Community characteristics and special education enrollment rates in Montana

Klarissa L. Jensen

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COMMUNITY CHARACTERISTICS AND SPECIAL EDUCATION

ENROLLMENT RATES IN MONTANA

By

Klarissa Jensen

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Community Characteristics and Special Education Enrollment Rates in Montana

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Social disorganization is the leading criminological theory that explains how and why community characteristics influence crime and delinquency rates. Community characteristics of social disorganization include poverty, cultural heterogeneity, and residential mobility. Social disorganization is associated with weakened social relationship ties and a loss of informal social control, resulting in high rates of community social problems.

This study extends social disorganization theory to predict special education enrollment rates in rural areas. An analysis of the structural correlates of special education enrollment rates in 56 Montana counties was conducted. This rural application of social disorganization theory to Montana counties held up fairly well with significant association between the structural characteristics and rates of special education enrollment as a social problem. Special education enrollment rates were found to be associated with low socioeconomic status, ethnic heterogeneity, and income inequality. However, the family disruption characteristic was highly correlated with ethnic heterogeneity, resulting in collinearity. Of the two, ethnic heterogeneity was a more powerful dependent predictor and kept in subsequent analysis. A path model and regression analysis was used to identify all direct and indirect influences on Montana special education enrollment rates. Ethnic heterogeneity was found to be the structural characteristic most influential in special education rates.
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Community Characteristics and Special Education Enrollment Rates in Montana

Across the state of Montana, enrollment rates in special education in public schools vary among counties, suggesting that community characteristics such as poverty, residential mobility, ethnic diversity, and family disruption influence such rates. If so, understanding how these factors affect enrollment rates may provide schools with new information useful for assisting students facing these vulnerabilities.

The notion that community characteristics influence the occurrence of various social problems is an old one, dating back to the turn of the century and the origins of the "Chicago School" of sociology. The Chicago School holds that characteristics of urban communities, especially those indicative of social disorganization significantly influence rates of social problems. The Chicago School advanced five key aspects of community social disorganization: (1) density; neighborhood crowding, (2) poverty; poor families, and single parent households, (3) mixed use; areas used for industry as well as residential space, (4) transience; high population turnover, (5) dilapidation; physical deterioration of neighborhoods (buildings, etc.) (Stark 1987:895). Social disorganization leads to a breakdown in informal control. Community informal control is the networks or ties with family, friends, and neighbors that produce supervision and guardianship of children and property (Sampson and Groves 1989). This type of breakdown produces an array of social vulnerabilities among residents and their neighborhoods, including crime and delinquency, drug and alcohol addiction, suicide, and school truancy/dropout. The influence of community characteristics on various social problems have been applied most extensively in the theory and research of Clifford Shaw and Henry McKay in an attempt to explain variations in delinquency rates across Chicago.
My research will apply the basic structural characteristics, ethnic heterogeneity, residential mobility and low socioeconomic status, found in Shaw and McKay's theory of social disorganization to special education rates in Montana. The application of this particular theory is significant in two ways. First, social disorganization was advanced as an urban phenomenon; however, here it is applied to a rural environment. For this rural application, I will draw upon the work of D. Wayne Osgood and Jeff M. Chambers who applied social disorganization theory to rural areas in an effort to explain variations in rates of delinquency. This new approach holds potential in extending our understanding of rural community influences. Second, in this study, special education enrollment rates will replace rates of crime and delinquency as a social problem explained by social disorganization.

The basic structural characteristics of social disorganization, ethnic heterogeneity, residential mobility, and low socioeconomic status, influence a community's ability to develop and maintain social networks needed for adequate informal social control. The research here will apply the same basic characteristics of social disorganization in identifying variations in special education enrollment rates throughout Montana. The main characteristics and influences found in social disorganization theory are first identified, followed by the recent rural application of D. Wayne Osgood and Jeff M. Chambers. A regression analysis of the data set is utilized in predicting special education enrollment. A discussion of relevant finding related to social disorganization theory will follow the data analysis.
LITERATURE REVIEW

Social Disorganization Theory

Growing out of the Chicago School of Sociology, social disorganization has been a leading criminological theory used by researchers to relate structural characteristics such as economic status, residential instability/mobility, ethnic diversity, and family disruption to rates of crime and delinquency as well as other social problems. The assumption is that communities have unique structural characteristics that distinguish one community from another. Communities experiencing these disadvantaged structural characteristics suffer a breakdown in the informal social control that once held the community together. A breakdown in informal control is a community’s inability to realize common goals and values necessary for the development of cohesive social networks and needed resources (Bursik and Grasmick 1993). Communities that experience this loss of informal social control are unable to control unwanted social problems effectively such as reported crime and delinquency (Shaw and McKay 1929, 1942, 1969; Bursik 1988; Bursik and Grasmick 1993). Communities experiencing these detrimental breakdowns become more readily available to the poor. This availability is driven by the community’s low socioeconomic position making housing more abundant and financially accessible. This can produce generational poverty and/or cycles of impoverished residents that move in and out pushing a community further into despair. Therefore, an identification of these specific disadvantaged community characteristics can provide insight into the social problems experienced in these areas.

Structural characteristics of a community can be influenced directly by its geographical location. Areas adjacent to city centers often transform from a residential to
a more industrial function as they grow and expand leaving city center residents and neighborhoods vulnerable to social disorganization. Shaw and McKay in their first analysis of these issues found that a communities geographic location influenced not only the development of unfavorable structural characteristics found in social disorganization theory (low economic status, ethnic heterogeneity, and residential mobility), but also produced higher rates of crime and delinquency (ecological distribution of crime and delinquency). Building on the concentric zone model of Robert Park and Ernest Burgess, Shaw and McKay (1929) found that residents caught in this unique community transformation faced the weakening, or in some cases the disappearance of the common values and norms once held (Shaw and McKay 1929, 1942 revised 1969; Stark 1987). Shaw and McKay ultimately classified these communities as socially disorganized due to the change in environment and value structure that led to a loss of social control of crime and delinquency. A clear understanding and identification of these three structural characteristics found in social disorganization theory may provide insight into how communities develop unwanted social problems.

**Structural Characteristics**

**Residential Mobility and Ethnic Heterogeneity.** Residential mobility is defined as an increase or decline in population and/or constant turnover. Ethnic heterogeneity is a rise in mixed ethnic populations resulting in competing cultures and backgrounds. Communities that experience residential mobility and/or ethnic change face a breakdown in relationships and communication. This breakdown emerges when residents no longer identify with one another due to their differing and/or competing cultures and traditions. These residents also suffer from a lack of collective experiences once shared with
neighbors in the community (Sampson and Groves 1989; Osgood and Chamber 2003).

