A Longitudinal Examination of the Association between Intelligence and Rearrest using a Latent Trait-State-Occasion Modeling Approach in a Sample of Previously Adjudicated Youth

Abstract

Recidivism remains a serious issue in the modern criminal justice system, with over 80% of those previously incarcerated being rearrested within nine years of release (Alper, Durose, & Markman, 2018). While previous studies have identified risk factors that increase the probability of rearrest, much remains unknown regarding the full constellation risk factors. One potential risk factor that has received limited attention is intelligence, as individuals with lower IQ scores have been found to be more likely to come into initial contact with the criminal justice system. Collectively, previous studies have provided preliminary evidence of intelligence as a risk factor for rearrest but have not fully explored this association. More specifically, it remains unclear whether the association between IQ and recidivism persists after controlling for time-invariant, individual-specific sources of variance in criminal behavior. The current study aimed to address this limitation and more closely examine the longitudinal association between IQ and rearrest with data from the Pathways to Desistance Study (*N* = 1,331 individuals). In order to distinguish variance in intelligence from time-stable, individual-specific variance in criminality, a latent trait-state-occasion (LTSO) model was estimated. A subsequent series of survival models, which included the previously estimated measure of criminality as a covariate, revealed a small and negative association between IQ and rearrest (*HR* = .95; *95% CI* = .92, .98), suggesting that IQ may play only a minor role in recidivism.

Keywords: intelligence; criminality; recidivism

Recidivism, or subsequent contact of previously incarcerated individuals with the criminal justice system, has long been one of the more pressing issues facing the modern criminal justice system in the United States. The results of a report recently compiled by the Bureau of Justice Statistics, indicated that of the over 400,000 state prisoners released in 2005, approximately 68% were rearrested within three years, 79% were rearrested within six years, and 83% were rearrested within the full nine-year follow-up period (Alper et al., 2018). The same report revealed that during the nine-year examination period, released inmates experienced an average of five subsequent arrests. In addition to the humanitarian costs associated with recidivism, the monetary costs are also extremely high. The state of Illinois reported a cost of more than $118,000 for a single recidivism event and an expected cost of over $16.7 billion over five years (Illinois Sentencing Policy Advisory Council, 2015).

Based on the prevalence and cost of recidivism, it stands to reason that previous research has been directed at identifying factors that increase the likelihood of arrest following a previous period of incarceration (Berg & Huebner, 2011; Clower & Bothwell, 2001; Hare, 1999; Hosser, Windzio, & Greve, 2008; Mears, Wang, Hay, & Bales, 2008; Mulder, Brand, Bullens, & Van Marle, 2010, 2011; Pedersen, Kunz, Rasmussen, & Elsass, 2010). This line of research has resulted in the identification of a reasonable number of risk factors, but additional sources of risk likely exist. One candidate source of risk is lower levels of intelligence. A well-developed body of research has revealed that individuals who score comparatively lower on IQ tests are significantly more likely to engage in criminal behavior (Beaver et al., 2013; Hirschi & Hindelang, 1977; Loeber et al., 2012; Lynam, Moffitt, & Stouthamer-Loeber, 1993; McGloin, Pratt, & Maahs, 2004; Mears & Cochran, 2013; Moffitt, Gabrielli, Mednick, & Schulsinger, 1981; Moffitt & Silva, 1988; Schwartz et al., 2015; Yun & Lee, 2013). While the accompanying effect size—as measured by a correlation coefficient—tends to range between -.20 and -.25 (Gottfredson, 2008), this association is robust and has been reported across studies that have analyzed different samples and have employed different measures of both criminal behavior and IQ. Despite the consistency of these findings, there is a paucity of research directly aimed at examining the association between intelligence and recidivism.

This distinction is important, as previous studies have pointed to divergent theoretical explanations for primary offending compared to subsequent—or secondary—offending (Becker, 1963; Lemert, 1951; Liberman, Kirk, & Kim, 2014; Matsueda, 2002; Wiley, Slocum, & Esbensen, 2013). Additionally, previous studies examining the association between IQ and offending have experienced a number of methodological limitations, raising concerns regarding the application of these findings to the IQ-recidivism association. For example, a substantial number of studies examining the IQ-offending association have relied on data tapping a restrictive period of the life course (Moffitt & Silva, 1988) or solely on the use of self-reported measures of both offending and contact with the criminal justice system (Beaver et al., 2013; Boccio, Beaver, & Schwartz, 2018; Yun & Lee, 2013). In addition, previous studies do not explore the possibility that *intelligence* and *criminality* are distinct time-invariant factors that differentially explain variation in recidivism risk. The current study aims to extend previous research by examining a longitudinal sample of previously adjudicated youth from the Pathways to Desistance (Pathways) study, which includes monthly self-reported offending measures as well as official record arrest data spanning seven years. These data offer the unique opportunity to examine the specific factors that underlie the association between IQ and recidivism, allowing for the most comprehensive examination of this association to date.

POTENTIAL RISK FACTORS FOR RECIDIVISM

Previous explanations of recidivism can be separated into two distinct, yet related, categories. First, previous studies have theorized that the difficulties that accompany contact with the criminal justice system—so called *collateral consequences*—accumulate and translate into blocked legitimate opportunities, additional offending, and, eventually, recidivism (for an overview, see Hagan & Dinovitzer, 2005). Directly in line with this possibility, previous studies have identified structural barriers faced by previously incarcerated individuals during the reentry process as contributing factors of recidivism. More specifically, difficulty in securing meaningful employment (Berg & Huebner, 2011), strained social ties (Cochran, 2014), housing difficulties (Clark, 2016), as well as general disadvantage and poverty (Holtfreter, Reisig, & Morash, 2006; Kubrin & Stewart, 2006; Wehrman, 2010) have been found to complicate reentry and increase the likelihood of recidivism. Previous research has also pointed to the importance of broader ecological constructs, such as the characteristics of the neighborhoods to which individuals return following incarceration. For example, Mears and colleagues (2008) found that individuals who return to geographic locations characterized by racial segregation and resource deprivation were significantly more likely to recidivate compared to their counterparts.

The second category of risk factors for recidivism is more centrally focused on individualized influences. The identification of such risk factors falls in line with the *population heterogeneity* perspective, which speculates that criminal offending is the result, at least in part, of time-invariant, individual-specific traits that increase underlying criminal propensity or *criminality* (Gottfredson & Hirschi, 1990; Nagin, Farrington, & Moffitt, 1995; Nagin & Paternoster, 1991, 2000). In this way, the population heterogeneity perspective differentiates between *criminality* and *criminal offending* as traditional measures of offending contain variance tapping internalized, time-stable latent sources of influence contributing to criminal behavior, but such measures also contain variance attributed to context specific factors such as peer influences (Warr, 2002), neighborhood experiences (Sampson, 1997), and socioeconomic factors (Chiricos & Waldo, 1975). While these latter influences are also important in the development of criminal behavior, they are not the focus of the population heterogeneity perspective. Directly in line with this possibility, previous research has identified various sources of individualized risk for recidivism, including psychiatric disorders (Colins et al., 2011), psychopathy (Hare, 1999; Pedersen et al., 2010), lower levels of impulse control (Malouf et al., 2014), lower conscientiousness and openness to experience (Clower & Bothwell, 2001), as well as increased levels of shame and lower levels of guilt (Hosser et al., 2008).

INTELLIGENCE AS A RISK FACTOR FOR RECIDIVISM

Lower levels of intelligence is another potential risk factor for recidivism, as previous research has demonstrated a consistent negative association between IQ and offending (Beaver et al., 2013; Hirschi & Hindelang, 1977; Loeber et al., 2012; Lynam et al., 1993; McGloin et al., 2004; Mears & Cochran, 2013; Moffitt et al., 1981; Moffitt & Silva, 1988; Schwartz et al., 2015). Previous studies have also found that this association is robust across a number of European cultures, with findings replicated in samples or cohorts in New Zealand (Moffitt & Silva, 1988), Denmark (Moffitt et al., 1981), Sweden (Hodgins, 1992), Finland (Schwartz et al., 2015), and the United Kingdom (Farrington, 1973; Farrington & West, 1971). The association between IQ and criminal behavior is not confined to broad indicators of offending (e.g., arrest), but has also been observed with more specific forms of criminal behavior including sexual assault (Cantor, Blanchard, Robichaud, & Christensen, 2005), murder (Dwyer & Frierson, 2006), and assault (Kearns & O'Connor, 1988). Studies have also reported that persons with lower IQ scores are more likely to commit violent offenses (Walsh, 1987), come into contact with the criminal justice system (Beaver et al., 2013; Loeber et al., 2012; Yun & Lee, 2013), and are more likely to be subjected to additional criminal justice processing including conviction (Schwartz et al., 2015) and incarceration (Beaver et al., 2013). Once in prison, lower IQ inmates have also been found to engage in more misconduct than higher IQ inmates (Diamond, Morris, & Barnes, 2012). Studies have also reported robust associations between IQ and a broad range of correlates of criminal behavior including self-control (Meldrum, Petkovsek, Boutwell, & Young, 2017), peer group formation (Boutwell, Meldrum, & Petkovsek, 2017), employment opportunities and performance (Gottfredson, 1997), and decision-making processes (Danner, Hagemann, Schankin, Hager, & Funke, 2011).

While not examining recidivism directly, studies that examine the IQ-arrest relationship while controlling for self-reported offending (Beaver et al., 2013; Boccio et al., 2018; Moffitt & Silva, 1988; Yun & Lee, 2013) provide additional preliminary support for association between IQ and recidivism. In perhaps the most well-known study examining this topic, Moffitt and Silva (1988) analyzed a birth cohort from the Dunedin Multidisciplinary Health and Development Study and compared the average IQ scores for subjects who were arrested by age 13 (n = 40) and subjects who had no arrests by age 13 (n = 69). The results indicated no significant differences in IQ between the two groups. Finally, a small number of studies have directly examined the association between IQ and recidivism (Ferguson, Ivory, & Beaver, 2013; Fergusson, Horwood, & Ridder, 2005; Loeber et al., 2012), and, once again, consistently report a negative and significant association.

THE CURRENT STUDY

The current study aims to further examine the potential association between IQ and recidivism using longitudinal data from the Pathways study. While this association has been documented previously, the current study addresses at least three existing limitations in the extant literature. First, while previous studies have employed self-reported offending measures as controls when examining the association between IQ and contact with the criminal justice system (Beaver et al., 2013; Boccio et al., 2018; Moffitt & Silva, 1988; Yun & Lee, 2013), such measures conflate time-varying and time-invariant sources of variance. This limitation is important, as criminal offending is likely the result of a combination of factors, some of which are context specific and vary over time and other time-invariant sources of variance that are unique to the individual. Situation-specific sources of variance may operate differentially than time-invariant, individually-specific sources. Additionally, intelligence has been consistently described as a relatively stable latent trait (Gottfredson, 1997). Based on these observations, and in line with the population heterogeneity perspective, it remains possible that intelligence is one of many factors that constitute variance in criminality. Alternatively, intelligence and criminality may reflect unique, stable sources of individual differences that covary. Making use of a longitudinal structural equation modeling (SEM) approach, the current study distinguishes between time-variant and time-invariant sources of variance in offending.

