Running Head: FEARLESS DOMINANCE AND CURVILINEARITY

Examining hypothesized interactive and curvilinear relations between psychopathic traits and externalizing problems in an offender sample using item response-based analysis

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Abstract

Fearless Dominance (FD) generally manifests null to small relations with externalizing problems, leading some researchers to propose alternative paths by which FD features may relate to these problems. The current study provides a test of two possibilities, namely that FD (a) interacts statistically with Self-centered Impulsivity (SCI) such that FD is associated with externalizing problems only at high levels of SCI; and (b) demonstrates curvilinear relations with externalizing problems such that FD is more strongly associated with these problems at high levels. We used a large correctional sample and item-response theory-related statistics to precisely estimate individuals' scores at the extremes of each major psychopathic trait. FD was not significantly associated with externalizing problems in interaction with SCI or at higher levels of FD, suggesting that psychopathic traits linked to boldness are not especially relevant to generalized externalizing behavior.

Keywords: moderation, curvilinearity, boldness, antisocial personality disorder, externalizing

General Scientific Summary: Psychopathic traits such as fearless dominance/boldness are not strongly related to many of the externalizing outcomes characteristic of psychopathy. This study examines whether fearless dominance/boldness is related to maladaptive outcomes more strongly in combination with other psychopathic traits or at higher levels of itself – two key hypotheses posed by proponents of the importance of these constructs. Examining these paths to maladaptive behavior bears important implications for the clinical utility of contemporary assessment instruments measuring psychopathy and the validity of mental health assessments more broadly, which tend to specify additive relations among disorder criteria that may be overly simplistic. Fearless dominance/boldness was not significantly associated with externalizing problems in interaction with other psychopathic traits or at higher levels of itself in a large offender sample.

Examining hypothesized interactive and curvilinear relations between psychopathic traits and externalizing problems in an offender sample using item response-based analysis

Although psychopathy is one of the most empirically examined and scientifically supported personality disorders, its essential features remain disputed. Among the main components (i.e., Antagonism/Meanness, Disinhibition, Fearless Dominance (FD)/Boldness) that have figured prominently in modern conceptualizations, FD/Boldness, which is characterized by emotional resilience, fearlessness, and social potency, is considered central and indispensable to psychopathy in some historical (e.g., Cleckley, 1941; Lykken, 1995) and contemporary (e.g., Lilienfeld et al., 2012, 2015; Patrick, 2009) formulations, but peripheral and perhaps even irrelevant in others (e.g., Gatner et al., 2016; Lynam & Miller, 2012; Miller & Lynam, 2012).

FD has been examined empirically in two main domains of research. In the first, scholars have debated FD's relevance by examining its degree of convergence with consensually-regarded psychopathy scales and classic conceptualizations, with the result being that FD appears to diverge from measures based on the Psychopathic Checklist-Revised (PCL-R, Hare, 2003; Miller & Lynam, 2012), while converging with others, such as the DSM-5 psychopathy specifier (Lilienfeld et al., 2015; Miller, Lamkin, Maples-Keller, Sleep, & Lynam, 2018). Similarly, FD is largely absent from some classic descriptions of psychopathy (McCord & McCord, 1964), but prominent in others (i.e., Cleckley, 1941; Crego & Widiger, 2016).

In the second domain of research, scholars have investigated the degree to which FD features are related to maladaptive behaviors of theoretical and practical importance, namely externalizing problems (EXT), given their consequences for the individual and society more broadly. Externalizing problems include a history of engagement in maladaptive use of substances; criminal and antisocial acts involving theft, destruction of property, and physical aggression towards others; and violations of rules of conduct.

The debate regarding FD's relevance to psychopathy can be divided roughly into two positions. On one side, scholars hold that determinations of FD's relevance to psychopathy is arbitrated by a number of criteria including its (a) instantiation in classical descriptions of the condition; (b) correlations with well-validated self-report measures of psychopathy; (c) masking of externalizing tendencies, as in Cleckley's (1941) classic clinical formulations; (d) relations with maladaptive outcomes; and (e) clinical utility. For these scholars, relations with externalizing problems is merely one criterion among several on which to adjudicate FD's relevance to psychopathy (Lilienfeld et al., 2012). Indeed, some scholars on this side regard EXT as a downstream consequence of psychopathy rather than a core component of psychopathy; as such, limited associations with EXT do not bear as heavily on a trait's relevance to the broader construct (e.g., Cooke & Michie, 2001; Skeem & Cooke, 2010; cf, Neumann, Hare, & Pardini, 2015). Most scholars from this side, however, do regard relations with maladaptive outcomes as having some bearing on the trait's perceived relevance to psychopathy relative to other psychopathic traits, and point to positive empirical relations between TriPM Boldness and at least some forms of antisocial behavior (e.g., violent crime, Drislane et al., 2014; verbal aggression, Fanti, Kyranides, Drislane, Colins, & Andershed, 2016). Nevertheless, meta-analytic reviews suggests these relations are at best small in magnitude (Miller & Lynam, 2012; Sleep, Weiss, Lynam, & Miller, in press).

For proponents, FD traits may be relevant also inasmuch as they "mask" more overtly maladaptive psychopathic traits such as dishonesty, callousness, guiltlessness, and poor impulse control, thereby enhancing access to social networks, facilitating deception and seduction, avoiding detection, and leaving others more vulnerable to manipulation or abuse (e.g., Cleckley, 1941; Lilienfeld, Watts, & Smith, 2015; Weiss, Lynam, & Miller, 2017). This latter “masking” hypothesis has received scant empirical attention to date. Furthermore, traits are considered relevant when they have utility for clinicians, corrections officers, and case managers. For example, even if FD bears small relations to maladaptive outcomes, its masking of overtly maladaptive psychopathic traits (Lilienfeld, Watts, & Smith, 2015) could produce the false impression of reduced risk of recidivism outcomes, and its relations with interpersonal dominance could lead to treatment failures (Rock, Sellbom, Ben-Porath, & Salekin, 2013).

On the other side of the debate, scholars hold that determinations of FD’s relevance to psychopathy should be adjudicated primarily based on its relations with maladaptive outcomes – whether through direct linear relations, curvilinear relations, interactive relations, or by masking of externalizing tendencies - and that criteria for personality disorders rarely emphasize features that are primarily or solely adaptive in nature (Lynam & Miller, 2012). According to these researchers, the severity of a psychopathic trait’s maladaptive effects should govern how centrally a psychopathic trait figures in scholars’ conceptualization and assessment of the disorder. The presence or absence of relations with externalizing problems or maladaptivity in general may not be the only criterion for judging the relevance of FD features to psychopathy, but is one of the main outcomes that has driven longstanding interest in the construct. In general, a trait is regarded as more relevant if it demonstrates relations with clinical impairment, one of two criteria (e.g., distress, impairment) that most scholars regard as defining attributes of mental illness (APA, 2013; Wakefield, 1992). Furthermore, a trait’s instantiation in classical descriptions of the condition is useful only insofar as classical descriptions point to relations between traits and outcomes of some interest – be they EXT outcomes or otherwise (i.e., traits should do *something* to warrant a continued place in a theoretical construct); otherwise, modern conceptions of psychopathy need not remain tethered to these descriptions. Scholars on this side of the debate point to meta-analyses and other studies showing small positive or null relations of FD with externalizing problems (e.g., antisocial and aggressive behavior, substance use, physical violence, aggression, and rule-breaking; Miller & Lynam, 2012; Sleep et al., in press), moderate negative relations with a number of maladaptive outcomes (e.g., reactive aggression, internalizing psychopathology; Miller & Lynam, 2012), and moderate positive relations with adaptive variables (e.g., emotional stability, positive emotionality, sociability, heroic altruism, leadership success, and emotion recognition; e.g., Crego & Widiger, 2014; Gatner et al., 2016; Miller & Lynam, 2012; Smith, Lilienfeld, Coffey, & Dabbs, 2013) including prototypicality ratings of a "healthy personality" (Bleidorn et al., in press).

In view of null to weak linear relations between FD and EXT, two hypotheses in recent years have suggested that FD features might relate to externalizing problems in more complex ways. They posit that FD may relate more strongly to externalizing problems (a) in concert with other psychopathic traits, such as Self-centered Impulsivity (SCI) (which we term the *moderation hypothesis*; Lilienfeld et al., 2012, 2015); and/or (b) at particularly high levels of FD features (which we term the *curvilinearity hypothesis*; first hypothesized by Blonigen, 2013). The moderation hypothesis is consistent with the view that psychopathy is a configural condition marked by statistical interactions among some or all of its constituent traits (Lilienfeld, 2013). For example, an individual with higher levels of both traits related to SCI (i.e., antagonism/meanness and disinhibition) and FD may be more prone to EXT than an individual with higher levels of SCI and lower levels of FD. Investigations of this hypothesis have examined myriad potential outcomes (e.g., antisocial behavior, substance use), yielding mixed and mostly negative results (e.g., Gatner et al., 2016; Maples et al., 2014; Miller, Maples-Keller,

& Lynam, 2016; Vize, Miller, Lynam, Lamkin, Miller, & Pardini, 2016). Studies that have supported the hypothesis have found relations between FD and treatment failure (Rock et al., 2013), sexually predatory attitudes (Marcus & Norris, 2014), and predatory aggression (Smith, Edens, & McDermott, 2013) at higher levels of PPI SCI.

Two published studies have examined Blonigen's (2013) curvilinearity hypothesis and neither has found support for it. The first prospectively investigated the effect of FD in early adolescence on EXT problems in adulthood, finding no curvilinear effects (Vize et al., 2016). The second investigated TriPM Boldness' curvilinear relation to antisocial behavior (Gatner et al., 2016), finding one small quadratic effect in relation to physical aggression that the authors interpreted as being too small to support the curvilinearity hypothesis. These studies, however, were not able to test lower-order components of FD and Vize and colleagues (2016) did not examine the link between FD and EXT concurrently in adulthood.

The purpose of the present study is to test the moderation and curvilinearity hypotheses in a large offender sample to determine whether FD-related traits show meaningful relations with EXT when testing these more nuanced, non-linear relations. More broadly, we examine potential trait by trait interactions and curvilinear effects, which have received insufficient attention in the psychopathology field at large. In addition to bearing important implications for the conceptualization and assessment of psychopathy, evidence of such effects would bear important implications for extant structural and etiological models of psychopathy, and perhaps classification systems of psychopathology more broadly. For example, all polythetic diagnostic criterion sets in the Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5; APA, 2013) and the International Classification of Diseases-11 (World Health Organization, 2018) imply additive relations among disorder criteria, but such additive models may be overly simplistic in view of new approaches that conceptualize psychopathological constructs as manifolds of interacting symptoms (e.g., dementia, functional disability; van Wanrooij, Borsboom, van Charante, Richard, & van Gool, 2019).

The Present Study

The goal of the present study was to test both the moderation and curvilinearity hypotheses of FD. First, to test the moderation hypothesis, we examined whether FD manifests relations with externalizing problems at high levels of SCI. Second, we examined whether FD manifests curvilinear relations with externalizing problems—specifically examining whether FD exhibits a convex pattern of curvilinear relations, characterized by a slope that increases towards the higher end of the distribution, indicating a pronounced likelihood of externalizing problems at extreme levels of FD. We conducted these tests of the moderation and curvilinearity hypotheses using traditional PPI higher-order factor scores (i.e., PPI FD, PPI SCI).[1] The present study evaluated these hypotheses using a large sample of adult criminal offenders, which is ideal for providing adequate statistical power to test the curvilinearity hypothesis given that such samples are not limited by restriction of range at the higher end of the EXT distribution.

Building on previous studies, we employed numerous indices of EXT, including self-report and diagnostic assessments of substance abuse and a range of antisocial behavior and traits, as well as records of post-assessment arrests (i.e., general and violent offenses). Furthermore, we used the ideal point Item Response Theory-based Generalized Graded Unfolding Model (GGUM; Roberts, Donoghue, & Laughlin, 2000), which is regarded as a more accurate approach for reproducing response patterns for self-report measures of personality (e.g.,

[1] For comprehensiveness and to examine narrower, unidimensional constructs (Smith, McCarthy, & Zapolski, 2009), we also tested interactive and curvilinear relations between PPI subscales and externalizing problems (presented in Appendix).

Stark, Chernyshenko, Drasgow, & Williams, 2006) and attitudes (e.g., Carter & Dalal, 2010) than traditional multiple regression approaches to curvilinearity. The ideal point approach to scoring more accurately recovers curvilinear relationships in simulated (Carter, Guan, Dalal, & LoPilato, 2015) and observed (Carter et al., 2014) data than the traditional IRT dominance approach. In this large data set, it provides a well-powered test of the hypothesis that FD bears stronger, positive relations with externalizing problems at particularly high levels of FD and SCI.

The present study operationalizes FD and SCI using the PPI and its revision, the Psychopathy Personality Inventory-Revised (PPI-R; Lilienfeld & Widows, 2005), which represent one of the most widely used self-report measures of psychopathy. The PPI/PPI-R comprises eight subscales, seven of which (excluding the Coldheartedness subscale) can be combined into two largely orthogonal higher-order factors (e.g., Benning et al. [2003], but see Ruchensky et al.'s [2017] meta-analysis for an alternative factor structure). The first factor (PPI FD) consists of Fearlessness, Stress Immunity, and Social Influence, which reflect social and physical boldness alongside emotional stability. The second factor (PPI SCI) consists of Carefree Nonplanfulness, Rebellious Nonconformity, Machiavellian Egocentricity, and Blame Externalization, and reflects an impulsive willingness to take advantage of others. The PPI Coldheartedness subscale does not load highly on the two higher-order factors and is treated as a standalone dimension reflecting guiltlessness, callousness, and lack of sentimentality. More recently developed measures such as the Triarchic Psychopathy Measure (TriPM; Patrick, 2010) and Elemental Psychopathy Assessment (EPA; Lynam et al., 2011) also include FD-like constructs as components of psychopathy (i.e., boldness, emotional stability). Given their considerable overlap (rs ≈ .80-.90; Sleep et al., in press), we use the terms FD and boldness interchangeably.

