Social Networks, Delinquency, and Gang Membership:

Using a Neighborhood Framework to Examine the Influence of Network Composition and Structure in a Latino Community

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Report Abstract

This study employed a social network framework to understand the patterns of relations among youth in a predominantly Latino[1] neighborhood and the nature of the links binding youth to groups and their social contexts. Three main research questions guided the study: (1) Are network/structural variables important predictors of delinquency and gang membership (beyond the traditional set of risk factors) across ego networks? (2) What are the properties and characteristics of the sociocentric (i.e., neighborhood-based) network as defined by overlapping egocentric networks? How do these characteristics relate to or influence delinquency and gang membership? and (3) How does an individual's position and connectedness within the whole network relate to his/her probability of being involved in delinquent behavior at the individual level? In other words, we determined how one's position at the sociocentric level relates to behaviors measured and modeled at the egocentric level and whether sociocentric level measures (e.g., centrality) improve our understanding of individual behavior. By examining two levels of social processes for the unit of analysis (individual and group relationships) through both egocentric and sociocentric network analysis, and extending our network analysis to include different types of relationships (e.g., friend, relative, neighbor), we are able to examine multiple research questions that have not yet been addressed in the delinquency and gang literature.

We selected one disadvantaged Latino neighborhood in Maryland that was home to a large proportion of high-risk youth. With the goal of surveying all youth between the ages of 14 and 21 living in the target neighborhood, we ultimately surveyed 147 youth. We used a network survey consisting of three basic parts: (1) questions about the ego, (2) the listing of 20 alters by respondents followed by a set of questions asked about each of those alters, and (3) an alter tie question that was

[1] The terms "Latino" and "Hispanic" are used interchangeably in this report.

used to create the structural links among members of the network (i.e., Does Juan know Marvin without the respondent?). After overlapping the networks of each of the 147 youth, we conducted both egocentric and sociocentric analyses. Results from our egocentric analyses showed that youth are highly connected to people from the neighborhood but that networks with a larger proportion of in-neighborhood relations are not significantly associated with delinquency, violence, or gang membership. Network density was not significantly associated with delinquency, but the number of components (i.e., subgroups) in one's ego network was marginally significant. This finding suggests that the more separate groups of relations one has, the more constraint on behavior and, hence, the less likely an individual is to be involved with delinquency. Egocentric analyses also revealed the importance of including non-peer relations when examining the effect of delinquent associations on delinquency: models using all relations provided a better fit to the data than those that only examined the delinquency of peer relations, controlling for other covariates. In addition, the effect of delinquency of all relations was larger in size than the measure for delinquency of just peers.

Finally, a complex picture of risk and protective factors emerged. Separation from U.S. culture (lower acculturation) was a significant predictor for delinquency (but not gang membership); a youth who was born abroad and remained more closely connected to the Spanish language was less likely to be involved in delinquency. Other risk and protective factors varied in their significance across delinquency outcomes.

The sociocentric analyses revealed that the density of the network has important implications for the selection of an appropriate intervention: networks with very low densities—as found in the current study—are more successful contexts for intervening. The most appropriate interventions, then, would *not* rely on pro-social, anti-delinquent messages being spread through the network via well-placed, influential individuals. Rather, more targeted efforts to get individuals involved might be required because the message might not be effectively spread throughout the relatively sparsely connected community

Within the network, we examined the role of central players, and for the most part, supported the notion that the central role allowed for greater autonomy and led to higher levels of delinquency. However, we found that central players were not necessarily more *violent* than peripheral players. In fact, many central players were less violent.

Given that many anti-gang and anti-delinquency programs are implemented in a selected geographic area, one of the main concerns was whether it was valid to approximate the neighborhood with a complete social network. Here, all delinquency measures were significantly higher for the in-neighborhood network, which indicated that there are systematic differences between the groups of people who are neighborhood residents and those who are not. This supports the notion that the neighborhood influences behavior, and in this specific case, stronger associations with the neighborhood tend to be associated with higher levels of delinquency.

The Influence of Social Networks on Delinquency and Gang Membership

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EXECUTIVE SUMMARY

INTRODUCTION

This research report summarizes findings from a social network study of youth living in a high-risk neighborhood in suburban Maryland. The study utilized a social network framework to understand the patterns of relations among youth in a predominantly Latino[2] neighborhood and the nature of the links binding youth to groups and their social contexts. In conducting this study, we sought to fill an important gap in the delinquency literature: How do interpersonal relationships and networks—beyond peer networks—shape social interaction, and, in turn, individual-level antisocial behavior? Do ties to the neighborhood elicit particular patterns in social networks that shape behavior? With recent sociological research suggesting that immigrant generational status is highly correlated with the commission of violence by Latino youth (Sampson, Morenoff, & Raudenbush 2005), and that Latinos have more co-offenders than offenders of other races/ethnicities (Daly & Johnson 2006), it becomes critical to take a closer look at risk factors for delinquency, violence and gang membership within Latino immigrant communities.

Indeed, during the past few years, there has been increasing interest in crime and delinquency among the Latino population (Krohn, Schmidt, Lizotte & Baldwin 2011). Not only is the Latino population now the largest ethnic or racial minority in the country, it is also growing at a faster rate than all other groups (U.S. Census Bureau 2011). Further, gang violence has been of particular concern in Latino communities. Although many recent initiatives give voice to best practices, there is astonishingly little research evidence to rely on when it comes to gang prevention and intervention in Latino communities. Similarly, although evidence-based practices exist for delinquency *prevention* with Latino youth, the research evidence is limited in telling us what particular components are most effective and why. The social network approach has emerged within criminology as a valuable approach for examining the complex mechanisms underlying group-based and delinquent behavior (Sarnecki 2001). Findings from network studies can help build a solid foundation for prevention and intervention (Bouchard & Spindler 2010; Haynie & Osgood 2005; McGloin & Piquero 2009).

The main goals of the study are to (1) assess the extent to which individuals and networks are related to delinquency, violence, and gang membership across a targeted neighborhood

[2] The terms "Latino" and "Hispanic" are used interchangeably in this report.

comprising at-risk youth, and (2) describe characteristics of the sociocentric, or whole, network—made up of overlapping personal networks of neighborhood youth—and their relationship to delinquency, violence, and gang membership. To achieve these two goals, we use personal social network data, collected via a culturally relevant survey, to assess the composition and influence of youth networks aggregated for all research participants into a complete social network (McCarty & Wutich 2005; McCarty & Bernard 2003). These network data are used to derive the structural properties that may have an influence on the commission of crime and gang membership. Our methodological strategy of aggregating—or overlapping—personal network data across all respondents allows us to assess how positional network-based variables from the whole network can be used in ego-level analyses to examine factors that influence the commission of crime and gang membership (at the individual level). And similar to the pioneering work of Jerzy Sarnecki examining subgroups across youth suspected of committing offenses in Stockholm, Sweden (2001), we can also examine how network linkages influence subgroups and the properties and behaviors characteristic of those subgroups. By understanding these dynamics and behaviors, we can not only add to the small body of knowledge on network-based risk factors, but also develop a greater understanding of the types of processes and programs that reinforce pro-social behavior and prevent or disrupt antisocial behavior.

RESEARCH QUESTIONS

Our work is guided by three main research questions and several subquestions, listed below:

1) Are network/structural variables important predictors of delinquency and gang membership (beyond the traditional set of risk factors) across ego networks? Related questions include:
   a) Do egocentric network density, proportion of delinquent peers, and other variables characterizing network composition influence delinquency and gang membership?
   b) What is the influence of <u>non-</u>peer (i.e., non-friend) relations on delinquency and gang membership? Are characteristics of <u>non-peer</u> relations important influences on delinquency and gang membership? For instance, are antisocial networks that include relatives, non-peer neighborhood connections and other adults important to understanding the nature and extent of youth crime, violence, and gang membership?
   c) Does having many neighborhood-based associations (versus networks not based in the community) influence participation in crime and gangs at the ego level? Are youth who are members of neighborhood-based groups or gangs involved in more serious delinquent or violent behavior?
   d) How does an individual's—in particular, a Latino's—level of acculturation influence his delinquent behavior and gang membership? How important is immigrant generational status and language use with regard to violence and gang membership across ego networks?

2) What are the properties and characteristics of the sociocentric (i.e., neighborhood-based) network as defined by overlapping egocentric networks? How do these characteristics relate to or influence delinquency and gang membership? Relatedly, we ask:
    a) What are the characteristics of those individuals who are the central players in the subgroups and in the overall network?
    b) Do dense subgroups of gangs or delinquent peer groups exist?
    c) Do variables related to acculturation or immigrant generation characterize subgroups? Or are the dominant characteristics of the subgroups rooted in neighborhood-based associations?
    d) How do the key characteristics that define delinquent or violent subgroups vary from subgroups not comprising delinquent or criminal individuals?
3) How does an individual's position and connectedness within the whole network relate to his/her probability of being involved in delinquent behavior at the individual level? In other words, how does one's position at the sociocentric level relate to behaviors measured and modeled at the egocentric level? How do such sociocentric level measures (e.g., centrality) improve our understanding of individual behavior?

By examining two levels of social processes for the unit of analysis (individual and group relationships) through both egocentric and sociocentric network analysis, and extending our network analysis to include different types of relationships (e.g., friend, relative, neighbor, etc.), we are able to examine multiple research questions that have not yet been addressed in the delinquency and gang literature. Our study draws on the research literature from a number of substantive areas related to antisocial behavior of individuals and groups—in particular, research on delinquency and youth violence, the peer context, gangs, acculturation, and social networks. Across these literatures, we specifically draw on three theories—social bonding/control theory, social learning theory, and routine activities theory—that hold central principles related to relationships and, hence, guide hypothesis development for this study.

OVERALL DESIGN AND DATA COLLECTION STRATEGY

The design and methodology of the study are based on the theoretical and analytical framework of the network approach. The data collection strategy involved (1) selecting an appropriate neighborhood to provide the framework for the whole network, (2) utilizing a census-based method to survey all youth between the ages of 14 and 21 living in the neighborhood, and (3) asking the youth to complete a network-based survey.

To determine the specific boundaries of the study area, we conducted field research that included focus groups, informal interviews, neighborhood ride-alongs, and examination of administrative and census data. The survey site consists of 853 households; over 60 percent of residents are foreign born, only 55 percent have high school degrees, and per capita income is less than half that of the county average.

There are three basic parts to the survey: (1) questions about the respondent, (2) the listing of 20 "alters" (individuals named by respondents) followed by a set of questions asked about every alter, and (3) the alter tie question that is used to create the structural links among members of the network. Given our research goals, and in order to create personal networks for each ego and then match up all egos and respondents into one large network, we chose to use a free recall method (Marin 2004) using a "name generator," or a question that asked respondents to name by memory 20 individuals (alters). The name generator question is critical to the study in that it defines the sample of network alters—or the people who are in an individual's social network. For our study, we wanted to capture the networks of youth that comprise people who are important to the youth and might influence the youth—either positively or negatively. Alters could be friends, parents, siblings, or anyone else the youth knows. Our name generator question reads:

> *Please list 20 people that you hang out with or might see regularly in a typical day. Start by thinking of the people you hang out with every day. Then, think of the people you talk to or see the most—it may be family members, friends, neighbors, or even people you don't like.*

On average, it took participants about one hour to complete a survey. The survey was administered at a recreation center on several Saturdays between December 2009 and March 2010. Respondents received $50 for participating in the survey. A total of 160 youth completed the survey over that period. We dropped 13 respondents found to be ineligible, giving us a final count of 147 valid surveys.

OVERLAPPING NETWORKS

While preparation of the egocentric data for analysis followed a standard process of cleaning and recoding data, preparing the sociocentric data required a very different approach. This process was required to allow visualization of the whole network of connected egos and alters, and to allow analyses of the "whole network" data. The database contained 160[3] unique ego names and 3,200 non-unique alter names; creating a whole network required the research team to determine which of the 3,200 alters matched egos and other alters.

[3] Even though only 147 were used in the final analyses, we cleaned data for all 160 respondents in case they provided information on others who were eligible and were included in the survey.

After going through each name, we were able to identify just over 2,500 unique individuals. All of the alter data had to be summarized for each unique individual. In other words, if one individual was named by 10 different egos, we had to summarize the 10 separate records for that one person, which may or may not report the same details/attributes. Two types of data needed to be summarized: the attribute data (including such items as age, ethnicity, and delinquency) and the tie data, which indicated whether one alter was tied to another. We used EgoNet to summarize the alter data. For the attribute data, where conflicts in alter records existed, we used the majority answer or, if there was no majority, a randomly selected response for that alter. For numeric data, values were averaged (e.g., for age). For ego-specific variables, where different egos could have different answers about the same alter, EgoNet created summary measures (e.g., percent of egos who called this alter a friend/sibling/cousin; percent of egos who would go to this alter for advice). We used those data instead of the "majority rule" alter data to represent the ego-dependent alter data.

MEASURES

The measures described below are only those measures used in final models—for a list of all measures created for this study and used in preliminary analyses, please see the full report. It is important to emphasize that ego-level self-report measures are used to create the measures that reflect the behavior of alters. Hence, for the attribute measures described below, when used in egocentric analysis, they are based on self-report; when used in sociocentric analyses, the attribute measures for all nodes that are not egos are based on report by others.

<u>Delinquency/Criminal Behavior Variables</u>

1. <u>Overall delinquency</u> is an additive scale of the following nine items: (a) damaged, destroyed, or marked up someone else's property on purpose; (b) avoided paying for things, like a movie, taking bus rides, or anything else; (c) tried to steal or actually stolen money or things worth $100 or less; (d) tried to steal or actually stolen money or things worth more than $100; (e) tried to steal or actually stolen a car or other motor vehicle, (f) been involved in a gang fight; (e) sold illegal drugs such as marijuana, crack, heroin, or methamphetamine; (f) used a weapon or force to get money or things from people; and (g) attacked someone with a weapon or with the idea of seriously hurting or killing them.
2. <u>Recent (past six months) delinquency</u> is an additive scale that includes the nine items above, but respondents were asked whether they did that crime "in the past six months."
3. <u>Serious delinquency</u> is an additive scale that included six of the nine items listed above (items excluded were damaging property, minor stealing [items less than $100], and avoiding paying for things like a movie).
4. <u>Member of a street gang</u> is a binary measure of whether the individual is in a street gang.

5. Gang fight is a binary measure that captures ever being involved in a gang fight.
6. Sold drugs is a binary measure capturing whether an individual has ever sold illegal drugs
7. Carried a weapon is a binary measure for whether the individual ever carried a weapon.
8. Attacked someone is a binary measure capturing whether the individual attacked someone with a weapon or with the idea of seriously hurting or killing them.
9. Serious delinquency-binary is a binary measure capturing any behavior that could be regarded as delinquent or criminal. Individuals receive a score of one if they answered yes to any of the following five items: ever a member of a street gang, ever in a gang fight, ever sold illegal drugs, ever carried a weapon, or ever attacked someone with a weapon or with the idea of seriously hurting or killing them.

Network Compositional Variables

Network compositional variables provide descriptive information about alter characteristics (i.e., delinquency, neighborhood, closeness to the respondent, number of subgroups in personal network) in aggregate form. Measures used in the final analyses include:

- Peers in network. The proportion of alters who were listed as a "friend" is used as a control variable. *Continuous variable, values range from 0 to 1.*
- Delinquent peers. The proportion of delinquent peers (friends) in the respondent's personal network. A friend is defined as delinquent if the ego responded that the friend was involved in any of the following five behaviors: ever a member of a street gang, participated in a gang fight, sold illegal drugs, carried a weapon, or used violence to get what he/she wants. *Binary variable, values are 0 or 1.*
- Delinquent alters. This variable is computed the same way as "delinquent peers" but includes any person named in the respondent's personal network (thus, it includes friends in addition to everyone else) that has been involved in any of the five delinquent behaviors listed above. *Binary variable, values are 0 or 1.*
- Same neighborhood friends. The proportion of peers (friends that are not relatives) who live in the same neighborhood as the respondent, as reported by the respondent. *Continuous variable, values range from 0 to 1.*
- Same neighborhood alters. The proportion of all alters who live in the same neighborhood as the respondent, as reported by the respondent.[4] *Continuous variable, values range from 0 to 1.*
- Advice support from pro-social alter is a measure capturing the proportion of alters in a respondent's network to whom the respondent would go for advice and are not delinquent/criminal. *Continuous variable, values range from 0 to 1.*

Acculturation

- Separation scale. We formed a scale composed of summing the following seven variables to measure the respondent's level of "separation" from (i.e., lack of assimilation) the United States: (1) the place of birth for the respondent—"were you born abroad?"(yes/no); (2) the place of

[4] The criteria "live in neighborhood" was subject to respondent interpretation of neighborhood; we did not provide maps of the target area to respondents, so it is possible that there are youth who reside across the street from or near the target area but not technically inside the target area.

birth of respondent's mother—"where was your mother born?" (recoded yes, respondent's mother was born abroad/no, respondent's mother was not born abroad);(3) the place of birth of respondent's father—"where was your father born?" (recoded yes, respondent's father was born abroad/no, respondent's father was not born abroad);(4) if the respondent speaks a language other than English (yes/no); (5) if the respondent speaks a language other than English at home (yes/no); (6) if the respondent speaks a language other than English with his/her friends (yes/no); and (7) an ordinal measure of the proportion of the respondent's lifetime spent abroad ranging from 0 (respondent spent no time abroad) to 4 (respondent spent more than 78 percent of his/her lifetime abroad).[5] A high score on this scale measures lower levels of acculturation (or more separation), whereas a low score on the scale measures higher levels of acculturation (less separation). Reliability was good. ($\alpha = 0.653$). *Values range from 0 to 9*.

Network Structure and Positional Measures–Ego Network

- The number of components is the number of subgroups in the respondent's personal network. Components are a measure of separately maintained groups (no link exists between any two nodes of the different groups) within the larger personal network. The measure only consists of a *count* of groups and does not contain information on type of group. This measure is automatically generated in EgoNet statistics for each ego network. Sociological research has suggested that as the number of groups within a person's network increase, the ego becomes more constrained to normative behavior (Krackhardt 1999; Krohn 1986). *Continuous, values range from 0 to 4*.

Network Structure and Positional Measures–Whole Network

- Density represents the number of actual ties between all members across the overlapping network as a proportion of all possible ties (if every node was connected to every other node). The measure provides insight into how tightly connected the individuals in the network are. Higher density values indicate a network in which nodes are closely connected, and lower density values indicate that fewer ties are present between nodes.
- Respondent as isolate. A dichotomous measure (isolate =1) was created to represent whether the respondent was an isolate in the whole network. In our study, an isolate is a respondent who was *not* named as an alter by any other respondent and did not have any alters who were also egos (i.e., surveyed). *Binary variable, values are 0 or 1*.
- Degree centrality is the most commonly used measure of centrality (Valente 2010) and represents the number of direct connections in a network. While degree can be calculated based on ties received ("in-degree") or ties sent ("out-degree"), our network data is non-directed, so we use (non-directional) degree centrality, counting all direct ties in the computation of degree.
- Betweenness centrality is the frequency a node lies on the shortest path connecting other nodes in the network, or the number of geodesics (shortest paths) connecting two nodes on which a third node lies. Betweeenness represents whether a node occupies a strategic position in the network. The term broker is often used to describe individuals in high betweenness positions. It represents a gatekeeper function.

[5] We made the proportion of the respondent's lifetime spent abroad an ordinal variable based on the distribution of responses across the sample (i.e., one standard deviation above and below the mean [but greater than 0] were coded 3 and 1, respectively, while the range in between was coded 2). If the respondent spent no time abroad, the variable was coded 0.

- Closeness centrality measures the distance from each node to each other node in the network, based on both direct and indirect ties (Valente and Forman 1998). Higher closeness values indicate that a node is able to reach all other nodes over shorter distances. The closeness measure can be thought of as a sort of "degree of separation" as it effectively counts, for each node to every other node in the network, the number of links with other nodes that are needed to reach every node. The closeness measure does suffer from some complications regarding its calculation when isolates exist in the network (isolates cannot be reached by all other nodes, so the distance between them and other nodes is effectively ∞), and it is subsequently not as widely used as the first two centrality measures described. The network closeness centralization value is the average closeness value for all nodes.
- Eigenvector centrality for a node is based "on the centrality of its neighboring nodes" (Valente 2010, 87). This measure is useful in large network studies because it takes into account the overall structure of the network; it is not as susceptible to more "local" patterns, or patterns of closeness or centrality that may exist in small subgroups but may not have a strong role or effect in the larger network structure.

Controls

Control variables included in final egocentric analyses include: age, gender (male = 1), Latino (Latino = 1), number of years lived at address, family cohesion scale, parental support for education (binary), adult graduated from high school (binary).

ANALYSES

To accomplish the research objectives, two types of analyses are employed: (1) egocentric network analysis and (2) sociocentric analysis. Egocentric networks refer to the composition and pattern of the social relations of an individual (McCarty & Wutich 2005). For this study, egocentric analysis is used to measure whether aspects of egocentric network composition and measures of network structure influence delinquency and crime. Guided by learning theory, bonding theories, and routine activities theory, using logistic regression, we modeled the likelihood that a youth/young adult would be involved (yes or no) in a variety of criminal behaviors, given the network characteristics and the youth's individual position and connectedness within the network, and controlling for important risk and protective factors identified in the criminological literature. We also attempted to predict the extent of involvement by modeling delinquency as a scale using negative binomial regression techniques. The network measures are those related to personal networks that characterize or quantify relations between a respondent and his/her 20 nominated alters. The sample for these ego-level models included only those individuals who responded to the survey (N = 147).

Sociocentric networks refer to the pattern of relationships between actors within a specific group. In the current study, sociocentric analyses involve a wide range of analyses that include description of the whole network, description of parts of the network framed using different characteristics, computation of network structural and positional measures, subgroup analyses, and predictive analysis using all nodes.

FINDINGS

Description of Surveyed Youth

The majority of youth surveyed were male (66 percent), with an average age of almost 18. Roughly three-quarters of youth surveyed (76.9 percent) identified their ethnicity as Latino; a little over a third of the youth were foreign born. Even though the majority (63 percent) of respondents was born in the United States, 84 percent have at least one parent who was born abroad, and 69 percent speak both Spanish and English. Fifty percent of respondents have lived abroad at some point in their lives. Almost half of the respondents were Guatemalan or Salvadoran, and 10 percent were Puerto Rican or of Caribbean descent. These characteristics of the youth surveyed generally reflect the characteristics of the target neighborhood.

Overall, our sample exhibits a number of very pro-social characteristics: 97 percent of respondents under age 18 are still in school, and 92 percent of respondents report parental support for attending school (based on past or present support, depending on whether the respondent was still in school). The majority of respondents over 18 (58 percent) are currently employed. Just over 50 percent attend religious services at least once a month.

Respondents reported lower levels of gang activity and individual delinquency than we anticipated. Only 34 percent reported seeing lots of gang activity in the neighborhood, and only 20 percent said they had ever been approached to join a gang. While the vast majority (75.5 percent) of our sample identified as being a member of a group (answering yes to whether they have a group of friends with whom they hang out), far fewer respondents (10 percent) reported being current or former gang members or having been in a gang fight at some point in their lives (17 percent). Of all the delinquent behaviors included as survey items, prevalence was highest for using drugs (27 percent), followed by carrying a weapon (23 percent).

Findings Related to Research Question 1: Are network/structural variables important predictors of delinquency and gang membership (beyond the traditional set of risk factors) across ego networks?

- For ego networks, the proportion of relations (alters) who are delinquent is highly significant across all binary outcomes where it is included in the model—serious delinquency, carried a weapon, sold drugs, and attacked someone. For instance, for every additional delinquent alter in an ego's network, the ego's probability of selling drugs increases by 38 percent. If the percentage of delinquent members in a respondent's network changes by 25 percent, that respondent's delinquent activity increases 119 percent. We find similar results looking at the corresponding alter delinquency variable when we examine the proportion of alters in a gang fight or in a gang, respectively. Individuals who named an individual in a gang fight are 1.6 times more likely to be in a gang fight themselves. Thus, having delinquent/criminal relationships appears to be a key factor in shaping an individual's likelihood of delinquency and gang membership.

