UCLA School of Law

PUBLIC LAW & LEGAL THEORY RESEARCH PAPER NO. 18-45

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In 34 JOURNAL OF QUANTITATIVE CRIMINOLOGY 887 (2018)

WHEN CRIMINAL COPING IS LIKELY: AN EXAMINATION OF CONDITIONING EFFECTS IN GENERAL STRAIN THEORY

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Running Head: Conditioning Effects in General Strain Theory

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Abstract

Objectives: This paper addresses perhaps the central problem in General Strain Theory (GST): the mixed results regarding those factors said to condition the effect of strains on crime. We test Agnew's (2013) assertion that a criminal response to strain is likely only when individuals score high on several factors that increase the propensity for criminal coping or possess markers that indicate a strong propensity for criminal coping.

Methods: We use survey data from nearly 6,000 juveniles from across the United States to examine whether the effect of criminogenic strains across several domains—perceptions of police, school environment, and victimization—on crime are conditioned by: (1) respondents' criminal propensity and (2) gang membership. To the best of our knowledge, this is the first criminological study to employ an analytical framework that simultaneously considers non-linear (i.e., curvilinear) dynamics, non-additive (i.e., interactive) effects, and non-normally distributed dependent variables. This approach has the advantage of properly differentiating non-linear and non-additive dimensions and therefore significantly improving our understanding of conditioning effects.

Results: We find considerable support for Agnew's (2013) postulation about conditioning effects and GST. Criminal behavior is more likely among those with a strong overall propensity for criminal coping and among gang members. Furthermore, we discover that the conditioning effects are, themselves, non-linear. Our models that simultaneously take into account both the non-additive and non-linear relationship between strains and criminal propensity on their impact on criminal offending better fit the data than models that consider these dimensions separately. These results hold whether examining a composite measure of criminal activity or, alternatively, three separate subscales indexing violent, property, and drug offenses.

Conclusion: Our study advances GST and the crime literature by identifying the types of strained individuals most likely to engage in criminal coping. Additionally, the analytical framework employed serves as a model for the correct measurement and interpretation of conditioning effects for criminological data, which almost invariably violate the assumptions of the linear regression model. Linear/Parametric interactions are the most commonly investigated type of interactions, but other kinds of interactions are also plausible and may reveal conditional relationships that are either overlooked or understated when analysts exclusively adopt. We demonstrate possible to have non-linear interactions in which a non-linear function of one variable is multiplied by a linear or non-linear function of one or more other variables to produce an interaction term.

Keywords: General Strain Theory; Interaction Effects; Non-linear Effects; Generalized Additive Models

1 Introduction

General strain theory (GST) has become one of the leading theories of crime. There is considerable evidence that the criminogenic strains identified by GST increase crime for the reasons indicated by GST, including their effect on negative emotional states such as anger (Agnew, 2006, 2012). But there is one critical area where the support for GST is mixed. GST argues that a range of factors influence whether individuals cope with strains through crime. Criminal coping is said to be most likely among those with poor coping skills and resources, little social support, low social control, beliefs favorable to crime, criminal associates, and opportunities for crime (Agnew, 2001). But the research on whether these factors influence or condition the effect of strains on crime has produced mixed results (Agnew, 2006, 2013). Sometimes significant conditioning effects are found and sometimes not. For example, some studies have found that strain is more likely to result in crime among those who associate with criminal peers, while other studies have not (Agnew, 2006).

Agnew (2013) recently discussed the possible explanations for these mixed results. He argued that the primary reason is that researchers typically examine whether one variable conditions the effect of strains on crime, with other conditioning variables controlled (Agnew, 2013). For example, they examine whether delinquent peer association conditions the effect of strains, with levels of social control, social support, and beliefs controlled. But the larger stress literature suggests that a single conditioning variable does not strongly constrain individuals to engage in a particular type of coping, in part because there are many coping strategies from which to choose. The stress literature, however, suggests that it is possible to roughly predict the choice of coping strategy if several conditioning variables are considered together. Agnew therefore argues that researchers should construct a measure of the individual's overall propensity for criminal coping, with this measure reflecting the individual's standing on several conditioning variables. Assuming there is adequate variation in these variables, those who score high on the overall measure should be more likely to cope with strains through crime. Also, researchers should examine whether criminal coping is more likely among certain categories of people known to have a strong propensity for criminal coping, such as gang members.

This paper tests Agnew's arguments using cross-sectional data from the Gang Resistance Education and Training (GREAT) study, which involves a survey of 5,935 eight-grade students in a diverse array of public schools (Esbensen, Peterson, Taylor, & Freng, 2010). The GREAT study is well suited for such a test. It measures several of the criminogenic strains identified by GST, such as criminal victimization. It also considers a range of key conditioning variables, such as impulsivity, maternal attachment, parental monitoring, beliefs favorable to crime, and time spent in unsupervised activities with peers. Further, a sizeable number of the respondents possess multiple risk factors for criminal coping (Esbensen, Peterson, Taylor, & Freng, 2009; Esbensen et al., 2010). The survey also measures gang membership, with 522 students reporting that they are gang members. Typically, tests for conditioning effects with survey data often suffer from limited variation in those variables that make up interaction terms, but this is not the case with the GREAT data.[1]

Agnew's arguments are tested by examining whether the effect of selected criminogenic strains on crime are conditioned by a) a measure of the overall propensity for criminal coping comprised of ten conditioning variables, and b) gang membership (Agnew, 2013). This is one of the few studies to employ an overall propensity measure and it builds on prior research in terms of the comprehensiveness of the measure, adequacy of the sample, and rigor of the test. Furthermore, to the best of our knowledge, this is the only study that examines whether gang membership, in and of itself, conditions the effect of strains on crime.[2] The paper begins with an overview of GST, including a discussion of the research on conditioning effects. It then discusses the possible reasons why such research has produced mixed results, with a focus on Agnew's core explanation (Agnew, 2013). The data and methods are then described, followed by a presentation of the results.

2 An Overview of General Strain Theory, with a Focus on Conditioning Effects

General strain theory (GST) postulates that certain strains or stressors increase the likelihood of crime (Agnew, 2006). Strains refer to events and conditions that are disliked. Strains are most likely to result in crime when they are high in magnitude, seen as unjust, associated with low social control, and create some incentive or pressure for criminal

[1] McClelland and Judd (1993) and Kromrey and Foster-Johnson (1999) provide excellent discussions of the difficulties associated with detecting statistically significant interaction effects in non-experimental research (e.g., survey data).
[2] Prior research has examined gang membership as one factor included in a multi-item criminal propensity measure, but did not investigate the unique conditioning effect of being a gang member on strain (see Ousey, Wilcox, & Schreck, 2015).

coping. GST list several criminogenic strains with these characteristics, including parental rejection, harsh and abusive discipline, school problems (low grades, negative relations with teachers), abusive peer relations, criminal victimization, residence in deprived areas with high levels of crime and incivility, economic problems, discrimination, and the inability to achieve certain goals – such as status/respect and autonomy (see, e.g., Agnew, Rebellon, & Thaxton, 2000; Kaufman, Rebellon, Thaxton, & Agnew, 2008; Thaxton & Agnew, 2004). Data suggest that these strains increase the likelihood of crime, with strains such as parental rejection and victimization being among the leading causes of crime (Agnew, 2006, 2012).

These strains are said to increase crime for several reasons. Most notably, they lead to anger and other negative emotions (Brezina, Piquero, & Mazerolle, 2001; De Coster & Zito, 2010). These emotions create pressure for corrective action and crime is one method of coping. Crime may allow individuals to reduce or escape from strains (e.g., steal the money they need, run away from abusive parents), seek revenge against the source of strain or related targets (e.g., assault the peers who bully them), or alleviate negative emotions (e.g., through illicit drug use) (Brezina, 1996). Research suggests that strains increase crime partly through their effect on negative emotional states, such as anger (Agnew, 2006, 2012). In addition, strains increase crime through the other mechanisms identified by GST: strains reduce social control, lead to beliefs favorable to crime, foster association with delinquent peers, and contribute to traits conducive to crime – such as negative emotionality (Agnew, 2006, 2012).

GST, however, states that while the above strains increase the likelihood of crime, people usually do not cope with strains through crime because there are a variety of ways to legally cope with strains (see, generally, Thoits, 1995). For example, one may cope with economic problems by getting a second job, working longer hours, taking out a loan, reducing expenses, selling possessions, and other methods. GST therefore describes those factors that increase the likelihood of criminal coping, with these factors affecting the ability to engage in legal and criminal coping, the costs of criminal coping, the disposition for criminal coping, and the opportunities for criminal coping. Such factors include poor coping skills and resources (e.g., poor problem-solving and social skills, low socioeconomic status, personal traits such as low constraint and negative emotionality), criminal skills and resources (e.g., large physical size, high criminal self-efficacy), low levels of conventional social support, low social control, association with criminal others, beliefs favorable to crime, and exposure to situations where the costs of crime are low and the benefits are high.

Many researchers have examined whether factors of the above type condition the effect of strains on crime (Agnew, 2006, 2013). Researchers usually examine conditioning effects by creating interaction or product terms, with the conditioning variable multiplied by the strain (Aiken & West, 1991; Friedrich, 1982; Jaccard, Turrisi, & Wan, 1990). Researchers typically focus on one conditioning variable at a time, determining whether it conditions the effect of strains on crime with other conditioning variables controlled. Such research has produced mixed results (see, e.g., Aseltine, Gore, & Gordon, 2000; Hoffman & Cerbone, 1999; Hoffman & Su, 1997; Oberlander et al., 2011). Some studies find that variables such as social control, delinquent peer association, and beliefs condition the effect of strains on crime, while other studies do not. These mixed results are not fatal to GST. It is still the case that criminogenic strains increase crime, largely for reasons identified by

GST. But these mixed results constitute the most serious challenge to GST. It is clearly the case that strains only result in crime in certain cases. Being able to describe those factors that increase the likelihood of a criminal response has the potential to greatly enhance the explanatory power of GST. It also has important policy implications. Since it is not possible to eliminate all exposure to criminogenic strains, it is desirable to reduce the likelihood that people will respond to such strains with crime (Agnew, 1995, 2006). Research that identifies those factors influencing the response to strains therefore has much policy relevance.

3 Explaining the Inconsistent Results on Conditioning Effects

Agnew (2013) reviews several explanations for the mixed results on conditioning effects, stating that all may have some merit. Among these explanations is the difficulty of detecting interaction effects using survey data, due largely to low residual variance of the product term (Echambadi & Hess, 2007; Kromrey & Foster-Johnson, 1999; McClelland & Judd, 1993).[3] It has also been argued that GST overlooks certain key conditioning variables—including bio-psychological factors that increase the sensitivity to stressors, individual characteristics such as optimism and attention deficit/hyperactivity, religiosity, and previous experience with stressors—which may impact the ability to effectively cope

[3] The residual variance of a product term should not be confused with the residual *error* variance of the dependent variable. The residual variance is simply the product of the component variances adjusted by the covariance, so when the constituent variables are highly correlated the residual variance will be low (and as a result, the corresponding effect size is low). This is an important issue in field research (i.e., non-experimental research) because the magnitude of the correlation between constituent variables is not under the direct control of the researcher (McClelland & Judd, 1993, p. 378). Small sample sizes and/or extremely skilled distributions of the constituent variables may exacerbate this problem. Our constituent variables exhibit significantly variability independent of their association with one another (e.g., the average bivariate correlation is $\rho = 0.22$), thereby reducing concern in this area.

with current stressors (De Coster & Zito, 2010; Jang & Johnson, 2005; Johnson & Kercher, 2007; Seery, Alison, & Silver, 2010; Stogner, 2015). Agnew (2013) acknowledges that such conditioning variables should be incorporated into GST. Agnew also emphasizes that more attention should be paid to the coping process itself, including the particular coping strategies that individuals employ over time when responding to stressors (Broidy, 2001). A more complete understanding of this process may help better identify when criminal coping is likely. Agnew's major explanation for the mixed results, however, is derived from the larger stress literature.

This literature has examined whether a range of variables condition the effect of stressors on outcomes such as physical and mental health (see, e.g., Aneshensel, 1992; Elder & Caspi, 1988; Thoits, 1995). As is the case with GST, the evidence regarding conditioning effects is mixed. This appears to be the case because there are a very large number of coping strategies, so "while particular variables may have some influence on the ability to employ and the disposition for certain coping strategies, most individuals still have a large number of coping strategies at their disposal" (Agnew, 2013, p. 661). But the stress literature suggests that it is possible to roughly predict the choice of coping strategy if several variables are taken into account, including the characteristics of the stressor and the individual's standing on other conditioning variables. Drawing on this literature, and crime theory and research, Agnew predicts that criminal coping is likely when individuals a) possess a *set* of characteristics that together create a strong propensity for criminal coping; b) experience criminogenic strains; and c) are in circumstances conducive to criminal coping.