Method

Participants

Participants included (a) prisoners and (b) individuals sentenced to court-ordered substance use treatment programs in Florida, Nevada, Oregon, Texas, Washington, and Utah (see Poythress et al., 2010, for additional detail). Four of the five treatment programs were community-based and one (Texas) was located within a prison. Participants were excluded if they were currently receiving psychotropic medications for active symptoms of psychosis or resided in a mental health unit in prison. Incarcerated participants were deemed eligible if they spoke English fluently and had an estimated IQ > 70 on the Quick Test, a brief screening measure of intellectual functioning (Ammons & Ammons, 1962). Individuals from substance use treatment programs were required to have completed all detoxification procedures prior to recruitment. At each site, participants were randomly recruited from lists of individuals who met the inclusion criteria. After obtaining informed consent, screening measures for IQ and reading ability were administered, followed by the research protocol for eligible participants. A subset of subjects (n = 1,087) were selected on the basis of being near the end of their incarceration to follow arrest activity in the community after release.

A total of 1,741 participants were enrolled in the study: 1413 men (81.2%), 299 women (17.2%), and 29 individuals (1.7%) with missing gender data. The self-reported ethnic and racial composition of the sample was as follows: 1079 Caucasians (62.0%), 595 African Americans (34.2%), and 67 participants (3.8%) with missing race data. In terms of recruitment site, 911 participants were drawn from prisons (52.3%) and 830 from substance use treatment programs (47.7%). The present analyses were based on 1701 eligible participants with available data on either psychopathy or the relevant criterion measures. The mean age across these participants at time of assessment was 31.04 years (SD = 6.60, range = 17.96–59.37).

Measures

Independent Variables: Psychopathy Measures.

PPI. The Psychopathic Personality Inventory (PPI; Lilienfeld & Andrews, 1996) consists of 187 items answered on a 4-point Likert-type scale (1 = False, 4 = True). The inventory yields a total score and scores on eight subscales (alphas for the subscales in this sample ranged from .79 to .91). Seven of the eight PPI subscales often coalesce into the two largely orthogonal higher-order factors of FD and SCI (Benning et al., 2003; Lilienfeld & Widows, 2005; c.f., Neumann et al., 2008; Ruchensky et al., 2017). PPI data were available for 1605 participants.

Model fit for traditional PPI two-factor model. We examined the model fit of the traditional two-factor model (Lilienfeld & Widows, 2001), in which PPI FD and PPI SCI form higher-order factors. Exploratory Factor Analyses (EFA) were conducted in lieu of Confirmatory Factor Analyses (CFA) in line with research suggesting that CFA can indicate poor fit for valid, albeit complex, personality measures that demonstrate good criterion-related validity (Hopwood & Donnellan, 2010). Parallel Analysis (PA; Horn, 1965) was conducted on GGUM-generated latent trait estimates of the seven PPI subscales that traditionally comprise PPI FD and SCI, and indicated that up to two factors could be extracted. A two-factor exploratory factor analysis (using oblimin rotation) was conducted and resulted in a solution in which two factors approximating PPI FD and PPI SCI emerged. PPI subscales exhibited factor loadings equal to or above .30 on factors corresponding to the traditional two-factor model. Deviations from the traditional model included PPI Carefree Nonplanfulness loading equally on the FD (λ = -.37) and SCI factors (λ = .34); and Fearlessness loading equally on FD (λ = .30) and SCI factors (λ = .31). A higher than typical (negative) relation between PPI FD and PPI SCI factors was observed (r =

-.29). Based on these results, a consolidated FD variable was computed by averaging z-scores of GGUM-generated thetas for PPI Fearlessness, PPI Stress Immunity, and PPI Social Potency; and a consolidated SCI variable was computed by averaging z-scores of GGUM-generated thetas for PPI Machiavellian Egocentricity, PPI Carefree Nonplanfulness, PPI Rebellious Nonconformity, and PPI Blame Externalization, according to the traditional two-factor model.

Dependent Variables: Measures of EXT.

PAI. The Personality Assessment Inventory (PAI; Morey, 1991) is a 344-item self-report inventory of personality and psychopathology. The indices of primary interest in this study were clinical scales reflecting externalizing psychopathology, including Aggression (AGG), Alcohol Problems (ALC), Drug Problems (DRG), and the Antisocial Behaviors subscale (ABS; αs ranged from .80 to .94). PAI data were available for approximately 1570 participants.

PDQ-4 Antisocial Personality Disorder. The Personality Diagnostic Questionnaire-4 Antisocial Personality Disorder (APD) scale (Hyler, 1994) is a self-report measure consisting of 22 true-false items, one for each APD childhood and adult criterion in DSM-IV (and now DSM-5). The 15-item APD childhood scale (α = .83) and the 7-item adult scale (α = .58) were used as separate outcomes. PDQ-4 APD adult criteria data were available for 1557 participants, whereas childhood criteria data were available for 1472 participants.

Interview measures of externalizing. Symptom counts of conduct disorder (CD) and adult antisocial behavior (AAB) were obtained using the APD module of the Structured Clinical Interview for DSM–IV Axis-II Personality Disorders (SCID-II; First, Gibbon, Spitzer, Williams, & Benjamin, 1996). This module, based on criteria from the Diagnostic and Statistical Manual of Mental Disorders (4th and 5th editions), yields dimensional scores for both CD and APD. In this study, the interrater reliability was high for total symptom count (ICC = .86; *n* = 46), along with similarly high internal consistency (α = .83). AAB data were available for 1,494 participants, and retrospective CD data were available for 1,212 participants.

Model fit for externalizing factors. To arrive at a parsimonious model that consolidated multiple externalizing-related variables, model fit for the six continuous criterion variables was evaluated. PA suggested the appropriateness of extracting two factors. A two-factor EFA with oblimin rotation revealed clearly demarcated factors: an Antisocial Behavior factor emerged in which PAI AGG, PAI ABS, PDQ-4 APD adult criteria, SCID-II AAB, PDQ-4 APD childhood scale, and SCID-II CD largely exhibited their highest loadings and loaded above .30; and a Substance Use factor emerged in which PAI ALC and PAI DRG loaded at above .40. It bears noting that PDQ APD adult criteria deviated from this structure in exhibiting roughly equal loadings on both the Substance Use factor (λ = .38) and Antisocial Behavior factor (λ = .32). The two-factor model is consistent with research showing that variance in substance use problems and aggressive behaviors can be accounted for by distinct latent factors in addition to a shared general latent factor (e.g., Krueger, Markon, Patrick, Benning, & Kramer, 2007). Antisocial Behavior and Substance Use factors were associated (r = .29). Based on these results, a consolidated Antisocial Behavior criterion variable was computed by averaging z-scores of GGUM-generated thetas for PAI AGG, PAI ABS, PDQ-4 APD adult criteria, SCID-II AAB, PDQ-4 APD childhood scale, and SCID-II CD; and a Substance Use criterion variable was computed by averaging z-scores of GGUM-generated thetas for PAI ALC and PAI DRG.

Criminal recidivism. We used arrest records of participants who were released into the community following protocol completion. Identifying information was used for all participants from drug treatment programs and for near-release prison inmates recruited into the study within 6 months of their sentence completion to search arrest records, both state and federal, archived by the Federal Bureau of Investigation. Two count variables were computed: (a) the number of times arrested for *any kind of offense (general offense arrest count)*; and (b) the number of times arrested for a *violent offense (violent offense arrest count).* Counts were assessed within the full follow-up period (range = 4 – 1590 days; median/mean = 838/800 days) following enrollment (drug treatment program participants) or following release from prison into the community (near-release prisoners). General offenses is a broad category that included seven arrest types (i.e., violent, potentially violent, other person, sexual, property, drug, minor) across 12 potential time points (i.e., times at which arrest history was recorded). Violent offenses included any assaultive act against another person (e.g., murder, manslaughter, assault, robbery, and rape or other sexual assault) across 12 time points. Data were available for 1,087 participants.

Data Analytic Plan

Analytic approach to evaluating the presence of moderation and curvilinearity. To evaluate moderation-based and curvilinear relations between psychopathic traits and externalizing-based outcomes, we conducted a series of hierarchical regression analyses. In all analyses, the linear effect was modeled in Step 1. In Step 2, the interaction term or quadratic term was added to test for moderation or curvilinearity. The presence of moderation or curvilinearity was evaluated using both statistical significance and meaningful improvements in model fit between steps 1 and 2. Specifically, the incremental contribution of the moderation-based (i.e., interaction term) or curvilinear effect for each model was evaluated using AIC (Bozdogan, 1987), R^2, Pseudo R^2 (McFadden, 1974), and the f^2 statistic (Aiken & West, 1991; Kenny, 2015). AIC was the primary fit index used when evaluating curvilinearity. McFadden's (1974) pseudo-R^2 calculation was planned for all Poisson or negative binomial models, which do not have a statistical equivalent to Ordinary Least Squares (OLS) R^2. However, although

McFadden's pseudo-R^2's intended use is similar to the OLS R^2 metric, its values tend to be much smaller and cannot be interpreted as variance accounted for by the model. For reference, McFadden pseudo-R^2 values ranging from .2 - .4 indicate excellent model fit, which are comparable to OLS R^2 values of .7-.9 (Domenich & McFadden, 1975). To interpret the size of quadratic and interaction terms (i.e., small, medium, large), we used the f^2 statistic, which equals the unique variance explained by the interaction term divided by the sum of the error and interaction variances (Aiken & West, 1991; Kenny, 2015).

Analytic approach for analyzing criminal recidivism count data. Because count data often do not meet the normality assumption of OLS regression, we applied alternative models designed to handle count data (i.e., Poisson regression, negative binomial regression; see Coxe, West, & Aiken, 2009). Negative binomial regression is unique from Poisson in accounting for any overdispersion that may be present (i.e., when variance exceeds the mean) by estimating a dispersion parameter (α) and applying more conservative tests of significance (Atkins, Baldwin, Zheng, Gallop, & Neighbors, 2013). Negative binomial regression was most appropriate for all analyses, based on evaluations of AIC, which includes a correction for increased complexity.

For Poisson and negative binomial models, all reported coefficients are reported in log units, which must be exponentiated (i.e., e^x) to convert them to count units. Once exponentiated, interpretation changes from additive to multiplicative (see Coxe, West, & Aiken, 2009). In addition, the time period during which participants' rearrests were recorded (i.e., follow up period) varied widely across participants. To control for the effect of the length of this follow-up period on rearrests, the follow-up period was included as a covariate.

IRT scoring methods. Research shows that implementing appropriate scoring rules for self-report agree/disagree measures is advantageous to uncovering curvilinear relationships when they exist and avoiding Type I errors when they do not (Carter et al., 2014, 2015, 2017). Accordingly, we compared the fit of a traditional *dominance* IRT model (i.e., the generalized partial credit model; GPCM) to the fit of an *ideal point* IRT model (i.e., the generalized graded unfolding model; GGUM, Roberts, Donoghue, & Laughlin, 2000) to produce latent trait estimates to be used in our primary analyses as indicators of the broader constructs described.

In contrast to models that hold dominance assumptions (e.g., GPCM), ideal point model assumptions recognize that items differ from one another in their level of extremity (e.g., "I sometimes like to go to parties" compared with "I always like to go to parties"), and that an individual fully endorses items (i.e., strongly agree) whose extremity coincides most closely with his/her own location on the latent trait scale. Furthermore, ideal point models such as GGUM rest on the understanding that individuals may be less likely to fully endorse an item (i.e., "strongly agree") because the item's extremity is above their latent trait level (i.e., as in the case of GPCM) *or* because the item is not extreme enough (e.g., a person who is extremely high on extraversion may disagree with the item, "I sometimes like to go to parties" because he/she *always* likes to). Dominance approaches do not take this tendency into consideration, meaning that they run the risk of underestimating some individuals' location on the latent trait scale. As a result, dominance models can cause disordering at the high ends of the trait distribution (Roberts, Laughlin, & Wedell, 1999), and thus distort tests of curvilinearity (Carter et al., 2017). Thus, we used the GGUM as our representation of the ideal point model. Item and person parameters were estimated using the GGUM2004 program (Roberts, Fang, Cui, & Wang, 2006), which uses MML estimation to determine item parameters and EAP estimation to determine persons' scores.

Preliminary psychometric analyses of scoring methods. The two scoring approaches used here (GPCM, GGUM) yield different indicators of score quality. In the following section, we present evidence of the quality of the measures used in this study using methods that are commonly applied to each respective scoring approach.[2] Model-data fit was generally acceptable, and most items met the $\chi^2/df < 3$ criteria. We also calculated the Akaike Information Criterion (AIC; see Bozdogan, 1987), which represents the difference in the model likelihoods but penalizes less parsimonious models (the GGUM is more complex). The AIC indicated that GGUM was the superior model. In only 2 of 18 measurement models did GPCM show better fit than GGUM according to AIC, and in most of these cases differences between GGUM and GPCM were not large in terms of AIC, and χ^2/df ratios were almost identical.

