Intelligence as a protective factor against offending: A meta-analytic review of prospective longitudinal studies

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ABSTRACT

Purpose: To synthesize results from major prospective longitudinal studies that investigated the extent to which intelligence may function as a protective factor against offending and violence.
Methods: Results are based on systematic searches of the literature across 18 databases. Papers are included in the meta-analyses if results are based on longitudinal data.
Results: Fifteen longitudinal studies investigate the extent to which an above-average intelligence may function as a protective factor. Meta-analytic results of studies on interactive protective factors suggest that a higher level of intelligence is a factor which can predict low levels of offending differentially within the high-risk (random effects model OR = 2.32; 95% CI: 1.49 – 3.63; p = 0.0001) and the low-risk (random effects model OR = 1.33; 95% CI: 0.88 – 2.01; p = 0.18) groups. A high intelligence level is differentially protective against offending within different levels of risk. In agreement with an interaction effect, the high-risk and low-risk effect sizes were significantly different (mixed effects meta-regression: point estimate = 0.509; SE = 0.175; p = 0.004). Meta-analytic synthesis of studies that looked at risk-based protective factors (i.e. analyses based only on high-risk individuals) is also presented and results are consistent with initial hypotheses.
Conclusions: This methodological demonstration paper confirms the variability in conceptualizations, theoretical approaches and methodological strategies used to investigate the protective effects of intelligence against offending. Intelligence can function as a protective factor for offending. Implications for policy and practice are highlighted.

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Introduction

Low intelligence is a well-known risk factor for criminal behavior, violence and conduct problems (e.g., Ellis & Walsh, 2003; Hirschi & Hindelang, 1977; Ward & Tittle, 1994; West & Farrington, 1973; Wilson & Herrnstein, 1985). Much less however, is known about a potential protective function of above-average intelligence against other risk factors. A few older studies suggest that good intelligence may buffer family and other social risks (Kandel et al., 1988; Lösel & Bliesener, 1994; Stattin, Romelsjo, & Stenbacka, 1997; Werner & Smith, 1982). Other research found a protective function only for specific subgroups or measurements (e.g., McCord & Ensminger, 1997; Stouthamer-Loeber et al., 1993).

Although there are different definitions, dimensional concepts and results on the underlying cognitive components of intelligence (e.g., Gardner, 1999; Sternberg, 2000), a protective function against

criminality is theoretically plausible. For example, intellectual ability can partly compensate for background disadvantage in educational and occupational attainment (Damian, Su, Shanahan, Trautwein, & Roberts, 2015), reduce biases in aggression-prone social information processing (Crick & Dodge, 1994), and indicate executive functions that are relevant for planning and self-control (Raine, 2013). Nevertheless, criminological research on the protective effects of intelligence is still scarce. This is surprising as protective effects of personal and social resources currently attract much interest in the academic community and are certainly relevant for prevention and intervention efforts.

Whereas research on risk factors has a long tradition in studies of antisocial behavior, there has been increased interest in recent years in factors that contribute to desirable behavioral outcomes. Various disciplines have driven this change of perspective, including research on resilience (Rutter, 2012), positive psychology (Seligman & Csikszentmihalyi, 2000), desistance from crime (Kazemian & Farrington, 2015), developmental prevention (Farrington & Welsh, 2007) and offender rehabilitation (Lösel, 2012). Focusing on protective factors and on building resilience is viewed as a more positive approach, and more attractive to

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Table 1
Details of Studies on IQ as a protective factor

Authors (publication date)	Study Name (Country)	Type of High-Risk/ 'Experimental' Group	Type of Comparison Group	Risk Factors (age at Measurement)	Age at Risk Measurement	Age at Protective Factors Measurement	Outcome Measure	Age at Outcome Measurement	Results
Andershed et al. (2016)	Individual Development and Adaptation Study (Örebro Study; Sweden)	Not applicable; analyses on the whole sample of males, with multivariate regression analyses with risk and protective factors as independent variables	Not applicable	Behavioral risk index score (teacher-rated combined score on aggression, concentration difficulties and motor restlessness)	Age 10	IQ measured with intelligence test at age 13 Other protective factors measured, falling within the individual, family and school domain	Official registered convictions of violent offending between ages 12 – 35	Between ages 12 to 35	Less violent males had higher IQ (OR = 0.672) Further analyses with IQ as part of an 'individual domain index score'
Bender et al. (1996)	Bielefeld-Erlangen Study on Resilience (Germany)	66 resilient adolescents (mean age: 15.5) from 27 residential homes with a high-risk load based on a 71-item index	80 deviant (mean age: 15.7) adolescents with a high-risk load based on a 71-item index	Resilient and Deviant adolescents had a similar average risk load (non-significant differences). In the 2-year follow-up Resilient Adolescents (N = 18; Age about 17.5) had scores below the 85th percentile on externalizing problems; Deviant Adolescents (N = 19; Age about 17.7) scored above the 85th percentile in either externalizing problems or on another scale	Not applicable: multiple risks (score index of 71 items) based on a range of life events	At the two-year follow-up, when the adolescents were about 17 – 18 years of age	IQ Level based on the Prüfsystem für Schul und Bildungs-beratung (PBS; Horn, 1969), assessing verbal intelligence, reasoning and technical/spatial intelligence	At the two-year follow-up, when the adolescents were about 17 – 18 years of age	Non significant differences on all three IQ measures for the two groups, shown in Cohen's d Verbal: 0.10 Reasoning: 0.14 Technical/ Spatial: 0.43
Dubow et al. (2016)	Columbia County Longitudinal Study (USA)	Not applicable; the male individuals of the sample (at the last two follow-ups) were divided in violent-non violent and differences in risk and direct protective (promotive) factors across the two groups were investigated	Not applicable		Age 8	IQ measured at Age 8	Adult violence, a composite score based on whether the participant had ever been arrested in adulthood for violence offense (all arrests reported since age 18 were included) and/or whether he was in the upper 25% on the severe self-reported (at ages 30 and 48) physical violence score	Assessed at Ages 30 and 48 (for self-reported physical violence) and Ages 18 onwards for official criminal records	No significant difference in IQ between violent and non-violent males (t = 1.57, p = ns). Finding not included in the meta-analysis due to biased results: at the age 48 follow-up, there was an attrition of 39% of the original sample which was differential for age 8 IQ (i.e. the re-interviewed participants had a significantly lower IQ compared to the not re-interviewed participants).
Farrington et al. (2016)	Cambridge Study in Delinquent Development (England)	Various high-risk categories created based on the worst quarter (the risk end) versus the remainder. Within each high-risk category, percent	Various low risk categories created based on the 'best quarter' (the promotive end) versus the remainder. Within each low-risk category,	Poor child rearing, low school achievement, high hyperactivity and other risk factors measured at age 8 – 10	Age 8 – 10	Non-verbal IQ measured using Raven's Progressive Matrices Test at age 8 – 10 Verbal IQ, based on verbal comprehension	Convictions from age 10 – 18 based on official data	Ages 10 to 18 inclusive	For males with high-risk (i.e. poor child rearing), 13.3% of high intelligence were convicted, compared to 40.3% of low intelligence.

Table 1 (*continued*)

