Schools and Neighborhood Crime

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CHAPTER I: INTRODUCTION

The objective of this research is to determine the degree to which neighborhood crime patterns are influenced by the location, level, and quality of neighborhood schools. A small body of research has investigated the link between schools and neighborhood crime (Roncek and Lobosco, 1983; Roncek and Faggiani, 1985; Roman, 2004; Kautt and Roncek, 2007). This body of research, as a whole, suggests that schools generate crime at the neighborhood level. Because neighborhood boundaries are difficult to identify, neighborhood level research generally defines neighborhoods using geographic boundaries defined by the U.S. Census Bureau (Sampson, Morenoff, and Gannon-Rowley, 2002). Research examining schools and crime has been uniformly conducted at smallest geographic unit defined by the U.S. Census Bureau: the block. The U.S. Census Bureau, however, releases data on a wider range of social indicators at larger levels of analysis (like the block group and tract). Consequently, previous research has been unable to control for a wide array of social-structural factors when examining the relationship between schools and neighborhood crime. Therefore, previous research on schools and crime cannot definitively demonstrate that schools are related to crime above and beyond factors like structural disadvantage, residential mobility, and family disruption.

In addition to limited controls for key structural determinants of crime, most studies examining schools and neighborhood crime focus exclusively on high schools. This is also problematic, as some research suggests that crime and victimization may be similarly elevated near elementary and middle schools (Nolin, Davies, and Chandler, 1996; Wilcox et al., 2005). Interestingly, the single neighborhood study (Kautt and Roncek, 2007) that has considered elementary, middle, and high schools together found that neighborhoods with elementary schools have more burglaries than those without elementary schools. The study, however, showed no such relationship when comparing neighborhoods with and without middle schools or high schools. At the very least, this work suggests that research examining the relationship between schools and crime rates should not focus exclusively on the effect of high schools. Moreover, no previous studies on schools and neighborhood crime have investigated the role of school quality. The social disorganization perspective argues that strong social institutions can prevent crime (Krivo and Peterson, 1996), suggesting that high quality schools may help prevent crime, while lower quality schools might foster crime.

In this study, we use incident-crime data from Albuquerque, New Mexico, to address some of the limitations of the current research on schools and crime at the neighborhood level. Specifically, we assess the influence of the presence and quality of elementary, middle and high schools on neighborhood crime rates, net of key structural correlates of crime. First, we utilize the block group as our level of analysis. This allows us to investigate the effects of schools, while controlling for a wider array of variables than previous studies. By controlling for concepts like structural disadvantage, residential mobility, and family disruption, we can be more certain that any significant relationship between schools and neighborhood crime is reflective of school effects and not of structural conditions. We also disaggregate our analysis by schools and by type of crime.

By including elementary, middle, and high schools in our analysis, we address the possibility that different levels of schools are related to neighborhood crime in different ways. Moreover, we consider the possibility that various characteristics of schools, including school quality and school size, moderate the relationship between school presence and neighborhood crime. And finally, we examine the relationship between schools and crime by time of day, in order to address the possibility that the effect of schools on crime may be constrained to the hours during which youth are likely to be in or around the school area. In each of these analyses, we examine the relationship between schools and a variety of different types of crime.

In sum, the current research examines the following questions: Are schools related to neighborhood crime? Does this relationship vary based on crime type, school type, school quality, and time of day?

This report is organized into five chapters. The second chapter presents a literature review of the research on this topic. In addition to reviewing previous research on schools and crime, this chapter also frames the topic in terms of relevant sociological theory. The third chapter describes the data and methodologies that we used to investigate the relationship between schools and crime. The fourth chapter presents the results of our research. The fifth and final chapter discusses these results, presents empirical and theoretical conclusions, and addresses directions for future research.

CHAPTER II: LITERATURE REVIEW

Research examining the relationship between schools and neighborhood crime is typically framed in terms of Routine Activities Theory and Social Disorganization Theory. In the following literature review, we briefly describe both theoretical traditions and explain how these perspectives address schools and neighborhood crime.

Routine Activity Theory

Routine Activity Theory states that criminal acts require the convergence of three elements: motivated offenders, suitable targets, and the absence of capable guardians (Cohen and Felson, 1979: 589). Building on utilitarian principles, the absence of any one of these elements increases the risks of crime relative to its rewards, making crime less likely. At the macro-level, Routine Activity Theory is rooted in the social and physical ecology perspective. According to this perspective, "crime rates are affected not only by the absolute size of the supply of offenders, targets, or guardianship, but also by the factors affecting the frequency of their convergence in space and time" (Sherman, Gartin, and Buerger, 1989: 30-31). In other words, specific places are likely to be crime prone, due to the convergence of would-be offenders, vulnerable victims, and a lack of guardianship. These high-crime places (that is, locations where there is more crime than would be expected by chance) are often referred to as hot spots.

Previous research utilizing the Routine Activity Theory as a framework has linked certain location types to crime, designating these locations as hot spots. A number of studies, for example, have identified bars as criminogenic locations (Roncek and Bell, 1981; Roncek and Pravatiner, 1989; Sherman, Gartin, and Beurger, 1989; Roncek and Maier, 1991; Block and Block, 1996). Sherman, Gartin, and Beurger (1989) found that hot spots can account for upwards of 50% of police service calls. In addition to bars, they identified such hot spots as liquor stores, parks, homeless shelters, theaters, malls, and convenience stores.

From a routine activities perspective, these locations are criminogenic because they provide an opportunity for the intersection of offenders and targets in the absence of guardianship. Bars, for example, are occupied by individuals who "are likely to have cash with them and thereby present opportunities for crime, especially if they become intoxicated (Roncek and Maier, 1991: 726). In other words, bar patrons carry cash, which makes them a suitable target for property offenses, and may be less capable of guarding themselves and their assets when intoxicated. In addition, bars can be activity hubs, where larger groups of individuals congregate. The density of individuals at bars can increase the likelihood of crime, by increasing anonymity and reducing the effects of supervision and guardianship (Roncek, 1981). Block and Block (1996) build on the density argument, noting that bars and dance clubs that are clustered in night-life areas are more likely to be hotspots than isolated bars and dance clubs.

It is important to note that the Routine Activity perspective argues that hot spots will generate crime both at the specific hot spot place and in the surrounding area. The hot spot, itself, is expected to generate crime due to the convergence of motivated offenders and suitable targets. The areas directly surrounding the hot spots are also expected to generate crime for the same reasons, as the areas around the hotspots will contain the routes to and from the hot spot. Moreover, the hot spots themselves may be more supervised than areas directly surrounding the hot spot. Bars, for example, may have security guards and bouncers that prevent crime within the actual building. The areas directly surrounding bars, however, may not be as supervised.

Routine Activity Theory and Schools

Schools are expected to be high-crime places for a number of reasons. First, schools are occupied by youth. Youths, especially older youths, are more likely to be offenders than individuals in any other age group (with the exception of young adults). The relationship between age and crime is widely accepted among criminologists and appears to hold true across race, gender, society, and time (Hirschi and Gottfredson, 1983). Moreover, youths are more likely than individuals in any other age group (with the possible exception of young adults) to be victims of crime (Rand and Catalano, 2007). Schools, therefore, bring together individuals from age groups that are characterized by higher offending and victimization rates. In that sense, schools ensure the convergence of motivated offenders and suitable targets.

A second reason that schools are expected to generate crime is that research suggests that a substantial proportion of youth victimization is related to the routine activities of attending school (Garofalo, Siegel, and Laub, 1987). Teacher student ratios in most schools are such that capable guardianship is often absent, a situation that is compounded in larger schools. This means that youth convene in and around schools with limited adult guardianship. Given the convergence of motivated offenders and suitable targets in the school environment, these limitations on capable guardianship should further increase crime and victimization at or near schools. These increases should be most notable during school hours (as well as the hours immediately before and after school).
Building on the Routine Activities perspective, empirical research on schools and neighborhood crime seems to suggests that schools are, in fact, associated with higher rates of crime at the neighborhood level. City blocks in San Diego, California that contain public high schools and blocks near public high schools have higher index crime rates than other blocks (Roncek and Lobosco, 1983). These results have been replicated in Cleveland, Ohio (Roncek and Faggiani, 1985). This research suggests that high school presence is associated with increases in a variety of crime types. In fact, high schools were associated with higher rates of all crime except homicide, rape, and motor vehicle theft (Roncek and Lobosco, 1983). Other research (Roman, 2004), investigating the effects of both middle schools and high schools in Prince George's County in Maryland also found that proximity to a middle school or high school was associated with higher rates of violent crime at the block level. It should be noted that these studies, which used the block level of analysis, were unable to control for a standard array of structural

controls. For example, Kautt and Roncek (2007), controlled for demographic structure, average housing value, and the percentage of dwellings that were vacant and used as apartments. But, given their level of analysis, they were unable to control for other known correlates of crime, like neighborhood unemployment, poverty, education, and mobility.

The empirical status of the relationship between schools and neighborhood crime is not completely straightforward. A more recent study examined the effects of elementary, middle, and high schools in Cleveland, Ohio on burglary at the city block level (Kautt and Roncek, 2007). Interestingly, this research suggests that high schools and middle schools are not associated with higher rates of burglary, while the presence of elementary schools is associated with increases in burglary at the block level. Clearly, additional research is needed regarding school level and crime.

Each of the studies described above was framed in terms of the routine activity perspective. That is, the authors argue that a significant relationship between school presence and crime at the block level suggests that schools allow for the convergence of motivated offenders and suitable targets. Research at this level, however, cannot definitively demonstrate that routine activity patterns are responsible for the relationship between schools and crime. Roman (2004) attempted to provide more substantial evidence for the routine activity perspective by disaggregating crime by time of the day. Her research suggests that schools generate more crime at the block level during certain hours than others. Specifically, schools are associated with higher rates of crime during the morning commute, school session, and afternoon commute hours.

