Fighting in Virginia High Schools: A Multilevel Analysis

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Abstract

Fighting is the most common type of violence in Virginia high schools. This article hypothesizes that fighting is linked to social disorganization. Prior research shows that both community level social disorganization and school level social disorganization can increase the prevalence of crime within the school. The analysis in this article utilizes multilevel modelling to simultaneously test the effects of community level and school level social disorganization on fighting. Further, this article also tests the effect of school punishment policy on fighting. The multilevel modelling shows that fighting is affected by both levels of social disorganization, and the results also show that punishment policy effects the rates of fighting in Virginia high schools. The article offers potential policy recommendations from these findings.

Introduction

Researchers have devoted a large amount of attention to crime and violence within the high school. However, most projects utilize measures of crime and violence that do not differentiate between types of offending (e.g., Limbos & Casteel, 2008). We

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contend that this obfuscates subtle differences between types of offenses, and we seek to examine one particular type of violence in the American high school: Fighting. In Virginia fighting is the most common types of violence within the school setting and presents policy problems for administrators, teachers, and law enforcement. This article examines the effect of fighting in Virginia high schools for the years of 2011-2016. Specifically, we seek to determine the impact of social disorganization variables on fighting through a multilevel analysis that features latent variable measures.

Prior Research

Social Disorganization, Disorder, and Crime.

Social disorganization theory has gone through several changes. The theory began with Park and Burgess (1921; 1925), was modified by Sutherland (1924) and Shaw & McKay (1942), and now exists in a more modern conceptualization exemplified by the work of Wilson (1996) and Sampson (2012). However, routine predictors continually emerge throughout this theoretical growth. These predictor variables can be segmented into measures related to population, poverty, socialization, social control, and population motility. Specifically, social disorganization theory states that certain theoretical factors related to a loosening of informal social controls (Park & Burgess, 1925) or a reduction in collective efficacy (Sampson, 2012) reduce a community's ability to self-police or control crime and disorder.

The effects of social disorganization are primarily active at the community level although they do serve as a predicate of individual behavior (Wilson, 1996). In terms of school crime and violence research has shown that social disorganization variables can be active at two levels: the surrounding community and within the individual school. Welsh, Stokes, and Greene (2000) utilized structural equation modelling to partially reveal the interrelationship between behavioral disorder, communal disorder, and crime within the school. Research has also shown that socially disorganized schools have higher rates of violence and other types of crime (Limbos & Casteel, 2008). Further, the characteristics of the student body, size of a school, staffing procedures, staff-to-student ratios, the presence of a school resource officer, and operational budget all effect school disorder, crime, and violence (Brookmeyer, Fanti, & Henrich, 2006; Haas, 1988; Gottfredson & Gottfredson, 1985; Welsh, Greene, & Jenkins, 1999; Theriot, 2009; Welsh, 2000; Wynne & Hoo, 2011). These internal factors may be related to the extra-institutional social disorganization within the community and neighborhood (Limbos & Casteel, 2008).

Violence, Fighting, and Disorder.

Current research contains multiple examinations into the causes, effects, and preventative measures related to school violence and crime. However, many of these articles utilize a measure of school crime and disorder that combines multiple levels of criminal offenses with non-criminal behavioral disorder and school misconduct (e.g., Limbos & Casteel, 2008; Welsh, Stokes, & Green, 2000). While these articles illustrate that different types of crime are undoubtedly related within the school setting, they do not allow for nuanced determinations about causal patterns within the different levels of crime and disorder. Earlier research has demonstrated a connection between minor forms of disorder and more serious crime within the community (Braga & Bond, 2008; Kelling & Wilson, 1982; O'Shea, 2006). Therefore, an examination of less serious forms of school crime may provide understanding into the causal patterns behind serious school violence and criminal offending.

Prior research has linked fighting in schools to the home environment of students. Malek, Chang, and Davis (1998) found that "students whose parents used nonviolent disciplinary techniques fought less frequently than those whose parents relied on hitting and more violent disciplinary methods". Some studies suggest that unstable family structures may be associated with the student's lack of academic achievement in school and create potential risk factors for engaging in physical violence or other types of crime (Coleman, 1988; Baumrind, 1991; Biblarz & Raftery, 1993). Other studies have highlighted race- and gender-based disparities in physical fighting (Wright & Fitzpatrick, 2006). Environmental stability and the witnessing of violence also predicts the prevalence of physical fighting in juvenile populations (Clausen, 1991; Wilson, 1991; Brunstein, 1993; Parrell & Bruce, 1997; Fitzpatrick, 1997). Further, international research has replicated these studies beyond the United States (Alikasifoglu, Erginoz, Uysal, & Iiter, 2004; Lewis, Qui, & Katz, 2005; Scheithauer, Hayer, Petermann, & Jugert, 2006).