- Because the current study asked respondents to nominate people—both other youth and adults—who were influential to them, this study also had the opportunity to assess whether relationships beyond peer relationships are associated with delinquency and gangs. Instead of examining nested models, in order to compare models, we examined effect sizes and model fit between sets of negative binomial models. Two sets of models were created for each dependent variable: one set that included the proportion of *peer* delinquency and one set that included the proportion of all alters (not just peers) who were delinquent/criminal. The results from these comparison models showed that although both models fit the data well, the "all alters" models fit significantly better, and the effect of the variable measuring the proportion of delinquent/criminal alters on delinquency was slightly larger in each model than the effect of the peer delinquency term.

- We also assessed the strength of *pro-social* ties by including a variable that measured the proportion of one's network comprising individuals to whom the respondent would go for advice and who were *not* delinquent/criminal. This measure was found to be significant (approaching significance at $p = 0.05$) in only one model—the model predicting "attack someone with intent to harm." In this model, every additional person in a network to whom the respondent would go for advice and who is not delinquent/criminal reduces the probability of attacking someone with a weapon by 7 percent. Note that we tested other measures of "strength of ties" in preliminary models (such as time spent with others), but these measures were not found to be significant.

- The proportion of one's network comprising individuals residing in the target neighborhood (i.e., the respondent's neighborhood) is not significantly associated with any of our delinquency outcomes.

- The number of components was a significant predictor of delinquency in the negative binomial models for all three scaled criminal behavior outcomes and in two of our binary outcomes (serious delinquency and weapon carrying). In both the peer and the alter models of overall delinquency, for instance, one additional component decreases the expected count of delinquency by about one-quarter.

- Our composite variable measuring separation from U.S. culture is a significant predictor of delinquency and serious delinquency in the negative binomial models. A one-unit decrease in the separation scale (read as increasing acculturation) translates into an 18 percent *increase* in the expected count of delinquency and an 11 percent decrease in expected count of serious delinquency. Note that a measure for ethnic identity (Phinney 1992) was not significant in any original models and hence, dropped from final models.

- Control variables varied in significance across models.

<u>Findings Related to Research Question 2: What are the properties and characteristics of the sociocentric (i.e., neighborhood-based) network as defined by overlapping egocentric networks? How do these characteristics relate to or influence delinquency and gang membership?</u>

In order to more fully assess the effects of network structure on delinquent behavior, we explored two different networks developed from our data: one comprising all egos and all alters named by any ego in the survey (the "whole network" with 2,521 members) and one comprising all egos and those alters who were named by at least two egos (the "2+ network" with 369 members). Eleven percent of the whole network members were also 2+ network members. The comparison of results for these two networks allowed greater insight into the mechanisms through which network structure can influence behavior for individuals within those networks.

- When we examined the in-neighborhood and out-of-neighborhood status for members of each of the sociocentric networks, we found that approximately one-third of the members of the whole network live in the neighborhood while nearly three-quarters of the members of the 2+ network live in the neighborhood. This finding was not surprising—it is more likely that those named by more than one ego are peers who live nearby. It also suggests that the core social network of youths is neighborhood based, as the individuals who were named most frequently do indeed reside in the neighborhood.

- In addition to comparing the whole network and the 2+ network, the sociocentric analyses looked at the neighborhood as a network, as one of the main goals of the research was to explore the accuracy and utility of defining a social network using geographic boundaries. The in-neighborhood group is significantly smaller of the two, at nearly half the size of the out-of-neighborhood group, and has significantly different characteristics: more parents and siblings were named by in-neighborhood nodes; more friends were named by out-of-neighborhood nodes. More in-nodes are Latino while more out-nodes were born abroad. In addition, the in-nodes have significantly higher levels of delinquency, for every measure examined.

  These patterns indicate that there are systematic differences between the groups of people who are neighborhood residents and those who are not. The differences also support the notion that neighborhood context is associated with behavior, and in this specific case, more associations with the neighborhood tend to be associated with higher levels of delinquency. Because we lack longitudinal data, we are unable to determine whether this is because of self-selection—where new residents tend to be similar to those who already live there, perpetuating the prevailing attitudes and norms in the area (in this case, to support certain levels of delinquency)—or because of influence—where new residents are eventually influenced by the attitudes and norms of the neighborhood.

- In addition to dividing up the whole network into in- and out-of-neighborhood networks, we also divided the whole network up into subgroups, here called "partitions" using the Girvan-Newman iterative algorithm. The optimum number of partitions in the whole network was 25, but one large faction comprised more than 65 percent of whole network members. Additional analyses not discussed in this report did not reveal any obvious reason why this partition was not divided into smaller subgroups. In addition, 17 of the partitions were actually ego networks—they included about 21 members: an ego and that ego's 20 alters. While these were interesting to explore descriptively, the partitioning did not provide us with a large amount of additional insight regarding network embeddedness of subgroups or how or why subgroups might be formed.

- At the whole network level, we considered the most central players to be those who had centrality scores on any of the three centrality measures that were in the top 1 percent. We found that central players were actually younger than the average whole network member by three to four years—a large difference. In addition, a much higher percentage of central actors were named as siblings and friends compared to all members in the whole network, and central actors were likely to be born in the United States. More than three-quarters (and for degree centrality, nearly 100 percent) of all central players live in the neighborhood. Finally, delinquency levels were significantly higher for central players: one-fifth to one-quarter of central actors was delinquent while only 8 percent of the whole network was.

<u>Findings Related to Research Question 3: How does an individual's position and connectedness within the whole network relate to his/her propensity to be involved in delinquent behavior at the individual level? In other words, how does one's position at the sociocentric level relate to behaviors measured and modeled at the egocentric level?</u>

- To examine the contribution of <u>betweenness centrality</u> and <u>isolate position</u> to delinquency and related outcomes, we re-ran the same basic logistic and negative binomial regression models from the ego-level analyses and added the two variables to each model. The isolate variable is not statistically significant in any of the models, and betweenness centrality approaches significance at the $p < 0.05$ level only in the model predicting drug selling. The model should be interpreted with caution however, because the effect size is basically zero, and no change of any real magnitude is predicted to take place based on changes in betweenness centrality.
- We also conducted binary logistic regression analyses using all members of the whole network (n = 2,521) to predict overall delinquency. The model was restricted by the availability of data for all alters. We tested each of the three centrality measures in separate models, with all other predictors the same in each model. We found, surprisingly, that <u>betweenness centrality</u> was the only centrality measure that was not significant; both <u>degree</u> and <u>closeness centrality</u> were significant for the whole network. Degree, or the number of direct ties an individual has, was associated with decreases in delinquency while closeness was associated with higher levels of delinquency.
- In the whole network regressions, <u>living in the neighborhood</u> also was significantly associated with higher levels of delinquency, (in contrast to our finding at the ego level that peers or alters living in the neighborhood did *not* significantly influence delinquency).

CONCLUSION AND FUTURE RESEARCH

The current study provides a much-needed quantitative examination of the network context of youth living in disadvantaged minority communities. It bears emphasizing that the core explanatory concepts in the criminological field refer to social relationships, but few studies examine the social relationship beyond simply the characteristics of individuals. A social network framework provides a theoretically grounded backdrop relevant to the exploration of micro-level social interaction and relations.

Furthermore, collecting network data on youth within a targeted geographic area for all important social relations provided the opportunity to examine how network structure and composition influence aspects of delinquency and related antisocial behavior beyond what has previously been studied in the extant literature. For instance, this study provided us the opportunity to examine how neighborhood-based relations may influence the delinquency of individuals or the formation of subgroups across the neighborhood. Results indicated youth are very connected to people from the neighborhood: for 30 percent of respondents, at least half of their alters lived in the neighborhood. The majority of peers nominated across respondents resided in the same neighborhood as the respondent, and were not necessarily school-based friends. Although our study did not find that having a larger proportion of in-neighborhood relations was significantly related to delinquency or other antisocial outcomes at the ego level, the measure was significant in regression models that included all nodes in the whole network. These findings have implications for <u>how</u> network studies collect data from youth. The reliance on peer-based networks to study the processes and risk factors related to delinquency overlooks the importance of non-peer relations as highlighted in our findings. We are able to better examine differential associations among youth simply because of the variety of associations studied, and can additionally utilize information about the strength of ties to assess the quality of associations. In addition, the findings from this study have shown that network *content* alone provides an incomplete picture: an understanding of network structure is also important for advancing delinquency research.

<u>Future Research</u>

As social network-based research becomes more commonplace in criminology, researchers can continue to articulate a vast range of testable hypotheses related to how social relations shape criminal behavior. We recognize that the current study is only one small step among many new network-based approaches that can help shed insight into the processes and dynamics that shape and reinforce (or buffer against) delinquent and criminal behavior. Below, we provide a few suggestions for future research.

First and foremost, research that attempts to replicate these findings in other Latino neighborhoods, as well as in neighborhoods comprising youth from different minority groups, would provide insight on the reliability of our findings. The findings from this study regarding the "typically studied" risk factors were mostly in line with past research. However, we examined a set of network compositional and structural measures that have not, to our knowledge, been examined in the study of delinquency. It will be important for future research to shed light on how these findings might vary (or not) across different communities. Second, as the cross-sectional nature of this study limited our ability to infer causal relationships, longitudinal research would provide the basis to obtain more insight on the particular aspects of relationships that influence behavior as well as how one's position in a network shapes opportunities to engage in crime. Specifically, longitudinal research in this field will help advance the debate on selection versus influence. Also, research has suggested that peer networks are rather fleeting; longitudinal research can inform hypotheses related to how changes in relationships impact behavior or influence the criminal career (or gang career), as very little is known about how pro-social or antisocial relationships influence desistance.

Our findings support the idea that widening the framework beyond schools for social network analyses seeking to inform delinquent, criminal, or gang-related behavior would yield substantial benefits for research, policy, and practice. Certainly self-report data collected on networks needs further exploration of their validity (and specifically with regard to using overlapping networks), but the point to be made is that exploration of neighborhood-based networks or more broadly, networks not bounded by a specific type of relation, will provide the opportunity to more directly examine core constructs and hypotheses from social learning, bonding, and routine activities theories as well as to test integrated models combining aspects of these theories—as many recent studies have suggested. But, analyses that fail to recognize the importance of non-peer relationships could suffer from bias and model misspecification.

Although we have demonstrated that the data collection strategy we devised can be successful—at least on a small scale—future research should attempt to replicate this study using neighborhoods with large numbers of youth (or perhaps more resources) that would enable recruitment of larger samples of youth. Research conducted simultaneously in more than one neighborhood would also enable some ego-level analyses to be conducted on a combined sample, and at the same time, buoy reliability. Solid planning and valid data on youth populations will enable future studies to make important gains.

It is also important to set aside resources to ensure that serious delinquents and gang members are recruited and represented in a study of this sort. In addition, future network studies seeking to understand delinquency would benefit from adding a qualitative component to the data collection effort, to explore with respondents the structure of their network, the key players, and the relationships between network members. Having respondents reflect on network graphics would allow researchers to explore additional hypotheses and follow up on any puzzling or unanticipated findings.

Larger sample sizes and a more comprehensive set of data on alters would also provide new opportunities to examine how non-peers influence youth behavior. This includes testing whether relations other than peers can be protective factors in a youth's life or whether, if these non-peers are delinquent or criminal, their negative behavior is more influential than such behavior among peers. Large samples and data collection techniques using different alter nomination strategies would provide new opportunities to test the tenets of current integrated theoretical models related to familial relations. The level of bonding to adults is important in understanding how adult role models facilitate maintenance of criminal careers or help delinquent youth desist from crime and gangs.

Although this study uncovered only a handful of delinquent peer groups and gang members, the data collection technique and analyses performed lend themselves easily to gang research. In gang communities, this type of study could help develop knowledge about delinquent and crew subgroups. Much research on gang violence has been conducted Los Angeles and Chicago, where gangs tend to have structure and organization. As such, current gang prevention, intervention, and suppression strategies, as well as drug market elimination, are often developed from efforts that target the behaviors of organized gangs, leaving little understanding of less organized criminal groups. Network research aimed at understanding how loosely based "crew" networks evolve and change over time, and how aspects of networks are related to changes in criminal behavior, would greatly assist intervention efforts.

We conclude with the suggestion that experts in network analyses and network programs continue to devise ways to make network research more practitioner-friendly. One of the ultimate goals of our research is to determine which particular network-based questions or network routines (in analyses) are the most salient for understanding who (i.e., which individual or group of individuals) should be targeted for different types of prevention and intervention efforts. The methods used here are not feasible or practical for most practitioners. But a short risk and network structure assessment instrument (based on our longer instrument) could make such considerations more accessible to practitioners. In this way, they could realistically use social network data to inform the development of an appropriate intervention strategy for individuals and/or entire neighborhoods.

CHAPTER 1

INTRODUCTION

This research report summarizes findings from a social network study of youth living in a high-risk neighborhood in suburban Maryland. The study utilized a social network framework to understand the patterns of relations among youth in a predominantly Latino[6] neighborhood and the nature of the links binding youth to groups and their social contexts. Social network data for youth age 14–21 and residing in the selected neighborhood were collected via an extensive computer-based survey. Using these data, we reconstructed a social network of the youth and used that network to explore a number of questions related to social ties, delinquency, gang membership, and acculturation.

In conducting this study, we sought to fill an important gap in the delinquency literature: How do interpersonal relationships and networks—beyond peer networks—shape social interaction and, in turn, individual-level antisocial behavior? Do ties to the neighborhood elicit particular patterns in social networks that shape behavior? With recent sociological research suggesting that immigrant generational status is highly correlated with the commission of violence by Latino youth (Sampson, Morenoff, & Raudenbush 2005), and that Latinos have more co-offenders than offenders of other races/ethnicities (Daly & Johnson 2006), it becomes critical to take a closer look at risk factors for delinquency, violence, and gang membership within Latino immigrant communities.

Indeed, during the past few years, there has been increasing interest in crime and delinquency among the Latino population (Krohn, Schmidt, Lizotte, & Baldwin 2011). Not only is the Latino population now the largest ethnic or racial minority in the country, it is also growing at a faster rate than all other groups (U.S. Census Bureau 2011). Furthermore, gang violence has been of

[6] The terms "Latino" and "Hispanic" are used interchangeably in this report.

particular concern in Latino communities, and federal, state, and local governments are spending hundreds of thousands of dollars annually to augment anti-gang programs and develop new suppression-focused tactics. Although many of the recent initiatives give voice to best practices, there is astonishingly little research evidence to rely on when it comes to gang prevention and intervention in Latino communities. Similarly, although evidence-based practices exist for delinquency *prevention* with Latino youth, the research evidence is limited in telling us what particular components are most effective and why. Many of the limitations are due to the dearth in knowledge about risk factors that pertain specifically to Latino youth and about possible differences in risk and protective factors across different subpopulations of Latino youth.

Hence, research is needed that takes a closer look at predictors of delinquency and related antisocial outcomes for Latino youth, in addition to research that critically examines the characteristics and predictors of group-based delinquency and delinquent/criminal associations. Similarly, gang experts have voiced the opinion in recent years that gang prevention and intervention strategies must include an understanding of the norms, beliefs, and practices that reinforce group-based criminal behavior (Fleisher & Kreinert 2004; Kennedy 2006; Klein 2006a; Vigil 2007). The social network approach has emerged within criminology as a valuable approach to examine the complex mechanisms underlying group-based and delinquent behavior, in that it overcomes many shortcomings of extant delinquency and gang research (Sarnecki 2001). Furthermore, findings from network studies can help build a solid foundation for prevention and intervention (Bouchard & Spindler 2010; Haynie & Osgood 2005; McGloin & Piquero 2009).

Social network analysis refers to both a perspective for examining social relations and a methodological technique for analyzing those relations. The technique has been used in fields ranging from sociology and anthropology to social psychology and criminology. The perspective of social network analysis is that relations between actors create patterns and, eventually, structures that in turn shape the behavior of individuals (Marsden 1990; Wasserman & Faust 1994). Social network data describe the contacts, ties, and attachments that one individual has to another. By examining these data, and recreating the social networks of each individual, researchers can reconstruct the patterns of interaction and social structures that influence behavior (see, for example, Carley, Lee, & Karckhardt 2002; Gould 1996; Granovetter 1973; Krebs 2002; Lin 1999; Neaigus 1998; Ryan & Gross 1943; and Valente & Rogers 1995). Krohn (1986) was the first to suggest that a social network approach was important for understanding delinquency. He articulated that the language of the network approach is consistent with key tenets of social control theory in that network characteristics such as multiplexity and density can result in more or less constraint on delinquent behavior.

Given the gaps in the delinquency and gang literature, we set out to study the social networks of disadvantaged high-risk Latino youth within a neighborhood setting. Our intent was to structure a study where we could unravel the types of relations between individuals and the association these relations have with different types of behaviors—whether positive or negative—within a specific neighborhood and cultural setting. As will be described in more detail in the methods section, we chose a disadvantaged neighborhood, based on research and input from neighborhood informants, where violent crime and gang activity were prevalent and youth were at risk of joining gangs. Focusing on high-risk youth living in one neighborhood, the study examines both group properties—the patterns of relationships that make up the neighborhood's social network—<u>and</u> individual properties—the specific characteristics of individuals in the network and their personal relationships with other network members.

A study using a neighborhood-based social network framework can examine how individuals and their relations are embedded (or not embedded) in neighborhood networks, including delinquent groups and gang networks. Social network analyses in this context can help provide more precise knowledge of the mechanics of individual and group-based behavior. Such knowledge can provide insight into possible strategies related to both how to target prevention and intervention efforts in a culturally competent way and who should be the target of those efforts. More specifically, a social network framework using data collected from youth living in a specific neighborhood allows one to move beyond descriptions of contextual factors that might be related to delinquency and crime, and provides insight into how relationships and structural position within and across individuals and groups in the neighborhood might influence behaviors across the specific context studied. This framework is potentially very important for advancing delinquency prevention and intervention efforts in that the neighborhood is a primary context for socialization (Bursik & Grasmick 1993). Peer relationships and other connections are those that, at least in part, are developed around geographic contexts. And it is the neighborhood or "community" that has been the testing grounds for effective delinquency prevention and intervention.

The Language of Social Network Analysis

Many of the terms (or jargon) used by researchers in the field of social network analysis are unique to the field and can be quite unfamiliar to those new to the methodology.

Ego is used to refer to a person in the network. For this research, we use the term more specifically to refer to any person who completed our survey—who reported on his own behavior and the behavior of members of his personal network. ***Alter*** is used to refer to individuals in an ego's personal network. One needn't be either an alter or ego; an individual can be both at one time, depending on from whose perspective he/she is being considered.

Egocentric refers to anything concerning the individual level, where the unit of analysis is a person. An egocentric network contains the personal relationships between an ego and his/her alters. At the ego level, we use ***peer*** to refer to an ego's friends, regardless of the person's age. Peers are distinguished from family members, teachers, coaches, or other individuals not identified as friends—these are ***non-peers***.

Sociocentric refers to anything concerning the group level—a sociocentric (or "whole") network refers to any group of people who are connected in a number of different ways. This type of network could include relationships among residents of a neighborhood or students in a school, for example. We also use the term ***whole network*** to describe the overlapping personal networks that we combined to create a sociocentric network of youths for this study.

GOALS AND OBJECTIVES

The main goals of the study are to (1) assess the extent to which individuals and networks are related to delinquency, violence, and gang membership across a targeted neighborhood comprised of at-risk youth; and (2) describe characteristics of the sociocentric, or whole, network—made up of overlapping personal networks of neighborhood youth—and their relationship to delinquency, violence, and gang membership. To achieve these two goals, we use personal social network data, collected via a culturally relevant survey, to assess the composition and influence of youth networks aggregated for all research participants into a complete social network (McCarty & Wutich 2005; McCarty & Bernard 2003). These network data are used to derive the structural properties that may have an influence on the commission of crime and gang membership. Our methodological strategy of aggregating—or overlapping—personal network data across all respondents allows us to assess how positional network-based variables from the whole network can be used in ego-level analyses to examine factors that influence the commission of crime and gang membership (at the individual level). And similar to the pioneering work of Jerzy Sarnecki examining subgroups across youth suspected of committing offenses in Stockholm, Sweden (2001), we can also examine how network linkages influence subgroups and the properties and behaviors characteristic of those subgroups. By understanding these dynamics and behaviors, we can not only add to the small body of knowledge on network-based risk factors, but also develop a greater understanding of the types of processes and programs that reinforce pro-social behavior and prevent or disrupt antisocial behavior.

RESEARCH QUESTIONS

Our work is guided by three main research questions and several sub-questions, listed below:

1) Are network/structural variables important predictors of delinquency and gang membership (beyond the traditional set of risk factors) across ego networks? Related questions include:
   a) Do egocentric network density, proportion of delinquent peers, and other variables characterizing network composition influence delinquency and gang membership?
   b) What is the influence of non-peer (i.e., non-friend) relations on delinquency and gang membership? Are characteristics of non-peer relations important influences on delinquency and gang membership? For instance, are antisocial networks that include relatives, non-peer neighborhood connections and other adults important to understanding the nature and extent of youth crime, violence and gang membership?
   c) Does having many neighborhood-based associations (versus networks not based in the community) influence participation in crime and gangs at the ego-level? Are youth who are members of neighborhood-based groups or gangs involved in more serious delinquent or violent behavior?
   d) How does an individual's—in particular, a Latino's—level of acculturation influence his delinquent behavior and gang membership? How important is immigrant generational status and language use with regard to violence and gang membership across ego networks?
2) What are the properties and characteristics of the sociocentric (i.e., neighborhood-based) network as defined by overlapping egocentric networks? How do these characteristics relate to or influence delinquency and gang membership? Relatedly, we ask:
   a) What are the characteristics of those individuals who are the central players in the subgroups and in the overall network?
   b) Do dense subgroups of gangs or delinquent peer groups exist?
   c) Do variables related to acculturation or immigrant generation characterize subgroups? Or are the dominant characteristics of the subgroups rooted in neighborhood-based associations?

d) How do the key characteristics that define delinquent or violent subgroups vary from subgroups that are not comprised of delinquent or criminal individuals?

3) How does an individual's position and connectedness within the whole network relate to his/her probability of being involved in delinquent behavior at the individual level? In other words, how does one's position at the sociocentric level relate to behaviors measured and modeled at the egocentric level? How do such sociocentric level measures (e.g., centrality) improve our understanding of individual behavior?

By examining two levels of social processes for the unit of analysis (individual and group relationships) through both egocentric and sociocentric network analysis, and extending our network analysis to include different types of relationships (e.g., friend, relative, neighbor, etc.), we are able to examine multiple research questions that have not yet been addressed in the delinquency and gang literature. A social network framework "facilitates the testing of structural hypotheses about patterns of relations, their properties and their effect on social and individual behavior" (Papachristos 2006, 100), and provides a rigorous methodological foundation for examining acculturation and cultural context (Bernard, Killworth, Evans, McCarty, & Shelley 1988).

BACKGROUND

Our study draws on the research literature from a number of substantive areas related to antisocial behavior of individuals and groups—in particular, research on delinquency and youth violence, the peer context, gangs, acculturation, and social networks. Across these literatures, we specifically draw on three theories—social bonding/control theory, social learning theory, and routine activities theory—that hold central principles related to relationships and, hence, guide hypothesis development for this study. Below, we briefly discuss these three theories, draw out the connections to network research, then highlight the important risk factors involved in delinquency and gang research. We conclude by addressing the social network literature relevant to our project.

Control Theory–The Social Bond

Social bonding and control theories do not ask why people commit crime, but instead focus on why people do *not* commit crime. Hirschi's social bonding theory (1969) posits that delinquent or criminal behavior begins when an individual's bond to society is weak or broken. Youth develop attachments to aspects of the social world—these attachments could be to people or institutions. Hirschi describes four components of bonds that are important for social control: attachment, commitment, involvement, and beliefs. Hirschi hypothesized that these elements of the social bond work to build a stake in conformity and thus limit involvement in normatively unconventional activities. Social networks are a natural fit within bonding theory: networks are "bonds" or linkages to others, and social network data collection can capture the strength of attachments to and involvement with people (both pro-social and antisocial others) in an individual's personal network as well as across a variety of types of networks—such as school, neighborhood, church, sports, etc. The strength of ties, or attachment, can be emotional or based on some descriptive characteristic, such as family-based ties or time spent with an individual. It is important to note, however, that Hirschi hypothesized that any bonds, even bonds to delinquent friends, would have a negative influence on delinquency. Hirschi's theory also suggests that delinquents generally lack any type of bonds, even bonds to delinquent others. Research has not supported these assertions (Giordano, Cernkovich & Pugh 1986; Kandel & Davies 1991; Simons, Simons, & Wallace 2004). Furthermore, empirical research testing bonding theory does not consistently support Hirschi's predictions for the different elements of the bond, and, not surprisingly, researchers have concluded that the theory is stronger when its concepts are applied in conjunction with other theories such as social learning theory (Shoemaker 2009).