In general, using the routine activity perspective we expect high schools to generate more crime than middle schools, which in turn, would be expected to generate more crime than elementary schools. Compared to middle and elementary schools, high schools are more densely populated and are populated with youth whose criminal involvement is beginning to peak (motivated offenders). Moreover, there are fewer teachers per student at high schools, decreasing capable guardianship. As well, parents are less active, involved and present at high schools, further decreasing guardianship. Finally, bigger schools mean more crime targets (both persons and their property). Regarding time periods, the routine activity perspective would predict that schools would be associated with higher rates of crime during the hours directly before, during, and after school. Working from this framework, we present the following hypotheses:

> H1: Neighborhoods containing schools will have more crime than neighborhoods without schools, controlling for other factors.
>
> H2: High schools will be associated with more crime at the neighborhood level than middle schools, which, in turn, will be associated with more neighborhood crime than elementary schools.
>
> H3: Neighborhoods containing schools will experience more crime during the hours directly before, during, and after school than during other time periods.

Social Disorganization Theory

The social disorganization perspective stems from Chicago school research conducted in the 1920’s and 1930’s. Shaw and McKay (1942), examining data from Chicago in the early 1900's, found that certain areas of the city were high in crime despite population turnover. Shaw and McKay (1942) described these criminogenic areas as being socially disorganized, which was indicated by high rates of residential mobility, racial/ethnic heterogeneity, and poverty.

The social disorganization framework, however, does not explicate how community and neighborhood factors influence behavior. Shaw and McKay (1942) focus on the formation of juvenile gangs in socially disorganized areas, caused by a decline in informal social controls and neighborhood supervision. However, Shaw and McKay have been critiqued for not clearly defining the concept of social disorganization and for being inconsistent in how they logically linked social disorganization to crime (Bursik, 1988). Contemporary work has attempted to clarify the concepts and processes central to social disorganization theory by combining Kornhauser's (1978) interpretation of Shaw and McKay's work with Kasarda and Janowitz's (1974) systematic model of community attachment.

Kornhauser's (1978) interpretation of social disorganization theory describes social organization as the ability of a community to self-regulate, therefore, tying social disorganization to neighborhood levels of informal social control. Kasarda and Janowitz's (1974) systemic model of community attachment emphasizes the importance of social ties and friendship networks. Taken together, contemporary social disorganization theory suggests that structural factors (like poverty, residential mobility, heterogeneity, and family disruption rates) influence the quality and quantity of neighborhood social ties and attachments, which, in turn, largely determines a community’s level of collective efficacy (Sampson, 1986; Sampson and Groves, 1989). Sampson and Wilson (1995) advanced this perspective further, noting that extremely disadvantaged neighborhoods are not only likely to be socially disorganized but are also likely to be socially isolated. In other words, these communities are unable to self-regulate and are also unlikely to have ties to outside resources and role models. Empirically, a substantial amount of research supports the contemporary social disorganization perspective (Sampson, 1986; Sampson and Groves, 1989; Sampson, Raudenbush, and Earls, 1997; Bellair, 1997).

Social Disorganization Theory and Schools

Working under the systemic model of social disorganization, neighborhood scholars have attempted to specify the processes through which community organization influences collective efficacy and informal social control. Building from Sampson and Wilson’s (1995) arguments regarding social isolation, some researchers have focused on the role of local institutions within socially disorganized communities. Krivo and Peterson (1996), note that:

> "disadvantaged communities do not have the internal resources to organize peacekeeping activities… and at the same time, local organizations (churches, schools, recreation centers) that link individuals to wider institutions and foster mainstream values are lacking" (1996: 622).

Krivo and Peterson are arguing that strong local institutions can mitigate the effects of structural disadvantage. One implication of this statement is that they expect local institutions, like schools, to be associated without social disorganization above and beyond structural predictors. There is some evidence to support this perspective. Peterson, Krivo, and Harris (2000), for example, found a modest negative relationship between the presence of community centers and crime.

Effective schools would seem likely to promote social organization. Schools are largely responsible for the creation of a number of social ties for both adults and adolescents. Moreover, schools promote the formation of local organizations, like parent-teacher associations, and add additional structure and supervision to the juvenile population, both through the process of schooling and through associated extracurricular clubs and activities. Indeed, social disorganization theorists have argued that the local organizations and youth supervision are important aspects of maintaining community organization (Shaw and McKay, 1942; Sampson and Groves, 1989). It may be the case that elementary schools are particularly effective at promoting this kind of social organization since they are generally smaller; fostering a more close knit school community. In addition, parents tend to be more involved in their children's education and related school activities during the elementary school years (Hill and Taylor. 2004; Eccles and Harold. 1996). Additionally, by high school, parents are notably less involved in their children's education. At this stage, adolescents are becoming more autonomous and the school curriculum becomes more advanced so students are less likely to seek parental involvement and parents feel less qualified to offer academic help (Hill and Taylor, 2004; Eccles and Harold, 1996).

Unfortunately, the relationship between local institutions and neighborhood crime has largely gone unexamined. Aside from Peterson, Krivo, and Harris' work on community centers and early research on bank loans and community crime by Velez (2006), social disorganization researchers have largely failed to examine the role of local institutions. In particular, no research in the social disorganization framework has examined the relationship between schools, social disorganization, and crime. The current research attempts to provide a starting point for examining social disorganization, schools, and crime. Building off of Krivo and Peterson's (1996) work, we present the following hypothesis:

> H4: Higher qualities schools will be associated with reduced levels of crime at the neighborhood level, while lower quality schools will be associated with increased levels of crime at the neighborhood level.

> H5: Elementary schools will be associated with reduced levels of crime at the neighborhood level, while high schools will be associated with increased levels of crime at the neighborhood level.

In addition to hypotheses 4 and 5, the social disorganization perspective would also assert that schools, as important local institutions, will be associated with crime at the neighborhood level, even after controlling for common structural predictors of social disorganization.

The Current Study

All of the previous research on schools and neighborhood crime rates has been conducted utilizing the routine activity perspective. The routine activity perspective posits that schools will generate crime at the neighborhood level, due to convergence of motivated offenders, suitable targets, and a lack of capable guardianship. Therefore, the routine activity perspective expects school presence to be associated with more crime at the neighborhood level.

Conversely, at its most basic level, the social disorganization perspective argues that schools can be a valuable local institution that can mitigate the effects of structural advantage. Again, taken at this basic level, the social disorganization perspective expects school presence to associated with lower rates of crime at the neighborhood level. At a more complicated level, the social disorganization perspective argues that effective schools should reduce crime, while ineffective schools should either be unrelated to or increase crime. At this level, it would be difficult to disentangle the role of routine activities and social disorganization in the production of crime for schools, as both perspectives seem to suggest that ineffective schools will be associated with higher crime rates.

Ultimately, it may not be fruitful to attempt to conceptually distinguish between the social disorganization and routine activity perspectives. While conceptually the perspectives are distinct, practically, the perspectives may overlap. In fact, it may be the case that routine activity patterns in socially disorganized communities are more conducive to crime than routine activity patterns in socially organized communities. In some sense, the routine activity and social disorganization perspectives may not be competing at all and, instead, might be better viewed as complimentary explanations. Therefore, the current research, instead of attempting to compare the routine activity and social disorganization perspectives, will draw on both perspectives to investigate the relationship between schools and crime. While we will reference the hypotheses listed above, we assert that research at this level is not necessarily capable of distinguishing between two overlapping theoretical perspectives. Recall that all of the research on schools and neighborhood crime has been conducted at the block level of analysis (Roncek and Lobosco, 1983; Roncek and Faggiani, 1985; Roman, 2004; Kautt and Roncek, 2007). Consequently, previous research on schools and crime has not controlled for a number of social indicators that are known to be predictors of social disorganization.

CHAPTER III: RESEARCH DESIGN

In order to address the research question and hypotheses described in the previous section, we constructed a variety of multivariate regression models using neighborhood level data. This section of the report describes the data and methods utilized in this research.

Theoretically, both the routine activity and social disorganization frameworks postulate that schools should be related to crime at the community and/or neighborhood level. Unfortunately, it is difficult to empirically specify neighborhoods and communities. Instead, most neighborhood research in criminology has used census defined jurisdictions, like census tracts, block groups, and blocks, to approximate neighborhoods and neighborhood patterns and trends (Sampson, Morenoff, and Rowley, 2002). While census designations are artificial and do not necessarily match the lived experience of being in a neighborhood and/or community, they are often the only option for researchers interested in meso-level processes, as they are easily identifiable and are connected a wide range of data collected by the U.S. Census Bureau.

Indeed, the schools and crime literature has relied on census boundaries to define the relationship between schools and neighborhood crime. In fact, every study to examine the relationship between schools and neighborhood crime has utilized the census block level of analysis (Roncek and Bell, 1981; Roncek and Faggiani, 1985; Roman, 2004; Kautt and Roncek, 2007). The block is the smallest of the census designations and has been used by most of these researchers to determine if schools produce crime in the areas directly surrounding their location. In order to account for the possibility that schools generate crime in other, further areas, these researchers often construct adjacency measures to account for blocks that are near blocks with schools.

For the current research, however, we have opted to utilize the block group level of analysis. Block groups are the second smallest census designation and are made up of blocks. While utilizing blocks would make the current research more directly comparable to previous research on schools and crime, doing so would limit our ability to account for the potential influence of social disorganization. The U.S. Census Bureau maintains significantly more social, economic, and demographic information at the block group level than it does at the block level. In particular, a variety of measures of structural disadvantage (including measures of education, income, and employment) are available only at the block group and larger levels of aggregation. By utilizing the block group level of analysis, we are able to provide a rough test of the link between social disorganizations, schools, and crime. While controlling for these variables does not provide a strict test of the social disorganization perspective, it does, in the very least, allow us to make statements about the relative importance of schools compared to other predictors of crime at the block group level.

Data

The data for this research cover three areas: crime, social and demographic features of neighborhoods, and schools.