Due to constant population turnover, differing values among residents, and lack of common goals, fear and mistrust develops, further weakening the social networks once used for informal and formal social control (Shaw and McKay 1929, 1942, revised 1969; Elliott 1996; Suttles 1968; Kasarda and Janowitz 1974; Sampson and Groves 1989). Constant population turnover provides residents with fewer opportunities to develop and maintain personal ties with one another and their community. The familiar resources such as government agencies, babysitting, and job resources, once used or known by residents change due to these community population shifts. The lack of interconnectedness among members produces less involvement in civil engagement and organized activities such as PTA (Parent Teacher Association), Community Development Associations, or any type of participation in local affairs (Fischer 1982; Irwin, Tolbert, and Lyson 1999; Barnett and Mencken 2002; Stark 1987). A combination of residential mobility and ethnic change produces a greater breakdown in a communities’ ability to function as a cohesive unit and source of social control (Kasarda and Janowitz 1974; Crutchfield et al. 1982; Smith and Jarjoura 1988; Sampson and Groves 1989; Stark et al. 1983; Stark 1987; Barnett and Mencken 2002).

**Low Socioeconomic Status.** Low socioeconomic status is defined as a specific economic level of a community. These low socioeconomic areas lack the resources and opportunities necessary for financial stability putting them below or in severe poverty. Socioeconomic status (SES) has long been used as an ecological correlate mainstay of crime and delinquency (Shaw and McKay 1942; Kornhauser 1978; Bursik 1984; Byrne and Sampson 1986; Elliott et al. 1996). Several studies have found that communities
characterized by high poverty also experience higher rates of delinquency (Osgood and
Chambers 2003; Warner and Pierce 1993). Shaw and McKay (1942: 317) observed,
"Variations in rates of officially recorded delinquents in communities of the city
correspond very closely with variations in economic status." Low SES communities
have weak organization due to economic strain and blocked common goals, which can
lead to involvement and/or association with criminal behavior. Communities
characterized as weakly organized have not developed the essential community ties
necessary for successful social control. In these communities, people feel vulnerable and
are less likely to get involved when they witness illegal activities for fear of reprisal.
Residents in these communities are also less likely to get involved due to self and/or
family member involvement in illegal activities brought on by economic hardships. This
involvement is based on a resident's need to gain economic security through whatever
means available even illegal. Therefore, communities faced with these economic strains
begin to see the criminal justice system as one that is working against them due to their
illegal activity. Association with criminal behavior furthers a community's social decline
by blocking the connections between residents and the criminal justice system, as well as
other government agencies (Kornhauser 1978; Bursik 1988; Sampson 1988; Sampson
These economic hardships and lack of access to opportunities and resources undermine
community social networks needed for informal social control, further compromising
community stability (Wilson 1987; McLoyd 1990; Thornberry et al. 1999). For the
residents that are financially unable to relocate, this disparity is passed from generation to
generation as a social tradition producing generational communities that are economically
blocked. As others gain financial ability to relocate, the area becomes more readily available to residents who share the same financial hardships experienced by those who remain. This population turnover, when combined with low socioeconomic status, further weakens the community and its networks.

Theorists have expanded low SES to include the stigmas that may be attached to the lower class. Communities and residents experiencing low socioeconomic status may also acquire inferior stigmas. This stigma or status can further block communities from opportunities to gain the desired success realized by other affluent neighborhoods. For example, businesses that could provide opportunities for residents become less inclined to develop in these areas due to their prevailing economic position. Residents who are more economically secure will relocate to a better area or will never enter the community in the first place, leaving only those residents who are unable to relocate. This pushes communities further into alienation, segregation, and discrimination brought about by low economic status. These low-income communities produce a “virtual under class” who are disproportionately involved in serious offenses due to their inability to secure legitimate economic means (Stark 1987: 894). The residents that remain in these stigmatized communities are blocked from secure employment, training, education, or other opportunities that would allow them to advance and succeed socially and economically.

Status and stigma are not exclusive to communities or residents; schools can also be subjected to stigmas. The schools’ geographical location in a neighborhood and students’ economic and/or social class can result in unwanted school stigmas and/or status. Where a school is located and what economic or social class attends will identify
the school as having a certain status or stigma. According to Gottfredson, the social class of a school had greater effects on delinquent activities and behaviors than the economic status of the individual and/or family (Gottfredson 1991: 201). Ultimately, a community that experiences a shift from social and economic advantage to disadvantage will suffer a decrease in organization and social control that influences all surrounding environments including schools.

**Social Disorganization Theory Expanded**

Shaw and McKay argue that communities in transition experience three main disadvantaged structural characteristics: low economic status, ethnic heterogeneity, and residential mobility. They classify these communities as socially disorganized with diminished social control. Over the years, several authors have interpreted and expanded on Shaw and McKay’s social disorganization theory.

**Income inequality as a structural characteristic.** Sampson and Groves (1989) expanded social disorganization theory and the focus of low SES to include income inequality. Low SES communities suffer income inequality due to the varying degrees of poverty. This added another dimension to the structural characteristics found to play key roles in increasing social disorganization and compromised community social control (Barnett and Mencken 2002). Like SES, income inequality can interfere with member communication and impede consensus on goals, values, and norms, leading to a breakdown in social control (Sampson and Groves 1989; Land et al. 1990; Messner and Rosenfeld 1994; Osgood and Chambers 2000; Barnett and Mencken 2002).

**Family Disruption as a structural characteristic.** Family disruption is defined as single parent households and/or limited opportunity of parental resources for money,
time, and energy. Sampson and Groves (1989) expanded social disorganization theory by adding family disruption to the disadvantaged structural characteristics. Due to this breakdown in the family unit, the prevalence and supervision of teenage peer groups and activities is directly affected (Thrasher 1936; Cohen and Felson 1979; Reiss 1986; Sampson and Groves 1989). According to Thornberry and his colleagues (1999: 1), family disruptions can “set in motion changes in residence, financial conditions, family roles, and relationships along with increased stress and conflict in the home.” Children that live with only one parent and/or are experiencing one or more of these disruptions are more likely to develop emotional and behavioral problems, such as delinquency (Sampson 1987; Thornberry et al. 1999).

Community influences on school attendance/truancy. Shaw and McKay drew several conclusions from their study of juvenile delinquency. For the purpose of this study, only the conclusions in reference to the community and school truancy will be listed.

1. There are marked variations in the rate of school truants, juvenile delinquency, and adult crime between areas in Chicago. Some areas are characterized by very high rates, while others show very low rates.

2. The rates of truancy, delinquency, and adult crime tend to very inversely in proportion to the distance from the city center. In general the nearer to the center of the city a given locality is, the higher will be its rates of delinquency. The central fact is that great differences in rates do exist between communities.

3. There is similarity in the distribution of truants, juvenile delinquents, and adult criminals in a city. Those communities that show the highest rate of juvenile delinquency also show, as a rule, the highest rates of truancy and adult crime.

4. Differences in rates of truancy, delinquency, and crime reflect differences in community background. High rates occur in areas, which are characterized by physical deterioration and declining population. Comparisons between high and low rate areas which are studied in detail
should reveal significant social factors in delinquent areas. (Shaw and McKay et al. 1929: 198-203).