In terms of quantitative tests, Agnew states that researchers should focus on the criminogenic strains listed by GST and measure the individual's overall standing on those conditioning variables said to increase the likelihood of criminal coping. It is not necessary to consider every conditioning variable, since the variables that increase the likelihood of criminal coping tend to be correlated with one another. Individuals who score high on several variables are therefore likely to score high on others.[4] Such individuals are also likely to regularly encounter circumstances conducive to criminal coping, such as unstructured, unsupervised interactions with peers. Further, Agnew argues that researchers can measure whether individuals possess certain "markers" or characteristics that indicate that they score high on a range of conditioning variables conducive to crime. One such characteristic is *gang membership*. Existing studies indicate that gang membership is strongly correlated with virtually all of the factors that increase criminal coping, such as low self-control, low social control, beliefs favorable to crime, and association with criminal others (Esbensen et al., 2009; Jankowski, 1991; Melde & Esbensen, 2011; Peterson, Taylor, & Esbensen, 2004; Shelden, Tracy, & Brown, 1997; Terence P. Thornberry, 2003).

Only five studies of which we are aware have examined individuals' overall propensity for criminal coping, as measured by their standing on several conditioning variables—two of these studies find support for the conditioning effects hypothesized by Agnew (2013), but three others fail to provide support. Mazerolle and Maahs (2000) were

[4] Individual risk items often suffer from random measurement error. When several items reflect the same underlying concept, including each item separately in a model can lead to problems of multicollinearity and unnecessarily complicated results. An index (i.e., scale) created from the individual items will tend to be more reliable than each item individually (Cureton & D'Agostino, 1983; Loehlin, 1998).

the first researchers to examine the direct and conditioning effects of an overall criminal propensity measure on delinquency. Their criminal propensity measure was created by summing scores on three variables: attitudes toward delinquency; the respondent's report of how many of their friends engage in delinquency; and the respondent's involvement in nine deviant and minor delinquent acts, such as lying about one's age, skipping school, and making obscene telephone calls. They then examined the effect of a composite measure of strain on delinquency among respondents who had a low, medium, and high overall propensity for criminal coping, and found strong support for the hypothesis that the overall propensity for criminal coping conditions the effect of strains on delinquency. For example, when the overall propensity for criminal coping is low, only 26% of respondents with high levels of strain engage in delinquency, versus 92% when the overall propensity for criminal coping is high. Lin and Mieczkowski (2010), tested hypotheses derived from GST among a group of 948 secondary school students in Taiwan. They measured the overall propensity for criminal coping by summing scores on four variables: self-esteem, self-control, moral beliefs regarding certain deviant acts, and association with delinquent peers, and found that their overall propensity measure significantly conditioned the effect of certain strains on delinquency, but not others.

Mazerolle and Maahs' (2000) and Lin and Mieczkowski (2010)'s research significantly contributes to our understanding of criminal coping among juveniles, but both studies have certain limitations which may undermine the generalizability of their findings of the conditioning effect of criminal propensity. Mazerolle and Maahs do not control for important background and demographic characteristics that are likely to be highly correlated with both their strain measure and the various conditioning factors, so it is uncertain whether the conditioning effects they discover are artifact of the absence of those key confounding variables. Also, two of the three risk factors for criminal coping in their study may be especially problematic because they appear to be tautological. Recent research suggests that self-reports of peer delinquency largely reflect the respondent's own delinquency (Young, Rebellon, Barnes, & Weerman, 2014). Another risk factor, minor delinquency and deviance, is itself a delinquency measure, albeit of a lower magnitude. Consequently, Mazerolle and Maahs' measure of the propensity for criminal coping may be confounded with the respondent's own crime, thereby increasing the likelihood of finding a strong conditioning effect.

Lin and Mieczkowski's small sample size and exclusive focus on Taiwanese respondents may have resulted in an insufficient number of students at high risk for criminal coping. As noted by the authors and others, Chinese culture and social life place much emphasis on self-restraint, conformity, social harmony, and the avoidance of conflict (Agnew, 2015; see, e.g., Chua, 2011; Chua & Rubenfeld, 2014; Xiao, 2001).[5] Consequently, the students in their sample may be more likely than those in Western samples to condemn delinquency, possess self-control, and associate with conventional others. In addition, their measure of the propensity for criminal coping provides information on the respondent's individual characteristics (self-esteem, self-control, and beliefs) and peer associations, but does not measure risk factors involving the family, school, or community. Research suggests that the risk for delinquency (and perhaps delinquent coping) is highest when risk factors are present in all major life domains—individual, family, peer, school, and community (Esbensen et al., 2009; Saner & Ellickson, 1996).

[5] For a critical assessment of the cultural value systems hypothesis, see Tamis-LeMonda et al. (2008).

Jang and Song's (2015), Craig, Cardwell, and Piquero's (2016), and Ousey, Wilcox, and Schreck's (2015) recent studies all fail to find support for Agnew's predictions about the conditioning effects of a composite criminal propensity on the impact of strain on delinquency. Jang and Song examine data from nearly 3,000 South Korean eighth-graders and constructed a criminal propensity scale from four subscales: low self-control, weak family bonds, poor commitment to school, and association with criminal peers. They examined two general strain scales: objective and subjective. The objective strain scale was comprised of various measures of actual and anticipated violent victimization, mistreatment by family members, neighborhood disorder, and school disorder. The subjective strain scale indexed a respondent's level of perceived stress from hassles related to parents, school, friends, and personal needs (e.g., health, physical appearance, and lack of money). Jang and Song find that neither the impact of objective nor subjective strain on various forms of non-drug delinquency and drug use is conditioned by respondents' criminal propensity. Similarly, Craig, Cardwell, and Piquero (2016) explore whether criminal propensity moderated the impact of strain on delinquency using data collected on nearly 1,400 adolescents from Arizona and Pennsylvania. Specifically, they tested whether a general criminal propensity measure—consisting of various items pertaining to psychological risk factors (e.g., impulsivity, paranoia, and hostility), pro-criminal beliefs, and the influence of anti-social peers—conditioned the effect of direct and vicarious victimization on delinquency. Contrary to the prediction of GST, the impact of both types of victimization did not significantly vary across levels of criminal propensity.

Ousey et al.'s (2015) measure the impact of violent victimization on violent and non-violent crime using data from approximately 2,500 students from urban and rural counties in Kentucky. They discovered that the impact of victimization on both types of offending was conditioned by a composite criminal risk index (reflecting poor pro-social bonds, low self-control, association with delinquent peers, pro-criminal beliefs, and gang membership); however, the direction of the conditioning effect was opposite of that predicted by GST. Specifically, they found that the effect of victimization on violent offending *decreased* as a respondent's risk of criminal offending increased. Conversely, students scoring low on the risk factor index were more likely to respond to violent victimization with crime (both violent and non-violent) than respondents scoring high on the risk factor index. They posited that an individual scoring high on the composite risk measure may experience a "saturation effect"—that is, the impact of any single factor contributing to crime is attenuated when the individual faces many concurrent criminogenic risk factors.

If Jang and Song's, Craig et al.'s, and Ousey et. al's findings are reproducible, then they pose a major challenge for GST, but it appears that all three studies have several limitations that may potentially undermine the validity and/or generalizability of their conclusions. First, the respondents in two studies—Jang and Song (2015) and Craig et al. (2016)—were part of a longitudinal data collection designs requiring active parental consent.[6] While longitudinal studies are especially useful for addressing questions of causal ordering, sample attribution coupled with parental consent may result in a high degree of self-sorting which may influence both participation and the candor of the

[6] Ousey et al. elected to use a single wave of a panel study because the particular wave contained better measures of respondents' criminal propensity.

respondents.[7] Second, the studies employ analytical techniques that potentially undermine their ability to uncover conditional effects that would be consistent with GST. Craig et al., Jang and Song, and Ousey et al. use variations of the regression model (i.e., ordinal regression and negative-binomial regression) that may be particularly problematic considering the distribution of their dependent variable (see Osgood, Finken, & McMorris, 2002).[8] Third, their investigations of conditioning effects problematically assume that the main ("direct") effect of violent victimization on criminal offending is monotonic (i.e., linear). Fourth, Ousey et al. and Craig et al. also divide their criminal propensity index into categories that may fail to sufficiently capture any potential non-linearity in the conditioning effect of the risk factor index. These cut-points appear somewhat arbitrary and may mask important differences between respondents that could be uncovered with a more granular, empirically-driven analysis.[9]

Finally, although Ousey et al.'s models examine gang membership as both a main effect and a risk factor in their composite risk index, they do not examine whether gang membership specifically conditions the effect of victimization on violence. As noted earlier, membership in a gang may be a particularly important marker for the risk of criminal coping and, therefore, its potential interactive effect with other types of criminogenic

[7] In the Ousey et al. study, less than a third of the targeted population of the study was examined, and there is a strong possibility that respondents at highest risk for serious criminal offending were underrepresented in the study (Terrence P. Thornberry, Lizotte, Krohn, Farnworth, & Jang, 1994). Craig et al. focused on respondents who already had committed serious offenses, thereby increasing the likelihood of containing significant numbers of juveniles at high risk of offending, but the parental consent requirement, coupled with the use of face-to-face interviews for data collection, may have potentially impact of the candor of the respondents.
[8] A detailed discussion of the problem with employing ordinal logistic regression models for delinquency data is provided below.
[9] Ousey et al. divide the risk factor index into the top quartile, middle 50%, and bottom quartile. Craig et al. divide their risk factor index into "low" based on the both two-thirds of the distribution of respondents and "high" based on the remaining one-third of the distribution.

strains should be investigated directly. This is especially true when the other variables comprising the risk index have a weaker association with crime/delinquency; as a result, the true conditioning effect of gang membership may be attenuated (Bollen, 1989).

So despite the important contributions of Mazerolle and Maahs (2000), Lin and Mieczkowski (2010), Jang and Song (2015), Ousey, Wilcox, and Schreck (2015), and Craig, Cardwell, and Piquero (2016), there remains a need for further research on whether the overall propensity for criminal coping conditions the effect of strains on crime. Ideally, such research should examine a sample with a significant number of individuals at high risk for criminal coping. Also, the overall propensity measure should contain major risk factors from several life domains, including individual, family, school, peer, and/or community. Measures of delinquent peer association should be avoided, however, unless such association is measured independent of respondent self-reports.

There is also a need for research on whether delinquent coping is greater among those who possess markers suggesting a strong propensity for delinquent coping, with gang membership being one such marker (Taylor, Peterson, Esbensen, & Freng, 2007). The failure of previous research to separately examine the conditioning effect of gang membership is surprising, given that gang membership is strongly correlated with most of the conditioning variables identified in GST and has a very strong effect on delinquency. This failure likely stems from the fact that gang membership is not measured in most surveys, perhaps because the school samples on which these surveys rely do not contain many gang members.

This study builds on the prior research on conditioning effects by employing a large sample with a sizeable number of individuals at high risk for criminal coping. A measure of the overall propensity for criminal coping is constructed, with this measure containing ten indicators from the individual, family, school, peer, and community domains. Further, the conditioning effect of gang membership is examined. The analytical approach we adopt in this paper permits the simultaneous consideration of non-linear (i.e., curvilinear) and non-additive (e.g., interactive) dynamics in the context of non-normally distributed data. As we describe in greater detail below, a non-linear effect represents variation in the marginal effect of a variable across its own range (e.g., a one-unit change at the low-end of the distribution of a variable that measures a respondent's level of anger has a stronger/weaker effect on delinquency than a one-unit change at the high-end of the distribution); whereas a non-additive effect captures the variation in the marginal effect of a variable across the range of another variable (e.g., the effect of anger on delinquency is stronger for males than females). A variable may have a non-linear effect, a non-additive effect, both, or neither (Cortina, 1993; Kromrey & Foster-Johnson, 1999). Graphically, a non-linear effect appears as a non-straight ("curved") line. A non-additive effect appears as two (or more) lines that are non-parallel (Wood, 2006a). Our approach significantly improves upon prior research through its flexible, yet statistically defensible, investigation of interaction effects that is capable of properly detecting such effects that prior approaches fail to uncover.