The incident-level crime data used in this report were provided by the Albuquerque Police Department (APD). The incident-level data include the date, time, location, and crime code and statute violation for a given incident. For this project, we included the following offenses: homicide, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, and narcotics violations. By including the part 1 violent and property offenses, as well as narcotics violations, we are able to investigate the link between schools and a variety of different forms of crime at the neighborhood level. While it is reasonable to assume that schools might be related to other less serious crime types (like, for example, vandalism and simple assault), we opted to exclude less serious crimes, as it is generally assumed that serious offenses are more often reported to and accurately counted by the police (Mosher, Miethe, and Phillips, 2002).

In order to examine neighborhood crime patterns, crime incidents from 2000 to 2005 were geocoded using ArcGIS mapping software. Once mapped, incidents were matched to census block groups and aggregated, providing a sum of crime incidents over that time period within each census block group in Albuquerque. These counts were summed from 2000 to 2005, to account for yearly fluctuations and to induce additional variation (thereby improving our ability to account variance in crime across block groups). These data were then exported to SPSS and linked to block group social and demographic data and to school data. A summary of the crime data included in this analysis is presented in table 3.1.

Table 3.1. Crime incidents from 2000 to 2005 by block group

	Mean	Standard Deviation	Minimum	Maximum
Part 1 Violent	38.32	41.47	0	396
Part 1 Property	234.41	308.82	0	2823
Homicide	0.37	0.71	0	4
Rape	3.47	4.37	0	41
Robbery	9.05	11.86	0	80
Aggravated Assault	25.43	27.84	0	279
Burglary	45.18	39.07	0	352
Larceny	155.85	258.21	0	2615
Motor Vehicle Theft	33.37	35.56	0	298
Narcotics Incidents	27.03	57.40	0	952

The social and demographic data for block groups were compiled from the Census 2000 Summary File 3. As previously mentioned, the U.S. Census Bureau provides substantially more information about block groups than blocks. In order to account for social disorganization explanations, we obtained data on a number of structural disadvantage and mobility variables, including: the percentage of renter occupied housing in a block group, the percentage of households with a single parent in a block group, the percentage of a block group that is unmarried, the percentage of the block group that has moved in the last 5 years, the percentage of housing that is vacant in a block group, the percentage of people with less than a high school education in a block group, the percentage of people living under the poverty line in a block group, the percentage of households in a block group receiving public assistance, and the joblessness (employed individuals plus those not in the labor market) in a block group.

As suggested by previous research on social disorganization, many of these variables are collinear (Sampson, Raudenbush, and Earls, 1997). Accordingly, we were unable to use all of these variables separately in our analysis. In order to address this collinearity, we utilized Principal Components Analysis (PCA) on this list of variables. PCA is a data reduction technique, which when performed on a matrix of variables, produces uncorrelated components (for details, see Dunteman, 1989). These components can be calculated as standardized scores, indicating whether a specific observation scores low, average, or high on that particular component.

For the current research, we utilized SPSS to conduct PCA on the list of variables above. This procedure, using a varimax rotation to improve interpretation, produced 2 components with eigenvalues greater than 1, which together, accounted for nearly 70% of the variance in the variables. The eigenvalues of the first two components, along with associated scree charts, allowed us to exclude the remaining components on the grounds that the first two components adequately address the variance in included variables.

The results of the PCA are listed below in table 3.2. This table, which is a principal components matrix of census variables, lists the correlation between each variable on the components produced from the PCA. The variables percentage of renter occupied housing, percentage of households with a single parent, percentage of people not married, percentage of people that have moved in the last 5 years, and percentage of housing vacant loaded on the first component. We argue that these variables capture the concept of instability, either through residential mobility or through family disruption. Using SPSS, we saved this component score as a variable and named it Instability.

The variables percentage with less than a high school education, percentage in poverty, percentage of households receiving public assistance, and percentage joblessness loaded on the second component. We argue that these variables capture the concept of structural disadvantage. Using SPSS, we saved this component score as a variable and named it Disadvantage.

In addition to the variables described above, we also gathered information on the total population of block groups, the percentage of the population that is Hispanic, and the percentage of the population 18 and under from the 2000 Census. Preliminary analysis of these variables suggested that they were not collinear with the Instability and Disadvantage measures described above and thus, they were maintained as separate independent variables.

Table 3.2. Principal Components Matrix of Census Variables using Varimax Rotation

Variable	Instability (Component 1)	Disadvantage (Component 2)
Percentage of Renter Occupied Housing	**0.903**	0.136
Percentage of Households with a Single Parent	**0.710**	0.319
Percentage Not Married	**0.750**	0.332
Percentage Moved in last 5 Years	**0.796**	-0.256
Percentage of Housing Vacant	**0.672**	0.195
Percentage with Less than a High School Education	0.103	**0.892**
Percentage in Poverty	0.495	**0.763**
Percentage of Households Receiving Public Assistance	0.244	**0.770**
Percentage Joblessness	-0.037	**0.805**
Eigenvalue	4.282	1.954

The school data came from two different sources: the National Center for Education Statistics (NCES) and the Albuquerque Public School's (APS) Research, Development, and Accountability Office. Using the NCES website, we obtained a list of public schools and their addresses in Albuquerque from 2002 to 2005. Using their addresses, we geocoded each school and associated it with a specific block group. This data was then merged with the crime and census data. The NCES website also provided information on the level of school, the pupil to teacher ratio, and the number of students receiving free or reduced lunches. Using the APS website, we obtained standardized reading and math scores from the 2002/2003, 2003/2004, and 2004/2005 school years.[1] For each school, we calculated a testing average, by summing their reading and math scores over the three year period and by dividing them by 6.

Using the merged, geocoded school data, we created three sets of dummy variables to indicate whether or not a block group contained a school. These sets of dummy variables were No Elementary School (scored 0) and Elementary School Present (scored 1), No Middle School (scored 0) and Middle School Present (scored 1), and finally No High School (scored 0) and High School Present (scored 1).

[1] High schools in Albuquerque did not report standardized test results for the 2002/2003 school year. Their testing score averages are based on the 2003/2004 and 2004/2005 school years.

While it is possible that school presence is simply enough to generate or prevent crime at the neighborhood level, it is also possible that other characteristics of schools moderate the relationship between school presence and crime. For instance, is possible that high performance schools may decrease crime, while low performance schools may increase crime. In order to address this possibility, we developed a categorization scheme for schools that classified the schools as being either "below" or "above" average. Initially, we intended to produce this classification scheme utilizing only standardized test scores. However, preliminary analysis revealed that standardized test scores are significantly related to the percentage of students receiving a free or reduced lunch and to the pupil to teacher ratio.

In order to classify the schools, we first disaggregated them by level of school. We did this so that we were comparing elementary schools to elementary schools, middle schools to middle schools, and high schools to high schools. This was necessary, as the percentage of students receiving a free or reduced lunch and the pupil to teacher ratio are correlated to school level. After separating the schools into groups by level, we used SPSS to perform a principal components analysis for each group of schools on the variables percentage of students receiving free or reduced lunch, average test scores, and pupil to teacher ratio[2]. The results of these PCAs are presented in table 3.3. For each group of schools, the PCA revealed only a single component with an eigenvalue greater than one. Therefore, using SPSS, we saved this component score as a variable called Quality of School.

We were unable to use this component score in our analysis of block groups and crime, as several block groups do not contain schools. Instead, we converted this Quality of School variable into a set of six dummy variables: Below Average Elementary School, Above Average Elementary School, Below Average Middle School, Above Average Middle School, Below Average High School, and Above Average High School. Block groups were assigned a 1 for a specific dummy variables if they contained a school that fit its criteria (that is, if there was an elementary school with a negative component score for the Quality of School variable, they were assigned a 1 for Below Average Elementary School). If a block group did not contain a school that met this criterion, they were assigned a 0 for that specific dummy variable. This coding strategy ensured that each block group was given an implicit "No School Present" reference category for each type of school.

[2] Some schools in our data set only reported math or reading proficiency scores from 2002 to 2004. We included these schools, but instead of using their testing averages, we used their average score for the test that they reported. We also performed the analyses described in this report without these schools and found substantively similar results.

Table 3.3. Principal Component Matrices School Characteristics

Variable	Elementary Schools	Middle Schools	High Schools
Percentage Free or Reduced Lunch	-0.949	-0.968	-0.958
Average Test Scores	0.911	0.973	0.954
Pupil to Teacher Ratio	0.742	0.910	0.863
Eigenvalue	2.281	2.712	2.572

Table 3.4 (below), presents the descriptive statistics for the independent variables included in this study. The Instability and Disadvantage indices are not included, as they are standard normal variables with means of 0 and standard deviations of 1. The dummy variables for below average and above average schools are included, as many block groups do not contain schools. It is also important to note that while there are 432 block groups in Albuquerque, our analysis is limited to the 430 block groups with populations greater than 0.

Table 3.4. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	N
Total Population	1288.61	650.85	0	4355	432
Percentage Hispanic	40.96	24.05	0	100	430
Percentage 18 or Under	24.98	8.32	3.33	71.99	430
Percentage with Below Average Elementary School	0.10	0.30	0	1	430
Percentage with Above Average Elementary School	0.07	0.26	0	1	430
Percentage with Below Average Middle School	0.04	0.18	0	1	430
Percentage with Above Average Middle School	0.03	0.16	0	1	430
Percentage with Below Average High School	0.02	0.14	0	1	430
Percentage with Above Average High School	0.01	0.11	0	1	430

Methods

We utilize regression techniques to determine the relationship between schools and quality of schools, at the block group level, and crime. Note, however, that because criminal incidents are discrete events and because many of the crime types covered in this analysis are heavily skewed to the right, traditional ordinary least squares regression techniques are inappropriate. Poisson regression, a variant of a generalized linear model, is typically preferred to ordinary least squares when dealing with count data (Osgood, 2000). The basic Poisson regression model is defined as:

$$\ln(\lambda_i) = \sum_{k=0}^{K} \beta_k x_{ik},$$

Where λ_i is the expected number of events (criminal incidents) for observation I, β_k is a vector of regression coefficients, and x_{ik} is the matrix of values for all 1 through *k* of the independent variables. This can be simplified to find the expected number of criminal incidents by exponentiating each side of the equation. This gives:

$$\lambda_i = e(\sum_{k=0}^{K} \beta_k x_{ik})$$

In a simple two variable case, this simplifies to:

$$\lambda_i = e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2)},$$

which suggests that a unit increase in an independent variable multiplies the expected count of criminal incidents by *e* to the regression coefficient. For example, a one-unit increase in x_1 would result in the expected count of criminal incidents being multiplied by e^{b_1}.