According to Shaw and McKay, communities that experienced high rates of school truancy also suffered from higher rates of juvenile delinquency and adult crime. Shaw and McKay (1942) furthered their study of the ecological distribution of delinquency in their book *Juvenile Delinquency and Urban Areas* (revised in 1969). Here they conclude that once again the data supports the original theory of a direct relationship between the structural characteristics of a community (low economic status, ethnic heterogeneity, and residential mobility) and variation in rates of crime and delinquency. They found that “Chicago rates of delinquency for many years have remained relatively constant in the areas adjacent to centers of commerce and heavy industry; despite successive changes in the nativity and nationality composition of the population supports emphatically the conclusion that the delinquency producing factors are inherent in the community” (Shaw and McKay 1942: 315). Communities experiencing these unfavorable structural characteristics suffer from competing values, ultimately influencing how residents form social attachments and organize daily routines. The differences observed in the behaviors of area residents are reflective of the adaptation to the social values, norms, and attitudes to which they are exposed through the community, family and friends.

*Change in Views of Social Disorganization Theory*

Ruth Kornhauser (1978) in her book *Social Sources of Delinquency* saw social disorganization as a lack of value consensus both within and between the different cultures that make up the community. She concludes that the social disorganization of
divergent cultures lacks the ability to establish social control. Building on Shaw and McKay, Kornhauser saw a chronological order to the structural characteristics of social disorganization theory. Low economic status, residential mobility, and ethnic heterogeneity, in this order, account for the variation in controls and collective supervision of children within communities. Kornhauser's new approach to social disorganization theory shifted the focus to social relationships within the community that function as social controls. This new theoretical perspective assumes the level of social disorganization can be calculated by the observed presence or absence of collective child supervision and social networks that function as informal and formal controls (Thomas and Znaniecki 1958; Shaw and McKay 1942, revised 1969; Kasarda and Janowitz 1974; Skogan 1986; Stark 1987; Sampson 1987; Sampson and Groves 1989; Gottfredson, McNeil, and Gottfredson 1991; Bursik and Grasmick 1993; Elliott et al. 1996).

Recent studies have focused on the mediating or intervening variables between a community's structural characteristics and individual behavior/development. These mediating or intervening components are the networks or ties with family, friends, and neighbors and the supervision and guardianship of children and property. However, these studies have still produced support for the direct impact of structural characteristics found in social disorganization theory. In their analysis of social disorganization, Sampson and Groves (1989) conclude that even though there were intervening/mediating variables, these variables did not mediate all structural effects found to influence communities and their residents. Sampson and Groves (1989) also concluded that structural characteristics might in fact influence the mediating or intervening variables found in the community. Delbert Elliott and colleagues (1996) found that structural characteristics substantially
influenced the mediating or intervening variables. From their analysis, they saw organization or disorganization of a community as mediating the effects of certain structural characteristics or ecological disadvantage on child development and behavior. They reveal that structural characteristics or disadvantage (poverty, mobility, family structure, and ethnic diversity) significantly affects the level of perceived informal control (Elliott et al. 1996: 413). The more a community experiences disadvantage the less informal control it has. Therefore, a community characterized as structurally disadvantaged with a loss of informal control has a direct influence on youth development and/or delinquent involvement.

Cantillon, Davidson, and Schweitzer (2003) also looked at the mediating or intervening effect of social relationships in communities. They saw social disorganization theory as an explanatory framework that links disadvantaged community characteristics with the level and extent of community organization, which in turn affects youth outcomes such as delinquency and GPA. Their focus was on the sense of community (SOC) measures and their mediating effects on youth outcomes such as delinquency, grade point average (GPA), and involvement in conventional activities. Sense of community has been conceptualized as four distinct aspects: “membership, influence, sharing of values with an integration and fulfillment of needs, and a shared emotional connection” (Cantillon, Davidson, and Schweitzer 2003: 324). According to Cantillon and his colleagues, SOC mediated the structural effects of the community on youth development and involvement in conventional activities. However, the level of SOC found was directly influenced by the communities’ disadvantaged structural characteristics. In their study, communities with high SOC also had students who were
more involved in school activities when compared to those with low SOC. Their study used participation in school activities as a measure of conventional student involvement, which was found to be the best predictor of GPA. Cantillon and his colleagues found that on average, communities identified with high SOC had higher participation in school activities and received better grades than those with low SOC. Based on their findings they conclude that local community characteristics play a key role in determining the level of SOC that influences a youths‘ ability to bond, participate and ultimately succeed in school. The more cohesive a community is the higher the level of SOC and the greater the effects on youth development. Therefore, the level of SOC in the area will evolve with the changing structural characteristics of the neighborhood, ultimately affecting youth development.

*Rural Area Application*

There are few known studies that have looked at variation of crime rates in rural areas: Arthur (1991) with a study of rural crime in 13 small Georgia counties, Wilkinson (1984) contrasting homicide rates to other social problems, and Petee and Kowalski (1993) with a brief study applying social disorganization theory to rural county level crime rates; and Barnett and Mencken who researched the influences of population change and low socioeconomic status (SES) on rural communities (Osgood and Chambers 2000: 83-84).

Wilkinson (1984b) used a systemic model that included mediating /intervening variables to account for the variations in crime rates, along with other identified social problems found in rural areas. He concluded that close family and friend relationships (informal control) in rural areas make up the majority of the social networks due to the
limited population. Strong networks establish social control and reduce crime rates. Therefore, residents with weak community ties lack support leaving them vulnerable to certain types of crimes.

In their brief article Petee and Kowalski (1993) tested social disorganization theory and rural crime rate prediction. In their study, some of the structural characteristics derived from Shaw and McKay were applied to rural areas. They found that residential mobility, family disruption, and heterogeneity affected rural crime rates, but excluded poverty and population density due to their nonsignificance.

Barnett and Mencken found that in non-metropolitan counties, population and low socioeconomic status (SES) interact to affect social control in disadvantaged rural communities. They also found rural areas that lost population experienced a greater influence of SES on crime. Population loss and low SES interact to influence social organization and support in rural areas. These communities ultimately lose the social structures and networks required for effective social control and support. This loss negatively affects the community and resident survival (Barnett and Mencken 2002: 386-9).

The theoretical and empirical research associated with social disorganization theory has been applied predominantly to urban areas. Osgood and Chambers were the first to systematically apply social disorganization theory to rural communities (Sampson 1985; Sampson and Groves 1989; Osgood and Chambers 2000: 83). The application of social disorganization theory to include rural areas has been supported through the use of national samples (Osgood and Chambers 2000). According to Osgood and Chambers, the relationship between the structural characteristics of social disorganization theory and
rates of crime “have long provided the core empirical support for this theory” (2000: 86). They contend “the only aspect of this theory that is uniquely urban is the explanation of why social disorganization develops in some geographic locations rather than others, such as Burgess’s (1925) notion of concentric rings of urban development” (Osgood and Chambers 2000: 85). Therefore, Osgood and Chambers argue that the same guiding principle found in the urban studies of social disorganization can be applied to rural areas. They do, however, modify the poverty structural characteristic by separating it into two components. The first, seen as simple poverty is defined as “the proportions of persons living below the poverty level.” The second, extreme poverty is defined as “the proportion of persons living below half of the poverty level” (Osgood and Chambers 2003:94-95).