Punishment and Policy.

Most research shows that the punishment of high school students involves iatrogenic effects. Alschuler (1980) believes that school punishment stems from the poor conflict management skills of educational staff, which results in illogical punishment responses. The American Psychological Association (2008) conducted an evidentiary review and found that increases in both the certainty and severity of punishment may create negative effects for both the school and the student.

Further, Maimon, Antonaccio, & French (2012) found that increases in punishment may decrease cognitive decision-making capabilities and lower self-control in student populations. However, economic theories of crime (Becker, 1968; Clarke & Cornish, 1985) contend that increases in punishment may decrease offending in the high school, but research is unclear as to whether juveniles are truly rational and to the effect of punishment in the high school setting (Anwar & Loughren, 2011; Maimon, Anotonaccio, & French, 2012; Melde, 2009).

Policy represents a public administrator's attempt to accomplish organizational goals through decisive action. The goals of high school education can be largely defined with two interrelated objectives. First, the school must educate their students to or above state defined standards. Second, the school must provide a safe and secure environment to accomplish their educational goals (New Jersey v. T.L.O, 1985). Schools can adopt different formal and informal policies to reach these goals, but administrators often set these polices with conscience direction. Further, policy can be changed if objectives are not being reached within current practice. We contend that punishment responses in schools are policy decision where administrators decide how frequently and severely to sanction misconduct and delinquency within the school environment.

Methods

Hypotheses

Hypothesis #1: Fighting and Social Disorganization.

Prior research illustrates that school disorder and crime are related to factors inside and outside of the school. We hypothesize that this multilevel relationship is visible in the variables that predict rates of fighting in high schools. Specifically, we hypothesize that there is a multilevel effect between district level and school level social disorganization variables and fighting in Virginia high schools.

Hypothesis #2: Punishment Responses and Fighting.

School administrators can adjust their punishment responses through policy decisions. To determine if these policy responses have an effect on fighting in high schools we utilize a measure of relative punishment frequency in our last multilevel model to determine any potential effect on the prevalence of fighting.

Data Sources

The sample of this study features N=302 Virginia High Schools for school years ending in 2011-2016. The sample contains most public high schools in Virginia, but it does exclude private schools, alternative schools, and high schools that operate within correctional institutes. Further, since the data related to offenses against the person operationalize into outcome variables, high schools (n=8) with incomplete disorder or offense data are excluded from the sample in this study. We recognize that interstate generalizability may be questionable as our sample only features Virginia high schools. However, the inclusion of all Virginia high schools allows us to use the natural features and variation within Virginia, which is a state that features dense urban centers, seaside population clusters, and mountainous rurality, to analyze urban and rural, low and high population, and ordered and disordered schools. We feel this establishes a modicum of generalizability in our results. We address this topic further in the limitations section.

The offense data originates from the Virginia Department of Education (VDOE). The offense data stems from school climate surveys related to school safety as completed by high school administrators. The use of self-report data can be problematic, but findings from self-report offense data have been shown to be valid and reliable (Apel, Pogarsky, & Bates, 2008). Further, collecting offense data within a high school population is problematic due to the special characteristics of juvenile research subjects. Therefore, we use the self-report data as our predictor and outcome variables while accepting any potential limitations.

A variety of publicly available sources provide the data related to our control variables. We use data from the 2010 United States Census for population and income related variables. We obtain data related to school level social disorganization variables through the VDOE. The full description of the operationalization of all variables is presented in the next section.

Unit of Analysis.

The analysis featured in this study utilizes two levels of measurement. First, random intercepts are assigned via a grouping variable based on school districts. Second, individual high schools provide the unit of analysis for the cases that are nested within the districts. This organization of data reflects the organization of Virginia's educational system under current VDOE practice. Virginia funds education by utilizing multiple funding sources. The state sets minimum Standards of Quality

(SOQs) related to funding, staffing, and other practices. The state then utilizes a mathematical formula to determine each districts ability to contribute to the funding necessary to meet the SOQs. Each district's ability to contribute to their budget is based upon wealth measures related to income, property tax, and sales tax. The state furnishes the necessary amount to reach the acceptable minimum as instituted by the SOQ beyond the required local contribution. The district then assigns funding to individual schools based upon this budget (Lou & Bragg, 2018).