Authors (publication date)	Study Name (Country)	Type of High-Risk/ 'Experimental' Group	Type of Comparison Group	Risk Factors (age at Measurement)	Age at Risk Measurement	Age at Protective Factors Measurement	Outcome Measure	Age at Outcome Measurement	Results
		convictions within protective and non-protective groups investigated	percent convictions within protective and non-protective groups investigated			and vocabulary tests, measured at ages 8 – 10 Other protective factors also measured			For males with low risk (i.e. good child-rearing), 25% of high intelligence were convicted, compared to 18.2% of low intelligence
Fergusson and Lynskey (1996)	Christchurch Health and Development Study (New Zealand)	20% of 940 adolescents (N = 171) with highest level of family adversity (based on a composite score of 39 risk factors)	679 adolescents with low risk background Note: For analyses on resiliency, data are based on 63 (36.8% of initial 171 high risk teenagers) adolescents with absence of externalizing behaviors versus the remaining teenagers from high risk backgrounds (N = 108)	Composite score of family adversity based on 39 risk factors measured between birth and age 15	Risk index score measured from birth to age 15	IQ measured at age 8 based on the Wechsler Intelligence Scale for Children-Revised (WISC-R; Wechsler, 1974). Levels of IQ (and other individual characteristics) investigated within resilient and non-resilient adolescents	Substance use, delinquency and school problems at aged 15 – 16 are used as outcome measures in comparing 171 high-risk with 679 low risk adolescents. For protective factors analyses, 63 resilient adolescents of the high risk background are compared with the remainder 108 adolescents	Outcomes at age 15 – 16	Resilient high-risk adolescents had a significantly (p < 0.005) higher IQ level (Mean = 97.9) compared to the non-resilient high-risk adolescents (Mean = 89.9). In subsequent logistic regression analysis (with the log odds of being resilient as the dependent variable), IQ level was a significant predictor of resiliency (b = 0.065, p < 0.001; N = 132)
Jaffee et al. (2007)	Environmental Risk Longitudinal Study (England)	72 resilient children who had been physically maltreated before the age of 5 years but whose antisocial behavior problems in a two-year follow-up fell within the normal range for similarly aged (and same sexed) children	214 non-resilient children who had been physically maltreated before the age of 5 years but whose antisocial behavior problems in a two-year follow-up were above the normal range for similarly aged (and same sexed) children	Physical maltreatment by the mother before the age of 5 years	Age 5	IQ measured using the short form of Wechsler Preschol and Primary Scale of Intelligence Revised (Wechsler, 1990) at Age 5	Antisocial problem behavior based on Achenbach's Teachers Report Form (Achenbach, 1991)	Outcome measured across two time-points by different teachers, at Ages 5 and 7	Of the 72 resilient children, 39% had above average IQ; of the 214 non-resilient children, 26% had above-average IQ (Table 1) Relative risk ratios (separately for boys and girls) also shown on table 3
Kandel et al. (1988)	Danish Birth Cohort of 1936 (Denmark)	Men at high-risk for serious criminal involvement, split into resilient (non- criminal) and non-resilient (criminal) groups	Men at low risk for serious criminal involvement, split into resilient (non- criminal) and non-resilient (criminal) group	Presence of severely sanctioned father, based on at least one prison sentence	N/A	At least 34 in 1972 (page 225)	Levels of IQ within each of the four groups of resilient and non-resilient adults	At least 34 in 1972 (page 225) Note: Risk and criminality are measured based on longitudinal data, but IQ is measured cross-sectionally, following measures of criminality	High-risk resilient men had higher IQ (M = 115.3, SD = 13.3) compared to high-risk non-resilient males (M = 102.7, SD = 15.1). High-risk resilient men had significantly higher IQ than all other three groups based on Scheffe post-hoc comparisons
Klika et al. (2012)	Lehigh Longitudinal Study (USA)	Not applicable; analyses based on the whole sample of children. The sample was recruited from multiple settings, including child welfare caseloads for child	None; analyses based on the whole sample investigating IQ as a moderator between child physical abuse and antisocial behavior in childhood	Child physical abuse measured via an 8-item weighted index; for the current analyses, parent-rated in the preschool wave of the study	Preschool assessment in 1976, when children were between ages of 18 months and 6 years	IQ measured during the school-age wave of the study using scores from the Wechsler Intelligence Scale for Children-Revised	Antisocial behavior and delinquency during the school-age wave of the study, based on parents' reports of antisocial behavior (18 items) and delinquency	Outcome measure assessed during the school-age years between 1980 and 1982, when children	A statistically significant interaction of child physical abuse with IQ in predicting antisocial behavior and delinquency (β = -0.12, p < 0.05)

		abuse and neglect, Head Start programs, daycare programs and middle-income nursery programs				(Wechsler, 1974)	(10 items)	were 8 – 11 years of age (elementary years)	
Kolvin et al. (1988)	Newcastle Thousand Family Study (England)	A deprived high-risk resilient (i.e. non-offending) group	A deprived high-risk non-resilient (i.e. offending) group	Participants defined as 'deprived' if their families had at least one out of five criteria of deprivation (marital disturbance; parental illness; overcrowding of family; poor mothering; poor physical care; social dependency)	All deprivation measures coded in 1952 (study began in 1947)	For current analyses, IQ measured at age of 11	Offending based on archives of the study but also based on official Home Office statistics	Offending up to age of 33	10% of the deprived delinquent (i.e. non-resilient) group had an IQ of 100 + as against 43% of the deprived non-delinquent (i.e. resilient) group Exact numbers for each group are not available, so no effect sizes can be calculated
Loeber et al. (2007)	Pittsburgh Youth Study (USA)	Not applicable; based on data from the youngest cohort, a total of 254 delinquents are compared with 193 non-delinquents	Not applicable	A wide range of neurocognitive (e.g. resting heart rate; anticipation responsivity), cognitive (e.g. IQ, verbal memory), child (e.g. substance use, truancy), parenting (e.g. supervision, parental stress), peer (i.e. peer delinquency) and community (e.g. housing quality, community crime) have been tested as both risk and direct-protective (promotive) factors	Up to age 16, preceding the measurement of the outcome (i.e. delinquency) Tests for promotive factors were based on the comparison between the lower 25% and the middle 50% on each variable. Tests for risk factors were based on the comparison between the upper 25% and the middle 50%	Up to age 16, preceding the measurement of the outcome (i.e. delinquency) Verbal and spatial IQ was measured at age 16, using the Wechsler Intelligence Scale for Children (Wechsler, 1991)	Moderate/severe delinquency based on the Self-Reported Delinquency scale (Loeber et al., 2008) and the Young Adult Self-Report (Achenbach, 1997) as well as incarceration	Ages 17 – 20	A significantly larger portion of non-delinquents than delinquents scored high on verbal IQ ($X^2 = 11.87^{***}$) but not in spatial IQ ($X^2 = 3.41$; ns)
Lösel and Bender (2014)	Erlangen-Nuremberg Development and Prevention Study (Germany)	A total of 207 (78 girls) high risk bullying group split into protective (high intelligence) and non-protective (low intelligence) category *Results based on email communication with authors and not based on the published paper	A total of 308 (187 girls) low risk bullying group split into protective (high intelligence) and non-protective (low intelligence) category	Bullying perpetration	Age 9 (SD = 0.9)	IQ (and other protective factors) measured right before Wave 6 with average Age M = 10.6 years (SD = 0.9) IQ measured with the German version of the Kaufman Assessment Battery for Children (Melchers & Preub, 1994)	Composite score of child rated and mother rated aggressive behavior, violent offences and delinquency	Age 13.7 (SD = 0.9)	Main effects of intelligence against mother-rated aggression and delinquency for both boys (b = - 0.41) and girls (b = -.16) and also interaction effects of IQ X bullying on outcomes. Main effects and also interaction effects of IQ X bullying on outcomes based on self-reported data for males and females also provided. Standardized regression coefficients provided, but not CI or SE that would allow use of data in meta-analysis
McCord and Ensminger	Woodlawn Cohort (USA)	Not applicable; analyses on direct protective	Not applicable; analyses on direct protective	Risk for measured based on teacher-rated	See previous column	IQ measured in first grade for individuals	Criminal violence, depression or	Between 1992 and 1994 when	For females, 2.2% of high intelligence

Table 1 (*continued*)

Authors (publication date)	Study Name (Country)	Type of High-Risk/ 'Experimental' Group	Type of Comparison Group	Risk Factors (age at Measurement)	Age at Risk Measurement	Age at Protective Factors Measurement	Outcome Measure	Age at Outcome Measurement	Results
(1997)		(promotive) factors based on the overall sample that was assessed in first grade in 1966 and was followed up in 1992-94	(promotive) factors based on the overall sample	aggressiveness in first grade; IQ levels assessed in first grade; mother-rated frequency of spanking measured in 1967; school attendance in first grade; retrospective measures (assessed in the 1992 follow-up) of leaving home and exposure to discrimination Note: IQ identified as 'risk factor' but analyses present IQ as direct-protective (promotive) factor		who entered first grade in 1966	alcoholism (results shown separately but also combined for comorbidity)	individuals were aged about 32 – 34	females (N = 45) were violent compared with 10.3% of low intelligence females (N = 301) who were violent (X^2 = 3.04; RR = 0.22; p = ns) For males, 23.5% of high intelligence males (N = 34) were violent compared with 41.2% of low intelligence males (N = 279) who were violent (X^2 = 3.98; RR = 0.57; p = 0.046)
Stattin et al. (1997)	Follow-up of Stockholm males who entered the military in 1969/70 and followed up in records up to age 36 (Sweden)	Representative sample of 7577 males who entered compulsory military service in 1969/70	Comparison offending outcomes of men with low IQ with those of high IQ and based on accumulation of risk factors	An aggregate index score of 5 home background risks and an aggregate index score of 8 behavioral risks. Both index scores measured retrospectively when the males joined the military	Retrospective measure for background risks up to age 18	Protective factors (including IQ) measured at age 18 'Intellectual capacity' measured based on a conventional IQ test administered at time of conscription and measuring verbal, logic-inducive and technical-mechanical abilities	Registered convictions from age 18-20 (when they joined the military) up to age 36 based on official records	(up to) Age 36	IQ was part of a 'personal resources' score. A 2-way anova with registered convictions as the dependent variable and the aggregated behavioral-risk and personal resource index as the independent factors revealed significant main effects for behavioral risks (F = 132 p < 0.001) and for personal resources (F = 19.86 p < 0.001) and a significant interaction effect (F = 10.08, p < 0.001) A separate figure (but with no numbers available) show that among subjects facing a high behavioral risk, the conviction rate was lower if they had documented high intelligence (pp. 212 – 213)
Werner & Smith, 1982)	Kauai Longitudinal Study (Hawaii)	High-risk resilient children who did not develop problems	High risk non-resilient children who developed problems	A combination of pre-natal and perinatal problems and risks within the family such as parental illnesses, death of sibling, mother working outside the	Prenatal/ perinatal measurement of risk, measurement of other risks during early childhood	PMA IQ test; reasoning factor measured at age 10 PMA IQ test; verbal factor measured at age 10 (results also shown	Delinquency outcome combined with other problems such as mental health problems, physical handicap, mental retardation	Age 18	High risk resilient females had a PMA reasoning factor score of 109.19 compared to a PMA reasoning factor score of 92.93 for the high-risk non-resilient