In later years, Hirschi, working with Gottfredson, melded together aspects of bonding theory to develop the general theory of low self-control (Gottfredson & Hirschi 1990). Gottfredson and Hirschi maintain that crime at all ages can be attributed to low self-control. They argue that once formed in childhood, an individual's level of self-control remains constant throughout his adulthood. Parental socialization—involving the correction of misbehavior combined with parental "warmth" (Hay & Forrest 2006)—and linkages to pro-social others during the childhood years—the main socialization period—are extremely important. These strong connections to pro-social networks at a young age help individuals to develop sufficient levels of self-control. Empirical research has confirmed that parental socialization (Hay 2001; Hay & Forrest 2006; Perrone, Sullivan, Pratt, & Margaryan 2004; Polakowsky 1994) and school socialization (Turner, Piquero, & Pratt 2005) are significant for developing self-control. The development of individual social-control, then, strongly relies on the influence of social networks.

Other relevant research has shown that low self-control is associated with deviant peer relationships. For instance, the results of Chapple's (2005) examination of data collected on youth as part of the National Longitudinal Survey of Youth suggest that youth with low self-control are rejected by pro-social peers and, in turn, seek deviant peers, resulting in higher levels of delinquency for those with low self-control. Essentially, Chapple found that deviant peer association had a significant relationship with crime, controlling for levels of self-control after establishing that self-control accounted for 11 percent of the variance in peer rejection. Other research, however, suggests that delinquency is mainly brought on by association with deviant peers—that the causal flow is from association with delinquent peers to delinquency (Kandel & Davies 1991; Warr 1993), an assertion that Hirschi and Gottfredson do not support.

Differential Association and Social Learning Theory

The basic assumption of social learning theory, and differential association theory before it (Sutherland 1947), is that people are first indoctrinated into deviant behavior by differential association with deviant peers and other significant relations in one's life. Essentially, for

Sutherland's theory, intimate social networks of individuals are the source of crime and delinquency. The frequency, duration, priority, and intensity of human relations are important facets of relationships that condition intimacy, and influence the likelihood of learning. Social learning theory (Burgess and Akers 1966; Akers 1998) extends differential association theory in that it goes beyond the concept of learned definitions to incorporate and more fully explain the mechanisms that lead individuals to continue delinquency or desist from it. Differential reinforcement becomes a key facet of social learning theory, in that individuals learn how to obtain rewards and avoid punishment by reference to the actual or anticipated consequences of given behaviors (Akers 1985).

The most commonly measured social learning variable is differential peer association (some studies use the terms "deviant peer bonding" or "delinquent opportunities") (Akers and Jensen 2006). Research consistently shows that delinquent peer influence has a strong positive relationship with delinquency, particularly during adolescence (Shoemaker 2005; Warr 2002; Battin-Pearson, Thornberry, Hawkins, & Krohn 1998; Lahey, Gordon, Loeber, Stouthamer-Loeber, & Farrington 1999; Maxson, Whitlock, & Klein 1998). In addition, having antisocial friends obstructs the aging-out process and facilitates the maintenance of delinquent and criminal careers (War 2002). Experts have stated that across research studies, association with delinquent peers is one of the strongest, most consistent predictors of delinquency (Battin et al. 1998; Loeber & Dishion 1987; Warr 2002). Furthermore, longitudinal studies suggest that although there may be some effect of *selection* of friends, selection is not the sole mechanism, but that learning plays a role, as delinquent behavior is amplified after association with delinquent peers (Chesney-Lind & Shelden 2004; Haynie 2001; Liu 2003).

Social learning theory suggests that, in addition to delinquent peers, any delinquent or criminal association in a youth's life will provide the opportunity to learn and reinforce criminal behavior. In other words, a parent's or family member's participation in criminal behavior can influence a child (Ardelt & Day 2002; McCord 1991; Rowe & Farrington 1997), with some studies finding that having delinquent same-sex older siblings is a particularly strong risk factor for delinquency (Ardelt & Day 2002). Bullock and Dishion (2002) found that sibling collusion (the process of forming sibling coalitions that promote delinquency and undermine parenting) uniquely predicted delinquency even above delinquent peer association. Furthermore, it is important to note that even controlling for a genetic component, familial associations have been found to be related to youth delinquency (Mednick, Gabrielli, & Hutchings 1984), suggesting that learning delinquent or criminal behavior, especially from family members, acts a causal mechanism for increased delinquency or criminal behavior on the part of the learner.

Similar to differential association theory, the *strength* of ties is an important consideration in social learning theory. The strength of ties become particularly relevant for familial relationships in that families are considered the primary group within which potentially strong relationships are developed and socialization takes place. Few studies, however, explicitly examine the contribution of different types of social relationships to delinquency or the influence of varying levels of intimacy or closeness on delinquency. It is more common for studies to incorporate basic measures of attachment to parents, based on bonding theory. Some studies that incorporate measures of both social learning and social bonding/control theories have found, for the most part, that the social learning variables of peer association, definitions favorable to law violation, and differential reinforcement have stronger effects than the social bonding variables (Akers & Cochran 1985; Akers & Lee 1999; Jensen 2003). Research also has shown that the influence of deviant peers can be magnified by lack of bonds to or involvement with parents or pro-social adults, such as teachers or coaches (Steinberg 1987; Warr 1993). A number of studies have shown that strong, positive parental influence can counteract the influence of delinquent peers (Warr 2002). In fact, some researchers consider attachment to parents as directly reducing delinquency.

Routine Activities

Routine activities theory falls under the umbrella of opportunity theories and hence is focused on the situation. The theory has little interest in individual socialization and learning from connected individuals. The theory is still relevant to social networks, however, in that research has shown that the routine activities of youth often include a large portion of unstructured and unsupervised time where youth are simply hanging out with other youth (Felson & Boba 2010; Osgood, Wilson, O'Malley, Bachman, & Johnston 1996), during which time they are learning and/or reinforcing different types of behavior—whether pro-social, deviant, or criminal (Osgood et al. 1996; Dishion 2000). Over the past decade, researchers expanding routine activities theory have suggested that it is important to account for the *social* context of routine activities in that differential social relations guide routine activities, in part, and that motivation is contingent on social environments (Bernburg & Thorlindsson 2001). Hence, neighborhood associations become important: youth spend an extraordinary amount of time hanging out in their own neighborhoods, and this may be particularly true of youth living in disadvantaged neighborhoods (Rankin & Quane 2000). Although the social capital school of thought might suggest that neighborhood ties are protective factors, research had found that local ties can confer antisocial influences in disadvantaged neighborhoods (Chung & Steinberg 2006). Research by Mennis and Harris (2011) also suggests that peer contagion has a strong neighborhood component, in that aggregate measures representing delinquent youth living nearby other delinquent youth have a strong positive effect on recidivism.

Similarly, Osgood and Anderson (2004) found that unstructured socializing with peers had both individual and contextual effects, explaining a great deal of the variation in delinquency rates across neighborhoods. In addition, monitoring by parents had a strong contextual effect on unstructured socializing, echoing one of the tenets of the general theory of low self-control.

Research by Dishion (2000; Dishion, McCord, & Poulin 1999) that set out to integrate social learning theory and routine activities theory suggests that time spent with delinquent peers becomes a type of “deviancy training” in that peers reinforce each other’s deviant attitudes and actions by laughing or accepting antisocial comments and behavior. His research found that reinforcement through such reactions was associated with increased substance use, delinquency, and violence.

Risk Factor Framework for Delinquency and Gang Membership

In addition to the three criminological orientations related to social networks (control theories, social learning theory, and routine activities theory), it is important to consider a risk factor framework. For our particular study, a risk factor framework highlights the importance of neighborhood risk factors and provides the foundation for examining causal relationships without being encumbered by testing any specific theory or theories, thus allowing for a broader assessment of the mechanisms that could support prevention and intervention (Farrington 1995). Studies like ours that set out to examine predictors of delinquency in hope of informing policy will need to control for a standard set of risk factors. With regard to this study, because our outcomes extend beyond delinquency to include gang membership, we also provide a discussion of the predictors that have particular salience related to gang membership.

Indeed, the factors associated with involvement in delinquency and youth violence have long been a focus of criminological research, with past studies identifying a multitude of risk factors stemming from behavioral, institutional, environmental and demographic characteristics (Saner & Ellickson 1996). Risk factors related to social networks include peer association, school-based risk factors, and family-based factors. The strongest risk factors include a lack of attachment to academic institutions and the family, parental attitudes favorable to violence, and reduced parental involvement with their children. Deviant peer association, which emerged from previous research (Farrington 1995; Hawkins, Herrenkohl, Farrington, Brewer, Catalano, and Hirschi 1998) and stems from the social learning perspective, is also a strong risk factor. Exposure to neighborhood violence, weapons and drugs, and exposure to *networks* that value violence and the use of weapons and drugs, similarly put youth at risk for involvement in delinquency.

Research has consistently shown that those at risk for delinquency are also at risk for joining a gang. Some researchers suggest that although each risk factor by itself may place an adolescent at risk for delinquency, the more risk factors that are present, the more likely the individual will join a gang (Howell & Egley Jr. 2005). With regard to neighborhood context, research has shown that youth from neighborhoods with a greater availability of drugs, as well as neighborhoods in which many young people are in trouble, have greater odds of joining a gang than those from areas without such issues (Hill, Howell, Hawkins, & Battin-Pearson 1999). On the other hand, recent area-level research examining concentrations of gang members finds that gang membership is less likely in social contexts characterized by residentially unstable population or changing structural conditions (Katz & Schnebly 2011), such as in areas undergoing gentrification.

Klein (2006) attests that what differentiates predictors of delinquency from predictors of gang membership is that only a subset of delinquency predictors are relevant to gang membership. Looking across a number of gang studies, Klein found that the following constructs were common predictors of gang membership:

- early involvement in delinquent activities
- early self-concept as a delinquent
- absence of helpful adults outside the family
- exposure to stressful life events
- family members in a gang or in serious legal trouble
- lower family supervision or parental monitoring
- delinquent friends and friends who endorse violence and violent forms of conflict resolution
- enjoyment from just hanging around the neighborhood with friends
- lower commitment to school, lower expectations for higher education
- higher levels of disrespect for police and other officials

In addition to a specification of risk factors that may differentiate gang youth from merely delinquent youth, research has found that gang members account for a disproportionate share of the crime problem (Dukes, Martinez, & Stein 1997; Esbensen & Huizinga 1993; Gordon, Lahey, Kawai, Loeber, Stouthamer-Loeber & Farrington 2004; Thornberry 1998), and that active gang membership facilitates participation in delinquency and violence such that individuals are much more involved in delinquency and violence during periods of gang membership than when they are not active gang members (Thornberry 1998).Thornberry's longitudinal study of Rochester youth found that gangs appeared qualitatively different from other delinquent peer groups. The study showed that at all eight waves, gang members reported committing violent offenses at significantly higher levels than did the non-gang members who associated regularly with delinquent peer groups. The same study also found that although only one-third of the sample consisted of gang members, they accounted for 70 percent of drug-selling behavior in the sample.

Research from the Seattle Social Development Project (Battin, Hill, Hawkins, et al. 1998) found that individuals who were gang members always had the highest rates of delinquency and substance use. Across 11 measures of delinquency and substance use measures, rates for gang members were significantly higher on 9 measures than those for youth with delinquent peers (but not in a gang). Even after controlling for the effects of delinquent peers and previous delinquency, the authors found that gang membership significantly predicted delinquency. These findings provide some support to social learning theory's assertion that behavior is the result of association with a delinquent group. Thornberry refers to the causal model as the "facilitation" model (Thornberry 1998, 159–60) but does not necessarily suggest that the mechanism at work is learning.

Race, Ethnicity, Acculturation, and Delinquency

Race and Ethnicity as Risk Factors

Race and ethnicity add to the complexity of the risk factor literature; race and ethnicity are each risk factors, and racial and ethnic differences exist *among* risk factors associated with delinquency. For example, several studies have shown that school behavior and school factors (e.g., low GPA and dropping out of school) better predicted delinquent behaviors of African American youth than white American youth (Joseph 1996; Voelkl, Welte, & Wieczorek 1999), while peer influence has been more strongly related to substance abuse among white American adolescents than among African American or Latino adolescents (Johnson & Hoffman 2000; Marsiglia, Kulis, & Hecht 2001).

Race and ethnicity do not uniformly predict delinquency for African American and Latino youth. For example, ethnic identity emerged as a predictor of attitudes toward fighting among African American youth but not among Latino youth, even after accounting for parental control and negative peer behavior (Arbona, Jackson, McCoy, & Blakely 1999). French, Seidman, Allen, and Aber (2000) surveyed adolescents in their last year of junior high school and one year later at the end of their first year of senior high school. They found that African American and Latino youth responded differently to similar experiences, suggesting that ethnic identity may mean very different things for these two groups.

Latino Ethnicity and Acculturation

In addition to exploring differences between African American and Latino youth, researchers have investigated important intra-ethnic differences among Latino subgroups. Latino "ethnicity" in the United States applies to a broad range of populations with roots in numerous countries, their connection or migration to the United States, and their level of integration into mainstream American society. Intra-ethnic differences among Latinos can prove instructive when examining the links between risk factors and delinquency or health outcomes. Chief among the concepts employed to explore such intra-ethnic differences stands "acculturation." Acculturation refers to a multifaceted process by which individuals of one culture adopt the language, values, customs, identity, and behaviors of another, usually more dominant, culture (Gil, Vega, & Dimas 1994; Gil, Wagner, & Vega 2000). Acculturation has been operationalized in many different ways, and most often as a single dimension or variable. More recently, however, researchers have made a strong case for examining acculturation as a complex, latent variable that has multiple components. With regard to Latinos, acculturation has been operationalized as language use (Gil, Vega, & Dimas 1994), a composite of language use and place of birth (Amaro, Whitaker, Coffman, & Heeren 1990), and cultural orientation (Vega, Koury, Zimmerman, Gil, & Warheit 1995).

A small but growing body of research evidence suggests that the longer Latinos live in the United States, the more likely they are to participate in at-risk and high-risk behaviors. The phenomenon has gained general recognition as the "immigrant paradox," named after the unexpected results of heightened resilience among less acculturated or first-generation youth compared to their more acculturated or second-generation counterparts. Specifically, greater levels of acculturation among Latino youth have been associated with increased rates of smoking, drinking, and substance abuse; lower rates of family formation; and increased rates of dependence on government assistance programs (Amaro et. al. 1990; Gil, Vega, & Dimas 1994; Gil, Wagner, & Vega 2000; Hayes-Bautista 1989).

In general, it appears that being less acculturated or being a recent immigrant functions as a protective factor in communities with a sizeable co-ethnic population, especially in the Southwest, Miami, and Chicago. Buriel, Calzada, and Vasquez (1982) found that among 81 Mexican American male adolescents in Los Angeles, third-generation individuals had lower expectations for themselves and higher rates of delinquency than those from first and second generations. Similarly, in their examination of 6th and 7th grade students in a Southwestern city (*n* = 1,170), Fridrich and Flannery (1995) found that after employing measures to account for parental monitoring, acculturation, and delinquent behavior, Mexican American acculturated individuals reported higher levels of delinquent behavior than those who were recent immigrants, Caucasian, or less acculturated by choice. Additionally, those falling into the recent immigrant category reported higher levels of parental monitoring than other groups. Coatsworth, Maldonado-Molina, Pantin, and Szapocznik (2005) found that youth who had assimilated had significantly higher scores on problem behavior scales, in addition to lower scores on the parental monitoring measure. Conversely, those considered bicultural had more familial resources and increased parental monitoring, as well as the most adaptive patterns. A study using data from the Project on Human Development in Chicago Neighborhoods (Sampson et al. 2005) found that third-generation Latinos were more likely to be involved in violence relative to first- and second-generation immigrants. These findings extend to substance abuse outcomes as well. Most studies have also found that greater levels of acculturation are associated with an increase in substance abuse (Amaro et al. 1990; Gil, Wagner, & Vega 2001; Martinez 2006; McQueen, Getz, & Bray 2003).

Race, Ethnicity, Acculturation, and Gangs

In contrast with the above studies, Lopez and Brummett (2003) examined acculturation within the specific context of Mexican gangs in Los Angeles and found that Latino gang members were less acculturated than non-gang members. The study employed a bicultural classification scale, and it challenges the broader literature on acculturation and delinquency. The study found that gang members, compared to non-gang members, associated more with Mexicans, had more Mexican friends, and were less accepting of non-Hispanic whites. The authors hypothesized that gang membership for Mexican Americans in Los Angeles is a variation of "reaction formation," or moving away from things American and toward original immigrant identities. Under this model, gang membership is just one manifestation of this reaction, and the joining of gangs as a way to embrace Latino culture is sometimes referred to as "choloization" (Lopez & Brummett 2003). Gang membership redirects resentment resulting from marginality and culture conflict (ibid, p.629). A recent study documented a similar phenomenon in the Southwest: utilizing a large sample of Mexican-American adolescents residing in low-income barrios in the Southwest, Miller, Barnes, and Hartley (2009) found that individuals who were "more assimilated into mainstream 'Anglo' culture" were less likely to report membership in a gang (p. 14), with ethnic marginalization mediating roughly 30 percent of the acculturation effects on likelihood of gang membership (p. 18). Related research on acculturation stress may explain why these gang membership findings contrast with the broader literature on delinquency and substance abuse.

Studies that measured the concept of acculturation stress have generally found that stress can yield increased deviance and substance abuse (Gil, Wagner, & Vega 2000). Studies of acculturation stress or conflict may explain why less acculturated Latino youth in the studies above reported a higher likelihood of gang membership. Coatsworth and colleagues (2005) studied Latino youth of various nationalities in Miami, and found that moderate or in-between acculturation types scored lower on general adaptation measures than youth who identified closely with their parents' culture ("Hispanicism") or mainstream culture ("Americanism"). Youth with high scores on measures of both Hispanicism and Americanism fared well compared to in-between acculturated youth who did not identify strongly with either. Vega and colleagues (1993) studied delinquency among Cuban youth in Miami and found an association between acculturation conflict and low self-esteem. They concluded that weakened family protective factors allow acculturation stress to play a strong role in promoting delinquency among less acculturated youth. Although neither study directly examined gang membership, their findings suggest that, unlike delinquency or substance abuse outcomes, gang membership may function as an outlet for Latino youth who experience acculturation stress or conflict and, at the same time, feel no strong attachment to their parents' culture or mainstream American culture.

Other research examines race-ethnic differences in gang membership, while empirically testing a "marginalization" theory that predicts gang involvement both globally and differentially by race-ethnicity. While not specifically focused on Latino populations like research discussed above, more global theories of marginalization dovetail nicely with that work; for instance, Lopez and Brummet (2003) discuss the process of joining a gang in response, in part, to marginalization of Latinos from mainstream American culture. Vigil's marginalization theory (1988, 2002) posits a series of macrohistorical and macrostructural forces that lead to economic insecurity and loss of informal and formal social control, and supposes that these influences interact to produce a cumulative effect of marginalization. Once marginalized, segregation and discrimination create a lack of connection to or involvement in society. Marginality is linked to difficulty in establishing a self-identity (Malec 2006; Vigil 1988). Gang membership, then, would represent an adaptation to marginalization and a group that provides socialization and a self-identity. Vigil developed the theory while working with Hispanic youth, and others have applied the theory to African American, Salvadoran, and Vietnamese populations (Vigil 2002).

Freng and Esbensen (2007) criticize Vigil's theory for its failure to articulate the nature and relative strength of each of the key factors and how they could lead to gang membership. Using cross-sectional data from the National Evaluation of G.R.E.A.T. (a sample of 8th graders in 11 sites), they found significant differences in current gang membership by race-ethnicity. For instance, the ecological stress variables did not predict gang membership for African Americans and Latinos but did for white Americans. Also, neutralization (justifying delinquent behavior because it seems warranted if, for instance, someone starts a fight with you, or you are just protecting yourself) predicted current gang membership for African Americans and white Americans, but not for

Latinos. More important, only four of the multiple marginality constructs tested (i.e., ethnic identity, parental attachment, parental monitoring, and limited educational opportunities) manage to perform equally across the three racial-ethnic groups examined—but each proved nonsignificant across the groups. Only attitudes toward the police and street socialization (with regard to current gang membership) were significant marginalization constructs for Latinos.

Freng and Esbensen suggest that specific factors may differ for gang membership across racial-ethnic groups, and that these factors lead to the recommendation of implementing different programs at various stages of gang involvement, particularly at the prevention stage. Race-specific programming may be warranted, a finding that could be extended to include tailored prevention programming for different groups of Latinos (e.g., less acculturated versus more acculturated, first generation versus later generations, large co-ethnic cohort versus small co-ethnic cohorts).

A more recent study used the longitudinal Rochester Youth Development Survey to test some of the tenets of Vigil's theory (Krohn et al. 2011) across different racial and ethnic subgroups and found that some predictors of joining a gang varied among racial-ethnic groups and hence, not all of Vigil's hypotheses were supported. It is also important to note that the authors found that speaking Spanish at home dramatically reduced the odds of gang membership by more than 70 percent—it did so by reducing the impact of risky time with close friends. Krohn and colleagues interpreted the finding as support for theories suggesting that youth more acculturated to the dominant American culture have negative outcomes with regard to gangs, but also suggested that, because some studies have found that higher levels of acculturation *reduced* chances of gang membership (Lopez & Brummett 2003; Miller et al. 2009), further research is needed that examines and compares different Latino subgroups.

SOCIAL NETWORKS, DELINQUENCY, AND GANGS

Historically, the use of social network analysis within the field of criminology has been limited. However, within the last decade there has been a growing interest in applying the methodology to the study of delinquency and gangs (McGloin & Kirk 2010). Because a strategic arena within social network research involves the study of social influence, the study of peer influence on delinquency within a social network frame becomes quite obvious. As discussed earlier, while not always explicit, social networks play a large role in a number of criminological theories—social control, learning theories, routine activities—and also others such as social disorganization and collective efficacy (Bursik & Grasmick 1993; Sampson, Raudenbush, & Earls 1997). As such, researchers—though not necessarily criminologists—have used social network analysis to examine individual antisocial outcomes such as aggressive behavior and illegal drug use.

For instance, social network analysis has been used to study peer relations with regard to drug use (Ennett & Bauman 1993; Henry & Kobus 2007; Williams & Latkin 2007), smoking (Abel, Plumridge, & Graham 2002; Mercken, Snijders, Steglich, Vartiainen, & de Vries 2010; Pearson & Michell 2000), and aggression (see for example, Cairns, Cairns, Neckerman, Gest, & Gariepy 1988; and Xu, Farver, Schwartz, & Chang 2004). Most of those researchers, however, come from the fields of developmental psychology or public health. In their assessment of drug use among adolescents, Henry and Kobus (2007) found that liaisons between groups (or individuals who link groups together) in a social network were more at risk for tobacco use than isolates (who are connected to no or few other members) or actual network members, which may be attributed to the fact that liaisons are more likely to interact with multiple groups at once and, as a result, may have a greater exposure to smoking. A Baltimore study of adult current heroin and cocaine users found that, using a scale of network attributes (drug-using ties, support for drug use, and connection to daily users) the odds of reporting current drug use for individuals with stronger drug influences was

8.5 times higher than for individuals with weaker drug influences (Williams & Latkin 2007). A 1988 study of aggression in 4th and 7th graders (Cairns et al. 1988) found that aggressive youth tended to be friends with other aggressive youth and although aggressive youth were less popular than control subjects in the overall social network, they were equally often identified as being nuclear members of social clusters.