Critics commonly complain that this funding schema results in subpar state level funding which then must be made up by local school districts. In 2002 the Joint Legislative Audit and Review Commission (JLARC) of the Virginia General Assembly conducted an examination of educational funding practices and found the current Virginia method to result in deficiencies in funding and related educational practices. The JLARC recommended that the state increase funding to a full SOQ appropriation. However, Virginia has decreased educational funding since that time (Lou & Bragg, 2018). In 2015 Virginia was ranked 29th out of the fifty states in terms of educational funding at the state level (Baker, Farrie, & Sciarra, 2018) even though the state ranked 38th in income as measured by real GDP (Bureau of Economic Analysis, 2019).

The units of analysis in this model reflect real policy concerns in Virginia high schools, and we expect there to be visible effects due to these different levels of analysis in our final models. Because of Virginia's funding policy local districts must utilize local contributions to bring funding up to SOQ levels. Therefore, the school district remains the primary grouping variable within any analysis of Virginia high schools. However, a cursory examination of the data reveals that the schools nested within each district can show different effects in terms of offense patterns, student population demographics, and other level-specific variables. To encompass all these different effect patterns in our models we utilize multilevel modelling as detailed below.

Variables.

Outcome Variable.

We utilize a multi-step method of analysis which features several models. However, our outcome variable remains the same in each model. VDOE data provides a measure of fighting for the Virginia high schools in this analysis. VDOE splits their offenses against the person into "serious" and "non-serious" offenses, and our fighting measure only utilizes "non-serious" offenses against the person. However, VDOE data does include fighting related offenses in their "non-serious" person

offenses like "fighting with injury" and "physical altercations", and we include these related offenses in our fighting measure since they reflect modifiers to the overall fighting offense category. Table 1 presents a list of all school-related variables with descriptive statistics.

We also utilize other measures of school crime and offending to construct a latent variable for use in our confirmatory factor analysis as described below. The VDOE provides information related to several other categories of school crime. These categories feature criminal offenses related to serious violence against staff and student, behavioral disorder and school misconduct, property offenses, and drug and alcohol crime.

Table 1. Descriptive Statistics of Fixed Effects and Outcome Variables Used in Regression Models (N=302)

Outcome Variable	M (SD)
Fighting	166.485 (1.46.023)
Predictor Variables	
% Students Graduating	91.50 (4.817386)
% Students with Free Lunch	0.40306 (0.1730116)
English Testing Score	89.49 (5.102437)
Student Population	5997.296(3531.052)
Punishment Ratio	0.5263 (0.4210)

Table 2. Descriptive Statistics for Transformed Predictor Variables (N=302)

Transformed Variables	M (SD)
Outcome Variables	
Fighting	1.666 (1.48)
Predictor Variables	
% Poverty	0.107 (0.059)
% Rented Houses	0.275 (0.108)
% Vacant Houses	0.102 (0.06)
District Poverty	3.223 (11.383)
Behavioral Disorder	0.62 (0.765)
Serious Crimes Against Person	0.509 (0.0189)
% Minority in County	0.276 (0.174)
Population Density	1.1180(1.506)
Student Population	5.997 (3.531)

Input Variables.

Table 2 features a list of all the remaining input variables with descriptive statistics. We have transformed these variables by dividing by constants in order to reduce scalar problems related to variance in our multilevel models. The input variables in this study all relate to different facets of social disorganization theory. The multilevel nature of this analysis subdivides the input variables into two levels: District and School. The district variables, which provide the community level social disorganization variables, are drawn from data collected during the United States Census of 2010. These variables reflect social disorganization concepts related to population size, population heterogeneity, community income and poverty, and local motility patterns in terms of home ownership.

Data from the VDOE provides school level variables. These variables are featured in Table 2. These variables measure social disorganization concepts within the individual school. Table 2 includes variables related to poverty in terms of free lunch program participation, educational attainment in terms of English testing scores, the percent of individuals who graduate from high school, racial demographics, and individual school population in terms of the average number of students per year in the timeline of the study. Unlike the Census variables for the district level all school variables are averaged across the years included in the study by dividing each variable by a constant of six.

VDOE statistics also provide data for the input variable related to Hypothesis #2. We construct a ratio/percentage measure of punishment policy by dividing the total number of punishments by the total number of offenses in the school for the time period. This ratio measure provides an operationalization of a school's willingness to punish. A school with a higher punishment ratio is more willing to punish individual offenses while a school with a lower punishment ratio is less willing to punish.