The structural characteristics of a community influence and in some cases destroy its ability to maintain informal social control. With diminished social organization and lack of relationships or social networks, communities suffer from unwanted social problems in both rural and urban areas. The structural influences change a community by breaking down and/or stopping the development and exchange of social networks and relationships that establish various needed ties between community, family and friends.

SOCIAL DISORGANIZATION THEORY AND RATES OF SPECIAL EDUCATION ENROLLMENT

The structural characteristics identified by Shaw and McKay, and the more recent work of Osgood and Chambers’ provide the framework for my analysis. The objective of this study is to test the theory’s applicability to rates of other social problems found in a community such as special education enrollment rates. My study will test social
disorganizations' structural characteristics (ethnic heterogeneity, residential mobility, low SES, income inequality, and family disruption) and their ability to predict special education enrollment rates in Montana. Enrollment rates in special education will replace delinquency as the primary social problem predicted by the above structural characteristics. To account for the systemic model (analysis of mediating/intervening variables) included in some social disorganization research, an integration of community and individual level analysis would need to be performed. Due to the limitation of my data, I will not integrate community and individual levels.

Below is a hypothesized linear causal flow model of how the structural characteristics of social disorganization theory influence enrollment rates in Montana counties special education programs.

![Figure 1. Hypothesized Linear Social Disorganization Model.](image)

Social disorganization theory identifies that certain disadvantaged structural characteristics influence a community’s ability to develop and maintain needed networks and ties for effective informal control. To test the theory’s ability to predict rates of special education enrollment in place of delinquency, I will examine the relationships of these structural characteristics to rates of enrollment in Montana. The relationships hypothesized between the five structural characteristics (ethnic heterogeneity, residential...
mobility, low SES, income inequality, and family disruption) and special education enrollment rates, replacing delinquency, coincide with previous research. These relationships have provided the core empirical support for the theory in rural areas and delinquency rates.

**Hypothesis 1.** Rates of special education enrollment in Montana counties will be positively related to *residential mobility*. Population turnover causes a break down in communication and in the community’s ability to function as an element of social control by weakening needed informal social networks and community organization (Shaw and McKay 1929, 1942, revised 1969; Bursik 1988; Elliott et al. 1996; Suttles 1968; Kasarda and Janowitz 1974; Sampson and Groves 1989; Osgood and Chambers 2000).

**Hypothesis 2.** Rates of special education enrollment in Montana counties will be positively related to *ethnic heterogeneity*. The decline in ethnic heterogeneity or change in a community’s population produces fear or mistrust among residents weakening social networks needed for informal social control (Shaw and McKay 1929, 1942, revised 1969; Elliott et al. 1996; Suttles 1968; Kasarda and Janowitz 1974; Sampson and Groves 1989).

**Hypothesis 3.** Rates of special education enrollment in Montana counties will be positively related to *low socioeconomic status program enrollment (low SES program enrollment)*, a county poverty indicator. This structural characteristic of social disorganization theory has been a mainstay for the ecological correlation of crime and delinquency. The relationship between low SES and rates of special education enrollment is hypothesized as being the same relationship as that found between low SES and delinquency. Studies done on urban communities have found that with higher rates of poverty there also is a higher rate of delinquency (Warner and Pierce 1993; Osgood
and Chambers 2000). Communities with low economic status / poverty lack the adequate money and resources needed for organization leaving them weak and vulnerable to crime (Sampson and Groves 1989). Incomes are a factor in determining social class of a community and according to Stark (1987) residents in these areas are disproportionately involved in crime. Gottfredson (1991) also found delinquency rates related to ascribed social class, but found that the status structure of the school had a greater impact on delinquent behavior. Therefore, low socioeconomic status program enrollment / poverty impacts community’s ability to maintain or develop the social organization needed for adequate informal social control.

**Hypothesis 4.** Rates of special education enrollment in Montana counties will be positively related to *income inequality*. Income inequality as a structural characteristic of social disorganization interferes with member communication impedes consensus on goals, values, and norms leading to a breakdown in informal social control (Sampson and Groves 1989; Land et al. 1990; Messner and Rosenfeld 1994; Osgood and Chambers 2000; Barnett and Mencken 2002).

**Hypothesis 5.** Rates of special education enrollment in Montana counties will be positively related to *family disruption* (divorced and/or single parent household). This is an addition by Sampson and Groves (1989) to the structural characteristics of Shaw and McKay (1929, 1942, and 1969). Researchers have found that rates of delinquency are higher in areas characterized by higher rates of family disruption. The relationship between family disruption and special education enrollment rates is hypothesized as being the same relationship as that found between family disruption and delinquency. According to Sampson (1988), parents under these circumstances experience a strain on
METHODS

Sample

This is a county-level analysis based solely on the state of Montana, including all fifty-six counties. Due to the availability of information at the county level, this becomes the most convenient unit of analysis to test structural characteristics on special education enrollment rates. The 2000 Montana Kids Count Book published by the Bureau of Business and Economic Research (BBER) provided the data for this study. The BBER obtained data from 2000 U.S Census, U.S Department of Commerce, Montana Dept. of Labor and Industry's Research and Analysis Bureau, Montana Department of Public Health and Human Services, and Montana Office of Public Instruction (OPI).

Measures

Dependent Variable: Special education enrollment rates. The Office of Public Instruction gathers county-level data yearly for the state of Montana. The measure of special education enrollment is the number of students enrolled in each county program. These data are the starting point for analysis of Montana special education enrollment rates, replacing the measure of rural delinquency/crime relied on in the previous county-
level studies. The measures used are the percentage of students **enrolled in Montana public schools’ special education program** for the 2000-2001 school year (OPI 2000-2001).

**Explanatory Variables.** The measures used for the explanatory variables were found in social disorganization theory.

1) **Residential mobility:** Following previous research residential mobility or instability is defined as the percent of individuals moving from or into an area in the previous ten years (Osgood and Chambers 2000; Sampson 1985; Warner and Pierce 1993). The measure used is the **percent population change** from Census 1990 to Census 2000 for Montana counties.

2) **Ethnic Heterogeneity:** Following previous research in this area, ethnic heterogeneity is defined as the percent of non-white populations in an area (Osgood and Chambers 2000; Sampson and Groves 1989). The measure used is the percentage of all **nonwhite residents under 18 years of age** in each Montana county for 2000 (Census 2000).