Second, the current study makes use of arrest measures obtained from official record data as opposed to self-reported arrest measures, which minimize variance stemming from shared methods (i.e., a common reporting source) and reduces measurement error due to recall or desirability bias. Third, while some previous studies examining related research questions have employed longitudinal research designs, many of these studies are limited to early stages of the life course (Moffitt & Silva, 1988) or only examine two time points (Beaver et al., 2013). The current study addresses these limitations by employing monthly life calendar data that include a total of seven years of development spanning from adolescence to early adulthood.

METHODS

Data

The current study analyzes data from the Pathways, a prospective, longitudinal study comprised of a sample of 1,354 previously adjudicated youth from two sites: Maricopa County, Arizona and Philadelphia, Pennsylvania (Mulvey, 2012). Data collection efforts included a baseline interview (wave 1) and 10 additional interview periods spanning a total of 84 months, with waves 2-7 collected at six-month intervals and the subsequent waves (8-11) collected annually. The Pathways team also collected official record information on arrests and court appearances across the entire study period. In addition to the primary interview periods, the Pathways also include monthly life-calendar data for a subset of measures. More information on the collection of the official record measures, life-calendar data, as well as other aspects of the Pathways study, can be found elsewhere (Mulvey et al., 2004; Schubert et al., 2004). The final analytic sample is comprised of 1,331 individuals with valid information on the examined study measures and a total of 3,968 arrests for a total sample size of N = 5,299. Means, proportions, and other descriptive statistics for all study measures are reported in Table 1. All data collection and study procedures pertaining the Pathways study were approved by each participating university's Institutional Review Board (IRB). The IRB at the University of Nebraska Medical Center deemed that the current study was exempt from approval as it involved secondary analysis of deidentified data.

Insert Table 1 about Here

Measures

Intelligence. Intelligence was assessed using the Wechsler Abbreviated Scale of Intelligence (WASI; Wechsler, 1999), which is a validated and widely used measure of intelligence. The WASI is comprised of two subscales—verbal intelligence and matrix reasoning—which are combined to provide full-scale IQ (FSIQ) measure. The WASI was administered on paper during the baseline interview and comprised of a total of 77 items tapping two subtests. The vocabulary subtest (42 items) required participants to orally define four images and 37 words presented both verbally and orally, while the matrix reasoning subtest (35 items) was comprised of incomplete grid patterns that required the participant to select the section that completed each grid from five possible choices. Responses were coded by trained research staff in line with the instructions contained in the WASI administrator manual to provide the full-scale IQ (FSIQ) measure. Importantly, when using the two-subtest version of the instrument provides only the FSIQ score (Wechsler, 1999).

Self-Reported Offending. Self-reported offending was assessed using information reported using the monthly life-calendar portion of the study tapping the number of delinquent and criminal behaviors each participant engaged in during a given month. Participants were provided a visual calendar that contextualized the timing of items around salient events during each recall period. A total of 21 items tapping both violent (e.g., beating someone up so badly it caused serious injury) and nonviolent (e.g., broken into a building to steal something) offending from the self-reported delinquency scale (Huizinga, Esbensen, & Weiher, 1991) were examined.[1] While monthly data were available for all 21 items, some included offenses were exceedingly

[1] The items included in the violent and nonviolent scales were intended to reflect "aggressive" and "income" offending scores created by the Pathways team, with three exceptions. First, two items (forcible rape and murder) were excluded from the violent offending category, as the prevalence of both items was extremely low across each year (< .01%). Second, to eliminate overlapping items in both scales, items tapping taking something by force with or without a weapon were only included in the violent offending category, as these items reflect the use of violence to take something. Third, three additional items were available in the monthly life-calendar data that were omitted from the aggressive and income delinquency measures: carjacking, driving drunk, and carrying a gun. Carjacking was included in the violent offending scale and the remaining two items were included in the nonviolent offending scale.

rare (e.g., setting a fire; shooting someone) and did not occur each month. In an effort to retain these indicators in the final measure, the annual prevalence was derived from the monthly measures, with the final measures coded such that 0 = *did not occur in the past year* and 1 = *happened at least once in the past year*. Factor scores (described in more detail below) were then estimated using the violent and nonviolent items from each year. This approach, which is similar to other scaling techniques (e.g., Rasch models; Osgood, McMorris, & Potenza, 2002), accounts for item severity, more accurately representing the unique contribution of each item.

Rearrest. Rearrest was measured using official record data. Juvenile and adult court record information was collected from information systems at each study site (Philadelphia, PA and Phoenix, AZ). In addition, FBI records were also examined for all study participants to account for arrests that occurred anywhere else in the United States. Due to the analytic strategy employed in the current study (described in more detail below), arrests were coded as the study month in which they occurred, and therefore, represent the number of months since the baseline interview each arrest occurred. For illustrative purposes, the arrest measure is summarized in Table 1 as the sum of all arrests during the study period, wherein participants experienced a minimum of 0 and maximum of 24 arrests, with an average of just over three arrests (M = 3.25, SD = 3.35), over the study period.

Statistical Covariates. To minimize omitted variable bias, a total of seven statistical covariates were also included in the multivariate statistical models. First, impulse control was assessed during the baseline interview using the impulse control subscale of the Weinberger Adjustment Inventory (WAI; Weinberger & Schwartz, 1990). Participants were asked to indicate how closely eight statements tapping behavioral control (e.g., I say the first thing that comes into my mind without thinking about it) resembled their behavior over the past six months, with responses ranging between 1 (*false*) and 5 (*true*). Responses were summed (α = 0.76) such that higher values indicate greater levels of impulse control (*M* = 2.96; SD = .95). Second, to control for exposure time, the number of months incarcerated during the study period was also included in the estimated multivariate models as a covariate. In line with other studies analyzing the Pathways data (Pyrooz, Gartner, & Smith, 2017), incarceration was assessed using monthly life calendar data, in which interviewers recorded the location the study participant resided for the majority of each month. Participants were coded as being incarcerated during a given month (= 1) if participants resided in any of the following locations for the majority of a month: 1) secure juvenile facilities; 2) jail/prison; or 3) detention facilities. Participants who lived in other locations were coded as 0. The total number of months incarcerated was then calculated by summing the monthly dummy indicator variables across all study months. The resulting measure ranged between 0 and 84 months (*M* = 20.09, SD = 22.85).

Third, each participants' parental socioeconomic status (SES) was measured during baseline interviews using Hollingshead's (1971) Index of Social Positions (ISP) which reflects occupational prestige and educational attainment (*M* = 51.41, SD = 12.30). Fourth, an indicator reflecting the two study sites (1 = *Philadelphia* and 2 = *Phoenix*) from which data were collected was included.[2] Finally, three demographic covariates were also included: age (measured continuously in years during the baseline interview); sex (coded dichotomously such that 0 = *female* and 1 = *male*); and race (coded as a series of dummy variables with White as the reference category).

Analytic Strategy

[2] Supplementary models in which the association was stratified across arrests and study sites were also fitted. The overall pattern of results was virtually unchanged.

The analytic strategy for the current study was conducted in three steps. First, in order to examine both violent and nonviolent self-reported criminal behavior across each examined year, confirmatory factor analysis (CFA) was used to create annual violent and nonviolent offending scales. Since the violent and nonviolent offending items were dichotomous, models were estimated using a weighted least squares estimator with robust standard errors and a probit link.[3]

In order to distinguish between offending and the trait of criminality, the second step of the analysis involved the estimation of a latent trait-state-occasion (LTSO) model, which is a longitudinal SEM aimed at partitioning stable and time-varying sources of influence on a given phenotype over time (Cole, Martin, & Steiger, 2005). When panel data are available, the influence of both time-invariant and time-varying sources of influence can be defined as a *state* or "an individual's actual feeling or condition at a particular point in time (*t*)" (Cole et al., 2005, p. 4). The variance of a given state can be defined as

$$S_t = T + O_t \qquad (1)$$

where S_t represents the latent state factor that is defined as the variance of multiple indicators at time *t*. This variance can be decomposed into a stable *trait* factor (T) and a time-specific *occasion* factor (O_t). The stable trait factor is defined as between-individual variance that is stable across the examined time period and the occasion factors represent situational sources of influence that are specific to each examined time point (i.e., within-individual variance over time). As indicated in Equation 1, states at time t would be defined as the collective variance of

[3] While factor scores estimated using continuous indicators typically yield measures with a mean of 0 and variance of 1, this is not the case for factor scores estimated using dichotomous or categorical indicators. Rather than setting the scale of the estimated latent factor to that of a selected continuous indicator, a one-unit change in the estimated latent variable results in a change of lambda (the factor loading) in the underlying continuous latent variable. This results in a change in the probability of the indicator, but is dependent upon the location of the latent variable scale, due to the non-linear association between the latent variable and the probability of changing from one category to the next on a given indicator (Muthén, du Toit, & Spisic, 1997).

both T and O_t. Within the current study, the LTSO model allows for the estimation of a stable criminality trait factor[4] by decomposing variance in the annual violent and nonviolent self-reported delinquency factor scores into a time-invariant and time-specific (and time varying) factors. The resulting criminality trait factor would be comprised of any observed between-individual variance across the examined violent and nonviolent delinquency items that is stable over the examined time period. Alternatively, the occasion factors would be defined as any within-individual variance in the same indicators across the same time period.

A path diagram of the LTSO model is presented in Figure 1. As can be seen in the figure, the factor scores for violent and nonviolent offending are used to measure state factors at each examined time point (annually), which are, in turn, decomposed into the single latent-trait factor (T) and the time-specific occasion factors (O_t).[5] As with previous studies employing LTSO models (Cole et al., 2005), and to aid in model convergence, a series of additional model

[4] We acknowledge that the term "trait" is often used to convey endogenous, stable sources of variance. The trait factor discussed above and derived from the estimated LTSO model captures time-invariant, stable sources of inter-individual differences, but such differences are expected to be comprised of both endogenous and exogenous sources of variation across the study period. In this way, the term *trait* in this context, and as used in the current study (i.e., criminality trait), refers only to the latent trait factor captured by the LTSO model.