Table 3. Exploratory Factor Analysis

District Social Disorganization				
Variable	**Factor 1***	**Factor 2***	**Factor 1**	**Factor 2**
% in Poverty	0.39	0.887		0.847
Percent Renter	0.998		0.929	
Percent Vacant House	-0.233	0.617		0.614
Minority County	0.581	-0.175	0.624	
Population Density	0.759	-0.297	0.816	
Unemployment Rate		0.786		0.815
% High School Grad		-0.886		-0.883
Physicians Per 1K	0.189	-0.477		
% Without Insurance	0.142			
Proportional Variance	0.242	0.325	0.639	0.632
School Crime and Disorder				
Variable	**Factor 3***	**Factor 4***	**Factor 3**	**Factor 4**
Fighting	0.632	0.481	0.819	
Violent Crime	0.539	0.6	0.761	0.823
Behavioral Misconducr	0.951	0.302	0.911	
Property Offense	0.489	0.51		0.694
Alcohol & Drug	0.201	0.613		0.681
Proportional Variance	0.374	0.264	0.693	0.499
School Social Disorganization				
Variable	**Factor 5***	**Factor 6***	**Factor 5**	**Factor 6**
% Graduating	0.765	-0.123	0.755	
% Free Lunch	-0.733	0.105	-0.738	
English Test Scores	0.832	0.201	0.816	
% Minority Students	-0.381	0.922		
% Freshman		-0.304		
Proportional Variance	0.393	0.202	0.594	

Note: "*" indicates an initial factor analysis before reduction. Variables were included in final models if they had a factor loading score greater that .6.
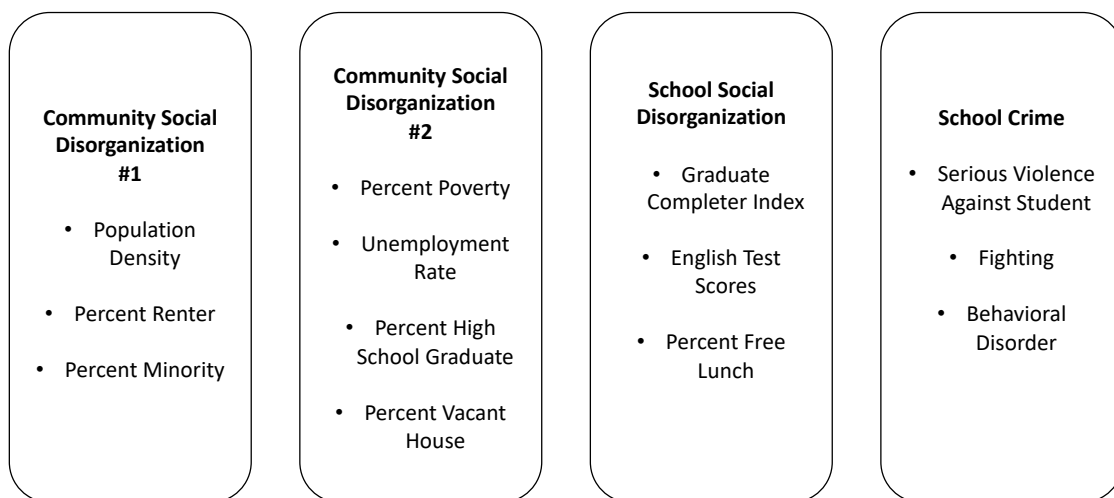
Analytical Plan

The analytical plan for this research features two general steps. First, we utilize exploratory and confirmatory factor analysis to select our input variables. Second,

we then place these variables into a series of linear models that allow for comparisons of model fit statistics to analyze potential patterns of causality.

The first step in our analytical plan features a latent variable analysis conducted with factor analysis. First, we place all input variables into three exploratory factor analyses. The first exploratory analysis, which featured district level input variables, yields two factors. We utilize a cutoff point of .6 when analyzing factor loading scores in determining factors. The first factor features three variables related to district populations: Population Density, Percentage of Renting Households, and Percentage of Minorities in Population. The second factor features variables related to poverty and other secondary effects of social disorganization: Percentage of Population in Poverty, Unemployment Rate, and Percentage of High School Graduates in Population. *Table 3* features the results of the exploratory factor analysis, and *Figure 1* features the final factors.