				household on a long-term basis, absence of the father, etc		for Cattell IQ test which was given at 20 months of age) Other protective factors also shown			females at age 18. Equivalent scores for PMA verbal factor scores were 101.57 and 89.95 respectively. High risk resilient males had a PMA reasoning factor score of 103.43 compared to a PMA reasoning factor score of 92.85 for the high-risk non-resilient males at age 18. Equivalent scores for PMA verbal factor scores were 99.83 and 89.69 respectively.
White et al. (1989)	Dunedin Multidisciplinary Health and Development Study (New Zealand)	Boys and girls assigned to high-risk status if their combined (teacher-reported and parent-reported) antisocial score at Age 5 placed them in the top third of the distribution of their respective genders. High-risk boys and girls were slit into (78 males and 96 females) resilient (non-delinquent) and into (15 males and 8 females) non-resilient (delinquent) groups	Boys and girls assigned to low-risk status if their combined (teacher-reported and parent-reported) antisocial score at Age 5 placed them below the top third of the distribution of their respective genders. Low-risk boys and girls were split into (294 males and 267 females) resilient (non-delinquent) and into (25 males and 21 females) non-resilient (delinquent) groups	Age 5 antisocial behavior rated by teachers and parents based on the 12-item Rutter Child Scales (Rutter et al., 1970)	Age 5	IQ measured with the Wechsler Intelligence Scale for Children-Revised (Wechsler, 1974) at ages 7, 9, 11 and 13. Scores were averaged across the four ages	Delinquency outcome across ages 13 and 15 based on the Self-Report Early Delinquency Protocol, along with: teachers' reports from the Rutter et al. (1970) antisocial subscale; parents' reports on the Socialized aggression subscale from the Quay and Peterson (1983) Revised Behavior Problem Checklist; and police contact records	Average delinquency across ages 13 and 15 (including 'mild' delinquents in the analyses)	Means and Standard Deviations (SD) for IQ total scores within groups: High-risk resilient males: M = 105.13 (SD = 11.61) High-risk non-resilient males: M = 98.64 (SD = 9.34) High-risk resilient females: M = 105.22 (SD = 11.76) High-risk non-resilient females: M = 97.75 (SD = 17.73) Comparisons within low-risk groups also shown

Note: SD = standard deviation; M = mean value; p = statistical significance level; OR = Odds Ratio; d = standardized difference in means; b = regression coefficient
Note: All effect sizes shown in the table are as reported in the relevant manuscripts

communities, than reducing risk factors, which emphasizes deficits and problems (Pollard, Hawkins, & Arthur, 1999).

Although there is much interest in desirable behavioral outcomes, well-replicated results on specific protective factors are still rare. This is partially because of the more complicated conceptual and methodological issues in protective factor research than in traditional risk factor research (Lösel & Farrington, 2012; Ttofi, Bowes, Farrington, & Lösel, 2014b). A criminological risk factor is defined as a variable that predicts a high probability of offending (for issues of causality see Kraemer, Lowe, & Kupfer, 2005). Risk factors are often dichotomized. This makes it easy to study interaction effects, to identify persons with multiple risk factors, to specify how outcomes vary with the number of risk factors, and to communicate results to policy-makers and practitioners as well as to researchers (Farrington & Loeber, 2000). There are also continuous analyses, and the order of importance of risk factors is mostly similar in dichotomous and continuous approaches.

In contrast to the risk concept, the term "protective factor" has been used inconsistently and operationalized in different ways. Some researchers have defined a protective factor as a variable that predicts a low probability of offending, or as the "mirror image" of a risk factor (see Loeber, Farrington, Stouthamer-Loeber, & White, 2008), while other researchers have defined a protective factor as a variable that interacts with a risk factor to nullify its effect (e.g., Rutter, 1987), or as a variable that predicts a low probability of offending among a group at risk (e.g., Werner & Smith, 1982). There are also other concepts of protective factors and mechanisms that may be found in other literatures (e.g., Luthar, Sawyer, & Brown, 2006; Masten & Cicchetti, 2010).

As mentioned, a protective factor is a variable that interacts with a risk factor to nullify its effect (Lösel & Farrington, 2012; Rutter, 1987), or alternatively a variable that predicts a low probability of offending among a group at risk. We will term the former "an interactive protective factor" (or a "buffering protective factor") and the latter "a risk-based protective factor". An interactive protective factor is defined as follows: When the protective factor is present, the probability of offending does not increase in the presence of the risk factor; when the protective factor is absent, the probability of offending does increase in the presence of the risk factor. An alternative way of interpreting this interaction effect is as follows: When a risk factor is present, the probability of offending decreases in the presence of a protective factor; when a risk factor is absent, the probability of offending does not decrease in the presence of a protective factor.

For example, in the Cambridge Study in Delinquent Development, Farrington and Ttofi (2011) investigated interaction effects among variables measured at age 8-10 in predicting convictions between ages 10 and 50. Among boys living in poor housing, 33% of those receiving good child-rearing were convicted, compared with 66% of those receiving poor child-rearing. Among boys living in good housing, 32% of those receiving good child-rearing were convicted, compared with 30% of those receiving poor child-rearing. Therefore, good child-rearing was a protective factor that nullified the risk factor of poor housing, or conversely (but perhaps less plausibly) good housing was a protective factor that nullified the risk factor of poor child-rearing. In the results section, we provide a graphic presentation of the methodological design for investigating both interactive protective and risk-based protective factors.

Inspired by Sameroff, Bartko, Baldwin, and Seifer (1998), Loeber et al. (2008) proposed that a variable that predicted a low probability of offending should be termed a "promotive factor" (what was later defined as a "direct protective or promotive" factor; see Hall et al., 2012). It might be argued that a promotive factor is just "the other end of the scale" to a risk factor, and therefore that calling a variable either a promotive factor or a risk factor is redundant and even misleading. However, this is not necessarily true, because it depends on whether the variable is linearly or nonlinearly related to offending. Loeber et al. (2008) trichotomized variables into the "worst" quarter (e.g., low intelligence), the middle half, and the "best" quarter (e.g., high intelligence).

They studied risk factors by comparing the probability of offending in the worst quarter versus the middle half, and they studied promotive factors by comparing the probability of offending in the middle half versus the best quarter. They used the odds ratio (OR) as the main measure of strength of effect.

If a predictor is linearly related to delinquency, so that the percent delinquent is low in the best quarter and high in the worst quarter, that variable could be regarded as both a risk factor and a promotive factor. However, if the percent delinquent is high in the worst quarter but not low in the best quarter, that variable could be regarded only as a risk factor. Conversely, if the percent delinquent is low in the best quarter but not high in the worst quarter, that variable could be regarded only as a promotive factor. Most studies of the predictors of delinquency label them as "risk factors" but researchers should distinguish these three types of relationships. Other ways of testing linearity are available (Cox & Wermuth, 1994).

Loeber et al. (2008) systematically investigated risk and promotive factors in the Pittsburgh Youth Study. For example, in predicting violence at age 20-25 from variables measured at age 13-16, the percent violent was 8% for boys with high achievement, 21% for boys with medium achievement, and 21% for boys with low achievement. It was, therefore, concluded that school achievement was a promotive factor but not a risk factor.