4 Data and Measures

Data are from the cross-sectional component of the National Evaluation of the Gang Resistance Education and Training (GREAT) program, a school-based prevention program

(Esbensen, 2003).[10] We do not use the longitudinal component of the GREAT data because of the extremely small number of gang members in those data. When examining the 1995 and 1996 waves, there are only 94 total gang members (37 remain in the estimation sample after listwise deletion). By contrast, the 1995 cross-sectional data include 522 gang members (244 after listwise deletion). Admittedly, our focus on the cross-sectional data precludes us from carefully disentangling questions of causal ordering; nevertheless, we believe our decision to concentrate on the cross-sectional data in order to maximize the number of gang members included in the analysis is warranted given our emphasis on examining the conditioning effect of gang membership. Future research should consider longitudinal designs to specifically address the causality issue. Nonetheless, it is worth noting that the prior studies by Jang and Song (2015) and Craig et al. (2016) examined longitudinal data and both discovered that criminal propensity and the various strain measures exert an independent effect on delinquency when controlling for prior delinquency, thereby suggesting a genuine causal relationship. Moreover, our analysis is primarily concerned with the functional form of the (joint) relationships—i.e., non-linear

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and non-additive effects—which is conceptually distinct from the question of causal ordering (Elwert & Winship, 2010).

The study was conducted in 1995 and involved a survey of eight-grade students in 42 public schools in 11 cities across the United States (*N*=5,935). While not a random sample of students, the students are from a wide range of schools and communities. These include large urban areas (e.g., Philadelphia, Phoenix, Milwaukee, and Kansas City), as well as medium and small-sized cities. The diverse sample is 52% female; 41% White, 27% African-American, and 19% Hispanic; 29% 13 years old, 60% 14 years, and 11% 15 years plus; 62% from two-parent families; and 34% with parents who have a high school education or less. Along with the demographic and regional diversity of the sample, the large sample size helps ensure a sufficient number of potentially high-rate offenders. Also, by confining the sample to eight-graders, the potential self-selection bias inherent in longitudinal studies of high schoolers is also minimized.[11]

<u>Delinquency Measure</u>. Our dependent variable is measured with a 16-item scale, with respondents being asked how many times in the last twelve months they had damaged or destroyed property, carried a hidden weapon, stolen something worth less than $50, stolen something worth more than $50, gone into a structure to steal something, stolen a car, hit someone, attacked someone with a weapon, used a weapon or force to get things, been in gang fights, shot at someone, sold marijuana, sold other illegal drugs, used marijuana, used paint/glue, and used other illegal drugs ($\alpha = .90$) (Cronbach, 1951). The

[11] Notable limitations of the study design have been discussed elsewhere—e.g., exclusion of private schools, truants, sick, and tardy students (Esbensen, Peterson, Taylor, & Freng, 2009).

items can be roughly categorized into three groups: crimes against property, crimes against persons, and drug offenses. Exploratory factor analytic models were investigated in order to determine whether our summation scale was truly reflective of a single underlying construct (Galbraith, Moustaki, Bartholomew, & Steele, 2002, p. 143; Kaplan, 2000, p. 40). Generally speaking, the proportion of the total variance explained by a factor should be reasonably high (Loehlin, 1998). Our analysis revealed that a single factor explains 86% of the total variance of 16 items. Two goodness-of-fit tests—the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)—also strongly suggest that a single factor model best fits the data (Akaike, 1973; Schwartz, 1978).[12] As a robustness check, we also examine each crime category separately. Following Esbensen et al. (2010), respondents who reported that they committed an act 12 or more times were coded as "12" to reduce skewness. Sixty-eight percent of the sample report committing at least one delinquent act (mean = 12.3; std. dev. = 22.6).

Strain Measures**.** The GREAT study contains information about three criminogenic strains. *Victimization* is measured by a four-item scale, with respondents indicating the number of times they have been: hit, robbed, attacked with a weapon, and had things stolen from them in the past year ($\alpha = .65$).[13] Agnew (2006) describes criminal victimization as a key strain, perhaps one of the most important causes of crime. Similar to the aforementioned delinquency scale, respondents reporting 12 or more victimizations for an item were coded as "12" to reduce skewness. *Police Strain* is measured by a six-item scale,

[12] Several confirmatory factor analytic (CFA) models were also investigated (Bollen, 1989). The results from these analyses also indicate that a multi-factor structure does not appreciably improve model fit.
[13] Whereas Ousey et al.'s (2015) and Craig et al.'s (2016) studies focus exclusively on violent victimization as a source of strain, our study investigates other forms of strain besides victimization.

with high scorers stating that the police are dishonest, rude, unfriendly, discourteous, disrespectful, and discriminate against minorities ($\alpha = .83$).[14] *School strain* is measured by an eight-item scale, with high scorers stating that there is a lot of gang activity in their school, students do not get along, there are fights at school, students beat up teachers, there is racial conflict, and they do not feel safe at school or in the neighborhood around school ($\alpha = .71$). Again, this measure captures both personal and vicarious experiences with strain.

Propensity for Criminal Coping (Index). Ten risk factors were used to create a measure of the overall propensity for criminal coping. These risk factors index the individual, family, school, peer, and community domains to varying extents (Esbensen et al., 2009, p. 311).[15] Each risk factor was coded "0" (does not possess the risk factor) or "1" (does possess the risk factor). For the scales below, respondents were coded "1" if they scored in the top quartile of the risk factor. Esbensen et al. employed the same cutoff point in their study of risk factors in the GREAT data and Mazerolle and Maahs employed a similar approach (Esbensen et al., 2009, 2010; Mazerolle & Maahs, 2000). As indicated below, this cutoff seems to provide a good indication of the presence of the risk factor. It should be noted, however, that a different cutoff point may be appropriate for a sample of more or less risky adolescents. The measure of the overall propensity for criminal coping

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[14] The police strain scale does not focus solely on the juvenile's personal experience with such treatment, so the scale may capture both personal and vicarious strain (see generally McGrath, Marcum, & Copes, 2011; Zavala & Spohn, 2012). As Agnew (2006) states, vicarious strain may increase crime, particularly when the strain is seen as severe and unjust. Numerous studies suggest that the perception of the police as unjust and overly harsh police treatment may increase crime, with this strain being particularly relevant for African Americans and Latinos (see, e.g., Hagan, Shedd, & Payne, 2005; Sampson & Bartusch, 1998; Unnever & Gabbidon, 2011).

[15] The U.S. Office of Juvenile Justice and Delinquency Prevention (OJJDP) has also adopted this approach in its efforts to address youth violence.

is the sum of the ten risk factors and ranges from 0 to 10 ($\alpha = .83$). The specific risk factors comprising the scale are:

Sex. An indicator variable coded as "0" for females and "1" for males.[16]

Low Attachment to Mother. A six-tem scale with those scoring "1" generally stating that they cannot talk to their mother, their mother does not trust them, their mother does not praise them, they never seek their mother's advice, their mother does not know their friends, and their mother doesn't understand them ($\alpha = .85$).[17]

Poor Parental Monitoring. A four-item scale, with those scoring "1" stating or tending to state that their parents do not know where they are or who they are with when they are not at home/school, that they do not tell their parents where they go, and they do not know how to contact their parents when their parents are away from home ($\alpha = .73$).

Impulsivity. A four-item scale, with those scoring "1" stating that they act on the spur of the moment, don't give much thought to the future, are more concerned with the short run, and do what brings them pleasure in the present ($\alpha = .63$).

Risk-Seeking. A four-item scale, with those scoring "1" stating that they take risks, like to test themselves, find it exciting to do things for which they

[16] Sex is typically included as a risk factor in delinquency research because it remains highly correlated with delinquency—especially serious delinquency—even after controlling for a wide range of confounding variables.
[17] The GREAT survey also inquired about adolescents' level of attachment to their father. This measure was omitted from the analyses due to the high number of missing cases.

might get in trouble, and that excitement and adventure are more important than security ($\alpha = .81$).

Neutralizations. A nine-item scale, with those scoring "1" accepting a range of neutralizations for crime and deviance, such as it is "okay" to (a) fight to stand up for your rights, (b) steal little things since it will not hurt stores, and (c) lie if it does not hurt anyone ($\alpha = .96$).

Low Guilt. A sixteen-item scale, with those scoring "1" stating that they would not feel guilty or would only feel "somewhat guilty" for committing various deviant and criminal acts, such as skipping school, theft, assault, drug selling, and drug use ($\alpha = .94$).

Low School Commitment. A seven-item scale, with those scoring "1" stating or tending to state that they dislike school, grades are not important to them, education is not important to them, they do not try hard in school, homework is a waste of time, they usually do not finish their homework, and they would rather go out with friends than study for good grades ($\alpha = .81$).

Delinquent Peer Commitment. A three-item scale, with those scoring "1" stating that if their friends were getting into trouble, they would still hang out with them ($\alpha = .84$).

*Time in Unsupervised Peer Activities***.** A single-item, with high scorers stating that they spend at least ten hours a week hanging out with friends "not doing anything in particular where no adults are present."

The frequency for the *Overall Propensity for Criminal Coping* index is shown in Table I, along with the mean number of delinquent acts committed by people with different propensity scores. Figure 1 is a visual depiction of the relationship between the criminal coping index and delinquency via a locally weighted scatterplot smoother (Cleveland, 1979). While most respondents possess "zero" or a small number of risk factors for criminal coping, 17% ($N = 649$) respondents have five or more risk factors and 4% ($N = 158$) respondents have eight or more risk factors. The overall propensity measure is strongly associated with delinquency, with those having a high propensity for delinquent coping committing many times more delinquent acts on average than those with a low propensity ($r = .60$). The relationship between the propensity measure and delinquency appears to be roughly linear until the number of risk factors reaches eight; there is a sharp increase in delinquency at eight and at ten risk factors (Esbensen et al., 2009; Saner & Ellickson, 1996). The fact that those with numerous risk factors are much more delinquent than those with a few suggests that there may be some advantage in having a comprehensive measure of overall propensity. Future research will hopefully identify those risk factors which are most relevant to criminal coping and therefore should be the focus of overall propensity scales.

<u>Gang Membership</u>. Gang membership was measured by asking respondents whether they are *currently* in a gang. Admittedly, this measure is imperfect, but prior research suggests that this simple measure provides a reasonably valid indicator of gang

membership (Esbensen et al., 2010; Esbensen, Winfree, He, & Taylor, 2001; Junger-Tas et al., 2010; Terence P. Thornberry, 2003). [18]

[Table I About Here]

[Figure 1 About Here]

4.1 Analytical Approach

Standard linear regression models are ill-suited for nearly all measures of criminal/delinquent offending because these measures have skewed, limited, or discrete distributions; therefore, alternative methods are needed to properly account for these non-standard distributions (Osgood et al., 2002).[19] These shortcomings are especially pronounced when non-additive and non-linear relationships are of substantive interest. As Osgood and colleagues note, "Applying least squares statistics to unsuitable data may reveal complexity in the form of interactions among explanatory variables and curvilinear relationships with the dependent variable[,] [but the] complexity is not necessarily substantively meaningful [and] could instead reflect a mismatch between the additivity assumption of a linear model and the skewed response scale, in which case all variables strongly related to the outcome will interact with one another" (Osgood et al., 2002, p. 321). As a consequence, researchers increasingly utilize statistical models that specifically account for the bounded and discrete nature of crime data. Popular choices include

[18] Gang membership is a transient state, with the average length of gang membership lasting one year or less (Peterson, Taylor, & Esbensen, 2004; Terence P. Thornberry, 2003). Prior research also suggests that individuals who associate with gang members, but do not consider themselves to be members of a gang, are more delinquent than non-gang members, but less delinquent than self-identified gang members (Melde & Esbensen, 2011, p. 523).

[19] For a detailed discussion of the limitations of standard regression models when analyzing non-continuous and non-normally distributed outcomes, see McCullagh and Nelder (1989).

censored (*Tobit*), ordered response (e.g., ordered logit/probit), and count-based (e.g., Poisson and negative binomial) models applied either directly to the variable of interest or a rescaled/transformed version of the variable (Osgood, 2000; Osgood et al., 2002; Ousey et al., 2015; Craig et al., 2016). These models, however, are not without complications that may ultimately undermine the proper modeling of interaction (non-additive) and curvilinear (non-linear) effects. Below we briefly describe these methods and highlight their main weaknesses. Following the discussion of these approaches, we present an alternative modeling framework, a hurdle model, that is especially well-suited for analyzing individual-level crime data. After discussing this alternative approach, we describe how to properly measure and interpret interaction effects in models analyzing non-normal outcome variables—especially when the variables constituting the interaction term may, themselves, have non-linear effects on the outcome variable (i.e., a self-interaction). Failure to properly take into account these two potential sources of variability in the effect of an explanatory factor on an outcome can mask the true effect of the variable and lead to erroneous conclusions about the impact of the variable on criminal and delinquent behavior.