The second exploratory factor analysis features input variables nested within the school level of analysis. We place all school level variables into the exploratory factor analysis, which provides for one factor with three variables: Percentage of Students Graduating, English Test Scores, and Percentage of Student with Free Lunch. Finally, in order to provide a measure of our outcome variable in the confirmatory factor analysis we place several school level offenses in an exploratory analysis, and one factor develops. This factor features three measures of school crime: Serious Violence Against Students, Fighting, and Behavioral Disorder.
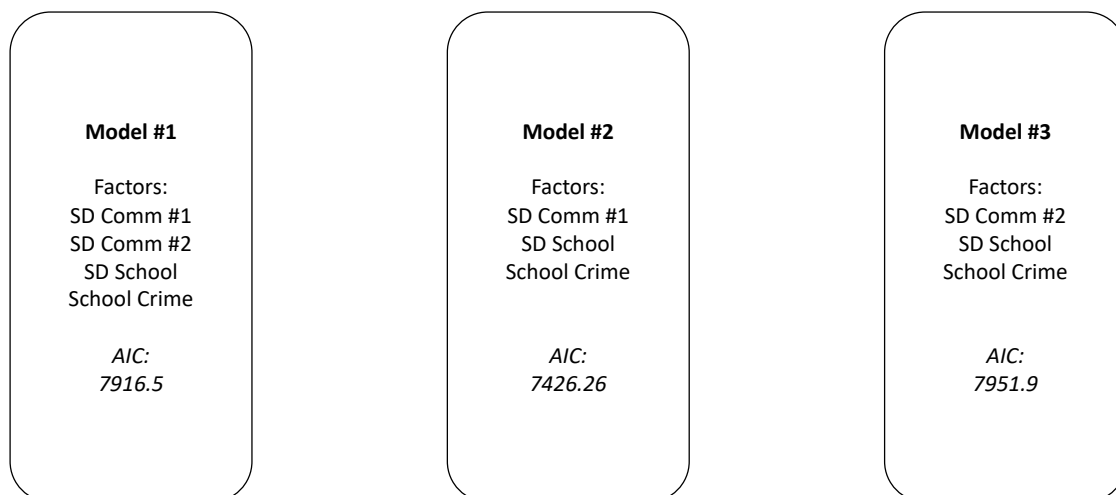
Figure 1.

Community Social Disorganization #1	Community Social Disorganization #2	School Social Disorganization	School Crime
• Population Density	• Percent Poverty	• Graduate Completer Index	• Serious Violence Against Student
• Percent Renter	• Unemployment Rate	• English Test Scores	• Fighting
• Percent Minority	• Percent High School Graduate	• Percent Free Lunch	• Behavioral Disorder
	• Percent Vacant House		

Note: All variables have loading scores about .6.

The results of the exploratory factor analysis provide latent variables for use in the confirmatory factor analysis. One of the purposes of the factor analysis is to obtain factor regression scores for individual districts in terms of social disorganization. These scores then become the variable providing random slopes in our multilevel models. Multiple random slope variables often create difficulties in multilevel models that result in errors related to variance and separations in the data. To overcome this problem we utilize only one latent variable to determine our random slopes. We choose the best fitting latent variable by comparing three CFA's as shown in Figure 2. Model #1 features all four factors in one model to provide a baseline for comparison. Model #2 and Model #3 each feature only one of the district level factors. The best fitting model between Model #2 and Model #3 will provide the district level factor that will then be utilized to manufacture the random slopes in a later multilevel model.
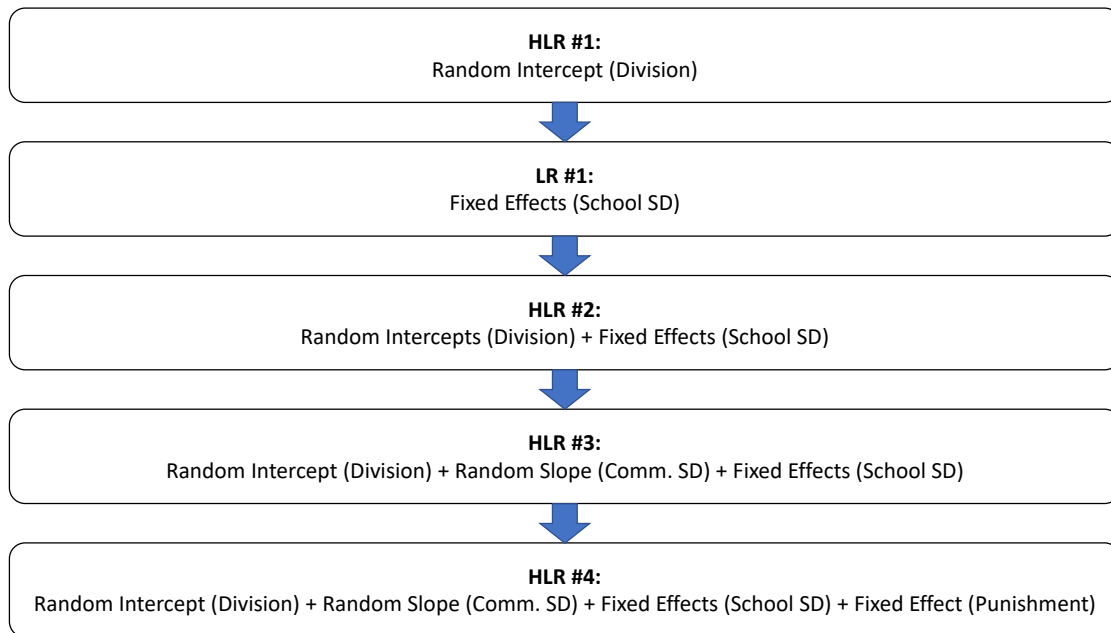
Figure 2.