[5] Based on simulation results from two studies (Ciesla, Cole, & Steiger, 2007; Cole et al., 2005), the use of two indicator measures per examined time period is acceptable and preferable over using a single item (e.g., combining the violent and nonviolent factor scores at each time period). The latter strategy would prevent the estimation of an LTSO model and require the use of a less desirable strategy (e.g., a trait state error model). While the use of only two indicators is not ideal, previous studies have indicated that such an approach is only problematic under specific conditions, like when factor loadings are small or when the variance captured by the estimated trait term was extremely high or low (Ciesla et al., 2007). While such conditions do not seem to apply for the current study, we estimated a supplementary set of models to ensure the robustness of our results. The LTSO model was estimated using the violent and nonviolent indicators as described for the primary analysis, but the time-varying impulsivity measure was also included as a third indicator (we are grateful to one of the anonymous reviewers for this suggestion). All other analyses were reestimated with this alternatively specified trait factor. The results of the models were virtually identical to the results from the primary analysis.

constraints were also applied.[6] First, an autoregressive function was applied to the occasion factors in which the resulting coefficients were fixed to equality. Second, the factor loadings of each indicator were fixed to equality over time. Since the LTSO model does not involve mean structures, previous studies have indicated that intercept invariance is unnecessary (Conway, Rutter, & Brown, 2016), but constraining the intercepts to equality across measurement periods did not worsen overall fit ($\Delta\chi^2 = 9.25(12)$, $p = .68$) or result in any substantive changes to results from the subsequent analysis. Finally, the residual variances for all time-specific state factors were fixed to zero, as all of the variance at each state should be decomposed into either the trait factor or the corresponding time-specific occasion factor.

Insert Figure 1 about Here

After the estimation of the LTSO model, the criminality trait factor can be used in subsequent analyses as an exogenous or endogenous variable. This is an important extension, as the resulting trait factor is parsed of any time-varying variance, effectively isolating time-invariant variance. This approach offers a distinct advantage, as the underlying trait estimated in the LTSO model would better approximate stable, individualized latent sources of variance that collectively contribute to criminal behavior. The LTSO model (as well as the offending measurement models) were estimated in M*plus* 8.2 (Muthén & Muthén, 2017) and model fit was

[6] It is worth noting that these additional constraints are not necessarily reflected in the standardized results (but are in the unstandardized results). This is due to the manner in which M*plus* standardizes coefficients, which are calculated as,

$$b_{StdYX} = b\left(\frac{SD(x)}{SD(y)}\right)$$

where b is the unstandardized path coefficient, $SD(x)$ is the sample standard deviation of x (the independent or exogenous variable), and $SD(y)$ is the model estimated standard deviation of y (the dependent or endogenous variable; Muthén & Muthén, 2017, p. 722). Since different standard deviations are used to compute the standardized coefficients, that is $SD(x)$, the resulting standardized values may differ despite equal unstandardized coefficients. In order to ease interpretation, standardized coefficients are reported in Figure 3, which do not necessarily reflect the imposed constraints applied to the model.

assessed using multiple indices (Hu & Bentler, 1999): comparative fit index (CFI); Tucker-Lewis index (TLI); and root mean square error of approximation (RMSEA). Missing values were handled using full information maximum likelihood (FIML).

The third step of the analysis was aimed at comparing the association between IQ and criminality with the association between IQ and rearrest. This step of the analysis is aimed at examining the potential distinction of the two associations, as a significant difference between them would provide preliminary evidence of IQ exerting a unique influence on recidivism above and beyond additional time-stable variance in self-reported offending. A path model aimed at simultaneously examining both pathways was estimated in which the total number of arrests across the study period was regressed on IQ and all other study covariates. This same model contained a second pathway in which the latent criminality factor was regressed on IQ and all other covariates. For paths examining the total number of arrests (an overdispersed count) as an endogenous variable, negative binomial regression was used. A *z*-score was used to compare the two paths. In order to further distinguish variance in IQ explained by criminality and rearrest, a linear regression model in which IQ is regressed on the total number of arrests across the study period and the latent criminality measure, along with all covariates, was also estimated.

The fourth and final step of the analysis was aimed at more closely assessing the longitudinal associations involving intelligence, criminality, and the probability of rearrest while controlling for all other covariates. In order to examine these associations across the examined timeframe, survival analysis was used. Since it was possible for each participant to experience multiple failures (i.e., arrests) over the examined time period, a series of Prentice-Williams-Peterson (PWP) models or "total time conditional models" were fitted (Box-Steffensmeier & Zorn, 2002; Prentice, Williams, & Peterson, 1981). This approach is appropriate for situations in which multiple failures may occur in the examined timeframe and differentiates between each failure by stratifying across the total number of failures (Prentice et al., 1981). In this way, a first arrest is distinguished from a second, which is distinguished from a third, and so on, but allows for the possibility that the probability of arrest may be correlated across more multiple arrests. This seems reasonable in the context of the current study, as a second (or fourth) arrest is likely to be directly impacted by previous interactions with the criminal justice system and law enforcement. Directly in line with this observation, previous studies examining arrests as an outcome have also employed PWP models (Kretschmar, Tossone, Butcher, & Marsh, 2018; Larney, Toson, Burns, & Dolan, 2012; Metcalfe & Baker, 2014). PWP models were fitted using an elapsed time approach using Stata MP 15.1 (StataCorp, 2017).

RESULTS

The first step in the analysis involved the estimation of two longitudinal CFA models, one for the annual violent offending measures and another for the nonviolent offending measures. As a preliminary step, measurement invariance of violent and nonviolent offending across the study period was tested. The estimated LTSO model assumes at least partial measurement invariance over time, as time-specific measurement characteristics may be conflated with meaningful change. A series of models were estimated for both sets of offending measures. First, a baseline model in which factor loadings were freed was fitted. Next, a model in which loadings were fixed to equality across measurement periods was estimated. In all models, error terms of the same offense across measurement periods and all latent variables were allowed to covary. Since both the baseline and nested models were estimated with a weighted least squares estimator and robust standard errors, the resulting Satorra-Bentler scaled χ^2 is not suitable for χ^2 difference testing (Satorra, 2000). Instead, a specialized procedure developed by

Satorra and Bentler (2010) that employs a scaling correction factor was used to compare changes in overall fit between the baseline and nested models.

For the violent offending items, constraining all loadings to equality worsened overall fit ($\Delta\chi^2(61) = 145.67$, $p < .001$). However, subsequent analyses in line with suggestions offered by Byrne, Shavelson and Muthén (1989) in which some loadings were freed, resulted in a nonsignificant change in overall fit ($\Delta\chi^2(46) = 50.77$, $p = .291$). The freed loadings followed no specific pattern and were nearly identical to the constrained loadings. The resulting model provided an adequate fit to the data (CFI = .920, TLI = .911, RMSEA = .019). The same procedures were employed for the nonviolent offending measures. Once again, constraining all loadings to equality over time worsened overall fit ($\Delta\chi^2(61) = 151.65$, $p < .001$), but freeing some loadings improved fit ($\Delta\chi^2(48) = 47.28$, $p = .502$), with the final model fitting the data closely (CFI = .977, TLI = .974, RMSEA = .012). As with the violent offending measures, none of the nonviolent offending measures appeared problematic. Following suggestions outlined in previous studies (Byrne et al., 1989), including those estimating LTSO models (Cole et al., 2017; Conway et al., 2016), the patterns of measurement nonequivalence detected in the longitudinal CFA models were retained before extracting the time specific factor scores from each model.[7]

The second step of the analysis involved the estimation of a LTSO model. The resulting model fit the data closely (CFI = .986; TLI = .971; RMSEA = .061) and the results, including standardized path coefficients, are presented in Figure 1. The factor loadings for the trait factor were used to create a criminality factor score, which was included in the subsequent analyses.

[7] Factor score determinacy coefficients (i.e., the correlation between the estimated factors and factor scores) were not available due to the use of a weighted least squares estimator, but supplemental analysis making use of maximum likelihood estimation (with robust standard errors) resulted in determinacy coefficients that ranged between .992 (violent offending at Time 1) and .998 (nonviolent offending at Time 7 and 8).

The factor score determinacy coefficient (i.e., the correlation between the estimated factor and the factor score) for the resulting trait factor was .878, just below the recommended cut-off of .90 suggested by Beauducel (2011).

The third step of the analysis involved the estimation of a path model aimed at simultaneously examining the association between IQ and criminality as well as the association between IQ and rearrest. The estimated model is presented in Figure 2 along with accompanying path estimates. The results revealed an association between IQ and criminality but in the opposite direction of what was expected (b = .08; *95% CI* = .03, .13), indicating that increases in intelligence were associated with increased levels of criminality. The results also revealed an association between intelligence and the overall number of arrests during the study period (b = -.06, *95% CI* = -.12, -.01), indicating that lower levels of IQ were associated with a greater number of rearrests during the study period. A z-score was used to compare these two path coefficients and revealed a significant difference ($z = 4.24$, $p < .001$), providing preliminary evidence that the association between IQ and rearrest is distinct from any potential association between IQ and criminality.

Insert Figure 2 about Here

Tto better distinguish between the variance in intelligence explained by rearrest and criminality, a linear regression model in which intelligence was regressed on the latent criminality measure and the total number of rearrests during the study period (along with all covariates) was estimated. The results are presented in Table 2 and revealed a positive association between criminality and intelligence (b = .10, *95% CI* = .04, .15) as well as a negative, but small, association between the total number of arrests and intelligence (b = -.02, *95% CI* = -.04, -.01).

Insert Table 2 about Here

The results of the analysis thus far suggest that the association between IQ and rearrest is unique from the association between criminality and rearrest. The fourth and final step of the analysis was aimed at further probing these findings with a series of PWP models. Prior to fitting the multivariable model, the bivariate association between IQ and rearrest was examined by plotting the survival function (i.e., the proportion of the sample that has not recidivated) during each study month and presented in Figure 3. The figure presents the survival function for participants scoring one standard deviation below the grand mean, at the grand mean, and one standard deviation above the grand mean on the IQ measure. The survival curves follow a pattern suggesting a negative association between IQ and rearrest, such that those scoring one standard deviation below the grand mean have a higher risk of rearrest and those scoring one standard deviation above the grand mean with a lower risk of rearrest. However, a closer examination of the survival curves indicates that the resulting association is small in magnitude as all three curves are tightly clustered. A similar approach was taken for criminality, with the results presented in Figure 4. The results suggest a positive longitudinal association such that those with a criminality score one standard deviation above the mean display greater risk of arrest and those with a score one standard deviation below the mean display lower risk.

Insert Figure 3 about Here

Insert Figure 4 about Here

Based on these findings, a series of PWP models were fitted to further examine the longitudinal association between IQ and the risk of rearrest while controlling for the criminality trait measure and all other covariates, with the results presented in Table 3. The first model (labeled Model 1) examined the association between IQ and the hazard rate of rearrest while controlling for the examined covariates (excluding criminality). The results indicated a small and negative association between IQ and rearrest (*b* = -.04, *95% CI* = -.07, -.001), wherein a one standard deviation increase in IQ resulted in a 4% ($[e^{.04} - 1] \times 100$) decrease in the hazard of rearrest. In this way, individuals with lower IQ scores were only slightly more likely to recidivate compared to individuals with higher IQ scores. The second model (Model 2) was identical to the first, but also included the criminality measure. While the criminality measure was associated with rearrest (*b* = .18, *95% CI* = .14, .21), the negative association between IQ and rearrest persisted but remained small in magnitude (*b* = -.05, *95% CI* = -.09, -.02).

