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Protection From Risk: An Exploration of When and How Neighborhood-Level Factors Can Reduce Violent Youth Outcomes

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Abstract

This research explores the ability of neighborhood-level factors to serve as either promotive or protective factors to reduce the risk of violent outcomes among adolescents. Unique contributions of this research include a novel definition of neighborhood constructed through a housing market study, the aggregation of individual-level survey responses to the newly defined neighborhoods, and the application ofhierarchical linear modeling to explore cross-level interaction (e.g., protective) effects. Using data from Waves 1–9 of the Rochester Youth Development Study, our analyses find little support for promotive effects at the neighborhood level. However, several of our constructs are revealed to provide protective effects across various domains of risk. In specific, we find that high-risk youths whose parents report high levels of social integration and neighborhood integration are less likely to experience violent outcomes than similar youth whose parents do not report high levels of integration. These findings were particularly strong in the domains of school and peer risk which may inherently reflect the "social" quality of risk in these realms.

Keywords

neighborhoods, risk and protection, violence, multilevel models

Introduction

Resilience is defined as "a dynamic process encompassing positive adaptation within the context of significant adversity" (Luthar, Cicchetti, & Becker, 2000, p. 543). Implied in this definition are two essential components. First, there must be a substantial degree of exposure to threat or adversity. In the criminal justice literature, such factors are often referred to as "risk factors," which are

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conditions that increase the probability of a negative outcome (Reppucci, Fried, & Schmidt, 2002; Richman & Fraser, 2001). The other component implied in the definition is that given such challenging or threatening circumstances, positive adaptation is still achievable. An interesting question thus emerges regarding when and how one achieves such a positive outcome in the face of adversity. Research by Rutter (1985) suggests that certain attributes of the individual and the environment might serve to buffer the impact of risk factors, thereby increasing the probability of a positive outcome. Such factors have become known as "protective factors."

Much of the work on risk and protective factors has focused on individual- or group-level variables involving family relations, school commitment, involvement and achievement, peer relations, and characteristics of the individual ranging from temperament to measures of educational aptitude (e.g., Farrington, 1995; Farrington, Loeber, Jolliffe, & Pardini, 2008; Fraser, Kirby, & Smokowski, 2004; Masten et al., 1999; Stouthamer-Loeber, Loeber, Wei, Farrington, & Wikstrom, 2002; Thornberry, Krohn, Lizotte, Smith, & Tobin, 2003). When environmental variables have been considered, they have usually been conceptualized and operationalized according to the traditional social disorganization framework (Shaw & McKay, 1942) and treated as risk factors. In other words, variables such as the percentage of the population living in poverty, the racial composition of the neighborhood, residential mobility, and neighborhood crime rates, have been conceptualized as risk factors that increase the probability of a negative outcome, or more specifically, the probability that individuals living in that neighborhood will turn to crime and violence (e.g., Brooks-Gunn, 1996; Brooks-Gunn, Duncan, Leventhal, & Abert, 1997; Bursik & Grasmick, 1993; Kornhauser, 1978). Few studies have examined the possibility that certain characteristics of the neighborhood could actually protect residents from the problematic influences that surround them. In part, this oversight was due to the focus on census measures of neighborhood data that are conceptually more consistent with risk than protective factors. More recently, greater efforts in the collection of individual-level data and advances in statistical techniques to more precisely measure contextual effects have allowed researchers from a variety of fields to examine how neighborhoods interact with individual-level risk factors to either increase or decrease the probability of crime (Beyers, Bates, Pettit, & Dodge, 2003; Kubrin & Weitzer, 2003; Sampson, Morenoff, & Earls, 1999; Sheidow, Gorman-Smith, Tolan, & Henry, 2001).

The current study builds upon and extends this approach by incorporating variables measured at, or aggregated to, the neighborhood level. These variables go beyond the traditional demographic information available via the census to reflect emerging concepts of neighborhood protection such as collective efficacy, integration, reciprocal exchange (Sampson, Raudenbush, & Earls, 1997), and neighborhood support and integration (e.g., Bursik & Grasmick, 1993; Smith & Jarjoura, 1988; Warner & Rountree, 1997). This study also takes a new and innovative approach to the definition of "neighborhood" by transcending the traditional use of census tracts to a more realistic measure of a neighborhood based on designations produced by the local real estate market. The findings of this study will fill an important gap in the existing literature by exploring the ability of a key set of neighborhood characteristics to "protect" youth from a variety of known risk factors. Before delving into our analytical approach, we begin with an overview of the conceptual issues relevant to this research.

The Risk and Protective Factors Approach

An early application of the risk factor approach in criminology dates back to the seminal longitudinal Cambridge Study of Delinquent Development in the 1970s (West & Farrington, 1973). Modeled after a public health approach, this study focused on identifying the correlates of criminal behavior and determining how to reduce the risk of those correlates. Although this approach has much currency in the research literature, there have been refinements in how the key concepts of risk, promotion, and protection have been defined.

For example, Rutter (1985) distinguished between what he refers to as promotive and protective factors. Promotive factors are the opposite end of the risk factor continuum, simply decreasing the probability of negative outcomes. More specifically, preventive promotive factors are defined as factors that predict a low probability of later delinquency, while remedial promotive factors predict desistance from offending of known delinquents (Farrington et al., 2008). Rutter suggests that we do not equate promotive factors with protective factors as was the case in a number of early studies (Fraser et al., 2004; Hawkins, Catalano, & Miller, 1992; Loeber & Farrington, 2000; Stouthamer-Loeber et al., 1993, 2002). Instead, Rutter (1985) suggests that we use the term protective factors as "influences that modify, ameliorate, or alter a person's response to some environmental hazard that predisposes to a maladaptive outcome" (p. 600). The implication of this definition is that factors should be considered protective if they differentiate between persons who face a comparatively high risk of disorder, but, in one case become deviant, and in the other, do not.

Applying the Risk and Protective Factor Approach to Neighborhood-Level Analysis

Social disorganization theory introduced the discipline to the importance of the neighborhood in explaining crime and remains the major theoretical perspective encompassing community-level variables. While the perspective has undergone significant changes since the works emanating from the Chicago School (Park & Burgess, 1925; Shaw & McKay, 1942), it remains the major theoretical perspective focusing on community-level variables in modern criminology (e.g., Bursik, 1988; Sampson & Groves, 1989; Sampson et al., 1997; Stark, 1987).

Much of the early research on social disorganization focused on how macro-level neighborhood variables increased crime rates in certain neighborhoods (Bursik, 1988; Kornhauser, 1978). For example, Stark (1987) contended that there are five aspects of urban neighborhoods—density, poverty, mixed use of land, transience, and dilapidation that would lead to moral cynicism among residents and diminished social control in the community. As a result, there would be increased opportunities for crime and delinquency, which further amplify the volume of crime and deviance by simultaneously attracting deviant and crime-prone people to the neighborhood and driving out the least deviant. In general, research has supported such notions and has evolved to include additional community-level considerations such as racial and ethnic heterogeneity, socioeconomic status (SES) and proportion of single-parent families, which have all been found to increase rates of crime and violence (Byrne & Sampson, 1986; Hipp, 2007; Miethe & Meier, 1994; Sampson & Groves, 1989; Shaw & McKay, 1942).