3) **Low Socioeconomic Status Program Enrollment (low SES program enrollment rates) indicators:** Following previous research in this area, my study will use available county-level data that indicates limited access to resources and certain income based program enrollment that indicates low SES (Shaw and McKay 1942; Kornhauser 1978; Wilkinson 1984; Bursik 1984; Byrne and Sampson 1986; Sampson and Groves 1989; Land et al. 1990; Conger et al. 1994; Elliott et al. 1996; Osgood and Chambers 2000; Barnett and Mencken 2002). One measure used as a low SES indicator is the percent of children enrolled in CHIP (a medical assistant program for children not covered by any
other insurance or ineligible for Medicaid services) for 2000. The second measure of low SES is the average number of children per month between ages 0-19 who are recipients of Medicaid for 2000 (Census 2000 and CHIP 2000). However, my study uses these as two separate measures, based on Osgood and Chambers' (2000) test of social disorganization theory, dividing poverty into two groups simple and extreme. Simple poverty is defined as “the proportions of persons living below the poverty level and extreme poverty is defined as “the proportion of persons living below half of the poverty level” (Osgood and Chambers 2003:94-95). These two divisions help divide CHIP and Medicaid enrollment into two separate measures based on differences in eligibility criteria for each program. CHIP is a program that provides medical assistance to those who do not or cannot obtain insurance due to low income (the working poor). Medicaid is a program providing assistance to those in a more severe state of poverty.

4) Income Inequality. Osgood and Chambers (2000) used unemployment rate as a poverty or economic resource variable in their analysis of social disorganization theory. For this study, two variables make up economic resources found in counties: the percent of the population currently not in the workforce and the counties’ estimated median income. The measures used for these two indicators of income inequality are the overall unemployment rate for 2000 (Local Area Unemployment Statistics (LAUS) data, Montana Dept. of Labor and Industry's Research and Analysis Bureau) and each Montana counties’ estimated median income for 2000.

5) Family disruption: According to Osgood and Chambers (2000), “the burden of monitoring the behavior of children and teens fell disproportionately on mothers in households with children, so that the proportions of mothers without partners would be
most relevant to delinquency.” The measure used is the percentage of female householders with no husband present and with children less than 18 years for 2000 (Census 2000).

**Statistical Methods**

Various correlation methods will be used to assess all possible effects and paths. The methods used for this study include descriptive, correlation, factor, reliability, multiple regression and path analysis.

**Analysis**

A descriptive analysis helped identify data errors, distributions and measures of central tendency (see Appendix Table). Variables in the model exhibited fairly normal distributions. On average, counties in Montana experienced only a 5.16 percent change in population from 1990-2000. For 2000 Montana counties had an average estimated median income of $31,228.23, average unemployment rate of 4.88 percent, an average Medicaid enrollment of 9.79 percent, average CHIP enrollment of 5.52 percent, average female head of house with children 0-18 of 4.84 percent, average county non-white population of 12.30 percent, and an average rate of special education enrollment of 8.67 percent.

A correlation matrix indicated the strength and direction of the relationships of interest (see Appendix Table 2). With a high correlation found among two of the independent variables ethnic heterogeneity and family disruption, factor analysis helped identify any variables that could be combined into one factor (see Appendix Table 3). From this there appeared to be two factors with most of the variables loading on the first. Female Head of House and Non-White population under 18 years of age loaded high on
the first factor. According to the reliability analysis these two variables were nonadditive and would need standardization (scaled the same) before being combined into one index (see Appendix Table 4). Before combining the variables into an index and after identifying the violations of the assumptions needed to perform regression, all single independent variables were regressed on Montana county special education enrollment rates. When testing the regression analysis with all independent variables the collinear relationship, a regression assumption violation, between Female Head of House and Non-white Population 0-18 years of age was not the only problem found. The variables Female Head of House and Non-white Population 0-18 years of age switched from a positive to a negative relationship with the dependent variable when holding everything constant. This switch indicated that Female Head of House was a suppressor variable. Due to this variable not being as strong a predictor and operating differently against the dependent, it was initially withheld from the model. The variable Non-white Population also acted as a suppressor, and theoretically, of the two collinear variables Non-white Population was more likely a constant in Montana counties. In addition, Non-white population was most likely predictive of Female Head of House in subsequent regressions with both measures being retained.

The overall theoretical Path Model, in figure 2, illustrates how each step builds on the previous to identify all possible main effects. The first step consisted of Estimated Median income for 2000 being regressed on two variables, Non-white populations under 18 years of age and Population change from 1990-2000. Then unemployment rate replaced Estimated Median income to be regressed on the same two variables. Similarly, Medicaid and CHIP provided the next two steps and were both regressed on all four
variables. The final step regressed Special Education Enrollment Rates on the pool of predictor variables in the model.

Figure 2. Special Education Enrollment Path Model.

Due to the limited number of counties in Montana, every relationship with a significance level of .09 or less was included in the final path model.

Non-white populations 0-18 years of age (Ethnic Heterogeneity) and population change 1990-2000 (Residential Mobility) in the front (left side) of the Path Model were independent of each other with no correlation. These two variables were fairly constant indicators in Montana Counties and due to their built-in exogenous character; they became the base-line predictors upon which all other variables were regressed.

When estimated median income (Income Inequality) was regressed on non-white population 0-18 years of age (Ethnic Heterogeneity) and population change 1990-2000 (Residential Mobility) that model explained approximately 23 percent of the variance in
income (see Appendix Table 5). Non-white population 0-18 years of age was statistically significant at the .08 level with a negative partial correlation of -.241 when holding Residential Mobility constant. This indicated that as non-white populations (Ethnic Heterogeneity) increased there was a decrease in the estimated median income. In other words, counties with greater Ethnic Heterogeneity tended to be those exhibiting Income Inequalities. Population change was significant at .01 with a positive partial correlation of .440 when holding Ethnic Heterogeneity constant. Population change (Residential Mobility) appeared to more powerfully drive the county’s estimated median income (Income Inequality). Counties with greater Residential Mobility, also experienced greater Income Inequality (see Appendix Table 6)

![Figure 3. Income Inequality (Estimated Median Income) Path Model.](image)

Population change (Residential Mobility) and non-white populations (Ethnic Heterogeneity) explained approximately 38 percent of the variance in the county unemployment rate (Income Inequality) (see Appendix Table 7). Population change was statistically significant at .03 with a positive partial correlation of .288 when holding Ethnic Heterogeneity constant. As population change (Residential Mobility) increased in counties, there was also an increase in unemployment rates (Income Inequality). Non-
white population was statistically significant \( (p < .0001) \) with a positive partial correlation of .588 when holding Population Change constant; i.e., non-white population (Ethnic Heterogeneity) appeared to more powerfully drive county unemployment rates (Income Inequality). (see Appendix Table 8)

\[
\begin{array}{c}
\text{Population} \\
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\text{Mobility}) \\
0.004 \text{ Correlation}
\end{array}
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\text{Heterogeneity}) \\
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0.288 \text{ Partial}
\end{array}
\begin{array}{c}
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\text{Rate} \\
(\text{Income Inequality}) \\
R^2 = .38
\end{array}
\begin{array}{c}
\text{Non-white} \\
\text{Population} \\
0-18 \\
0.571 \text{ Beta} \\
0.588 \text{ Partial}
\end{array}
\]