GGUM scale construction. Constraints related to GGUM scale construction required two adjustments. First, we modified two constructs to negotiate scoring issues. Two items from the PDQ-4 7-item APD adult scale were removed (i.e., PDQ-4 items 46 and 75) due to (a) a GGUM2004 singularity-related error and (b) an error in scale administration (item 75 was not administered). One item out of 19 from the PPI Fearlessness subscale was removed (i.e., item 34) due to extremely high χ^2/df ratios when included in the model. Second, because GGUM can only be used for unidimensional models, we were unable to generate ideal point estimates of multidimensional factor-level scores (i.e., PPI SCI and PPI FD). To assess curvilinearity and moderation at this level, averages of GGUM-generated latent trait estimates of PPI subscales were used (i.e., the three PPI subscales traditionally related to FD; the four PPI subscales traditionally related to SCI). Averaging GGUM-generated estimates reintroduces some degree of imprecision to scores at the extremes of the trait distributions. Analyses at the PPI subscale level,

[2] The quality of IRT-based scoring approaches is assessed by inspection of model-data fit statistics. To assess absolute and relative fit of IRT models, adjusted χ^2/df ratio was used (Chernyshenko et al., 2001; Drasgow et al., 1995) using the MODFIT v2.0 program (Stark, 2007). The χ^2/df ratio assesses the extent to which the IRT models' predictions about item endorsement rates are close to the actual observed endorsement rates. The statistic is "adjusted" to approximate the model data fit that would be found if $N = 3,000$ to avoid Type II errors. Adjusted χ^2/df ratios less than 3 are considered to have acceptable fit (Cherynyshenko et al., 2001).

which provide more precise estimates of scores at the extremes, are provided in the Appendix.

Power analysis. Monte Carlo simulations were conducted to evaluate a priori power (see Appendix [Tables S1 - S5] for details). In curvilinearity simulations, we specified linear and quadratic terms that would reflect Blonigen's (2013) hypothesis involving an increase in relation with EXT at higher ends of the psychopathic trait spectrum. In curvilinearity simulations, we specified low and high linear and quadratic effect sizes to estimate power at different effect size levels. To determine power for interaction and curvilinearity simulations, simulations were run in which either the interaction term or the quadratic term was set to zero. A significance cutoff was identified using the 95th percentile of all interaction or quadratic coefficients. One thousand new datasets for each model were simulated with the addition of a non-zero positive interaction term value or a quadratic term value of .064 (see Appendix). Power was determined by calculating the proportion of interaction term or quadratic term coefficients that fell above the 95% cutoff.

Handling missing data. To maximize statistical power and avoid deleting viable data, analyses were conducted using a pair-wise deletion approach. If a participant had data available for a given analysis, those data were used even if the participant lacked data for other analyses. Sample size varied across analyses from 1,026 to 1,526.

Results

In the following section, we report the results of correlational and hierarchical regression analyses. We adopted a significance threshold of $p < .01$ to balance the risk for Type I and Type II errors (36 analyses in total). Plots of all significant quadratic effects that improved model fit are presented in the Appendix (Figures 4 - 8). A negative quadratic term coefficient indicates *decreasing* strength of relations at higher levels of the predictors (counter to the tested hypothesis), whereas a positive quadratic term coefficient indicates *increasing* strength of relations at higher levels of the predictors in a manner consistent with this hypothesized effect. For analyses with continuous outcomes, coefficients can be interpreted as standardized given that latent trait theta scores for predictors and outcomes were standardized. In addition, the Appendix contains (a) correlations between manifest and GGUM-generated PPI factors and subscales (Table S7); (b) correlations between manifest and GGUM-generated externalizing criterion variables (Table S8); (c) confirmatory factor analyses of PPI higher-order factors (Table S9); (d) hierarchical regression analyses examining GGUM-generated PPI subscales and EXT composites (Tables S10 - S12); and (e) hierarchical regression analyses examining typically-scored PPI factors and EXT composites (Table S13).

Correlations between PPI Factors and EXT

Correlations were examined between PPI factors and all EXT outcomes including composites, general and violent offense arrests, and individual criterion variables (e.g., PAI Aggression). Results indicated generally null to negative linear relations between PPI FD and EXT variables. PPI FD evinced null relations with eight of twelve outcomes. Among statistically significant relations, PPI FD exhibited weak negative relations with Antisocial Behavior (r = -.08, p < .01), Substance Use (r = -.19, p < .01), and PDQ-4 Antisocial Personality Disorder (r = -.12, p < .01); and one weak positive relation with SCID-II Conduct Disorder (r = .13, p < .01). PPI SCI evinced mostly statistically significant positive relations with EXT outcomes, with correlations ranging from -.01 (violent offense arrest count, p = ns) to .64 (Antisocial Behavior, p < .01). Results are provided in Table 1.

Evaluating whether PPI FD moderates the relation between PPI SCI and EXT

To examine the association between PPI FD and EXT problems at elevated levels of PPI SCI, four analyses were conducted in which PPI FD could interact statistically with PPI SCI (i.e., in the prediction of Antisocial Behavior, Substance Use, general and violent offense arrests). There were no significant interactions, with interaction coefficients ranging from -.09 (Substance Use) to .014 (General offense arrest count). Results are provided in Table 2.

Evaluating Curvilinear Relations between PPI Higher-order Factor Scores and EXT Problems

To examine curvilinear relations between PPI higher-order factor scores and EXT problems, two analyses were conducted for each EXT problem – one for PPI FD and one for PPI SCI. Results are provided in Table 3.

PPI Fearless Dominance. In Step 1, PPI FD showed significant linear effects when predicting Antisocial Behavior (B = -.08) and Substance Use (B = -.23) but not for general or violent offense arrests. In Step 2, PPI FD evinced no significant quadratic effects, indicating that FD did not exhibit an increasing or decreasing slope at higher trait levels of any EXT variable. Quadratic coefficients ranged in size from -.13 (Violent offense arrest count) to .00 (Substance Use).

PPI Self-centered Impulsivity. In Step 1, PPI SCI manifested significant linear effects when predicting Antisocial Behavior (B = .55) and Substance Use (B = .40), but not general or violent offense arrests. In Step 2, PPI SCI yielded a small positive statistically significant quadratic effect when predicting Antisocial Behavior (B = .06).[3] AIC indicated that adding the quadratic term improved model fit. The curvature pattern of this relation was a 90 degree parabolic shape (see Appendix, Figure 4) indicating positive relation at all levels of SCI, but exponentially stronger (amplified) relations to antisocial behavior at higher levels.

[3] Interpretations of quadratic/interactive effect sizes vary by subject area, but Kenny (2015) suggested ascribing small, medium, and large to f^2 effect sizes of .005, .01, and .025, respectively, in view of evidence that the average effect size associated with including interaction terms is .009 (Aguinis, Beaty, Boik, & Pierce, 2005).

Discussion

According to some conceptualizations, traits related to Fearless Dominance/Boldness (FD) are important components of psychopathy (e.g., Cleckley, 1941; Lilienfeld et al., 2012; 2015). At the same time, meta-analytic examinations of FD's relations with externalizing problems, viewed as central to psychopathy by many scholars (Hare & Neumann, 2010; Lykken, 1995; Miller & Lynam, 2015), have revealed null, weak, or even negative relations in most cases (Miller & Lynam, 2012; Sleep et al., in press). These findings raise questions for some (but not all; Lilienfeld et al., 2012; see also Skeem & Cooke, 2010) scholars regarding the relevance of FD to the broad psychopathy construct (e.g., Lynam & Miller, 2012). In view of the observed relations between FD and EXT, researchers have offered two alternative scenarios under which relations between FD and externalizing problems might be found, namely the moderation and curvilinearity hypotheses.

Our analysis yielded two key findings. First, our results did not provide support for the moderation hypothesis. Specifically, none of the analyses indicated increased and positive associations between FD and EXT at higher levels of SCI. These results were consistent with subsidiary PPI *subscale* analyses not reported in the main text, in which FD subscales did not show stronger relations with EXT at higher levels of SCI subscales (see Appendix). A priori power analysis simulations were conducted to evaluate our capacity to detect interactive effects (see Appendix for details). Results indicated generally sufficient power (i.e., .96) to detect fairly small interactive effects approaching B = .10.

Second, our results similarly did not support the curvilinearity hypothesis. Specifically, FD did not show significant curvilinear relations with EXT outcomes at higher levels. Examining FD at the subscale level in subsidiary analyses also did not provide support for Blonigen's

(2013) hypothesis; in fact, Fearlessness showed a concave relation with continuous externalizing outcomes (i.e., decelerating relations between Fearlessness and EXT at higher levels of Fearlessness; see Appendix). Although not bearing on the validity of Blonigen's (2013) hypothesis, it is notable that SCI showed positive curvilinear relations with EXT outcomes, indicating an increased association between SCI and EXT at higher trait levels. The curvature pattern of these relations was a 90 degree parabolic shape, indicating a positive relation at all levels of SCI, but amplified relations to antisocial behavior at higher levels (see Appendix, Figures 4 - 6). In other words, traits assessed by SCI (i.e., antagonism and disinhibition) —particularly at high levels—are strongly associated with externalizing problems, including antisocial behavior and substance abuse. Power analysis simulations were also conducted to evaluate our capacity to detect a curvilinear effect that approximated Blonigen's (2013) hypothesized curvature (see Appendix for details). This effect was specified in efforts to be small enough that any lower positive coefficient would be fairly linear, and thus not meaningfully supportive of Blonigen's hypothesis. Using Monte Carlo simulations, we observed power exceeding .95 for detecting this curvature in models involving ordinary least squares regression, which accounted for two of four outcomes. Notably, however, significantly lower power was found for negative binomial (power = .65) models, which accounted for criminal recidivism-related outcomes.

In sum, using a large sample of offenders and a well-powered examination of psychopathic traits' relations with EXT, we found little support for either the moderation or curvilinearity hypotheses for FD. Although inconsistent with previous hypotheses (Blonigen, 2013; Lilienfeld et al., 2012, 2015), these findings are consistent with those of several studies (e.g., Gatner et al., 2016). The present study represents the most rigorous test of extant explanations for FD's null, weak, or negative relations with externalizing problems (Miller & Lynam, 2012) and marks a meaningful methodological improvement over previous studies, which either used sample types with less optimal external validity (e.g., undergraduates with lower externalizing, forensic with schizophrenia-spectrum disorders [i.e., Smith, Edens, & McDermott, 2013]), examined maladaptive outcomes peripheral to EXT (e.g., treatment failure; Rock et al., 2013), or did not examine FD and EXT concurrently in adulthood (Vize et al., 2016). Indeed, our sample consisted of approximately 1,500 offenders who exhibit relatively high levels of psychopathic traits and EXT, conditions that are potentially critical for observing curvilinear and interactive effects. Furthermore, previous studies have not leveraged IRT-based GGUM, which is the most precise statistical technique for estimating extreme ends of a latent trait, and may be indispensable for detecting curvilinearity and statistical interaction among latent traits (Carter et al., 2014, 2015, 2017). Taken together, the methodological strengths of the present study – sample size, coverage of EXT, and the use of a sample with sufficiently high mean levels of psychopathic traits – render the likelihood of alternative explanations for our findings (e.g., sampling bias, restriction of range, small sample size, measurement error) less compelling.

Limitations and Conclusions

Despite its strengths, some limitations must be acknowledged. First, although records of criminal recidivism are particularly valuable indices of EXT, they are imperfect. For example, they capture only antisocial behavior that is detected by law enforcement officers. Second, we operationalized recidivism in a manner that failed to fully account for participants' varying time at risk for such behavior, given different lengths of observation in the community. We mitigated the effect of length of follow-up by including it as a covariate in our analyses, but this statistical operation may not fully address its confounding influence. Thus, results related to indices of future criminal behavior should be interpreted cautiously. Third, our findings are limited to externalizing problems—emphasizing criminal behavior, substance abuse, and antisocial traits. We did not examine specific antisocial behavior that might be tied to short-term interpersonal success, such as deception, manipulation, fraud, romantic seduction, and mate-poaching. Such behaviors might be especially relevant to FD/Boldness given that they are ostensibly tied to superficially adaptive social functioning (Lilienfeld et al., in press).

Additional investigations of the clinical utility of FD features, which remain scarce, are strongly encouraged. Testable hypotheses include the positive statistical effects of FD features on proactive aggression (e.g., Cima & Raine, 2009), treatment failure (Rock et al., 2013), sexually predatory behavior (Marcus & Norris, 2014), as well as the role of FD features in "masking" more overtly maladaptive psychopathic traits, which may assist in enabling entry into social networks and avoiding detection (Lilienfeld, Watts, & Smith, 2015). The "mask" hypothesis is rooted in classic clinical descriptions of psychopathy (e.g., Cleckley, 1941) and contemporary theories of successful psychopathy (Lilienfeld et al., 2015), but has yet to be examined systematically or comprehensively. More robust findings for these relations using rigorous methodologies might demonstrate the utility and relevance of FD features, whereas well-powered replication failures would have important contrary implications.