While these findings are critical to our understanding of how neighborhood factors are important in explaining crime rates, they address only part of the argument inherent in the social disorganization perspective. Kornhauser (1978) clarifies this point by situating the social disorganization perspective within the broader category of social control theories since its basic assumptions are consistent with them. Essentially, social control theories assume that deviant behavior, including crime and violence, is attractive and therefore we must explain why individuals do not commit crime, rather than seeking reasons why they do. Shaw and McKay's (1942) basic premise of a "disorganized community" is one that lacks the ability to evoke both informal and formal social controls. Specifically, their theory identified three structural neighborhood factors—low economic status, residential instability, and ethnic heterogeneity, that lead to the disruption of community social organization rendering the community incapable of maintaining effective social controls. High rates of crime and violence thus naturally occur in these areas.

In addition to highlighting connections to the social control perspective, Kornhauser (1978) brought renewed attention to the social disorganization perspective by pointing out that the primary overlooked components of Shaw and McKay's work were the processes through which social disorganization at the neighborhood level is linked to individual delinquency. Not only are community structural characteristics important to understanding neighborhood risk, the social processes, or organization within the neighborhood is also crucial (Kornhauser, 1978; Wilson, 1987). Kasarda and Janowitz (1974) introduced the systemic model of neighborhood, in which "the local community is viewed as a complex system of friendship and kinship networks, as well as formal and informal associational ties rooted in family life and ongoing socializing processes" (p. 329). Coleman (1988) then argued that it is the resources transmitted through social ties, not the ties per se that are key to facilitating neighborhood social control. Sampson, Raudenbush, and Earls (1997) further adopted the concept of collective efficacy to capture residents' willingness to intervene for the common good (Sampson et al., 1997).

Tests of the role of such intervening social processes have reshaped the face of community-level research. For example, Sampson and Groves (1989) found that communities characterized by low SES, residential instability, ethnic heterogeneity, and family disruption had lower social ties and informal social control represented by sparse local friendship network, unsupervised teenage peer groups, and low organizational participation of residents. Lower social integration then resulted in higher rates of crime and delinquency. Sampson and Groves (1989, p. 791) concluded that "the three dimensions of community social disorganization mediate over one-half of the effects of Shaw and McKay's three structural factors (SES, mobility, heterogeneity) on the most general indication of crime—total victimization rate."

Subsequently, Sampson et al. (1997) proposed modifications to the intervening measures of social disorganization. They argued that social networks and resources are necessary, but not sufficient, for neighborhood social control. Residents must develop a sense of belonging and willingness to take action to combat crime in local communities. Thus, they proposed a new construct, collective efficacy, to capture the linkage of trust and intervention for the common good. Empirical evidence shows that their hypothesis was confirmed. Coefficients for social compositional factors were substantially smaller than they had been without a control for collective efficacy, meaning that collective efficacy partially mediated the relationship between neighborhood social composition and violence. In addition, even after prior offenses were controlled, the coefficient for collective efficacy remained statistically significant in the expected direction (Sampson et al., 1997; see also Sampson, 1997; Sampson, Morenoff, & Gannon-Rowley, 2002).

Bellair (1997) also found that social interaction among neighbors was important in that it may reduce burglary, theft, and robbery rates. Sampson and Raudenbush (1999) further found that high levels of collective efficacy were negatively correlated with neighborhood observed disorder and burglary, homicide, robbery, and victimization. A study by Elliott et al. (1996) found that neighborhood informal control measured by mutual respect, institutional controls, social control, and neighborhood bonding was negatively associated with youth problem behavior in Chicago neighborhoods. This same study also found that informal networks, a measure built from the proportion of friends and number of relatives or family members who live in the neighborhood, was negatively associated with youth problem behavior in Denver. Similarly, Simons, Simons, Conger, and Brody (2004) found that after controlling for various individual-level variables, neighborhood collective socialization is negatively related to child conduct problems.

Although existing studies provide substantial knowledge of how neighborhood structural or social processes may function as risk, or simply the opposite, as promotive factors for juvenile delinquency and violence, we propose that knowing how neighborhood features might actually protect at-risk individuals from becoming involved in delinquency and violence is even more desirable. That is, while there is a high degree of agreement among scholars in the ecological/social disorganization tradition that community social processes mediate the relationship between social structural characteristics like poverty, heterogeneity, and residential mobility and crime (e.g., Bellair, 1997; Bursik, 1988; Kornhauser, 1978; Sampson, 1991; Warner & Rountree, 1997), we are interested in applying the logic of the risk and protective approach to community-level variables and view community process variables as not only potential promotive and mediating factors but also as protective factors. Indicators of community-level social integration or collective efficacy are viewed as serving as protective factors that will enable residents to be constrained from crime even for those who have high individual risk of participating in crime.

It is worth noting that prior studies that have examined neighborhood protective factors have operationalized such as reported by individuals (e.g., individual-level) but have not aggregated the data to create characteristics of the neighborhood. Rather it is simply an individual's perception of neighborhood social processes such as collective efficacy and neighborhood satisfaction. For instance, Yonas et al. (2010) provided evidence that positive neighborhood processes like collective efficacy moderate the relationship between earlier neglect and externalizing behaviors at age 12. "Collective efficacy was associated with a reduction in externalizing scores for the neglected group, but had no effect for the non-neglected group" (p. 43). Kowaleski (2000) also found that residential stability and the high quality of schools have protective effects on adolescent risk-taking behaviors when considering the size of adolescents' families.

In addition to advances in conceptual measures of neighborhood-level risk and protective factors, recent developments in statistical techniques, particularly hierarchical linear modeling (HLM), has enabled researchers to further disentangle the impact of individual-level and neighborhood-level (e.g., contextual) effects and are particularly useful for the exploration of "protective" effects. As is further detailed in the Method section below, HLM specifically allows a researcher to isolate contextual effects and to examine cross-level interaction effects by estimating the impact of a community-level characteristic on an individual-level outcome. This technique was used by Oberwittler (2004) in the examination of two West German cities and some surrounding rural communities. This study found that the concentration of social disadvantage in neighborhoods had an independent contextual effect on adolescents' serious offending behaviors after controlling for measures of individual-level risk. Similarly, Haynie, Silver, and Teasdale (2006) found that adolescents residing in more economically disadvantaged neighborhoods were more likely to be involved in a range of serious violent behaviors regardless of individual-level risk. The ability of this technique to separate levels of impact further allowed Weijters, Scheepers, and Gerris (2007, 2009) to show that that family disruption affects youth delinquency at the individual-, neighborhood-, and city-levels.

The review of the literature emphasizes the importance of the ability and willingness of residents to do something about their community. This includes notions of social interaction among neighbors (social networks), the degree to which they are willing to help one another out (reciprocal exchange), and to organize to assist in the socialization of youth (collective efficacy). In the next section, we further elaborate the research on the importance of individual risk in determining criminal and violent outcomes and relate these to ways in which we expect neighborhood factors to mediate and moderate such risk.