This regression model, therefore, describes the relationship between a set of independent variables and the expected count of a dependent variable. The Poisson regression model, however, assumes that the mean is equal to the standard deviation. For our data, however, all of the crime variables included in this analysis, with the exception of homicide, are over-dispersed (that is, they have a variance significantly greater than the mean). In these cases, it is common to utilize negative binomial regression. Negative binomial regression, while not a member of the generalized least squares, possesses qualities similar to Poisson regression, while including an extra term to account for overdispersion. Specifically, negative binomial regression maintains the same *e* to the b style of interpretation as Poisson regression. In the results chapter, the regression results dealing with homicide utilize Poisson regression, while the regression results dealing with all other dependent variables utilize negative binomial regression. All regression models were estimated using STATA software.

Poisson and negative binomial regressions are utilized when the dependent variable is discrete. In this case, the dependent variables are crime counts. However, it may be the case that block groups with more people have more crime. In order to account for this possibility, we control for population in our regression models. Instead of including population as a normal independent variable, which would suggest that population has a direct and substantively interesting relationship with crime counts, we include population as an exposure variable. The natural logarithm exposure variable is entered into the right hand side of Poisson or negative binomial regression and is given a fixed coefficient of one, which essentially changes Poisson and negative binomial regression from an analysis of crime counts to an analysis of crime rates per capita (Osgood, 2002: 27).

We also addressed spatial dependency in each of the regression models presented in the results section of this paper. Spatial dependency is the idea that geographically close units are likely to be more similar to each other than to units that are geographically distant. Spatial dependency can come from multiple sources, including the artificial nature of census jurisdiction and "spillover".[3] Significant spatial dependency can lead to issues of spatial autocorrelation in statistical procedures. Spatial autocorrelation is a substantial problem, as it suggests that observations are not independent. For regression analyses, spatial autocorrelation can result in unstable regression coefficients and inaccurate standard error estimates. In other words, it is difficult to determine the effects of independent variables in the presence of spatial autocorrelation.

Using the CrimeStat Spatial Statistics program, we calculated Moran's I for each of the dependent variables utilized in our analysis. Moran's I is a common measure of spatial autocorrelation, which uses a weighted correlation technique to determine if data are independently distributed across space (Anselin, 1992). As indicated in table 3.5, each of our dependent variables demonstrated significant clustering (that is, they had I values that were significantly greater than expected under the assumption of spatial independence).

In order to address this spatial autocorrelation, we used GeoDa software to calculate spatial lags for each dependent variable in our analysis. The spatial lag is defined as:

$$\sum_j \omega_{ij} x_j ,$$

Where x_j is the j-th observation of variable x and ω_{ij} is the weight from the i-th row of the spatial weights matrix (Anselin, 1992). This is essentially the weighted average of

[3] Spatial dependency can result from census jurisdictions in that they may not accurately capture the active units of analysis. For example, suppose crime in a pair of block groups stems from a set of neighborhood processes and structures. If the block groups cut that neighborhood in half, then each of the block groups is expected to have a similar count of criminal incidents. Spatial dependency resulting from spillover suggest that geographic areas affect and are affected by neighboring areas. While conceptually distinct from the problem of artificial jurisdictions, spillover will also result in block groups that are expected to have similar counts of criminal incidents. In both cases, these similarities suggest that crime may not be independently distributed across geographic units.

values in adjacent block groups. Therefore, spatial lags account for spatial autocorrelation by controlling for levels of a variable in surrounding areas.

Table 3.5. Moran's I results

Variable	Moran's I value (expected:-.0023)	99 permutations significance	999 permutations significance
Property sum	.1498	.01	.001
Homicide	.0926	.01	.003
Violent sum	.2886	.01	.001
Rape	.2044	.01	.001
Robbery	.1967	.01	.001
Aggravated assault	.3217	.01	.001
Burglary	.3226	.01	.001
Motor vehicle theft	.3035	.01	.001
Larceny	.1030	.01	.002
Narcotics	.1597	.01	.001

And finally, it should be noted that we do not include an overall adjacency measure for schools in our regression analyses. Many of the previous studies on schools and neighborhood crime have included adjacency measures (Roncek and Lobosco, 1983; Roncek and Faggiani, 1985; Kautt and Roncek, 2007). Typically, these adjacency measures are dummy variables that indicate whether or not an adjacent geographic unit (always the census block in previous research) contains a school. This measure is typically intended to capture the effects of schools on crime in nearby areas.

We do not include this measure for two reasons. First, we are utilizing a larger unit of analysis. As block groups are made up of blocks, significant results in our analysis suggest that schools influence crime in the block group, not just in the specific block in which they are located. Secondly, at this level of analysis of analysis, 400 of the 432 block groups in Albuquerque are adjacent to one or more block groups that contain a school. In other words, at larger levels of aggregation, there is not enough variation to warrant the inclusion of an adjacency measure. Ultimately, this is a trade off for using the block group level of analysis. The block group allows us to control for more social and economic indicators and thus to give the social disorganization perspective a more thorough test. However, because block groups are larger and because schools are spread across the city, we are unable to test for adjacency effects and therefore, can only make general conclusions about block groups and not about surrounding areas.

CHAPTER IV: RESULTS

In order to investigate the relationship between schools and crime at the block group level, we estimated a number of regression equations testing the relationship between schools and crime, and examining the influence of a variety of theoretically relevant independent variables. All of the results presented below are for negative binomial regression, except for the results associated with homicide, which utilize Poisson regression.

Control Variable Models

Before investigating the relationship between schools and crime, we present a baseline control model, using all of our other independent variables. Tables 4.1 and 4.2 present these results. Table 4.1 presents the results for violent crimes, with the Violent Offenses column being the sum of all violent part 1 offenses and each following column being a specific part 1 violent offense.

Table 4.1: Regression Results: Block Group Characteristics and Violent Crime Incidents

	Violent Offenses	Homicide	Rape	Robbery	Aggravated Assault
Lag	0.006** (0.001)	-0.200 (0.226)	0.033 (0.017)	0.058** (0.009)	0.007** (0.002)
Disadvantage	0.297** (0.044)	0.417** (0.092)	0.211** (0.055)	0.274** (0.077)	0.299** (0.041)
Instability	0.345** (0.032)	0.393** (0.081)	0.399** (0.043)	0.313** (0.054)	0.356** (0.030)
% Hispanic	0.010** (0.002)	0.017** (0.005)	0.011** (0.003)	0.003 (0.003)	0.012** (0.002)
% 18 or Under	-0.010** (0.002)	-0.039** (0.011)	-0.016** (0.005)	-0.023** (0.007)	-0.020** (0.004)
Constant	-3.818** (0.106)	-8.062** (0.297)	-6.262** (0.115)	-5.236** (0.200)	-4.338** (0.100)
LL	-1804.17	-299.73	-890.79	-1303.91	-1588.16
Pseudo R^2	0.0882	0.1390	0.0957	0.0545	0.1124

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 4.2 presents the results of this baseline control model for property and narcotics offenses. The Property Offenses column shows the regression results using the sum of all part 1 property incidents (the sum of burglary, larceny, and motor vehicle theft), as the dependent variable. The middle columns present the results for individual part 1 property offenses, while the last column displays the results for narcotics violations. The narcotics offenses are included with property offenses in this table, and in all of the following tables, to save space.

Table 4.2: Regression Results: Block Group Characteristics and Property/Narcotics Crime Incidents

	Property Offenses	Burglary	Larceny	Motor Vehicle Theft	Narcotics Violations
Lag	0.001** (< 0.001)	0.010** (0.001)	0.002** (< 0.001)	0.012** (0.001)	0.005** (0.002)
Disadvantage	0.267** (0.035)	0.163** (0.040)	0.054 (0.053)	0.191** (0.041)	0.464** (0.068)
Instability	0.094* (0.047)	0.167** (0.028)	0.286** (0.041)	0.328** (0.031)	0.376** (0.050)
% Hispanic	0.006** (0.002)	0.003 (0.002)	0.007** (0.002)	0.003 (0.002)	0.012** (0.003)
% 18 or Under	-0.022** (0.004)	-0.015** (0.004)	-0.026** (0.005)	-0.014** (0.004)	-0.030** (0.005)
Constant	-1.819** (0.114)	-3.596** (0.100)	-2.121** (0.128)	-4.015** (0.103)	-4.040** (0.005)
LL	-2635.02	-1871.68	-2495.42	-1735.63	-1683.15
Pseudo R^2	0.0323	0.0528	0.0276	0.0766	0.0758

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

The spatial lag variable is significant for virtually all offenses included in these baseline models. This suggests that there is considerable clustering of these offenses. The lag is not a significant predictor of homicide or rape. These offenses are comparably infrequent compared to the other violent and property offenses included, and thus, it is not surprising that these offenses are not highly clustered.

The regression results are fairly consistent across crime types. The Disadvantage and Instability components, described in the Research Design chapter, are significant, positive predictors of virtually all crime. This suggests that block groups that are characterized by higher levels of disadvantage and instability are likely to experience a larger volume of violent, property, and drug crime than block groups with lower levels of disadvantage and instability. The only exception to this is that disadvantage does not appear to be significantly related to larceny rates. Therefore, while block groups with higher levels of instability report higher counts of larceny than other block groups, block groups with higher levels of disadvantage do not appear to be any different in terms of larceny incidents than other block groups.