Model #1	Model #2	Model #3
Factors: SD Comm #1 SD Comm #2 SD School School Crime	Factors: SD Comm #1 SD School School Crime	Factors: SD Comm #2 SD School School Crime
AIC: *7916.5*	*AIC:* *7426.26*	*AIC:* *7951.9*

The next step in our analytical plan involves a series of five different linear models as illustrated in Figure 3. HLM #1 is a random-intercept model where intercepts are defined only by districts. LR #1 is a linear regression model featuring only school level input variables. Due to the more accommodating nature of individual units of analysis we deconstruct the latent school-level social disorganization variable from the factor analysis into individual variables in this and all other models. Finally, we also include a measure of student population to act as a control variable for school size. HLM #2 is a multilevel model featuring all school level effects along with random intercepts as defined by districts. HLM #3 is a

multilevel model featuring school level variables, random intercepts, and random slopes as defined by the factor loading scores from the district level social disorganization factor. HLM #4 is a multilevel model featuring all components of HLM #3 along with a measure of school punishment.

Figure 3.

| HLR #1: |
| Random Intercept (Division) |

↓

| LR #1: |
| Fixed Effects (School SD) |

↓

| HLR #2: |
| Random Intercepts (Division) + Fixed Effects (School SD) |

↓

| HLR #3: |
| Random Intercept (Division) + Random Slope (Comm. SD) + Fixed Effects (School SD) |

↓

| HLR #4: |
| Random Intercept (Division) + Random Slope (Comm. SD) + Fixed Effects (School SD) + Fixed Effect (Punishment) |

Each additional model represents an addition of variables that should increase the explanatory power of each model as measured by AIC. Therefore, if HLM #3 contains a significantly lower AIC as compared to preceding models, then we conceptualize this as providing support for Hypothesis #1. Further, if the addition of the punishment measure in HLM #4 results in a lower AIC, then we conceptualize this as providing support for Hypothesis #2. We also provide an analysis concerning any change of effect size, direction of effect, and significance with the addition of each new group of variables in additional models.

Results

Factor Analysis

Table 2 contains the results of the exploratory factor analysis. The final factors all feature variables that loaded with a score of .6 or greater. Two factors present themselves when analyzing district level disorganization. Factor 1 contains three

variables related to social motility (% of Renters), population heterogeneity (% Minority), and population density. Factor 2 contains four variables related to poverty (% in Poverty), housing (% Vacant Housing), unemployment rate, and educational attainment (% High School Graduates). The variables in Factor 1 all load on a latent variable related to population characteristics in terms of movement and composition while the variables in Factor 2 load on a latent variable related to poverty concerns.

Factor 3 and Factor 4 contain latent variables related to school crime. Factor 3 contains variables related to violent crime, fighting, and behavioral misconduct. Factor 4 contains variables related to violent crime, property crime, and alcohol & drug offenses. Factor 3 features our outcome variable "Fighting", and we utilize this in our CFA models. Further, this model has a higher amount of explanatory power in terms of variance. Finally, only one factor manifests from our measures of school level social disorganization. Factor 5 features three measures related to graduation rates, school poverty as measured by free lunch program participation, and educational attainment as measured through English testing scores.

