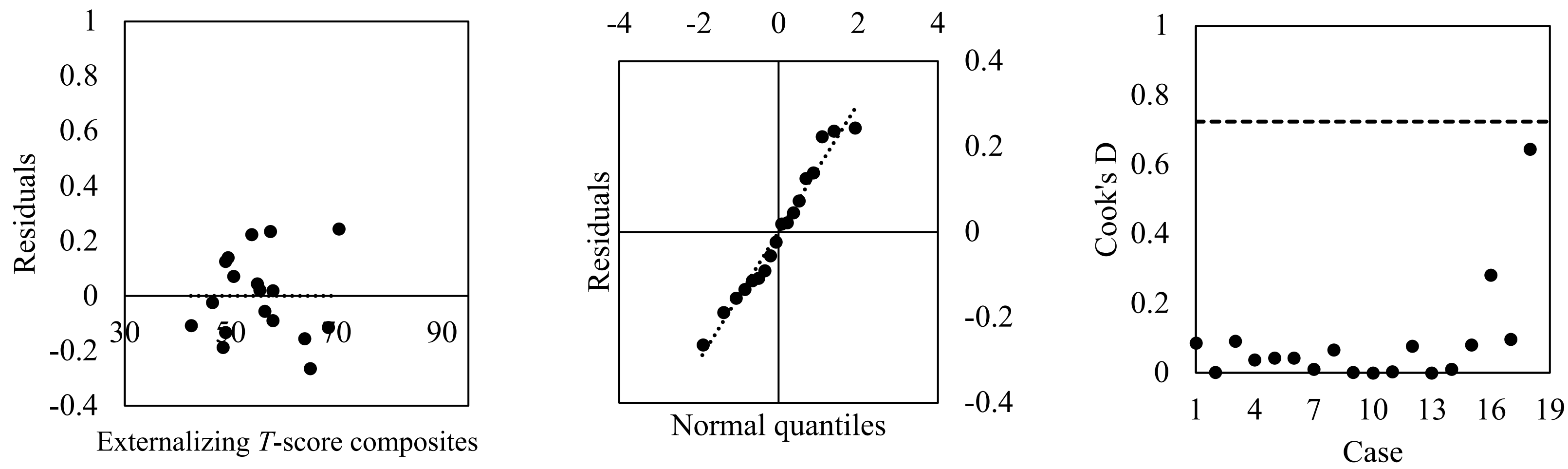

Figure F-9. Regression diagnostics: a_r lean on Externalizing *T*-score composites