Insert Table 3 about Here

Supplemental Analyses

To examine the robustness of the results from the PWP models, three sets of supplementary analyses were conducted. First, as indicated in the descriptive statistics presented in Table 1, there were a number of participants included in the final analytic with a WASI score that fell two or more standard deviations below the grand mean (*n* = 39). To examine the extent to which these outliers exerted influence, these models were reestimated with outliers excluded. The results from these supplemental models were largely similar to the primary analysis with one important exception. In the baseline model examining the association between IQ and rearrest (but excluded the latent criminality measure), the magnitude of the association between IQ and rearrest remained consistent with the primary analysis, but the accompanying 95% confidence interval included one (*HR* = .96, *95% CI* = .93, 1.00). The results of these supplemental models, along with the results from all other supplemental analyses discussed below, are presented in the accompanying online information.

Second, the PWP models were estimated a second time, but the elapsed time approach was replaced with the gap time approach, which resets time to zero after each arrest, allowing for the modeling of time between arrests rather than the time to each arrest (Box-Steffensmeier & Zorn, 2002). The results of the models employing the gap time approach directly align with those reported in the primary analysis wherein the baseline association between IQ and rearrest was negative, but small in magnitude (*HR* = .96, *95% CI* = .93-.99). Adding the latent criminality measure (*HR* = 1.18, *95% CI* = 1.14, 1.22) revealed a similar pattern of results (*HR* = .95, *95% CI* = .91-.98).

Third, a set of multilevel logistic regression models that accounted for repeated measures of the same constructs across time were estimated. The annual violent and nonviolent factor scores included in the LTSO model were included in the multilevel models along with the IQ measure. To maintain consistency in the examined timeframe, arrest measures were pooled across 12-month intervals (0 = *no arrests* and 1 = *one or more arrests*). The same set of statistical covariates included in the PWP models were also included in the multilevel models, with two minor exceptions. To control for time-stable variance, all time-varying covariates were group-mean centered. Second, to account for the mean trajectory of arrest across the study period, a quadratic time trend term was also included. The results of the supplementary models indicated that lower IQ scores (*OR* = .84, *95% CI* = .77, .93) and within-individual increases in nonviolent offending (*OR* = 3.85, *95% CI* = 3.27, 4.52) were associated with a greater likelihood of rearrest. However, within-individual changes in violent offending (*OR* = 1.01, *95% CI* = .85, 1.19) and impulse control (*OR* = 1.03, *95% CI* = .85, 1.19) were not associated with rearrest.

DISCUSSION

The current study aimed to compare the influence of IQ with a latent measure of criminality that captures stable inter-individual differences on recidivism (or rearrest) in an effort to examine the extent to which both factors uniquely contribute to variation in rearrest over time. Findings from the Pathways study indicated that even after controlling for the covariance between rearrest and the latent trait of criminality, both measures were associated with IQ. A similar pattern of results was observed from a path model directly comparing the associations and revealing a substantive difference. One particularly interesting, and unexpected, finding from both of these models was a positive association between IQ and the latent trait of criminality, which indicates that those with greater IQ scores also displayed greater levels of criminality. While a limited number of previous studies have reported a positive association between IQ and criminal behavior (Oleson, 2016), this pattern of findings is unique and the majority of previous studies have reported a negative association.

While only speculative, this unexpected result may be a consequence of examining such a unique population, as the Pathways is comprised of a sample of high risk, previously adjudicated youth. It remains possible that such a population may exhibit a unique concentration of various traits, behaviors, and characteristics that ultimately translate into different correlational patterns than what is observed in a more representative sample. In line with this possibility, the majority of previous studies reporting a negative correlation between IQ and offending are based on more generalizable samples or cohorts (Beaver et al., 2013; Loeber et al., 2012; Moffitt et al., 1981; Schwartz et al., 2015), while the primary study reporting a positive association was performed with a high risk sample of incarcerated individuals (Oleson, 2016). Another possibility stems from the current study's focus on *criminality* rather than *criminal offending*. It is possible that the time-varying and time-invariant portions of offending differentially correlate with IQ, suggesting both sources of variance have overlapping, but distinct, etiological properties. For example, it is possible that occasion-specific variance (i.e., time-varying sources of variance) in offending may suppress the overall association between IQ and offending, resulting in a negative association. Finally, it is important to keep in mind that the outcome examined in the current study was *rearrest* as all study participants were initially arrested prior to being enrolled in the study. In this way, it remains possible that if IQ is associated with *initial* arrest, high IQ individuals in the current sample may also differentially possess other traits (e.g., lower conscientiousness) that increase the likelihood of initial arrest. The estimates presented for rearrest, therefore, may represent a lower bound estimate of the association if the model had not been selected on the basis of initial arrest. These possibilities remain speculation and future research aimed at disentangling them, as well as the generalizability of the findings from the current study, is warranted.

Another key finding from the current study is that the association between lower IQ scores and rearrest is distinct from the association between IQ and the latent trait of criminality. This pattern of results stemmed primarily from the regression and path models, but was also reflected in the PWP models, which revealed a negative association between IQ and the hazard of rearrest and positive association between the latent trait of criminality and rearrest. This association, however, should be interpreted carefully, as the size of the effect of IQ on rearrest was quite small (HR = .95). This finding is further illustrated in Figure 3, wherein the survival curves for participants at the grand mean closely resemble the curves for those that fall one standard deviation above or below the mean. Based on the small magnitude of the association between IQ and rearrest observed in the PWP models, and the well powered sample employed, these results indicate that IQ has limited influence on rearrest in the examined sample.

Importantly, these findings do not align with previous studies examining associations between arrest more broadly (Beaver et al., 2013; Boccio et al., 2018) and recidivism more specifically (Ferguson et al., 2013; Fergusson et al., 2005; Loeber et al., 2012). The primary source of the discrepancy in these findings remains unknown, but the current study provides the most robust and comprehensive examination of these associations to date, addressing many limitations of previous studies. Future research would benefit from examining such differences more closely. One potential avenue that may be fruitful in this regard would be to better identify the underlying mechanisms that ultimately differentiate intelligence from additional sources of variance that constitute the underlying latent trait of criminality. As mentioned above, previous studies have reported associations between intelligence and other correlates of crime (Boutwell et al., 2017; Danner et al., 2011; Gottfredson, 1997; Meldrum et al., 2017), but the extent to which these correlates covary with intelligence, criminality, or a combination of the two has not yet been examined. Such an investigation would shed light on the extent to which such factors contribute to the development of intelligence, criminality, or both.

Despite these contributions to the existing literature, the current study is not without its own limitations and the reported findings should be interpreted in light of at least four observations. First, the Pathways study only assessed IQ at one time point (the baseline interview). Multiple measures of IQ would have allowed for additional modeling strategies aimed at distinguishing between time-stable and time-varying variance within IQ scores over the study period (e.g., LTSO or multilevel models). Even so, multiple studies have found moderate to large stability coefficients (ranging from .50 to .60) when examining within-variability in IQ scores over time (for a recent summary, see Deary, 2014). Second, and directly related, the Pathways only includes a comprehensive, or full-scale, IQ measure, while previous studies have explicitly noted the importance of examining multiple domains of *g* (e.g., verbal IQ scores vs. working memory; Nisbett et al., 2012). However, much like the observed stability in IQ scores over time, previous studies have noted the overlap in performance and scoring in multiple tests that are "highly *g* loading" or have been found to be robust indicators of general intelligence (Johnson, te Nijenhuis, & Bouchard, 2008). Despite these findings, future research would certainly benefit from the examination of additional samples that contain repeated measures of full-scale IQ as well as other domains of *g* over an extended period of time.

Third, while the LTSO approach takes into account latent sources of variation that collectively contribute to intra-individual stability in criminal behavior over a specified timeframe, future research may benefit from disentangling such factors in an effort to better understand what specific sources of influence or theoretical processes ultimately contribute to individual differences in criminality. While such an inquiry could potentially illuminate the processes that contribute to both time-specific and time-stable sources of variance in criminal behavior, these questions fall outside the primary goals of the current study. Fourth, while the Pathways offers many unique advantages, it is based on a previously adjudicated sample of youth, and, therefore, may not generalize to a larger population. Additionally, a more criminogenic or high-risk sample offers other unique challenges (as discussed above). For example, correlations may exist within such samples that are not typically observed in more generalizable samples (e.g., higher levels of IQ may be associated with traits like conscientiousness and low agreeableness), and this particular limitation may undergird the positive association between IQ and criminality observed in the current study. In this way, future research would benefit from examining the extent to which the pattern of findings reported in the current study generalize to larger, more diverse populations.

With these limitations in mind, the results of the current study add a wrinkle to the existing literature focused on the association between IQ and offending. Our findings indicate that after taking into account the latent trait of criminality (and a host of additional covariates) the longitudinal association between IQ and rearrest is quite small, and perhaps even nonexistent. This pattern of results, however, does not "close the book" on concept of intelligence in criminological theorizing. To the contrary, these findings raise new questions surrounding intelligence and offending, focused on the etiological development of both concepts as well as any covariance between them. The complexity of such questions increases rapidly as we begin to consider time-varying versus time-invariant sources of variance, longitudinal patterns, and more unique samples. These questions, and their accompanying complexity, lead us to echo previous calls for greater attention directed toward the concept of intelligence in criminological theorizing. Both classic (Hirschi & Hindelang, 1977) and more contemporary studies (Beaver et al., 2013; McGloin et al., 2004; Mears & Cochran, 2013; Schwartz et al., 2015) have recognized the importance of the further exploration of intelligence in the etiological development of criminal offending and we concur. Much remains left to unpack and as the various ways in which intelligence and offending covary become more clear, fuller explanations of offending become possible better informing theory and future research.

References

Alper, M., Durose, M. R., & Markman, J. (2018). *Special Report 2018 Update on Prisoner Recidivism: A 9-Year Follow-up Period (2005-2014)*. Retrieved from https://www.bjs.gov/content/pub/pdf/18upr9yfup0514.pdf

Beauducel, A. (2011). Indeterminacy of Factor Score Estimates In Slightly Misspecified Confirmatory Factor Models. *Journal of Modern Applied Statistical Methods*, *10*(2), 583–598. https://doi.org/10.22237/jmasm/1320120900

Beaver, K. M., Schwartz, J. A., Nedelec, J. L., Connolly, E. J., Boutwell, B. B., & Barnes, J. C. (2013). Intelligence is associated with criminal justice processing: Arrest through incarceration. *Intelligence*, *41*(5), 277–288. https://doi.org/10.1016/j.intell.2013.05.001

Becker, H. S. (1963). *Outsiders: Studies in the Sociology of Deviance*. New York: Free press.