The percentage Hispanic variable is a significant, positive predictor of most types of crime. This suggests that block groups with a higher proportion of Hispanic residents, controlling for other factors, are likely to report more crime than block groups with lower proportions of Hispanic residents. Interestingly, percentage Hispanic is not a significant predictor of robbery, burglary, or motor vehicle theft counts.

The percentage of the population 18 and under is significantly and negatively associated with all types of crime included in this analysis. This suggests that block groups with a larger proportion of minors, controlling for other factors, are likely to report fewer crime incidents than block groups with fewer minors. This result may seem counter-intuitive; given the robust individual-level relationship between age and crime that other researchers have found (Hirschi and Gottfredson, 1983). However, this result is not uncommon. A number of researchers have found a negative relationship between youth population and crime at aggregate levels (for example, see Jackson, 1991; Krivo and Peterson, 1996; Peterson, Krivo and Harris, 2000; Steffensmeier and Haynie, 2000; and Haynie and Armstrong, 2006). It may be that areas with more minors are also likely to have more families and more community-level supervision, and thus, higher levels of informal social control.

And finally, it should be noted that the model fit measures for these control variable models are fairly modest. While there are some shortcomings with these pseudo R-squared measures, the overall implication is that this group of variables does not account for the majority of the variance in block group crime counts.[4]

School Presence

The next set of regression models includes school presence as an independent variable. In each case, we have included a dummy variable for Elementary School (equal to 1 if there is an elementary school in the block group, else 0), Middle School (equal to 1 if there is a middle school in the block group, otherwise is equal to 0), and High School (equal to 1 if there is a high school in the block group, otherwise it is equal to 0). Therefore, including these variables allows us to test the expected difference between block groups with and without schools, controlling for spatial lag, disadvantage, instability, percentage Hispanic, and the percentage under the age of 18.

As with the control variable regression results, the school presence results are organized into two tables. The first table, 4.3., presents the regression results for violent incidents. The second table, 4.4., presents the regression results for property and narcotics incidents.

The relationship between the control variables and crime counts are similar to those presented in the control variable regression models. In other words, controlling for school presence does not seem to dramatically alter the relationship between disadvantage, instability, percentage Hispanic, and percentage 18 and under and crime. More specifically, disadvantage and instability are still positively related to most crime outcomes. Like the previous models, disadvantage is not a significant predictor of larceny. Similarly, percentage Hispanic is positively related to all crime types, except

[4] Indeed, in some instances, pseudo R-squared measures have a maximum possible value that is less than 1, suggesting that these measures will be artificially lower than the traditional R-squared measure used in ordinary least squares regression (Dobson, 2002).

robbery, burglary, and motor vehicle theft. And finally, the percentage of the population aged 18 and under is negatively related to all crime types. Moreover, the results regarding spatial lags are also similar. Again, the spatial lags are significant for all crime types examined, except homicide and rape.

Table 4.3: Regression Results: Schools, Block Group Characteristics and Violent Crime Incidents

	Violent Offenses	Homicide	Rape	Robbery	Aggravated Assault
Lag	0.006** (0.001)	-0.199 (0.226)	0.034* (0.017)	0.058** (0.009)	0.007** (0.002)
Disadvantage	0.311** (0.044)	0.420** (0.095)	0.238** (0.055)	0.289** (0.077)	0.314** (0.040)
Instability	0.336** (0.032)	0.392** (0.084)	0.408** (0.043)	0.301** (0.055)	0.350** (0.030)
% Hispanic	0.009** (0.002)	0.017** (0.005)	0.009** (0.003)	0.002 (0.003)	0.012** (0.002)
% 18 or Under	-0.021** (0.004)	-0.039** 0.011)	-0.015** (0.005)	-0.023** (0.007)	-0.020** (0.004)
Elementary School	-0.004 (0.078)	0.002 (0.219)	0.239* (0.104)	-0.015 (0.135)	-0.005 (0.073)
Middle School	0.192 (0.127)	-0.007 (0.337)	0.270 (0.162)	0.168 (0.218)	0.214 (0.117)
High School	0.373* (0.168)	0.057 (0.378)	0.300 (0.203)	0.384 (0.283)	0.348* (0.156)
Constant	-3.838** (0.106)	-8.061** (0.301)	-6.318** (0.145)	-5.249** (0.199)	-4.357** (0.099)
LL	-1788.10	-299.72	-885.32	-1302.49	-1583.36
Pseudo R^2	0.0904	0.1390	0.1013	0.0556	0.1151

While the inclusion of the school dummy variables does not appear to change the relationship between the control variables and crime counts, these variables suggest that school presence, controlling for included social indicators, is related to certain types of block group crime. However, different types of schools appear related to different types of crime. Elementary schools, for example, seem to be mostly unrelated to violent crime. That is, the relationship between the presence of an elementary school and the number of reported violent crime incidents in a block group is not statistically significant for most crime types. The exception is that the presence of elementary schools is positively and significantly related to an increase in the expected count of rapes. In other words, block groups with elementary schools report more roughly 27% ($e^{0.239}$) rape incidents than block groups without elementary schools, controlling for other factors.

Similarly, block groups with high schools are statistically more likely to report aggravated assaults, and by association, violent crime incidents, than block groups without high schools. Specifically, block groups with high schools report 41.6% more aggravated assaults than block groups without high schools.

Table 4.4: Regression Results: Schools, Block Group Characteristics and Property/Narcotics Crime Incidents

	Property Offenses	Burglary	Larceny	Motor Vehicle Theft	Narcotics Violations
Lag	0.001** (<0.001)	0.010** (0.001)	0.002** (<0.001)	0.012** (0.001)	0.006** (0.002)
Disadvantage	0.108* (0.045)	0.163** (0.040)	0.071 (0.051)	0.200** (0.041)	0.497** (0.062)
Instability	0.233** (0.034)	0.158** (0.029)	0.240** (0.039)	0.319** (0.031)	0.339** (0.046)
% Hispanic	0.006** (0.002)	0.003 (0.002)	0.006* (0.002)	0.002 (0.002)	0.012** (0.003)
% 18 or Under	-0.022** (0.004)	-0.012** (0.003)	-0.025** (0.004)	-0.014** (0.004)	-0.030** (0.005)
Elementary School	-0.195* (0.084)	-0.133* (0.068)	-0.249* (0.097)	-0.057 (0.075)	-0.002 (0.108)
Middle School	0.021 (0.138)	0.009 (0.112)	0.013 (0.160)	0.112 (0.122)	0.677** (0.174)
High School	0.843** (0.184)	0.088 (0.148)	1.061** (0.212)	0.212 (0.161)	1.502** (0.230)
Constant	-1.838** (0.111)	-3.584** (0.100)	-2.150** (0.123)	-4.015** (0.104)	-4.279** (0.138)
LL	-2618.53	-1869.62	-2474.63	-1733.91	-1643.55
Pseudo R^2	0.0384	0.0538	0.0357	0.0755	0.0975

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

School presence is also related to property and narcotics offenses, even after controlling for other variables. Block groups with elementary schools are found to report having significantly fewer property crime incidents than block groups without elementary schools. Specifically, block groups with elementary schools report 12.4% fewer burglaries and 22.0% fewer larcenies than block groups without elementary schools, controlling for other factors. Conversely, block groups with high schools report significantly more property crime than block groups without high schools, driven mostly by the relationship between high school presence and larceny (block groups with high schools report 189% more larcenies than block groups without high schools, controlling for other factors).

Middle school and high school presence is also related to narcotics incidents. Block groups with middle schools report 96.8% more narcotics incidents than block groups without middle schools, while block groups with high schools report 349% more narcotics incidents than block groups without high schools.

The inclusion of the school dummy variables modestly increases the pseudo R-squared values of the regression models. For example, the pseudo R-squared value of the control variable regression model on violent crimes was 0.0882, while the pseudo R-squared value of the comparable model including the school dummy variables is 0.0904. Similar small increases are found for the other dependent variables. However, when comparing nested generalized linear models, however, the log-likelihood ratio test is usually preferred to comparing pseudo R-squared values. The log-likelihood ratio test assumes that twice the difference between the log-likelihood values of nested models has a chi-squared distribution with degrees of freedom equal to the number of new parameters. In formula form, the log likelihood ratio test is:

$$D = -2(LLn_0 - LLn_1),$$

where D ~ $\chi^2(k_{advanced)} - k_{(simple)}$ and where k is the number of independent variables.

For our regression models, the log likelihood test statistics can be calculated by inserting the log-likelihood value from the appropriate control variable model into LLn_0 and the log-likelihood value from the model that includes the theoretically relevant variable (in this case school presence) into LLn_1 and performing the arithmetic indicated in the formula above. Because we have included dummy variables for elementary schools, middle schools, and high schools, the degrees of freedom for each log-likelihood test is 3.

For example, the log-likelihood value for the control variable regression model on the sum of violent crime incidents is -1804.17. The log-likelihood value for the school presence regression model on the sum of violent crime incidents is -1788.10. Inserting these values into the appropriate locations in the log-likelihood ratio test formula, we get:

= -2(-1804.17 - (-1788.10))
= -2(-16.07)
= 32.14

Using a chi-squared table, this value is revealed to be significant up to and beyond the 0.001 level of significance. Therefore, we can conclude that including the school dummy variables improved the fit of the negative binomial regression model on the sum of violent crime incidents. The results of the remaining log-likelihood ratio tests are presented below in table 4.5.

This table (below) suggests that adding the school presence variables improves the model fit of several of the regression models. At the block group level, schools appear related to rape, aggravated assault, larceny, and narcotics incidents. Schools appear unrelated to homicide, robbery, burglary and motor vehicle theft.

Table 4.5 Log-likelihood ratio tests comparing control models to models with school presence indicators.