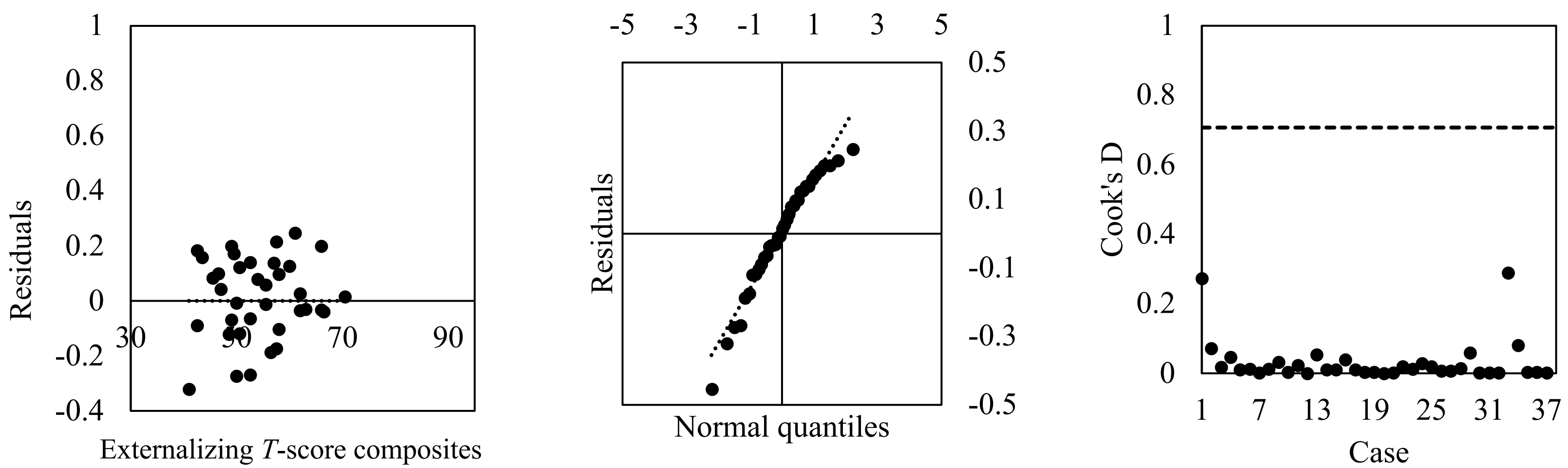

Figure F-10. Regression diagnostics: a_r rich on Externalizing *T*-score composites