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Tables

Table 1

Correlations of GGUM-generated PPI Factors and EXT Criterion Variables

	PPI FD	PPI SCI
Antisocial Behavior	-.082*	.640*
Substance Use	-.190*	.358*
General Offense	.013	.043
Violent Offense	.029	-.005
PAI AGG	-.058	.522*
PAI ABS	.000	.520*
PDQ-4 APD Adult	-.121*	.518*
SCID-II AAB	-.020	.373*
PDQ-4 APD Child	.020	.409*
SCID-II CD	.132*	.265*
PAI ALC	-.162	.226*
PAI DRG	-.154	.371*

Notes. General Offense = General Offense Arrest Count; Violent Offense = Violent Offense Arrest Count; PAI AGG = PAI Aggression Scale; PAI ABS = PAI Antisocial Behavior Subscale; PDQ-4 APD Adult = PDQ-4 Antisocial Personality Disorder Adult Criteria; SCID-II AAB = SCID-II Adult Antisocial Behavior; PDQ-4 APD Child = PDQ-4 Antisocial Personality Disorder Childhood Scale; SCID-II CD = SCID-II Conduct Disorder; PAI ALC = PAI Alcohol Problems; PAI DRG = PAI Drug Problems; n of analyses ranged from 1027 – 1526; *p < .01.

Table 2

Results of Interactive Regression Analyses for GGUM-generated PPI Factors and Externalizing

		Linear Model			Interactive Model			
Externalizing Outcome	Parameter	B	AIC	R^2	B	AIC	R^2	ΔR^2
Antisocial Behavior	Intercept	-.024	2162	.413	-.024	2164	.413	.000
	FD	.053*			.053*			
	SCI	.560*			.560*			
	FD x SCI				.005			
Substance Use	Intercept	.001	3557	.141	-.009	3553	.145	.004
	FD	-.143*			-.158*			
	SCI	.370*			.376*			
	FD x SCI				-.089			
General Offense Arrest Count	Intercept	-.007	3688	.029	-.006	3690	.029	.000
	Follow up	.001*			.001*			
	FD	.058			.059			
	SCI	.057			.057			
	FD x SCI				.014			
Violent Offense Arrest Count	Intercept	-3.062*	603	.015	-3.068*	606	.015	.000
	Follow up	.001			.001			
	FD	.177			.171			
	SCI	-.015			-.010			
	FD x SCI				-.073			

Notes. *n* for ASB analyses = 1519; *n* for Substance Use analyses = 1526; *n* for General Offense and Violent Arrest Count analyses = 1027; Values in the R^2 column for General Offense Arrest Count and Violent Offense Arrest Count represent Pseudo R^2; *$p < .01$.

Table 3

Results of Regression Analyses for GGUM-generated PPI Factors and Externalizing

		PPI Fearless Dominance							PPI Self-centered Impulsivity						
		Step 1			Step 2				Step 1			Step 2			
Externalizing Outcome	Parameter	B	AIC	R^2	B	AIC	R^2	ΔR^2	B	AIC	R^2	B	AIC	R^2	ΔR^2
Antisocial	Intercept	-.024	2958	.007	.004	2954	.011	.004	-.024	2168	.410	-.055*	2158	.414	.005
	Linear	-.076*			-.063*				.550*			.562*			
	Quadratic				-.059							.055*			
Substance Use	Intercept	-.001	3732	.036	-.002	3734	.036	.000	.000	3579	.128	-.012	3580	.128	.000
	Linear	-.229*			-.230*				.399*			.404*			
	Quadratic				.003							.022			
General Offense Arrest Count	Intercept	-.012	3687	.028	.013	3688	.029	.001	-.005	3687	.028	-.013	3688	.028	.000
	Follow up	.001*			.001*				.001*			.001*			
	Linear	.045			.055				.047			.051			
	Quadratic				-.063							.022			
Violent Offense Arrest Count	Intercept	-3.06*	602	.015	-3.009*	603	.016	.001	-3.067*	603	.012	-3.083*	605	.012	.000
	Follow up	.001			.001				.001			.001			
	Linear	.181			.215				-.052			-.043			
	Quadratic				-.131							.037			

Note. Antisocial = Antisocial Behavior; *n* for ASB analyses = 1519; *n* for Substance Use analyses = 1526; *n* for General Offense and Violent Arrest Count analyses = 1027; Values in the R^2 column for General Offense Arrest Count and Violent Offense Arrest Count represent Pseudo R^2; *$p < .01$.

Appendix

Power Analysis

Monte Carlo simulations were conducted to evaluate power for the present analyses (Table 1-5). Hypothetical personality trait levels were simulated for two subsamples from a normal distribution (N = 1027, M = 0, SD = 1 [for models involving arrest offenses]; and N = 1491, M = 0, SD = 1 [for models involving self-reported externalizing problems (EXT)]). The simulated predictor scores were then used to generate simulated outcomes of known distributions (i.e., negative binomial, normal) with known relations to the predictor variable.

Curvilinearity Simulations. To determine the generating parameters for our power models, we specified linear and quadratic terms that would reflect Blonigen's (2013) hypothesis involving an increase in relation with EXT at higher ends of the psychopathic trait spectrum. Values were utilized on the basis of constituting reasonably small effects that are large enough for detection. Accordingly, we utilized b_1 = .16, as this corresponds to a ~1-point increase in EXT in moving from the -3rd to +3rd standard deviation of a continuous, normally distributed predictor (i.e., 6*.16). For the quadratic term, we utilized the value of b_2 = .064, as this value (in combination with the above linear term) results in a model that predicts an additional increase of roughly .75 in EXT when moving from the -3rd to +3rd standard deviation of the predictor. All simulated b_2 coefficients are positive as these power analyses were conducted with a directional hypothesis in mind. The quadratic model evaluated is shown in Figure 1.

We next derived the generating parameters for the negative binomial model. The negative binomial model is the same as the Poisson, with the addition of an overdispersion parameter, □, to account for zero-inflation (i.e., where values of zero are disproportionately represented in the outcome distribution). Mathematically, the Poisson model (assuming an intercept of 0) can be stated as:

$$E(Y|X) = e^{\mathbf{b}(\mathbf{X})} , \qquad \text{(A1)}$$

where **b** represents a matrix of regression weights and **X** represents a matrix of predictors corresponding to the elements of the **b** matrix. The negative binomial model is the same, but includes the additional overdispersion parameter, □, to account for zero-inflation:

$$E(Y|X) = e^{\mathbf{b}(\mathbf{X})+\kappa}\ , \qquad \text{(A2)}$$

As such, we entered □ as a generating parameter into our power function for negative binomial models. To determine the value of □ in our power analyses involving the quadratic model, we selected the largest value from the results of all curvilinear negative binomial models (i.e., models spanning both outcomes predicted using negative binomial regression [i.e., general arrests/offenses, violent arrests/offenses]). For example, for general arrests/offenses the mean was 1.83, and its largest overdispersion parameter (□□□in our analyses was 1.026.

Two separate distributions were utilized in our simulations, which corresponded to distributions of our measured outcomes. A standard normal distribution was utilized for modeling error in Y for normally distributed outcomes (e.g., Antisocial Behavior), and a negative binomial distribution was utilized for modeling error in Y for count outcomes (e.g., general offense arrests).

One thousand datasets were simulated for each model. Type 1 error was evaluated when simulated outcomes were regressed on the simulated personality trait predictors in models that included no curvilinear effect. Using a α cutoff of .05, roughly 6-7% of the time, a statistically significant curvilinear effect (b_2) was found when no curvilinearity was present (see Table 1), indicating that the nominal 6-7% Type 1 error rate could be expected in the current study.

To determine power, Monte Carlo simulations were run in which b_2 was set to zero. A significance cutoff (or nominal Type 1 error rate) was identified using the 95th percentile of all interaction (b_2) coefficients. This cutoff represents the value above which only five percent of b_2 coefficients would fall given a null curvilinear effect. One thousand new datasets for each model were simulated with the addition of a b_2 value of .064. Power was determined by calculating the proportion of b_2 coefficients that fell above the 95% cutoff identified in the Type 1 error simulations (i.e., the proportion of simulations in which the interaction coefficient exceeded the significance cutoff).

A total of two power analyses were conducted to evaluate curvilinearity, which corresponded to a negative binomial model and an OLS model. The negative binomial model was simulated using the largest dispersion parameter identified within the relevant sample. As indicated in Table 1, the estimated power of negative binomial models was .65, and the estimated power of OLS models was .98. These simulations indicated that our analyses involving normally distributed outcomes are sufficiently powered to detect relatively modest curvature in most instances, while analyses involving non-normally distributed outcomes (e.g., arrests/offenses) exhibit lower than optimal power.

Interaction Simulations. When simulating hypothetical personality trait levels for the interaction simulations, it was necessary to account for covariance between predictor variables (e.g., FD x SCI). Two sources were utilized to identify covariance parameters for the PPI. A recent study with a large sample was utilized to identify covariance parameters for combinations of PPI subscales (Crowe et al., under review), and a meta-analysis was utilized to identify the covariance parameter for FD x SCI (Miller & Lynam, 2012) (see Table 6 for covariances).

Generating linear term (i.e., b_1, b_2) parameters for the power analyses is typically conducted by selecting known linear relations with measured outcomes. However, because linear relations were not readily available in the literature for most outcomes (e.g., general arrests/offenses), we tested a series of models containing permutations of high and low estimates for linear relations with our measured outcomes (i.e., b_1 = low, b_2= low; b_1 = high, b_2 = low; b_1 = high, b_2 = high). A model involving b_1 = low, b_2 = high was not tested as, in the context of our simulations, its results are equivalent to a model involving b_1 = high, b_2 = low. These low and high estimates corresponded to 1 SD below and above the mean for all linear coefficients generated from original interactive models of the same regression type (e.g., a value corresponding to 1 SD above the mean of all original linear coefficients from interactive negative binomial models across outcomes was utilized as the high estimate). Further, each of the three power analysis models was conducted in conditions of low effect size and high effect size (for the interaction term) in order to estimate power across a range of interactive effect sizes. The low interaction term estimate was determined from the mean of all interaction term coefficients for a given regression model type (e.g., negative binomial). Taking the mean as the low estimate was appropriate given the low incidence of significant interactions in our sample (see Results). The high interaction term estimate was set as 1 SD above this mean. In total, six power analyses were tested for each combination of predictors (e.g., FD x SCI) and for each regression model type (i.e., negative binomial, OLS). Dispersion parameters for the negative binomial models were identified using a method identical to that described within the curvilinearity simulations.

Power analyses for interaction effects were conducted in a manner consistent with the curvilinearity simulations. One thousand datasets were simulated for each model. Type 1 error was evaluated when simulated outcomes were regressed on the simulated personality trait predictors in models that included no interaction effect. Using a α cutoff of .05, for OLS models, roughly 4% of the time, a statistically significant interaction effect (b_3) was found when no interaction was present (see Table 1-5), indicating that the nominal 4% type 1 error rate could be expected. However, for negative binomial models, roughly 7% of the time, a statistically significant interaction effect (b3) was found when no interaction was present (see Table 1-5), indicating that a nominal 7% type 1 error rate could be expected in models involving general and violent arrests/offenses.

To determine power, Monte Carlo simulations were run in which b_3 was set to zero. A significance cutoff was identified using the 95th percentile of all interaction (b_3) coefficients (which also corresponds to the nominal Type 1 error rate). One thousand new datasets for each model were simulated with the addition of a non-zero positive b_3 value. Power was determined by calculating the proportion of b_3 coefficients that fell above the 95% cutoff identified in the Type 1 error simulations (i.e., the proportion of simulations in which the interaction coefficient exceeded the significance cutoff).

A total of 236 power analyses were conducted to evaluate the interaction models (i.e., 118 negative binomial models and 118 OLS models). Again, each of the 118 negative binomial models were simulated using the largest dispersion parameter identified in our sample. See Tables 1-5 for power estimates. Results indicate that our analyses were fairly well-powered to detect modest interactions across negative binomial (i.e., b_3 = .10) and OLS models (i.e., b_3 = .09).

Correlations of Psychopathic Trait Variables

Intercorrelations between manifest (i.e., typically-scored) psychopathic trait variables and GGUM-generated latent-trait estimates of psychopathic trait variables can be found in Table 7.

Correlations of Continuous EXT outcomes

Intercorrelations between manifest (i.e., typically-scored) and GGUM-generated latent trait estimates of continuous criterion variables are provided in Table 8.

Accounting for atypical correlations between SCID-II Conduct Disorder and convergent antisocial subscales. An atypical pattern of correlations was observed for typically-scored SCID-II Conduct Disorder (CD) such that typically-scored SCID-II CD exhibited low correlations with a number of antisocial subscales containing convergent item content, such as the PDQ-4 Antisocial Personality Disorder Childhood Scale (i.e., $rs < .14$; see Table 8). In contrast, the GGUM-generated latent trait estimate of SCID-II CD showed higher correlations with convergent antisocial constructs (e.g., $r = .60$ with PDQ-4 Childhood Scale, $r = .35$ with PAI Aggression). Item Response Theory-related item and test characteristic curves were examined in efforts to account for these divergent patterns of correlations. Characteristic curves display points of asymmetry between GGUM-generated latent trait estimates and sum scores in line with Classical Test Theory, which holds as an at times problematic assumption that higher agreement to items translates into higher standing on the trait being examined. At least four items showed evidence of unfolding at higher GGUM-generated theta levels, meaning that extremely high standing on GGUM-generated trait estimates of the SCID-II CD construct was not associated with stronger agreement to these items. Such items contained content related to being physically cruel to others, using a weapon to cause physical harm to others, stealing while confronting a victim, and breaking into others' property. The pattern of results suggest that these items inadequately discriminate individuals with conduct disorder when scored outside of an IRT context. Figure 2 displays the test characteristic curve, which illustrates that at trait levels above two standard deviations, GGUM-generated latent trait estimates of standing on SCID-II CD are either no longer associated or negatively associated with increases in CTT sum scores of SCID-II CD. This pattern can be contrasted with the test characteristic curve for PDQ-4 Childhood Scale, which closely resembles SCID-II CD item content. Figure 3 illustrates the more consistent convariance between GGUM-generated latent trait estimates of PDQ-4 Childhood Scale and CTT sum scores. Collectively, this evidence suggests that SCID-II CD may be particularly prone to measurement error at higher levels of the SCID-II CD construct.