Within criminology, there are only a handful of network studies based on self-report that examine delinquency outcomes. In one of the first studies of its kind, Haynie (2001) used data from the National Longitudinal Study of Adolescent Health (Add Health) to map out the delinquent context of adolescent friendship networks. Haynie, situating her research in differential association and social learning theories, posited that the proportion of delinquent friends in the network, as well as the absolute level of delinquency of those peers, will be predictors of delinquency. She found that the proportion of delinquent friends is strongly associated with delinquency, controlling for prior delinquency, but that the absolute level of peer delinquency is not a statistically significant predictor of delinquency when proportion of delinquent friends is in the model.

Haynie's later study using Add Health data (2002) examined the influence on delinquency of important network structural variables, such as density, centrality, and popularity. Initial findings suggested that structural characteristics of friendship networks were unassociated with delinquency when peer delinquency is accounted for, but Haynie then examined interaction effects between peer delinquency and each network characteristic. She found that each of the three network structural characteristics condition the delinquency-peer association. In a more recent social network study examining selection effects versus socialization, Haynie and Osgood (2005) found that delinquency is causally influenced by peer socialization, with adolescents affecting one another regardless of the strength of their attachments, or the amount of time spent together.

Other network studies that assess delinquency using social network methods are often set within European countries and approach the research questions in a variety of ways—not necessarily to examine structural effects of networks on delinquency outcomes. In their assessment of networks and delinquency among a sample of high school–age students, Baerveldt, Völker, and Van Roessem (2008) found that delinquent students preferred to establish friendships with other delinquent students, with such delinquent networks becoming more closely connected over time. Weerman and Bijleveld (2007) found that although friendship networks consisted of both delinquent and nondelinquent peers, friends and best friends from the same delinquency category (nondelinquent, minor delinquent, serious delinquent) are nominated more often than other students. Additionally, it was established that minor delinquent boys were more popular than nondelinquent or seriously delinquent individuals, in addition to exhibiting more central positions in the network.

Dijkstra and colleagues (2010) examined network dynamics for weapon carrying among a sample of middle- and high school–age boys in a predominantly Hispanic area of New Jersey. Those who carried weapons had an increased number of best friend nominations received, yet gave fewer best friend nominations, and the authors concluded that weapon carrying is deemed popular, with those actually doing the weapon carrying being more selective in terms of whom they choose to be in their network. It was also revealed that adolescents chose to model their weapon-carrying behavior to resemble that of their friends, alluding to the fact that networks are extremely influential in terms of peer behavior, specifically as it relates to weapon carrying.

Recently, researchers have begun to use network analysis in the study of gangs (Fleisher 2002, 2006; Papachristos 2005; McGloin 2004). The studies can take either an egocentric approach, considering impacts at the individual level (Fleisher 2002), or a sociocentric approach (McGloin 2005; Papachristos 2005), where the analysis spans multiple groups (i.e., gangs) (McGloin 2005; Papachristos 2005) or takes place within one gang or criminal network (Natarajan 2006). The research most relevant to our study is Fleisher's (2002) study of women in gangs in Champaign, Illinois. Fleisher used network methods, in combination with participant observation, to create what he called a "more nuanced analysis" of adolescent gang life in a specific ecological niche. His research highlighted the importance of egocentric (individual-level) networks, as he showed that ego-gang networks of female gang members were socially flexible in that they included male and female gang members and male and female *non*-gang members. Papachristos's network analysis of gang homicide in Chicago (2005) is also important to the current study in that he found that violence was a contagious process sustained by the group nature of gang activity and driven by norms supporting violence that defined both the group and individual identities. His research findings support the notion that the structural processes of the group can greatly influence behavior—in this case, how individual and group responses to threats can result in homicide.

The Current Study

We sought to advance both the substantive and methodological literature pertaining to delinquency and other high-risk behaviors in a number of ways: (1) by collecting in-depth network data from high-risk youth within one neighborhood to examine how neighborhoods influence relationships and, in turn, delinquency and group-based behavior; (2) by going beyond the typical school-based network found in most network studies of delinquent behavior to include all important social relations in a youth's life; (3) by creating a whole network through overlapping egocentric (individual) networks in order to provide insight into group dynamics; (4) by examining how structural characteristics (such as centrality) created from the sociocentric (or overlapped) network might influence individual- and group-level behavior; and (5) by paying close attention to how dimensions of culture, ethnic identity, and acculturation might relate to delinquent behavior and gang membership.

RESEARCH HYPOTHESES

Below, we first outline egocentric (individual-level) hypotheses as derived from the goals and objectives of the current study, and then set forth our sociocentric network–level hypotheses related to research that will be conducted using overlapping networks. The relevant research question with which each hypothesis is associated is denoted in parentheses.

(1) The strength of ties—as defined by the amount of time one spends with delinquent others or whether one would go to a delinquent relation for advice—will be significant predictors related to delinquency and gang membership (Q1a).

(2) Individuals who are brokers across the whole network will be more likely to be involved in selling drugs (in particular) and other delinquent behavior (Q1a, Q3a).

(3) The number of subgroups within a personal network (i.e., components) will influence delinquency in that as the number of subgroups increases, behavior is more constrained to the norm. Hence, as the number of subgroups increases, the odds of being delinquent will decrease (Q1a).

(4) Associations with delinquent and/or gang youth will influence a youth's participation in delinquency and gangs, but the effect of associations with *all relations* that are delinquent/criminal (i.e., delinquent peers and non-peers) will be larger than that of just including delinquent peers (Q1b).

(5) Having many ties to youth living within the same neighborhood will increase an individual's likelihood of being in a gang, selling drugs, and other delinquent behavior (Q1c).

(6) Higher levels of acculturation will be associated with delinquency and drug dealing, while lower levels of acculturation, and, more specifically, a separation from American culture, will be associated with gang membership. In addition, high levels of ethnic identity and

cultural cohesiveness will act as a protective factor from all antisocial behavior, including gang membership (Q1d).

Whole Network Hypotheses

The hypotheses below are divided into those related to the search for community structure, or the existence of distinct, coherent subgroups (here called factions or Newman-Girvan subgroups), and those related to individual position within the overall structure.

(7) Within the whole network, we will be able to identify a small set of central network members who are well connected.

(a) The central players will have high levels of acculturation and will be identified more frequently than others as individuals to whom others go to for advice (Q2a).

(b) Central individuals will tend to be more delinquent, as more powerful or central individuals will feel less pressure to conform to the norm whereas less central players will be more constrained by the behaviors of those around them (Q2a, Q3a).[7]

(c) Most central players will live in the neighborhood; within a neighborhood-based network, presence in the neighborhood and strength of ties to others in the neighborhood are important to maintaining a central position (Q2a).

(8) Within the whole network, we will be able to identify distinct clusters, or subgroups, of individuals.

[7] It is important to note the distinction between the two hypotheses stated above. On the surface, hypotheses 3 and 7b appear to contradict each other; one (3) suggests that those connected to more groups will find their behavior constrained, thus participating in fewer delinquent behaviors, while the other (7b) suggests that those who are central to the network, and presumably have ties to a number of different nodes from which they derive their central positions, will be less constrained to act pro-socially and will actually demonstrate higher levels of delinquency. Actually, the two hypotheses are talking about two very different concepts: hypothesis 3 refers to a network characteristic akin to degree, but regarding ties between nodes in different groups (it is not enough to be tied to several people in the same group). Despite ties to nodes in different groups, a person in this position may not be central in any of the groups, and juggling relationships across a number of groups may actually prevent the individual from increasing his centrality in any one group. Hypothesis 7, on the other hand, regards an individual's centrality and is only concerned with connections between nodes, regardless of whether the nodes are in the same group or in different groups. Thus if a person is central, connected to many different individuals, he may not feel reliant on any one node for acceptance or friendship and may feel more emboldened to act independently with fewer constraints on his behavior. In this way, centrality can actually increase one's likelihood of being delinquent.

(a) The subgroups will be homophilous[8] in terms of demographics (Q2b, c, d).

(b) The networks for groups comprising mostly individuals with lower levels of acculturation (those who are foreign born and Latino) will be dense and have fewer "external" ties to individuals outside the group. These groups will also have lower levels of delinquency (Q2c, d).

(c) The subgroups that have more delinquent members will be denser with one or a few central players. Those in more loosely connected groups are more constrained by the behaviors of others and are thus be less likely to be delinquent (Q2b, c, d).

(d) Subgroups that have more delinquent or violent members will also have more ties to individuals in the neighborhood (Q2c, d).

The following chapter discusses the design of the study, the data collection methods, and measures used in the analyses, and then presents the analysis plan.

[8] Homophilous literally means "love of the same," but it is commonly used to refer to the phenomenon where similar people tend to gravitate toward each other and spend more time together.

CHAPTER 2

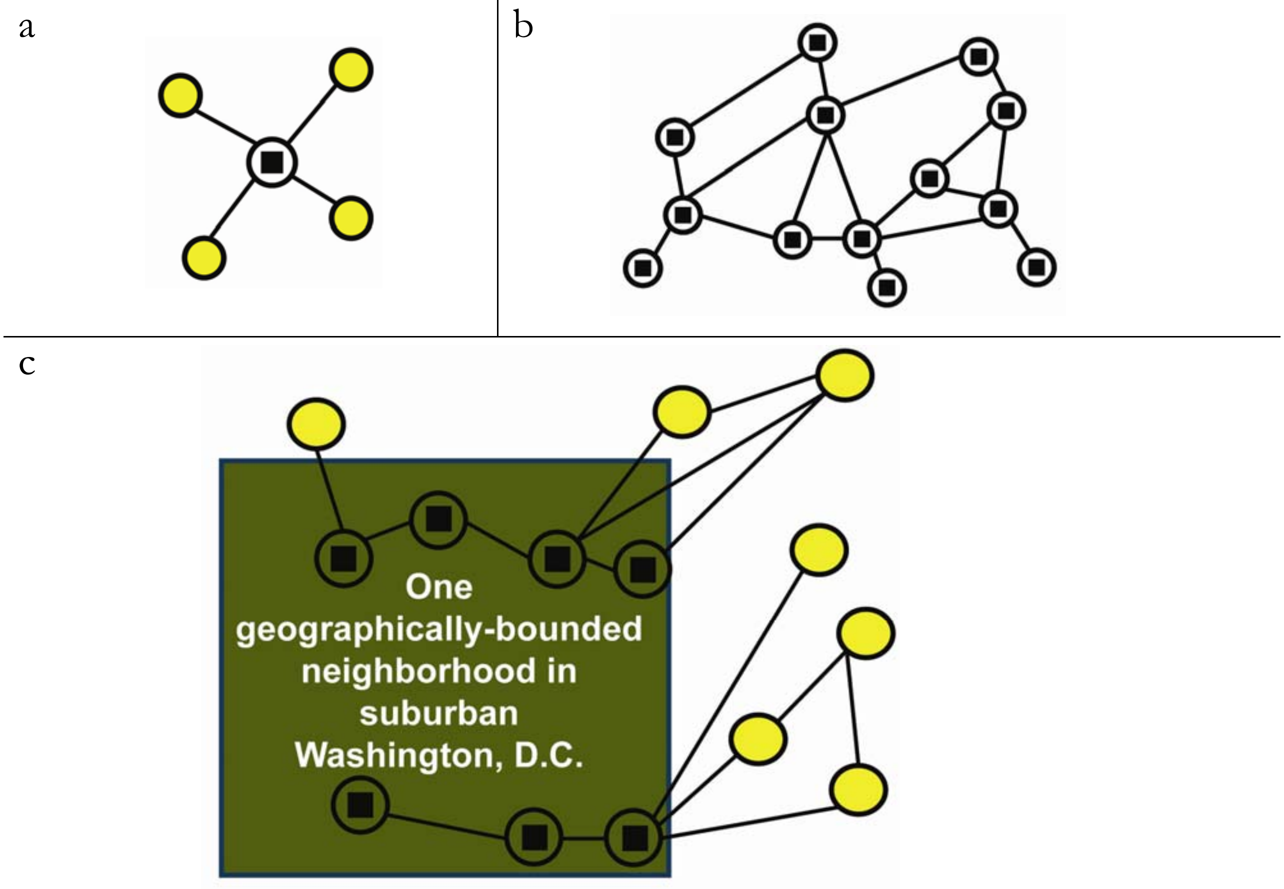
DESIGN AND METHODOLOGY

The design and methodology of the study are based on the theoretical and analytical framework of the network approach. A central hallmark of network analysis is its emphasis on relationships. The network framework is designed to capture how the structure of relations influences the dynamic individual and group processes that both shape and are shaped by criminal behavior. For our particular study, because we planned to conduct both egocentric analysis and sociocentric analysis using overlapping networks, we required a data collection strategy that allowed for the wide range of analytic possibilities. Figure 1 graphically illustrates the difference between three different networks and the sampling techniques that yield data for different types of analyses (and answer different research questions). Network data can be collected in various ways, and each method yields its own set of data that then provide unique management and analysis requirements (Valente, 2010). Our intention in collecting egocentric data for use in whole network analysis via overlapping networks required a specific method, described in more detail below. We first describe the research site and sample, and then describe the data collection strategy, followed by a detailed description of data preparation for whole network analysis and measures. We conclude the chapter with a description of the analysis plan for both the egocentric and sociocentric analyses.

THE SITE

We chose a small neighborhood in Montgomery County, Maryland, just north of the District of Columbia. Montgomery County was chosen as the research site for several reasons: evidence of a variety of active Latino groups/gangs existed, the research team had familiarity with the neighborhoods and a general understanding of the nature of gang/groups in the county, and the

Figure 1. Illustration of Three Different Types of Networks; (a) Egocentric, (b)Whole Network via Surveying All Individuals, (c) Whole Network via Linking/Overlapping Ego Networks



Nodes with squares inside indicate survey respondents; gray nodes indicate that data on these nodes are not based on self-report, but on report by those surveyed (or, in the case of figure 1-c, average/majority of responses for nodes).

research team had already built a solid relationship with a community organization (Identity, Inc.,) that works closely with high-risk and gang-involved Latino youth. In addition, Identity, Inc., reported that gang activity and gang structure in the county were greatly influenced by level of acculturation. Staff from Identity, Inc., shared with us a community assessment they conducted 2006, providing further evidence of the high-risk nature of youth in target site.

Because we intended to choose one well-defined neighborhood, we conducted focus groups and spent time in the field to learn about perceptions of neighborhood boundaries, youth attachments, gangs, and crews. We examined crime data, parcel data, and census data for areas in

Table 1. Census Characteristics for County and Survey Site

	Montgomery County, Md.	Survey Site
Male	47.8%	51.0%
Population under 18 years	25.3%	28.9%
Population over 65 years	10.2%	5.2%
Population 14–21	8.9%	15.9%
Black	15.0%	17.9%
Hispanic/Latino	11.5%	59.0%
Female-headed households with children under 18	14.4%	23.8%
Speaks English "not well" or "not at all," ages 5–17	0.8%	3.7%
Speaks English "not well" or "not at all," ages 18–65	5.2%	26.9%
Foreign born	26.7%	62.3%
New resident since 1995	47.3%	61.5%
High school degree or higher	90.3%	55.2%
Unemployed	2.2%	5.9%
Below poverty level	5.4%	17.5%
Per capita income (1999)	$35,684	$14,100
Renter-occupied units	30.3%	74.0%
Vacant units	3.0%	2.2%
Large (6+) households	4.2%	13.2%

Source: U.S. Census, 2000.

suburban Maryland that were predominantly Latino neighborhoods. We conducted informal, unstructured interviews with neighborhood leaders and youth informants. We drove around the neighborhoods with our informants to gain an understanding of neighborhood boundaries and whether there were common definitions of what constituted a "neighborhood" for youth. Data from the unstructured fieldwork and focus groups were used to revise the research design, finalize the sampling process, inform study protocols, and develop survey recruitment procedures. We also used the fieldwork to explore whether highly secretive gangs (if identified) would be amenable to being subjects of this research.

The target area selected is residential and mostly comprises low-rise apartment buildings and a few single-family homes. There are a park and an elementary school within the target area and a recreation center just outside the boundaries. The area is approximately one mile from a major interstate, has public bus stops within the boundaries, and is located a few miles from a metro station. Table 1 provides U.S. Census-based characteristics (from 2000) for the target area and for the county in which the site is located. As can be seen in the table, the survey site consists of households where over 60 percent of residents are foreign born, only 55 percent have high school degrees, and per capita income is less than half that of the county average. Other important characteristics to note are higher than average residential instability, a large population of youth, and a large percentage of large households.

THE SAMPLE

The Neighborhood as the Network

The neighborhood constitutes the framework for the group "network." The particular neighborhood was chosen because it is a disadvantaged, high-crime neighborhood that has variation on characteristics important to the goals of our study: respondent country of birth, age, participation in criminal behavior, and gang membership. For a number of reasons, the sample was purposely designed to be a census of the neighborhood youth. First, crime prevention and intervention programs, particularly anti-gang programs, are most often neighborhood-based with the expectation that a program will target youth "in the neighborhood." Neighborhood-based programming is based on the idea that one can address issues that are rooted in the socioeconomic structure of the neighborhood and the associated problems that are coupled with disadvantage. Second, scholars know little about how neighborhood context and contacts influence networks and behavior, yet entire bodies of research have suggested that neighborhoods influence outcomes with regard to criminal behavior (for example, social disorganization theory and research, and other opportunity theories). Third, network studies that concentrate only on school networks or friendship networks are missing important links that shape behavior (see full discussion on this below in the whole network methods section). Hence, we determined that an innovative way to understand networks and to learn the most we could from our study would be to carve out the framework for the network as a bounded neighborhood.

The fact that this is not a random sample of the youth population has analytical advantages for exploring the relationship of social networks with delinquency and gang membership. Since all respondents are members of "the neighborhood," we are able to examine how personal networks of all respondents may be linked together or overlap, yielding insight into the connections within and beyond the neighborhood that might influence delinquent behavior in ways that have not been explored. For instance, we can examine the influence of relationships that are formed beyond peer networks, which may be rooted in the community or in other contextual aspects of the social environment. In addition, we can examine how position within the neighborhood network, as well as the personal characteristics of the respondents (egos) and relations (alters), influence the likelihood that an ego is involved in delinquent or violent behavior.

To develop our sample, using a geographic information system, we overlaid parcel/address data on the specified neighborhood boundary with the intent of surveying all youth between the ages of 14 and 21 living in the defined area. There were 853 addresses within the target area. Our study did not conduct a census of households before outreach and recruitment for the survey administration began. Given a specific amount of resources, we chose to increase the canvassing and recruiting time per staff member, as opposed to using funds to launch a separate effort to conduct a detailed census of households. Furthermore, as one of the aims of our study was to create a whole network of all the respondents in order to gauge the structure of subgroups within the neighborhood network, we would be able to obtain data on the characteristics and behaviors of neighborhood-based individuals *who were not surveyed*. Given the likelihood that more than one respondent listed the same youth who was not surveyed, we can use those multiple data points for the same individual to verify the characteristics and behaviors of the nonrespondents.

A key facet for our study is that we will use all relations named across all respondents as the basis for our whole network analysis (described in detail in later sections). This forms the basis for the whole network analysis—we use the data for all alters across all respondents and examine the structure of groups and subgroups that appear across all relations, regardless of whether they live in the target neighborhood or out of the target neighborhood, or whether they are peers or not.

The Survey Protocol: Egocentric Data

The survey protocol was developed to be primarily a network-related survey that would allow us to create a whole network from overlapping personal networks. There are three basic parts to the survey: (1) questions about the ego, (2) the listing of 20 alters by respondents followed by a set of questions asked about every alter, and (3) the alter tie question that is used to create the structural links among members of the network. The first part of the survey resembles any other youth risk survey, and includes questions in a number of risk domains, guided by the criminological literature reviewed in Chapter 1. The protocol can be found in Appendix A. Key domains included on the survey are listed below:

- respondent demographics
- acculturation and ethnic identity
- attachment to institutions (school, employment, church/religion, sports, community)
- family bonding and family encouragement in school
- reasons for hanging out with friends
- at-risk and criminal behavior; gang membership

Items were derived from a few key sources or previous criminological studies. We relied on the Rochester Youth Development Study for the delinquency items, and borrowed many items from Maxson's U.S. Department of Education–funded study "School-based Protection of Youth At Risk for Joining Gangs" (Maxson & Whitlock 2004) and Fleisher's network study of girls in gangs in Champaign, Illinois. But it should be noted that since there have been few network studies of delinquency, and none that utilize our data collection method, many of the survey questions were developed specifically for this study, with input from a core team of senior advisors.

The Survey Protocol: Collecting Alter Data

The second section of the survey begins by requiring the respondent to name 20 people that he/she knows and with whom he/she interacts. This is where personal network data collection diverges from typical surveys used in social science research. A standard method for collecting network data from youth—even peer data—has not arisen from the delinquency (or substance abuse) literature (Kirke 1996). The roster, or list, method, however, is probably the most common way to construct personal networks among youth. This method is typically done in school-based or other settings where the whole network of interest (e.g., a classroom, grade, or whole school) is well defined and all members are known.

Given our research goals, and in order to create personal networks for each ego and then to match up all egos and respondents into one large network, we chose instead to use a free recall method (Marin 2004) using a name generator, or a question that asked respondents to name by memory 20 individuals. We used the name generator to elicit from egos the names of people they know (alters). The name generator question is critical to the study in that it defines the sample of network alters—or the people who are in an individual's social network. For our study, we wanted to capture the networks of youth that comprise people who are important to the youth and might influence the youth—either positively or negatively. The people elicited could be friends, parents, siblings and other relatives, even teachers, coaches, and people met just hanging out in the neighborhood. We worked closely with delinquency and gang experts, as well as social network experts, to create a meaningful question that would reduce measurement error in the production of personal networks. Our name generator question reads:

> *Please list 20 people that you hang out with or might see regularly in a typical day. Start by thinking of the people you hang out with every day. Then, think of the people you talk to or see the most–it may be family members, friends, neighbors, or even people you don't like.*

We required that respondents listed a specific number of people (20). This method of requiring a set number of alters is specifically used to ensure that respondents are thinking comprehensively about the people in their lives and will be less likely to leave anyone important out, and it avoids missing data and bias issues that can arise when egos are not asked to name a specific number of alters (McCarty, Killworth, & Rennell 2007). In addition, previous research has shown that if egos are not required to list a specific number of alters, they are more likely than not to exclude important individuals because they simply forget about them (Brewer 2000; Brewer & Webster 1999; Marin 2004). Also note that a geographic limit was not imposed.

We have not found any examples of delinquency or gang research that have used this method of social network analysis collection, and very few studies in other fields have even employed it. As mentioned above, most network research involving youth uses the roster method. In this type of network data collection, the survey instrument includes a roster or list of all individuals in the network. Respondents are asked to nominate a certain number of individuals from the list who fit specified criteria (e.g., "your five best friends" or "ten people who pick on you") and then answer questions about those selected individuals. A benefit of this method is that the "boundaries"—or complete membership of the whole network—are known, and researchers don't have to spend time determining whether respondent A is talking about, for instance, the same James as respondent B. The roster thus prevents any ambiguities as to who is being described in the alter questions. Response rates and the extent of missing data are also easier to estimate when the size of the whole network is known.

On the other hand, many youth have friends or contacts who do not attend the same school—they may be on the same extramural sports team or know each other through their family or their neighborhood. These individuals who do not attend the same school as respondents may be influential in a respondent's life but would not be included in the survey analysis. This exclusion of possible influential individuals in a youth's life could lead to biased or misleading results when analyses are performed on the data. This is an especially relevant consideration for research on delinquency and gangs in particular, where older individuals and individuals not in school are likely to have strong influences on the delinquent behaviors of youth in school—those influences would be missed were a delinquency study to exclude anyone not in the same school (class, grade) as the respondent.

Another drawback is that when youth are provided with a list of names from which to choose alters, they may pick the individuals that they see first on the list, potentially excluding individuals who may be more influential from their responses. In addition, the roster method typically asks students to nominate relatively few individuals who form (part of) their social network—typically 10 or fewer individuals. Again, delinquency and gang studies present unique challenges than studies on other phenomena; youth may be strongly influenced by people that they would not call their best friends (e.g., older siblings/family members who are in gangs), and if they are in a gang, they may spend a lot of time with, and follow directions or advice from, individuals that they don't necessarily like. In these cases, asking youth to name just a handful of their closest friends at school would exclude a large part of their social networks that influences their behavior.