<u>Censored Models</u>. Individual-level crime data typically have a large amount of "zeros" because many individuals do not engage in criminal behavior. Censored regression models, commonly called Tobit models, can account for the qualitative difference between limit (zero) and non-limit (continuous) observations (Tobin, 1958). Some analysts have argued the Tobit model is only appropriate for situations in which the dependent variable is censored or truncated at certain values, but can theoretically assume values beyond the censoring/truncation point (Maddala, 1992). In the case of a crime measure, the variable

must be able to take on values below zero. While this may seem like an implausible assumption, it may not be problematic for the purposes of the study of individual-level criminal behavior if the latent variable underlying the delinquency scale represents criminal/delinquent utility (Sigelman & Zeng, 2000). That is, the utility of engaging in criminal/delinquency behavior must exceed a certain threshold before the respondent engages in any criminal/delinquent act.[20]

Recent work by Wooldridge (2002, 2003) suggests that Tobit models are, in fact, appropriate when the outcome variable is bounded and cannot theoretically assume values beyond the censoring point. This situation, common in econometrics and criminology, occurs when the outcome variable takes on the value greater than zero with positive probability, but is a continuous variable over strictly positive values. One can imagine many juveniles deciding the optimal choice is to *not* engage in delinquency. Wooldridge refers to this type of outcome variable as a "corner solution outcome" and the resulting model a "corner solution model." The concern, then, is not data observability (i.e., what "would" the value be if it was observed?); rather interest lies in features of the distribution of the outcome variable given the explanatory variables. Under both the "censored outcome" and the "corner outcome" views, individual-level delinquency scales often satisfy that particular assumption of the Tobit model.[21]

[20] Criminal *propensity* and *utility* are distinct concepts. Propensity is an inclination or tendency to behave in a particular manner; whereas utility is the benefit or satisfaction derived from a particular action or series of actions.

[21] In a Tobit regression, there are a variety of marginal effects that may be of interest to the analyst (Roncek, 1992; Wooldridge, 2003), but the expected value of the *censored* variable is often of primary interest to researchers.

One major shortcoming of the Tobit model is its heavily reliance on assumptions about the error term—namely, normality and homoscedasticity. In fact, Tobit regression is much more sensitive to violations of these assumptions than the standard linear model because the distribution of latent variable hinges on these two assumptions. Most individual-level crime data are bounded at zero and have a long right-tail, so the normality assumption is rarely satisfied, even when the crime measure is rescaled in order to bring in the long tail (e.g., a natural logarithmic transformation). Another potential disadvantage of the Tobit model is the assumption that the censoring and outcome processes are based on the same underlying model (Cameron & Trivedi, 2005, p. 544). In practice, this means that the effects of the explanatory variables on whether an observation is censored and the expected value of the outcome variable for an observation that is not censored must be proportional and in the same direction across to the two equations. This assumption is often unrealistic.[22] These potentially problematic features of the model—questionable distributional assumptions about the error term and the relationship processes responsible for crime participation and frequency—can negatively influence the examination of interaction effects precisely because the model can erroneously mask or reveal non-additive and non-linear effects in the data.

<u>Ordered Response Models</u>. Ordinal models group possible outcomes into a pre-determined number of ordered categories and posit that an underlying latent (continuous) variable determines what category is actually observed. When the latent variable crosses a

[22] This assumption can be relaxed with a "hurdle model" where the censoring mechanism and outcome may be modeled using separate processes (Cameron & Trivedi, 2005, p. 544). The censoring model (i.e., first part) applies to all observations in the sample, whereas the participation model (i.e., second part) only applies to observation with a positive non-zero outcome. The hurdle framework is described in greater detail below.

particular "threshold," the observed response falls into a specific category. The ordered response model does not suffer from the same limitation as the count-based models with respect to accounting for the excess zeros in crime data because the zero responses are simply treated as the first category (Min & Agresti, 2002). Nonetheless, the ordered response model does present some new complications; three are particularly relevant to the current discussion. First, ordinal models assume the effects of explanatory variables are the same for each threshold (sometimes called the parallel regression assumption or proportional odds assumption). This can be unrealistic for crime data.[23] Second, the manner in which the scale is collapsed into categories is arbitrary. Finally, important distinctions between observations may be lost by grouping the data. The latter two complications are especially problematic because the rescaling of the variable through the use of a small number of discrete categories and the loss of information about individuals via the grouping can impact the detection of non-additive and non-linear effects.

Count-based Models. Traditional count-based models also underestimate the number of zeros in crime data, and as a result, lead to incorrect estimates of the effects of explanatory variables. These count-based models can be augmented to account for excessive zeros, called "zero-inflated" models, but such models remain ill-suited for most crime data because of the important distinction between "structural zeros" and "sampling zeros." Structural zeroes occur when some subjects are not at risk for the behavior of interest (e.g., juvenile delinquency); whereas sampling zeros are responses that can be greater than zero, but are zero due to sampling variability (a juvenile decides to engage in

[23] The ordinal response model has been generalized in an attempt to relax the parallel regression assumption (R. Williams, 2009), but applications of the modified model in criminology are extremely rare (e.g., Gabbidon & Jordan, 2013).

delinquency, but just by chance, did not commit any delinquent acts). Sampling zeros (also called random zeros) are likely to be present when the period under investigation is of short duration (e.g., number of delinquent acts in the previous day or week), but not for longer time periods, such as the previous twelve months. Clearly the zeros in our individual-level crime data are all structural zeros, so the zero observations can come from only one structural source: those not at risk for delinquent behavior. Zero-inflated models assume that structural zeros cannot be distinguished from sampling zeros, so delinquency responses are modeled a mixture of the two types of zeros. By incorrectly modeling some structural zeros as sampling zeros, zero-inflated models can distort the relationships between explanatory variables and the outcome variable, as well as the interpretation of those relationships (Hu, Pavlicova & Nunes 2011).[24] This results in certain realized values occurring with too large or too small frequency than is consistent with the zero-inflated model (Min & Agresti, 2002). In cases where this distinction is known (i.e., structural zeros can be distinguished from sampling zeros), it is important to take advantage of the additional information (by excluding structural zeros from the analysis) and apply a more appropriate statistical model: a hurdle model.

Hurdle Model. Hurdle models have important advantages over Tobit, ordered response, and zero-inflated count models.[25] Unlike the Tobit and zero-inflated models, the model assumes a two-stage (i.e., sequential) decision-making process, rather than

[24] For example, consider a study of the number of cigarettes smoked during the last month. One can safely assume that only non-smokers will smoke zero cigarettes during the last month and smokers will report some positive (non-zero) number of cigarettes during the last month. Thus, the zero observations can come from only one "structural" source, the non-smokers. If a subject is considered a smoker, she or he does not have the ability to report zero cigarettes smoked during the last month.
[25] Hurdle models are also called "two-part" models—the terms are interchangeable. For historical reasons, the label "two-part" is typically used when the outcome is continuous over the positive range, whereas the model is called a "hurdle" model when the outcome is a count variable (Cameron and Trivedi 2005: 680).

constrain the two processes generating zeros and the non-zero responses to be the same (Cameron and Trivedi 2005: 680-81). As stated earlier, this constraint leads to the over- or under-prediction of realized values, and as a result, a distortion the true relationship between the explanatory variables and the outcome measure. The hurdle model framework posits two separate process: (1) the juvenile's decision to engage in any delinquent behavior (participation decision), and (2) the amount of delinquent behavior in which she or he engages (frequency decision). As a result, all "zeros" come from non-delinquents and all positive outcomes came from those who decided to engage in delinquent behavior ($Y > 0$). Consistent with prior research, we adopt a binary regression model specification for the first stage (participation decision) in the form: $Pr(Y = 1 \,|\boldsymbol{Z}), = g^{-1}(\boldsymbol{Z}\gamma)$, where g^{-1} is either the inverse logistic function (for logit) or inverse normal cumulative distribution function (for probit), $\boldsymbol{Z}$ is an $N \times j$ matrix of explanatory variables, and γ is a $j \times 1$ column vector of regression coefficients. The second stage can be modeled with a variety of distributions; we employ the most appropriate considering the observed distribution of our outcome measure: a truncated count (negative binomial) distribution (Cameron and Trivedi 2005: 679).[26]

In this section, we have described a modeling framework amenable to the distributional assumptions of individual-level crime data. We now turn our attention to the proper modeling and interpretation of non-additive and non-linear effects for such data. Because considerable confusion still remains over the proper way to examine interactive

[26] The hurdle model takes advantage of the basic rule of probability: $\mathbb{E}(y) = Pr(y > 0) \times \mathbb{E}(y|y > 0)$ (Cameron and Trivedi 2005). We checked the robustness of our result by also examining a positively skewed continuous distribution (i.e., *Gamma* distribution) for the second stage equation (McCullagh & Nelder, 1989). The results from both models were nearly identical.

and curvilinear relationships for these models, the following discussion provides a very detailed explanation of interaction effects in order to establish the necessary foundation for more complex models that will be discussed in the section that follows.

Parametric Interaction Effects in Linear Models. A statistical interaction occurs when the effect (regression coefficient) of one explanatory variable on the dependent variable changes depending on the level of another explanatory variable (i.e., non-additivity). This can be distinguished from the situation when the effect of an explanatory variable changes depending on the value of the same explanatory variable (i.e., non-linearity) (see, e.g., Cortina, 1993). Often non-linear effects are labelled "self-interactions." The self-interaction may be multiplicative, but can assume other forms as well (e.g., logarithmic). Failing to take into account potential non-linearity in the main effects of the constituent variables may incorrectly lead analysts to conclude that a moderated (i.e., interactive) relationship exists (Cortina, 1993; Kromrey & Foster-Johnson, 1999). A "simple effect" is the effect of one constituent variable at a particular level of the other constituent variable comprising the interaction (McClelland & Judd, 1993). In contrast, a "main effect" is the effect of the particular component variable on the dependent variable, ignoring the potential conditioning effect of the other component variable. In general, there is one "main effect" for every independent variable in a study.

It is customary (and advisable) to mean-center component variables prior to creating the multiplicative term in order to provide a more intuitive interpretation of the "simple effects" of the component variables.[27] Specifically, for the (simplified) model:

[27] Mean-centering has also been advocated by scholars for in order to reduce of the covariances between the component variables and the multiplicative term (Aiken & West, 1991; Jaccard, Turrisi, & Wan, 1990), but

$\mathbb{E}(y \mid x_1, x_2) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$, where α (the constant term) is the expected value of the delinquency scale when $x_1 = x_2 = 0$. A value of "zero" for mean-centered variables is the "average value" of that variable. Naturally, $x_1 x_2 = 0$ when either x_1 or x_2 is zero. The coefficients, β_1 and β_2, are interpreted as the simple effects of x_1 and x_2, respectively, at the mean values of the other component variable. The slope coefficient for the interaction term, β_3, describes the change in the slope of x_1 with every one-unit change x_2 (alternatively, β_3, describes the change in the slope of x_2 for every one-unit change in x_1). The simple effect of x_1 on y at any particular level of x_2 is calculated as $\frac{\partial y}{\partial x_1}\mathbb{E}(y \mid x_1, x_2) = (\beta_1 + \beta_3 x_2)$ and the simple effect of x_2 on y at any particular level of x_1 is calculated as $\frac{\partial y}{\partial x_2}\mathbb{E}(y \mid x_1, x_2) = (\beta_2 + \beta_3 x_1)$.

Analysts commonly interpret β_3 as the "marginal effect" of the interaction term, but this interpretation is incorrect because only the component terms have true marginal effects (Richard Williams, 2012). The slope estimate for the interaction term is not the effect of the interaction on the outcome variable; rather it merely describes how the slope of the constituent terms vary across the levels of each other. The interaction term may reveal that the magnitude of a component variable will vary across levels of another variable (quantitative interaction) or reveal that the direction of the effect will vary across levels of the other variable (qualitative interaction) (Aiken & West, 1991).[28]

the impact of this rescaling on multicollinearity has been recently subject to intense criticism (see, e.g., Echambadi & Hess, 2007; Kromrey & Foster-Johnson, 1998).

[28] Including an interaction term, but omitting the component variables yields model results that are difficult to interpret. This holds true even when the main effects of the component variables are not statistically significant (Tsai and Gill 2013: 93).

Just as the β_1 and β_2 are conditional slopes, the standard errors for those coefficients, $s(\beta_1 + \beta_3 x_2)$ and $s(\beta_2 + \beta_3 x_1)$, are conditional as well, and describe the variability in the slopes at specific levels of the component variable (Friedrich, 1982).[29] The obvious implication is that standard errors will be larger or smaller than the standard errors in an non-interactive model, so the statistical significance of the "simple effect" of an component variable may vary across the range of the conditional variable as well (Friedrich, 1982, p. 810; Jaccard et al., 1990, p. 27).