Figure 2 contains the three models for our CFA of these factors. Figure 2 presents the results of these models. AIC scores show that Factor 1 within the district social disorganization measures allows for the best model fit. In fact the removal of Factor 1 from Model #1 results in no AIC reduction. However, the removal of Factor 2 from Model #1 reduces AIC by 490.5, a - 6.2% change. The significant reduction in AIC (Burnham & Anderson, 2002) illustrates that Factor 1 provides the most explanatory power in our CFA analysis, and this variable will provide the random slopes in our multilevel linear models.

Multilevel Models

Hypothesis #1: Social Disorganization and Fighting

Table 4 presents the results for the multilevel models in this study. HLM #1 and LR #1 allow for the comparison of a random intercept model featuring schools grouped by district and a traditional OLS regression model with no variance at the district level. We see that the addition of the social disorganization variables at the school level reduces the AIC by -289 points, which illustrates that school level variation explains more variance than district identification alone. HLM #2 combines these two models and results in additional drop of AIC by -33 points. This illustrates that district level variation does account for variation in fighting beyond

that provided by school level variables. HLM #4 features the addition of a random slope measure based upon the district social disorganization factor from the CFA process. At this point the AIC reduces by another -20 points. Therefore, the addition of both a district level social disorganization measure and a school level social disorganization measure results in the best model fit, which provides support for our first hypothesis.

Table 4. Regression Results. Behavior Versus Social Disorganization and Punishment Variables (N=302)

	b(se)				
	HLR #1	LR	HLR #2	HLR #3	HLR #4
Random Effects:					
STCOU	0.6473(0.8046)	X	0.3721(0.6100)	0.1807(0.4250)	0.1556(0.3945)
factor	X	X	X	0.3139(0.5603)	0.2656(0.5153)
Residual	1.4819(1.2174)	X	0.6515(0.8072)	0.6253(0.7908)	0.5985(0.7736)
Fixed Effects:	1.6135(0.1075)*	X	14.34467(1.60395)*	13.95032(1.54062)*	14.34182(1.49026)*
GCI Average	X	-0.09519(0.01760)*	-0.09466(0.01566)*	-0.08643(0.01495)*	-0.07094(0.01483)*
Free Lunch	X	2.17648(0.047299)*	1.61408(0.48181)*	0.82590(0.46615)	0.72863(0.44614)
Average	X	-0.06679(0.01789)*	-0.06647(0.01765)*	-0.06707(0.01684)*	-0.07876(0.01640)*
English Test	X	0.21179(0.01870)*	0.22002(0.01911)*	0.20524(0.01862)*	0.19001(0.01822)*
Average	X	X	X	X	-0.98723(0.20294)*
Population					
Students Punished					
AIC Value	1150.168	861.5452	828.6214	808.1285	788.9802

Table 3 shows the regression results from all models tested (HLR #1, LR, HLR #2, HLR #3, and HLR #4). The "X" denotes the variables omitted from the models when tested. Please note that * denotes that the p-value is significant, where p is less than or equal to 0.05.

Further, the reduction of residuals in the random effects portion of the multilevel models provide support for Hypothesis #1. With the addition of the random slopes residual variance drops by .2. The addition of the random slopes also results in a loss of significance for one fixed effect: Percentage of Students on Free Lunch Programs. The loss of significance for this variable may illustrate that our school poverty measure is mainly a function of district level social disorganization as measured by our factor variable.

Hypothesis #2: Punishment and Fighting

The results show tentative support for our hypothesis that punishment responses effect the level of fighting in a school. Earlier research shows unclear effects for punishment in relation to total delinquency and crime (Klein & Egan, 2018a) and behavioral disorder (Klein & Egan, 2018b). The addition of the punishment variable results in a -19-point decrease in AIC. Further, the addition of the punishment variable has effects on the explanatory power of other variables in

the model. First, the punishment variable decreases the coefficients of all variables in the fixed effects. Second, the punishment variable decreases the explanatory power as measured by variance in the random effects, and the residual variance also decreases. The decrease of these variables shows that punishment, which is a policy response, can reduce the effects of other detrimental social disorganization variables. However, as we mention in our limitations any punitive recommendation should be tentative at this point due to questions of causality.

Discussion

Hypothesis #1: Social Disorganization and Fighting.