Individual Risk Factors

Although social disorganization theory provides a useful framework for examining potential neighborhood risk and protective factors, as it is a macro-level theory, it does not speak directly to individual-level risk and protective factors and/or their interaction with the macro-level structure. To guide our research in this area, we therefore turn to an additional theoretical tradition. Thornberry's interactional theory (Thornberry, 1987) is a complex causal model that elaborates on social control theory by incorporating variables from both strain and social learning to account for delinquent behavior. Research on risk factors among adolescents focuses on those dimensions that are most salient in the lives of teenagers (see Farrington, 1995). To provide some theoretical coherence to this approach, these separate variables have been grouped into what some have referred to as domains, representing arenas in adolescents' lives. In prior work, interactional theory (Thornberry, 1987; Thornberry & Krohn, 2001, 2005) was used to identify domains of individual risk factors (e.g., Jang, 1999; Smith, Lizotte, Thornberry, & Krohn, 1995; Thornberry et al., 2003). Specifically, risk factors from the individual, family, peer, and school domains are of particular interest in the current study. Although interactional theory arrays the variables within each domain in a causal model, we simply use the theory to identify variables that place individual at risk for serious, violent behavior. Prior research has found that factors from each domain, measures accumulating these factors within domains, and measures that accumulate these factors across domains are related to problematic behaviors (e.g., Belsky, Woodworth, & Crnic, 1996; Gilliom, Shaw, Beck, Schonberg, & Lukon, 2002; Jang & Smith, 1997; Jang & Thornberry, 1998; Krohn, Lizotte, Thornberry, Smith, & McDowall, 1996; Krohn, Thornberry, Collins-Hall, & Lizotte, 1995; Patterson, Reid, & Dishion, 1992; Smith et al., 1995; Stern & Smith, 1995; Thornberry et al., 2003). The construction of specific measures is discussed in the Method section below.

Summary

Neighborhood-level variables have by and large been treated only as risk factors. One noted exception is recent research on the role of collective efficacy as a potential protective factor. For example, work by Maimon and Browning (2010) explores the impact of living in a high-collective efficacy neighborhood on the risk of violent outcomes. This study finds that collective efficacy has both a direct effect on reducing violent outcomes and an indirect effect through its role in reducing unstructured socializing of peer groups. However, the vast potential of characteristics of neighborhoods to protect individuals from criminal behavior in the face of individual risk has been far from adequately explored.[1] This lack of research constitutes an important research gap in the growing literature on multilevel research of neighborhood effects on child and adolescent development in general and juvenile delinquency and violence in particular. The current study moves beyond individual-level research on neighborhood domain protective factors. In the following analysis, we focus on how neighborhood-level protective factors such as neighborhood collective efficacy, reciprocal exchange, and social and neighborhood integration may serve to buffer individual risk.

Sample

The Rochester Youth Development Study

Data from the Rochester Youth Development Study (RYDS), an ongoing longitudinal study investigating the causes and consequences of serious, violent, and chronic delinquency, are used in the current study. The Rochester study has followed a panel of juveniles from their early teenage years through age 31, completing 14 interviews with the respondents. The study began in 1988, at which time 1,000 seventh- and eighth-grade students were sampled from public schools in Rochester, New York. Subjects were interviewed every 6 months from the spring of 1988 until the spring of 1992. Subjects' primary caregivers (most often the biological mother) were also interviewed at these times adding additional information on family and neighborhood factors that might impact the youth. The subjects are referred to as G2 respondents and their caregivers as G1s throughout the remainder of this study. In addition to interview data, RYDS collected child maltreatment information from the Department of Social Services and official arrest data from the Rochester police department.

In creating the original sample, the RYDS oversampled youth at high risk of serious delinquency and drug use because the base rates for these behaviors are relatively low (Elliott, Huizinga, & Menard, 1989; Wolfgang, Thornberry, & Figlio, 1987). To do this, the sample was stratified on two dimensions. First, males were oversampled (75% vs. 25%) because they are more likely than females to be chronic offenders and to engage in serious and violent delinquency (Blumstein, Cohen, Roth, & Visher, 1986; Huizinga, Morse, & Elliott, 1992). Second, students from areas of the city with high-resident arrest rates were oversampled based on the assumption that adolescents who live in such areas are at greater risk of offending than are those living in low arrest rate areas. In order to identify these areas, each census tract in Rochester was assigned a resident arrest rate reflecting the proportion of the tract's total adult population arrested by the Rochester police in 1986.

The current analysis uses data from Waves 2–9, as this is the period that corresponds to the subjects' adolescent years. Of the 1,000 youths originally sampled, follow-up information after Wave 2 is not available on 53 subjects, thus this study began with a sample of 947 youths. Data from multiple waves are used to assure the proper time order of variables, thus retaining the integrity of the causal model. It is hypothesized that neighborhood-level protective factors will mediate, moderate, or have both effects on the impact of individual risk factors on later violent outcomes. Individual risk measures are taken from Wave 2 and violent outcomes are taken from Wave 9 (the period corresponding to late adolescence and the last year of high school).[2] Proposed neighborhood-level promotive and protective measures are then taken from Waves 5 and 6 representing the mid-point of the adolescent years. Specific variables are defined further below.

Neighborhood Creation

Identifying the geographical boundaries that define a neighborhood area is one of the primary challenges to neighborhood-level research. This challenge is exacerbated because official crime data are traditionally only available for larger units of analysis, such as cities, Standard Metropolitan Statistical Areas, counties, and states. Subsequently, much neighborhood research has come to rely on self-report measures of crime and violence. In order to supplement these self-report measures with neighborhood-level demographic data, researchers most often have turned to the U.S. Census. Tract-level data are most often used by researchers because it is the lowest level of aggregation for which the majority of data are available. Although this approach is logical given the format of available data, it does not necessarily reflect the construct of a neighborhood as experienced by the individuals living there.

The current study applies a new approach to the definition of neighborhood based upon an actual study of communities in the Rochester area. The Rochester City—Wide Housing Market Study RHMS, which was initially conducted in 1988 and just recently updated in 2007, identified 36 distinct residential, commercial, and industrial neighborhoods in Rochester that are based on the actual demographics of the city and the interactional patterns of residents rather than on Census tracts or other artificial measure of "neighborhood" (City of Rochester's Bureau of Business and Housing Development, 1988, 2007). The RHMS also provided Census data aggregated to these new unit measures for key constructs typical of social–ecological research, such as rate of home ownership, racial make-up of communities, and percentage of residents living below the poverty line.

These data are supplemented with the rich data available through the RYDS study. We are able to aggregate individual G1 and G2 interview responses to the neighborhood level to create other important constructs, such as measures of collective efficacy and neighborhood integration[3] (these measures are further detailed below). Table 1 provides basic descriptive statistics for each neighborhood including the number of G2 respondents residing in each neighborhood, demographic information provided by the RHMS, and the newly calculated aggregate measures of proposed promotive and protective factors.