Based on these conceptual clarifications, the present article assembles current evidence of a protective effect of intelligence against criminal, delinquent, violent, and other forms of antisocial behavior. Studies will be grouped together based on whether they investigate intelligence as an interactive protective factor, or a risk-based protective factor or a promotive factor. We systematically searched the relevant literature and meta-analyzed data from prospective longitudinal studies. We chose longitudinal studies because a protective factor should operate before or at the same time as a risk factor, and both should, ideally, occur before the outcome. Since intelligence is a complex construct and we had to work with the concepts that have been used in the primary studies, we took a pragmatic approach. Our working definition follows the famous statement of Boring (1923) that intelligence is what the tests of intelligence measure (because there is a common factor in many abilities). Major prospective longitudinal studies measure IQ based on what could be described as 'first generation' intelligence tests (Naglieri, 2015) and our meta-analytic findings are limited by this fact. We concentrate on traditional cognitive test measures of general intelligence. Because of a lack of differentiated primary studies, we will not investigate sub-factors such as fluid and crystallized intelligence, or reasoning, perception, fluency, or (working) memory. We will concentrate on direct test measures of intelligence and exclude proxy variables such as school achievement.

We will also not deal with 'emotional intelligence' (Goleman, 1995) because its measurement and validity is not yet comparable to the traditional concept of (cognitive) intelligence (e.g., Harms & Credé, 2010). Additionally, we will not deal with 'executive functions'. Despite the amount of variance shared between executive functioning and intelligence and the activation of highly similar brain networks (Barbey et al., 2012; Schretlen et al., 2000), we exclude studies on executive functioning as a proxy for intelligence. A recent review of the evidence on the association between executive functioning and intelligence underscores the benefits in treating them as different psychological constructs, despite the fact that their definitions significantly overlap and that they seem to be drawing resources from the same underlying processes (Duggan & Garcia-Barrera, 2015).

Methodology

We conducted systematic searches of the literature on protective factors against delinquency, violence and offending, in 18 databases (see Appendix Table 1) and in 68 journals, details of which can be given upon request. The time frame for the searches was from the

inception of the journal or database until the end of May 2015. We conducted searches with a combination of key words: protective factors; resilience; buffering factors; offending; crime; delinquency; violence; antisocial.

Keyword searches were not restricted to the title or the abstract but included the whole text of each manuscript, ensuring wide coverage of the relevant literature on resilience and protective factors. Initial searches resulted in thousands of hits, but many of the titles were eliminated as they were outside the field of criminology and focused more on the general concept of 'competence' within various fields of (cognitive, developmental, clinical, etc.) psychology, education, etc.

We have located 700 potentially relevant manuscripts, many of which were either based on cross-sectional data or presented various undesirable outcomes (such as drug misuse, teen pregnancy, alcohol dependence, etc.) but not outcomes on offending. In the end, we downloaded and screened a total of 177 papers with relevant longitudinal data (based on short-term or longer-term follow-up studies). These papers were categorized based on whether the protective factors presented in analyses fell within the individual, family, school, or neighborhood domains.

Within the framework of the current paper, we investigate the extent to which intelligence may function as a protective factor against delinquency, violence and crime based on longitudinal data. Short-term and long-term prospective longitudinal studies on resilience are the focus of this paper because resilience is a dynamic developmental construct (Luthar, Cicchetti, & Becker, 2000).

Inclusion and Exclusion Criteria

Studies were included if they presented longitudinal data on intelligence as a protective factor against delinquent or antisocial behavior, violence and/or general offending behavior. In all includable studies, the outcome measure (i.e., delinquent or antisocial behavior, violence and/or offending behavior) followed the risk factors. With regard to protective factors, ideally, they should precede offending, but in a few papers, these factors were investigated at the same time as the outcome measure. Papers based on prospective longitudinal studies but with relevant analyses based on within-wave (i.e., cross-sectional) data were excluded. For example, a paper based on the National Longitudinal Survey of Youth (Dubow & Luster, 1990) was excluded since data analyses on both risk/protective factors and antisocial outcomes were based on the combined mother-child dataset that was collected in 1986 only (based on over 90% of mothers who originally participated in 1979).

Studies on academic achievement (e.g., Loeber et al., 2008; Stouthamer-Loeber et al., 1993; Piquero & White, 2003), or on 'cognitive attainment' (e.g., a competency index based on the British Ability Scale and tests on reading/ mathematics abilities; Osborn, 1990), or executive neuropsychological functioning (Moffitt, 1993) as a proxy for intelligence, were excluded. Studies on maternal intelligence as a protective factor against a child's problem behavior were also excluded (e.g., Burchinal, Roberts, Zeisel, Hennon, & Hooper, 2006). Studies on intelligence as a protective factor against criminal recidivism were also excluded (Salekin, Lee, Schrum Dillard, & Kubak, 2010) since our focus is on how intelligence protects against the commission of crime in the first place.

In the case of multiple papers based on the same longitudinal study (e.g., the Bielefeld-Erlangen Study on Resilience) the most recent publication (i.eBender, Bliesener, & Lösel, 1996) was chosen over older ones (i.e., Lösel & Bliesener, 1994) so as to include the most up-to-date relevant data. Similarly, for the Cambridge Study in Delinquent Development, the most recent publication (i.e., Farrington, Ttofi, & Piquero, 2016) was also chosen over older manuscripts (i.e., Farrington & Ttofi, 2011; Farrington & West, 1993).

Results

Fifteen studies investigated the extent to which an above-average intelligence may function as a protective factor against delinquency and offending. Eight out of 15 studies were based in Europe, five in America and two in New Zealand. Table 1 presents detailed information on the location of the study, the type of risk factors investigated and at which age, what instrument (at what age) was used to measure intelligence, and the outcome measure.

We have meta-analyzed data by synthesizing studies which fell within the same methodological design (discussed below), irrespective of whether they presented dichotomous or continuous data or correlation/regression coefficients or other statistical measures.

In the meta-analytic sections below, results are presented in the form of the Odds Ratio (OR), a statistic formula measuring the association of intelligence with offending. ORs are presented with their accompanying 95% confidence intervals (CIs). Following the notion of resilience, the outcome measure is lower offending. Therefore, an OR larger than 1 would mean that more resilient individuals (i.e., non-offenders) are more likely to have higher intelligence compared with non-resilient individuals (i.e., offenders). Conversely, an OR greater than 1 could mean that high IQ individuals are less likely than low IQ individuals to be offenders.

CIs including the value of 1 suggest a non-significant effect that could be attributable to low numbers in the analyses or low base rates of offending, or to genuinely null effects of intelligence. The random effects computational model has been used for the calculation of the summary effect size as it provides more balanced study weights (Borenstein, Hedges, Higgins, & Rothstein, 2009). Relevant forest plots provide results for both the fixed-effects and the random-effects models. In the Appendix Notes, we also present results based on another computational method for calculating a weighted mean effect size, namely the Multiplicative Variance Adjustment (MVA) method, proposed by Jones (2005) and tested by Farrington and Welsh (2013).

Within this review, *interactive protective factors* (or 'buffering' factors) are defined as those variables that predict a low probability of an undesirable outcome in the presence of risk when the attribute (i.e., protective factor) is present but not when the attribute is absent (Lösel & Farrington, 2012; Luthar et al., 2000; Luthar et al., 2006). In the case of interactive protective factors, data analyses essentially focus on interaction effects, which are evidenced when individuals with an attribute (here, higher intelligence) manifest greater adjustment overall (i.e., lower offending) than those without it, namely children with lower intelligence (Luthar et al., 2000, p. 547). Essentially, it is hypothesized that a higher proportion of resilient individuals (i.e., 'non-offenders') are likely to exhibit the attribute (i.e., the presence of a protective factor, namely high intelligence), while a higher proportion of non-resilient individuals (i.e., 'offenders') are likely to lack the attribute (i.e., have lower intelligence); and that this pattern is stronger within the high risk group rather than the low-risk group.

This methodological design is shown in Fig. 1. Following previous debates in the field of resilience (Garmezy, Masten, & Tellegen, 1984; Luthar et al., 2000; Rutter, 1987), we argue that this is the most cogent methodological design for investigating "protective effects" in comparison with analyses of "direct ameliorative effects' (see Fig. 3 below). A total of six longitudinal studies investigated the extent to which intelligence is an interactive protective factor against later delinquency and/or offending (i.e., Farrington et al., 2016; Kandel et al., 1988; Kolvin, Miller, Fleeting, & Kolvin, 1988; Lösel & Bender, 2014; Stattin et al., 1997; White, Moffitt, & Silva, 1989), two of which lacked sufficient statistical information for inclusion in a meta-analytic investigation (i.e., Kolvin et al., 1988; Stattin et al., 1997). With the exception of Kandel et al. (1988), the other five studies investigated IQ before the outcome measure of offending/delinquency.