Dependent Variable	LLn_0	LLn_1	D
Violent Crime	-1804.17	-1788.10	32.14**
Homicide	-299.73	-299.72	0.02
Rape	-890.79	-885.32	10.94*
Robbery	-1303.91	-1302.49	2.84
Aggravated Assault	-1588.16	-1583.36	9.60*
Property Crime	-2635.02	-2618.53	32.98**
Burglary	-1871.63	-1869.62	4.02
Larceny	-2495.42	-2474.63	41.58**
Motor Vehicle Theft	-1735.63	-1733.91	3.44
Narcotics	-1683.15	-1643.55	79.20**

* $p < 0.05$, ** $p < 0.01$

Quality of Schools

The next set of regression models disaggregates school presence by school quality. In these models, we include dummy variables for "Below Average" and "Above Average" school of each level present, with "No School" of that level used as the reference category. Again, we present two tables. Table 4.6 presents the regression results for violent crime, while table 4.7 displays the results for property and narcotics offenses.

The quality of school regression models present different results for middle and high schools than the school presence regressions. In the school presence models, for example, middle schools are unrelated to all forms of violent crime. In the quality of school models, however, block groups with below average middle schools are associated with higher counts of rape and aggravated assault than block groups without middle schools or block groups with above average middle schools. High schools, in the school presence model, are associated with higher counts of aggravated assault and violent crime in general. When disaggregated by school quality, however, only block groups with above average high schools report significantly more aggravated assault than block groups without high schools.

Table 4.6: Regression Results: Quality of Schools, Block Group Characteristics and Violent Crime Incidents

	Violent Offenses	Homicide	Rape	Robbery	Aggravated Assault
Lag	0.006** (0.001)	-0.230 (0.228)	0.034 (0.017)	0.058** (0.009)	0.007** (0.002)
Disadvantage	0.311** (0.043)	0.416** (0.094)	0.232** (0.055)	0.297** (0.055)	0.311** (0.040)
Instability	0.335** (0.032)	0.393** (0.084)	0.409** (0.043)	0.297** (0.077)	0.351** (0.030)
% Hispanic	0.010** (0.002)	0.016** (0.005)	0.009** (0.003)	0.002 (0.004)	0.013** (0.002)
% 18 or Under	-0.022** (0.004)	-0.037** (0.011)	-0.014** (0.005)	-0.023** (0.007)	-0.021** (0.004)
Below Avg. Elementary School	-0.098 (0.101)	0.147 (0.239)	0.201 (0.127)	-0.139 (0.176)	-0.081 (0.094)
Above Avg. Elementary School	0.108 (0.114)	-0.544 (0.522)	0.322* (0.161)	0.119 (0.196)	0.100 (0.109)
Below Avg. Middle School	0.320* (0.161)	-0.179 (0.405)	0.472* (0.190)	0.293 (0.274)	0.334* (0.147)
Above Avg. Middle School	-0.029 (0.192)	0.127 (0.594)	-0.297 (0.303)	-0.042 (0.339)	-0.007 (0.182)
Below Avg. High School	0.373 (0.224)	0.208 (0.445)	0.455 (0.258)	0.658 (0.375)	0.157 (0.205)
Above Avg. High School	0.379 (0.250)	0.061 (0.933)	0.015 (0.330)	-0.105 (0.432)	0.570* (0.232)
Constant	-3.844** (0.106)	-8.040** (0.301)	-6.315** (0.145)	-5.247** (0.199)	-4.364** (0.099)
LL	-1786.42	-298.79	-882.08	-1300.76	-1581.05
Pseudo R^2	0.0912	0.1417	0.1046	0.0568	0.1163

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

There are also interesting differences in the property crime and narcotics regressions between block groups with above and below average schools. Block groups with below average schools, for example, are associated with lower counts of burglary and larceny than other block groups, controlling for other factors. Block groups with below average high schools are associated with more larcenies than other block groups. Block groups with below average middle schools and high schools, of either sort, are expected to have significantly more narcotics incidents than other block groups. Interestingly, block groups with above average high schools are expected to report more narcotics incidents than block groups with below average or no high schools.

Table 4.7: Regression Results: Quality of Schools, Block Group Characteristics and Property/Narcotics Crime Incidents

	Property Offenses	Burglary	Larceny	Motor Vehicle Theft	Narcotics Violations
Lag	0.001** (0.002)	0.010** (0.001)	0.002** (<0.001)	0.013** (0.001)	0.006** (0.002)
Disadvantage	0.114* (0.044)	0.163** (0.039)	0.078 (0.050)	0.200** (0.041)	0.486** (0.062)
Instability	0.229** (0.034)	0.157** (0.029)	0.236** (0.039)	0.318** (0.031)	0.348** (0.046)
% Hispanic	0.006** (0.002)	0.003 (0.002)	0.006** (0.002)	0.003 (0.002)	0.013** (0.003)
% 18 or Under	-0.022** (0.004)	-0.016** (0.004)	-0.025** (0.004)	-0.014** (0.004)	-0.030** (0.005)
Below Avg. Elementary School	-0.336** (0.111)	-0.274** (0.090)	-0.392** (0.129)	-0.156 (0.098)	-0.008 (0.140)
Above Avg. Elementary School	-0.048 (0.120)	0.023 (0.098)	-0.103 (0.139)	0.060 (0.109)	0.024 (0.160)
Below Avg. Middle School	0.133 (0.177)	0.041 (0.141)	0.142 (0.206)	0.244 (0.154)	0.790** (0.222)
Above Avg. Middle School	-0.018 (0.201)	-0.006 (0.165)	-0.048 (0.233)	0.082 (0.181)	0.407 (0.261)
Below Avg. High School	1.104** (0.247)	0.145 (0.197)	1.353** (0.285)	0.306 (0.215)	1.015** (0.310)
Above Avg. High School	0.404 (0.268)	-0.018 (0.219)	0.549 (0.309)	0.035) (0.240)	1.916** (0.335)
Constant	-1.855** (0.111)	-3.608** (0.100)	-2.161** (0.123)	-4.032** (0.104)	-4.292** (0.138)
LL	-2614.81	-1866.76	-2471.38	-1731.48	-1641.39
Pseudo R^2	0.0397	0.0553	0.0369	0.0788	0.0987

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 4.8 presents the log-likelihood ratio tests comparing the quality of school models to the school presence models. This table indicates that disaggregating schools by quality does little to improve model fit compared to a model with only the control variables. This suggests that the results from these models should be viewed cautiously.

Table 4.8 Log-likelihood ratio tests comparing control models to models with school presence indicators.

Dependent Variable	LLn_1	*LLn2*	*D*
Violent Crime	-1788.10	-1786.42	3.36
Homicide	-299.72	-298.79	1.86
Rape	-885.32	-882.08	6.48
Robbery	-1302.49	-1300.76	3.46
Aggravated Assault	-1583.36	-1581.05	4.62
Property Crime	-2618.53	-2614.81	7.44
Burglary	-1869.62	-1866.76	5.72
Larceny	-2474.63	-2471.38	6.50
Motor Vehicle Theft	-1733.91	-1731.48	4.86
Narcotics	-1643.55	-1641.39	4.32

* $p < 0.05$, ** $p < 0.01$ (Chi-squared Test of Significance)

Temporal Analysis

In order to provide a more complete test of the routine activities perspective, we also conducted several regressions on our crime data disaggregated by time of day. Following Roman (2000), we disaggregated our crime data into the Morning Commute Hours, School Hours, Afternoon Commute Hours, Evening Hours, Weekend Hours, and Summer Hours.

As described in previous chapters, we disaggregated our crime data by time because schools might matter more or less during certain times of the day. From the routine activities perspective, block groups with schools are expected to have more crime directly before, during, and directly after school than during other time periods. Adolescents do not occupy routes to and from school, nor do they converge at schools in the same numbers during the evening, weekend, and summer hours. At the same time, from a social disorganization perspective, the influence of schools should hold regardless of time of day, week or year. If schools promote social organization more generally, there is no reason to believe that social organization is confined to school hours. Rather, it should permeate the community and reduce crime more broadly rather than only reducing crime at specific times. All data disaggregation was performed using SPSS. A description of these disaggregated time periods is presented in table 4.9.

Table 4.9. Time Periods (Non-Summer Hours)

Time Period	Days	Hours
Morning Commute Hours	Monday-Friday	0600-0829
School Hours	Monday-Friday	0830-1459
Afternoon Commute Hours	Monday-Friday	1500-1759
Evening Hours	Monday-Thursday	1800-0559
Weekend Hours	Friday-Monday	1800-0559

The Summer Hours category was included to account for the period of the year in which schools are less used and less likely to be routine activity nodes. For the purposes of this research, we defined the summer as the months of June and July. In reality, Albuquerque Public Schools starts school sometime in August and end school sometime in May. However, the specific dates change each year and can vary between schools. Therefore, we opted to construct a more conservative Summer category that likely misses some summer days, but that includes summer days that are shared by all schools in Albuquerque.

After disaggregating our data, we constructed several additional regression models to examine the relationship between school presence and crime at different times of day and different times of the year. Tables 4.10 through 4.15 display these results, with each table containing the results for a specific time of day/year. In order to save space, we only present the results for the sum of violent incidents, the sum of property incidents, and for narcotics incidents. The results are substantively similar when further disaggregating violent and property incidents into their component crimes. Moreover, as detailed in the conclusion chapter, the results for the quality of school regressions are complicated and require additional attention. While we could have completed the following temporal analyses using our quality of school indicators, we opted to use our school presence measures to provide more streamlined and interpretable results regarding schools, crime, and time.

In our discussion of these regression models, we focus most of our attention on the school presence indicators. The control variables maintain a similar relationship with temporally disaggregated crime as previous models. There are some interesting differences with certain variables being insignificant during certain time periods. However, to keep our discussion focused, we will not address these results.

Tables 4.10 through 4.12 display the regression results for the morning commute, school session, and afternoon commute hours. The routine activity perspective would suggest that schools will promote crime during these hours, as this is when they physically provide for the convergence of motivated offenders and suitable victims.