Table 1. Rochester Neighborhoods

Neighborhood	*N*	Collective Efficacy	Reciprocal Exchange	Social Integration	Neighbor Support	Nhood Integration	Home Ownerhip	Percent Poverty	Percent Hispanic	Percent Black
14,621	195	3.00	1.78	2.56	1.85	2.11	.41	.29	.27	.45
19th ward	95	3.13	1.90	2.64	2.02	2.21	.58	.15	.03	.70
Altantic university	2	4.00	2.50	3.00	2.00	2.71	.10	.12	.05	.21
B.E.S.T.	10	3.33	1.90	2.72	1.98	2.26	.00	.00	.00	.00
Beechwood	57	2.82	1.98	2.74	1.92	2.30	.37	.33	.13	.58
Brown square	6	3.83	2.13	3.17	2.42	2.57	.12	.40	.39	.31
Browncroft	1	1.67	3.00	3.33	4.00	3.14	.60	.08	.02	.06
Central business district	1	4.00	2.00	4.00	3.00	2.86	.02	.38	.09	.38
Charlotte	5	2.87	1.56	2.25	1.90	1.86	.55	.11	.05	.05
Cobbs hill	1	2.00	2.75	2.33	1.25	2.57	.75	.04	.03	.05
Cornhill	6	2.00	1.79	2.44	2.58	2.07	.32	.15	.04	.38
Culver-Winton	4	3.33	3.06	3.75	2.13	3.36	.64	.09	.05	.15
East Avenue	2	4.00	2.25	3.00	2.00	2.57	.16	.05	.04	.12
Edgerton	34	2.52	1.64	2.64	2.16	2.06	.23	.39	.18	.40
Ellwanter-Barry	11	2.52	1.64	2.64	2.16	2.06	.48	.11	.04	.12
Genesee-Jefferson	64	3.12	1.94	2.64	1.99	2.24	.43	.28	.03	.94
Highland	4	3.50	1.94	2.92	2.13	2.36	.39	.08	.05	.08
Homestead heights	2	4.00	2.88	3.33	2.13	3.07	.65	.18	.11	.41
J.O.S.A.N.A	36	2.72	1.87	2.87	2.14	2.30	.26	.49	.24	.49
Lyell-Otis	33	2.92	1.94	2.65	2.05	2.24	.53	.19	.13	.27
Maplewood	16	3.31	2.25	2.71	2.15	2.45	.51	.14	.09	.21
Mayors heights	36	2.92	1.75	2.62	1.85	2.12	.23	.33	.03	.88
N. Marketview heights	68	2.98	1.94	2.69	1.96	2.26	.36	.33	.34	.58
Northland-Lyceum	1	1.00	1.00	1.67	1.00	1.29	.60	.09	.15	.28
P.O.D.	22	2.74	2.01	2.72	2.05	2.32	.36	.40	.19	.33
Park Avenue	5	2.67	1.90	2.80	1.77	2.29	.23	.03	.03	.05

(continued)

Table 1 (continued)

Neighborhood	*N*	Collective Efficacy	Reciprocal Exchange	Social Integration	Neighbor Support	Nhood Integration	Home Ownerhip	Percent Poverty	Percent Hispanic	Percent Black
Pearl-Meigs-Monroe	6	3.33	2.40	2.67	2.10	2.51	.15	.30	.06	.23
Plymouth-exchange	40	2.82	2.02	2.79	2.11	2.35	.30	.39	.04	.89
S. Marketview heights	38	2.33	1.65	2.20	1.67	1.88	.20	.37	.22	.67
South Wedge	19	2.88	2.02	2.54	2.03	2.24	.18	.45	.08	.44
Strong	2	3.50	2.83	2.83	2.75	2.64	.30	.10	.05	.12
Susan B. Anthony	2	3.00	3.00	3.00	2.50	3.29	.20	.36	.03	.83
Swillburg	4	1.75	1.75	2.25	1.63	1.96	.50	.15	.08	.15
U.N.I.T.	9	2.33	1.81	2.29	1.69	2.02	.47	.32	.08	.44
Upper falls	100	3.02	1.86	2.65	1.93	2.20	.18	.48	.35	.62
Upper Monroe	4	2.50	1.44	2.50	1.94	1.89	.33	.11	.05	.09

Of the 947 youth available for study after Wave 2, 6 could not be placed in neighborhoods due to insufficient information. Thus, the sample was further reduced to 941 subjects.

Individual Risk Factors

Risk factors are collected from Wave 2, corresponding to G2 respondents at approximately 14 years of age. As much of the literature on risk factors identifies factors within various domains of a youth's life (e.g., Jang, 1999; Thornberry et al., 2003), this research begins with four domain-specific measures of risk. Each of these cumulative measures was created in three steps. First, continuous variables were dichotomized with values at and above the upper quartile being coded "1" for being "at risk." Scores on each of the variables comprising the domain were summed to create the cumulative risk score and then divided by the total possible risk score in order to standardize the measure. The first cumulative variable, Personal Risk, measures characteristics of the individual that were proposed to influence risk of later violence. It is the sum of dichotomous measures based on G2's self-reported levels of depressive symptoms and stressful life events. The second domain, Family Risk, measures potential risk factors occurring within G2's family. This measure is based on the dichotomies of three individual variables as follows: (a) official reports by the Monroe County Department of Social Services regarding maltreatment of G2 by any perpetrator during the years up to and including the age of 14,[4] (b) G1's report of the level of severity of their discipline strategies, and (c) G1's report of the level of hostility within the home. The third measure, Peer Risk measures risk in the domain of the peers with which G2 identifies. It is the sum of three variables as reported by G2 as follows: (a) the level of delinquent acts in which G2 believes his or her peers engage, (b) G2's perception of their peers' delinquent values, and (c) the amount of time they engage in risky behaviors with friends, such as getting together where no adults are present. The last domain-specific cumulative variable measures risk factors related to scholastic achievement. School risk represents the sum of two measures, truancy from school anytime in Wave 2 and an index of school risk that includes such measures as poor standardized test scores and failing core subjects.

Because a large body of literature also suggests that risk is cumulative not only within but potentially across domains (e.g., Belsky et al., 1996; Gilliom et al., 2002; Jang & Smith, 1997; Jang & Thornberry, 1998; Krohn, Thornberry, et al., 1995; Krohn, Lizotte, et al., 1996; Patterson et al., 1992; Smith et al., 1995; Stern & Smith, 1995; Thornberry et al., 1999; Thornberry et al., 2003), we also utilize two additional measures of risk that are of a more comprehensive nature. The first of these measures, total risk, combines the variables used to create the domain-specific measures with four additional risk factors proposed to influence later violence. The first is a measure of the number of family transitions occurring between Waves 1 and 2. The remaining three variables measure risk related to G1, as reported by G1 including: attaining less than a high school diploma, receiving public assistance, and being unemployed.

The final measure of risk used in the current analysis takes a slightly different approach. This measure is an assessment of G2's propensity for violence at Wave 2. This variable, Risk Propensity, is measured as the predicted value of the incidence of violence in an equation that uses the four domain-specific cumulative risk measures described above, along with the prevalence of G2's self-reported gang violence and violence from Wave 1, as independent variables.[5] Table 2 provides summary statistics of all Level-1 variables.

Neighborhood-Level Promotive and Protective Factors

As previously discussed, promotive factors are described as those that reduce the likelihood of delinquency or increase the probability of desistance while protective factors specifically interact or modify the influence of risk for those individuals facing greater levels of adversity. This theoretical

Table 2. Sample Descriptive Statistics

Categorical Variables	Percent			
Gender				
Male	72.6			
Female	27.4			
Race				
Black	68.9			
Hispanic	16.4			
White	14.8			
Continuous Variables	*M*	*SD*	Minimum	Maximum
Level 1				
Age	14.49	0.79	11.9	16.2
Personal risk	29.79	34.07	0.00	100.00
Family risk	19.29	25.09	0.00	100.00
Peer risk	18.98	17.40	0.00	100.00
School risk	14.51	26.89	0.00	100.00
Total risk	22.53	15.4	0.00	71.43
Propensity for violence	0.50	0.47	0.02	2.18
Level 2				
Collective efficacy	2.90	0.69	1.00	4.00
Reciprocal exchange	2.06	0.46	1.00	3.06
Social integration	2.72	0.43	1.67	4.00
Neighbor support	2.08	0.41	1.00	4.00
Neighborhood integration	2.36	0.42	1.29	3.36
Families in poverty	0.23	0.15	0.00	0.49
Home ownership	0.35	0.19	0.00	0.75
Percent Black	0.36	0.27	0.00	0.94

specification does not necessarily imply that promotive and protective factors are different in content, but rather, in effect. That is, one could assess a variable such as "good parenting" as a promotive factor if it reduces delinquency in general. However, the effect of the same variable would be interpreted as "protective" if it mattered only for, or perhaps more for, individuals facing high levels of risk.