The data shows that social disorganization variables do have an impact on fighting. As social disorganization measures increase fighting increases in Virginia high schools. At the school level decreased graduation rates, increased poverty, and decreases in educational test scores all lead to higher rates of fighting even with a control variable for student population. However, the model that contains a district level random effect that measures social disorganization through population measures increases model fit when included with school level fixed effects. This speaks to the fact that the amount of fighting in a Virginia high school is related to both the effects of social disorganization within the school and outside of the school. In fact the inclusion of the measures of community level social disorganization causes the school poverty measure to some of its explanatory power. We now make two tentative conclusions.

First, school level social disorganization is not automatically a function of the community level disorganization. The increased model fit with the addition of both the district and school level measurements may illustrate differentiation between the two levels of measurement, which shows that schools within the same district can have different patterns of social disorganization. Second, the effects of the variables in this study may reflect funding decisions and strategies by the VDOE and local agencies. The VDOE's funding mechanisms provide funding to districts, which can influence the random effects in this model, and school districts could be making differential allocations of state and local funding to different schools within their jurisdiction, which then may increase or decrease the fixed effects in this model.

While we do not feel confident in making any sure conclusions beyond the fact that fighting seems to be influenced by the interplay of two levels of social

disorganization, we do offer one tentative recommendation. School level social disorganization variables related to educational attainment and graduation rates decrease minor violence in the form of fighting, which then may decrease the likelihood of other serious crimes. We contend that these variables can be changed through the use of smart policy, and educational authorities should implement rational strategies when allocating funding to tackle problems related to social disorganization within individual schools. We find further support for this recommendation in the discussion of our next hypothesis.

Hypothesis #2: Punishment & Fighting.

The model that includes the measure associated with punishment is the best fitting model within this analysis. It appears that more frequent punishment can decrease fighting. Earlier research conducted with this dataset shows different efficacies of punishment within different categories of offenses and in different time periods (Klein & Egan, 2018a; 2018b). This indicates that the effect of punishment on offending is unclear. However, we do believe that the explanatory power of punishment in this study contains potential ramifications for policy.

The willingness of a school to punish offenders is undoubtedly a policy decision, and our results show that policy can potentially lower rates of fighting. Further, the inclusion of this policy variable also reduces the variance explained by community level social disorganization. A reduction in the variance explained by community level factors with the inclusion of a policy variable speaks to the power of making sound policy decisions to counteract community level disadvantage. If this holds true for fighting in this setting and other settings then policy can theoretically lower other forms of school delinquency and mitigate the harmful effects of community level disorganization.

Conclusion

The results in this study show that social disorganization effects the prevalence of fighting in Virginia high schools on two levels. The inclusions of both district level social disorganization measures related to population characteristics and school level social disorganization measures into one model provides the best fit. Further, it is possible that correct policy changes may mitigate the effect of these variables and lower the rates of fighting. Fighting is the most common type of violence in Virginia high schools, and if criminological theory is correct (Braga & Bond, 2008; Kelling & Wilson, 1982; O'Shea, 2006) then this minor type of violence may lead to more serious crimes. Fighting and any type of violence undoubtedly interferes with

educational goals, and schools must make the correct policy decisions to control this disruptive behavior.

Limitations.

1) The most obvious limitation of this study is the geographical isolation involved in only using Virginia schools. While the use of one state controls for interstate influences, generalizability is questionable. Although Virginia provides several different regional differences that may magnify the generalizability of our study, future research should replicate our methodology in other states to test for regional differences. Finally, multilevel methodologies may be able to combine these individual studies into one analysis that will allow for greater theoretical elucidation.

2) Our study only analyzes high schools and utilizes a cross-sectional methodology that aggregates six years of data. Future research should examine if our findings extend to middle school environments. Further, time series analysis should examine trends in offense rates in schools to see how historical effects impact our findings.

3) The crime and delinquency data in this analysis stems from self-report data as completed by school administrators, which is similar to the data collection procedures within the Uniform Crime Report (UCR). The data in this study could be influenced by underreporting as found in the UCR (Mosher, Miethe, & Hart, 2002) as school administrators may be trying to reduce the public perception of danger or delinquency in their school. Future studies should replicate this methodology with other data types to triangulate the findings in this analysis and uncover any potential biases.

4) We make tentative conclusions about the efficacy of punishment in controlling fighting in this article. However, the exact causative process in this analysis is arguable. We feel that the data and results fits the idea that punishment is a cause rather than an effect of disorder, but we do not have certain evidence that this assertion is true. It could be possible that schools grow more punitive as disorder increases, which would still provide the effects seen in this analysis. Therefore, we recommend that further research examine the causative relationship between punishment and disorder more fully.

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