**Figure 4. Income Inequality (Unemployment Rate) Path Model.**

When CHIP enrollment (Low SES) was regressed on these four variables, they accounted for approximately twenty-six percent of the total variance (see Appendix Table 9). The variables with statistical significance were non-white population (Ethnic Heterogeneity) and estimated median income (Income Inequality). Non-white population 0-18 was significant \( (p < .004) \) with a negative partial correlation of -.385, holding other predictors constant. Estimated median income also had a negative partial correlation of -.345 with other predictors held constant and a significance level of .01. Population change (Residential Mobility) and unemployment rates (Income Inequality) were not significant and had very little direct correlation on CHIP enrollment (Low SES program enrollment). Non-white population 0-18 (Ethnic Heterogeneity, 15%) and estimated median income (Income Inequality, 12%) for counties contributed most of the explained

26
variance found in CHIP enrollment (*Low SES program enrollment*). However, the
relationships were negative, so counties with a higher estimated median income (*Income Inequality*) and non-white population 0-18 (*Ethnic Heterogeneity*) had significantly lower enrollment in CHIP (*Low SES program enrollment*). (light blue path below and see Appendix Table 10)

![Figure 5. Low SES Program Enrollment (CHIP) Path Model.](image)

Population change (*Residential Mobility*), non-white population 0-18 (*Ethnic Heterogeneity*), estimated median income (*Income Inequality*), and unemployment rates (*Income Inequality*) together accounted for approximately 55 percent of the total variance in Medicaid enrollment (*Low SES program enrollment*) (see Appendix Table 11). Non-white population 0-18 was statistically significant (*p < .0001*) with a positive partial correlation of .479 holding other predictors constant. Unemployment rate was also statistically significant at *p < .008* with a positive partial correlation of .358 when holding
other variables constant. Therefore, counties with higher unemployment rates (Income Inequality) and non-white population 0-18 (Ethnic Heterogeneity) exhibited higher Medicaid enrollments (Low SES program enrollment). Population change and estimated median income were not statistically significant, contributing little explained variance. Even though estimated median income was not significant it was the only variable in the regression model that had a negative correlation with Medicaid (i.e., the higher the county's median income, the lower its Medicaid rate) (brown paths in model below and see Appendix Table 12).

**Figure 6. Low SES Program Enrollment (Medicaid) Path Model.**

Population change (Residential Mobility), non-white population 0-18 (Ethnic Heterogeneity), estimated median income (Income Inequality), and unemployment rates (Income Inequality), CHIP enrollment (Low SES program enrollment), and Medicaid enrollment (Low SES program enrollment) together accounted for approximately 41
percent of the total variance in explaining special education enrollment rates in Montana counties (see Appendix Table 13). Population change was not statistically significant ($p < .211$) and had a negative partial correlation of $-1.78$ holding everything constant. The more a population grew ($Residential Mobility$) in a county the lower enrollment they had in special education. Non-white population 0-18 was statistically significant ($p < .001$) with a negative partial correlation of $-0.440$ holding other predictors constant. Counties with high non-white population 0-18 ($Ethnic Heterogeneity$) had lower enrollment in special education when compared to those counties with low Non-white population. Estimated median income was significant ($p < .08$) with a negative partial correlation of $-0.245$ holding everything constant; i.e., counties with a higher estimated median income ($Income Inequality$) exhibited lower enrollment rates in special education.

Unemployment rate was significant ($p < .09$) with a positive partial correlation of $0.241$ holding other variables constant. Counties with higher unemployment rates ($Income Inequality$) had higher special education enrollment rates. CHIP enrollment was statistically significant at $.001$ with a negative partial correlation of $-0.463$ when holding everything constant. Counties with higher CHIP enrollment ($Low SES program enrollment$) exhibited lower enrollment rates of special education. Medicaid enrollment was significant at ($p < .054$) with a positive correlation of $0.271$ holding other predictors constant; i.e., counties with higher Medicaid enrollment ($Low SES program enrollment$), exhibited higher enrollment rates in special education (see Appendix Table 14).
DISCUSSION

Based on the findings of this analysis (see model above) the themes of social disorganization theory in a rural application to crime rates compared fairly well to rural Montana and county enrollment rates of special education. Montana special education enrollment rates were correlated with most of the structural characteristics found in social disorganization theory. Of the five characteristics first hypothesized to influence
Montana special education enrollment rates only one, family disruption (female head of house with children) was not included in the final model. The family disruption characteristic was highly correlated with ethic heterogeneity resulting in collinearity. Of the two, ethic heterogeneity was the more powerful predictor; therefore, to address the multicollinearity in the model female head of house with children/family disruption was eliminated. Of the remaining structural characteristics, low SES measures of program enrollment (CHIP and Medicaid), ethnic heterogeneity (non-white population 0-18), and indicators of income inequality (estimated median income and unemployment rates) were all statistical significance ($p < .08$) and directly affected county special education enrollment rates when holding everything else constant. Residential mobility was not statistically significant at the .08 level and did not influence county special education enrollment in the direction that social disorganization theory predicted. This negative correlation contradicted both previous urban and rural area studies and the finding that residential mobility directly and positively influencing rates of crime. However, residential mobility did have indirect effects through both income inequality indicators (estimated median income and unemployment rates).

The two income inequality indicators, estimated median income and unemployment rate, supported the theoretical prediction that counties that experience higher income inequality in the form of poverty or socioeconomic status also experience higher rates of special education enrollment in Montana Counties. Medicaid, the low SES program enrollment indicator, also supported previous research with a positive relationship to rates of county special education enrollment. These findings lend support
to the use of social disorganization theory in predicting rates of other social problems in rural counties.

Ethnic heterogeneity and CHIP, the second low SES program enrollment indicator, however, contradicted theory prediction by their negative directional influence on county rates of special education enrollment in Montana. Ethnic heterogeneity had the largest statistically significant effect on rates of county special education enrollment. This result could mean that counties with large non-white population 0-18 years of age contained students who were potentially underserved. However, this negative correlation between ethnic heterogeneity and county rates of special education could be the result of the breakdown itself in the system to provide services required. The breakdown could be the result of differing cultures, values, or income that are needed to build networks, recognize opportunities and resources that help produce involvement in all types of community associations such as PTA.

The contradiction of the theory produced by CHIP enrollment, the low SES program enrollment indicator, could be explained as the difference in poverty levels. This could work in two ways, either these counties with high CHIP enrollment due to the socioeconomic stress are blocked from recognizing opportunities and building the networks needed to find resources, or they are more prosperous and therefore do not require resources such as special education. These ideas coincide with the main influences hypothesized by social disorganization theory, that income or lack thereof is still a key association in predicting rates of social problems in a community.