For the current study, we created five neighborhood-level components that reflect constructs from prior studies of neighborhoods and crime to explore for possible promotive effects, protective effects, or both. Each measure was created by aggregating individual responses to questions up to the neighborhood-level based on the neighborhood structure described above. Thus, every individual in a given neighborhood will be assigned the "mean" score for that neighborhood as defined by summing the individual responses of all members of that neighborhood and dividing by the number of respondents residing in said neighborhood.[6]

The measures are as follows:

Collective efficacy: This measure is designed to capture the "action" component of community organization. That is, whether or not community members actually rise to the occasion to take action toward socializing youth. In specific, this measure asks G1 if he or she believes neighbors would intervene if they saw their child using drugs and/or alcohol. In addition, this measure asks G1 what his or her response would be if he or she witnessed one of the G2's friends engaged in this same type of behavior. Possible choices were to talk to the child or call the parent (coded as high levels of collective efficacy), or call the police or do nothing (coded as low levels of collective efficacy).

Social integration: A measure of the number of neighbors G1 reports knowing (a lot, some, a few, and none) and whether G1 reports knowing these neighbors by (a) sight, (b) by name, and/or (c) to talk to on a regular basis.

Reciprocal exchange: A measure designed to assess how often neighbors help each other out. This 4-item scale includes measures of how often: (a) G1 borrows things like tools or recipes from neighbors, (b) neighbors ask each other to watch each other's children, (c) neighbors talk to each other, and (d) neighbors ask each other to drive children somewhere.

Neighbor support: A measure of how many people G1 feels he or she can count on. In specific, this 4-item scale derived from Wave 5 asks G1 how many people in the neighborhood G1 feels he or she could count on (a) in an emergency, (b) to talk to about raising G2, (c) to talk to when he or she is upset/angry, and (d) to care about him or her no matter what is happening.

Neighborhood integration: *This i*s a comprehensive measure of the social ties and networks between community residents. This is a 12-item scale measured by G1 responses at Wave 5. It is more of an omnibus measure that includes components of both social networks (knowing neighbors) and reciprocal exchange. Because this measure includes several concepts already measured separately, it is assessed in a separate model due to issues of collinearity.

Because all neighborhood-level measures were created by aggregating individual-level data, missing data at the individual level had to be dealt with. This was done in two ways. First, if a measure was missing at Wave 5, attempts were made to collect that information at Wave 6. Thus, for those missing information on key variables at Wave 5 but including such information at Wave 6, the latter measure was used. For the few respondents that were still missing information,[7] the mean score for the variable was imputed. Sensitivity analyses were performed to ensure that this technique did not impact later findings.

In addition, traditional social–ecological variables provided by the RHMS are included in all models including percent of population living in poverty, the percent of the population owning rather than renting homes and racial distribution (percent minority). These variables are added primarily to control for neighborhood risk as the analysis attempts to better isolate the possible promotive and protective influences of positive neighborhood influences in the face of risk. Table 2 provides a summary of all Level-2 variables.

Dependent Variable

The dependent variable for this analysis is the number of violent incidences reported by G2 respondents at Wave 9 (1991). At this time, respondents would have been seniors in high school if still in school and approximately at age 18—for example, at the peak years for violence. Incidence of violence ranged from 0 for a large portion of the sample all the way up to 87 incidents for one individual. As might be expected, this measure is highly skewed (Skewness = 15.8 and Kurtosis = 283.7). To address this issue, we added 1 to the value and then took the natural log of violent incidence. The new range of the dependent variable is then 0–4.48 with a skewness of only 4. Eighty-seven individuals were missing information on the dependent variable at Wave 9.[8] The analysis presented in the Results section eliminates these individuals from the sample resulting in a final sample size of 854 individuals.

Method

Because the primary purpose of the current study is to assess the ability of neighborhood-level factors to reduce violence in the presence of risk, the data are structured to place each youth within his or her home neighborhood as previously described. With youth thus nested within these community settings, it is important to select an analytical technique that accounts for this feature of the data. We employ HLM (Byrk & Raudenbush, 1991) in the current study because this particular method provides several benefits for the purpose at hand. First, it allows us to partition the variance in violent outcomes within and across neighborhoods. This allows us to assess the portion of variation that exists at each level of analysis. Second, because individuals are nested within larger neighborhoods, similarities among residents in a neighborhood will likely lead to a violation of the independent error structure assumption essential to traditional ordinary least squares regression. HLM incorporates a random effect for each Level-2 unit of analysis (e.g., neighborhood) which corrects for this problem and results in more accurate estimates of both coefficients and standard errors. Another advantage of HLM is that rather than simply controlling for Level-2 variation as a fixed-effect model would, it allows us to actually model and explain such variation. For example, it allows for the direct assessment of "contextual" or neighborhood effects that impact each youth within that neighborhood (e.g., a promotive effect) above and beyond that individual's value on the given variable. In addition, this software allows for the estimation of cross-level interaction effects in which a contextual factor might moderate an individual-level risk factor (e.g., a protective effect). Finally, HLM also employs a precision weighting technique that is valuable when Level-2 units, in this case neighborhoods, do not all have the same number of Level-1 units. This is indeed the case for the RYDS data with the neighborhoods specified containing anywhere from a low of 1 youth to a high of 195 youths.

The general form for the HLM equation is as follows:

Level-1 (Persons) Model:

$$Y = B_0 + B_1X_1 + \ldots + B_kX_k + e,$$

Where X indicates Level-1 explanatory variables and subscript 1 through k indicates the range of possible explanatory variables.

Level-2 (Neighborhoods) Model:

$$B_0 = G_{00} + G_{01}W_{1j} + \ldots + G_{0k}W_{kj} + U_{0j},$$

$$B_1 = G_{10} + G_{11} + (U_{1j}),$$

$$B_k = G_{k0} + (U_{kj}),$$

Where B_0 represents the intercept for neighborhoods after adjusting for X_1 through X_k. Error term U_{oj} represents the Level-2 residual error after controlling for G_{01} through G_{0k}. Error terms U_{1j} through U_{kj} are optional error terms that can be added to the model if it is found that the slope B varies across neighborhoods. G_{11} is also an optional term which when added interacts the Level-2 variable G_{01} with the Level-1 variable B_1—that is, it assesses the impact of a unit increase or decrease in G_{01} on the slope of B_1. Throughout our results and discussion, we use models reporting robust standard errors.