Confirmatory Factor Analytic Evaluation of Typically-scored Two-factor PPI FD and PPI SCI Model Fit

In view of evidence suggesting that the factor structure of PPI subscales in the incarcerated population may vary considerably from other sample types (e.g., Neumann, Malterer, & Newman, 2008; see Ruchensky et al., 2018 for meta-analysis), we examined the degree to which a two-factor PPI FD and PPI SCI fit the present data using confirmatory factor analysis.

To examine whether the two-factor PPI model was a good fit, we estimated two confirmatory factor analytic models in which each of seven PPI subscales loaded onto their respective broad PPI factors (Table 9). In the first, indicators included GGUM-generated latent trait estimates of PPI subscales. The two-factor model did not fit the data well: X^2 (1605)=705.99, p<.001, RMSEA=.182 [90% CI: .171; .194], and SRMSR of .103. CFI and TLI were low at .774 and .635, respectively. In addition, the model resulted in negative error variances, which makes the model inadmissible.

In the second confirmatory factor analytic model, indicators included typical scores of the PPI subscales (Table 8). The two-factor model did not fit the data well: X^2(1604) = 1594.09,

$p<.001$, RMSEA=.275 [90% CI: .264; .287], and SRMSR of .221. CFI and TLI were low at .544 and .263, respectively. In addition, the model resulted in negative error variances, which makes the model inadmissible.

CFA is not the only viable means of estimating model fit as CFA may excessively penalize models containing cross-factor loading as has been demonstrated with respect to the PPI (e.g., Hopwood & Donnellan, 2010). Accordingly, we used exploratory factor analyses in the main text. Nevertheless, in view of evidence that the incarcerated population may exhibit a substantially different pattern of inter-correlations among PPI subscales (Ruchensky et al., 2018), PPI subscale-level analyses were important to include.

Supplemental Hierarchical Regression Analyses

In the following section, we evaluate moderation-based and curvilinear relations between (a) PPI subscales and EXT outcomes; and (b) typically-scored PPI higher-order factors and EXT outcomes using hierarchical regression analyses. In all analyses, the linear effect was modeled in Step 1. In Step 2, the interaction term or quadratic term was added to test for moderation or curvilinearity. The presence of moderation or curvilinearity was evaluated using both statistical significance and meaningful improvements in model-data fit between steps 1 and 2. Specifically, the incremental contribution of the moderation-based or curvilinear effect for each model was evaluated using AIC (Bozdogan, 1987), R^2, Pseudo R^2 (McFadden, 1974), and the f^2 statistic (Aiken & West, 1991; Kenny, 2015). AIC was the primary fit index used when evaluating curvilinearity. McFadden's (1974) pseudo-R^2 calculation was planned for all Poisson or negative binomial models, which do not have a statistical equivalent to Ordinary Least Squares (OLS) R^2. However, although McFadden's pseudo-R^2's intended use is similar to the OLS R^2 metric, its values tend to be much smaller and cannot be interpreted as variance accounted for by the model. For reference, McFadden pseudo-R^2 values ranging from .2 - .4 indicate excellent model fit, which are comparable to OLS R^2 values of .7-.9 (Domenich & McFadden, 1975). To interpret the size of quadratic and interaction terms (i.e., small, medium, large), we used the f^2 statistic, which equals the unique variance explained by the interaction term divided by the sum of the error and interaction variances (Aiken & West, 1991; Kenny, 2015). Statistical significance was determined using alpha equal to $p < .01$; we adopted a somewhat more conservative alpha level to balance the risk for Type I and Type II errors given the large number of analyses (130 analyses in total). Unless otherwise noted, a negative quadratic term coefficient indicates *decreasing* strength of relations at higher levels of the predictors, whereas a positive quadratic term coefficient indicates *increasing* strength of relations at higher levels of the predictors in a manner consistent with this hypothesized effect (Blonigen, 2013). For analyses containing continuous outcomes, coefficients can be interpreted as standardized given that latent trait theta scores generated for predictors and outcomes were standardized.

For all count models (i.e., models containing General and Violent offense arrest outcomes), over-dispersion was evaluated by comparing the AIC fit of the Poisson model to the negative binomial model. Results indicated that negative binomial regression was appropriate for all analyses; both Poisson and negative binomial regression predict the natural log of the expected count variable. All reported coefficients were reported in log units. To convert coefficients to count units, they must be exponentiated (i.e., e^x). However, doing so changes their interpretations from additive to multiplicative (see Coxe, West, & Aiken, 2009, for review). In addition, the time period during which participants' rearrests were recorded (i.e., follow up period) varied widely across participants. To control for the effect of the length of this follow-up period on rearrests, the follow-up period was included as a covariate.

Examining PPI subscales. Although most research focuses on the two higher-order PPI factors, there is utility in focusing alternatively on subscale-level analyses for three main reasons. First, the two-factor structure of the PPI has not consistently fit the offender population, evidenced by variable subscale inter-correlations across offender samples (e.g., Neumann, Malterer, & Newman, 2008; Smith, Edens, & Vaughn, 2011). Second, the traditional PPI two-factor model showed poor model fit using CFA in the present analysis (Table 9), although exploratory structural equation modeling showed acceptable model fit (see Method in main text). Third, in view of heterogeneity among subscales, examinations of PPI higher-order factors may dilute or obscure subscale-level relations between FD features and EXT. Indeed, the psychometric limitations of working with heterogeneous domains rather than narrower, unidimensional constructs are well established (Smith, McCarthy, & Zapolski, 2009).

Evaluating whether PPI FD subscales moderate the relation between PPI SCI subscales and EXT. Eighteen analyses were conducted for each of our four EXT outcomes (72 analyses in total) in which all possible pairs among PPI subscales were allowed to interact with each other (e.g., Stress Immunity x Coldheartedness; Stress immunity x Rebellious Nonconformity). Although not originally hypothesized by Lilienfeld et al. (2012, 2015), analyses were conducted in which interactions between FD subscales were included (e.g., Fearlessness x Stress Immunity). Two significant interactions (approximately 2.7% of analyses conducted) were found that improved model fit.

In these two cases, coefficients for the interaction term were negative, indicating a decrease in the statistical effect of FD subscales at elevated levels of other psychopathic traits. This pattern is inconsistent with the standard moderation hypothesis and indicates that PPI FD features are more likely to operate as protective as opposed to potentiating factors for EXT broadly construed. First, Stress Immunity interacted with Coldheartedness in the prediction of Substance Use problems. As Coldheartedness increased, the magnitude of the association between Stress Immunity and externalizing decreased (low Coldheartedness: $B_{StressImmunity} = -.22$, $p < .01$; high Coldheartedness: $B_{StressImmunity} = -.33$, $p < .01$). f^2 indicated a small effect size.[4] Second, Stress Immunity interacted with Fearlessness in the prediction of Antisocial Behavior. As Stress Immunity increased, the magnitude of the association between Fearlessness and externalizing decreased (low Stress Immunity: $B_{Fearlessness} = .19$, $p < .01$; high Stress Immunity: $B_{Fearlessness} = .10$, $p < .01$). f^2 indicated a medium effect size.

Conclusion. Collectively, moderation-based analyses at the subscale level provided little support for the hypothesis that FD traits are related to EXT at higher levels of other psychopathic traits (Lilienfeld et al., 2012; 2015). Of the 72 analyses conducted, none indicated increased and positive associations between FD traits and EXT at higher levels of SCI traits. As noted above, power analysis simulations were conducted to evaluate our capacity to detect true interactive effects. Results indicated generally sufficient power (i.e., .96) to detect fairly small interactive effects approaching .10.

Evaluating potential curvilinear relations between PPI subscales and EXT. Eight analyses were conducted for each of our four EXT outcomes (32 analyses in total). Results are provided in Tables 10 and 11, and a summary is provided in Table 12. Plots of all significant quadratic effects that improved model fit are provided in Figures 4 to 8.

Antisocial Behavior. In Step 1, all PPI subscales showed significant linear effects when separately predicting antisocial behavior. In Step 2, three PPI subscales (i.e., Coldheartedness [large effect size], Carefree Nonplanfulness [medium], Fearlessness [very large]) yielded statistically significant quadratic effects (effect size indicated in brackets). AICs indicated that these quadratic effects represent meaningful improvements. Quadratic term coefficients ranged in magnitude from -.17 (Fearlessness) to .05 (Coldheartedness). The quadratic term coefficient for Coldheartedness and Carefree Nonplanfulness was positive, whereas the quadratic term coefficient for Fearlessness was negative and inconsistent with the curvilinearity hypothesis. Specifically, Coldheartedness and Carefree Nonplanfulness exhibited an increasing slope at higher trait levels, while Fearlessness exhibited a decreasing slope at higher trait

[4] Interpretations of interactive effect sizes vary by subject area, but Kenny (2015) suggests ascribing a small, medium, and large to f^2 effect sizes of .005, .01, and .025, respectively, in view of evidence that the average effect size associated with including interaction terms is .009 (Aguinis, Beaty, Boik, & Pierce, 2005).

levels.

Substance Use. In Step 1, all PPI subscales with the exception of Coldheartedness showed a significant linear effect when separately predicting substance use problems. In Step 2, Fearlessness yielded a large and statistically significant quadratic effect (B = -.13) that improved model fit. Fearlessness exhibited a decreasing slope at higher trait levels.

General Offense Arrest Count. No PPI subscales or higher-order factors showed significant linear or quadratic effects when separately predicting general recidivism.

Violent Offense Arrest Count. No PPI subscales or higher-order factors showed significant linear or quadratic effects when separately predicting violent recidivism.

Conclusion. Contrary to the curvilinearity hypothesis, FD traits did not exhibit concave curvilinear relations across externalizing-related outcomes. Where curvilinearity was found, Fearlessness exhibited a decreasing association with EXT at higher ends of the trait spectrum (See Figures 7, 8). These results suggest that Fearlessness tends to bear a weak positive relation with EXT among individuals with below average to average levels of Fearlessness, but negative associations with these problems among individuals with above average levels. In general, high levels of Fearlessness appeared protective against externalizing problems, at least in the current sample.

Evidence was found for curvilinear relations between SCI traits and antisocial behavior, such that certain SCI traits were associated with increasing slopes at higher trait levels. In particular, findings involving Coldheartedness suggest that individuals who are particularly lacking in concern for others and emotional empathy may be at exponentially greater risk of engaging in antisocial behavior. Coldheartedness consistently showed substantially smaller linear relations with externalizing problems than did other PPI SCI traits, a result consistent with previous findings (e.g., Crego & Widiger, 2014; Miller, Maples-Keller, & Lynam, 2016). Our curvilinear results suggest that Coldheartedness' ostensibly weak linear relations with EXT may belie its stronger association with maladaptive behavior at higher levels of the trait. Findings involving Carefree Nonplanfulness similarly suggest that impulsivity and lack of deliberation may be more strongly associated with antisocial behavior at higher levels of the trait.

There were at least two curvature patterns that emerged among instances of positive curvilinear relations. The first pattern, characterizing PPI Coldheartedness was a fairly symmetrical parabolic shape, which indicated weak linear relations between the psychopathic trait and EXT at below average to average levels of the trait and stronger relations at higher levels of the trait (e.g., Figure 5). The second pattern, characterizing Carefree Nonplanfulness was a 90 degree parabolic shape (e.g., Figures 6) indicating positive relations at all levels of the trait, but exponentially stronger (amplified) relations to EXT at the higher levels.

Examinations of linear effects of FD traits suggest that Stress Immunity consistently evinced negative linear relations across externalizing-related outcomes and showed no evidence of curvilinear relations consistent with Blonigen's (2013) hypothesis. These findings suggest that among FD subscales, Stress Immunity may be least relevant to externalizing problems, although its converse (i.e., stress reactivity) may hold potential clinical utility for predicting future externalizing problems. In addition, both Social Potency and Stress Immunity bore negative relations with substance use. Overall, FD traits exhibited null to weak linear relations with externalizing problems, in line with previous literature (e.g., Miller & Lynam, 2012). Although these relations were positive and statistically significant in two of 12 cases (related to PPI Fearlessness), their meaningfulness may be best judged using standards of clinical utility.

Examining typically-scored PPI higher-order factors and EXT. To compare results using GGUM-generated latent trait estimates to results using typically-scored variables, a series of hierarchical regression analyses were conducted that mirrored analyses conducted in the main text (see Results). To match results in the main text, in models containing Antisocial Behavior and Substance Use, z-scores of PPI FD, PPI SCI, Antisocial Behavior, and Substance Use were used; and in models containing General and Violent Offense Arrest Counts, z-scores of PPI FD and PPI SCI were used. Results for curvilinear analyses are provided in Table 13.

Evaluating whether Typically-scored PPI FD moderates the relation between Typically-scored PPI SCI and EXT. To examine the association between PPI FD and EXT at elevated levels of PPI SCI, four analyses were conducted in which PPI FD was allowed to interact statistically with PPI SCI, yielding no significant results.

Evaluating potential curvilinear relations between Typically-scored PPI higher-order factor scores and EXT.