Berg, M. T., & Huebner, B. M. (2011). Reentry and the ties that bind: An examination of social ties, employment, and recidivism. *Justice Quarterly*, *28*(2), 382–410. https://doi.org/10.1080/07418825.2010.498383

Boccio, C. M., Beaver, K. M., & Schwartz, J. A. (2018). The role of verbal intelligence in becoming a successful criminal: Results from a longitudinal sample. *Intelligence*, *66*. https://doi.org/10.1016/j.intell.2017.10.003

Boutwell, B. B., Meldrum, R. C., & Petkovsek, M. A. (2017). General intelligence in friendship selection: A study of preadolescent best friend dyads. *Intelligence*, *64*, 30–35. https://doi.org/10.1016/j.intell.2017.07.002

Box-Steffensmeier, J. M., & Zorn, C. (2002). Duration models for repeated events. *Journal of Politics*, *64*(4), 1069–1094. https://doi.org/10.1111/1468-2508.00163

Byrne, B. M., Muthèn, B. O., & Shavelson, R. J. (1989). Testing the Equivalence of Factor

Covariance and Mean Structure: The Issue of Partial Measurement Invariance. *Psychological Bulletin*, *105*(3), 456–466. https://doi.org/10.1037/0033-2909.105.3.456

Cantor, J. M., Blanchard, R., Robichaud, L. K., & Christensen, B. K. (2005). Quantitative reanalysis of aggregate data on IQ in sexual offenders. *Psychological Bulletin*, *131*(4), 555–568. https://doi.org/10.1037/0033-2909.131.4.555

Chiricos, T. G., & Waldo, G. P. (1975). Socioeconomic Status and Criminal Sentencing: An Empirical Assessment of a Conflict Proposition. *American Sociological Review*, *40*(6), 753–772. https://doi.org/10.2307/2094178

Ciesla, J. A., Cole, D. A., & Steiger, J. H. (2007). Extending the trait-state-occasion model: How important is within-wave measurement equivalence? *Structural Equation Modeling*, *14*(1), 77–97. https://doi.org/10.1207/s15328007sem1401_4

Clark, V. A. (2016). Predicting Two Types of Recidivism Among Newly Released Prisoners: First Addresses as “Launch Pads” for Recidivism or Reentry Success. *Crime and Delinquency*, *62*(10), 1364–1400. https://doi.org/10.1177/0011128714555760

Clower, C. E., & Bothwell, R. K. (2001). An Exploratory Study of the Relationship between the Big Five and Inmate Recidivism. *Journal of Research in Personality*, *35*(2), 231–237. https://doi.org/10.1006/jrpe.2000.2312

Cochran, J. C. (2014). Breaches in the Wall: Imprisonment, Social Support, and Recidivism. *Journal of Research in Crime and Delinquency*, *51*(2), 200–229. https://doi.org/10.1177/0022427813497963

Cole, D. A., Martin, J. M., Jacquez, F. M., Tram, J. M., Zelkowitz, R., Nick, E. A., & Rights, J. D. (2017). Time-varying and time-invariant dimensions of depression in children and adolescents: Implications for cross-informant agreement. *Journal of Abnormal Psychology*, *126*(5), 635–651. https://doi.org/10.1037/abn0000267

Cole, D. A., Martin, N. C., & Steiger, J. H. (2005). Empirical and conceptual problems with longitudinal trait-state models: Introducing a trait-state-occasion model. *Psychological Methods*, *10*(1), 3–20. https://doi.org/10.1037/1082-989X.10.1.3

Colins, O., Vermeiren, R., Vahl, P., Markus, M., Broekaert, E., & Doreleijers, T. (2011). Psychiatric Disorder in Detained Male Adolescents as Risk Factor for Serious Recidivism. *The Canadian Journal of Psychiatry*, *56*(1), 44–50. https://doi.org/10.1177/070674371105600108

Conway, C. C., Rutter, L. A., & Brown, T. A. (2016). Chronic environmental stress and the temporal course of depression and panic disorder: A trait-state-occasion modeling approach. *Journal of Abnormal Psychology*, *125*(1), 53–63. https://doi.org/10.1037/abn0000122

Danner, D., Hagemann, D., Schankin, A., Hager, M., & Funke, J. (2011). Beyond IQ: A latent state-trait analysis of general intelligence, dynamic decision making, and implicit learning. *Intelligence*, *39*(5), 323–334. https://doi.org/10.1016/j.intell.2011.06.004

Deary, I. J. (2014). The Stability of Intelligence From Childhood to Old Age. *Current Directions in Psychological Science*, *23*(4), 239–245. https://doi.org/10.1177/0963721414536905

Diamond, B., Morris, R. G., & Barnes, J. C. (2012). Individual and group IQ predict inmate violence. *Intelligence*, *40*(2), 115–122. https://doi.org/10.1016/j.intell.2012.01.010

Dwyer, R. G., & Frierson, R. L. (2006). The presence of low IQ and mental retardation among murder defendants referred for pretrial evaluation. *Journal of Forensic Sciences*, *51*(3), 678–682. https://doi.org/10.1111/j.1556-4029.2006.00115.x

Farrington, D. P. (1973). Self-Reports of Deviant Behavior: Predictive and Stable? *The Journal of Criminal Law and Criminology*, *64*(1), 99–110. https://doi.org/10.2307/1142661

Farrington, D. P., & West, D. J. (1971). A comparison between early delinquents and young aggressives. *British Journal of Criminology*, *11*(4), 341–358. https://doi.org/10.1093/oxfordjournals.bjc.a046332

Ferguson, C. J., Ivory, J. D., & Beaver, K. M. (2013). Genetic, maternal, school, intelligence, and media use predictors of adult criminality: A longitudinal test of the catalyst model in adolescence through early adulthood. *Journal of Aggression, Maltreatment and Trauma*, *22*(5), 447–460. https://doi.org/10.1080/10926771.2013.785457

Fergusson, D. M., Horwood, L. J., & Ridder, E. M. (2005). Show me the child at seven II: Childhood intelligence and later outcomes in adolescence and young adulthood. *Journal of Child Psychology and Psychiatry and Allied Disciplines*, *46*(8), 850–858. https://doi.org/10.1111/j.1469-7610.2005.01472.x

Gottfredson, L. S. (1997). Why g matters: The complexity of everyday life. *Intelligence*, *24*(1), 79–132. https://doi.org/10.1016/s0160-2896(97)90014-3

Gottfredson, L. S. (2008). Of what value is intelligence? In A. Prifitera, D. Saklofske, & L. G. Weiss (Eds.), *WISC-IV applications for clinical assessement and intervention*. Amsterdam: Elsevier.

Gottfredson, M. R., & Hirschi, T. (1990). *A General Theory of Crime*. Stanford: Stanford University Press.

Hagan, J., & Dinovitzer, R. (2005). Collateral Consequences of Imprisonment for Children, Communities, and Prisoners. *Crime and Justice*, *26*, 121–162. https://doi.org/10.1086/449296

Hare, R. D. (1999). Psychopathy as a risk factor for violence. *Psychiatric Quarterly*, *70*(3), 181–197. https://doi.org/10.1023/A:1022094925150

Hirschi, T., & Hindelang, M. J. (1977). Intelligence and Delinquency : A Revisionist Review. *American Sociological Review*, *42*(4), 571–587. https://doi.org/10.2307/2094556

Hodgins, S. (1992). Mental Disorder, Intellectual Deficiency, and Crime: Evidence from a Birth Cohort. *Archives of General Psychiatry*, *49*(6), 476–483. https://doi.org/10.1001/archpsyc.1992.01820060056009

Hollingshead, A. B. (1971). Commentary on The Indiscriminate State of Social Class Measurement. *Social Forces*, *49*, 563–567.

Holtfreter, K., Reisig, M. D., & Morash, M. (2006). Poverty, State Capital, and Recidivism Among Women Offenders. *Criminology & Public Policy*, *3*(2), 185–208. https://doi.org/10.1111/j.1745-9133.2004.tb00035.x

Hosser, D., Windzio, M., & Greve, W. (2008). Guilt and shame as predictors of recidivism: A longitudinal study with young prisoners. *Criminal Justice and Behavior*, *35*(1), 138–152. https://doi.org/10.1177/0093854807309224

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huizinga, D., Esbensen, F.-A., & Weiher, A. W. (1991). Are There Multiple Paths to Delinquency? *The Journal of Criminal Law and Criminology*, *82*(1), 83. https://doi.org/10.2307/1143790

Illinois Sentencing Policy Advisory Council. (2015). *Illinois Results First: The High Cost of Recidivism*. Retrieved from http://www.icjia.state.il.us/spac/index.cfm?metasection=publications.

Johnson, W., te Nijenhuis, J., & Bouchard, T. J. (2008). Still just 1 g: Consistent results from five test batteries. *Intelligence*, *36*(1), 81–95. https://doi.org/10.1016/j.intell.2007.06.001

Kearns, A., & O'Connor, A. (1988). The Mentally Handicapped Criminal Offender a 10–year Study of Two Hospitals. *British Journal of Psychiatry*, *152*(6), 848–851. https://doi.org/10.1192/bjp.152.6.848

Kretschmar, J. M., Tossone, K., Butcher, F., & Marsh, B. (2018). Examining the impact of a juvenile justice diversion program for youth with behavioral health concerns on early adulthood recidivism. *Children and Youth Services Review*, *91*, 168–176. https://doi.org/10.1016/j.childyouth.2018.06.010

Kubrin, C. E., & Stewart, E. A. (2006). Predicting who reoffends: The neglected role of neighborhood context in recidivism studies. *Criminology*, *44*(1), 165–197. https://doi.org/10.1111/j.1745-9125.2006.00046.x

Larney, S., Toson, B., Burns, L., & Dolan, K. (2012). Effect of prison-based opioid substitution treatment and post-release retention in treatment on risk of re-incarceration. *Addiction*, *107*(2), 372–380. https://doi.org/10.1111/j.1360-0443.2011.03618.x

Lemert, E. M. (1951). *Social Pathology: A Systematic Approach to the Theory of Sociopathc Behavior* (McGraw-Hil). New York.