Results

We began the analysis by exploring a fully unconditional model that simply partitions the variance between Level-1 (person) and Level-2 (neighborhood). As is often the case, there is a great deal more variance between persons than between neighborhoods. Indeed, since our dependent variable measuring violent incidents is a relatively rare outcome, occurring in less than 15% of the sample,

Table 3. Base Models for Direct Effects

	Model 1			Model 2			Model 3		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Level 1									
Age	.0341	.0219	.120	.0117	.0248	.637	.0339	.0254	.184
Male	.1123	.0390	**.005**	.1288	.0309	**.001**	.1095	.0308	**.001**
Black	.0447	.0571	.434	.0291	.0332	.382	.0390	.0371	.294
Hispanic	−.0102	.0667	.879	−.0485	.0294	.099	−.0151	.0328	.645
Neighborhood integration control				−.0114	.0234	.624			
Personal risk				.0008	.0005	.096			
Family risk				.0014	.0007	**.041**			
Peer risk				.0024	.0006	**.000**			
School risk				.0013	.0006	**.048**			
Total risk				.0050	.0010	**.000**			
Propensity for violence				.1875	.0430	**.000**			
Level 2									
Goo	.1534	.0253	.000	.1684	.0244	.000	.1438	.0261	.000
Percent Black	.1001	.1170	.397	.0445	.1166	.725	.0853	.1179	.475
Percent Hispanic	.1534	.1923	.431	.1111	.1849	.662	.1136	.1828	.539
Percent own home	−.2992	.1866	.119	−.2165	.1786	.235	−.2871	.1831	.127
Percent in poverty	−.1772	.3044	.564	−.2141	.2873	.462	−.1418	.3025	.642
Reciprocal exchange							−.0749	.0601	.222
Collective efficacy							−.0478	.0606	.437
Social integration							−.0817	.0897	.370
Neighbor support							−.0559	.0743	.458
Neighborhood integration							−.0911	.0777	.251

Note. Control variables reported from models with total risk at Level 1 and neighborhood integration at Level 2 to represent models with most comprehensive risk and promotive measures.

the variance at the neighborhood level (Level-2) is perhaps even smaller often representing only 2–3% of the total variance. In simple terms what this means is that while violence may be higher or lower across neighborhoods, there is a great deal more variation between persons than between neighborhoods. While this does make the task of identifying neighborhood influences slightly more difficult, it speaks to the nature of violence in general. More importantly, as we are seeking potential interactions between neighborhood protective factors and individual-level risk factors, our models will rely inherently on variation at both levels of analysis.

Table 3, Model 1 presents what we refer to as the base model that includes person level (Level-1) and neighborhood level (Level-2) control variables. Interestingly, most of the controls are not statistically significant. In fact, none of the neighborhood control variables representing traditional social disorganization constructs achieves statistical significance although most are in the expected direction (percent living in poverty being the only noted deviation from expectations). At the person level, gender is statistically significant with being male substantially increasing the risk of violent incidence. Since our sample is comprised primarily of same-age individuals, it is not surprising that the control for age does not achieve significance as we have very little variation on this variable.

Model 2 then presents the results from several models which introduced our domain-specific and cumulative person-level risk factors. With the exception of the personal risk measure, all other domains and cumulative measures are significantly related to violent incidence. The strongest effect shown is by our measure of propensity for violence. Total cumulative risk and risk measured in the

Table 4. Neighborhood Promotive and Protective Factors by Domain

	Individual			Family			Peers			School		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Promotive												
Reciprical exchange	–.067	.058	.256	–.082	.065	.215	–.077	.057	.191	–.074	.058	.211
Collective efficacy	–.042	.061	.490	–.065	.067	.338	–.046	.056	.417	–.050	.058	.396
Social integration	–.073	.090	.425	–.113	.093	.237	–.072	.083	.393	–.076	.087	.392
Neighbor support	–.048	.074	.525	–.078	.077	.320	–.045	.067	.504	–.054	.072	.464
Neighborhood integration	–.082	.077	.294	–.111	.084	.198	–.099	.072	.233	–.089	.075	.250
Protective												
Reciprocal exchange	–.003	.002	.060	.000	.003	.900	–.006	.004	.136	–.006	.003	.072
Collective efficacy	.000	.001	.511	–.004	.002	.078	–.004	.002	.145	–.003	.002	.202
Social integration	–.003	.002	.136	.000	.004	.902	**–.010**	**.003**	**.001**	**–.008**	**.003**	**.001**
Neighbor support	–.002	.002	.181	.001	.003	.671	*–.008*	*.004*	*.063*	**.006**	**.003**	**.043**
Neighborhood integration	**–.003**	**.002**	**.045**	.000	.004	.973	**–.008**	**.004**	**.032**	**–.008**	**.003**	**.008**

peer domain were also highly significant ($p < .000$), while risk in the family and school domains were more modestly significant ($p = .041$ and $p = .048$, respectively).

Finally, Table 3, Model 3, presents the results from the models including all neighborhood (Level-2) independent variables in search of contextual promotive (e.g., direct) effects. As is evident, when added as a group, none of the variables achieve statistical significance, although their effects are all in the anticipated direction.[9] Moreover, post hoc hypothesis tests on model fit revealed that as a group, these variables did not significantly improve the fit of the model.

Table 4 presents the results of subsequent models in which we searched for moderating effects of the Level-2 variables by specific domain of risk. For the personal domain, we find that although the neighborhood-level main effects (promotive) are all in the direction that would be expected, none achieve statistical significance. Although the coefficient for personal risk was not significant, we do find a modest interaction effect when interacting our omnibus measure of neighborhood organization—neighborhood integration—with personal risk ($B = -.003$, $p = .045$).

The next set of models explored risk in the family domain. Here, we find that none of the neighborhood-level factors examined in this study offered a buffering effect as either promotive or protective influences. The strongest effect in this domain was the interaction of collective efficacy with family risk ($B = -.004$), which approached, but did not achieve, significance ($p = .078$).

The plot thickens, however, when exploring the domains of peer and school risk factors. Models examining risk in the peer domain reveal protective effects for measures of social integration and total neighborhood integration. Specifically, high levels of parental (G1) reports that they knew neighbors by sight, name and to talk to, interacted with a youth's risk in the peer domain to reduce the youth's likelihood of a violent outcome ($B = -.010$, $p = .001$). In other words, when parents know and interact with many neighbors, the impact of risky peer interactions on a youth's violent outcomes is buffered. Based on the manner in which our risk domains were constructed, this is best interpreted as follows: For youths who score 1 *SD* above the mean on the measure of "peer" risk, the impact of this peer influence is reduced by .01 if the caregiver reports high level of social integration. Similarly, when G1s report high levels of neighborhood integration, the risk of a violent outcome presented by risky peers is reduced by $-.008$ ($p = .032$). Interestingly, the measure of neighbor support had an effect that was identical in magnitude ($B = -.008$) but failed to achieve statistical significance ($p = .063$).

Table 5. Neighborhood Promotion and Protection for Cumulative Measures of Risk and Violence

	Total Risk			Propensity for Violence		
	B	*SE*	*p*	*B*	*SE*	*p*
Promotive						
Reciprocal exchange	–.074	.059	.224	–.099	.064	.135
Collective efficacy	–.048	.057	.408	–.058	.060	.345
Social integration	–.069	.086	.429	–.099	.093	.295
Neighbor support	–.045	.0688	.519	–.046	.070	.520
Neighborhood integration	–.084	.076	.278	–.119	.086	.179
Protective						
Reciprocal exchange	–.012	.006	.062	–.402	.288	.164
Collective efficacy	–.007	.004	.098	–.269	.168	.108
Social integration	*–.013*	*.007*	*.059*	**–.485**	**.224**	**.030**
Neighbor support	–.010	.007	.138	–.325	.344	.347
Neighborhood integration	**–.015**	**.007**	**.042**	*–.513*	*.285*	*.071*

The same neighborhood factors also presented protective effects against risk experienced in the school domain. That is, high levels of G1 social integration reduced the impact of risk in the school domain ($B = -.008$, $p = .001$), as did high levels of neighborhood integration ($B = -.008$, $p = .008$). In this instance, the interactive effect of neighbor support with school risk also achieved significance ($B = -.006$, $p = .042$).

As previously noted, because risk has shown to be cumulative in nature not only within but also across domains, we examined two additional measures of risk. As shown previously in Table 2, Model 2, both total cumulative risk and our measure of propensity for violence had strong independent effects on individual's log incidence of violence. Again, however, Table 5 reveals that none of the neighborhood-level contextual factors were able to serve as promotive factors by mediating this effect. However, the models do indicate the existence of several significant cross-level interaction effects further supporting our findings so far that certain neighborhood-level factors can protect individuals at high levels of risk from experiencing negative outcomes.