The Add Health data, an extensive dataset that includes network data collected via the roster method in multiple schools, has been used in a large number of social network analyses on youth behavior by different researchers. The availability of these data are part of what make the roster method one of the most common used in youth-focused social network analyses (for examples, see Haynie 2002; Haynie & Osgood 2005; Kreager 2004; and Young 2010). The method is popular, however, even among researchers not using Add Health data (for examples, see Faris & Felmlee 2011; Kreager, Rullison, & Moody 2011; and Young, Barnes, Meldrum, & Weerman 2011).

Secondary data sources can also be used to create networks that can then be analyzed using social network analysis techniques. In delinquency studies, these sources are often arrest or court records for a specific jurisdiction. These data can provide such information as who is co-offending together (if arrested together or listed together as suspects for a specific crime) or which individuals are in the same gang (if police or other agencies are tracking gang membership). These data are often restrictive in their utility in social network analyses, as they rely on a third party (the police or courts) to record co-offending behaviors, and they typically connect just two people (dyads) instead of connecting multiple people together into a full network. Nonetheless, if readily available, such records make social network analysis more accessible because they don't require extensive primary data collection. Schaefer's (2011) study of co-offending in Maricopa County, Arizona, relied on court records and offender home addresses to study neighborhood effects on delinquency and offending patterns.

For several reasons, we chose not to use the roster method or secondary data (e.g., court records or Add Health) that were already collected. First, we were explicitly interested in the neighborhood network—not a school-based network—because we were interested in exploring the efficacy of place-based anti-delinquency programming. Second, given our expectation that adults and other individuals not in school could strongly influence youth behavior, we did not want to restrict youths' networks to classmates or schoolmates; we wanted them to tell us about anyone—peers, siblings, family members, neighbors—who was influential in their lives. We also did not want to restrict their networks only to those with whom they were friends; youth may spend a large amount of time with fellow gang members that they do not like but who nonetheless influence their behavior.

In addition, we did not want respondents to name only individuals who fit one category (e.g., were bullies, were bullied by respondent) as was done in Add Health and other existing social network data sets (Faris & Felmlee 2011). Finally, instead of looking only at personal ties, where dyadic data may have been sufficient, we wanted to create a "whole network"—connecting everyone who took the survey (egos) and everyone who was named in the survey (alters) in order to get an overall picture of social ties in the area. Therefore, we needed data on how each individual's alters were connected, and we needed more than just a handful of alters from each ego.

The Survey Protocol: Identifying 20 Alters and Connecting Them

Respondents could name any person as an alter, regardless of whether he/she lived in the same neighborhood (i.e., within the target area). Previous network research estimating general personal network sizes (Zheng, Salganik, & Gelman 2006) suggests that respondents would be able to list at least 20 people, although this type of research, and particularly research not using the roster method, has rarely been conducted with youth. While we did have some concern that youth would have trouble reaching 20 alters, McCarty, Killworth, and colleagues' work (2007) demonstrated that most network measures stabilized between 10 and 20 alters; that is, asking alters to name more than 20 alters did not significantly change any of the standard network measures, while dipping below 10, or even 15, could cause some instability in network measures. We therefore chose 20 so youth could name all required alters yet we could most accurately model network properties using the alter data. We found that most youth were able to name 20 individuals with no problem, and only a handful required some prompting or help brainstorming for additional alters.[9] This indicates that for the age range of respondents (14–21), 20 is an appropriate number of alters.

After the respondent lists the full names of the 20 people, he/she is asked a series of 19 questions about the characteristics and behaviors of those alters and their relationship to the respondent. The questions are listed below in Table 2. The last part of the survey consists of one question and is used to obtain the structural data by asking the respondent whether the people (alters) that were named in his/her network know each other. The structural or "alter tie" question is:

> *What is the likelihood that X and X talk to each other or hang out with each other without your involvement or independently of you? Think about any kind of interaction, even if the two don't get along. Would you say not at all; they might, but not sure; or definitely?*

With regard to collecting the structural data, respondent burden can be a serious issue (McCarty, Killworth, et al. 2007). Not only are we asking the youth to report answers to 19 questions for each of the 20 names generated (19 multiplied by 20), but we are asking youth to evaluate alter-alter ties among of network of 20 individuals, which requires 190 evaluations.

[9] If respondents had difficulty completing the list or submitted partial names, survey staff would brainstorm with the youth to think of additional people (reiterating that it was not limited to friends or peers) and encourage more complete names. For example, if a nickname was provided for a first name, staff would suggest the respondent move the nickname to the next page (where nicknames or alternate names are asked) and put the person's first name instead. Some respondents also left out last names when initially entering the alter list; when this occurred, staff would remind youth that the information is confidential and that people outside the research team would never have access to this list or their other responses. In some cases, youth could not remember or did not know last names; when this occurred, staff encouraged initials or partial last names (when possible) and detailed descriptions of the alter (e.g., tattoos, distinctive features, nicknames) to help link or identify the alter later.

Table 2. Questions about the Alter

1. What are $$'s nicknames or other names that friends and family use to refer to __________?
2. How old is __________?
3. Is ___________ male or female?
4. Can you name one thing to describe __________ so that we can tell the difference between this __________ and another __________?
5. Who is ______________? (relationship)
6. Does ______________ live in your neighborhood?
7. How did you meet ______________?
8. Is ______________of Hispanic, Latino, or Spanish origin or descent?
9. What country was ______________ born in?
10. How much time do you spend each week hanging out with ______________?
11. How much do you like ______________?
12. If you needed some information or advice about something, is ______________ someone you could go to?
13. How likely is it that ______________ carries a gun (including in his/her car)?
14. Has ______________ ever sold illegal drugs such as marijuana, cocaine, or crack?
15. How likely is it that ______________ has been in a gang fight over the <u>last year?</u>
16. Would you consider ______________ to be in a gang?
17. Would you be willing to tell me what name _________'s gang goes by? If so, what is it?
18. Have you ever in your life committed a crime with ______________? Please think of any crime that you know is against the law.
19. How likely is ______________ to use violence to get what he/she wants?

Finalizing the Survey and Preparing for Administration

We conducted a number of pilot tests over a two-month period using at-risk Latino youth who lived near (not in) the target area. To ensure that youth would be willing to report on their own possible gang involvement and that of peers, we recruited youth currently known to be in a gang. During the pilot testing, we tried different data collection methods and made notes on respondents' comments on the wording of questions, language of the survey, and their comfort in answering the questions, especially the more sensitive questions about delinquent behavior. After all changes had been made to the protocol, the survey was programmed into a social network software program called EgoNet. EgoNet is a free software program designed by one of the project's expert consultants, Christopher McCarty, that allows you to collect data from respondents about interaction with network members (alters). EgoNet was originally designed to collect and analyze information on personal networks, and was not set up to analyze whole networks. However, at the time our study began, Dr. McCarty was developing functionality in EgoNet to allow for analysis of whole networks. We worked closely with Dr. McCarty and his programmers to develop the functionality that would allow the program to compare names of alters and egos across all respondents and match names together to form an overlapping network.

The survey was developed in English for EgoNet and translated into Spanish for a paper version of the survey for staff interviews with youth who could not take the electronic English version. All respondents took the survey in English when possible, although a bilingual speaker was available to conduct interviews in Spanish when necessary.

Survey Recruitment and Administration

For survey administration, we sought a site that could accommodate multiple survey-takers at one time (on separate computers), that had flexible hours, and that was easily accessible to youth. We also required the location to be neutral in terms of gang or group affiliation. Based on these requirements, we selected a county-operated recreation center that was directly across the street from the target neighborhood. The location was a neutral and safe location for respondents; it was convenient (within walking distance of homes) for youth; it was well known by residents; and it was large, housing various activities and programs throughout the day, and therefore not raising unusual attention to youth respondents, since youth are constantly coming in and out of the building. The facility worked with the survey staff to accommodate our space and time needs.

Two training sessions were held for staff involved in recruiting and surveying youth. Staff were provided training on outreach strategies, the door-to-door recruitment process, determining eligibility of potential respondents, consenting youth and parents, and responding to questions or concerns. The training session also included a review of the study's goals, the potential risks and benefits to respondents, and safety precautions in the field. In addition, staff members were trained to administer the survey. Perhaps most important, the training emphasized that the project aimed to conduct a census of youth residing within the target neighborhood boundaries. Conducting a census instead of using a sampling plan meant that careful record had to be made of which residential units were visited, on which day and at what time, and what the result of each visit was. This information was crucial to estimating not only how many youth in the target age range lived in the neighborhood but also how likely it was that we could recruit youth with additional outreach or canvassing efforts.

In addition to formal training, staff members also received project identification badges and t-shirts to clearly identify them as survey staff while in the field. Staff dressed casually (e.g., jeans and project t-shirts) so they would not be perceived as government or immigration service employees. This was a notable concern in this particular community, since many immigrants reside in the target area and the local police department had recently indicated that it would begin asking residents for identification.

The survey recruitment process involved several strategies. First, outreach efforts took place both before and during the survey period. Bilingual mailings were sent to all eligible households (defined as those located within the community boundaries); bilingual flyers were distributed throughout the neighborhood and signs were posted in the local community center (where the survey was administered); a toll-free number was designated for the study, where English- and Spanish-speaking project managers were available to answer questions from parents, youth, or other community members and schedule survey appointments; and information about the study and the survey was circulated by word of mouth by our community partner.

In addition to these outreach strategies, door-to-door recruitment took place from November 2009 to March 2010. The recruitment teams of two persons each were made up of one staff member from both the research team and the community organization. In addition to the age and organizational diversity of research agency and community organization teams, these teams were diverse in gender, ethnicity, and Spanish-speaking ability. Having Spanish-speaking recruiters proved crucial for this project, as the vast majority of residents (especially parents) in the community spoke Spanish and many of the households did not have any English-speaking residents.

Recruitment teams were given specific areas within the neighborhood within which to canvass, and the teams documented recruitment results at each household (e.g., knock but no answer, no youth living at the address, appointment(s) made, requests for returning to the address or scheduling appointments, refusals, and any relevant notes). To increase the likelihood of reaching all the eligible youth in the neighborhood, recruitment teams would often ask neighbors whether nearby households not answering knocks had eligible youth living there. Recruiters would also ask those answering the door but requesting a return visit for their telephone contact information. Recruitment teams attempted to knock on each non-answering household door at least four times throughout the data collection period. Although all-day recruiting on Saturdays was the most popular day and time for multiple teams to recruit, teams of two also went out into the community on weekday nights to reach those who were unavailable or working on weekends and increase the response rate (see the Response Rate section below for more information on these results).

The Survey Process and Procedures

While several pairs of survey staff were engaged in Saturday door-to-door recruitment, other team members simultaneously set up a survey room in the community recreation center. When recruiting door to door on Saturdays, teams could direct youth immediately to the community center throughout the day. When a potential survey participant would arrive at the community center, eligibility was verified. Youth were asked to fill out a contact information card (also called a locator form); from that form, the person's address and age were used to determine eligibility. If both requirements were met, any youth under age 18 were then required to have parental consent before continuing. After parental consent was obtained[10] (or for those age 18 or over), the youth consent was then administered. Both the youth and parental consent described the purpose of the project, the voluntary nature of the survey, the process for keeping all respondents and responses protected and confidential, the potential risks and benefits of their participation, the $50 incentive each respondent received for taking the survey, and the time commitment involved in participating.

The surveys were conducted on encrypted, password-protected laptops using EgoNet. Youth were spread out in the room and seated at different tables when possible; as much as possible, the laptop screens were also positioned so they were not visible to other youth in the room. The research team had at least 20 laptops ready for use each survey day; on a few occasions, the room was almost filled to capacity.

After a youth had consented and was ready to begin the survey, a researcher explained the computer administration process to the youth and sat with her/him as she completed two practice questions. The staff member also explained at that time that there were several "stop points" that were used throughout the survey, and that respondents should ask staff at any point if they had questions or were confused by anything in the survey. The stop points were built into the survey to provide additional confidentiality to respondents; every respondent was required to raise his hand a minimum number of times during the survey, so if an individual had a personal question for a staff member regarding the survey, it would not be out of the ordinary or draw attention to raise his hand for assistance.

On average, it took participants about one hour to complete a survey, although some respondents took up to two hours, mostly based on English language speaking ability. As soon as a respondent completed the survey, he was provided with a $50 Visa gift card, signed a receipt, and

[10] Parental consent was most often obtained in person by recruitment staff going door to door in the neighborhood; the forms were transferred to the survey location so consent could be confirmed. In other cases, parents came into the center or survey staff spoke with parents over the phone to confirm consent. Over-the-phone consent was approved by the Urban Institute's IRB after we had difficulties obtaining in-person parental consent.

left the room. The respondent's survey was immediately copied onto a jump drive, and the survey file on the laptop was destroyed. The survey jump drive was always kept on a research staff person or in a secure locked file box; upon transfer back to the evaluation team's office, the jump drive was also kept in a locked cabinet when not in use.

The survey was administered at the recreation center on several Saturdays between December 2009 and March 2010. A total of 160 youth completed the survey over that period. After cleaning the data, research staff found 10 youth who lived at least one or two streets outside the specified target area and 3 youth who were outside the targeted ages; we dropped those ineligible individuals, giving us a final count of 147 valid surveys.

Response Rate. It is not possible to calculate a true response rate because, as stated earlier, our study did not conduct a census of households before outreach and tracking before survey administration began. Using 2000 Census data, the study team estimated that there were roughly 440 youth within the target area. This is a very rough estimate in that the Census data were old, residential mobility is very high, and Census data do not provide a specific estimate for our target age group. The survey yield is shown in Table 3. As mentioned earlier, the research team initially identified 853 addresses within the community. Of these homes, approximately 49 percent (n = 417) did not have any youth.

Table 3. Survey Yield

Tracking Outcome	N (%)
Number of addresses in target area	853
No shows	44 (5.2)
Two knocks, no answer	105 (12.3)
At least three knocks, no answer	74 (8.6)
Invalid address/vacant	96 (11.3)
No youth age 14–21	417 (48.9)
Refused	28 (3.3)
Number of addresses that yielded participants	89 (10.4)

Preparing Whole Network Data for Analysis

As mentioned briefly in earlier sections, whole network analysis is very different from ego analysis. Whole network analyses for the current study are conducted using data from overlapping egocentric network data. The process involves taking all the data for egos and alters and determining for whom we have multiple data points, and then supplying a "true" value on that characteristic or behavior for that node in the social network. Essentially, the alters become nodes in the whole network and hence will have their own position and structural characteristics across the whole network.

While preparation of the egocentric data for analysis followed a standard process of cleaning and recoding data, preparing the sociocentric data required a very different approach. This process, described below, was required to allow visualization of the whole network of connected egos and alters, and to allow analyses of the "whole network" data. The database contained 160[11] unique ego names and 3,200 non-unique alter names; creating a whole network required the research team to determine which of the 3,200 alters matched egos and other alters.

The first step in this process was to gather data on respondents and egos from a variety of sources. Throughout the data collection process, respondents were asked to fill out various forms, such as parental consent forms, youth consent forms, and contact information cards (locator forms). The consent forms were required as part of the human subjects protection efforts of the project, but they were also useful in providing additional information on respondents, such as additional last names that may be in use in their household (e.g., if the parent that signed the form had a different last name), siblings in the household (all youth in one household could use one parental consent form), and correct full names of the youth and actual birthdate (instead of age).

The locator forms were used by the research team to verify eligibility when youth came in to take the survey; youth were required to list their name, age, and address. In addition, planning for the possibility of replications of the work in the same area, we asked for a parent name if the youth

[11] Although only 147 were used in the final analyses, we cleaned data for all 160 respondents in case they provided information on others who were eligible and were included in the survey.

was under 18 and the name of someone who "usually knows how to get in touch with you" so we could locate respondents for a possible second survey. Youth were allowed to list anyone on the locator form, and that gave us an additional individual who was connected to the respondent, even if they did not list that person as an alter in the actual survey. Finally, the survey team also recorded the date and time each individual took the survey along with where in the room each respondent sat. This allowed us to determine during the cleaning process which youth had come in together and near whom each respondent sat while taking the survey.

The survey itself also contained a number of items useful in helping the research team make matches of two individuals with the same or similar names. For each alter, respondents had to give us the individual's full name (to the best of their ability), nickname(s), a brief physical description (e.g., tall or blonde hair), age, sex, relationship to respondent, whether he/she lived in the neighborhood, and his/her ethnicity. These questions, together with information gathered from the various consent and check-in forms, allowed the research team to make informed decisions on matching individuals.

While the survey software used for the project, EgoNet, was useful in collecting social network data, its utility for the name cleaning/matching process was limited. We therefore exported the alter names and demographics to an Excel spreadsheet, joined in information from the forms that had been entered into an electronic spreadsheet, and conducted the name matching outside EgoNet. Two members of the research team were responsible for making all decisions on name matching. This ensured that the decisions made were as consistent as possible, and having two individuals review different data sources both made the process faster and guaranteed that two people had agreed on whether a match should be made.

The Name Matching Process in Practice

The process started by examining a given alter name (however complete or incomplete it may have been), and then looking for first, last, and nicknames that might match. The names database might contain the following name: Juan Ramos. After looking at all possibilities, we might determine that the following alters were possible matches: John Ramos, Juan R, Ramosy, and JR. We would then look at the demographics for all five individuals to determine whether they were similar in age, race, and ethnicity. Then we would consider the nicknames—in this case we would start by checking whether any of the "real" names (Juan Ramos, John Romas, Juan R) had nicknames like Ramosy or JR listed. We would then check the physical descriptions given for each person to see if any descriptions conflict. If we still couldn't make a determination, we would turn to the information from the consent and locator forms to see if additional light could be shed on the individuals. In some cases, we did not have enough information to make a clear decision and no match was made.

The actual matching process was an iterative one and started by cleaning names that were misspelled and running frequencies on those names. The first pass through the data sought those individuals who occurred most frequently and were likely to have many matches. We considered first, last, and nicknames separately: for each name appearing in the dataset, we checked other similar first names, last names, and nicknames for possible matches. When we found two names that might be a match, we checked ages, physical descriptions, and other alter data to determine how likely it was that the two individuals were indeed the same person. When we determined that two (or more) alter records were the same person, those two (or more) records were given the same ID number.

We encountered a number of different challenges during the name-matching process. First, spelling was not consistent across many alters, even those that we determined were the same person. While the actual spelling of the name was irrelevant in terms of the research, in order to run frequencies to assist us with the matching, we had to do some basic corrections of typos and misspellings; otherwise the frequency was no more helpful than the original list of names. Second, many individuals in our survey had similar names. For males, Jose, Carlos, Alex, Luis, and Juan were the most popular, with each appearing more than 30 times (Jose appeared 90 times in the name list). For females, Maria, Ana, Jennifer, Jessica, and Rosa were the most common, each appearing more than 15 times (Maria appeared 29 times in the name list). These common names, especially if listed with no last name or an equally common last name, were difficult to confidently match with other alters as the same individual. For these and other very common names, we relied heavily on nicknames, ages, and physical descriptions. We also had a large number of alters where incomplete names were given; most of the incomplete alters had a first name and last initial although some listed only a nickname as the full name. In these cases, we also had to rely on alternate sources of data to make match decisions. Finally, we had to contend with inconsistent reports of alter characteristics. For example, Juan Ramos might appear in the names list twice but his age might be listed as 14 and 16 by two different egos. In these cases, we had to use other data sources and our best judgment as to whether they were the same person or not (e.g., we might assume Juan's older brother who named him would be a better judge of Juan's age than a cousin or friend).

Inconsistent reports of alters posed a challenge beyond simply matching names, however. After going through each name in the database, we were able to identify just over 2,500 unique individuals. Before moving to visualization of the whole network and analysis of the data, all of the alter data had to be summarized for each unique individual. In other words, if one individual was named by 10 different egos, we had to summarize the 10 separate records for that one person, which may or may not report the same details. Two types of data needed to be summarized: the attribute data, including such items as age, ethnicity, and delinquency, and the tie data, which indicated whether one alter was tied to another.

We used EgoNet to summarize the alter attribute data; the software could read in the IDs for each unique individual that were created during the name matching process and summarize the data based on those IDs. For these data, where conflicts in alter records existed, the software would take the majority answer; if no majority answer existed, it would use a value for the variable from one randomly selected record. In addition, if this process was necessary across multiple variables for one individual, EgoNet would take answers from different egos for each variable, so that one ego didn't supply all of the answers about the individual. For numeric data, the software would average the values (e.g., for age).

Some alter variables were ego-specific, meaning that we would expect different egos to have different answers about the same alter, such as the relationship between the ego and alter and whether the ego and alter had committed any crimes together. EgoNet can create summary measures for each possible item response value by ego (e.g., percent of egos who called this alter a friend/sibling/cousin; percent of egos who would go to this alter for advice). We used those data instead of the "majority rule" alter data to represent the ego-dependent alter data. Finally, using the alter measures, we created an alter delinquency index consistent with the ego-level delinquency index described in the above section. This allowed all egos and alters to be analyzed together using consistent measures.

Next, we had to resolve conflicts within the alter tie question. This question asks egos to report, for each alter, that person's likelihood of talking with all other alters that person named. In many cases, two egos named the same two alters, and we thus have multiple reports on whether alters are connected to each other. Two egos may differ on whether they think two alters will speak with each other, and those differences needed resolution. EgoNet can handle this process, and the software offers some summarization options for creating the whole network. First, it allows you to choose whether you want a network containing only those individuals who appeared at least twice in the dataset (e.g., were named by at least two egos), whether you always include egos (regardless of whether they were named by someone else as an ego), and how alter discrepancies should be resolved. The most conservative way to resolve conflicts is to require that at least one ego says the alters should be tied and none say they should not be tied (the minimum number of ties); the most liberal way to resolve conflicts is to require that at least one ego says the alters should be tied and disregard any that say they should not be tied (the maximum number of ties). For the present study, we used the "majority" criterion to resolve conflicts, where the majority answer was used. As with the attribute data, if no majority existed, no tie would be made. If the individual was an ego (i.e., if he/she also took the survey), his report on whether he/she is tied to another individual overrides others' reports.

Our data contained individuals who were named by up to 11 respondents, but 30 percent of egos were not named by any other respondents. The dataset contained 369 people, or about 15 percent of individuals, who were named more than twice; nearly 90 percent of the individuals were named only once. This high number of individuals named only once stems partially from our design that allowed respondents to name any individual in his/her life, instead of limiting it to peers or schoolmates. The design resulted in many respondents naming siblings or parents—individuals that may only be influential in their lives, and not the lives of their peers in the neighborhood. This could also partially be a result of our inability to match individual names as the same person due to lack of complete information on an alter. While some analyses employ only nodes who were named more than once, we chose to compare results for the network that includes all network members and one that includes those named two or more times. We decided to explore the network with all members, despite their being less connected than others, for two main reasons: first, we would lose a significant number of network members if we imposed stricter criteria (dropping from 2,521 to 369); and second, our theoretical design backs inclusion of everyone who was named, as we are seeking a greater understanding of who influences whom; without all members, we could not fully assess that question.

Missing Data. With any survey data collection effort, there is likely to be missing data in the form of items that were not completely filled out by respondents who took the survey but also in the form of missing respondents. Understanding the extent and nature of these missing respondents was of utmost importance to this research given our goal of conducting a census of youth in the target area. Due to the unique nature of the data collected, we were able to both estimate the number of missing respondents and collect data on those individuals via others who did take the survey.

Because we are using overlapping personal networks to create a whole network, in many cases more than one respondent provided evaluations of a single individual's behavior—whether or not that individual also took the survey. Missing respondents for this project are considered to be those youth age 14–21 who live in the target area but were never interviewed. Usually, the problems associated with sampling and missing data in whole network analysis stem from the inability of researchers to interview or observe network members (McCarty, Molina, Aguilar, & Rota 2007). But missing data of this type (missing respondents) is less problematic for the present study than it is for a typical whole network study because we have data on missing respondents provided via actual respondents. In addition, in many cases, we have multiple evaluations of those "missing respondents." Therefore, we can not only assess the number of individuals who we should have interviewed (because they were in our target age and lived in the neighborhood) but in many cases we also have multiple informants providing information on those individuals. We view the values attributed to those "missing but reported on" individuals as much less likely to have respondent bias than if only one person reported on him/her.