PPI Fearless Dominance. In Step 1, PPI FD showed a significant linear effect when separately predicting Antisocial Behavior (positive) and Substance Use (negative). In Step 2, PPI FD evinced no significant quadratic effects.

PPI Self-centered Impulsivity. In Step 1, PPI SCI showed significant positive linear effects when separately predicting Antisocial Behavior and Substance Use. In Step 2, PPI SCI evinced no significant quadratic effects.

Plots of Significant Quadratic Effects

Graphical plots of significant quadratic effects that improved model fit are displayed in Figures 4 – 8.

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Table 1.
Power Analysis - Curvilinearity models and Interaction Models FD*SCI

	NB Model Parameters							OLS Model Parameters					
	N	κ	b_1	b_2	b_3	T1E	Power	N	b_1	b_2	b_3	T1E	Power
Curvilinearity Models													
	1027	1.026	.16	.064		.07	.65	1491	.16	.064		.06	.98
Interaction Models													
FD*SCI	1027	1.026	.01	.01	.05	.08	.27	1491	.07	.07	.04	.05	.44
FD*SCI	1027	1.026	.16	.01	.05	.07	.28	1491	.35	.07	.04	.05	.44
FD*SCI	1027	1.026	.16	.16	.05	.06	.35	1491	.35	.35	.04	.05	.44
FD*SCI	1027	1.026	.01	.01	.1	.08	.68	1491	.07	.07	.09	.05	.96
FD*SCI	1027	1.026	.16	.01	.1	.07	.72	1491	.35	.07	.09	.05	.96
FD*SCI	1027	1.026	.16	.16	.1	.06	.76	1491	.35	.35	.09	.05	.96

Note. FD = Fearless Dominance; SCI = Self-centered Impulsivity; NB = Negative Binomial Regression; OLS = Ordinary Least Squares Regression.

Table 2.
Power Analysis - Interaction Models SP*PPI subscales

	NB Model Parameters							OLS Model Parameters					
	N	κ	b_1	b_2	b_3	T1E	Power	N	b_1	b_2	b_3	T1E	Power
SP*ME	1027	1.026	.01	.01	.07	.07	.29	1491	.07	.07	.04	.04	.43
SP*ME	1027	1.026	.16	.01	.07	.09	.27	1491	.35	.07	.04	.04	.43
SP*ME	1027	1.026	.16	.16	.07	.07	.28	1491	.35	.35	.04	.04	.43
SP*ME	1027	1.026	.01	.01	.1	.07	.71	1491	.07	.07	.09	.04	.96
SP*ME	1027	1.026	.16	.01	.1	.09	.71	1491	.35	.07	.09	.04	.96
SP*ME	1027	1.026	.16	.16	.1	.07	.72	1491	.35	.35	.09	.04	.96
SP*RN	1027	1.026	.01	.01	.07	.07	.28	1491	.07	.07	.04	.05	.44
SP*RN	1027	1.026	.16	.01	.07	.09	.27	1491	.35	.07	.04	.05	.44
SP*RN	1027	1.026	.16	.16	.07	.06	.29	1491	.35	.35	.04	.05	.44
SP*RN	1027	1.026	.01	.01	.1	.07	.70	1491	.07	.07	.09	.05	.96
SP*RN	1027	1.026	.16	.01	.1	.09	.72	1491	.35	.07	.09	.05	.96
SP*RN	1027	1.026	.16	.16	.1	.06	.73	1491	.35	.35	.09	.05	.96
SP*BE	1027	1.026	.01	.01	.07	.07	.26	1491	.07	.07	.04	.04	.46
SP*BE	1027	1.026	.16	.01	.07	.06	.354	1491	.35	.07	.04	.04	.46
SP*BE	1027	1.026	.16	.16	.07	.07	.351	1491	.35	.35	.04	.04	.46
SP*BE	1027	1.026	.01	.01	.1	.07	.69	1491	.07	.07	.09	.04	.97
SP*BE	1027	1.026	.16	.01	.1	.06	.74	1491	.35	.07	.09	.04	.97
SP*BE	1027	1.026	.16	.16	.1	.07	.71	1491	.35	.35	.09	.04	.97
SP*CN	1027	1.026	.01	.01	.07	.07	.25	1491	.07	.07	.04	.04	.46
SP*CN	1027	1.026	.16	.01	.07	.06	.354	1491	.35	.07	.04	.04	.46
SP*CN	1027	1.026	.16	.16	.07	.07	.24	1491	.35	.35	.04	.04	.46
SP*CN	1027	1.026	.01	.01	.1	.07	.69	1491	.07	.07	.09	.04	.97
SP*CN	1027	1.026	.16	.01	.1	.06	.74	1491	.35	.07	.09	.04	.97
SP*CN	1027	1.026	.16	.16	.1	.07	.63	1491	.35	.35	.09	.04	.97
SP*C	1027	1.026	.01	.01	.07	.09	.27	1491	.07	.07	.04	.05	.45
SP*C	1027	1.026	.16	.01	.07	.07	.26	1491	.35	.07	.04	.05	.45
SP*C	1027	1.026	.16	.16	.07	.06	.352	1491	.35	.35	.04	.05	.45
SP*C	1027	1.026	.01	.01	.1	.09	.67	1491	.07	.07	.09	.05	.96
SP*C	1027	1.026	.16	.01	.1	.07	.69	1491	.35	.07	.09	.05	.96
SP*C	1027	1.026	.16	.16	.1	.06	.75	1491	.35	.35	.09	.05	.96

Note. FD = Fearless Dominance; SCI = Self-centered Impulsivity; ME = Machiavellian Egocentricity; RN = Rebellious Nonconformity; BE = Blame Externalization; CN = Carefree Nonplanfulness; C = Coldheartedness; F = Fearlessness; SP = Social Potency; SI = Stress Immunity; NB = Negative Binomial Regression; OLS = Ordinary Least Squares Regression.

Table 3.
Power Analysis - Interaction Models Fearlessness*PPI subscales

	NB Model Parameters							OLS Model Parameters					
	N	κ	b_1	b_2	b_3	T1E	Power	N	b_1	b_2	b_3	T1E	Power
F*ME	1027	1.026	.01	.01	.05	.07	.34	1491	.07	.07	.04	.04	.46
F*ME	1027	1.026	.16	.01	.05	.08	.30	1491	.35	.07	.04	.04	.46
F*ME	1027	1.026	.16	.16	.05	.08	.30	1491	.35	.35	.04	.04	.46
F*ME	1027	1.026	.01	.01	.1	.07	.77	1491	.07	.07	.09	.04	.98
F*ME	1027	1.026	.16	.01	.1	.08	.77	1491	.35	.07	.09	.04	.98
F*ME	1027	1.026	.16	.16	.1	.08	.75	1491	.35	.35	.09	.04	.98
F*RN	1027	1.026	.01	.01	.05	.06	.36	1491	.07	.07	.04	.04	.52
F*RN	1027	1.026	.16	.01	.05	.07	.34	1491	.35	.07	.04	.04	.52
F*RN	1027	1.026	.16	.16	.05	.06	.31	1491	.35	.35	.04	.04	.52
F*RN	1027	1.026	.01	.01	.1	.06	.81	1491	.07	.07	.09	.04	.99
F*RN	1027	1.026	.16	.01	.1	.07	.82	1491	.35	.07	.09	.04	.99
F*RN	1027	1.026	.16	.16	.1	.06	.81	1491	.35	.35	.09	.04	.99
F*BE	1027	1.026	.01	.01	.05	.08	.28	1491	.07	.07	.04	.05	.44
F*BE	1027	1.026	.16	.01	.05	.08	.28	1491	.35	.07	.04	.05	.44
F*BE	1027	1.026	.16	.16	.05	.06	.31	1491	.35	.35	.04	.05	.44
F*BE	1027	1.026	.01	.01	.1	.08	.69	1491	.07	.07	.09	.05	.96
F*BE	1027	1.026	.16	.01	.1	.08	.71	1491	.35	.07	.09	.05	.96
F*BE	1027	1.026	.16	.16	.1	.06	.74	1491	.35	.35	.09	.05	.96
F*CN	1027	1.026	.01	.01	.05	.07	.30	1491	.07	.07	.04	.04	.45
F*CN	1027	1.026	.16	.01	.05	.08	.28	1491	.35	.07	.04	.04	.45
F*CN	1027	1.026	.16	.16	.05	.07	.31	1491	.35	.35	.04	.04	.45
F*CN	1027	1.026	.01	.01	.1	.07	.71	1491	.07	.07	.09	.04	.97
F*CN	1027	1.026	.16	.01	.1	.08	.74	1491	.35	.07	.09	.04	.97
F*CN	1027	1.026	.16	.16	.1	.07	.74	1491	.35	.35	.09	.04	.97
F*C	1027	1.026	.01	.01	.05	.07	.31	1491	.07	.07	.04	.04	.45
F*C	1027	1.026	.16	.01	.05	.08	.28	1491	.35	.07	.04	.04	.45
F*C	1027	1.026	.16	.16	.05	.08	.30	1491	.35	.35	.04	.04	.45
F*C	1027	1.026	.01	.01	.1	.07	.73	1491	.07	.07	.09	.04	.97
F*C	1027	1.026	.16	.01	.1	.08	.72	1491	.35	.07	.09	.04	.97
F*C	1027	1.026	.16	.16	.1	.08	.69	1491	.35	.35	.09	.04	.97

Note. FD = Fearless Dominance; SCI = Self-centered Impulsivity; ME = Machiavellian Egocentricity; RN = Rebellious Nonconformity; BE = Blame Externalization; CN = Carefree Nonplanfulness; C = Coldheartedness; F = Fearlessness; SP = Social Potency; SI = Stress Immunity; NB = Negative Binomial Regression; OLS = Ordinary Least Squares Regression.

Table 4.
Power Analysis - Interaction Models Stress Immunity*PPI subscales

	NB Model Parameters							OLS Model Parameters					
	N	κ	b_1	b_2	b_3	T1E	Power	N	b_1	b_2	b_3	T1E	Power
SI*ME	1027	1.026	.01	.01	.05	.08	.27	1491	.07	.07	.04	.05	.44
SI*ME	1027	1.026	.16	.01	.05	.07	.28	1491	.35	.07	.04	.05	.44
SI*ME	1027	1.026	.16	.16	.05	.06	.35	1491	.35	.35	.04	.05	.44
SI*ME	1027	1.026	.01	.01	.1	.08	.68	1491	.07	.07	.09	.05	.96
SI*ME	1027	1.026	.16	.01	.1	.07	.72	1491	.35	.07	.09	.05	.96
SI*ME	1027	1.026	.16	.16	.1	.06	.76	1491	.35	.35	.09	.05	.96
SI*RN	1027	1.026	.01	.01	.05	.06	.28	1491	.07	.07	.04	.06	.47
SI*RN	1027	1.026	.16	.01	.05	.05	.31	1491	.35	.07	.04	.06	.47
SI*RN	1027	1.026	.16	.16	.05	.05	.32	1491	.35	.35	.04	.06	.47
SI*RN	1027	1.026	.01	.01	.1	.06	.71	1491	.07	.07	.09	.06	.96
SI*RN	1027	1.026	.16	.01	.1	.05	.72	1491	.35	.07	.09	.06	.96
SI*RN	1027	1.026	.16	.16	.1	.05	.72	1491	.35	.35	.09	.06	.96
SI*BE	1027	1.026	.01	.01	.05	.06	.32	1491	.07	.07	.04	.04	.47
SI*BE	1027	1.026	.16	.01	.05	.05	.33	1491	.35	.07	.04	.04	.47
SI*BE	1027	1.026	.16	.16	.05	.07	.24	1491	.35	.35	.04	.04	.47
SI*BE	1027	1.026	.01	.01	.1	.06	.74	1491	.07	.07	.09	.04	.98
SI*BE	1027	1.026	.16	.01	.1	.05	.75	1491	.35	.07	.09	.04	.98
SI*BE	1027	1.026	.16	.16	.1	.07	.63	1491	.35	.35	.09	.04	.98
SI*CN	1027	1.026	.01	.01	.05	.07	.25	1491	.07	.07	.04	.05	.46
SI*CN	1027	1.026	.16	.01	.05	.06	.30	1491	.35	.07	.04	.05	.46
SI*CN	1027	1.026	.16	.16	.05	.07	.25	1491	.35	.35	.04	.05	.46
SI*CN	1027	1.026	.01	.01	.1	.07	.67	1491	.07	.07	.09	.05	.97
SI*CN	1027	1.026	.16	.01	.1	.06	.71	1491	.35	.07	.09	.05	.97
SI*CN	1027	1.026	.16	.16	.1	.07	.69	1491	.35	.35	.09	.05	.97
SI*C	1027	1.026	.01	.01	.05	.07	.33	1491	.07	.07	.04	.04	.45
SI*C	1027	1.026	.16	.01	.05	.07	.28	1491	.35	.07	.04	.04	.45
SI*C	1027	1.026	.16	.16	.05	.08	.30	1491	.35	.35	.04	.04	.45
SI*C	1027	1.026	.01	.01	.1	.07	.74	1491	.07	.07	.09	.04	.97
SI*C	1027	1.026	.16	.01	.1	.07	.75	1491	.35	.07	.09	.04	.97
SI*C	1027	1.026	.16	.16	.1	.08	.73	1491	.35	.35	.09	.04	.97

Note. FD = Fearless Dominance; SCI = Self-centered Impulsivity; ME = Machiavellian Egocentricity; RN = Rebellious Nonconformity; BE = Blame Externalization; CN = Carefree Nonplanfulness; C = Coldheartedness; F = Fearlessness; SP = Social Potency; SI = Stress Immunity; NB = Negative Binomial Regression; OLS = Ordinary Least Squares Regression.