Parametric Interaction Effects in Non-linear Models. The interpretation of the effects of interaction terms is particularly complicated for non-linear models, encompassing binary, count, truncated, and bounded (i.e. censored) outcomes (Tsai & Gill, 2013). The difficulty arises because of the distinction between the scale of interest (i.e., natural scale) and the scale of estimation. A non-linear transformation of the conditional mean of the outcome variable may be necessary to properly estimate the model, but substantive interest lies in the relationship between the explanatory variables and the natural scale of the outcome variable. In non-linear models, interactions are *automatically* specified on the natural scale of the linear predictor (though not necessarily on the transformed scale), even when no interaction term is expressly included in the model. This results from the fact that there will always be partial effects for a given variable that are dependent on the level of that particular variable and the other explanatory variables (Cameron and Trivedi 2005: 122). Given the non-interactive model, $\mathbb{E}(y \mid x_1, x_2) = g^{-1}(\alpha + \beta_1 x_1 + \beta_2 x_2)$, where $g^{-1}(\cdot)$ is a nonlinear function, the marginal effect of x_1 is

[29] In the simple case where there are only two interacting variables, the standard error of the conditional slope, $(\beta_1 + \beta_3 x_2)$, is defined as: $[\mathrm{var}(\beta_1) + x_2^2 \times \mathrm{var}(\beta_3) + 2x_2 \times \mathrm{cov}(\beta_1, \beta_2)]^{\frac{1}{2}}$. The formula becomes more cumbersome when there are more than two interacting variables (Tsai & Gill, 2013).

given by: $\frac{\partial g^{-1}(\cdot)}{\partial x_1} = \beta_1 \times g^{-1}(\beta_1 x_1 + \beta_1 x_2)$.[30] Even in the bivariate case, the marginal effect of x_1 depends on its own value: $\frac{\partial g^{-1}(\cdot)}{\partial x_1} = \beta_1 \times g^{-1}(\beta_1 x_1)$, so there is no single marginal effect; rather, there are several. In the case of the interactive model, $\mathbb{E}(y \mid x_1, x_2) = g^{-1}(\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2)$, the full interaction effect is $\frac{\partial^2 g^{-1}(\cdot)}{\partial x_1 \partial x_2} = \beta_{12} \times g^{-1}(\cdot) + (\beta_1 + \beta_3 x_2)(\beta_2 + \beta_3 x_1) \times (g^{-1})'(\cdot)$. As a consequence, the magnitude, sign, and significance of the interaction coefficient may not yield reliable information about the true effect of the variable of interest (Ai & Norton, 2003; Tsai & Gill, 2013).

Although interactions are naturally produced in non-linear models when the effect of variables on the natural scale of the outcome variable are of substantive interest, the analyst may still examine whether hypothesized interaction effects—referred to by Nagler (1994) as "variable-specific" interactions—have a meaningful impact beyond those implied by the model and improve overall model fit. The best way to understand interaction effects in non-linear models is taking *cross/first differences* (Ai and Norton 2003: 129; Tsai and Gill 2013: 98). This involves selecting two levels of interest for a given explanatory variable and calculate the difference of the impact on the outcome variable holding all of the other variables constant. In the context of interactions, it is necessary to include all interacting coefficients in the cross/first difference calculation, making sure all other variables are set at their means. This procedure, sometimes called "conditional cross/first differences," calculates the observed difference that includes the main effect as well as all of the interaction effects that include a particular variable. The standard errors of these

[30] In the case of count models, such as the hurdle model employed in the current study, $g^{-1}(\cdot)$ is the log link function, so the marginal effect of a predictor variable is: $\frac{\partial g^{-1}(\cdot)}{\partial x_j} = \beta_j \times e^{(\beta x_i)}$ (Hilbe, 2011, p. 126).

differences are also calculated by including the effects of the relevant interaction terms, so the same formula for calculating conditional standard errors in the linear model context that was described earlier also applies in the non-linear context (Tsai and Gill 2013: 99).[31] In addition to the calculation of simple effects, it is advisable to explore any potential improvement in model fit (e.g., AIC) in assessing the relevance of an interaction term in the model precisely because it can be difficult to detect statistically significant interaction effects for the reasons described earlier in the paper.

Semiparametric Models. The aforementioned discussion of the effects of explanatory variables assumed a certain parametric form—i.e., the change of the effect of a particular slope coefficient would increase (or decrease) by a rate determined by the parameter estimate for the interaction term. This assumption applies to both linear and non-linear models because, although the calculation of the interaction effects in the non-linear context required special techniques to take into account the nonlinear effect of explanatory variables and their interactions, the simple slopes still describe a specific rate of change (when all other variables were held constant)—typically either additive or multiplicative (Cameron and Trivedi 2005: 122).[32] This assumption may be overly restrictive (Beck & Jackman, 1998), so it is relaxed in our analyses through the use of semiparametric additive regression models. A detailed discussion of these models in beyond the scope of this paper, but comprehensive descriptions are available from Hastie and Tibshirani (1990), Ruppert, Wand, and Carroll (2005), and Wood (2006a). Our semiparametric additive model

[31] Some software programs include routines that will perform the correction calculations for conditional first differences and their associated standard errors when examining conditional effects on the natural scale of the outcome variable. We used *Stata* 14 and its associate "margins" command to perform our calculations.
[32] The marginal effects of a continuous predictor in a hurdle model vary across observations.

assumes the following form: $\mathbb{E}(y_i \mid \boldsymbol{X}) = g^{-1}\left(\alpha + \beta_j x_{ij} + f_j(x_{ij})\right)$, where α is a constant term, β represents the parametric effect, $f(\cdot)$ represents a nonparametric smooth function to be estimated from the data,[33] i indexes the respondent, and j indexes the explanatory variable (Hastie & Tibshirani, 1990). The combination of parametric, β, and nonparametric, $f(\cdot)$, terms yields a semiparametric model.[34] The parametric effect, β_j, can be interpreted in the usual manner, however the smoothing functions do not provide traditional regression coefficients; rather, estimates of $f_j(x_j)$ are produced for every value of x_{ij}. The coefficient on each $f_j(x_j)$ is typically set to one by construction, so the predicted smooth, $\hat{f}_j(x_j)$, represents the relationship between x_j and the y, holding constant the other variables in the model (Wood, 2006b). As a consequence, the interpretation of the effects of these smoothing functions is accomplished through visualization—i.e., a plot of x_j versus the fitted smooth.

As discussed earlier, the delinquency scales analyzed in this paper follow a non-standard distribution, so special approaches are also required to properly examine these data in our semiparametric models. Similar to our earlier discussion of the parametric hurdle model, our semiparametric model also follows a two-part structure: (1)

[33] "A smoother is a tool for summarizing the trend of a response measurement, y, as a function of one or more predictor measurements, x_k, [and] produces an estimate of the trend that is less variable than y itself" (Hastie & Tibshirani, 1990, p. 9). Smoothers can take many forms, but typically yield similar results in the univariate context. The smooths adopted in this paper are based on penalized regression splines because they are best suited for multivariate smooths (i.e., interactions) that are employed in these analysis (Wood, 2006a, pp. 146–160, 2006b, pp. 1025–1026). The basic idea of a smoothing spline is to divide the data into smaller adjoining pieces and fit simpler models to each of the subintervals (with linear, quadratic, or cubic polynomials being sufficient to fit small intervals). In order for the resulting function to be continuous, without any jumps, the separate pieces connect at the boundaries of the intervals and produce a smooth curve over the entire range of the data.

[34] Semiparametric models are also appropriate when the distribution of the error term is unknown (Powell, 1994; Robinson, 1988).

participation and (2) frequency (conditional on participation) (Rigby & Stasinopoulos, 2005; Stefansson & Palsson, 1997). This model is also a combination of the binary regression and truncated regression models, and the parameters (and smooths) of the truncated model are estimated independently.[35]

The semiparametric approach allows us to explore interaction effects in a completely nonparametric fashion (Hastie & Tibshirani, 1990). Under this approach, the interaction is a product of the smoothing function in one variable multiplied by smoothing function in the other variable (Wood, 2006a).[36] We examine *hierarchal* models that include both the main effects of the component variables and the interaction: $\mathbb{E}(y_i|\boldsymbol{X}) = g^{-1}\left(\alpha + f_1(x_1) + f_2(x_2) + f_3(x_1, x_2) + \beta_j x_{ij}\right)$; where $f_3(x_1, x_2)$ is a nonparametric smooth from which the main effects have been excluded (but are added separately to the model). It should be emphasized that the main effects, e.g., $f_1(x_1), f_2(x_2)$, are modelled nonparametrically as well.[37] A nonparametric term may also be conditioned by a discrete variable. This interaction is commonly referred to as a "factor smooth interaction" or a "factor-by-curve" interaction (Ruppert et al., 2005, p. 226). For these models, the interaction is a product of the smooth term $f\left(x_{ij}\right)$ and the factor variable z_{ij}, thereby producing the model: $\mathbb{E}(y_i|x, z) = g^{-1}\left(\alpha + f(x_{ij}) \times z_{ij}\right)$. This type of interaction is

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[35] We adopt a probit model specification for the binary model, but logit and complementary log-log specifications yielded similar results. Also, similar to our fully parametric models, we explored a positively skewed continuous distribution (*Gamma*) for the second stage. Again, the substantive results were nearly identical.

[36] We use tensor product smooths for the non-parametric interaction terms because the constituent variables are measured in different units (Ruppert, Wand, & Carroll, 2005; Wood, 2006b).

[37] In the hierarchical model framework, a non-additive model is appropriately *nested* in the interactive model, thus permitting, *inter alia*, analysis of variance (ANOVA) decompositions in order to determine whether the inclusion of the interaction term significantly improves model fit (Wood, 2006b). In addition to analysis to ANOVA, various information-based indices (e.g., AIC) can also be used to compare model fit (Akaike, 1973; Bozdogan, 1987; Schwartz, 1978; Sclove, 1987).

particularly useful when a population (or sample) can be divided into non-overlapping groups (e.g., gang/non-gang member) and the analyst wishes to determine if the non-linear effect of one variable significantly differs across the subgroups.[38]

5 Results

Parametric Models. Tables II and IV report results from the parametric models, including the coefficient for the interaction term. The first set of regressions, reported in Table II, focus on the overall propensity for criminal coping (i.e., "risk"). The first two columns of Table II show, respectively, the unstandardized (*b*) and standardized (*beta*) effects of the strains and overall propensity measure on delinquency. All four predictors have significant positive effects on delinquency. The third and fourth columns show results when the interactions between the overall propensity measure and each of the three strains were added to the model. Again the "main" effects of the risk and strain measures are statistically significant and positively associated with delinquency. Two of the three interactions—*victimization-risk* and *police strain-risk*—are statistically significant, but neither are in the direction predicted by GST (compare Ousey et al., 2015). The addition of the three interactions increases the improvement of the model fit according to the AIC measure.

[38] A "rough" approximation of this approach can be accomplished in the fully parametric context by using higher-order polynomials (e.g., quadratic or cubic terms) for both the main and interactive effects. This approach would still require an *a priori* specification of the functional form of the relationships between the explanatory variables and the outcome variable, not to mention it will significantly increase the number of parameters required to be estimated by the model because product terms must be included for all combinations of the higher-order polynomials (Wood, 2006a).

[Tables II and III About Here]

Similarly, Table IV reports positive and statistically significant effects for gang membership and the three strain measures in model without interaction terms (first two columns), as well as positive and statistically significant effects for those constituent variables in the model including interaction terms (last two columns). As with the strain-risk models, two of the three interaction strain-gang terms are statistically significant, but in the opposite direction than predicted by GST. The additional of the three interaction terms also improves model fit according to the AIC.

[Tables IV and V About Here]

As noted earlier, caution must be taken when interpreting the regression coefficients reported in Tables II and IV because they represent the marginal effects of the variables on the natural scale of the delinquency measure (i.e., number of delinquent acts). The effects of the variables, including the interaction terms, are nonlinear so the parameter estimates are the effects of the variables when every variable included in the model is set to its average value. As a result, the conditional effect of each strain measure based on an individual's level of risk of criminal coping cannot be determined by simply looking at sign and magnitude of the coefficients for the constituent variables in the overall model. Tables III and V list the correct conditional effects from the strain-risk factors and strain-gang membership interactions.