We estimated the number of youth who live in the target area but were <u>not</u> interviewed by examining alter names provided by all egos as living in the target neighborhood and being between the ages of 14 and 21 and then checking those names against the list of actual respondents. Individuals who were not in the list of respondents were counted as missing respondents. We estimate that about 330 youth were in the target age group and lived within the target area but were not interviewed. But, as noted above, we do not view this information as missing—we have information on these youth from actual respondents.

As further support for the accuracy of the size of the missing respondent pool, we estimated the total size of the target population at about 440 youth using census data; given that we interviewed 147 youth, that would mean we had missed 293 eligible youth. Our estimate that we missed 330 respondents is thus an accurate estimate of the actual number of missed respondents. Also keep in mind that the criteria "live in neighborhood" was subject to respondent interpretation of neighborhood; we did not provide maps of the target area to respondents, so it is possible that there are youth who reside across the street from or near the target area but not technically inside the target area. Therefore, our estimates should be considered just that—our best guesses at the number of respondents we missed.

After the name cleaning, matching, and resolution of alter attribute and tie data were complete, we were able to create a whole network. We exported the final dataset from EgoNet, made any needed adjustments or edits in another statistical software package, and then imported the data into UCINet. The next section describes the analysis plan for both the egocentric analyses and the whole network, or sociocentric, analyses.

MEASURES[12]

Dependent Variables

For the ego network analyses, we focused on a number of outcome variables that measure different types of delinquent and criminal behavior, as well as gang membership. We created two *additive delinquency scales* that capture the various survey items that represent delinquent and criminal behavior. The first scale is based on whether the respondent "ever" committed the offense; the second scale was based on whether the respondent committed the offense "in the past six months." The nine items included in the scales are:

1. Avoided paying for things, like a movie, taking bus rides, or anything else
2. Tried to steal or actually stolen money or things worth $100 or less
3. Damaged, destroyed, or marked up someone else's property on purpose
4. Tried to steal or actually stolen money or things worth more than $100
5. Tried to steal or actually stolen a car or other motor vehicle
6. Been involved in a gang fight
7. Sold illegal drugs such as marijuana, crack, heroin, or methamphetamine
8. Used a weapon or force to get money or things from people
9. Attacked someone with a weapon or with the idea of seriously hurting or killing them

The "ever" and "recent" overall delinquency scale scores range from zero to nine. Reliability was high for both scales (overall delinquency scale: $\alpha = 0.83$; six months prior delinquency scale: $\alpha = 0.82$). We also created a "serious delinquency" additive scale that excluded three items, related to damaging property and minor stealing (avoiding paying for things like a movie and stealing items worth less than $100). Reliability was good ($\alpha = 0.77$).

We also developed a *binary serious delinquency* measure to capture *any* behavior that could be regarded as delinquent or criminal. The respondent received a score of one if they answered yes to any of the following five items:

1. Ever a member of a street gang
2. Ever in a gang fight
3. Ever sold illegal drugs such as marijuana, crack, heroin, or methamphetamine
4. Ever carried a weapon such as a gun or knife

[12] Detailed descriptions of all measures can be found in Appendix C.

5. Ever attacked someone with a weapon or with the idea of seriously hurting or killing them

These items were chosen in part because they mirror the items that are available to measure the criminality or delinquency of alters—the 20 individuals nominated by each respondent. Note that these elements of crime are on the more serious end of the spectrum for youth than other delinquency measures available for egos, but for the sake of consistency with alter data, we use the term delinquency.

We also examined five important delinquent/criminal outcomes individually in binary form (yes/no):

1. Ever a member of a street gang
2. Ever in a gang fight
3. Ever sold illegal drugs such as marijuana, crack, heroin, or methamphetamine
4. Ever carried a weapon such as a gun or knife
5. Ever attacked someone with a weapon or with the idea of seriously hurting or killing them

With the exception of "member of a street gang," each outcome above was measured using one survey item that directly asked whether the respondent had participated in that behavior. For "member of street gang," respondents either answered yes to "have you ever been a member of a street gang?" or answered yes to being a "member of a group,"[13] and then to "is that group a street gang?" In summary, the dependent variables that were created for the ego-level analyses include the following:

- Scale measures:
  - "Ever" overall delinquency: sum of nine binary "ever" delinquency measures; ranges from zero to nine.
  - "Recent" overall delinquency: sum of nine binary "last six months" delinquency measures; ranges from zero to nine.
  - "Ever" serious delinquency: sum of seven binary "ever" delinquency measures (excludes property damage and petty theft); ranges from zero to six.
- Binary measures

[13] We asked respondents if they could think of a group of friends that they regularly hung out with, and then asked whether they considered that group a street gang. This was done so we could develop different criteria for considering someone to be in a gang beyond simple self-reported involvement.

  - Overall (serious) delinquency: equals one if yes to any of five delinquency measures.
  - Individual delinquency: individual binary measures for each of the five delinquent behaviors.

The next sections discuss different types of independent variables, including control and predictor variables.

Personal Network Variables

We created specific measures to examine the characteristics of each respondent's personal network. These variables are referred to as *network compositional* variables; essentially, the measures provide descriptive information about alter characteristics in aggregate form. Because we wanted to examine any differences between variables that only include peer alters (or, alters named as friends) versus all types of alter relationships (mother, father, sibling, teacher, aunt, etc.), we created a series of variables first using only alters designated as friends[14] by the respondents, and then created similar variables using any type of relation. Only examining the influence of peer networks, as opposed to individuals' entire social network, can be limited in that it ignores the role of other important or influential persons in one's life (Keisner, Kerr, & Stattin 2004). Our definition of peer strictly uses classification as a friend and does not include siblings or cousins. The following are the network compositional variables created for use in the egocentric analysis:

- Peers in network. The proportion of alters who were listed as a friend is used as a control variable. *Continuous variable, values range from 0 to 1.*
- Delinquent peers. The proportion of delinquent peers (friends) in the respondent's personal network. A friend is defined as delinquent if the ego responded that the friend was involved in any of the following five behaviors: ever a member of a street gang, participated in a gang fight, sold illegal drugs, carried a weapon, or used violence to get what he/she wants. *Binary variable, values are 0 or 1.*
- Delinquent alters. This variable is computed the same way as "delinquent peers," but includes any person named in the respondent's personal network (thus, it includes friends) that has been involved in any of the five delinquent behaviors listed above. *Binary variable, values are 0 or 1.*

[14] Respondents were specifically asked to name the relationship they had with their alters—friend was one option.

- Same neighborhood friends. The proportion of peers (friends) who live in the same neighborhood as the respondent, as reported by the respondent. *Continuous variable, values range from 0 to 1.*
- Same neighborhood alters. The proportion of all alters who live in the same neighborhood as the respondent, as reported by the respondent.[15] *Continuous variable, values range from 0 to 1.*
- Males in network. The proportion of all alters who were males was used as a control in the original analyses. *Continuous variable, values range from 0 to 1.*
- Average age of network. The average age of all alters in each personal network was computed and used as a control in the original analyses. *Continuous variable, values range from 13 to 37.*

Acculturation

We use two measures to assess the level of acculturation of respondents.

- Ethnic identity scale. We used the Multigroup Ethnic Identity Measure (MEIM) as developed by Phinney (1992). This scale includes 12 items assessing the respondent's familiarity with the customs and traditions of his/her ethnicity; the respondent's attachment to and understanding of ethnic identity; and the respondent's positive feelings about being a member of his/her ethnic group. Internal reliability is high ($\alpha = 0.892$). *Interval variable, values range from 20 to 60.*
- Separation scale. We formed a scale composed of summing the following seven variables to measure the respondent's level of "separation" from (i.e., lack of assimilation) the United States: (1) the place of birth for the respondent—"were you born abroad?"(yes/no); (2) the place of birth of respondent's mother—"where was your mother born?" (recoded yes, respondent's mother was born abroad/no, respondent's mother was not born abroad);(3) the place of birth of respondent's father—"where was your father born?" (recoded yes, respondent's father was born abroad/no, respondent's father was not born abroad);(4) if the respondent speaks a language other than English (yes/no); (5) if the respondent speaks a language other than English at home (yes/no); (6) if the respondent speaks a language other than English with his/her friends (yes/no); and (7) an ordinal measure of the proportion of the respondent's lifetime spent abroad ranging from 0 (respondent spent no time abroad) to 4 (respondent spent more than 78 percent of his/her lifetime abroad).[16] A high score on this scale measures lower levels of acculturation (or more separation), whereas a low score on the scale measures higher levels of acculturation (less separation). Reliability was good. ($\alpha = 0.653$). *Interval variable, values range from 0 to 9.*

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[15] The criteria "live in neighborhood" was subject to respondent interpretation of neighborhood; we did not provide maps of the target area to respondents, so it is possible that there are youth who reside across the street from or near the target area but not technically inside the target area.

[16] We made the proportion of the respondent's lifetime spent abroad an ordinal variable based on the distribution of responses across the sample (i.e., one standard deviation above and below the mean (but greater than 0) were coded 3 and 1, respectively, while the range in between was coded 2). If the respondent spent no time abroad, the variable was coded 0.

Strength of Ties and Homophily in Personal Networks

Because a key component of this study is assessing how relations influence an individuals' network, it is important to examine the *strength of ties* among and across network relationships. Tie strength is a quantifiable property that characterizes specific properties of links between two individuals or nodes. Granovetter (1973) asserts that tie strength generally includes four properties: amount of time spent with someone; emotional intensity of the relationship, intimacy (e.g., friend vs. best friend), and whether reciprocal services are provided or the relationship itself is reciprocated. Other theorists and researchers have suggested that plausible indicators of tie strength also include emotional support or advice given and/or received (Lin, Ye, & Ensel 1985; Matthews, White, Soper, & van Bergen 1998; Wellman 1982), duration of relationship (Marsden & Campbell 1984), and contextual factors such as social and demographic homogeneity and shared affiliations (Alba & Kadushin 1976). However, few quantitative studies exist (let alone within criminology itself) that include measures of tie strength (Matthews et al. 1998; Petroczi, Nepusz, & Bazsó 2007). As reviewed earlier, some criminological theories, such as bonding and learning theories, support the idea that strength of attachment will influence delinquent outcomes.

Our survey included three questions that tap into the strength of ties between egos and alters. We asked each ego to report on (1) how much time he/she spends with each alter per week, (2) how much does he/she like each alter, and (3) whether he/she would go to alter for advice. Based on responses to these questions, we developed several measures pertaining to strength of ties. The measures were used to assess each ego's attachment to his/her entire personal network (see Appendix C for a complete list of variables and associated definitions):

- High frequency of contact with network is a measure of the proportion of alters in the respondent's network with whom the respondent said they spent "a whole lot of time" during the week. Values for this measure ranged from 0 percent (respondent does not spend a lot of time with any alters) to 100 percent (respondent spends a lot of time with all alters).*Continuous variable, values range from 0 to 1.*
- Likable network relationships is a measure of the proportion of alters in the respondent's network that the respondent likes a lot. Values for this measure ranged from 0 percent (respondent does not like any alters a lot) to 100 percent (respondent likes all alters a lot). *Continuous variable, values range from 0 to 1.*

- Advice support is a measure capturing the proportion of alters in a respondent's network to whom the respondent would go for advice. Values for this measure ranged from 0 percent (respondent would not go to any alters for advice) to 100 percent (respondent would go to all alters for advice). *Continuous variable, values range from 0 to 1.*

Because the strength of tie measures described above do not take into account whether a respondent is close to a delinquent/criminal relation versus a nondelinquent/criminal relation, it is likely that these measures are not particularly relevant with regard to antisocial outcomes. Hence, for each of the measures above, we created variables that measured a respondent's closeness (on each type of strength of tie measure) to delinquent alters and to nondelinquent alters. For instance, if half of an ego's network was delinquent/criminal, then we only summed the responses on "go to for advice" for those delinquent alters. We did the same for nondelinquent alters because, as articulated by Sutherland in differential association theory, we wanted to examine the possibility that the strength of attachment to delinquent alters matters differently than strength of attachment to nondelinquent (or pro-social) alters.

We also created a number of new measures at the alter level that would capture similarity between ego and alter on certain characteristic. Similarity between two nodes in networks is referred to as "homophily," and the literature on adolescents suggests homophily can represent an aspect of attachment or closeness in such that distance in terms of social characteristics translates into network distance (McPherson, Smith-Lovin, & Cook 2001). Research has shown that youth are more likely to be friends with someone who is similar to themselves with regard to age, gender, or race/ethnicity, but the tendency for homophilous friendships decreases as the closeness of friendship decreases and also decreases with age (Joyner & Kao 2000; Kao & Joyner 2004). The tendency for friendship homophily in youth also varies by race/ethnicity (Kao & Joyner 2004). Some research suggests that homophily in race and ethnicity create the strongest divides in personal environments (i.e., friendship groups are divided based on race and ethnicity), followed by age, religion, education, occupation, and gender (McPherson, Smith-Lovin, & Cook 2001).

We first created a set of homophily measures for ego-alter links based on four characteristics: age, gender, ethnicity and nationality. For age homophily, we considered the ego and the alter to be similar if the alter was within (plus or minus) one year of the age of the respondents. Using this information, we constructed a binary variable where age homophily = 1. For ethnic homophily, an alter scored a 1 if he/she was the same ethnicity (response to item: "do you consider yourself to be Hispanic or Latino") as the ego. For nationality homophily, an alter scored a 1 if the country of nationality of the alter was the same as the birthplace of ego's mother or father, or if ego and alter were both born in the United States. Ego and alter must be the same sex for alter to score a 1 on gender homophily. After these alter-level homophily variables were created, we created a summed homophily scale for each respondent's alter; the alter was given a score ranging from 0 (does not match the respondent on any of the four homophily measures) to 4 (is approximately the same age, same ethnicity, same nationality, and same gender as the respondent). We then summed across all 20 alters for each ego to create the final homophily scale. Essentially, we used the alter-level homophily variables to create one final network-related homophily scale that incorporates the various characteristics across all alters.

Ego-Level Network Structure Variables

Two variables were created to measure features of a respondent's personal network structure, as well their relationship to the whole network. The measures were calculated using EgoNet. The network structure variables used for this work are as follows:

- The number of components is the number of subgroups in the respondent's personal network. Components are a measure of separately maintained groups (no link exists between any two nodes of the different groups) within the larger personal network. The measure only consists of a *count* of groups and does not contain information on type of group. This measure is automatically generated in EgoNet statistics for each ego network. Sociological research has suggested that as the number of groups within a person's network increase, the ego becomes more constrained to normative behavior (Krackhardt 1999; Krohn 1986). *Continuous, values range from 0 to 4.*
- Personal network density is a measure of the connections among alters within the respondent's personal network, and uses only those connections where the respondent said his/her alters "definitely" knew each other. EgoNet calculated a mean density measure of the respondent's personal network, using the number of these "definite" connections between alters. *Continuous variable, values range from 0 to 19.*

Sociocentric Network Structure Variables

The sociocentric level measures used for this work focus on measuring two main network characteristics: cohesion and centrality. Here, cohesion of the network is measured using overall network density. Density, also calculated for each egocentric network and described above, measures the overall intensity of the connected actors. Another cohesion measure, calculated for use in the regression analyses, was respondent as isolate. This measure captures those nodes that have little to no connection to other nodes in the network. Centrality measures can be calculated at both the whole network level, when they are referred to as "centralization" measures, or at the individual level, when they are referred to as simply centrality measures. Centralization indicates whether ties are primarily concentrated on a small number of nodes (hierarchical) or are spread evenly across members (decentralized) (Valente 2010). The individual centrality measures (described below) are used to calculate the overall network centralization measure; there are thus several different types of centralization, depending on which centrality measure is used in its calculation.

The following describe the cohesion and centrality measures employed for this research. All formulas provided below are from the UCINet software documentation. The first set of measures describes individual position within the network and the second set describes whole network measures.

- Measures of Individual Position in Network
    - Respondent as isolate. A dichotomous measure (isolate = 1) was created to represent whether the respondent was an isolate in the whole network. In our study, an isolate is a respondent who was *not* named as an alter by any other respondent and did not have/list any alters who were also egos (i.e., surveyed). *Binary variable, values are 0 or 1.*

    - Degree centrality is the most commonly used measure of centrality (Valente 2010), and represents the number of direct connections in a network. While degree can be calculated based on ties received ("in-degree") or ties sent ("out-degree"), our network data is nondirected, so we will simply use (nondirectional) degree centrality, counting all direct ties in the computation of degree.

- Betweenness centrality is described by Valente (2010) as "akin to bridging and centrality combined" (p. 87), with an emphasis not on degree but on total distance between nodes—using both direct and indirect ties. Specifically, betweenness is "the frequency a node lies on the shortest path connecting other nodes in the network" (p. 87), or the number of geodesics (shortest paths) connecting two nodes on which a third node lies.
  Description of betweenness centrality formula: "Let bjk be the proportion of all geodesics linking vertex j and vertex k which pass through vertex i. The betweenness of vertex i is the sum of all bjk where i, j and k are distinct" (Borgatti, Everett, & Freeman 1999).

- Closeness centrality measures the distance from each node to each other node in the network, based on both direct and indirect ties (Valente & Forman 1998). Higher closeness values indicate that a node is able to reach all other nodes over shorter distances. The closeness measure can be thought of as a sort of "degree of separation" as it effectively counts the number intermediate nodes that are needed to make a connection between two nodes. This is done for each node to every other node in the network. The closeness measure does suffer from some complications regarding its calculation when isolates exist in the network (isolates cannot be reached by all other nodes, so the distance between them and other nodes is effectively ∞), and it is subsequently not as widely used as the first two centrality measures described.
  Closeness centrality formula, using Valente-Foreman reversed distances:

$$\sum \frac{1}{(Diameter\ of\ the\ network) - \ (Geodesic\ distance)}$$

  The sum is computed for the shortest possible connections between all node pairs. The geodesic distance is the shortest distance between two vertices or nodes.

- Eigenvector centrality for a node is based "on the centrality of its neighboring nodes" (Valente 2010, 87). This measure is useful in large network studies because it takes into account the overall structure of the network; it is not as susceptible to more "local" patterns, or patterns of closeness or centrality that may exist in small subgroups but may not have a strong role or effect in the larger network structure.
  Explanation of the eigenvector centrality formula is beyond the scope of this report; please see the UCINet documentation for the exact formula.

- Network-Level Measures (computed or either ego network or whole network)
  - Density represents the number of actual ties between all members as a proportion of all possible ties (if every node was connected to every other node). The measure provides insight into how tightly connected the individuals in the network are. Higher density values indicate a network in which nodes are closely connected and lower density values indicate that fewer ties are present between nodes.

Density formula:

$$\left(\frac{actual\ ties}{possible\ ties}\right) * 100$$

- Degree centralization is the network-level measure based on degree centrality. It is similar to standard deviation measures from descriptive statistics (Knoke & Yang 2008) and provides an overall measure of degree for the whole network—however it is defined—instead of just for individual network members.
  Degree centralization formula (individual-level degree centrality is simply a count):

$$\frac{\left(\sum\left(c_{max} - c(v_i)\right)\right)}{c_{max\ possible}} * 100$$

  where $c(v_i)$ is the centrality of vertex v_i and c_{max} is the maximum degree centrality in the network and $c_{max\ possible}$ is the maximum possible degree centrality for the network. The measure, then, is expressed as a percentage of the maximum possible degree centrality.

- Betweenness centralization is the network-level measure based on betweenness centrality. It is calculated using the same formula as used for degree centralization.

- Closeness centralization is the network-level measure based on closeness centrality. The network closeness centralization value is the average closeness value for all nodes (Borgatti, Everett, & Freeman 1999).

- Eigenvector centralization is the network-level measure based on eigenvector centrality. Please see UCINet documentation (Borgatti, Everett, & Freeman 1999) for a full description of its computation.

Control Variables

We included the following ego-level independent variables in our initial models as control variables:

- Family cohesion. We used the cohesion subscale of the Family Relationship Characteristics scale (Tolan, Gorman-Smith, Huesmann, & Zelli 1997), developed to help predict risk of antisocial behavior. The 10 items included in this scale address how close the respondent feels to his/her family; whether the respondent communicates well with family members; and whether the respondent's values and views are similar to his/her family members. We also included an additional item, "Compared to most families, would you say yours was very close to each other, somewhat close, not very close, or not close at all?" from Cheryl Maxson's Family Scale (Maxson & Whitlock 2004). The 11 items had high internal reliability ($\alpha = 0.898$).
- Parental support for education. A dichotomous measure (school support = 1) was created to capture the response to the question: "Does a parent or guardian regularly insist that you go to school and do well?" *Binary variable, values are 0 or 1.*

- Religiosity. This measure represents the response to one item: how often he/she attends religious services (never = 0, seldom = 1, once a month = 2, almost every week = 3, every week or more = 4). A higher score signifies greater religiosity. *Interval variable, values range from 0 to 4.*

We also controlled for key demographics in each of our models, including the respondent's age (continuous variable), gender (male = 1) and ethnicity (Latino/Hispanic = 1). In addition, we controlled for the amount of time the respondent had lived at his or her current address, as well as whether the respondent's parent/guardian/adult in household had graduated from high school (yes = 1).

The next section describes the analysis process used for the study, discussing both ego-level and network-level analyses.

ANALYSIS PLAN

To accomplish the research objectives, two types of analyses are employed: (1) egocentric network analysis and (2) sociocentric analysis. As described earlier, egocentric networks refer to the composition and pattern of the social relations of an individual (McCarty & Wutich 2005). Sociocentric networks refer to the pattern of relationships between actors within a specific group. These two types of network analyses allow us to provide not only a picture of how personal networks influence delinquency and crime, but also provide a comprehensive picture of subgroup formation and group attachments and network structure across the larger network of neighborhood and non-neighborhood affiliations.

Egocentric Network Analysis Plan

Egocentric network analysis is ideal for understanding the way the social environment of a particular group member impacts norms, attitudes, and behaviors. For this study, egocentric analysis is used to measure whether aspects of egocentric network composition—the characteristics of the

Table 4. Descriptive Statistics for Dependent Variables (N = 147)

	Min	Max	Mean	S.D
Overall delinquency scale	0	9	1.64	2.21
Recent delinquency scale	0	9	0.76	1.58
Serious delinquency scale	0	6	0.84	1.41
Binary delinquency measure (violence)	0	1	0.37	0.49
Carried a weapon	0	1	0.23	0.42
Sold illegal drugs	0	1	0.09	0.28
Attacked someone with a weapon	0	1	0.1	0.3
Ever involved in a gang fight	0	1	0.17	0.38
Ever in a gang	0	1	0.1	0.3

Table 5. Model Comparison—Overall Delinquency

Goodness of Fit–Negative Binomial Regression, Overall Delinquency			
	Sig.	**df**	**Value/df**
Deviance	129.824	131	0.991
Scaled Deviance	129.824	131	
Pearson Chi-Square	111.417	131	0.851
Scaled Pearson Chi-Square	111.417	131	
Log Likelihood	-225.915		
Goodness of Fit–Poisson Regression, Overall Delinquency			
	Sig.	**df**	**Value/df**
Deviance	277.945	131	2.122
Scaled Deviance	277.945	131	
Pearson Chi-Square	265.01	131	2.023
Scaled Pearson Chi-Square	265.01	131	
Log Likelihood	-246.415		

network members, such as the proportion of the personal network that is delinquent—and measures of network structure influence delinquency and crime. Essentially, these measures provide insight into the individual-level and network properties that reinforce or deter criminal behavior over and above characteristics of the individuals themselves.

We relied on the software EgoNet for data collection, cleaning, and new variable creation. EgoNet outputs several files. One of the files includes a flat file that combines information about the respondent, summaries of information about the network members (compositional data) and summaries of the ties between network members (structural data). Additional files include adjacency matrices that help to create network visualizations. EgoNet output files were then analyzed in SAS and SPSS.