During the morning commute, block groups with middle schools report significantly more violent and narcotic incidents than block groups without middle schools. Similarly, block groups with high schools are expected to report more narcotics incidents during the morning commute hours than block groups without high schools. Elementary schools, which were negatively related with property crime in previous regression models, are unrelated to crime during the morning commute hours. This might suggest that while elementary schools generally protect against and prevent crime, during key routine activity hours, block groups with these schools are less protected.

During school hours, block groups with middle schools report significantly more violent and narcotics incidents than block groups without middle schools. Block groups with high schools, on the other hand, are expected to report more violent, property, and narcotics incidents during school hours than block groups without high schools. Therefore, while there is little difference between the morning commute and school session hours for block groups with middle schools, block groups with high schools report substantial increases in the high school effect during school hours.

During school hours, block groups with elementary schools report fewer property crime incidents than block groups without elementary schools. This suggests that while elementary schools are not necessarily a protective factor during the morning commute hours, they may be a protective factor during school hours.

Table 4.10: Regression Results: School Presence, Block Group Characteristics and Crime Incidents during Morning Commute Hours

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.003 (0.002)	0.001** (<0.001)	0.001 (0.003)
Disadvantage	0.322** (0.070)	0.085 (0.045)	0.435** (0.115)
Instability	0.280** (0.059)	0.234** (0.034)	0.323** (0.090)
% Hispanic	0.008* (0.004)	-0.003 (0.002)	0.009 (0.006)
% 18 or Under	-0.014 (0.008)	-0.004 0.004	-0.049** (0.012)
Elementary School	0.182 (0.137)	-0.082 (0.081)	0.257 (0.214)
Middle School	0.714** (0.185)	0.097 (0.133)	1.087** (0.290)
High School	0.066 (0.261)	0.202 (0.174)	1.579** (0.350)
Constant	-7.441** (0.206)	-4.223** (0.110)	-7.272** (0.289)
LL	-555.82	-1637.62	-413.08
Pseudo R^2	0.0951	0.0409	0.1089

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 4.11: Regression Results: School Presence, Block Group Characteristics and Crime Incidents during School Hours

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.004**	0.002**	0.004*
	(0.002)	(0.002)	(0.002)
Disadvantage	0.333**	0.151**	0.0593**
	(0.049)	(0.045)	(0.083)
Instability	0.293**	0.250**	0.278**
	(0.037)	(0.035)	(0.060)
% Hispanic	0.006**	0.002	0.009*
	(0.002)	(0.002)	(0.004)
% 18 or Under	-0.020**	-0.025**	-0.041**
	(0.005)	(0.004)	(0.007)
Elementary School	0.012	-0.169*	0.114
	(0.091)	(0.084)	(0.143)
Middle School	0.558**	0.132	1.657**
	(0.135)	(0.137)	(0.210)
High School	0.871**	0.833**	2.816**
	(0.171)	(0.181)	(0.270)
Constant	-5.564**	-2.895**	-5.743**
	(0.124)	(0.112)	(0.192)
LL	-1067.74	-2094.54	-951.72
Pseudo R^2	0.1065	0.0511	0.1371

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Table 4.12: Regression Results: School Presence, Block Group Characteristics and Crime Incidents during Afternoon Commute Hours

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.001 (0.002)	0.001** (<0.001)	0.005** (0.002)
Disadvantage	0.321** (0.058)	0.103 (0.054)	0.569** (0.084)
Instability	0.285** (0.046)	0.242** (0.041)	0.436** (0.063)
% Hispanic	0.009** (0.003)	0.009** (0.003)	0.006 (0.004)
% 18 or Under	-0.020** (0.006)	-0.029** (0.005)	-0.037** (0.008)
Elementary School	0.057 (0.109)	-0.242* (0.101)	0.336* (0.147)
Middle School	0.439** (0.163)	-0.007 (0.164)	0.366 (0.234)
High School	0.491* (0.212)	1.316** (0.211)	0.979** (0.286)
Constant	-6.063** (0.152)	-4.051** (0.133)	-6.214** (0.199)
LL	-902.31	-1692.04	-765.14
Pseudo R^2	0.0830	0.0596	0.1309

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

Block groups with high schools continue to report more violent, property, and narcotics incidents than block groups without high schools during the afternoon commute. Block groups with middle schools report more violent crime incidents than block groups without middle schools, but do not indicate a continued increase in narcotics incidents. Elementary schools, on the other hand, are significantly associated with smaller counts of property and larger counts of narcotics incidents during the afternoon commute hours.

Next, we present a series of regression models where, from a routine activities perspective, schools are expected to be less important predictors of crime at the block group level. Tables 4.13 through 4.15 display the regression results for the evening hours, weekend hours, and summer months. To the extent schools still matter during these times, the social disorganization perspective would seem more relevant.

Table 4.13: Regression Results: School Presence, Block Group Characteristics and Crime Incidents during Evening Hours

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.006** (0.002)	0.001** (<0.001)	0.006** (0.002)
Disadvantage	0.289** (0.051)	0.198** (0.049)	0.517** (0.070)
Instability	0.403** (0.039)	0.309** (0.037)	0.391** (0.053)
% Hispanic	0.008** (0.003)	0.009** (0.002)	0.012** (0.003)
% 18 or Under	-0.019** (0.005)	-0.023** (0.004)	-0.023** (0.006)
Elementary School	-0.001 (0.095)	-0.188* (0.090)	-0.042 (0.124)
Middle School	0.006 (0.152)	0.077 (0.147)	0.413* (0.196)
High School	0.222 (0.194)	0.750** (0.192)	0.265 (0.262)
Constant	-5.226** (0.131)	-3.891** (0.121)	-5.780** (0.161)
LL	-1249.42	-1803.92	-1090.88
Pseudo R^2	0.0967	0.0642	0.1167

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

During the evening hours, block groups with elementary schools reported fewer property crime incidents than block groups without elementary schools. Conversely, block groups with middle schools reported more narcotics incidents than block groups without middle schools, while block groups with high schools reported more property crime incidents than block groups without high schools.

Table 4.14: Regression Results: School Presence, Block Group Characteristics and Crime Incidents During the Weekend

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.007**	0.001**	0.003*
	(0.002)	(<0.001)	(0.001)
Disadvantage	0.318**	0.076	0.421**
	(0.047)	(0.051)	(0.058)
Instability	0.357	0.272**	0.374**
	(0.036)	(0.039)	(0.043)
% Hispanic	0.009**	0.009**	0.012**
	(0.002)	(0.002)	(0.003)
% 18 or Under	-0.023**	-0.026**	-0.029**
	(0.005)	(0.005)	(0.005)
Elementary School	-0.002	-0.259**	0.029
	(0.086)	(0.096)	(0.103)
Middle School	0.128	-0.074	0.036
	(0.139)	(0.157)	(0.166)
High School	0.203	0.925**	0.457*
	(0.181)	(0.205)	(0.212)
Constant	-5.063**	-3.557**	-5.162**
	(0.119)	(0.128)	(0.137)
LL	-1287.53	-1915.91	-1213.74
Pseudo R^2	0.1140	0.0497	0.1131

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$

During the weekend, block groups containing elementary schools reported significantly fewer property crime incidents than block groups without elementary schools. Block groups with high schools reported more property and narcotics incidents than block groups without high schools. Middle schools were unrelated to crime during the weekend hours.

Table 4.15: Regression Results: School Presence, Block Group Characteristics and Crime Incidents During the Summer

	Violent Incidents	Property Incidents	Narcotics Incidents
Spatial Lag	0.006**	0.001**	0.013**
	(0.002)	(<0.001)	(0.001)
Disadvantage	0.270**	0.078	0.252**
	(0.050)	(0.049)	(0.068)
Instability	0.366**	0.228**	0.264**
	(0.039)	(0.037)	(0.051)
% Hispanic	0.013**	0.005*	0.012**
	(0.003)	(0.002)	(0.003)
% 18 or Under	-0.024**	-0.020**	-0.023**
	(0.005)	(0.004)	(0.006)
Elementary School	-0.037	-0.159	-0.197
	(0.094)	(0.089)	(0.125)
Middle School	-0.107	-0.005	-0.104
	(0.154)	(0.147)	(0.194)
High School	0.011	0.655**	-0.489
	(0.196)	(0.192)	(0.255)
Constant	-5.660	-3.664**	-6.404
	(0.128)	(0.119)	(0.172)
LL	-1101.86	-1861.69	-889.49
Pseudo R^2	0.1176	0.0435	0.1693

In order to consolidate our findings, we present tables 4.16 through 4.18, which display the regression coefficients for the school presence variables in different models. For example, in table 4.16, the original model column contains the regression coefficient for the elementary school dummy variable for the violent, property, and narcotics regressions. The next column, morning commute, displays the regression coefficient for the elementary school dummy variable for the morning commute regressions.

Table 4.16. Comparing Elementary School Presence Coefficients Across Models

	Original Model	Morning Commute	School Session	Afternoon Commute	Evening	Weekend	Summer
Violent	-0.004	0.182	0.012	0.057	-0.001	-0.002	-0.037
Property	-0.195*	-0.082	-0.169*	-0.242*	-0.188*	-0.259**	-0.159
Narcotics	-0.002	0.257	0.114	0.336*	-0.042	0.029	-0.197

In the original model, block groups containing elementary schools reported **17.7%** fewer property crime incidents than block groups without elementary schools, controlling for other factors. This result is fairly consistent across time of day and year, although it should be noted that the effects are strongest during the afternoon commute and weekend hours, and weakest during the morning commute hours.

Regardless of time of day or year, elementary school presence does not seem to be associated with violent crime incidents. This is also mostly true for narcotics incidents, although block groups containing elementary schools do report significantly more narcotics violations during the afternoon commute hours than block groups without elementary schools.