Table III provides a better sense of the nature of the interactions reported in Table II. The table displays the unstandardized effect of each strain measure on delinquency *when the strain measure is set to its mean* and overall propensity for criminal coping is at one standard deviation below its mean (low propensity), at its mean (medium propensity), and one standard deviation above its mean (high propensity). It is important to examine the effect of the strain measure at a set value because, as previously explained, the effect is nonlinear as well as non-additive when interpreting the effect of the explanatory variables on the natural scale of the dependent variable. In other words, the simple slope of each type of strain will vary according to an individual's propensity for criminal coping *and* the individual's level of strain on each particular measure. The regression coefficient represents the change in the conditional mean (i.e., expected value) of delinquency for a unit change in the strain measure *from the mean value* of the strain measure (Cameron and Trivedi 2005: 122).[39] Table III reveals that each type of strain has a much larger effect on delinquency when the overall propensity for criminal coping is high. These results are consistent with GST, but are masked when simply examining the coefficient for the interaction term in Table II. In fact, interpreting the interaction terms in Table II as one would in a standard linear regression model leads to the opposite and erroneous conclusion that impact of the various strains on delinquency *decreases* as an individual's propensity for criminal coping increases.

[39] Technically speaking, the regression coefficient represents the instantaneous rate of change when the explanatory variable is continuous, and a one-unit change when the explanatory variable is discrete. Nonetheless, the marginal effect of a continuous predictor is often described as a unit change, so we adopt the interpretation to avoid creating unnecessary confusion.

The left panels of Figures 2, 3, and 4 provide a three-dimensional representation of the parametric interactive effects between criminal propensity and, respectively, victimization, police strain, and school strain from the hurdle models *on the natural scale of the delinquency measure*. These graphs—typically called wireframe plots, surface plots, or perspective plots—allow the reader to visualize the effects of the interacting variables on delinquency. The joint effects of the variables on delinquency is evaluated on a grid, and the grid values of the interacting values, along with the predicted values of delinquency from the model, form a set of points in three-dimensional space. The three-dimensional plot renders line segments that connect these points. Two aspects of the rendering—perspective and occlusion of features in the background by features in the foreground, provide the three-dimensional effect. The box drawn around the connected line segments not only displays the axes, but also contributes to the perception of depth (Cleveland, 1993, p. 249).

[Figures 2, 3, and 4 About Here]

The statistical significance of the simple slopes in Table III reveals that the effect of the particular strain on delinquency *at that level of risk for criminal propensity* is different from zero; however, it does reveal whether the slopes at the different levels of criminal propensity are significantly different from one another. In order to determine whether the simple slopes are meaningfully different, we use the slope at each strain when criminal propensity is "zero" as the baseline and compare the difference between the slopes of the strain measures at every other level of criminal propensity. From these comparisons, we obtain an overall test of significance and a test for each pairwise comparison of the slopes. Each interaction is significant: *Victimization* ($\chi^2(4) = 190.03, p < .001$); *Police Strain* ($\chi^2(4) = 80.23, p < .001$); and School Strain ($\chi^2(4) = 10.92, p < .05$). The pairwise comparisons are depicted graphically in Figure 5. It is clear from this figure that the differences between the slopes for the strain measures are not statistically significant at every level of risk for criminal coping. The important lesson is that the overall significance tests cannot be interpreted as indicating that the slopes significantly differ across the entire range of the risk factor scale.

[Figure 5 About Here]

A second set of regressions, reported in Table IV, focuses on gang membership. As background, gang membership is significantly correlated with each of the risk measures in the overall propensity for criminal coping scale, as well as moderately correlated with the overall propensity ($r = .37$) and delinquency scales ($r = .51$). There is therefore some reason to believe that gang membership may serve as a good surrogate for the overall propensity for criminal coping. The results in the second column of Table IV indicate that, all else equal, gang members commit about 19 more criminal/delinquent acts than non-gang members. The third column includes the interaction terms between gang membership and the various strains. The *victimization-gang* and *police strain-gang* interactions are statistically significant, but in the opposite direction predicted by GST.

Similar to the strain-risk interactions, the coefficients for the multiplicative terms lack any meaningful interpretation because the effects for the constituent terms and the product terms are non-linear. Table V presents the true effects of the interactions for each strain across the gang membership category.[40] Specifically, each strain measure has a stronger effect on delinquency when the respondent is a member of a gang *when the strain measure is set to its mean.* The statistical significance of the simple slopes in Table V reveals whether that the effect of the particular strain on delinquency by gang membership is different from zero. For the school strain-gang interaction, the effect of school strain on delinquency when school strain is at its mean is not distinguishable from zero (b = 0.53, *s.e.* = 0.36, p = 0.15). As stated earlier, we also explore whether the slopes for gang members are meaningfully different from non-gang members with an overall test of significance and a test for each pairwise comparison of the slopes *when each strain is at its average level*. Only one of the strain measures, police strain, has a significantly different effect for gang members relative to non-gang members when the strain is set to its mean: Victimization ($\chi^2(1) = 0.73, p > .05$); Police Strain ($\chi^2(1) = 6.23, p < .05$); and School Strain ($\chi^2(1) = 1.05, p > .05$). The pairwise comparisons are depicted graphically in Figure 9. It is important to note that pairwise comparisons for the victimization-gang interaction reveal a marginally statistically significant difference in slopes when respondents' level of reported victimization is extremely high (99th percentile), albeit in the direction contrary to GST ($\chi^2(1) = 3.67, p < .10$).[41]

[40] The results in Table V are not directly comparable to Table III because the analysis of the gang interactions did not take into account the overall propensity for criminal coping, since gang membership is viewed as a rough surrogate for this propensity.

[41] Zero-inflated count models were also examined. These models provide an alternative method for accounting for excessive zero counts on our delinquency scale (Hilbe, 2011). As noted earlier, zero-inflated models may not be appropriate for analyzing our dependent variable because of the distinction between structural and sampling zeroes; nonetheless, these models were examined to ascertain the robustness of our results. Both the ZIP and ZINB models provided similar results to the hurdle analyses. Specifically, all interaction effects were significant and in the hypothesized direction; moreover, the interactive models fit the data better according to the AIC measure.

[Figures 6, 7, and 8 About Here]

[Figure 9 About Here]

The left panels of Figures 6, 7, and 8 depict the parametric interactive effect of gang membership with victimization, police strain, and school strain, respectively. The graphs show the effect of each of the strains on delinquency for gang members and non-gang members. Consistent with the results described in Table V, these visualizations show that the impact of the various strains on delinquency is much stronger for those who self-report membership in a gang. It must be emphasized that, although the differences between the slopes for gang members and non-gang members were statistically insignificant for victimization and school strain, this should not be interpreted as meaning the interactions are not meaningful. The AIC statistic listed at the bottom of Table IV indicates that the interactive models fit the data better than the non-interactive models. The failure of those specific interactions to achieve statistical significance despite the improvement in model fit may imply that the relationships between the constituent variables included the interaction terms and delinquency do not meet the assumptions of the parametric model. Indeed, Figure 9 reveals statistically significant pairwise differences at a particular range of the victimization scale. In the next section, we explore non-parametric interactions that permit a more flexible examination of the interaction effects.

Semiparametric Models. The graphs in the right columns of Figures 2, 3, and 4 display the results of the nonparametric models for the *strain-risk* interactions. It is clear that the effect of certain strains on delinquency is highly contingent upon the individual's risk for criminal coping—even more so than suggested by the parametric interaction models depicted in the left columns of Figures 2, 3 and 4. Particularly noteworthy is the more pronounced change in the slopes of the constituent variables for individuals scoring high on both the risk ("criminal propensity") and strain dimensions. The non-parametric models do not provide traditional regression coefficients, so the relative fit of the parametric and nonparametric interactive models can be evaluated via testing whether the nonparametric smooths of each strain significantly vary across levels of criminal propensity and comparing overall model fit with the AIC measure. Across all three interactions, nonparametric smooths significantly vary across risk levels: *Victimization* ($\chi^2(3.4) = 48.06, p < .001$); *Police Strain* ($\chi^2(1.4) = 7.13, p < .01$); and *School Strain* ($\chi^2(3.8) = 25.51, p < .001$). The nonparametric models also provide better model fit: victimization (nonparametric AIC = 16469; parametric AIC = 16547); police strain (nonparametric AIC = 16486; parametric AIC = 16502); and school strain (nonparametric AIC = 16484; parametric AIC = 16507).[42]

The panels on the right of Figures 6, 7, and 8 display the nonparametric interaction effects between gang membership and, respectively, victimization, police strain, and school

[42] We also assessed the model fit of the nonparametric interaction models relative to the nonparametric additive models using the aforementioned AIC measure (with a lower AIC indicating a better fitting model). The interactive specifications improved model fit across the three types of strains.

The AIC statistics cannot be compared to the AIC statistics listed in Tables II and IV because those models included all three of the interactions in a single model, whereas the current comparisons examined each interaction separately.

strain. Recall that these "factor smooth/factor-by-curve" interactions permit the examination of differences in the non-linear effect of variables across subgroups (Ruppert et al., 2005). Instead of providing a slope coefficient for gang and non-gang members as was the case with parametric gang-interaction models, these graphs show the non-linear effects of the various strains for gang and non-gang members. These graphs reveal three important pieces of information. First, the effects of all three strains are noticeably different than assumed by the parametric models. For each type of strain, the non-linear effect captured by the semiparametric model significantly improved the fit of the model compared to the effect assumed by the fully parametric model for both gang and non-gang members, even after taking model complexity into account.[43] Victimization and school strain in the semi-parametric models have effects that are most distinguishable from the fully parametric model; police strain appears to have the least distinguishable effect, although the effect of police strain on delinquency for gang members is understated in the fully parametric model. Second, the non-linear effects of the strains appear to be different for gang and non-gang members. This is evident from the fact that the curvilinear relationships for gang and non-gang members do not run parallel. These differences underscore that the strains have both non-linear and non-additive effects (associated with gang membership) that are not completely captured by the fully parametric models. Finally, the point at which the differences in effect of the strains on delinquency between gang and non-gang members is most noticeable is not uniform across all three strains. The

[43] The non-parametric smooth for school strain for the *gang member* category provided only a marginally significant improvement over the parametric effect ($\chi^2(1) = 3.5, p < .10$); whereas the non-parametric smooth for school strain for *non-gang members* resulted in a much more significant improvement ($\chi^2(4) = 26.9.06, p < .001$).

difference between gang and non-gang members in the effects of victimization and police strain on delinquency is most pronounced at the high end of the strain scales, with the effect being stronger for gang members. For school strain, however, the effect is strongest for non-gang members at the high end of the scale. We also test whether the differences in the nonparametric smooths across gang and non-gang members is statistically significant and find that the nonparametric smooths significantly vary according to gang membership for victimization ($\chi^2(2) = 237.38, p < .001$), police strain ($\chi^2(2) = 232.07, p < .001$), and school strain ($\chi^2(2) = 230.23, p < .001$). Moreover, all of the nonparametric interaction models fit the data better than the parametric interaction models: victimization (nonparametric AIC = 20108; parametric AIC = 20114), police strain (nonparametric AIC = 20114; parametric AIC = 20131), and school strain (nonparametric AIC = 20118; parametric AIC = 20136).[44]

Robustness Check: Delinquency Subscales. General delinquency scales, such as the one employed in this study, are often dominated by trivial offenses (Ousey et al., 2015). The key advantage of aggregating different types of delinquent activity into a single scale is that it provides analysts with a delinquency measure that exhibits greater overall variability, and therefore typically facilitates the detection of distinctions between respondents that might otherwise be overlooked. The major drawback of the general scale is the potential distortion of the measurement of the relationships between key explanatory variables (and their interactions) and particular types of crimes—especially more serious offenses. We examined the robustness of our results by disaggregating the general delinquency measure into violent, property, and drug crimes and re-analyzing both

[44] The nonparametric interactive models fit the data better than the nonparametric additive models.

the parametric and non-parametric models. The results for the subscales were very similar to the results for the overall scale. Specifically, for both the *strain-risk* and *strain-gang* interactions, the nonparametric models outperformed the parametric models for violent,[45] property,[46] and drug offenses.[47]

Robustness Check: Clustering. The clustered design of our data potentially induces dependence between the respondents due to unobserved or unmeasured factors associated with the grouping of the respondents into larger units. In our data, this clustering occurs at multiple levels: city, school, and classroom; however, our primary interest lies in school-level clustering. We examined the sensitivity of our results to potential school effects through two variations of the cluster-specific effects model: a school-specific random-effects models and a school-specific fixed-effects model (Wooldridge, 2002). The results from both types of models were nearly identical and did not substantively alter any of our results.

[45] *Violent Offenses*: Victimization-Risk (nonparametric AIC = 14491; parametric AIC = 14492); Police Strain-Risk (nonparametric AIC = 10755; parametric AIC = 10782); School Strain-Risk (nonparametric AIC = 10754; parametric AIC = 10780); Victimization-Gang (nonparametric AIC = 13173; parametric AIC = 13195); Police Strain-Gang (nonparametric AIC = 13177; parametric AIC = 13211); School Strain-Gang (nonparametric AIC = 13176; parametric AIC = 13205).