Not surprisingly, the measure of neighborhood integration ($B = -.015$, $p = .042$) achieves significance in this model. In addition, the variables of reciprocal exchange ($B = -.012$, $p = .062$), and social integration ($B = -.013$, $p = .059$), approach significance in this model. The remaining neighborhood-level measures of collective efficacy and neighbor support, however, do not approach significance.

When examining propensity for violence, while all measures have effects in the anticipated direction, only one neighborhood factor appears to have a protective impact in the face of risk—social integration ($B = -.485$, $p = .030$) although neighborhood integration again approaches significance ($B = -.513$, $p = .071$).

Because our measures of risk are not intuitively easy to interpret, such cross-level interaction effects become particularly troubling to discuss as a net effect on the dependent variable (in this case, the natural log of incidence of violence). As a picture is said to be worth a thousand words, we therefore present a visualization of this "buffered" risk or slope effect to exemplify our findings. Specifically, Figure 1 provides visual representation of the differing impact of the neighborhood-level protective factor of neighborhood integration on total risk of individuals with a risk score of 0, 25, 50, 75, and 100.

Notice the slope for those at risk living in neighborhoods with only the mean level of neighborhood integration increases at a rate greater than those living in a neighborhood that scores just 1

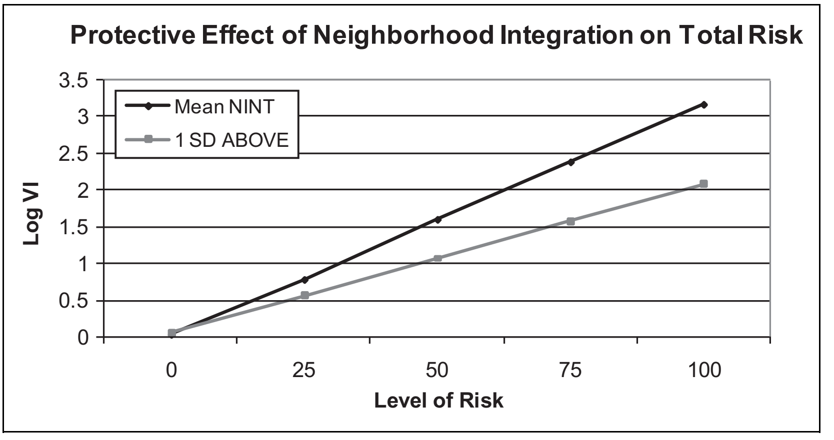

Figure 1. Protective effect of neighborhood integration on total risk.

SD higher on values of integration. This is indeed the very definition of a "protective factor," one that can reduce the probability of a negative outcome even in the face of risk! Although we do not graph the remaining significant interaction terms, they work in a similar fashion either decreasing, or even negating, the positive slope experienced in the face of risk.

Discussion

Since the seminal work of Shaw and McKay in the early parts of the 20th century, criminologists have been intrigued by the empirical connections between neighborhood-level characteristics and variations in crime. While earlier theorizing focused mainly on macro-level patterns, noting social correlates that were related to sustained high levels of crime in a given area or community, later work began to bridge the gap between macro- and micro-level theorizing. That is, although some communities suffer perpetually high crime rates, the undeniable truth is that not every individual in such a community will commit crime. Thus, one of the most intriguing questions that has elevated social ecology to the forefront of the criminological enterprise has been why some individuals living in risky environments turn to crime and why others do not.

As previously noted, the work of Kornhauser (1978) is often credited with reviving this perspective by noting the inherent connections between social disorganization at the community level and the break down in individual social controls. Later research by noted scholars such as Bursik (1988) and Sampson and Groves (1989) proved fruitful in elaborating the social processes that lead to such a link. While macro-level studies indicated early on that factors such as the percentage living in poverty, the mobility of residents in and out of neighborhoods, and the heterogeneity of the population were all connected to the break down in social controls (Hipp, 2007; Miethe & Meier, 1994; Sampson et al., 1997; Stark, 1987), this later research specified *how* and *why* such connections exist.

The social–ecological tradition has recently been incorporated into the ongoing study of risk and protective factors as researchers have begun to explore the relative importance and interaction of such risk and protection across various domains of life. That is, in addition to individual risk and protection, research indicates the presence of risk and protection in social institutions such as the schools, social networks such as peers and support groups, and the greater neighborhood or community environment (Hawkins et al., 1992). Guided by Rutter (1985), in this study, we distinguished between promotive and protective effects. Promotive effects being those that reduce negative outcomes in general (e.g., for everyone), while protective factors are specified as those that modify or "ameliorate" negative outcomes in the face of risk. Specifically, this study explored the ability of neighborhood-level factors specified by the social–ecological tradition to serve as "protection" for individuals at high levels of risk.

As Rutter (1985) noted the influence of both promotive and protective factors, we explored each of our neighborhood-level concepts as direct, mediating, and moderating processes. Across the board, we found no evidence of direct or mediating effects. That is, none of five neighborhood-level factors was significant as a main effect, and the addition of these variables into the model did not serve to reduce the primary impact of any of our domain-specific or cumulative measures of individual risk. However, it should be noted that for the most part each of the variables did have an effect in the intended direction, (e.g., reducing deviance); however, these effects did not achieve statistical significance. Due to the rarity of violence in our sample, and the fact that we had much greater variation between individuals than neighborhoods, we feel it would be premature to conclude that these concepts do not serve a promotive effect. Rather we suggest that a larger sample of neighborhoods representing more diverse areas might be required to reveal their true impact.

Our findings became significantly more interesting, however, when searching for protective factors. That is, interacting neighborhood-level factors in the face of individual levels of risk. Particularly interesting were the domain-specific risk investigations. While none of our measures moderated the impact of family at a statistically significant level, effects were found in the exploration of personal, peer, and school domains. Most notably, across all these domains, it was the same protective factors that emerged significant or approached significance: social integration and neighborhood integration. Social integration was a simple measure of how many neighbors one knows by sight, name, and to speak to in passing. It is interesting that this very basic measure of social networks achieved significance as it does not necessarily speak to the sharing or common values, greater levels of social cohesion, and/or the willingness to take action to enforce social control. One possibility is that this measure of social integration taps into another concept not included but oft found to be highly related to community social control—residential mobility (Kasarda & Janowitz, 1974; Kowaleski, 2000). That is, the more stable the residency of a neighborhood, the more likely it is that people get to know each other at least in recognition. It could also be related to issues such as land use within the neighborhood as areas with mixed land use are more likely to have strangers coming in and out of the neighborhood making it more difficult to identify community members.

The measure of neighborhood integration is a more comprehensive measure that included both aspects of knowing neighbors by sight and name as well as notions of reciprocal exchange (e.g., being able to rely on neighbors to borrow a needed item, to watch one's child, or even to drive one's child to an activity). This more complex measure we suggest better represents the notion of social capitol, that is, the social resources one has to draw upon in one's neighborhood.

Interestingly, neighbor support, representing G1s ability to rely on neighbors for help in given situations, also achieved borderline significance when interacted with risk in the peer domain, and achieved significance when interacted with risk in the school domain. This particular measure asked questions regarding what we feel is a deeper level of trust or social cohesion among neighbors such as being able to rely on a neighbor in an emergency, to turn to a neighbor for help when upset or angry and, most importantly, to discuss issues of child rearing. That is, it takes a certain level of trust to rely on someone in emergency situations and perhaps even more trust and the sharing of common values to rely on someone for advice in the raising of your child.