Table 5.
Power Analysis - Interaction Models FD subscales

	NB Model Parameters							OLS Model Parameters					
	N	κ	b_1	b_2	b_3	T1E	Power	N	b_1	b_2	b_3	T1E	Power
SP*SI	1027	1.026	.01	.01	.05	.07	.34	1491	.07	.07	.04	.04	.46
SP*SI	1027	1.026	.16	.01	.05	.08	.30	1491	.35	.07	.04	.04	.46
SP*SI	1027	1.026	.16	.16	.05	.08	.30	1491	.35	.35	.04	.04	.46
SP*SI	1027	1.026	.01	.01	.1	.07	.77	1491	.07	.07	.09	.04	.98
SP*SI	1027	1.026	.16	.01	.1	.08	.77	1491	.35	.07	.09	.04	.98
SP*SI	1027	1.026	.16	.16	.1	.08	.75	1491	.35	.35	.09	.04	.98
F*SI	1027	1.026	.01	.01	.05	.07	.35	1491	.07	.07	.04	.04	.48
F*SI	1027	1.026	.16	.01	.05	.06	.31	1491	.35	.07	.04	.04	.48
F*SI	1027	1.026	.16	.16	.05	.07	.30	1491	.35	.35	.04	.04	.48
F*SI	1027	1.026	.01	.01	.1	.07	.77	1491	.07	.07	.09	.04	.98
F*SI	1027	1.026	.16	.01	.1	.06	.77	1491	.35	.07	.09	.04	.98
F*SI	1027	1.026	.16	.16	.1	.07	.77	1491	.35	.35	.09	.04	.98
F*SP	1027	1.026	.01	.01	.05	.07	.33	1491	.07	.07	.04	.04	.45
F*SP	1027	1.026	.16	.01	.05	.07	.29	1491	.35	.07	.04	.04	.45
F*SP	1027	1.026	.16	.16	.05	.08	.28	1491	.35	.35	.04	.04	.45
F*SP	1027	1.026	.01	.01	.1	.07	.75	1491	.07	.07	.09	.04	.98
F*SP	1027	1.026	.16	.01	.1	.07	.73	1491	.35	.07	.09	.04	.98
F*SP	1027	1.026	.16	.16	.1	.08	.74	1491	.35	.35	.09	.04	.98

Note. FD = Fearless Dominance; SCI = Self-centered Impulsivity; ME = Machiavellian Egocentricity; RN = Rebellious Nonconformity; BE = Blame Externalization; CN = Carefree Nonplanfulness; C = Coldheartedness; F = Fearlessness; SP = Social Potency; SI = Stress Immunity; NB = Negative Binomial Regression; OLS = Ordinary Least Squares Regression.

Table 6.
Covariance parameters for Interactive power analyses

Interaction	***r***
FD x SCI	.048
Social Potency x Machiavellian Egocentricity	.14
Fearlessness x Machiavellian Egocentricity	.29
Stress Immunity x Machiavellian Egocentricity	.048
Social Potency x Rebelious Nonconformity	.11
Fearlessness x Rebelious Nonconformity	.5
Stress Immunity x Rebelious Nonconformity	.00
Social Potency x Blame Externalization	-.17
Fearlessness x Blame Externalization	.08
Stress Immunity x Blame Externalization	-.32
Social Potency x Carefree Nonplanfulness	-.15
Fearlessness x Carefree Nonplanfulness	.21
Stress Immunity x Carefree Nonplanfulness	-.07
Social Potency x Coldheartedness	.22
Fearlessness x Coldheartedness	.25
Stress Immunity x Coldheartedness	.02
Fearlessness x Social Potency	.27
Social Potency x Fearlessness	.29
Fearlessness x Social Immunity	.33

Note. Source for FD x SCI correlation: Miller & Lynam, 2012; Source for PPI subscale interactions: Crowe et al., under review).

Table 7.

Correlations of PPI Variables

	PPI FD	PPI SCI	PPI Cold	PPI Blame	PPI Carefree	PPI Rebel	PPI Mach Ego	PPI Fearless	PPI Stress Immunity	PPI Social Potency
PPI										
FD		-.21*	.13*	-.28*	-.31*	.01	-.06	.63*	.72*	.73*
SCI	.06		.10*	.69*	.69*	.81*	.83*	.14*	-.54*	-.04
Coldheartedness	.08*	.06		-.21*	.24*	.08*	.19*	.04	.23*	-.01
Blame Externalization	-.12*	.70*	-.22*		.21*	.39*	.46*	.01	-.51*	-.07*
Carefree Nonplanfulness	-.21*	.67*	.21*	.26*		.42*	.42*	.03	-.41*	-.28*
Rebellious Nonconformity	.27*	.72*	.01	.37*	.37*		.62*	.25*	-.30*	.06
Mach Egocentricity	.18*	.88*	.15*	.47*	.46*	.54*		.12*	-.39*	.16*
Fearlessness	.70*	.39*	-.02	.16*	.14*	.53*	.37*		.14*	.17*
Stress Immunity	.56*	-.50*	.26*	-.50*	-.43*	-.21*	-.36*	.07*		.35*
Social Potency	.83*	-.01	.03	-.10*	-.27*	.10*	.17*	.28*	.40*	

Note. Typically-scored manifest PPI variables below diagonal; GGUM-generated PPI factor/subscale latent trait estimates above diagonal; Cold = PPI Coldheartedness; PPI Blame = PPI Blame Externalization; PPI Carefree = PPI Carefree Nonplanfulness; PPI Rebel = PPI Rebellious Nonconformity; PPI Mach Ego = PPI Machiavellian Egocentricity; PPI Fearless = PPI Fearlessness; *n* for analyses ranged from 1604 – 1608; **p* < .01.

Table 8.

Correlations of Continuous GGUM-generated Criterion Variables

	PAI AGG	PAI ABS	PDQ-4 APD Adult	SCID-II AAB	PDQ-4 APD Child	SCID-II CD	PAI ALC	PAI DRG
PAI Aggression		.50*	.33*	.33*	.45*	.35*	.19*	.20*
PAI Antisocial Behavior Subscale	.53*		.41*	.35*	.51*	.32*	.23*	.45*
PDQ-4 APD Adult Criteria	.48*	.51*		.34*	.36*	.20*	.20*	.35*
SCID-II Adult Antisocial Behavior	.38*	.40*	.45*		.32*	.33*	.16*	.29*
PDQ-4 APD Childhood Scale	.49*	.59*	.53*	.40*		.60*	.14*	.15*
SCID-II Conduct Disorder	.10*	.07*	.07*	.10*	.13*		.03	.01
PAI Alcohol Problems	.20*	.22*	.25*	.13*	.15*	.06		.40*
PAI Drug Problems	.22*	.42*	.44*	.28*	.25*	.03	.43*	

Note. Typically-scored manifest criterion variables below diagonal; GGUM-generated criterion variables above diagonal; PAI AGG = PAI Aggression Scale; PAI ABS = PAI Antisocial Behavior Subscale; PDQ-4 APD Adult = PDQ-4 Antisocial Personality Disorder Adult Criteria; SCID-II AAB = SCID-II Adult Antisocial Behavior; PDQ-4 APD Child = PDQ-4 Antisocial Personality Disorder Childhood Scale; SCID-II CD = SCID-II Conduct Disorder; PAI ALC = PAI Alcohol Problems; PAI DRG = PAI Drug Problems; *n* of analyses ranged from 1151 – 1642; *$p < .01$.

Table 9.
Model Fit Indices for Two-Factor PPI FD and PPI SCI model

Model	X^2	df	RMSEA	SRMR	CFI	TLI
PPI FD & PPI SCI (GGUM)	705.99*	13	.182 (.171 to .194)	.104	.774	.635
PPI FD & PPI SCI (Typically-scored)	1594.09*	13	.275 (.264 to .287)	.221	.544	.263

Note. PPI FD = PPI Fearless Dominance; PPI SCI = PPI Self-centered Impulsivity; PPI FD & PPI SCI (GGUM) = Model containing GGUM-generated PPI subscale latent trait estimates as indicators; PPI FD & PPI SCI (Standard) = Model containing PPI subscale standard scores as indicators; *$p < .001$.

Table 10.
Results of Regression Analyses for GGUM-generated PPI Subscales and Antisocial Behavior

		Antisocial Behavior							Substance Use						
		Step 1			Step 2				Step 1			Step 2			
Externalizing Outcome	Parameter	B	AIC	R^2	B	AIC	R^2	ΔR^2	B	AIC	R^2	B	AIC	R^2	ΔR^2
Coldheartedness	Intercept	-.025	2940	.019	-.073*	2922	.032	.013	-.002	3787	.000	.021	3787	.002	.002
	Linear	.088*			.096*				-.010			-.014			
	Quadratic				.049*							-.023			
Blame External	Intercept	-.024	2776	.119	-.019	2778	.119	.000	-.001	3765	.015	.010	3766	.015	.000
	Linear	.223*			.222*				.102*			.100*			
	Quadratic				-.005							-.011			
Carefre Nonplan	Intercept	-.023	2573	.229	-.053*	2567	.233	.004	.001	3532	.154	-.002	3534	.154	.000
	Linear	.309*			.315*				.330*			.331*			
	Quadratic				.030*							.004			
Rebel Nonconfor	Intercept	-.026	2512	.260	-.003	2507	.263	.003	-.002	3645	.089	.021	3644	.091	.002
	Linear	.328*			.329*				.250*			.251*			
	Quadratic				-.024							-.023			
Mach Egocentr	Intercept	-.024	2328	.344	-.026	2330	.344	.000	.000	3679	.069	.023	3677	.071	.002
	Linear	.377*			.377*				.219*			.219*			
	Quadratic				.003							-.023			
Fearlessness	Intercept	-.025	2935	.022	.148*	2755	.132	.110	-.002	3778	.007	.125*	3725	.041	.034
	Linear	.095*			.128*				.067*			.093*			
	Quadratic				-.172*							-.126*			
Stress Immunity	Intercept	-.023	2775	.120	.002	2772	.122	.002	.001	3637	.094	.015	3638	.095	.001
	Linear	-.222*			-.219*				-.257*			-.255*			
	Quadratic				-.025							-.014			
Social Potency	Intercept	-.025	2967	.001	-.045	2966	.003	.002	-.002	3743	.029	-.024	3743	.030	.001
	Linear	.016			.014				-.142*			-.145*			
	Quadratic				.020							.022			

Note. Blame Extern = Blame Externalization; Caref Nonplan = Carefree Nonplanfulness; Rebel Nonconf = Rebellious Nonconformity; Mach Ego = Machiavellian Egocentricity; *n* for ASB analyses = 1519; *n* for Substance Use analyses = 1526; *$p < .01$.

Table 11.

Results of Negative Binomial Regression Analyses for GGUM-generated PPI Subscales and Criminal Recidivism

		General Offense Arrest Count							Violent Offense Arrest Count						
		Step 1			Step 2				Step 1			Step 2			
PPI subscale	Parameter	B	AIC	Pseudo-R^2	B	AIC	Pseudo-R^2	ΔPseudo-R^2	B	AIC	Pseudo-R^2	B	AIC	Pseudo-R^2	ΔPseudo-R^2
Coldheartedness	Intercept	-.010	3687	.027	-.038	3688	.028	.001	-3.059*	620	.022	-3.093*	602	.023	.001
	Follow up	.001*			.001*				.001			.001			
	Linear	-.002			.008				.225			.225			
	Quadratic				.026							.037			
Blame Extern	Intercept	-.016	3683	.031	-.037	3685	.032	.001	-3.083*	621	.016	-2.915*	599	.031	.015
	Follow up	.001*			.001*				.001			.001			
	Linear	.078			.078				.156			.194			
	Quadratic				.022							-.218			
Caref Nonplan	Intercept	-.020	3686	.028	-.035	3688	.029	.000	-3.128*	620	.020	-3.167*	602	.021	.001
	Follow up	.001*			.001*				.001			.001			
	Linear	-.039			-.038				-.194			-.178			
	Quadratic				.018							.043			
Rebel Nonconf	Intercept	-.003	3687	.028	-.020	3688	.029	.001	-3.108*	621	.018	-3.194*	600	.027	.009
	Follow up	.001*			.001*				.001			.001			
	Linear	.033			.032				-.163			-.140			
	Quadratic				.024							.106			
Mach Ego	Intercept	-.009	3687	.028	.002	3689	.028	.000	-3.067*	622	.015	-3.098*	604	.015	.001
	Follow up	.001*			.001*				.001			.001			
	Linear	.032			.032				.128			.122			
	Quadratic				-.011							.031			
Fearlessness	Intercept	-.010	3687	.028	.015	3688	.028	.000	-3.063*	623	.012	-3.153*	604	.014	.002
	Follow up	.001*			.001*				.001			.001			
	Linear	-.028			-.024				-.028			-.039			
	Quadratic				-.023							.078			
Stress Immunity	Intercept	-.010	3687	.027	.020	3688	.029	.001	-3.061*	622	.012	-3.01*	604	.014	.002
	Follow up	.001*			.001*				.001			.001			
	Linear	.011			.015				.054			.065			
	Quadratic				-.039							-.077			
Social Potency	Intercept	-.018	3684	.030	-.028	3686	.031	.000	-3.069*	620	.022	-3.086*	602	.022	.000
	Follow up	.001*			.001*				.001			.001			
	Linear	.073			.069				.216			.208			
	Quadratic				.011							.021			

Note. Blame Extern = Blame Externalization; Caref Nonplan = Carefree Nonplanfulness; Rebel Nonconf = Rebellious Nonconformity; Mach Ego = Machiavellian Egocentricity; Pseudo-R^2 value was calculated using McFadden's (1974) formula; rPseudo-R^2 indicates change in Pseudo-R^2 between linear and quadratic models; *n range* for Arrest Count analyses = 1026-1027; **p* < .01.