We meta-analyzed data from four studies, investigating the extent to which a higher level of intelligence was a factor which could predict low levels of offending differentially within the high-risk and the low-
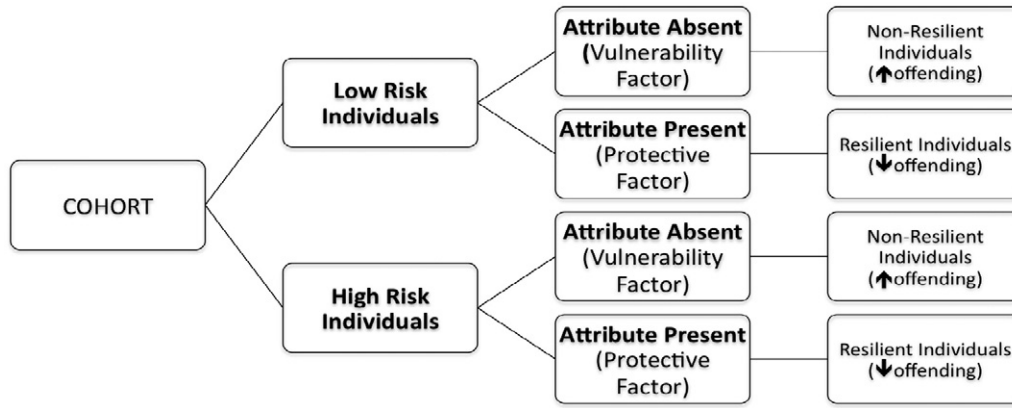
Fig. 1. Methodological Design for Interactive Protective Factors.

risk groups. In two of these studies, the outcome measure in the data analyses was intelligence, with authors presenting the mean intelligence level of delinquents versus non-delinquents (White et al., 1989) and criminals versus non-criminals (Kandel et al., 1988) within both high-risk and low-risk groups. In the other two studies (Farrington et al., 2016; Lösel & Bender, 2014), the outcome measure in the data analyses was offending, with authors investigating the prevalence of offenders versus non-offenders within the protective (high intelligence) and non-protective (low intelligence) category for both high-risk and low-risk individuals. Data from these four studies could be synthesized since they all essentially deal with the same association. For the Farrington et al. (2016) study, effect sizes are based on a combined summary effect size across all significant and non-significant interaction effects shown on Table 4 of their manuscript. For the Lösel and Bender (2014) study, effect sizes are based on data sent via email communication (Lösel & Bender, 2016).

Consistent with the initial hypothesis, within the high-risk group (i.e. individuals exposed to other risk factors for offending), resilient individuals were much more likely to have a high intelligence level compared with non-resilient individuals (random effects model OR = 2.32; 95% CI: 1.49 – 3.63; p = 0.0001) with all individual effect sizes in the predicted direction (Fig. 2). Conversely, within the protective category (i.e., high intelligence) high-risk individuals were more likely to be resilient, as shown by the smaller fraction of offenders within this group. Publication bias analyses, using the Trim and Fill method, suggested a slight overestimation of the summary effect size. Specifically, under
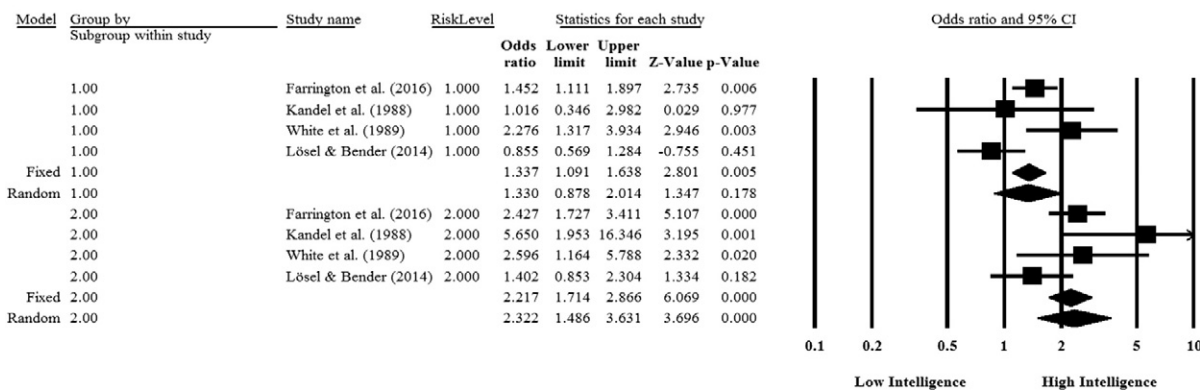
the random effects model, the point estimate was 2.32 and the 95% confidence interval was 1.49 – 3.63. Using Trim and Fill, the imputed point estimate was an OR of 2.04 and the 95% confidence interval was 1.26 – 3.30. However, Rosenthal's Classic fail-safe N method suggested that we would need to locate and include 34 'null' studies in order for the combined 2-tailed p-value to exceed 0.05. It is unlikely that our search process would have missed this many studies.

Within the low-risk group (i.e. those not exposed to other risk factors), resilient individuals were not more likely to have a higher intelligence level compared with non-resilient individuals (Fig. 2), suggesting that the proportion of offenders was similar within the protective (i.e., high intelligence) and non-protective (i.e., low intelligence) categories (random effects model OR = 1.33; 95% CI: 0.88 – 2.01; p = 0.18). Given the non-significant results, we have not conducted any analyses for publication bias.

Overall, meta-analytic results of studies on interactive protective factors suggest that a higher level of intelligence was a factor which could predict low levels of offending differentially within the high-risk and the low-risk groups. A high intelligence level is differentially protective against offending within different levels of risk. In agreement with an interaction effect, the high-risk and low-risk effect sizes were significantly different (mixed effects meta-regression: point estimate = 0.509; SE = 0.175; p = 0.004; fixed effects meta-regression: point estimate = 0.506; SE = 0.167; p = 0.003).

Within this paper, main effects are investigated through *risk-based protective factors*, namely factors that predict a low probability of an

Intelligence as a Protective Factor against Offending for Low and High Risk Individuals

Model	Group by Subgroup within study	Study name	RiskLevel	Odds ratio	Lower limit	Upper limit	Z-Value	p-Value	Odds ratio and 95% CI
	1.00	Farrington et al. (2016)	1.000	1.452	1.111	1.897	2.735	0.006	
	1.00	Kandel et al. (1988)	1.000	1.016	0.346	2.982	0.029	0.977	
	1.00	White et al. (1989)	1.000	2.276	1.317	3.934	2.946	0.003	
	1.00	Lösel & Bender (2014)	1.000	0.855	0.569	1.284	-0.755	0.451	
Fixed	1.00			1.337	1.091	1.638	2.801	0.005	
Random	1.00			1.330	0.878	2.014	1.347	0.178	
	2.00	Farrington et al. (2016)	2.000	2.427	1.727	3.411	5.107	0.000	
	2.00	Kandel et al. (1988)	2.000	5.650	1.953	16.346	3.195	0.001	
	2.00	White et al. (1989)	2.000	2.596	1.164	5.788	2.332	0.020	
	2.00	Lösel & Bender (2014)	2.000	1.402	0.853	2.304	1.334	0.182	
Fixed	2.00			2.217	1.714	2.866	6.069	0.000	
Random	2.00			2.322	1.486	3.631	3.696	0.000	

Low Intelligence   High Intelligence

Meta Analysis of Prospective Longitudinal Studies for Interactive Protective Factors

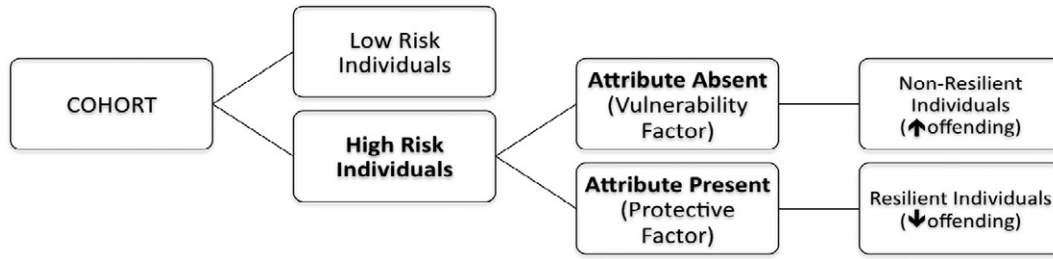**Fig. 2.** Forest Plot for IQ as an Interactive Protective Factor.