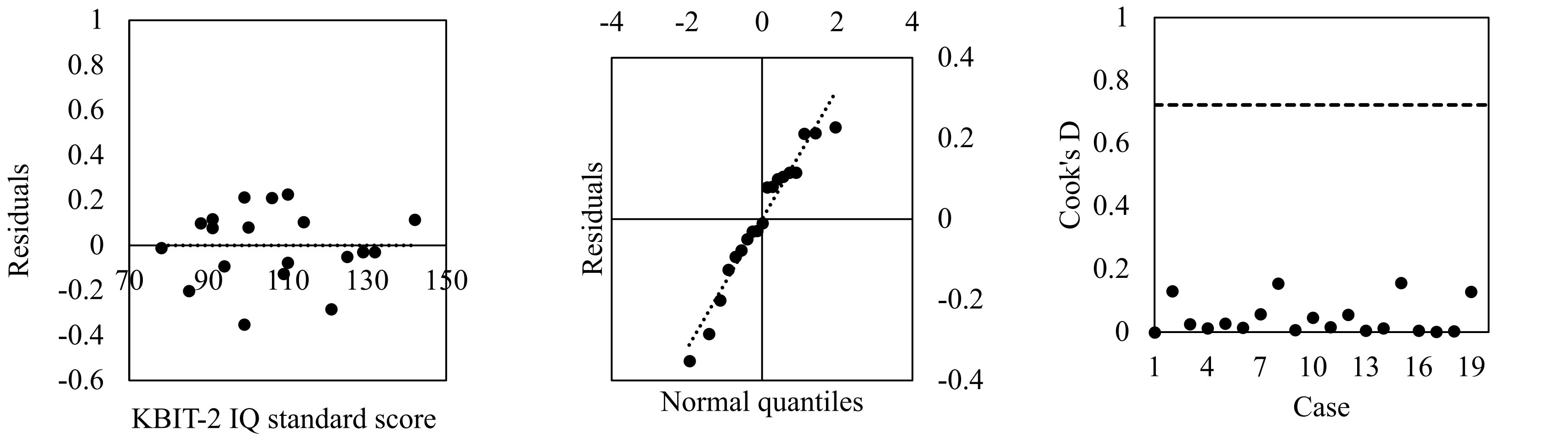

Figure F-11. Regression diagnostics: a_r lean on KBIT-2 IQ standard scores

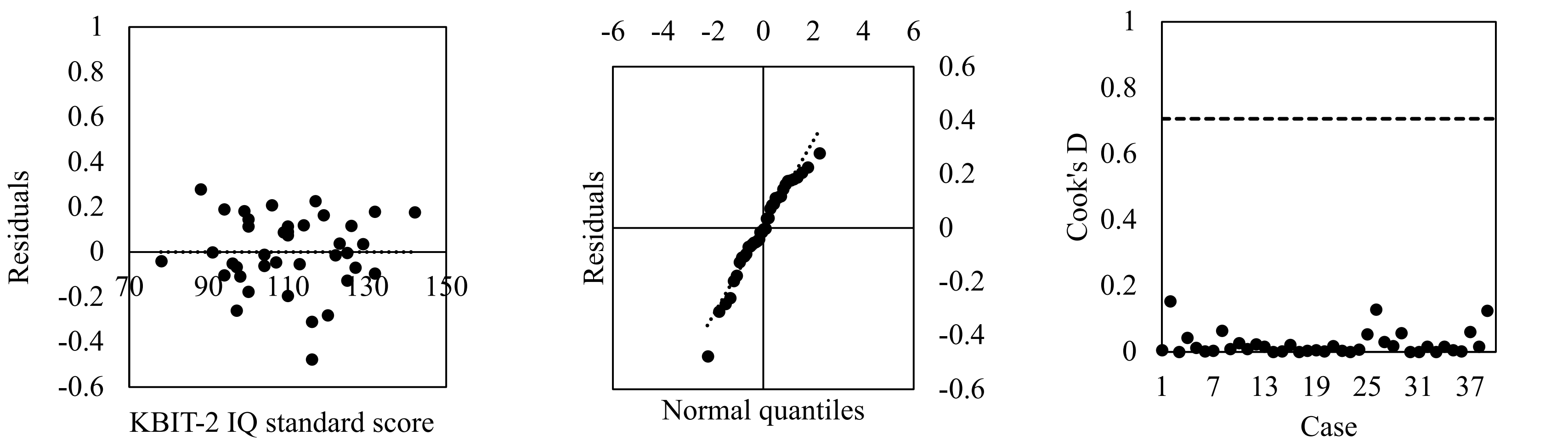

Figure F-12. Regression diagnostics: a_r rich on KBIT-2 IQ standard scores

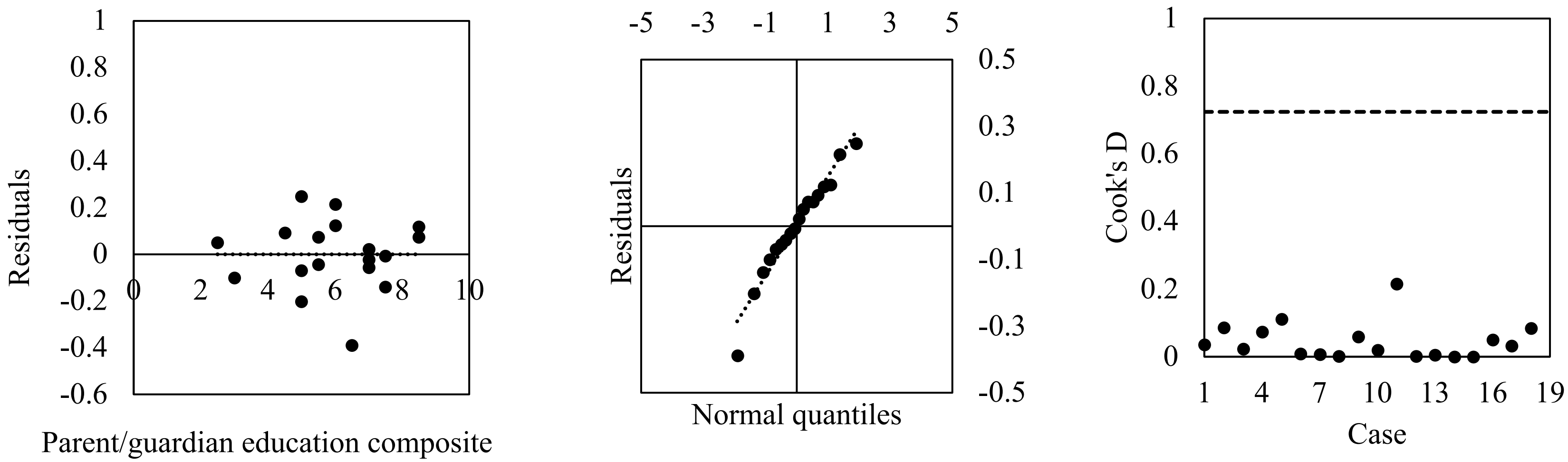

Figure F-13. Regression diagnostics: a_r lean on parent/guardian education composites