After we created our dependent variables, we examined the distribution of each scale to determine what type of regression model would be appropriate. Descriptive statistics for the dependent variable can be found in Table 4. Based on the skew in our scaled outcome measures, the means for our delinquency scales, which were 1.64 (overall delinquency over lifetime), 0.76 (delinquency in the last six months) and 0.84 (serious delinquency over lifetime) and the large percentage of respondents who reported no delinquency (48.3 percent), we determined that the data violated the normality assumption of OLS, and that a negative binomial regression model (designed to handle many zero values and high skewness) would be more appropriate. To confirm that negative binomial regression was the best fit for our model, we used the GENLIN procedure in SPSS to compare the goodness of fit between the negative binomial regression model and the Poisson regression model using both the overall delinquency and recent delinquency scales as

Table 6. Model Comparison—Recent Delinquency

Goodness of Fit–Negative Binomial Regression, Recent Delinquency

	Sig.	Df	Value/df
Deviance	118.651	131	0.906
Scaled Deviance	118.651	131	
Pearson Chi-Square	132.331	131	1.01
Scaled Pearson Chi-Square	132.331	131	
Log Likelihood	-149.07		

Goodness of Fit–Poisson Regression, Recent Delinquency

	Sig.	Df	Value/df
Deviance	206.442	131	1.576
Scaled Deviance	206.442	131	
Pearson Chi-Square	243.725	131	1.86
Scaled Pearson Chi-Square	243.725	131	
Log Likelihood	-164.599		

dependent variables. We used a basic set of predictor variables in the models testing fit.[17] The fit statistics are shown in Tables 5 and 6.

In reviewing the goodness of fit statistics for both models, we focused primarily on the value divided by the degrees of freedom and log likelihood for both models. Based on the lower value of the deviance statistic and the lower log likelihood values for the negative binomial regressions, we determined that those models had better fit than the Poisson models, and were most appropriate for our dataset. Hence, we selected negative binomial regression models for use in predicting the scaled delinquency outcomes (modeled with SPSS). For the binary outcomes (a) been in gang, (b) gang fight, (c) sold drugs, (d) carried a weapon, and (e) attacked someone, we developed logistic regression models in SPSS.

Because we have a relatively small sample of youth, as well as a wide age range, we wanted to limit the number of predictors used in final regression models. We thus examined correlations among all variables created (and described in the preceding sections). The full correlation matrix can be found in Appendix B. For the purposes of the following discussion, all correlations are significant at the $p < 0.05$ level. First we examined the correlations between the network compositional variables and the delinquency measures. The number of components in the respondent's personal network was negatively correlated (-0.18) to overall delinquency (binary variable). The measure of betweenness within a respondent's personal network was positively correlated to whether she had carried a weapon (0.16). The respondent's personal network density and isolate measures were not significantly correlated to any delinquency variable.

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[17] The following predictor variables were entered into the models to compare negative binomial and Poisson distributions: the proportion of delinquent alters; the proportion of alters who live in the respondent's neighborhood; the proportion of alters to whom the respondent goes for advice and are not delinquent; the number of components in the respondent's personal network; whether the respondent is an isolate; the respondent's betweenness centrality; the respondent's age, gender, and ethnicity; the proportion of friends in the respondent's network; if the respondent has an adult family member who graduated from high school; if the respondent's parent(s) support him/her in school; the respondent's level of family cohesion; the respondent's separation from U.S. culture; and the number of years the respondent has lived at his/her current address.

We then examined the correlations between our strength of ties/homophily measures and our delinquency measures. None of the overall tie strength or homophily measures was significantly correlated to any delinquency variable, with the exception of being in a gang, which was positively correlated (0.26) to the proportion of alters whom the respondent spends a lot of time with. All delinquent tie strength measures (e.g., proportion of alters whom respondent goes to for advice and are delinquent, etc.) were positively correlated to all three delinquency scales (0.39 to 0.46). The measure of closeness between the respondent and nondelinquent alters (as measured by the whether the respondent goes to the alters for advice) were negatively correlated to the delinquency scales (-0.19 to -0.23). The homophily index for delinquent alters in the respondent's network was positively correlated to the three delinquency scales (0.4 to 0.5).

Looking at the basic demographic variables we planned to enter as control measures in the regression models for our delinquency scales, we noted several significant correlations. Age was negatively correlated to recent delinquency (-0.18), and gender was positively correlated to overall delinquency and serious delinquency (0.23), suggesting that respondents who were older and male were more likely to have higher scores on the delinquency scales.

Because our correlation analyses showed that our strength of ties and homophily measures had either insignificant or small significant correlations to our delinquency measures, we ran a series of regression models to see if any of the strength of tie/homophily measures were significant predictors. We first ran regressions testing a full suite of variables including the key strength of ties variables. We determined that only one of the strength of tie variables should be included in the final model, and that the strength of ties measure should capture connection to delinquent alters versus nondelinquent alters. As we pared down our key variables and ran additional regressions using all dependent variables (including binary measures), it also became clear that our measures of ethnic identity, religiosity, and personal network density[18] should be dropped from the final analytical model. Appendix D contains the output of the regression with all variables before the final models were developed.

We tested these variables in our model with the overall delinquency scale as a dependent variable, running the models with and without a measure of the proportion of the respondents' alters or peers who are delinquent. The measure of the strength of a respondent's ties to nondelinquent alters or peers was not significant in any models, and the measure of the respondent's attachment to delinquent alters or peers controlled for the effects of the proportion of delinquent alters or peers in the respondent's network, so neither variable was significant. However, because the proportion of alters to whom the respondent goes for advice and who are not delinquent was negatively correlated to the three delinquency scales and the binary delinquency variables (-0.19 to -0.23) we determined that this would be the most appropriate strength of tie measure to include in our models.

With regard to the network structure and composition measures, we determined that the proportion of friends in a respondent's network would be the best control variable to include in our models, particularly because of the missing data imputation that was required for this variable.[19] While the proportion of male friends was found to be significant in prior research (Haynie 2002), it was not a significant predictor in our sample and we deemed it an unnecessary control variable, particularly because we were including gender and proportion of friends in network as control variables in our models.

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[18] We determined that personal network density was similar to the number of components (which was already in our models), and that betweenness could more accurately measure the respondent's connection to the whole network.

[19] Of the 2,940 alters in the dataset, 22 percent (N = 647) were missing age data. Five respondents did not report on the ages for any of their alters. To address this problem of missingness, we imputed the whole network mean age based on the alter's relationship (e.g., the mean age for all alters who are listed as friends in the network) for alters who did not have age data.

Final Models for Ego Analysis

As discussed above, a number of nonsignificant variables were dropped from final models, both to improve fit and to avoid over-fitting the models given our small sample size. Upon determining the predictor and control variables we would include in our final models, we then tested our independent variables on one of our binary dependent variables—if the respondent exhibited any delinquency in his/her lifetime—to determine if multicollinearity was an issue in our regression models. Based on the tolerance and VIFs in the model as shown in Table 7,[20] we determined that collinearity is not present in our models.

The variables included in Table 7 are the full set of variables that are used, in different combinations, in the predictive models for each of the different dependent variables, using only the egos as observation (N = 147). The results of those models are presented below in the Findings section. It should also be noted that, where possible, additional models are developed using the much more limited alter data. These models include all members of the whole network and thus have the advantage of using a larger number of observations for the estimation procedures (N = 2,521). The models, however, suffer from far more limited availability of data—we are restricted to only the variables that were collected for alters. These models are thus considered very preliminary and as such were not subjected to the extensive exploration and testing that were conducted for the ego-level models. Nonetheless, they do indicate a future direction for research and point to a potential utility of our methods of network data collection for providing sample sizes not limited to those who responded to the survey.

[20] We ran collinearity tests on all our delinquency models, and found no tolerance levels higher than 1 and no VIF levels higher than 2. For parsimony, we show only one model (overall delinquency, binary outcome) in this report.

Table 7. Tests for Collinearity, Overall Delinquency (Binary Outcome) Model

	Tolerance	VIF
Alter variables		
Proportion delinquent alters	0.71	1.417
Proportion alters live in same neighborhood	0.86	1.157
Proportion go to for advice (not delinq.)	0.75	1.328
Network structure variables		
Number of components	0.93	1.072
Isolate	0.88	1.133
Betweenness centrality	0.82	1.216
Controls		
Age	0.86	1.166
Male	0.86	1.161
Latino	0.71	1.418
Proportion of peers in network	0.81	1.238
Family member completed high school	0.80	1.245
Parent-school encouragement	0.85	1.178
Family cohesion	0.74	1.344
Separation from U.S. culture	0.64	1.568
Num. years at address	0.85	1.174

Whole Network Analysis Plan

Over the last two decades, despite a recent explosion in the research of social networks, only a limited number of studies have reported the use of sociocentric ("whole network") analysis (for example, see Abbasi, Uddin, & Hossain 2011; and Hirdes & Scott 1998) and very few of those focused on youth behaviors, delinquency, or criminal behavior (for example, see Faris & Felmlee 2011; McGloin 2005; and Natarajan 2006). Many studies that consider the effects of the whole network actually conduct their analyses using dyads or triads, instead of conducting analyses with all network members together (for example, see Baerveldt, van Duijn, Vermeij, & van Hemert 2004; Faust 2008; and Goodreau, Kitts, & Morris 2009). In addition, most of the analyses on true whole networks (as opposed to dyads or triads) employed descriptive methods for investigations of the whole network as opposed to developing predictive models, but for good reason. The nature of whole network data—matrices indicating connections between all included individuals—create difficulties in performing traditional predictive modeling, which is more easily done when conducting egocentric or dyadic data analysis. The present study, then, is unique in its exploration not only of personal networks and how an individual's connections to different types of people influence his/her behavior, but also how everyone is connected to a larger network, and how different elements of the network (e.g., subgroups) and one's position within the whole network and the network elements can influence the pro-social and delinquent or criminal behavior of individuals.

Sociocentric network analysis is accomplished using UCINet, a program that can be used to conduct numerous different analysis routines on social network data, and NetDraw, a program that creates network visualizations, but also has some analytic capabilities similar to that provided by UCINet. EgoNet is capable of producing some basic social network measures and can create some limited network visualizations, but its main utility is for data collection, not analysis or visualization.

We conduct identical analyses on the whole network (which includes everyone who was named any number of times) and the network comprised of only those named two or more times. We refer to this second network as the "2+ network."

Describing the Whole Network

We first provide descriptive information on the characteristics of the members of the whole network, including demographic characteristics and delinquent or pro-social behavior. These are different than the descriptive characteristics that are first provided in the egocentric analysis findings (see Findings section) as they provide information on all members of the network—egos and alters—whereas the egocentric analysis focuses only on the characteristics and behavior of the egos.

Computing Network Structural Measures

We then compute a number of network structural measures used to describe the form of the network, including the frequency of connections between actors and the degree of hierarchy in the network. After considering the characteristics of the whole network, we look at individual positions within the network, with an emphasis on identifying those individuals with the highest potential for the diffusion of ideas (e.g., nonviolence messages) or for influence on other network members. Work on identifying such nodes has typically focused on individual measures of centrality. Centrality analysis can provide a picture of how knowledge is communicated across members by identifying those nodes with a disproportionately high number of links with other nodes (whether direct or indirect). A number of different measures of centrality have been developed and our investigation of nodal positions will thus entail a multifaceted centrality analysis employing some of the most popular centrality measures among researchers. The centrality measures, described in the Measures section, are calculated at both the network level (centralization) and the individual level (centrality), and include

- density: proportion of actual ties to possible ties (network level only);
- isolate: network members not connected to other nodes;
- degree centrality: the number of direct connections a node has;
- betweenness centrality: how much of a bridging role each node performs;
- closeness centrality: the total distance from each node to every other node in the network; and
- eigenvector centrality: the importance of a member in a network based on centrality of the node's connections.

While we are exploring centrality through four different measures, the theoretical importance of the betweenness centrality measure for this work should be emphasized. Valente and Fujimoto (2010) suggest that nodes in central positions but with fewer direct ties (i.e., lower degree centrality)—sometimes called "bridges"—may more efficiently spread messages throughout the network because they have fewer individuals to convince of their message. They also suggest that such individuals might be more "receptive to behavior change and more likely to be persuaded by targeted communications" (212). Kadushin (2002) also explores the roles of those in such bridging positions, describing them as "structurally autonomous" and able to play nodes off of each other, thus gaining power and control over other members or components of a network. Betweenness centrality is one way to measure the "bridging" between different nodes.

While receptivity to behavior changes, structural autonomy, and control in a network certainly depend on personal characteristics, individuals with high betweenness may hold the key to most effectively spreading messages throughout a network. In this sense, betweenness becomes a very important measure for the policy implications present in this study in that identifying those individuals who are not only central but could also convincingly and efficiently spread nonviolence or pro-social messages through a network would be of utmost importance to decreasing and preventing gang involvement and delinquent behavior (Objective 5). As described earlier in the Measures section of this report, we also use betweenness centrality as a predictor of delinquency (and specifically, drug dealing) in egocentric analysis. It is not a stretch to hypothesize that those individuals who are very well connected (and closely connected with regard to social distance) to a lot of other individuals, would make good (i.e., successful) drug dealers.

As part of the centrality analysis, we will also be able to determine the importance of cultural characteristics across members of the network. Here, we can explore the characteristics of the most central players (as determined through any one of the above measures), including their ethnicity and whether they are foreign born. We will also examine the levels of delinquency of the most central players to determine how they might be influencing those around them, and how far their reach of influence within the network travels.

Community Structure of the Network

After sufficiently describing the properties of the two networks, we will investigate, using two social network analysis methods, the existence of subgroups, or subcomponents, within the larger network. There are numerous ways to examine the "community structure" of whole networks, or the division of the network into smaller, cohesive groups, but we will focus our efforts on one common method: Newman-Girvan modularity. This is considered a top-down approach as it starts with the whole network itself and then focuses on areas of especially high density within the overall network structure (Hanneman & Riddle 2005).

The Newman-Girvan modularity algorithm is based on the idea that subgroups within a whole network can be completely inward-looking; that is, all nodes within the subgroup could be connected to each other and none would be connected to nodes outside the subgroup. While this is rarely, if ever, the case in practice, the algorithm attempts to divide nodes into a set of partitions that most closely replicates this "ideal" faction structure, and then assesses the degree to which the structure approximates that ideal structure (Hanneman & Riddle 2005). The Newman-Girvan routine offers a goodness-of-fit measure to assess the number of partitions into which a network should be divided. It should be noted that though we expect that while we will be able to coherently divide the whole network into subgroups—especially those based on gangs or delinquent behaviors—there is no a priori expectation of the number of subgroups that we expect to find. Rather, this portion of the whole network analysis involves exploring the community structure of the whole network to understand how delinquent and nondelinquent youth cluster within a larger social network.

As part of the community structure analysis of the whole network, we calculate standard measures for each subgroup that were calculated at the level of the whole network, including size, density, and centrality measures. We also explore the demographic characteristics of the subgroups and the levels of delinquency among members of different subgroups in order to expand our knowledge of the characteristics upon which youth in the whole network cluster. Finally, we examine ties between different subgroups (via ties between two nodes in different subgroups).

The next chapter presents the findings of the different analyses organized according to the three different research questions. We first present the descriptive analyses for the egocentric analyses (based on ego networks), followed by the predictor modeling aimed to answer research question 1. We then present the results of the sociocentric analysis directed at answering research question 2. Last, we present the results of the egocentric analyses utilizing the measures created from the whole network.

CHAPTER 3

FINDINGS

EGOCENTRIC DESCRIPTIVE ANALYSES

Respondent Characteristics

As described earlier, our data collection strategy was designed as a census of all youth, both males and females, between the ages of 14 and 21 who reside in the designated target area. Table 8 below provides a detailed description of the 147 survey respondents. The majority of youth surveyed were male (66 percent), with an average age of almost 18. Roughly three-quarters of youth surveyed (76.9 percent) identified their ethnicity as Latino; a little over a third of the youth were foreign born. Even though the majority (63 percent) of respondents was born in United States, 84 percent have at least one parent who was born abroad, and 69 percent speak both Spanish and English. Fifty percent of respondents have lived abroad at some point in their lives. These characteristics of the youth surveyed generally reflect the characteristics of the target neighborhood (Table 1).

Parents' place of birth (Table 9) provides information on nationality for the surveyed youth. Table 9 shows that almost half of the respondents were Guatemalan or Salvadoran, and 10 percent were Puerto Rican or of Caribbean descent.

Table 10 provides the descriptive characteristics on delinquency and group activity. Overall, our sample exhibits a number of very pro-social characteristics: 97 percent of respondents under 18 are still in school, and 92 percent of respondents report parental support for attending school (based on past or present support, depending on whether the respondent was still in school). The majority of respondents over 18 (58 percent) are currently employed. Just over 50 percent attend religious services at least once a month.

Given that we were targeting a high-crime area, respondents reported lower levels of gang activity and individual delinquency than we anticipated. Only 34 percent reported seeing lots of gang activity in the neighborhood, and only 20 percent said they had ever been approached to join a gang.

While the vast majority (75.5 percent) of our sample identified as being a member of a group (answering yes to whether they have a group of friends with whom they hang out), far fewer respondents (10 percent) reported being current or former gang members or having been in a gang fight at some point in their lives (17 percent). Of all the delinquent behaviors included as survey items, prevalence was highest for using drugs (27 percent), followed by carrying a weapon (23 percent).

Table 11 provides a picture of the differences among respondents who have been gang members, in a gang fight, or are in a group. Not surprisingly, reported delinquency is significantly higher among respondents who have been in a gang or in a gang fight, while the respondents who are members of a group have delinquency rates that are similar to the overall sample.

We also examined the distribution of a series of network composition measures to determine the structure of the respondents' personal networks. Key measures include the number of components (i.e., groups) within respondents' personal networks; ties between alters (all alters, delinquent alters and nondelinquent alters) in respondents' personal networks; respondent's betweenness centrality to the whole network; and betweenness centrality within respondents' personal networks (across delinquent and nondelinquent alters) (Table 12). The average number of network components (number of subgroups within personal network) was just over 1, but it ranged from 0 to 4. With a mean density of 0.04, the statistics for the density measure indicate that individual-level networks are not very dense.[21] The measure of betweenness centrality calculated from whole network represents the "brokering" position across the whole (overlapped) network.

[21] Density is sometimes listed as a proportion on a scale of 0 to 1 and sometimes reported as a percent, ranging from 0 to 100. We report all density measures on a 0–1 scale.

Table 8. Descriptive Statistics, Basic Demographics

	% Respondents (N = 147)
Demographics	
Average age	17.8
Male	66.0
Ethnicity/Nationality	
Hispanic/Latino(a)	76.9
Born abroad	36.1
Either parent board abroad	84.4
Lived abroad	49.9
Separation from U.S. culture (mean)	4.16
Ethnic attachment (mean)	45.62
Language	
Only Spanish	5.4
Only English	14.3
Spanish and English	69.4
Multiple	7.5
Other	3.4
School/Parental Status	
Currently living with parent(s)	82.3
Currently in school (under 18)	96.7
Currently in school (18 or over)	46.5
Parent support in school	91.8
Adult in family graduated high school	70.1
Family cohesion (mean)	44.61
Employment	
Currently have a job (under 18)	11.5
Currently have a job (18 or over)	58.1
Religion	
Christian	81.0
Attends services	
At least once a month	50.3
Never	27.9

Table 9. Nationality of Respondents, as Indicated by Place of Birth for Parents

Respondents' nationality (N = 147)	Mother born in... (%)	Father born in... (%)
United States	13.6	13.6
Mexico	4.8	4.1
El Salvador	33.3	36.7
Guatemala	15.6	14.3
Honduras	4.1	2.7
Nicaragua	3.4	4.1
Puerto Rico, the Dominican Republic, or other Caribbean country	10.2	10.2
Bolivia	0.7	0.7
Columbia	1.4	0.0
Other South American country	1.4	2.0
Other country not listed	11.6	10.9
Don't know	0.0	0.7
Mother/father born in same country = 84%		

Table 10. Group Activity and Delinquency

Group Activity	%
See lots of gang activity in neighborhood	34.0
Approached to join gang	19.7
Thought about joining gang	15.6
Pressure to join a gang	12.2
In a group	75.5
Thinks of group as gang	5.4
In a gang	10.2
In a gang fight	17.0
In a gang fight but not in a gang	7.5
Delinquent Behavior[22]	
Used drugs	26.5
Used drugs in last six months	12.2
Sold drugs	8.8
Sold drugs in last six months	5.4
Stolen goods more than $100	17.7
Stolen goods +$100 in last six months	7.5
Carried weapon	23.1
Carried weapon in last six months	6.7
Attacked someone with idea of hurting or seriously injuring them	10.2
Attacked someone in last six months	4.8

[22] The percentage of respondents who report recent delinquent activity is based on the percentage of the total sample, not the number of respondents who reported delinquent activity over the course of their lifetime.

Table 11. Delinquent Behavior and Gang Association

	% Respondents (N = 147)	In a Gang (N = 15)	In a Gang Fight (N = 25)	In a Group (N = 111)
Used drugs	26.5	66.7**	60.0**	29.7
Sold drugs	8.8	40.0**	40.0**	10.8**
Stolen goods more than $100	17.7	53.3**	44.0**	18.9
Carried weapon	23.1	60.0**	60.0**	27.9**
Attacked someone with idea of hurting or seriously injuring them	10.2	33.3**	32.0**	12.6**

** $p < 0.05$

Significance levels represent significant differences between the respondents in the specified category (e.g., in a gang, in a gang fight, or in a group) compared to those who are not.

Table 12. Descriptive Statistics for Network Measures

Network Measures (N = 147)	Min	Max	Mean	S.D
Number of components in personal network	0.00	4.00	1.07	0.70
Proportion of ties in personal network (density)	0.00	19.00	4.19	4.24
Betweenness centrality of ego/alter nodes, calculated from whole network	0.00	295,446.81	389,15.55	55,935.56

<u>Relationships within Ego Networks</u>

Table 13 summarizes the characteristics of the alters in respondents' personal networks, including the relationship and similarities between the respondent and the alters. The statistics provide some interesting insight on *who* is important in the lives of the surveyed youth. Prior literature focuses almost exclusively on the importance of peers in influencing youth behavior. And not surprisingly, three-quarters of the respondents named peers (friends) for half of their alters. Although the term peers is often used to include siblings or cousins who close in age, for the purposes of understanding the influence of the different types and categories of relationships, we exclude siblings and other young relatives from the definition of peers.

It is interesting to note, however, that when given the opportunity to name the 20 people most involved in their lives, 91.8 percent of youth surveyed named at least one individual who could be considered something other than a friend. Forty-one percent of respondents named at least one parent. We thought this percentage would be higher, but it could be a function of the phrasing we

Table 13. Alter Characteristics

Respondents' Alter Characteristics	% Respondents (N = 147)
More than half of alters were friends	78.2
Two or more alters were siblings	36.1
At least one alter was a parent	40.8
Respondent would go to at least half of alters for advice	56.5
Respondent likes more than half of alters a lot	47.6
At least half of alters live in the same neighborhood	29.9
More than half of alters were born in the United States	57.1
More than half of alters were born in Latin America	33.3

used for the name generator. We asked respondents to think first of people they "hang out" with, and respondents might not have considered their parents to be people they "hang out" with, even if their parent is influential in their lives.

Not surprisingly, respondents are not equally close with all their alters. Only roughly half (56.5 percent) would go to at least half of their alters for advice and just under half (47.6 percent) indicated that they like more than half of their alters "a lot." That means there are a large number of alters for each respondent that he/she doesn't like a lot or to whom he/she would not go for advice. Almost one-third of respondents (29.9 percent) indicated that at least half of their alters lived within the target neighborhood. While not necessarily surprising, this supports our idea that school-based network analyses may be missing key individual's in a youth's life. The nearby high school that most school-age youth in the neighborhood attend is several miles away and draws teenagers from a large area. This gives youth the opportunity to develop friendship networks with individuals who do not necessarily live close, yet at least one-third of individuals spend most of the their time with others from within the neighborhood. Whether this is out of convenience or for another reason, we cannot judge, but regardless, it does demonstrate the utility of the "neighborhood as network" design. Table 14 below shows the breakdown of relations listed across categories of respondents (all respondents, delinquent and not delinquent). We did not incorporate t-test results into these tables due to the small number of alters in certain categories (e.g., aunt/uncle, grandparent, etc.), which tended to inflate the significance levels, but we want to point out possibly interesting differences among groups. Delinquent youth were more likely to list a cousin than nondelinquent respondents.