Fig. 3. Methodological Design for Risk-Based Protective Factors.

undesirable outcome within a risk category. These factors are usually found in research designs focusing on high-risk individuals (Lösel & Farrington, 2012) some of whom show the predicted undesirable outcome (e.g., offending later in life) while others do not (i.e., seem to have resilience to the negative impact of earlier adversities). Alternatively and equivalently, the high-risk group can be split into those with or without the protective factor and then the percentage of offenders within each category can be investigated. Following the relevant resilience literature (Garmezy et al., 1984; Lösel & Farrington, 2012; Luthar et al., 2000), we argue that this is the most cogent methodological design for investigating "direct ameliorative effects" in comparison with analyses of direct protective or promotive factors. This methodological design is shown in Fig. 3.

Essentially, it is hypothesized that a higher proportion of resilient individuals (i.e., 'non-offenders') are likely to exhibit the attribute (i.e., the protective factor, namely high intelligence), while a higher proportion of non-resilient individuals (i.e., 'offenders') are likely to lack the attribute (i.e., have lower intelligence). The presence of the positive attribute (i.e., risk-based protective factor) is what differentiates resilient from non-resilient individuals who share the same lever of risk. Conversely, within the protective category (i.e., high-risk individuals who have higher intelligence) a larger proportion would be resilient (i.e., would have not offended rather than offended) compared to the non-protective category.

Four longitudinal studies investigated the extent to which intelligence is a risk-based protective factor against later delinquency and/or offending (Bender et al., 1996; Fergusson & Lynskey, 1996; Jaffee, Caspi, Moffitt, Polo-Tomas, & Taylor, 2007; Werner & Smith, 1982). With one exception (i.e., Bender et al., 1996), the measurement of the protective factor occurred before the measurement of the outcome. We were unable to include one study (Bender et al., 1996) in the meta-analysis due to insufficient data for calculation of an effect size (i.e., standardized mean differences are provided, but without their accompanying 95% confidence intervals or standard errors). Under the

random effects model, the summary effect size across these three studies was an OR of 2.28 (95% CI: 0.96 – 5.42; p = 0.062).[1] In the final meta-analysis, we also included relevant statistical information for the high-risk groups presented in the papers by: Farrington et al. (2016), Kandel et al. (1988), Lösel and Bender (2014) and White et al. (1989), making a total of seven reports. The relevant analyses and forest plot is shown in Fig. 4.

All individual effect sizes were in the expected direction. Under the random effects model, the summary OR was 2.32 (95% CI: 1.50 – 3.60; p = 0.0001), showing that resilient individuals were much more likely to have a high intelligence level compared with non-resilient individuals. Conversely but equivalently, within the protective category (i.e., high intelligence) individuals were more likely to be resilient, as shown by the smaller fraction of offenders within this group. Publication bias analyses suggest a slight overestimation of the summary effect size, with one imputed study to the left of the mean (under the random effects model) that would reduce the summary effect size to an OR of 1.99 (95% CI: 1.31 – 3.03). Rosenthal's Classic Fail-Safe N test suggested that we would need to locate and include a total of 131 'null' studies in order for the combined 2-tailed p-value to exceed 0.050. Therefore, we can be confident that high intelligence is protective against offending among high-risk individuals.

Attention should be drawn to the fact that in one study (Jaffee et al., 2007) the outcome of antisocial behavior was measured (based on a two-year follow-up) at a very young age (average 6.5 years). In another study (Werner & Smith, 1982), the outcome of delinquency was combined with other problems such as mental/physical health. However, the Kauai Longitudinal Study of Werner and Smith is a seminal study of resilience and it was felt that exclusion of it could not be justified. Given the small number of studies that investigated direct ameliorative effects using this design, a decision was made to include these two studies.

In a recent coordinated effort, the Centers for Disease Control and Prevention's Expert Panel on protective factors against youth violence
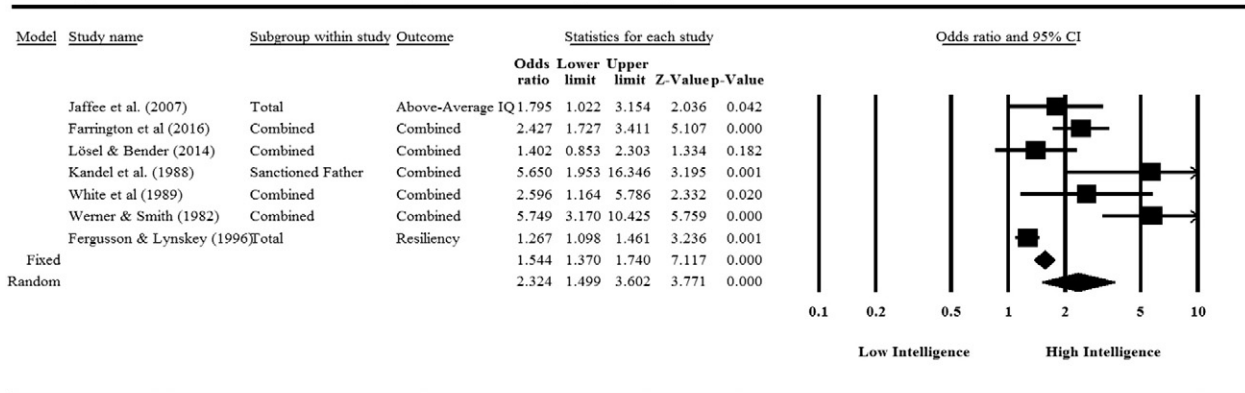
Fig. 4. Forest Plot for IQ as a Risk-Based Protective Factor.

perpetration defined *direct protective/promotive factors* as factors that precede youth violence perpetration and predict a low probability of youth violence perpetration in the general population (Hall et al., 2012, p. 3). This is consistent with previous terminology (Lösel & Farrington, 2012). We followed this terminology and we were able to locate some studies that looked at the extent to which intelligence predicted a low probability of an undesirable outcome and these are shown on Table 1 (Andershed, Gibson, & Andershed, 2016; Dubow, Huesmann, Boxer, & Smith, 2016; Klika, Herrenkohl, & Lee, 2012; Loeber, Pardin, Stouthamer-Loeber, & Raine, 2007; McCord & Ensminger, 1997). We have not meta-analyzed data from these five studies since only one of them investigated issues of linearity so as to distinguish promotive effects from the 'opposite side' of risk effects (see: Loeber et al., 2008).

All five of these studies focused on either chi-squared or regression analyses based on the overall sample rather than differentiating between low-risk and high-risk individuals. With one exception (Dubow et al., 2016), the findings suggest that a higher intelligence level predicted less delinquency, offending and violence. Data analyses by