Table 4.17. Comparing Middle School Presence Coefficients Across Models

	Original Model	Morning Commute	School Session	Afternoon Commute	Evening	Weekend	Summer
Violent	0.192	0.714**	0.558**	0.439**	0.006	0.128	-0.107
Property	0.021	0.097	0.132	-0.007	0.077	-0.074	-0.005
Narcotics	0.677**	1.087**	1.657**	0.366	0.413	0.036	-0.104

In the original model, block groups with middle schools were statistically no different in terms of violent crime than block groups without middle schools. Interestingly, during the morning commute, school session, and afternoon commute hours, block groups with middle schools report significantly more violent crime incidents than block groups without middle schools. Similarly, while block groups containing middle schools reported significantly more narcotics incidents than block groups without middle schools in the original model, the time disaggregated models reveal that these differences are most substantial during the morning commute and school session hours.

Table 4.18. Comparing High School Presence Coefficients Across Models

	Original Model	Morning Commute	School Session	Afternoon Commute	Evening	Weekend	Summer
Violent	0.372*	0.066	0.871**	0.491*	0.222	0.203	0.011
Property	0.873**	0.202	0.833**	1.316**	0.750**	0.925**	0.655**
Narcotics	1.502**	1.579**	2.816**	0.979**	0.265	0.457*	-0.489

In the original model, block groups containing high schools reported significantly more violent, property, and narcotics incidents than block groups without high schools. When disaggregated by time of day, block groups containing high schools report significantly more crime during the school session and afternoon commute hours. Similarly, the effect of high school presence on narcotics incidents is largest during the morning commute, school session, and afternoon commute hours. Interestingly, high schools are nearly always associated with increases in property incidents, with the exception being during the morning commute hours.

CHAPTER V: DISCUSSION AND CONCLUSION

There are several conclusions that can be drawn from the results presented in the previous chapter. First, and foremost, the results of our regression analyses suggest that schools are related to certain types of crime at the block group level. Therefore, we find partial support for hypothesis 1, which stated that schools are related to neighborhood crime. The Wald tests of significance for the school presence coefficients suggest that, for certain types of crime, block groups with schools differ from block groups without schools. Moreover, the log-likelihood ratio tests reported in the results section suggest that the inclusion of school presence variables improves the model fit for the regressions on rape, aggravated assault, larceny, and narcotics incidents above and beyond structural disadvantage, instability, and population makeup. Beyond issues of statistical significance, many of the correlations for school presence are quite large (see, for example, the coefficients for high school presence associated with narcotics violations). Conversely, both the Wald and log-likelihood ratio tests suggest that schools are largely unrelated to homicide, robbery, burglary, and motor vehicle theft at the block group level.

Our regression results using school presence indicators suggest that different types of schools have different relationships with crime at the block group level. Specifically, high schools appear to be associated with increases in aggravated assaults, larceny, and narcotics crime at the block group level. Middle schools appear to be associated with increases in narcotics offenses at the block group level. Elementary schools, with the exception of a positive relationship with rape, are generally unrelated to violent crime at the block group level. However, block groups with elementary schools have significantly less burglary and larceny, suggesting that elementary schools might be a protective factor against property crime at the block group level. These results, however are not consistent for all crime types, as evidenced by the significant positive relationship between elementary schools and rape. These results provide partial support for hypothesis 2, which stated that high schools would be associated with more neighborhood crime than middle schools, which, in turn, would be associated with more neighborhood crime than elementary schools. In addition, these results offer some support for hypothesis 5, which suggests that elementary schools will offer more protection from crime at the community level than other types of schools since they promote more community involvement than do middle and high schools.

The majority of our results can be explained from the routine activity and social disorganization perspectives. The routine activity perspective argues that areas with schools should have higher crime rates to the convergence of offenders and victims. However, high school aged students are more likely to be both offenders and victims of crime than middle school and elementary school aged children (Farrington, 1986). Therefore, it is unsurprising that high schools appear to generate more crime than middle schools and elementary schools. Moreover, it is also unsurprising that school presence is unrelated to serious crimes like homicide, robbery, burglary, and motor vehicle theft. Juveniles are more likely to be the offenders and victims of less serious crimes and thus, the convergence of students at school would not necessarily lead to increases in serious crimes.

The social disorganization and routine activity frameworks can also provide explanations for the seemingly protective nature of elementary schools. Block groups with elementary schools are likely to be occupied by more families and the families are more likely to be involved in school-related activities. This suggests that these neighborhoods may be more likely to be socially organized. Bivariate correlations, however, do not provide strong evidence of this possibility. While the correlation between elementary school presence and instability is significant (r= - 0.95), it is of modest strength. Moreover, the correlation between disadvantage and elementary school presence, while also negative, is not statistically significant. Of course, our disadvantage and instability measures are rough indicators of social disorganization. It may be the case better measures of social organization (i.e., actual measures of neighborhood networks and collective efficacy) might demonstrate a stronger link between elementary school presence and social organization. The student to teacher ratio is also smaller for elementary schools than for other schools, suggesting a greater amount of supervision and adult presence. And finally, elementary school aged-children are less likely to be offenders and victims. This increased supervision and relative absence of motivated offenders and suitable targets suggests that the routine activity patterns of these neighborhoods may not be conducive to crime.

Some of our results, however, are less straightforward. The positive relationship between rape and elementary schools, for example, is surprising. It seems unlikely that the elevated rape counts in block groups with schools are the result of the presence of motivated elementary-school aged offenders. It may be the case that rape is more likely to be reported in neighborhoods with elementary schools. Unfortunately, we are only able to speculate on the relationship between elementary schools and rape at the block group level. Additional research, in other cities, should be conducted in order to determine if this finding is part of a larger trend or something specific to Albuquerque.

The regression results using quality of school indicators are less clear than the results using school presence indicators. Both the social disorganization and routine activity perspectives would seem likely to predict that below average schools should be more strongly related to crime than above average schools. Controlling for other factors, this was the case for middle schools, where block groups with below average middle schools reported significantly more crime than block groups without middle schools and block groups with above average middle schools. Similarly, block groups with below average high schools reported significantly more larcenies than block groups without high schools or block groups with high schools. However, block groups with above average high schools reported more aggravated assaults and narcotics incidents than block groups with below average or no high schools. And block groups with below average elementary schools reported significantly less burglaries and larcenies than block groups with above average elementary schools and block groups with no elementary schools. In sum, the current research did not support hypothesis 4, which stated that higher quality schools would be associated with lower levels of crime, while lower quality schools would be associated with higher levels of crime.

Ultimately, it is not clear that quality of school is related to crime at the block group level. While the coefficients for the disaggregated school quality indicators suggest, in certain cases that block groups with below or above average schools will have a significantly different amount of crime than other block groups, the log-likelihood ratio tests suggest that these measures did not improve model fit. In other words, it is not clear that including quality of school measures is statistically superior to including school presence measures.

The temporal analyses, conversely, produced several interesting results that seem to support a routine activity perspective. In general, these results supported hypothesis 3, which stated that schools would be associated with higher levels of crime during the hours directly before, during, and after school. For example, middle schools were largely unrelated to violent crime in the original school presence model. When disaggregated by time, however, block groups with middle schools reported significantly more crime in the morning commute, school session, and afternoon commute hours than block groups without middle school. Similarly, the coefficients for high school presence were larger and more significant in the school session and afternoon commute than during any other times of the day. Interestingly, block groups with high schools were not significantly different than block groups without high schools during the morning commute hours. This may be due to the fact that a large proportion of high school students commute to school in cars, thus minimizing their contact with each other. Of course, these students are also likely to drive home. It may be the case however, that they are more likely to converge with each other after school in nearby areas, thus accounting for the increases during the afternoon commute hours. Conversely, the relationship between elementary schools and property crime was fairly consistent, regardless of time of day. This may suggest that the organizing influence of elementary schools as a local institution are more important in terms of reducing crime than any routine activity patterns associated with elementary school presence. This conclusion is more in line with the social disorganization perspective than the routine activities perspective. In sum, the temporal results suggest that the relationship between schools and crime at the block group level varies by time of day. The fact that this relationship varies in strength and significance seems to support the routine activity perspective that sees schools as a nexus in which offenders and victims meet in the absence of capable guardians.

There are several limitations to this research. First, and foremost, our data come from a single city over a specific time period. Additional research in different contexts is necessary before hard conclusions about the relationship between schools and crime at the block group can be made. Also, this research is largely descriptive in nature. While we have attempted to control for a wide variety of social and economic indicators, it is still possible that other, unmeasured factors account for the relationship between schools and crime at the block group level. Additional research, both in the form of longitudinal quantitative work and qualitative studies, is needed to get a better understanding of the role that schools play in neighborhood crime.

We find that our results largely support a routine activity perspective on the relationship between schools and crime. Unfortunately, our data cannot describe the processes through which schools either promote or prevent crime. Therefore, while our findings are supportive of certain theoretical traditions, we are unable to verify that these processes are definitely at work. Moreover, because we do not have data on the ages and addresses of offenders in our sample we are unable to make any definitive claims regarding the offenders within block groups. If the routine activity perspective is correct, it would seem logical that high school and middle school students were responsible for a large proportion of the crime that happens in block groups with school. Of course, the presence of schools might also attract both recent graduates, who have ties to other individuals in the schools, and older offenders to neighborhoods. Future research on schools and crime should consider the characteristics of offenders within neighborhoods in order to better specify how and why schools are related to crime.

In addition to these issues, our research may be critiqued for unduly focusing on serious offenses. It should be noted that there are several reasons to examine serious crimes. First, serious offenses are less likely to suffer from underreporting. Second, serious offenses are likely to cause more societal harm. It may be the case that schools are more likely to be related to less serious crimes. Future research focusing on the relationship between schools and less serious offenses seems fruitful.

Despite these limitations, we feel that the current research is valuable in many ways. This research has demonstrated that schools are associated with certain types of crime at the block group level, even after controlling for a number of factors that are known to be associated with crime. Beyond this, this research also suggests that school level moderates the relationship between school presence and crime in varying ways. And finally, our temporal analyses lend weight to the routine activity perspective, as we find that schools are more strongly associated with crime during the morning commute, school session, and afternoon commute hours.

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