Liberman, A. M., Kirk, D. S., & Kim, K. (2014). Labeling effects of first juvenile arrests: Secondary deviance and secondary sanctioning. *Criminology*, *52*(3), 345–370. https://doi.org/10.1111/1745-9125.12039

Loeber, R., Menting, B., Lynam, D. R., Moffitt, T. E., Stouthamer-Loeber, M., Stallings, R., … Pardini, D. (2012). Findings from the Pittsburgh youth study: Cognitive impulsivity and intelligence as predictors of the age-crime curve. *Journal of the American Academy of Child and Adolescent Psychiatry*, *51*(11), 1136–1149. https://doi.org/10.1016/j.jaac.2012.08.019

Lynam, D., Moffitt, T., & Stouthamer-Loeber, M. (1993). Explaining the relation between IQ and delinquency: class, race, test motivation, school failure, or self-control? *Journal of Abnormal Psychology*, *102*(2), 187–196. https://doi.org/10.1037/0021-843X.102.4.552

Malouf, E. T., Schaefer, K. E., Witt, E. A., Moore, K. E., Stuewig, J., & Tangney, J. P. (2014). The Brief Self-Control Scale Predicts Jail Inmates' Recidivism, Substance Dependence, and Post-Release Adjustment. *Personality and Social Psychology Bulletin*, *40*(3), 334–347. https://doi.org/10.1177/0146167213511666

Matsueda, R. L. (2002). Reflected Appraisals, Parental Labeling, and Delinquency: Specifying a Symbolic Interactionist Theory. *American Journal of Sociology*, *97*(6), 1577–1611. https://doi.org/10.1086/229940

McGloin, J. M., Pratt, T. C., & Maahs, J. (2004). Rethinking the IQ-delinquency relationship: A longitudinal analysis of multiple theoretical models. *Justice Quarterly*, *21*(3), 603–635. https://doi.org/10.1080/07418820400095921

Mears, D. P., & Cochran, J. C. (2013). What is the effect of IQ on offending? *Criminal Justice and Behavior*, *40*(11), 1280–1300. https://doi.org/10.1177/0093854813485736

Mears, D. P., Wang, X., Hay, C., & Bales, W. D. (2008). Social ecology and recidivism: Implications for prisoner reentry. *Criminology*, *46*(2), 301–340. https://doi.org/10.1111/j.1745-9125.2008.00111.x

Meldrum, R. C., Petkovsek, M. A., Boutwell, B. B., & Young, J. T. N. (2017). Reassessing the relationship between general intelligence and self-control in childhood. *Intelligence*, *60*, 1–9. https://doi.org/10.1016/j.intell.2016.10.005

Metcalfe, C. F., & Baker, T. (2014). The Drift From Convention to Crime: Exploring the Relationship Between Co-Offending and Intermittency. *Criminal Justice and Behavior*, *41*(1), 75–90. https://doi.org/10.1177/0093854813500775

Moffitt, T. E., Gabrielli, W. F., Mednick, S. A., & Schulsinger, F. (1981). Socioeconomic status, IQ, and delinquency. *Journal of Abnormal Psychology*, *90*(2), 152–156. https://doi.org/10.1037/0021-843X.90.2.152

Moffitt, T. E., & Silva, P. A. (1988). IQ and Delinquency: A Direct Test of the Differential Detection Hypothesis. *Journal of Abnormal Psychology*, *97*(3), 330–333. https://doi.org/10.1037/0021-843X.97.3.330

Mulder, E., Brand, E., Bullens, R., & Van Marle, H. (2010). A classification of risk factors in serious juvenile offenders and the relation between patterns of risk factors and recidivism. *Criminal Behaviour and Mental Health*, *20*(1), 23–28. https://doi.org/10.1002/cbm.754

Mulder, E., Brand, E., Bullens, R., & Van Marle, H. (2011). Risk factors for overall recidivism and severity of recidivism in serious juvenile offenders. *International Journal of Offender Therapy and Comparative Criminology*, *55*(1), 118–135. https://doi.org/10.1177/0306624X09356683

Mulvey, E. P. (2012). Research on Pathways to Desistance [Maricopa County, AZ and Philadelphia County, PA]: Subject Measures, 2000-2010 ICPSR29961-v2 2012-08-20 2013 Inter-university Consortium for Political and Social Research (ICPSR).

Mulvey, E. P., Steinberg, L., Fagan, J., Cauffman, E., Piquero, A. R., Chassin, L., … Losoya, S. H. (2004). Theory and Research on Desistance from Antisocial Activity among Serious Adolescent Offenders. *Youth Violence and Juvenile Justice*, *2*(3), 213–236. https://doi.org/10.1177/1541204004265864

Muthén, B. O., du Toit, S. H. C., & Spisic, D. (1997). Robust inference using weighted least squares and quadratic estimating equation in latent variable modeling with categorical and continuous outcomes. Unpublished technical appendix.

Muthén, L. K., & Muthén, B. O. (2017). *Mplus: Statistical analysis with latent variables. User's guide* (8th ed.). Los Angeles, CA: Muthén & Muthén.

Nagin, D. S., Farrington, D. P., & Moffitt, T. E. (1995). Life-course trajectories of different types of offenders. *Criminology*, *33*(1), 111–139. https://doi.org/10.1111/j.1745-9125.1995.tb01173.x

Nagin, D. S., & Paternoster, R. (1991). On the relationship of past to future participation in delinquency. *Criminology*, *29*(2), 163–189. https://doi.org/10.1111/j.1745-9125.1991.tb01063.x

Nagin, D. S., & Paternoster, R. (2000). Population heterogeneity and state dependence: Future research. *Journal of Quantitative Criminology*, *16*(2), 117–144. https://doi.org/10.1023/A:1007502804941

Nisbett, R. E., Aronson, J., Blair, C., Dickens, W., Flynn, J., Halpern, D. F., & Turkheimer, E. (2012). Intelligence: New Findings and Theoretical Developments. *American Psychologist*, *67*(2), 130–159. https://doi.org/10.1037/a0026699

Oleson, J. C. (2016). *Criminal genius : a portrait of high-IQ offenders*. Oakland, CA: University of California Press.

Osgood, D. W., McMorris, B. J., & Potenza, M. T. (2002). Analyzing multiple-item measures of crime and deviance I: Item response theory scaling. *Journal of Quantitative Criminology*, *18*(3), 267–296. https://doi.org/10.1023/A:1016008004010

Pedersen, L., Kunz, C., Rasmussen, K., & Elsass, P. (2010). Psychopathy as a risk factor for violent recidivism: Investigating the psychopathy checklist screening version (PCL:SV) and the comprehensive assessment of psychopathic personality (CAPP) in a forensic psychiatric setting. *International Journal of Forensic Mental Health*, *9*(4), 308–315. https://doi.org/10.1080/14999013.2010.526681

Prentice, R. L., Williams, B. J., & Peterson, A. V. (1981). On the regression analysis of multivariate failure time data. *Biometrika*, *68*(2), 373–379. https://doi.org/10.1093/biomet/68.2.373

Pyrooz, D. C., Gartner, N., & Smith, M. (2017). Consequences of incarceration for gang membership: A longitudinal study of serious offenders in philadelphia and phoenix. *Criminology*, *55*(2), 273–306. https://doi.org/10.1111/1745-9125.12135

Sampson, R. J. (1997). Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science*, *277*(5328), 918–924. https://doi.org/10.1126/science.277.5328.918

Satorra, A. (2000). Scaled and adjusted restricted tests in multi-sample analysis of moment structures. In R. D. . Heijmans, D. S. . Pollock, & A. Satorra (Eds.), *Innovations in multivariate statistical analysis* (pp. 233–247). London: Kluwer Academic Publishers.

Satorra, A., & Bentler, P. M. (2010). Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika*, *75*(2), 243–248. https://doi.org/10.1007/s11336-009-9135-y

Schubert, C. A., Mulvey, E. P., Steinberg, L., Cauffman, E., Losoya, S. H., Hecker, T., … Knight, G. P. (2004). Operational Lessons from the Pathways to Desistance Project. *Youth Violence and Juvenile Justice*, *2*(3), 237–255. https://doi.org/10.1177/1541204004265875

Schwartz, J. A., Savolainen, J., Aaltonen, M., Merikukka, M., Paananen, R., & Gissler, M. (2015). Intelligence and criminal behavior in a total birth cohort: An examination of functional form, dimensions of intelligence, and the nature of offending. *Intelligence*, *51*, 109–118. https://doi.org/10.1016/j.intell.2015.06.001

StataCorp. (2017). Stata Statistical Software: Release 15. College Station, TX: StataCorp LLC.

Walsh, A. (1987). Cognitive Functioning and Delinquency: Property versus Violent Offenses. *International Journal of Offender Therapy and Comparative Criminology*, *31*(3), 285–289. https://doi.org/10.1177/0306624X8703100309

Warr, M. (2002). *Companions in crime*. New York: Cambridge University Press.

Wechsler, D. (1999). *Wechsler Abbreviated Scale of Intelligence*. New York: The Psychological Corporation: Harcourt Brace & Company.

Wehrman, M. M. (2010). Race, concentrated disadvantage, and recidivism: A test of interaction effects. *Journal of Criminal Justice*, *38*(4), 538–544. https://doi.org/10.1016/j.jcrimjus.2010.04.024

Weinberger, D. A., & Schwartz, G. E. (1990). Distress and Restraint as Superordinate Dimensions of Self- Reported Adjustment: A Typological Perspective. *Journal of Personality*, *58*(2), 381–417. https://doi.org/10.1111/j.1467-6494.1990.tb00235.x

Wiley, S. A., Slocum, L. A., & Esbensen, F. A. (2013). The unintended consequences of being stopped or arrested: An exploration of the labeling mechanisms through which police contact leads to subsequent delinquency. *Criminology*, *51*(4), 927–966. https://doi.org/10.1111/1745-9125.12024

Yun, I., & Lee, J. (2013). IQ and Delinquency: The Differential Detection Hypothesis Revisited. *Youth Violence and Juvenile Justice*, *11*(3), 196–211. https://doi.org/10.1177/1541204012463410

Table 1. Descriptive Statistics for All Study Measures

Study Measures	**Mean/%**	**SD**	**Range**
Intelligence Measure			
Wechsler Abbreviated Scale of Intelligence (WASI)	84.525	12.030	55-128
Criminality Measures			
Violent Criminality Measures			
Year 1	.111	.801	-.907-3.039
Year 2	.130	.781	-.843-3.334
Year 3	.132	.781	-.838-2.826
Year 4	.135	.764	-.773-2.699
Year 5	.150	.762	-.744-3.187
Year 6	.148	.726	-.640-2.744
Year 7	.142	.709	-.638-3.382
Nonviolent Criminality Measures			
Year 1	.170	.707	-.513-3.007
Year 2	.175	.718	-.537-3.033
Year 3	.188	.717	-.533-3.181
Year 4	.199	.701	-.491-3.196
Year 5	.205	.697	-.474-3.010
Year 6	.207	.684	-.456-2.699
Year 7	.209	.663	-.418-2.733
Criminality Trait Measure	.000	.459	-.609-1.760
Official Record Arrests			
Total Number of Arrests during Study Period (Years 1-7)	3.255	3.355	0-24
Statistical Covariates			
Impulse Control	2.962	.950	1-5
Months Incarcerated during Study Period (Years 1-7)	20.094	22.847	0-84
Parental Socioeconomic Status	51.409	12.299	11-77
Study Site (%)			0-1
Philadelphia	51.700	--	
Phoenix	48.300	--	
Age (Baseline)	16.044	1.143	14-19
Sex (%)			0-1
Male	86.410	--	
Female	13.590	--	
Race (%)			1-4
White	20.240	--	
Black	41.430	--	
Hispanic	33.530	--	
Other	4.800	--	

Note: Arrests in the current study were measured as the study month (i.e., the months since the baseline interview) in which the arrest occurred, the total number of arrests are presented here to provide more context surrounding the analytic sample. Violent and nonviolent criminality measures estimated as annual factor scores. Impulse control measured as the impulse control subscale of the Weinberger Adjustment Inventory (WAI). Months incarcerated reflects the number of months during the study period participants spent incarcerated. Parental socioeconomic status (SES) was measured during baseline interviews using Hollingshead's (1971) Index of Social Positions (ISP).