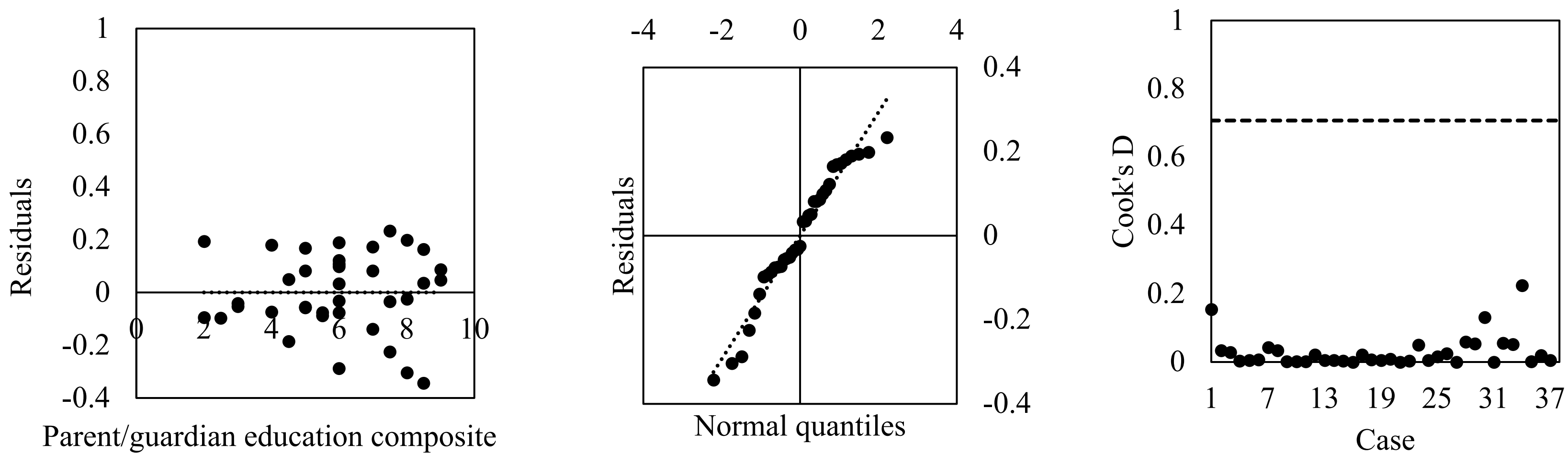

Figure F-14. Regression diagnostics: a_r rich on parent/guardian education composites

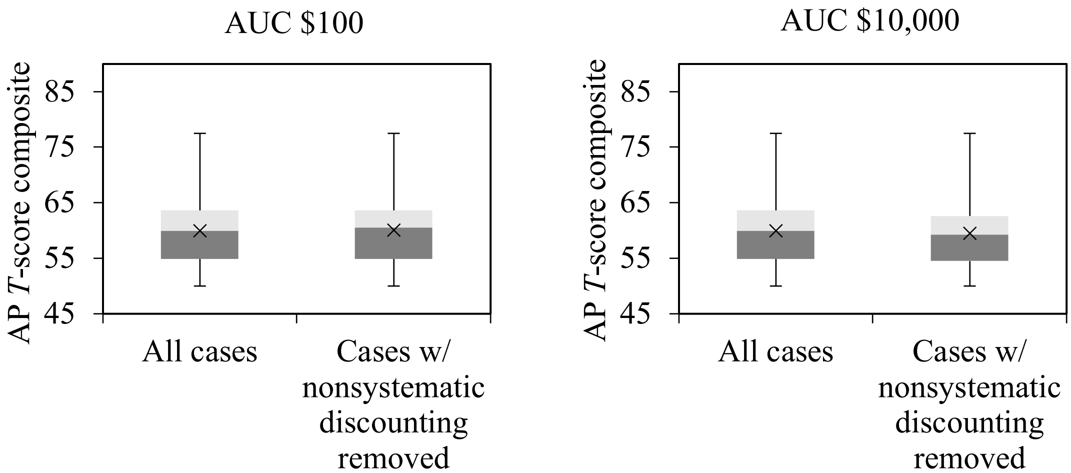

Figure F-15. Effect of removing nonsystematic discounting data on range of AP *T*-score composites