[46] *Property Offenses*: Victimization-Risk (nonparametric AIC = 11853; parametric AIC = 11861); Police Strain-Risk (nonparametric AIC = 11855; parametric AIC = 11865); School Strain-Risk (nonparametric AIC = 11855; parametric AIC = 11867); Victimization-Gang (nonparametric AIC = 14487; parametric AIC = 14487); Police Strain-Gang (nonparametric AIC = 14489; parametric AIC = 14492); School Strain-Gang (nonparametric AIC = 9554; parametric AIC = 9564).

[47] *Drug Offenses*: Victimization-Risk (nonparametric AIC = 7647; parametric AIC = 7652); Police Strain-Risk (nonparametric AIC = 7647; parametric AIC = 7654); School Strain-Risk (nonparametric AIC = 7645.; parametric AIC = 7652); Victimization-Gang (nonparametric AIC = 9551; parametric AIC = 9556); Police Strain-Gang (nonparametric AIC = 9554; parametric AIC = 9563); School Strain-Gang (nonparametric AIC = 9554; parametric AIC = 9564).

6 Discussion

GST is unique among the major theories of crime in its emphasis on: (a) strains or stressors than increase the likelihood of crime, (b) the negative emotions (especially anger) resulting from those strains which create pressure for corrective action, and (c) the factors that influence or condition the likelihood of criminal coping. Prior research has found that the strains described by GST increase the likelihood of crime, partly through their effect on negative emotions, but the research on conditioning effects has produced mixed results. This study tested Agnew's (2013) explanation for these mixed effects. Following Agnew, we examined whether the effect of selected strains on delinquency was conditioned by an overall measure of criminal propensity and by gang membership, which serves as a marker for a strong propensity for criminal coping. The results provided support for Agnew (2013); criminal coping is more likely among those with a strong overall propensity for criminal coping, as measured by their standing on several conditioning variables, and among gang members. The interactive effects that emerged were substantively meaningful, improving model fit in both the *criminal propensity-strains* and *gang-strains* models.[45] The GREAT data used in this study facilitated the detection of conditioning effects due to the large sample size and non-trivial number of people at high risk for criminal coping—including a sizeable number of gang members. These results, of course, need to be replicated in other studies and with other criminogenic strains before concluding that Agnew's (2013) arguments regarding conditioning effects are correct.

Ideally, future research will employ samples with a meaningful number of individuals at high risk for criminal coping—especially serious forms of juvenile delinquency. These replication efforts should also construct measures of the overall propensity for criminal coping that include numerous risk factors from multiple life domains. Among these risk factors, researchers should pay particular attention to markers for a strong propensity for criminal coping, such as gang membership and chronic high-rate offending.[48] If subsequent research confirms the results of this study, it will provide significant insight into what is the central problem of general strain theory: explaining why strains only lead to crime in some cases. This study suggests that individuals must possess a range of factors conducive to criminal coping before a criminal response to strain is likely. As Agnew (2013) notes, this idea is compatible with the larger stress research and the qualitative research on crime. There are a large number of ways to cope with strains, most of which are legal, and there are frequently compelling reasons *not* to respond to strains with crime. Thus before criminal coping is likely, individuals must score high on a range of factors that reduce the ability for legal coping, reduce the costs of crime, and/or increase the disposition and ability for criminal coping.

Further, this study is perhaps the first in the criminology literature to employ a suite of techniques for examining interactions that simultaneously considers non-linear dynamics, non-additive effects, and non-continuous dependent variables in a unified framework. The strengths of this technique, as illustrated in this study, call into question a sizeable body of prior research on interaction effects in criminological research—not just that research focusing on GST. Conditioning effects play a significant role in research on crime and delinquency, so appropriately modeling and interpreting such effects should be a primary concern for quantitatively oriented analysts. The arguments and analyses in this

[48] While the measure of gang membership used in this study did condition the effect of strains on crime, it did not function as well as the overall propensity measure. It may be possible, however, to further refine this measure, taking account of such things as the length and centrality of gang membership.

study demonstrate that special care must be taken when analyzing conditioning effects on the natural scale of the dependent variable when the underlying statistical model is based on a non-linear transformation of that variable to take into account its non-standard distribution (e.g., binary, ordered, or bounded). These non-linear transformations implicitly induce interactions between *all* of the variables in the model when interpreting the marginal effects of the variables on the natural scale, so one cannot meaningfully interpret the regression coefficient for the multiplicative term included in the model as representing a true interaction effect. We also demonstrate that it is crucial for the analyst to determine whether curvilinear linear effects are present, in addition to interaction effects, because such effects may impact the nature of the interaction effect. Also, as is consistent with practices outside of criminology, we emphasize the importance of assessing model fit in the presence of interaction terms for models analyzing discrete/bounded dependent variables, and not solely testing for the statistical significance of the regression parameters for the interaction terms. These three key improvements—(1) selecting the appropriate underlying statistical model based on the distribution of the dependent variable, (2) properly interpreting interactive effects on the natural scale of the dependent variable, especially in presence curvilinear effects, and (3) assessing the relevance of interaction effects both visually and based on overall model fit—will hopefully provide a template for future researchers.

Table I: Mean Number of Delinquent Acts by Overall Propensity for Criminal Coping

Propensity Score	Number of Respondents	Delinquent Acts
0	775	2.29
1	967	4.04
2	690	8.00
3	443	12.61
4	300	17.48
5	213	25.28
6	159	32.13
7	119	39.79
8	87	55.94
9	50	61.16
10	21	93.57

Table II: Delinquency Regressed on the Overall Propensity for Delinquent Coping Scale, Victimization, Police Strain, School Strain, and Interactions

		<u>*b*</u>	<u>*beta*</u>	<u>*b*</u>	<u>*beta*</u>
Propensity for Criminal Coping		2.81***	6.26	3.05***	6.81
Victimization		0.54***	3.13	0.65***	3.92
Police Strain		0.53***	2.64	0.57***	2.60
School Strain		0.15**	0.72	0.13*	0.62
Propensity X Victimization				-0.08***	-1.11
Propensity X Police Strain				-0.06**	-0.61
Propensity X School Strain				-0.001	-0.14
AIC		16250		16173	

Note: * $p < .05$; ** $p < .01$; *** $p < .001$. *Beta*'s are partially standardized coefficients. Explanatory variables are centered at their means with unit variance, but the latent variable retains its original scale. All models control for race/ethnicity and family status (i.e., two parents, one parent, other).

Table III: Probing the Nature of the Interactions between the Overall Propensity for Criminal Coping and the Three Strains

The Unstandardized Effect of Each Strain on Delinquency When the Each Strain Is at Its Mean and Propensity for Criminal Coping Measure is Low (Mean – 1 S.D.), Medium (Mean) and High (Mean + 1 S.D.)

	Effect of Strains on Delinquency		
	Victimization	Police Strain	School Strain
Propensity for Criminal Coping			
Low	0.39***	0.33**	0.08*
Medium	0.57***	0.49***	0.14**
High	0.78***	0.72***	0.24**

Table IV: Delinquency Regressed on Gang Membership, Victimization, Police Strain, School Strain, and Interactions

	b	*beta*	*b*	*beta*
Gang Membership	19.03***	19.03	24.44***	24.44
Victimization	0.63***	3.98	0.71***	4.43
Police Strain	0.98***	4.70	1.01***	4.85
School Strain	0.21***	1.05	0.22***	1.07
Gang X Victimization			-0.41***	-2.61
Gang X Police Strain			-0.39***	-1.88
Gang X School Strain			-0.02	-0.11
AIC	19695		19584	

Note: * $p < .05$; ** $p < .01$; *** $p < .001$. *Beta*'s are partially standardized coefficients. Explanatory variables are centered at their means with unit variance, but the latent variable retains its original scale. All models control for race/ethnicity and family status (i.e., two parents, one parent, other).

Table V: Probing the Nature of the Interactions between Gang Membership and the Three Strains			
The Unstandardized Effect of each Strain Is at Its Mean on Delinquency among Gang and non-Gang Members			
Effect of Strains on Delinquency			
	Victimization	Police Strain	School Strain
Gang Membership			
Yes	1.01***	2.11***	$0.53^{n.s.}$
No	0.71***	1.01***	0.22*

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Figure 1: Nonlinear Relationship Between Risk Factors and Delinquency (Non-Parametric Scatterplot Smoother)

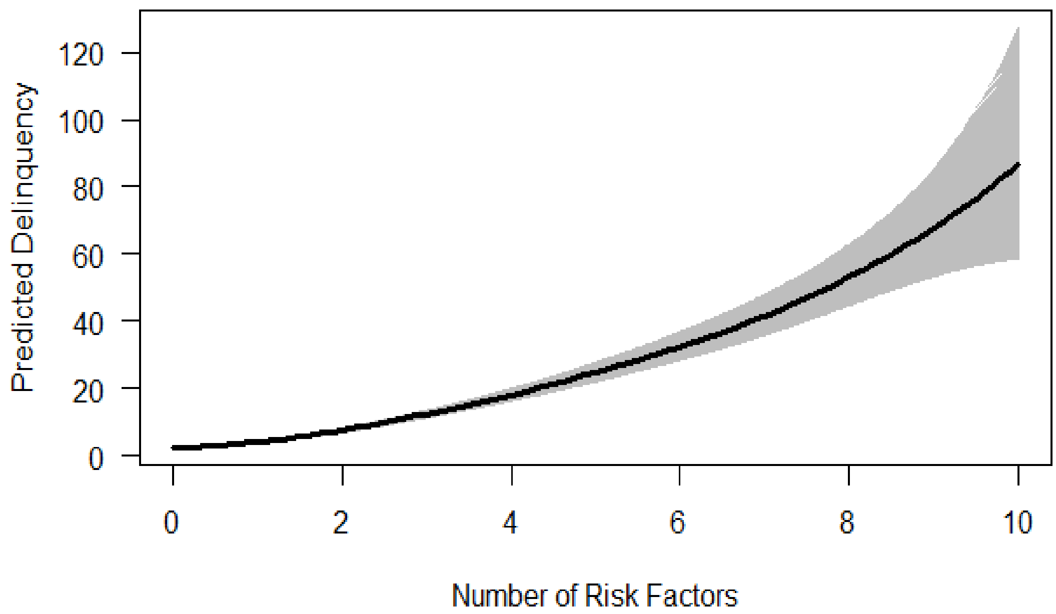


Figure 2: Interactive Effects of Criminal Propensity and Victimization on Delinquency

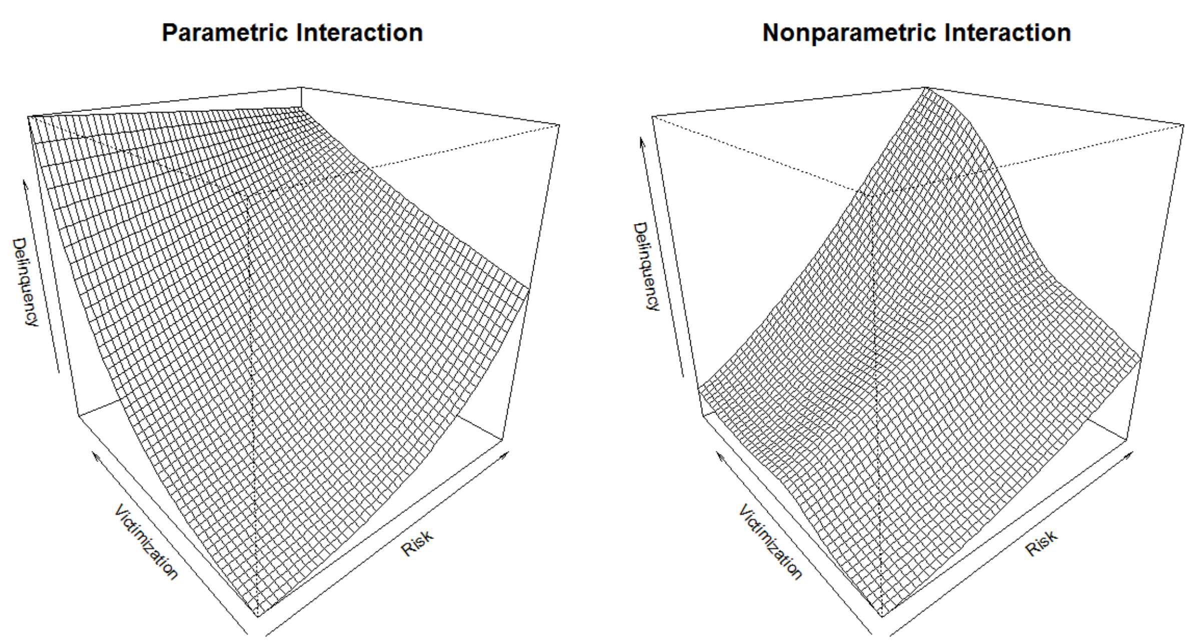


Figure 3: Interactive Effects of Criminal Propensity and Police Strain on Delinquency