Table 2. Linear Regression Model Examining the Associations between Intelligence, Criminality, and Total Number of Arrests

Study Measures	***b***	***95% CI***	***β***	***p*-value**
Criminality and Arrests				
Criminality	.096	.041; .152	.096	.001
Total Number of Arrests	-.023	-.039; -.008	-.078	.003
Covariates				
Impulsivity	.070	.014; .125	.066	.014
Months Incarcerated	.004	.001; .006	.082	.002
Parental SES	-.015	-.020; -.011	-.190	<.001
Study Site				
Philadelphia (Reference Category)				
Phoenix	.571	.444; .698	.286	<.001
Age	.024	-.019; .066	.027	.278
Sex	.087	-.062; .235	.030	.254
Race				
White (Reference Category)				
Black	-.461	-.617; -.305	-.227	<.001
Hispanic	-.477	-.621; -.334	-.226	<.001
Other	-.351	-.599; -.103	-.074	.006
N		1,331		

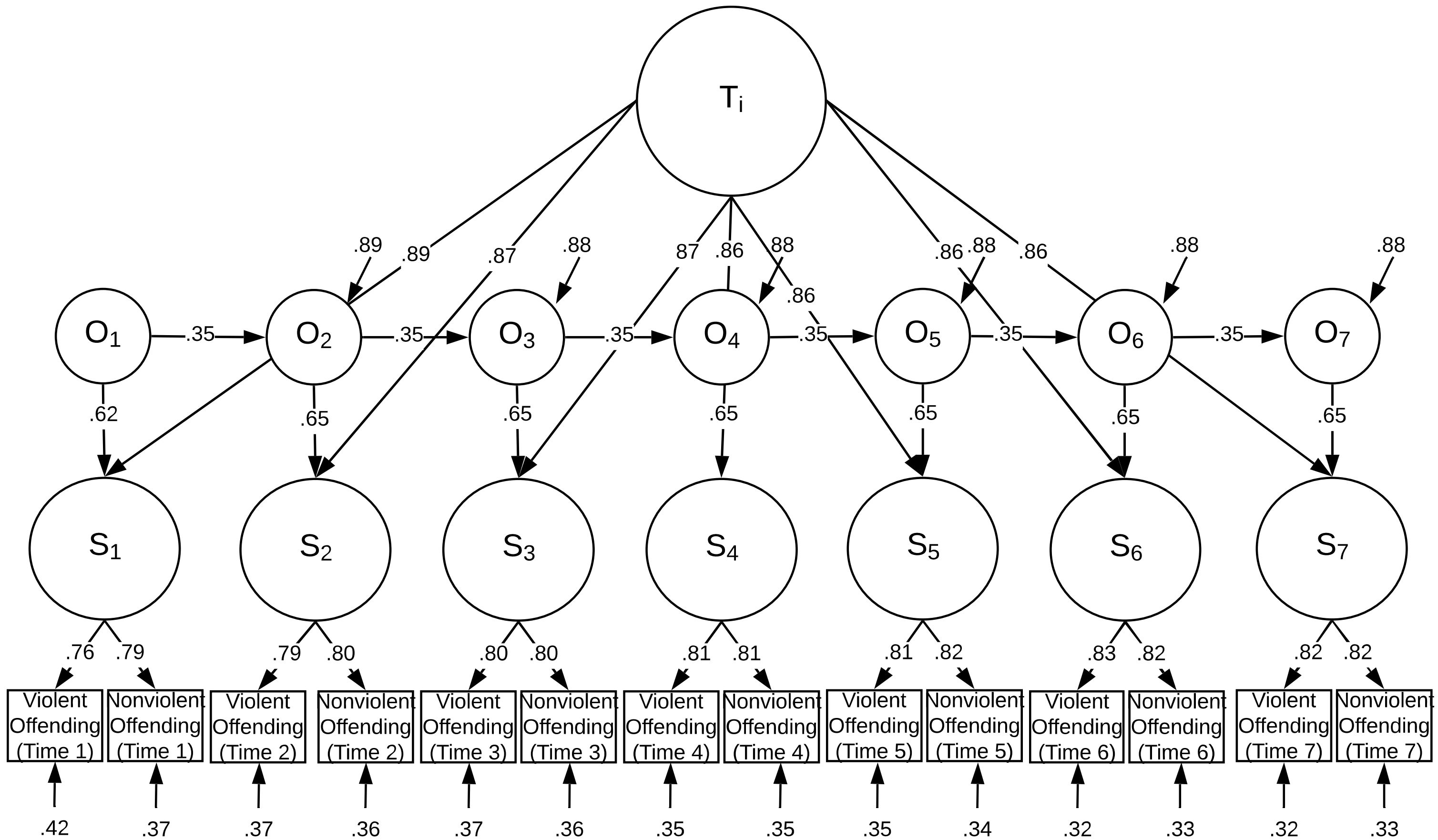
Note: Unstandardized coefficients presented with accompanying 95% confidence intervals (95% CI), standardized coefficients (β), and *p*-values.

Table 3. Survival Analysis Results for Models Examining the Hazard Rate of Arrest

	Model 1					Model 2				
Study Measures	***b***	**SE**	**HR**	**95% CI**	***p*-value**	***b***	**SE**	**HR**	**95% CI**	***p*-value**
<u>IQ and Criminality</u>										
Full-Scale IQ	-.037	.018	.964	.930; .999	.044	-.053	.018	.948	.915; .982	.003
Criminality	--	--	--	--	--	.176	.019	1.193	1.149; 1.238	< .001
<u>Covariates</u>										
Impulsivity	-.058	.020	.944	.910; .982	.004	-.011	.020	.989	.951; 1.029	.597
Months Incarcerated	.002	.001	1.001	1.000; 1.003	.044	.000	.001	1.000	.999; 1.001	.966
Parental SES	-.001	.002	.999	.995; 1.002	.358	-.001	.002	.999	.996; 1.002	.606
Study Site										
Philadelphia (Reference Category)	--	--	--	--	--	--	--	--	--	--
Phoenix	-.005	.049	.995	.904; 1.095	.920	-.015	.047	.985	.899; 1.080	.754
Age	-.018	.014	.982	.955; 1.010	.206	-.006	.015	.995	.966; 1.024	.698
Sex	.451	.090	1.569	1.315; 1.873	< .001	.389	.090	1.476	1.238; 1.760	< .001
Race										
White (Reference Category)	--	--	--	--	--	--	--	--	--	--
Black	-.007	.061	.993	.880; 1.119	.904	.022	.060	1.022	.909; 1.150	.712
Hispanic	-.045	.054	.956	.860; 1.064	.409	-.029	.053	.971	.875; 1.078	.585
Other	-.063	.099	.939	.773; 1.140	.525	-.059	.094	.943	.783; 1.134	.531
N	5,299					5,299				
-2 log likelihood	20376.98					20326.57				

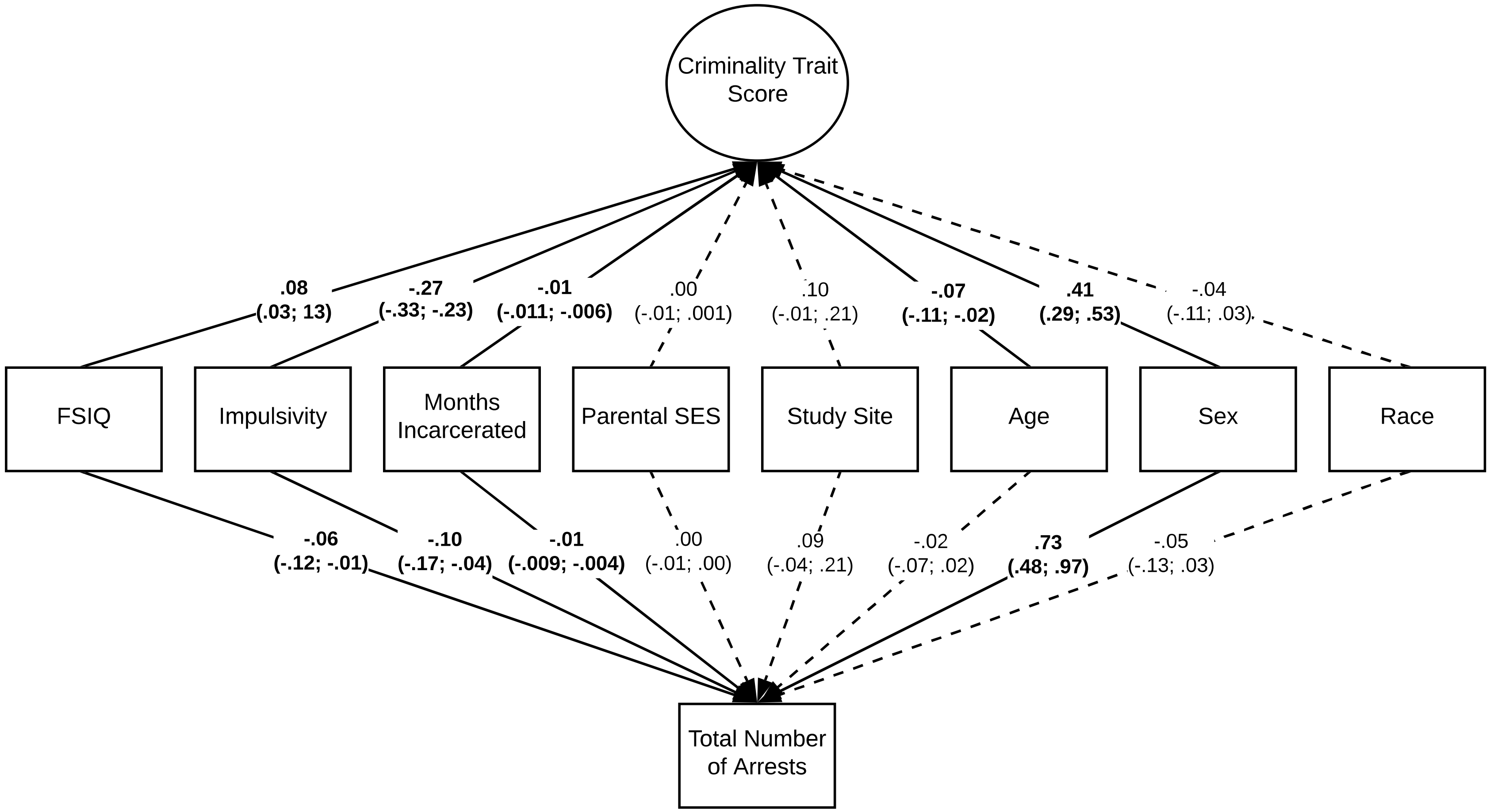
Note: Models stratified across each arrest. Standard errors and 95% confidence intervals adjusted for repeated arrest across the study period. The included intelligence and criminality measures were *z*-transformed. Sample size reflects total number of arrests (*N* = 3,968) for all examined participants (*N* = 1,331). Abbreviations: SE = standard error; HR = hazard ratio; 95% CI = 95% confidence interval.