These findings suggest that it is important to consider the source of risk as well as its level. For example, this research suggests that all risk factors are not equal. It appears that neighborhood-level protective influences are able to infiltrate more readily risk posed in the peer and school domains which represent more "social" interactions than risk purely in the personal domain or that occurs within the family setting. On the surface, this seems to make some logical sense as it is interactions with peers and at school that are more "public" and thus may be more permeable to outside influences.

Moreover, it suggests that some influences might be masked when summing or cumulating risk across domains. For example, a G2 with a high score on our total cumulative risk could achieve such a score based on measures mostly observed at the individual or family domain. A second G2 could have the same score but could have achieved such a score based on factors experienced in the peer and school domain. Thus, our neighborhood protective factors would act differently on these individuals thus masking or even potentially nullifying true effects. This is perhaps evidenced by the fact that when examining the cumulative measure of risk that sums risk factors across domains, the results do not simply produce a higher level of significance or greater magnitude of effect.

In sum, this study found that neighborhood-level factors can reduce violent outcomes, particularly serving to temper levels of risk experienced in the peer and school domains. On the other hand, we also found it interesting that none of the examined neighborhood factors served to mediate the impact of high risk experienced in the personal or family domain. This could simply mean that other neighborhood factors not examined here are important for amending risk in these domains. On the other hand, it could suggest that as these types of risk play out more in the home environment than the greater community context (e.g., peer and school interactions happen mainly outside the home), and that a different approach to prevention and intervention is required to combat such risk.

Contributions and Cautions

This research contributes both methodologically and substantively to the current literature on risk and protective factors and the social ecology of crime. First, by utilizing a housing-market study to represent neighborhoods as those communities with which individuals associate themselves, we validate the utility of exploring new and diverse measures of community. Second, by using individual-level survey data to aggregate responses to these new geocoded areas, we further demonstrate the ability to create new and diverse measures at the community-level that reflect emerging constructs in the ecological study of crime. Our use of HLM to explore both community-level promotive contextual effects and protective cross-level interaction effects reveals that much of the action may indeed be occurring in the protective, rather than, promotive domain that would be missed by many traditional regression techniques.

Substantively, our findings contribute to both the social–ecological literature and the risk and protective factor approach to the study of violence. To the first literature, our findings speak to the importance of neighborhood and social integration as key factors that may reduce violent outcomes. Combined with the risk/protective factor approach, our findings show that these neighborhood-level effects tend to interact with, rather than mediate, overall levels of risk and are more efficient at "buffering" certain types of risk. Particularly, risk occurring in a social domain such as the school or within-peer interactions, rather than risk occurring within the home.

Despite these significant contributions, we would be amiss not to mention some key limitations to the current study. The sampling strategy was designed to ensure that a significant number of serious, violent offenders were included in the study. To do this, neighborhoods with high crime rates were oversampled. This has resulted in some neighborhoods having relatively small number of participants. We suspect that if we had a more equal distribution across the 36 neighborhoods, our results may have been stronger than those reported.

This sampling strategy also has implications for our technique of aggregating individual measures to the neighborhood level. That is, this particular study was not designed to be representative of members of a community, thus our community measures represent only the views of select parents and youths in a community. If high-risk youths and their caregivers are for some unidentified reason prone to view neighborhoods and neighbors differently than others in the community then our results would be biased in this direction. While we have no certain method for detecting any such bias, we believe that if any exists it would be logical that high-risk youths and their parents might be more suspect of others and thus underrepresent levels of social and neighborhood integration.

Also as noted, there were several individuals for whom we could not determine a neighborhood, and some individuals were missing data on the mediating variables collected at Wave 5. Whenever data are missing, there is also concern that the missingness may not be random and this could ultimately bias findings. However, because in this case, the number of missing values was small (under 5%) and we used imputation of the mean values to allow us to include these cases. We also performed a sensitivity analysis merely eliminating these cases and found this did not alter our findings.

We would also like to note that our measure of collective efficacy was not ideal. More specifically, our measure is limited to information on what people would do if they witnessed problematic behavior on part of one of their child's friend or how they believe their neighbors would respond to such behavior if exhibited by their child. To be sure, these are key components of the construct. However, the dimension of mutual trust among neighbors is not represented in our measure. It is possible that a measure that better reflected both dimensions of collective efficacy may have been more successful in mediating or moderating the relationship between risk and violent behavior.

In spite of these limitations, this study has presented intriguing results that have both theoretical and applied implications. Theoretically, by conceptualizing neighborhood variables as protective as well as promotive factors, the possibility that there are positive effects, as well as problematic effects, of neighborhood characteristics is underscored. Practically, the nuanced findings showing how the protective effect of neighborhood factors varied across different domains of risk factors may lead to more efficient ways of designing prevention and treatment programs that would be dependent on the primary sources of risk.

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Notes

1. Although it is theoretically possible to examine neighborhood social processes that buffer against neighborhood structural risk, no empirical study has ever done this. There exists overwhelming evidence that neighborhood social processes are highly, positively correlated with neighborhood structural characteristics (but for exceptions, see Duncan, Duncan, Okut, Strycker, & Hix-Small, 2003).
2. Wave 1 data are not generally used in analyses of RYDS data. These are considered bounding interviews that allow respondents to become familiar with the interview process and with issues of confidentiality.
3. Although this approach allows us to gain important information on community-level variables, it is limited in that values for the community are based on the small sample of community members selected for inclusion in the RYDS study. That is, they represent the opinions of only those youths and their guardians selected for participation in the RYDS study rather than a more representative sample of community members. The measure could then be biased to the extent that these youths and their guardians do not represent general attitudes toward the community shared by the greater population of the area.
4. The dichotomous measure is not based on the upper quartile of the distribution for this variable. Rather, G2s for whom there is any record of maltreatment is coded as being at risk. These data were not

collected solely at Wave 2; rather, they were collected for the years during which G2 was 14 years of age or younger.

5. This measure is a propensity score that was created by regressing the independent variables individual risk, family risk, peer risk, school risk, gang violence at Wave 1, and any violence at Wave 1 on the dependent variable violent outcome (yes/no). A higher "propensity" score represents a greater risk of violence. The key difference between this variable and the other measures is that it includes actual indicators of self-reported violence at Wave 1, thereby allowing earlier behavior to serve as a predictor of later behavior.
6. When using aggregated variables at Level-2 as in the case here, it is important to also control for the effect of that variable at Level-1, thus all individual-level variables used to form aggregate measures will be included in the Level-1 models. However, for reasons of parsimony, these coefficients will not be presented in the tables.
7. Less than 10% of information was missing on all variables and for most only 2–3% was missing.
8. Those missing information on the final outcome had a significantly different score on two of the included independent variables. First, regarding individual risk, those missing the final outcome had a lower score (24.14 compared to 30.36, $p = .001$). Second, this group had a higher risk score in the school domain (20.7 compared to 13.9). Although the groups reveal these differences in mean scores on these specific risk factors, we have no reason to believe that this should alter the overall pattern of the relationship between these risk factors and the final outcome.
9. It should be noted that the statistic for neighborhood integration is from a separate model as this variable was highly collinear with the other neighborhood-level constructs. All person-level and control variable statistics are from the model incorporating the remaining four neighborhood-level constructs (e.g., know neighbors, collective efficacy, reciprocal exchange, and parental support).

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