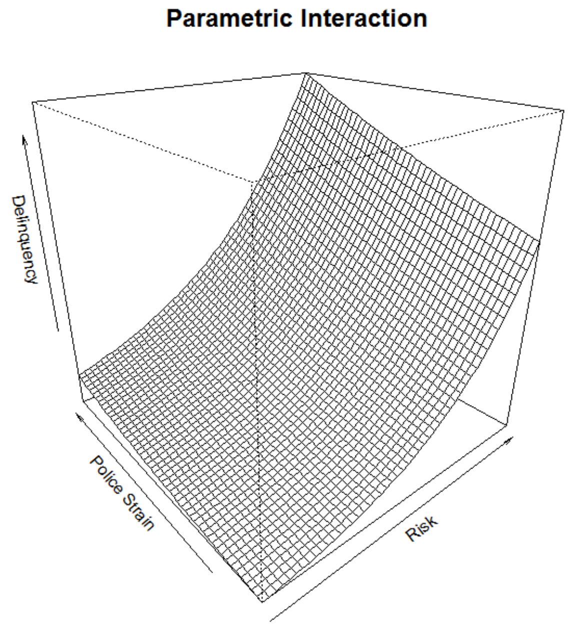


Figure 4: Interactive Effects of Criminal Propensity and School Strain on Delinquency

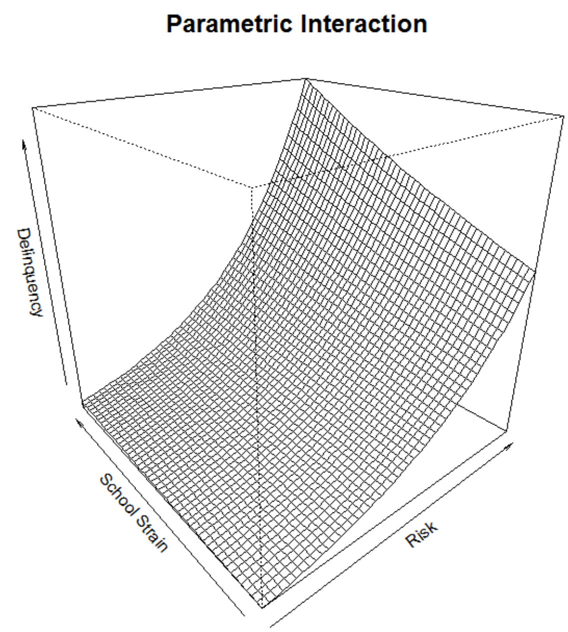
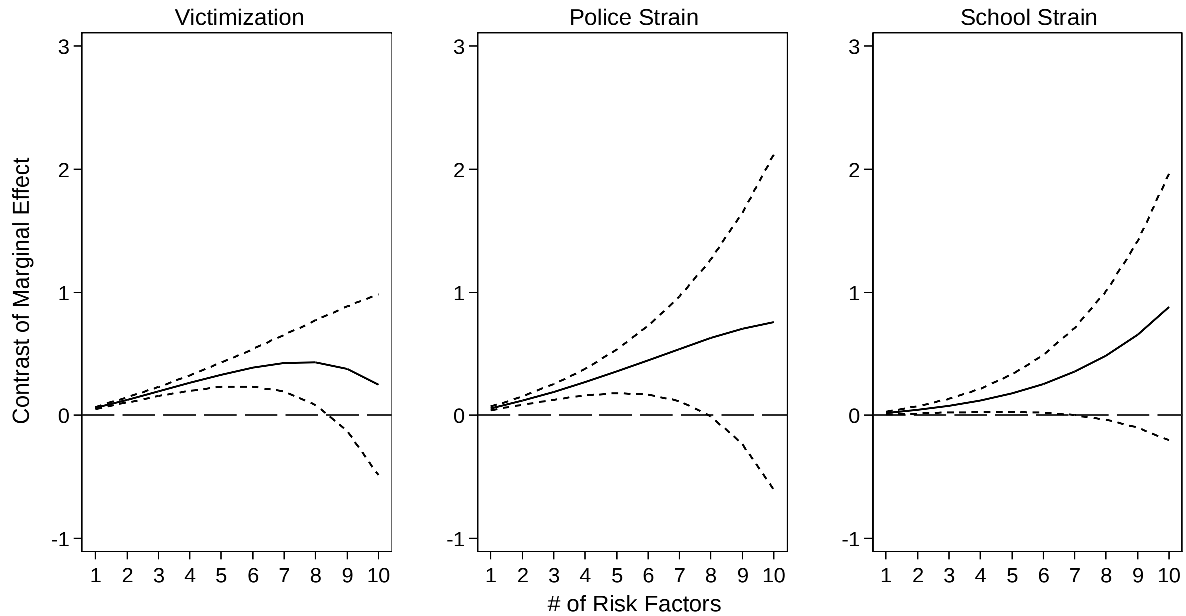


Figure 5: Contrasts of Conditional Cross-Differences for Various Strain Measures across Levels of Risk Factors (Parametric Models)



Note: Contrast with baseline risk level.

Figure 6: Interactive Effects of Gang Membership and Victimization on Delinquency

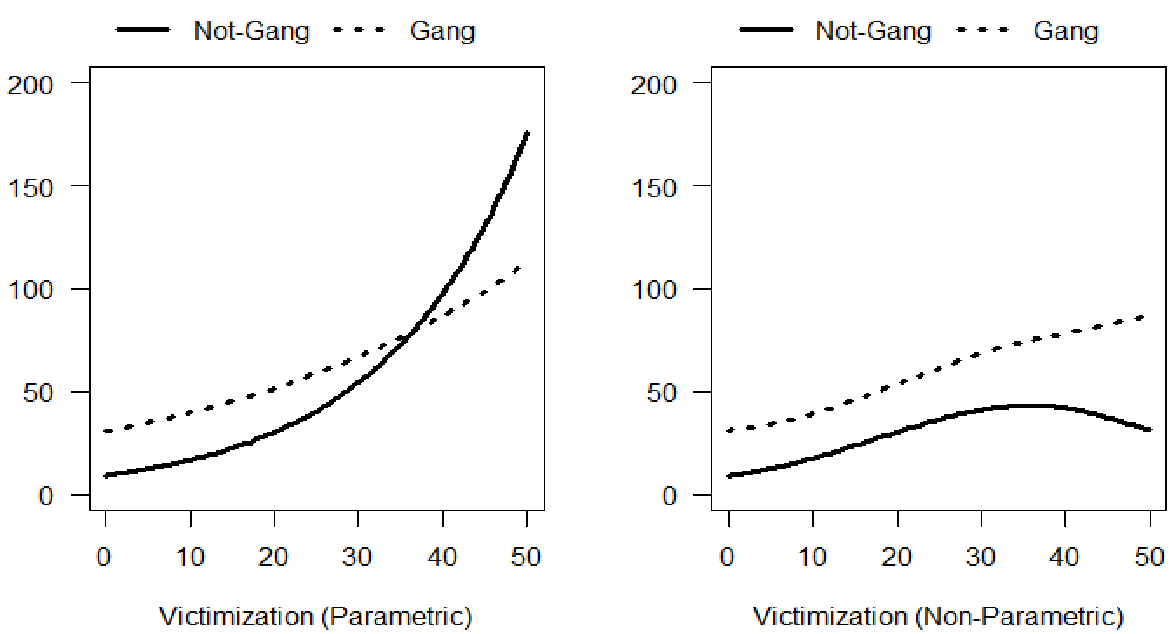


Figure 7: Interactive Effects of Gang Membership and Police Strain on Delinquency

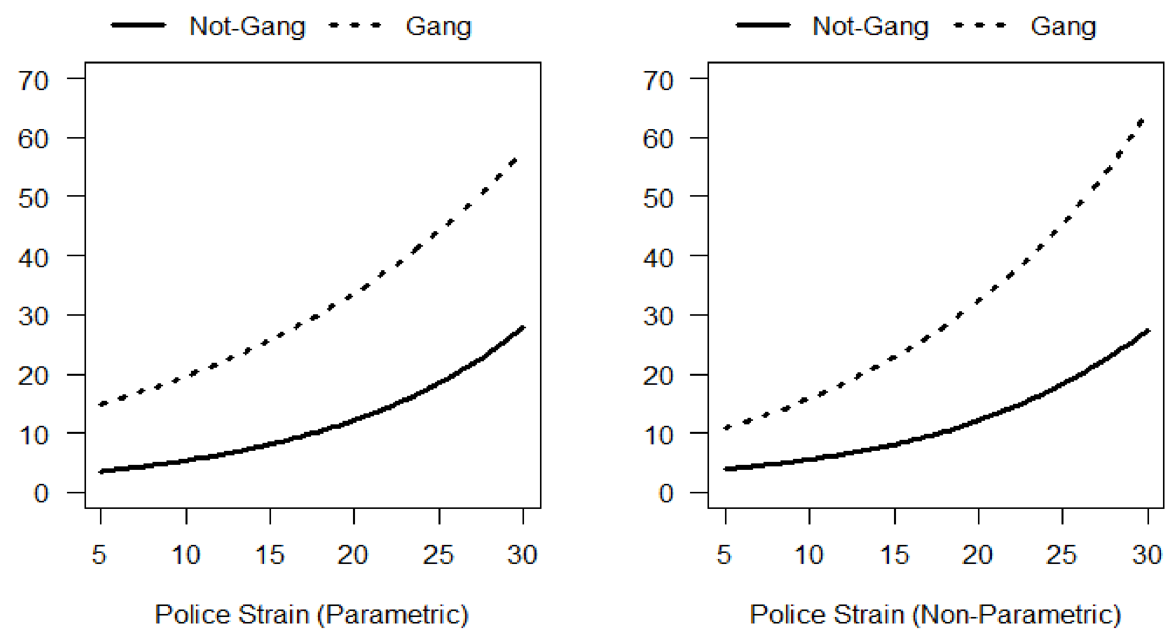


Figure 8: Interactive Effects of Gang Membership and School Strain on Delinquency

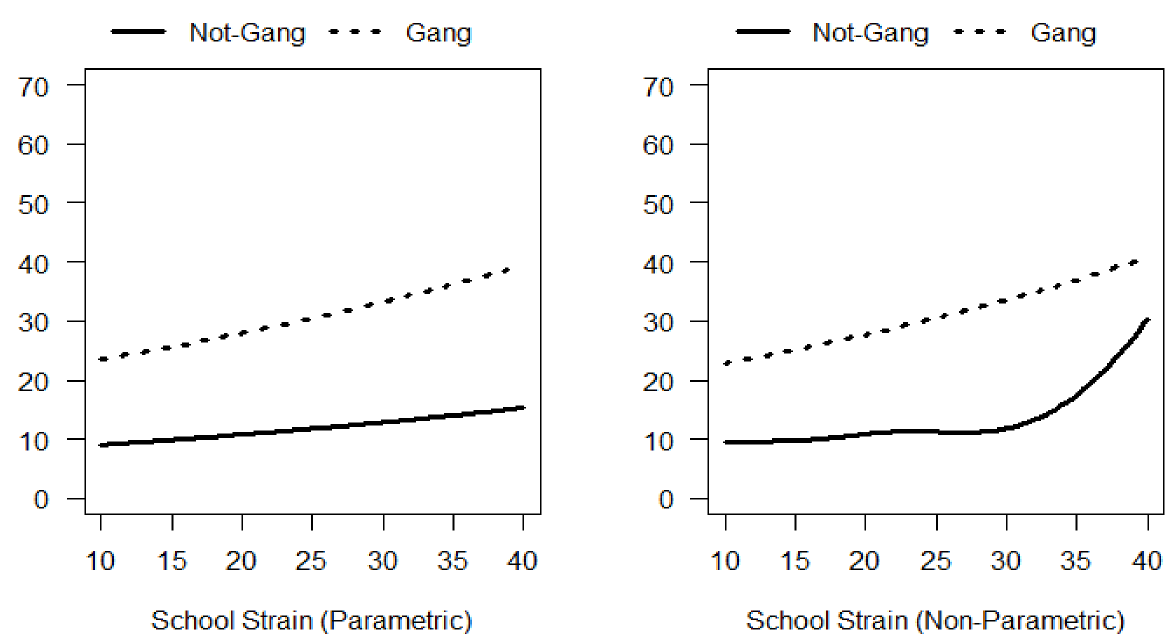


Figure 9: Contrasts of Conditional Cross-Differences for Non-Gang Members versus Gang Members for Various Strain Measures (Parametric Models)