Figure 1. Results of the Latent Trait State Occasion Model



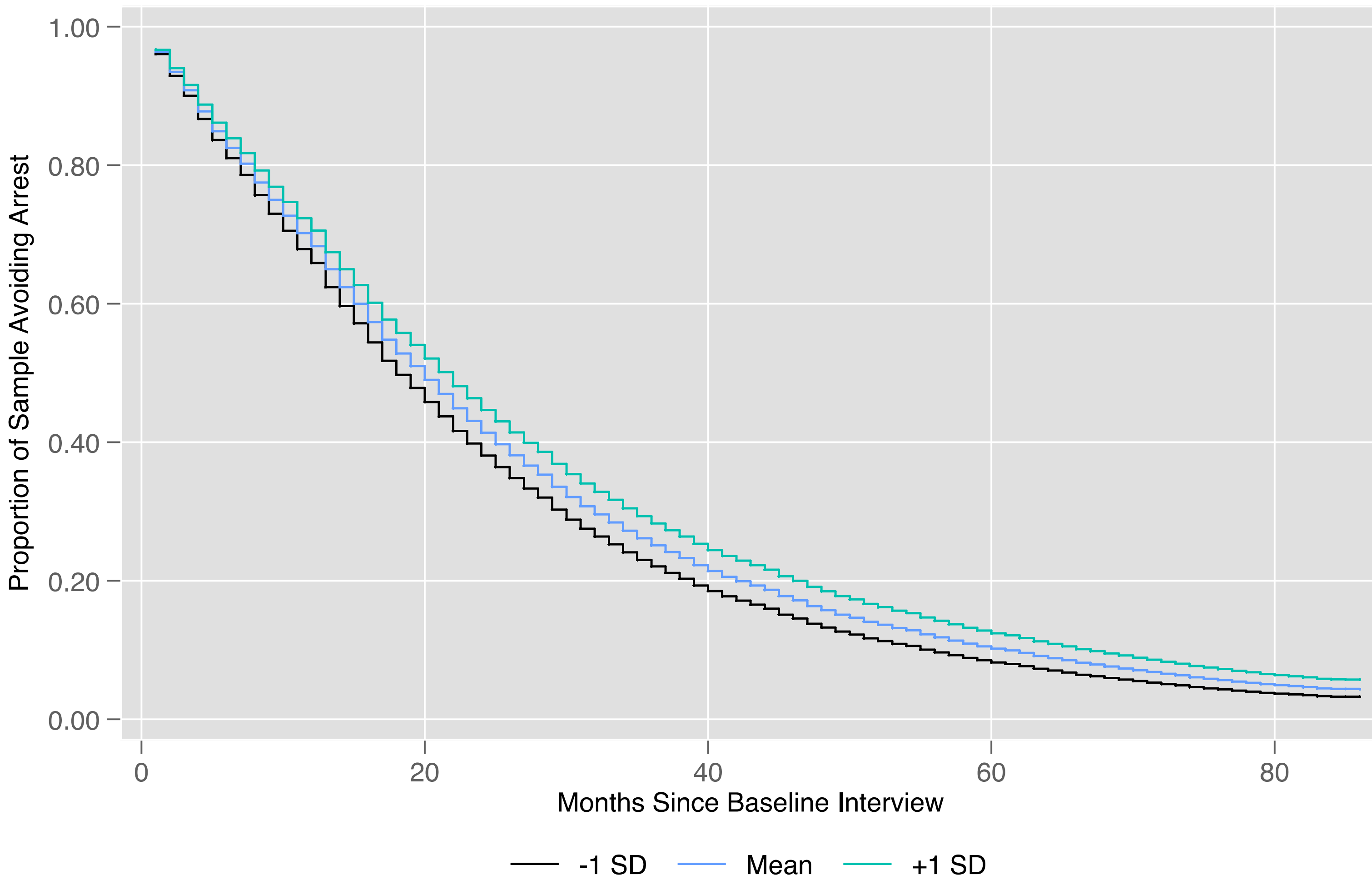
Note: Standardized coefficients from the latent trait state occasion model (LTSO) presented. Observed variables are factor scores of violent and nonviolent offending items across each examined year. S_1 - S_7 are the state factors and are decomposed into the stable trait factor (T_i) and O_1 - O_7, the occasion specific factors, which capture variance unique to each examined time point. The single headed arrows connecting each of the occasion factors represent the autoregressive function of the model. All coefficients significant at the $p < .01$ level. Model fit: CFI = .987; TLI = .972; RMSEA = .035.

Figure 2. Results of the Latent Trait State Occasion Model



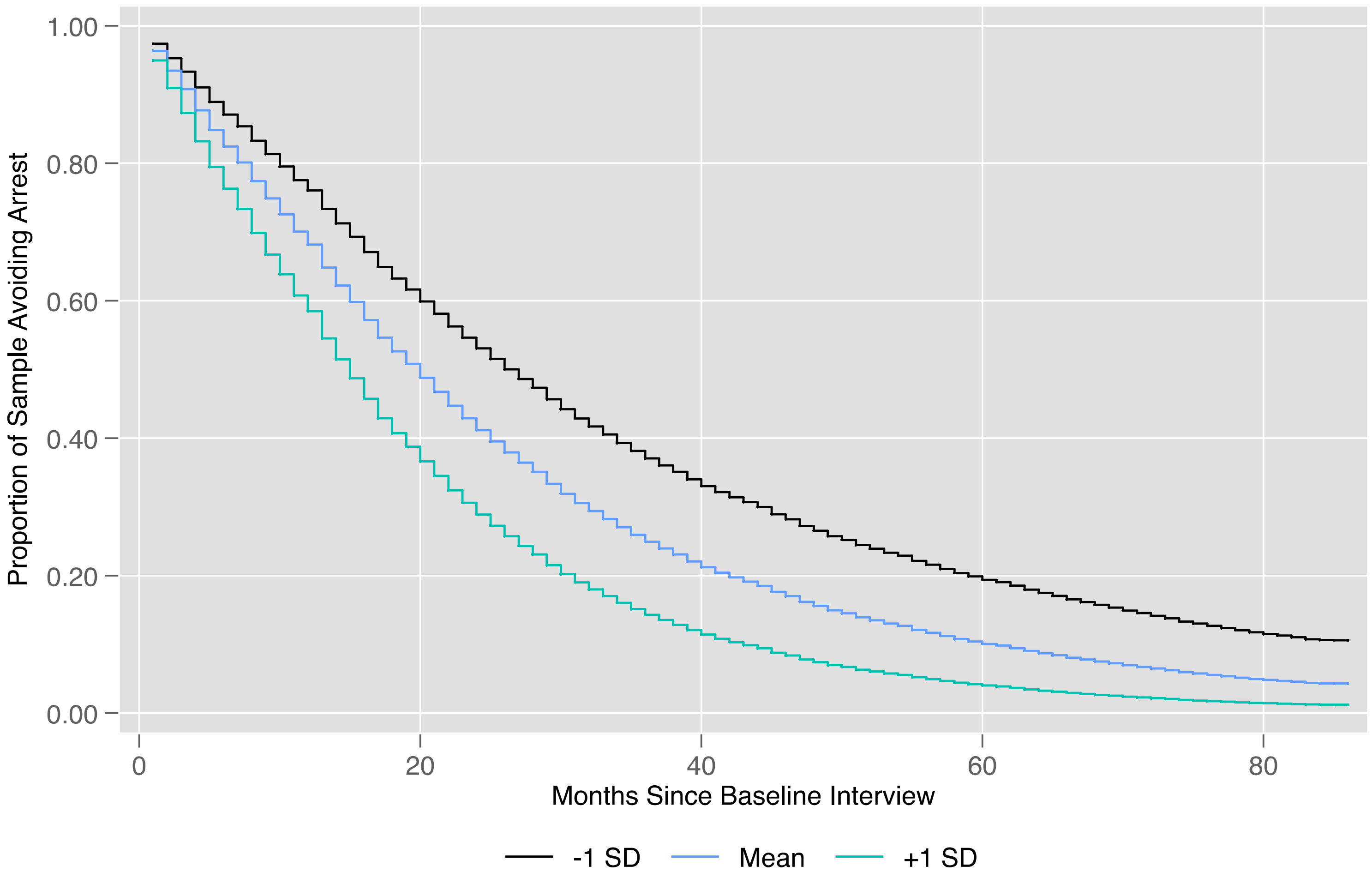
Note: Unstandardized coefficients presented. Accompanying 95% confidence intervals are presented in parentheses. Bolded coefficients (and solid paths) are significant at the $p < .05$ level, while dashed paths were nonsignificant. Paths in which total number of arrests (an overdispersed count) was endogenous were estimated using negative binomial regression. The paths estimating the associations between intelligence and criminality and intelligence and the total number of arrests were compared with a *z*-score and revealed a significant difference between the paths ($z = 4.24$, $p < .001$).

Figure 3. Survival Curve Plotted as a Function of Intelligence



Note: Survival functions for participants at one standard deviation (-1 SD) below the grand mean, at the grand mean, and one standard deviation above the grand mean (+1 SD) of the examined intelligence measure (*N* = 5,299).

Figure 4. Survival Curve Plotted as a Function of the Criminality Trait Measure



Note: Survival functions for participants at one standard deviation (-1 SD) below the grand mean, at the grand mean, and one standard deviation above the grand mean (+1 SD) of the estimated criminality trait measure (*N* = 5,299).