Andershed et al. (2016), based on a sample of Swedish males, suggest that less violent males had higher intelligence (OR = 0.67). McCord and Ensminger (1997), based on American data, found a similar statistically significant effect of intelligence for males ($X^2 = 3.98$, p = 0.46) but not quite for females ($X^2 = 3.04$, p = ns), while Loeber et al. (2007), using data from their youngest American cohort from Pittsburgh, PA, found statistically significant differences between delinquents and non-delinquents for verbal ($X^2 = 11.87$, p < 0.001) but not spatial ($X^2 = 3.41^{ns}$) intelligence. In the Dubow et al. (2016) study, based on American data, there was no significant difference in IQ between violent and non-violent males (t = 1.57, p = ns). However, this finding should be treated with caution since, at the age 48 follow-up, there was an attrition of 39% of the original sample which was differential by the age 8 IQ (i.e., the re-interviewed participants had significantly lower intelligence compared to the not re-interviewed participants). Finally, one study reported significant interaction effects between intelligence and another variable in predicting reduced levels of an undesirable outcome (Klika et al., 2012), but without a plot showing what this interaction
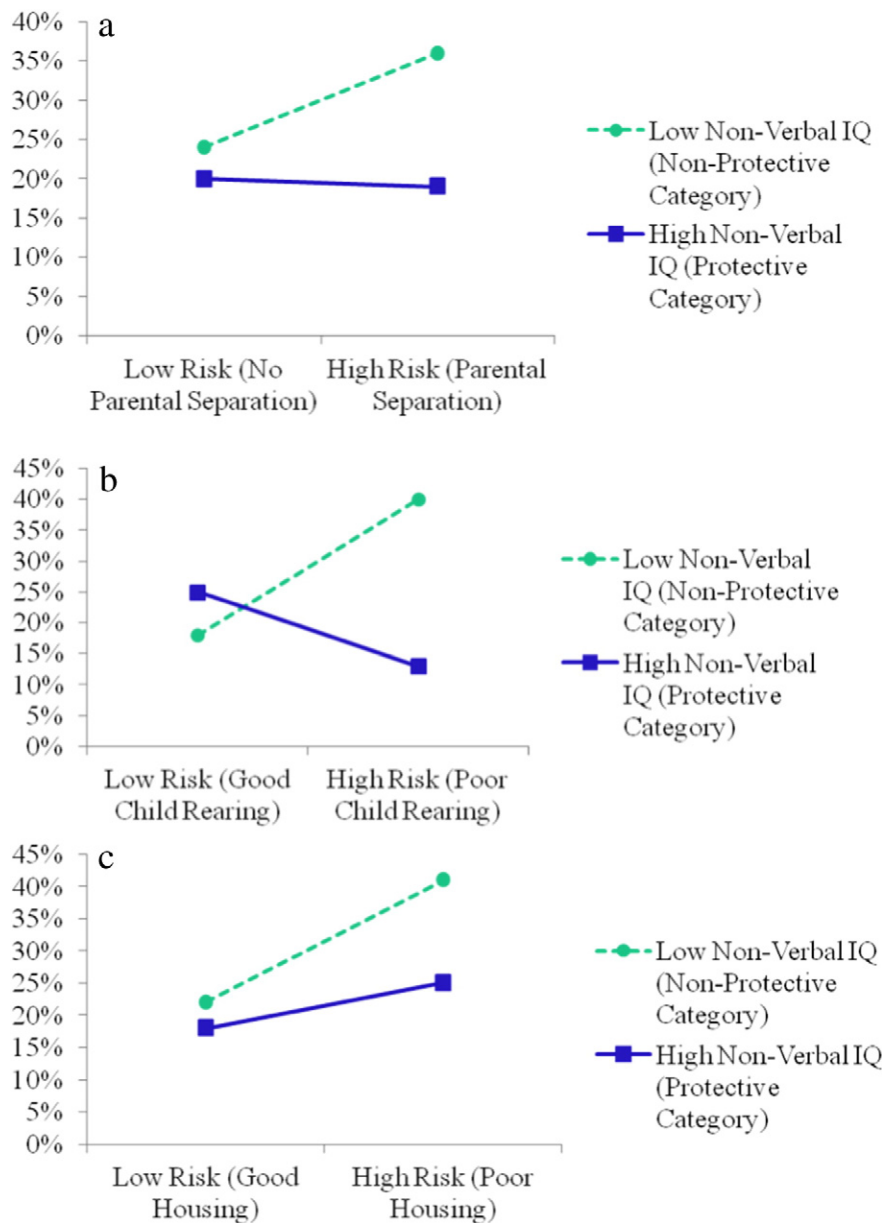

Fig. 5. Percentage of Offenders as a Function of Increasing Risk within High and Low IQ. Note: Results are based on interaction effects based on data from the Cambridge Study in Delinquent Development (Farrington et al., 2016; Table 4). A = Protective Stabilizing Effect; B = Protective Enhancing Effect; C = Protective Reactive Effect.

term actually means and what the direction of effect is. Because this study did not report sufficient statistical information, it could not be included in the meta-analyses of interactive protective factors.

Previous research (Farrington, 1997; Luthar et al., 2000) highlighted the importance of moving beyond the mere presentation of significant interaction terms and indicating what each interaction term actually means in such a way that salient vulnerability and resilience processes/mechanisms are clearly labeled. In a previous edited volume of the *Journal of School Violence* on protective factors that interrupt the continuity from youth aggression to later adverse outcomes (Ttofi, Farrington, & Lösel, 2014a; Ttofi et al., 2014a), coordinated cross-national efforts have been made by leading teams of major prospective longitudinal studies to investigate such effects in relevant plots. Protective and vulnerability effects were discussed based on the work of Luthar et al. (2000) in the systematic review included in the edited volume (Ttofi et al., 2014b, p. 12). Fig. 5 presents examples of protective effects from the Cambridge Study in Delinquent Development (see Farrington et al., 2016, Table 4, current issue). The plots present the interactive effects of non-verbal intelligence with three different risk factors against offending (showing percentages of offenders within each category).

Following the terminology used by Luthar et al. (2000), intelligence had a "protective stabilizing" effect against parental separation since the protective factor conferred stability in competence (i.e., no increase in offending) despite increasing risk. With regard to the interaction between intelligence and child rearing in predicting offending, intelligence had a "protective enhancing" effect since the positive attribute (i.e., high intelligence) allowed high-risk individuals to 'engage' with stress such that their competence was augmented compared with low-risk individuals (what Farrington, 1997, defined as 'expected crossover effect'). Finally, intelligence had a "protective but reactive" effect against the impact of quality of housing on offending in that the attribute (i.e., high intelligence) protected against offending but did not reduce the probability of offending to the same level as in the low risk category (as in Fig. 5A).

Discussion

The significant negative association of intelligence with violent or serious delinquency (Lipsey & Derzon, 1998), conduct disorder (Moffitt, 1993) and juvenile recidivism (Cottle, Lee, & Heilbrun, 2001) has been well-established. Delinquents score on average eight IQ points lower than non-delinquents (or a deficit of one-half standard deviation) on standard intelligence tests (Hirschi & Hindelang, 1977; Wilson & Herrnstein, 1985). Notably, intelligence relates to delinquency and crime about as strongly as do measures of class or race (Hirschi & Hindelang, 1977), while the strength of association remains robust even when looking at female delinquency alone (Hubbard & Pratt, 2002).

Despite the wealth of literature reviews on the intelligence-offending link, to the best of our knowledge, there has been no earlier synthesis of the literature on how intelligence may function as a protective factor against offending. We addressed this gap in research literature by systematically searching and meta-analyzing data from prospective longitudinal studies.

Scholarly interest in resilience within the field of developmental psychopathology (Luthar et al., 2000; Masten, Best, & Garmezy, 1990; Rutter, 1987, 2012) looked at children of schizophrenic mothers (e.g., Garmezy, 1974) and children of socioeconomic disadvantage and other associated risks (e.g., Werner & Smith, 1982) in an attempt to explain individual variations in response to adversity. A consistent pattern that emerges from that literature relates to the protective effects of intelligence. Specifically, children who experience chronic adversity fare better or recover more successfully when they are good learners and problem solvers (Masten et al., 1990) although, further protective factors from the individual, family and other domains are equally important.

Translating relevant concepts from the field of developmental psychopathology (Luthar et al., 2000; Masten et al., 1990; Rutter, 2012) into the field of criminology, we looked at the extent to which intelligence may explain resilience (in the form of reduced offending) against childhood adversities differentially for high-risk and low-risk individuals. We included all relevant studies that claimed to have looked at the protective effects of intelligence and we coded them based on their methodological rigor.

We located fifteen longitudinal studies. The conceptualization and empirical testing of protective effects of intelligence against offending varied notably across these studies. This is consistent with previous critical appraisals of the resilience literature, which raised concerns about the ambiguities in the definitions and terminology used across studies (Luthar et al., 2000; Masten & Cicchetti, 2010). Potentially, this may relate to the negative association between intelligence and offending which could be wrongly translated into a 'protective effect' of high intelligence against offending, without careful consideration of a methodologically rigorous approach to data analysis (Garmezy et al., 1984; Rutter, 2012).

Taking into account issues of methodological quality (Garmezy et al., 1984; Luthar et al., 2000; Rutter, 2012), all fifteen studies were ranked into three categories. Six studies (i.e., Farrington et al., 2016; Kandel et al., 1988; Kolvin et al., 1988; Lösel & Bender, 2014; Stattin et al., 1997; White et al., 1989) were coded as of the highest methodological quality because they investigated the buffering effect of intelligence against offending with increasing risk. Meta-analytic results support the interactive protective effects of intelligence against offending differentially within the high-risk (a significant OR of 2.3) and the low-risk (a non-significant OR of 1.3) groups. Translating this finding into policy and practice, attention should be paid to the cognitive development of high-risk individuals, potentially via intellectual enrichment, tutoring, or other individual and school programs (Farrington, Ttofi, & Lösel, In press).

Since a small fraction of high-risk individuals are responsible for the majority of offenses committed (Blumstein, Cohen, Roth, & Visher, 1986; Piquero, Farrington, & Blumstein, 2003) it is best to address not only the deficits but also the strengths of these high-risk youth rather than targeting the wider population of youth. Research on offender treatment shows that programs are more effective with high-risk offenders rather than low-risk offenders. This is an element of the Risk-Need-Responsivity model for offender assessment and treatment (Andrews, Bonta, & Hoge, 1990).