Table 12.
Summary of the Presence of Positive and Negative Curvilinear Effects

PPI Subscale	Antisocial Behavior	Substance Use	General Arrest Count	Violent Arrest Count
Coldheartedness	+			
Blame Externalization				
Carefree Nonplanfulness	+			
Rebellious Nonconformity				
Machiavellian Egocentricity				
Fearlessness	-	-		
Stress Immunity				
Social Potency				

Note. "+" or "-" = Significant positive or negative curvilinear effect that improved model fit.

Table 13.

Results of Regression Analyses for Typically-scored PPI Factors and EXT

		PPI Fearless Dominance							PPI Self-centered Impulsivity						
		Step 1			Step 2				Step 1			Step 2			
EXT Outcome	Parameter	B	AIC	R^2	B	AIC	R^2	ΔR^2	B	AIC	R^2	B	AIC	R^2	ΔR^2
Antisocial	Intercept	-.027	4422	.016	-.069*	4417	.020	.004	-.027	4041	.223	-.020	4043	.223	.000
	Linear	.122*			.122*				.461*			.461*			
	Quadratic				.041							-.007			
Substance Use	Intercept	.004	4381	.012	-.035	4378	.015	.003	.003	4201	.117	-.001	4203	.117	.000
	Linear	-.108*			-.107*				.341*			.342*			
	Quadratic				.039							.004			
General Offense Arrest Count	Intercept	-.013	3686	.028	-.018	3688	.028	.000	-.007	3680	.028	-.003	3682	.028	.000
	Follow up	.001*			.001*				.001*			.001*			
	Linear	.043			.043				.038			.038			
	Quadratic				.006							-.004			
Violent Offense Arrest Count	Intercept	-3.057*	602	.014	-3.069	604	.014	.000	-3.058*	603	.012	-3.060	605	.012	.000
	Follow up	.001			.001				.001			.001			
	Linear	.113			.110				.022			.022			
	Quadratic				.016							.003			

Note. Antisocial = Antisocial Behavior; *n* for Antisocial analyses = 1591-1592; *n* for Substance Use analyses = 1552-1553; *n* for General and Violent Offense Arrest Count analyses = 1026-1027; To match analyses in main text, for ASB and Substance Use analyses, PPI FD, PPI SCI, ASB, and Substance Use are z-scored, and for General and Violent Offense Arrest Count analyses, PPI FD and PPI SCI variables are z-scored; Values in the R^2 column for General Offense Arrest Count and Violent Offense Arrest Count represent Pseudo R^2; $*p < .01$.

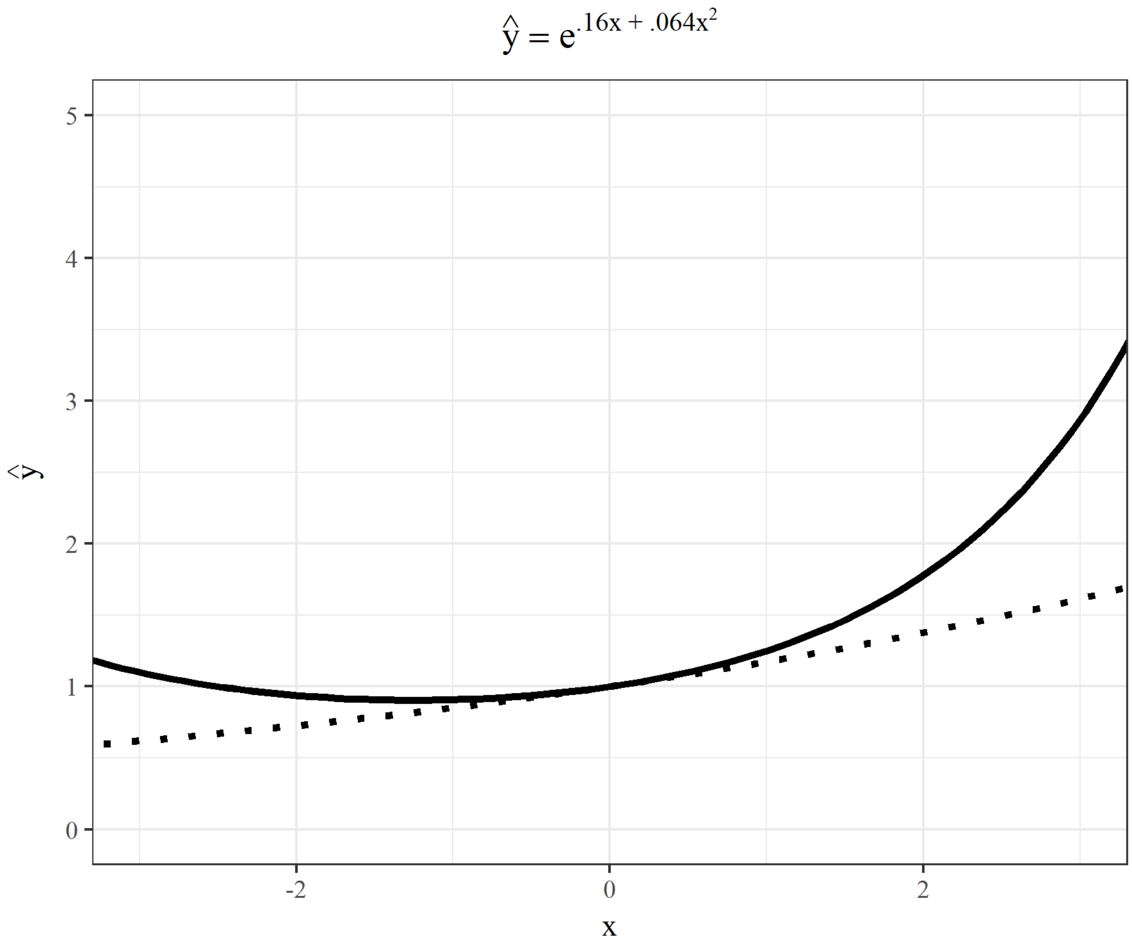

Figure 1. Depiction of the curvilinear effect being evaluated in power analysis. Dashed line indicates the same linear effect with no quadratic parameter.

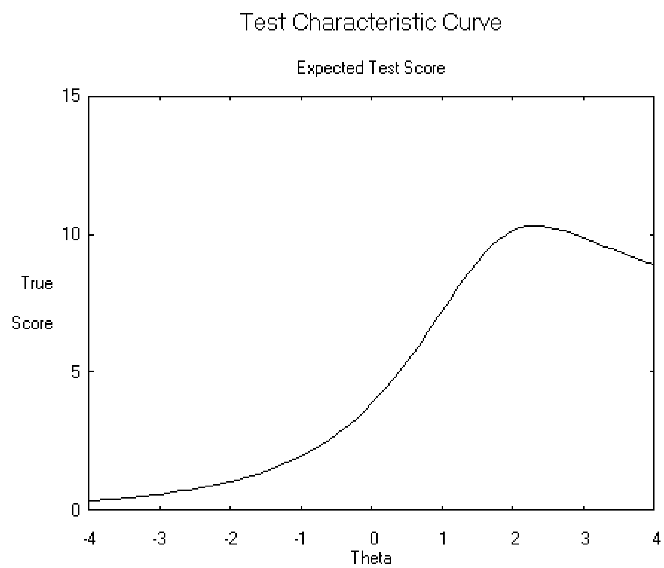

Figure 2. Test Characteristic Curve for SCID-II Conduct Disorder

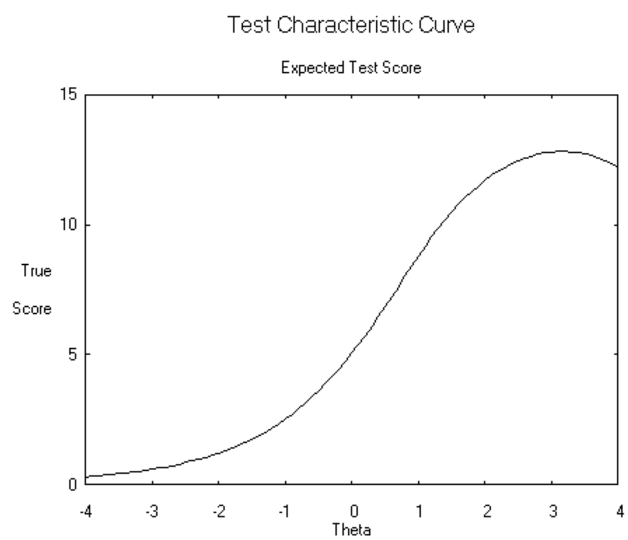

Figure 3. Test Characteristic Curve for PDQ-4 Antisocial Personality Disorder Childhood Scale

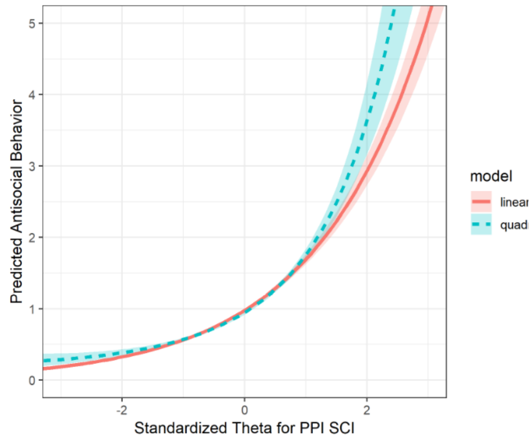

Figure 4. PPI SCI and Antisocial Behavior

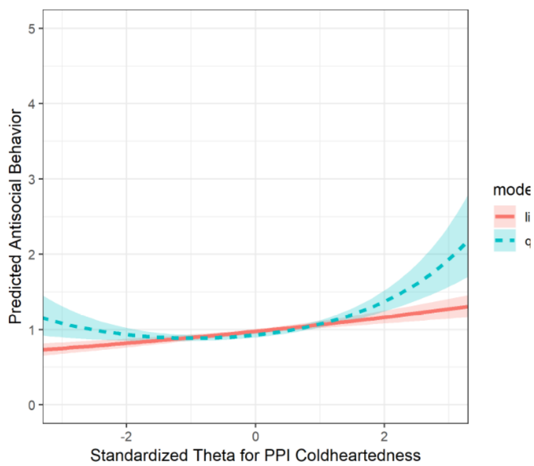

Figure 5. PPI Coldheartedness and Antisocial Behavior

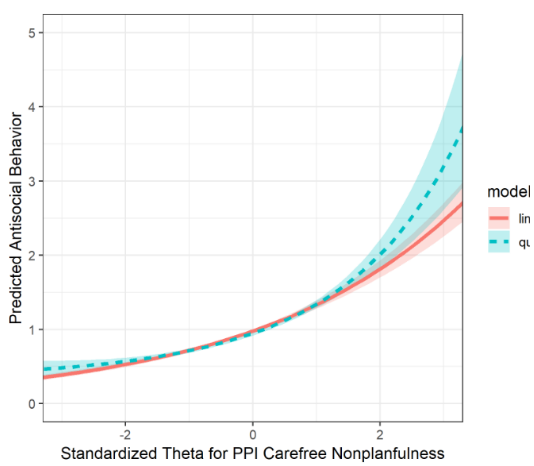

Figure 6. PPI Carefree Nonplanfulness and Antisocial Behavior

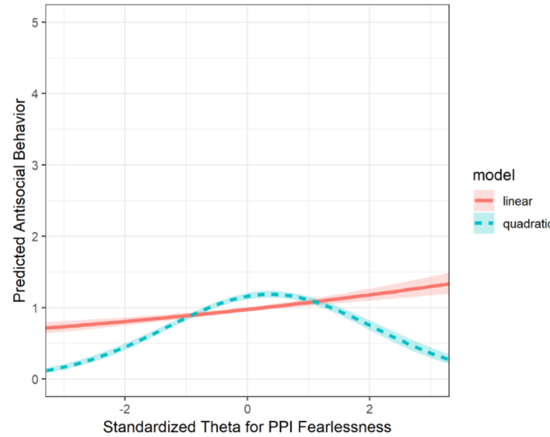

Figure 7. PPI Fearlessness and Antisocial Behavior

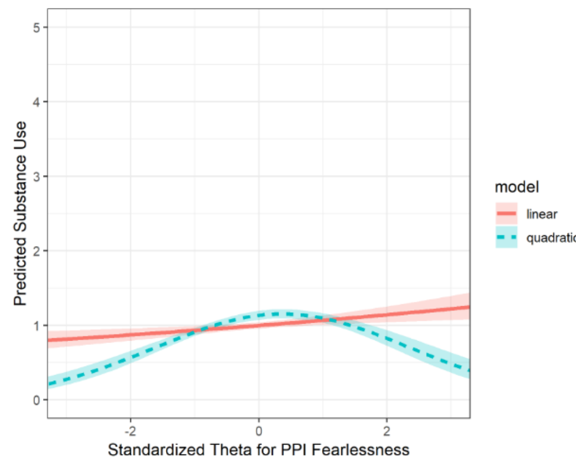

Figure 8. PPI Fearlessness and Substance Use