Low SES program enrollment (CHIP and Medicaid) were the two main effects on Montana county rates of special education enrollment. Higher rates of ethnic
heterogeneity and income inequality, specifically unemployment rates, appear to cause higher enrollment rates in Medicaid. Ethnic heterogeneity is clearly a driving force in Montana Medicaid enrollment. An ethnic change in the populations, whether an increase/decrease in an area’s white or non-white population, can result in competing culture with differing backgrounds and traditions, diminishing the common goals and collective experiences once held. These breakdowns due to the competing cultures may tend to produce economic strain in a county ultimately driving low SES program enrollment. The structural characteristics that directly and significantly affect CHIP are county income inequality, specifically estimated median income, and ethnic heterogeneity. Both of these two structural characteristics of income inequality negatively influence CHIP enrollment. The negative correlation found between ethnic heterogeneity and CHIP enrollment could be the result of the differing resources available to the various levels of poverty. Due to the strong and positive correlation found between ethnic heterogeneity and Medicaid enrollment, it would appear that CHIP and Medicaid are measuring two different levels of county poverty. This would not only support previous research, but would provide a reason for why counties with high rates of ethnic heterogeneity experience low rates of CHIP enrollment. Counties due to their socioeconomic level are blocked or do not qualify for this level of program. The high negative correlation between estimated median income/income inequality and CHIP enrollment lends added support for this being a measure of income or income based program.

Both indicators of income inequality are directly and significantly effected by residential mobility and ethnic heterogeneity. Residential mobility and ethnic
heterogeneity positively effect unemployment rates as a measure of income inequality. Counties that experience high residential mobility and high ethic heterogeneity suffer a greater breakdown in the ability to function as a cohesive unit and source of social control. This breakdown in the cohesive units and lack of social control further blocks counties from needed employment opportunities. Residential mobility and ethnic heterogeneity are opposite in their influences on the estimated median income part of income inequality. Residential mobility is positively correlated with estimated median income/income inequality, while ethnic heterogeneity is negatively correlated. Ethnic changes or high heterogeneity in a county can produce an array of detrimental effects not only on income opportunities, but on the county as a whole and how it functions on a day-to-day basis due to the competing cultures and beliefs. Following social disorganization theory, as counties experience an increase in residential mobility they also suffer breakdowns in collective experiences, values, common goals, and social networks that influence income and other opportunities further driving income inequality. Counties with substantial income inequalities may produce lower estimated median incomes.

The indirect effects of these structural characteristics on Montana special education enrollment rates were also identified. Residential mobility only indirectly affects rates of special education enrollment in Montana counties through income inequality, both in unemployment rates and estimated median income. Ethnic heterogeneity has a strong indirect effect through every intervening indicator or structural characteristic in the model. Income inequality as it pertains to unemployment rates has a significant indirect effect through Medicaid on county rates of special education
enrollment. Estimated median income only has a slightly more significant indirect rather than direct effect on rates of enrollment in special education through CHIP.

Limitations to these data exist and may be problematic for testing social disorganization theory. The first limitation is the small number of counties and the use of only one state and the second, most variables only containing population counts for children zero to eighteen, each make the results difficult to generalize. According to Osgood and Chambers (2000), county-level data is not the ideal unit of analysis for testing the concepts of social disorganization and provides weak foundations for the generalization of results. Also, results would be more meaningful if based on more than one state (Bursik 1988; Osgood and Chambers 2000).

CONCLUSIONS

This rural application of social disorganization theory to Montana counties held up fairly well with significant associations between the structural characteristics and rates of county special education enrollment. The structural characteristics of social disorganization theory were found to directly and indirectly influence Montana county enrollment rates in special education. Montana counties that experienced high rates of certain income inequality and low SES program enrollment also had higher rates of special education enrollment. In these Montana counties, rates of special education enrollment were significantly associated with ethnic heterogeneity, both income inequality measures, and both low SES program enrollment measures.

A key finding was the strength and direction of the correlation between ethnic heterogeneity and the other structural characteristics. Shaw and McKay (1942) and
Osgood and Chambers (2003) saw ethnic heterogeneity as a mediating component between poverty and crime. In Osgood and Chambers' (2003) study, the connection between ethnic heterogeneity and poverty was canceled out by the negative correlation with residential mobility. However, this study found ethnic heterogeneity to be a critical element of social disorganization in Montana counties. From the aspect of social disorganization theory, this suggests that counties with non-white population 0-18 years of age are blocked from opportunity and goal attainment due to their differing traditions and values. As a result, non-white resident (0-18 years of age) counties are critically impoverished and under serviced in school-based programs such as special education.

This study demonstrates that the main concepts of social disorganization theory apply to counties of various sizes. These main theoretical concepts can also be used to predict a variety of social problems, not only delinquency/crime. For future directions, a study of intermediating variables would be beneficial to assess the direct effects on county rates of special education in Montana. Future research could include a cluster analysis of these variables that would help distinguish various types of Montana county special education enrollment. An analysis of all indirect effects on special education enrollment would allow for further identification of structural characteristic influences. It would also be worthwhile to expand the study to include other counties in other states to ensure the findings generalize beyond Montana.
REFERENCES


### Table 1. Descriptive Statistics

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*Correlation is significant at the 0.05 level (2-tailed).**Correlation is significant at the 0.01 level (2-tailed).
Table 3. Component Matrix

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Extraction Method: Principal Component Analysis, a 2 components extracted.

Table 4. Reliability Analysis

***** Method 2 (covariance matrix) will be used for this analysis *****

**RELIABILITY ANALYSIS - SCALE (ALPHA)**

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**Covariance Matrix**

\[
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4.8443 & 56.0 \\
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N of Cases = 56.0

**Statistics for Scale**

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<td>8.5739</td>
<td>4.8443</td>
<td>2.2081</td>
<td>56.0</td>
<td></td>
</tr>
</tbody>
</table>

**Item Means**

<table>
<thead>
<tr>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Max/Min</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>17.1478</td>
<td>4.8443</td>
<td>12.3035</td>
<td>7.4591</td>
<td>2.5390</td>
<td>27.8194</td>
</tr>
</tbody>
</table>

**Item Variances**

<table>
<thead>
<tr>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Range</th>
<th>Max/Min</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>174.5736</td>
<td>4.8757</td>
<td>344.2715</td>
<td>339.3958</td>
<td>70.6094</td>
<td>57594.7445</td>
</tr>
</tbody>
</table>

**Item-total Statistics**

<table>
<thead>
<tr>
<th>Mean</th>
<th>Variance</th>
<th>Item-</th>
<th>Squared</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>12.3035</td>
<td>344.2715</td>
<td>.8310</td>
<td>.6905</td>
<td>.</td>
</tr>
</tbody>
</table>