Four studies (Bender et al., 1996; Fergusson & Lynskey, 1996; Jaffee et al., 2007; Werner & Smith, 1982) were coded as having used the most cogent methodological design for investigating "direct ameliorative effects" in that they looked at the extent to which intelligence predicted a low probability of offending among a group at risk. Essentially, in these studies a high-risk group was split into those with or without the positive attribute (i.e., intelligence) and then the percentage of offenders within each category was investigated. It was found that within the protective category (i.e., high intelligence) individuals were more likely to be resilient (as shown by the smaller fraction of offenders within this group), supporting the direct ameliorative effect of intelligence against offending for high-risk individuals (a significant OR of 2.3).

Finally, five studies were ranked third in their methodological rigor in that they investigated the protective effects of intelligence against offending in the general population (combining high-risk and low-risk individuals), what has previously been termed as a direct protective (or promotive) effect (Hall et al., 2012; Loeber et al., 2008). Of those studies, only one investigated issues of linearity so as to distinguish promotive effects from the 'opposite side' of risk effects (i.e., Loeber et al., 2008). These studies essentially support what was previously suggested about the negative association between intelligence and offending (Hirschi & Hindelang, 1977; Moffitt, 1993).

This methodological demonstration paper has confirmed the variability in conceptualizations, theoretical approaches and methodological strategies used to investigate the protective effects of intelligence

against offending. We agree with previous critical appraisals of the resilience literature and underscore the need for careful consideration of methodologically rigorous approaches to data analysis (Garmezy et al., 1984; Luthar et al., 2000; Rutter, 2012). Our meta-analytic results support differences in results generated from high-risk versus low-risk samples. Future research should assess whether meta-analytic findings on other factors within the individual, family, or school domains will replicate existing findings about the stronger protective effects within high-risk groups.

It is also plausible that accumulated protective factors have a much stronger effect in encouraging non-offending than do single factors (e.g., Jaffee et al., 2007; Stattin et al., 1997) and, in fact, scholars have previously highlighted the complex developmental processes and interactions that take place across domains (Masten & Cicchetti, 2010). Nevertheless, it is equally important to first investigate the actual protective effects of individual factors by systematically searching and meta-analyzing all relevant literature. Also, although accumulations of both risk and direct protective/buffering protective factors may enhance predictive validity, heterogeneous indices make the meaning of the respective constructs unclear. As a consequence, causal inferences are more difficult to draw than in studies that only address single variables or homogeneous constructs (Lösel & Farrington, 2012, p. S17). Similarly, it is more challenging to 'translate' cumulative protective effects into policy and practice.

Our meta-analytic findings investigated the prevalence of offending within the protective and non-protective categories. Ideally, it would be interesting to know more about the exact protective mechanisms that link intelligence to resilience (Masten et al., 1990; Rutter, 1987). It is plausible that protective mechanisms relate to how school performance (Lynam, Moffitt, & Stouthamer-Loeber, 1993), self-control (McGloin, Pratt, & Maahs, 2004), motivation to change (Salekin et al., 2010), and other variables mediate the relationship between intelligence and offending. Also, 'resilience' is a dynamic construct underpinning developmental changes within the individual (Luthar et al., 2000, 2006).

Protective (but also risk) mechanisms and effects are part of the natural life course of individuals and cannot always be subject to randomization and experimental manipulations (Lösel & Farrington, 2012; Murray, Eisner, & Farrington, 2009). Therefore, within-individual analyses may be better suited to investigate such protective (and risk) processes rather than analyses based on between-individual designs. Our meta-analytic review is limited to between-individual analyses provided by existing longitudinal data. Future studies should focus more on within-individual analyses to differentiate between protective effects that are truly causal effects rather than mere correlations (Farrington, 1988).

All studies in this review were conducted in high-income countries in North America, Europe and New Zealand. Another important question for future research is whether intelligence has similar protective effects in low- and middle-income countries, many of which are characterized by high rates of violence, and multiple adverse conditions for early development (Murray, Cerqueira, & Kahn, 2013; Walker et al., 2007). To our knowledge, only two longitudinal studies in low- and middle-income countries have examined the association between intelligence and antisocial behavior. In the Mauritius Child Health Project, low spatial intelligence, but not verbal intelligence, at age three years predicted persistent antisocial behavior between ages 8 and 17 (Raine, Yaralian, Reynolds, Venables, & Mednick, 2002). In a study of Polish children aged seven and nine years, higher intelligence was weakly and negatively associated with aggression over the next two years for boys ($r = - 0.17$); but the association for girls ($r = - 0.13$) was nonsignificant (Fraczek, 1986). Experimental and observational studies in low- and middle-income countries show that breastfeeding increases intelligence in both childhood and adulthood (Kramer et al., 2008; Victora et al., 2015). Therefore, public health policies to promote breastfeeding might help protect children from developing antisocial and criminal behavior. However, a Brazilian study found no association between duration of breastfeeding and violent crime (Caicedo, Gonçalves, González, & Victora, 2010). This could be because individual factors like intelligence do not have the same protective effects in contexts of high cumulative social risk (Raine, 2013). Hence, more research is needed to identify the protective effects of intelligence in countries with high rates of social disadvantage and crime.

It is hoped that the current meta-analytic investigation has advanced knowledge about the protective effects of intelligence against offending. Future meta-analytic reviews should investigate the protective effects of other factors from the individual, family, school and other domains by carefully synthesizing studies of similar methodological design.

Appendix Note: Measuring Effect Sizes using the Multiplicative Variance Adjustment Method

Farrington and Welsh (2013) argued that the two commonly used methods of estimating a weighted mean effect size in meta-analysis (i.e. the fixed effects and random effects models) raise concerns when there is significant heterogeneity of the effect sizes. Specifically, the fixed effects model can be problematic when there is significant heterogeneity because it assumes that all effect sizes are distributed randomly about the mean, and heterogeneity measures the extent to which this assumption is incorrect. The random effects model can be problematic when there is significant heterogeneity because significant heterogeneity causes all the effect sizes to be similarly weighted, whereas effect sizes from larger studies should be given more weight in estimating the mean.

Farrington and Welsh used one of the methods proposed by Jones (2005) for calculating a weighted mean effect size, namely the Multiplicative Variance Adjustment (MVA) method in order to overcome these problems. In this method, the variance of each effect size based on the fixed effects model is multiplied by Q/df, where Q is the heterogeneity and df is the degrees of freedom on which it is based. This model exactly fits the data and exactly adjusts for the heterogeneity of the effect sizes. It yields the same weighted mean effect size as the fixed-effects model (appropriately giving more weight to larger studies) but a larger variance.

Using the MVA method, the weighted mean OR for the low risk studies is 1.337 (CI = 0.942 to 1.897, z = 1.63, ns). For the high risk studies, the weighted mean OR is 2.217 (CI = 1.511 to 3.250, z = 4.07, p < .0001). Thus, using this method does not change our conclusion that intelligence is a significant protective factor in the high risk category but not in the low risk category. Furthermore, these two ORs are significantly different (z = 2.70, p = .007), confirming the likely interaction effect.

The weighted mean ORs in the risk-based analysis illustrate the flaws of the two common methods. The fixed effects model yields an OR of 1.544, while the random effects model yields an OR of 2.324. Why do the two methods give such different results? This is because the fixed effects model gives more weight to larger studies such as Fergusson and Lynskey (1996), which has a relatively low OR of 1.267. In contrast, the random effects model gives more similar weights to all studies, whether small or large. By inappropriately overweighting the smaller studies, the random effects model overestimates the mean effect size. However, because of the high heterogeneity (Q = 40.647, 6 df, p < .0001), the fixed effects model underestimates the variance of the mean effect size. The MVA model overcomes both of these flaws and yields OR = 1.544 (CI = 1.131 to 2.108, z = 2.74, p = .006). However, it does not change our conclusion that intelligence is a significant protective factor in these risk-based studies.

Appendix Table 1. List of Databases Searched

1.	Child Development and Adolescent Studies (EBSCOHost)
2.	Criminal Justice Abstracts (EBSCOHost)
3.	Education Resource Information Center (ERIC)
4.	Embase
5.	Ethos
6.	Google Scholar

Note

[1] Under the fixed-effects model, the summary OR was 1.40 (95% CI: 1.22 – 1.60; p = 0.0001). Publication bias analyses using Trim and Fill suggested no imputed studies for the random effects model to either the left or the right of the mean, suggesting no over-estimation or underestimation of the summary effect. For the fixed-effect model, publication bias analyses suggested an imputed point estimate of 1.27 (95% CI: 1.12– 1.44), an indication of a slight overestimation for this computational model.

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