**RELIABILITY ANALYSIS - SCALE (ALPHA)**

**Analysis of Variance**

<table>
<thead>
<tr>
<th>Source of Variation</th>
<th>Sum of Sq.</th>
<th>DF</th>
<th>Mean Square</th>
<th>F</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between People</td>
<td>11473.9960</td>
<td>55</td>
<td>208.6181</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within People</td>
<td>9286.9893</td>
<td>56</td>
<td>165.8391</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between Measures</td>
<td>1557.8887</td>
<td>1</td>
<td>1557.8887</td>
<td>11.0859</td>
<td>.0016</td>
</tr>
<tr>
<td>Residual</td>
<td>7729.1006</td>
<td>55</td>
<td>140.5291</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonadditivity</td>
<td>7592.1284</td>
<td>1</td>
<td>7592.1284</td>
<td>2993.1261</td>
<td>.0000</td>
</tr>
<tr>
<td>Balance</td>
<td>136.9722</td>
<td>54</td>
<td>2.5365</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>20760.9853</td>
<td>111</td>
<td>187.0359</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tukey estimate of power to which observations must be raised to achieve additivity = -.8700
Hotelling's T-Squared = 11.0859  \quad F = 11.0859  \quad \text{Prob.} = 0.0016 \\
\text{Degrees of Freedom:}  \quad \text{Numerator} = 1  \quad \text{Denominator} = 55

Reliability Coefficients 2 items \\
\text{Alpha} = 0.3264  \quad \text{Standardized item alpha} = 0.9077

Table 5. Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.481(a)</td>
<td>0.231</td>
<td>0.202</td>
<td>3645.95155</td>
<td>2.207</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), PERNONWH, PERPPCH  
b Dependent Variable: ESTMEDCM

Table 6. Coefficients

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Correlations</th>
<th>Other Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>11170.791</td>
<td>613.132</td>
<td>50.84</td>
<td>.000</td>
</tr>
<tr>
<td>PERPPCH</td>
<td>125.134</td>
<td>35.043</td>
<td>.430</td>
<td>3.571</td>
</tr>
<tr>
<td>PERNONWH</td>
<td>-47.844</td>
<td>26.496</td>
<td>-.217</td>
<td>1.806</td>
</tr>
</tbody>
</table>

a Dependent Variable: ESTMEDCM

Table 7. Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.619(a)</td>
<td>0.383</td>
<td>0.360</td>
<td>1.9105</td>
<td>2.253</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), PERNONWH, PERPPCH  
b Dependent Variable: URATE
### Table 8. Coefficients

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Correlations</th>
<th>Other Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>3.765</td>
<td>.321</td>
<td>11.718</td>
<td>.000</td>
</tr>
<tr>
<td>PERPPCH</td>
<td>.040</td>
<td>.018</td>
<td>2.191</td>
<td>.033</td>
</tr>
<tr>
<td>PERNONWH</td>
<td>.074</td>
<td>.014</td>
<td>5.294</td>
<td>.000</td>
</tr>
</tbody>
</table>

a. Dependent Variable: URATE

### Table 9. Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.510(a)</td>
<td>.260</td>
<td>.202</td>
<td>2.91721</td>
<td>1.630</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), URATE, PERPPCH, PERNONWH, ESTMEDCM
b Dependent Variable: PER_CHIP

### Table 10. Coefficients

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Correlations</th>
<th>Other Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>15.960</td>
<td>4.226</td>
<td>3.777</td>
<td>.000</td>
</tr>
<tr>
<td>PERPPCH</td>
<td>.005</td>
<td>.035</td>
<td>.022</td>
<td>.146</td>
</tr>
<tr>
<td>PERNONWH</td>
<td>-.078</td>
<td>.026</td>
<td>-.445</td>
<td>-.2983</td>
</tr>
<tr>
<td>ESTMEDCM</td>
<td>.000</td>
<td>.000</td>
<td>-.396</td>
<td>-.2623</td>
</tr>
<tr>
<td>URATE</td>
<td>.080</td>
<td>.230</td>
<td>.059</td>
<td>.347</td>
</tr>
</tbody>
</table>

a. Dependent Variable: PER_CHIP

### Table 11. Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.741(a)</td>
<td>.549</td>
<td>.514</td>
<td>3.82881</td>
<td>2.107</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), URATE, PERPPCH, PERNONWH, ESTMEDCM
b Dependent Variable: PERMEDIC
**Table 12. Coefficients**

<table>
<thead>
<tr>
<th></th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Correlations</th>
<th>Other Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>6.447</td>
<td>5.547</td>
<td>1.162</td>
<td>.251</td>
</tr>
<tr>
<td>PERPPCH</td>
<td>.000</td>
<td>.046</td>
<td>.000</td>
<td>.004</td>
</tr>
<tr>
<td>PERNONWH</td>
<td>.134</td>
<td>.034</td>
<td>.454</td>
<td>3.898</td>
</tr>
<tr>
<td>ESTMEDCM7.509E-05</td>
<td>.000</td>
<td>-.056</td>
<td>-4.74</td>
<td>.638</td>
</tr>
<tr>
<td>URATE</td>
<td>.828</td>
<td>.302</td>
<td>.360</td>
<td>2.739</td>
</tr>
</tbody>
</table>

*a. Dependent Variable: PERMEDIC*

**Table 13. Model Summary**

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.641(a)</td>
<td>.411</td>
<td>.339</td>
<td>2.05656</td>
<td>1.785</td>
</tr>
</tbody>
</table>

*a Predictors: (Constant), PERMEDIC, PERPPCH, PER_CHIP, ESTMEDCM, PERNONWH, URATE

*b Dependent Variable: PERSPCED*

**Table 14. Coefficients**

<table>
<thead>
<tr>
<th></th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Correlations</th>
<th>Other Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>13.881</td>
<td>3.502</td>
<td>3.964</td>
<td>.000</td>
</tr>
<tr>
<td>PERPPCH</td>
<td>-.031</td>
<td>.25</td>
<td>-.173</td>
<td>-1.267</td>
</tr>
<tr>
<td>PERNONWH</td>
<td>-.074</td>
<td>.022</td>
<td>-.546</td>
<td>-3.432</td>
</tr>
<tr>
<td>ESTMEDCM</td>
<td>.000</td>
<td>.000</td>
<td>-.262</td>
<td>-1.767</td>
</tr>
<tr>
<td>URATE</td>
<td>.306</td>
<td>.176</td>
<td>.289</td>
<td>1.742</td>
</tr>
<tr>
<td>PER_CHIP</td>
<td>-.375</td>
<td>.103</td>
<td>-.484</td>
<td>-3.656</td>
</tr>
<tr>
<td>PERMEDIC</td>
<td>.154</td>
<td>.078</td>
<td>.335</td>
<td>1.972</td>
</tr>
</tbody>
</table>

*a. Dependent Variable: PERSPCED*