Table 14. Alter Characteristics, by Proportion Delinquent/Criminal[23]

	% Respondents (N = 147)	% Delinquent (N = 55)	% Not Delinquent (N = 92)
All peers	8.2	5.5	9.8
No peers	0.7	0.0	1.1
At least half family	13.6	12.7	14.1
Peers/immediate family only	17.7	10.9	21.7
Peers/family only	65.3	70.9	62.0
At least one cousin	60.5	72.7	53.3
At least one aunt/uncle	32.0	7.3	30.4
At least one grandparent	10.9	34.5	13.0
At least one teacher	8.8	5.5	10.9

Nondelinquents were more likely to list an aunt or uncle, but were less likely to mention a grandparent. It could be that delinquent youth are more likely living with a grandparent as opposed to a parent, indicating the absence of a parent or both parents in the youth's life. Nondelinquent youth were also twice as likely to mention a teacher as delinquent youth.

In addition to examining the types of relations in respondents' personal networks, we looked at the behavior among respondents' alters (shown in Table 15 below), as reported by the respondent. There are a number of notable differences between the behavior of respondents' alters and respondents' behavior themselves (all as reported by the respondents). While only 9 percent of respondents said they sold drugs, 29 percent said at least one of their alters sold drugs. While only 10

Table 15. Alter Behavior

	% Respondents (N = 147)
Respondents who…	
Co-offend with at least one alter	19.7
Commit violence with at least one alter	12.9
Have at least one alter in a gang	29.3
Have at least one family member in a gang	8.8
Have at least one alter who has been in a gang fight	17.7
Have at least one alter who carries a gun	16.3
Have at least one alter who sold drugs	29.3

[23] We did not incorporate t-test results into these tables due to the small number of alters in certain categories (e.g., aunt/uncle, grandparent, etc.), which tended to inflate the significance levels.

Table 16. Proportion of Ego Network that is Delinquent, by Respondent Delinquency

Proportion of respondent's alters who exhibit delinquent behavior	# Respondents (N = 147)	# Delinquent Respondents (N = 55)	# Nondelinquent Respondents (N = 92)
0 %	88	17	71
5 %	23	13	10
10 %	10	5	5
15 %	5	3	2
20 %	7	6	1
25 %	4	3	1
30 %	3	3	0
35 %	1	1	0
40 %	2	1	1
45 %	2	1	1
90 %	1	1	0
100 %	1	1	0

percent of respondents reported being in a gang, 29 percent said at least one of their alters was in a gang.

In order to better understand which respondents included delinquent alters in their networks, we stratified the sample by self-reported delinquent behavior (delinquent meaning that the individual participated in at least one of the five main delinquent behaviors). We then examined the proportion of alters who committed at least one type of delinquent behavior, as reported by the respondent (ego). Table 16 reveals that 71 youth (77 percent) who were *not* delinquent also did not report any delinquent alters. At the other extreme, only one delinquent respondent reported that his/her network consisted of all others who *were* delinquent. The table indicates that there is likely little over-exaggeration of alter characteristics in that most delinquent respondents only report a very small portion of their personal network to be delinquent. Essentially, 96 percent of the 55 delinquent respondents report that less than half their alters were delinquent, while 17 (31 percent) of respondents who were delinquent reported no delinquent or violent behavior for their alters.

T-Test Analyses

We conducted a series of t-tests (Table 17a–g) to establish any significant differences in means for our final independent measures across key delinquency variables: overall delinquency (as a binary outcome), carrying a weapon, selling drugs, being in a gang fight and being in a gang. These tables provide a first look at how our independent variables might vary in importance across the different delinquency and crime outcomes. The t-tests compare the mean of each independent variable (e.g., gender, birthplace, family support) across the delinquent and nondelinquent groups. The tables thus report, for example, the percentage of delinquent respondents who are male and whether that figure is significantly different from the percentage of nondelinquent respondents who are male.

Consistent with the research literature, significantly more male respondents reported overall delinquency and weapon carrying. Significantly more respondents who were delinquent or who used drugs were also born in the United States, hinting that higher levels of acculturation might be associated with negative outcomes. Similarly, respondents who reported overall delinquency, carrying a weapon, or being in a gang fight had significantly lower levels of separation from the United States (were more acculturated), than respondents not reporting these behaviors, and respondents who reported overall delinquency had significantly lower levels of family cohesion.

Table 17a. T-Test Results by Delinquency Measure

	% Delinquent (N = 55)	% Not Delinquent (N = 92)
Male**	**83.6**	**55.4**
Born abroad**	**21.8**	**44.6**
Either parent born abroad	81.8	85.9
Parent support in school	90.9	92.4
Adult in family graduated	70.9	69.6
High ranking on scales:		
Family cohesion**	**10.9**	**23.9**
Ethnic attachment	14.5	17.4
Religiosity	7.3	6.5
Separation from U.S.**	**14.5**	**35.9**

** $p < 0.05$

Table 17b.

	% Carried Weapon (N = 34)	% Did Not Carry Weapon (N = 114)
Male**	**91.2**	**58.4**
Born abroad	76.5	39.8
Either parent born abroad	82.4	85
Parent support in school	94.1	91.2
Adult in family graduated	76.5	68.1
High ranking on scales:		
Family cohesion	14.7	20.4
Ethnic attachment	17.6	15.9
Religiosity	5.9	7.1
Separation from U.S.	17.6	31

** $p < 0.05$

Table 17c.

	% Used Drugs (N = 39)	% Did Not Use Drugs (N = 108)
Male	74.4	63
Born abroad**	**17.9**	**42.6**
Either parent born abroad	82.1	85.2
Parent support in school	92.3	91.7
Adult in family graduated	71.8	69.4
High ranking on scales:		
Family cohesion	10.3	22.2
Ethnic attachment	17.9	15.7
Religiosity	5.1	7.4
Separation from U.S.**	**15.4**	**32.4**

** $p < 0.05$

Table 17d.

	% Sold Drugs (N = 13)	% Did Not Sell Drugs (N = 134)
Male	84.6	64.2
Born abroad	23.1	37.3
Either parent born abroad	61.5	86.6
Parent support in school	76.9	93.3
Adult in family graduated	69.2	70.1
High ranking on scales:		
Family cohesion	15.4	19.4
Ethnic attachment	15.4	16.4
Religiosity	7.7	6.7
Separation from U.S.	15.4	29.1

** $p < 0.05$

Table 17e.

	% Attacked with Intent (N = 15)	% Did Not Attack with Intent (N = 132)
Male**	**86.7**	**63.6**
Born abroad	80	62.1
Either parent born abroad	73.3	85.6
Parent support in school	86.7	92.4
Adult in family graduated	80	68.9
High ranking on scales:		
Family cohesion	13.3	19.7
Ethnic attachment	6.7	17.4
Religiosity	6.7	6.8
Separation from U.S.	13.3	29.5

** $p < 0.05$

Table 17f.

	% In a Gang Fight (N = 25)	% Not in a Gang Fight (N = 122)
Male	76	63.9
Born abroad	24	38.5
Either parent born abroad	80	85.2
Parent support in school	84	93.4
Adult in family graduated	68	70.5
High ranking on scales:		
Family cohesion	12	20.5
Ethnic attachment	8	18
Religiosity	8	6.6
Separation from U.S.**	**12**	**31.1**

** $p < 0.05$

Table 17g.

	% In a gang (N = 15)	% Not in a Gang (N = 132)
Male	60.0	66.7
Born abroad	20.0	37.9
Either parent born abroad	86.7	84.1
Parent support in school	80.0	93.2
Adult in family graduated	73.3	69.7
High ranking on scales:		
Family cohesion	13.3	19.7
Ethnic attachment	13.3	16.7
Religiosity	6.7	6.8
Separation from U.S.**	**6.7**	**30.3**

** $p < 0.05$

Because it is apparent that respondents' country of birth (whether U.S.-born or not) and level of acculturation are important—our measure of "separation from the U.S. culture" was significant in four of the six t-test analyses—we explored the level of separation from U.S. culture across our sample (Table 18) to obtain some insight on what types of individuals might have high or low separation. We examine delinquency, age, ethnicity, and gender for the different separation levels. Categories of "low" and "high" are defined as one standard deviation below and above the mean, respectively. None of the differences shown below are statistically significant, meaning that the level of a respondent's separation from the United States did not vary significantly based on delinquency, age, ethnicity, or gender. This is important context for the regression analyses discussed later on in this chapter.

Table 18. Separation from the United States

	% Low Separation (N = 16)	% Medium Separation (N = 94)	% High Separation (N = 37)
Delinquency scale	1.94	1.92	.90
Age	17.81	17.48	18.46
Percent Hispanic	48.06	45.71	44.46
Percent male	75.00	63.30	68.30

** $p < 0.05$

EGOCENTRIC PREDICTIVE ANALYSES

Logistic Regression Model Results (Binary Outcome Measures)

In this section we describe the findings from the logistic regression models developed for six binary variables: serious delinquency, carried a weapon, sold drugs, attacked someone with the intent to harm, been in a gang fight, and been in a gang. Discussion of the change in the dependent variables is not as straightforward for logistic regression results as it is for other types of regression models. The coefficients that are produced by the model are actually in log form. In order to describe change in a unit scale that is sensible, we use both the odds of the outcome of interest (i.e., the dependent variable) for each of the models, or the odds ratio (OR). The OR is calculated by exponentiating the regression coefficient; in the tables below, it is also identified as Exp(B). We also convert the odds ratio into probability terms and discuss the probability that, given a certain magnitude of change in an independent variable, the dependent variable would equal one (in other words, that the respondent would be delinquent).

While discussing results in terms of probabilities makes a model's outcomes easier to understand, the conversion from ORs to probabilities is not a straightforward process. The relationship between odds ratios and probabilities differ depending on the size of the probability (i.e., the relationship is not linear).[24] We thus compute the hypothetical change given an (arbitrarily) selected baseline probability of the dependent variable; here, we use the "centered" case (Liberman 2005), which is 0.5 (the center of the range for a binary variable). In other words, we assume that at baseline, respondents have a 50 percent chance of being delinquent. We then use this as the starting figure from which to calculate change in probability given changes in the respondent's other characteristics (i.e., given changes in the independent variables). We illustrate the probability of delinquency for this centered case given a one-unit change in each independent variable. As part of the conversion from ORs to probabilities, we also computed the risk ratios (RRs); these allow results to be discussed in terms of how many more times likely an event (here, delinquency) is to occur. The RRs provide an alternative way of considering the impacts of the independent variables on the dependent variable. The results of the binary logistic regression models and the conversion from ORs to probabilities for all six dependent variables are provided in Table 19a through 19f.[25]

Of the alter variables measuring composition of individual ego networks, the only variable that is significant is the proportion of delinquent alters, and it is significant across all four

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[24] While calculating probabilities from odds ratios is not always straightforward, and there are a number of ways to handle the conversion, a full explication of those methods is beyond the scope of this report. We follow Liberman's (2005) suggestions on calculating changing probabilities using the centered case. See Liberman (2005) for a full explanation of these methods.

[25] It should be noted that while we report the Cox and Snell R^2 values with the binary logistic results, these goodness-of-fit statistics are quite low compared to typical linear regression results (Hosmer & Lemeshow 2000). The low value should not be taken as a sign of poor fit for the models.

delinquency models where it is included. Its effect is strongest in the model for selling drugs, where an increase of one additional delinquent alter to an ego's network increases the ego's probability of selling drugs by 38 percent. For the "gang fight" and "in a gang" models, we use corresponding alter variables instead of the general delinquent alter variable ("proportion of alters in a gang fight" and "proportion of alters in a gang," respectively). These versions of the alter delinquency variable are also significant; those who named an individual in a gang fight or in a gang are more than 1.5 times more likely to be in a gang fight or a gang themselves (1.59 and 1.57 times more likely, respectively).

The number of components in a respondent's network is a significant predictor of serious delinquency ($p < 0.10$) and carrying a weapon ($p < 0.10$); one additional group in a respondent's network decreases his odds of serious delinquency and carrying a weapon by 1.43 times and 1.47 times, respectively. The gender variable (male) was significant across all models except in the one predicting gang membership. In some cases, the variable had a rather large impact on the probability of a delinquent outcome. Being male had the biggest impact on selling drugs; males are more than 14 times more likely than females to sell drugs. The large effect size is not surprising, as our sample comprised a larger number of males and males tend to participate in more delinquent behaviors than do females at all ages. What is surprising is that being male is not associated with gang membership.

At the outset of the modeling effort, we were interested in the relationship between acculturation and participation in delinquent behaviors. The binary logistic analysis revealed that separation from U.S. culture (lower level of acculturation) is highly significant in the serious delinquency model but not significant for the other outcomes. For serious delinquency, the model indicates that increasing one's acculturation (read as a one-unit decrease in the separation scale) results in an 18 percent increase in the probability of delinquency. Parent-school encouragement was significant in four models, and had a large negative effect on the delinquency measure in those three models: drug selling, being in a gang fight, and being in a gang. Those with parents who encouraged them in school were nearly one-ninth as likely to sell drugs, and one-third as likely to be in a gang or a gang fight.

Having a family member who completed high school was only significant in the drug-selling model, but it did have a large negative effect (decreasing the likelihood of selling drugs by 1/3). Finally, residential stability (as measured by the number of years spent at one's current address) appears to be a risk factor for most antisocial outcomes—one additional year at the same address increases the probability of selling drugs by more than 6 percent and increases the probability of being in a gang fight or in a gang by 5 and 6 percent, respectively. This variable can be interpreted as a partial test of the validity of both our use of the neighborhood as a network and our selection of the specific neighborhood where we conducted the survey. We expected that additional time in the neighborhood would result in an individual becoming more connected to others within the neighborhood, and therefore, more likely to spend time with delinquent others, and more likely to become delinquent him/herself.

Across the binary dependent variables, we compared the results of the bivariate correlation analyses (Appendix C) to the logistic regression model results, and noted a few findings that did not carry over from the bivariate correlations into the regressions. While the proportion of alters who live in the same neighborhood as the respondent is positively correlated to the respondent's serious delinquency and whether he carries a weapon ($p < 0.05$), these correlations are not reflected in the regression models. The proportion of nondelinquent alters to whom the respondent would go for advice is negatively correlated to the respondent's serious delinquency ($p < 0.01$), carrying a weapon ($p < 0.05$), selling drugs ($p < 0.10$), and being in a gang fight ($p < 0.10$), but these correlations were also not reflected in the regression models. A negative correlation between age and being in a gang was not reflected in the regression model. The proportion of peers in the respondent's network is negatively correlated with selling drugs and attacking someone with the intent to harm ($p < 0.10$), but these relationships are not significant in the regression models.

Table 19a. Binary Logistic Regression Results Predicting Overall Delinquency

	Overall Delinquency						
	Coeff.	S.E.	Exp(B) (OR)[2]	p	*RR*[3]	Δp[4]	Δp (%)[5]
Constant	1.54	2.56	4.66	0.55			
Alter variables							
Proportion delinquent alters[1]	6.61**	2.51	1.39	0.01	1.18	0.08	17.97%
Proportion alters live in same neighb.[1]	0.93	0.95	1.05	0.33			
Proportion go to for advice (not delinq.)[1]	-0.11	0.88	0.99	0.90			
Personal network structure variables							
Number of components	-0.71†	0.40	0.49	0.07	0.70	0.18	-29.85%
Acculturation							
Separation from U.S. culture	-0.34*	0.13	0.71	0.01	0.84	0.08	-15.55%
Controls							
Age	0.05	0.09	1.05	0.61			
Male	2.01**	0.59	7.46	0.00	2.73	0.46	173.19%
Latino	1.04	0.68	2.83	0.12			
Proportion of peers in network[1]	-0.44	1.04	0.98	0.67			
Family member completed HS	-0.38	0.51	0.69	0.46			
Parent-school encouragement	-0.24	0.86	0.79	0.79			
Family cohesion	-0.08*	0.04	0.93	0.03	0.96	0.02	-3.92%
No. years at address	0.06	0.04	1.06	0.12			
Goodness-of-fit measures							
Cox & Snell R Square			0.33				
Cox & Snell R Square (model with peer vars)			0.32				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in p is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in p (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 19b. Binary Logistic Regression Results Predicting Weapon Carrying

	Carried a Weapon						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	-2.90	2.95	0.06	0.33			
Alter variables							
Proportion delinquent alters[1]	7.26 **	2.17	1.44	0.00	1.20	0.09	19.89%
Proportion alters live in same neighb.[1]	1.30	1.12	1.07	0.24			
Proportion go to for advice (not delinq.)[1]	0.35	1.02	1.02	0.74			
Personal network structure variables							
Number of components	-0.78 †	0.44	0.46	0.08	0.68	0.19	-32.12%
Acculturation							
Separation from U.S. culture	-0.08	0.15	0.93	0.63			
Controls							
Age	0.03	0.11	1.03	0.80			
Male	3.34 **	1.10	28.16	0.00	5.31	0.68	430.69%
Latino	-0.25	0.75	0.78	0.74			
Proportion of peers in network[1]	-0.75	1.17	0.96	0.52			
Family member completed HS	-0.17	0.61	0.84	0.78			
Parent-school encouragement	0.39	1.14	1.48	0.73			
Family cohesion	-0.04	0.04	0.96	0.30			
No. years at address	0.06	0.04	1.06	0.14			
Goodness-of-fit measures							
Cox & Snell R Square			0.29				
Cox & Snell R Square (model with peer vars)			0.26				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 19c. Binary Logistic Regression Results Predicting Drug Selling

	Sold Drugs						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	-7.51	5.88	0.00	0.20			
Alter variables							
Proportion delinquent alters[1]	12.80**	3.80	1.90	0.00	1.38	0.16	37.70%
Proportion alters live in same neighb.[1]	-1.57	2.25	0.92	0.49			
Proportion go to for advice (not delinq.)[1]	0.48	2.14	1.02	0.82			
Personal network structure variables							
Number of components	0.46	0.74	1.58	0.53			
Acculturation							
Separation from U.S. culture	-0.47	0.37	0.62	0.20			
Controls							
Age	0.17	0.21	1.19	0.42			
Male	5.36*	2.54	211.90	0.04	14.56	0.87	1355.60%
Latino	-0.11	1.34	0.90	0.94			
Proportion of peers in network[1]	-0.30	2.28	0.99	0.90			
Family member completed HS	-2.09†	1.25	0.12	0.10	0.35	0.48	-64.88%
Parent-school encouragement	-4.35*	1.82	0.01	0.02	0.11	0.80	-88.63%
Family cohesion	0.03	0.07	1.04	0.62			
No. years at address	0.14*	0.07	1.15	0.04	1.07	0.04	7.36%
Goodness-of-fit measures							
Cox & Snell R Square			0.27				
Cox & Snell R Square (model with peer vars)			0.25				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 19d. Binary Logistic Regression Results Predicting Attacking Someone

	Attacked Someone with Intent to Harm						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	-4.65	3.92	0.01	0.24			
Alter variables							
Proportion delinquent alters[1]	5.18*	2.13	1.30	0.02	1.14	0.06	13.83%
Proportion alters live in same neighb.[1]	-0.87	1.50	0.96	0.57			
Proportion go to for advice (not delinq.)[1]	-3.05†	1.58	0.86	0.05	0.93	0.04	-7.35%
Personal network structure variables							
Number of components	-0.06	0.53	0.94	0.90			
Acculturation							
Separation from U.S. culture	-0.08	0.20	0.93	0.71			
Controls							
Age	0.12	0.15	1.13	0.40			
Male	2.59†	1.35	13.36	0.06	3.65	0.57	265.46%
Latino	0.27	0.98	1.31	0.78			
Proportion of peers in network[1]	-1.24	1.49	0.94	0.41			
Family member completed HS	-0.32	0.86	0.72	0.71			
Parent-school encouragement	-0.51	1.16	0.60	0.66			
Family cohesion	0.02	0.05	1.02	0.71			
No. years at address	-0.03	0.06	0.97	0.62			
Goodness-of-fit measures							
Cox & Snell R Square			0.17				
Cox & Snell R Square (model with peer vars)			0.14				

† $p < 0.10$; *$p < 0.05$; ** $p < 0.01$; ***$p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 19e. Binary Logistic Regression Results Predicting Participation in Gang Fight

	Been in a Gang Fight						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	3.64	3.09	38.04	0.24			
Alter variables							
Proportion of alters in a gang fight[1]	18.45**	6.01	2.52	0.00	1.59	0.23	58.60%
Proportion alters live in same neighb.[1]	-0.13	1.17	0.99	0.92			
Proportion go to for advice (not delinq.)[1]	0.57	1.15	1.03	0.62			
Personal network structure variables							
Number of components	-0.41	0.47	0.66	0.39			
Acculturation							
Separation from U.S. culture	-0.28	0.18	0.76	0.12			
Controls							
Age	-0.17	0.13	0.84	0.17			
Male	1.51*	0.77	4.52	0.05	2.13	0.36	112.65%
Latino	0.83	0.90	2.29	0.36			
Proportion of peers in network[1]	0.67	1.43	1.03	0.64			
Family member completed HS	-0.86	0.65	0.42	0.18			
Parent-school encouragement	-2.13*	0.99	0.12	0.03	0.34	0.49	-65.60%
Family cohesion	-0.04	0.04	0.96	0.28			
No. years at address	0.09*	0.04	1.10	0.04	1.05	0.02	4.66%
Goodness-of-fit measures							
Cox & Snell R Square			0.23				
Cox & Snell R Square (model with peer vars)			0.23				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 19f. Binary Logistic Regression Results Predicting Gang Membership

	Been in a Gang						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	-1.54	4.17	0.22	0.71			
Alter variables							
Proportion of alters in a gang[1]	17.98**	5.22	2.46	0.00	1.57	0.22	56.75%
Proportion alters live in same neighb.[1]	-0.79	1.64	0.96	0.63			
Proportion go to for advice (not delinq.)[1]	2.03	1.68	1.11	0.23			
Personal network structure variables							
Number of components	-0.79	0.71	0.46	0.27			
Acculturation							
Separation from U.S. culture	-0.29	0.24	0.75	0.23			
Controls							
Age	-0.01	0.17	0.99	0.95			
Male	-0.03	0.85	0.97	0.97			
Latino	2.27	1.61	9.72	0.16			
Proportion of peers in network[1]	3.37	2.57	1.18	0.19			
Family member completed HS	-0.86	0.95	0.42	0.37			
Parent-school encouragement	-2.28*	1.14	0.10	0.05	0.32	0.52	-68.02%
Family cohesion	-0.08	0.06	0.93	0.18			
No. years at address	0.12*	0.06	1.12	0.05	1.06	0.03	5.92%
Goodness-of-fit measures							
Cox & Snell R Square			0.24				
Cox & Snell R Square (model with peer vars)			0.22				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Negative Binomial Regression Results (Scaled Outcome Measures)

We also examined predictors of delinquency using our three scaled outcomes (overall delinquency, delinquency in past six months, and serious delinquency over one's lifetime) as scales capture more information than binary measures. The results of the negative binomial models are presented in Table 20 through Table 22. As discussed in the Analysis Plan section, the models include all variables deemed appropriate for final inclusion. Table 20 through Table 22 each include two models: Model 1 includes peer-related alter variables (which consider only alters named as friends), network variables, and control variables. Model 2 employs all alter variables instead of the peer-only variables. These sets of models are shown side by side as a way to compare the fit of the models and determine whether we gain any important information by considering complete personal networks (with all alters) as opposed to only peer networks (with only friends) as they relate to delinquency and gang membership. As discussed in the literature review, almost all network analyses examining self-reported delinquency have focused solely on peer networks (and many have just used school networks). We utilized the Akaike Information Criterion (AIC) to compare the fit of the models. A smaller AIC signifies a better fit, with the criteria for a significant difference being a difference of 2.5 or more (Hilbe 2007) for sample sizes around 200.

In addition to providing the coefficients from the regression models, the tables include the exponentiated coefficients (exp(B)) for ease of interpretation. We can express a measure's effect in terms of the percent change in the dependent variable as ([exp(B)–1] ∗ 100). For the binary logistic regression analyses, we interpret the odds ratio; for the negative binomial regression analyses, we calculate the percent change in delinquent activity. The percent change is interpreted differently depending on the type of predictor variable (proportion vs. count). To discuss the magnitude of the effects of the proportion variables (e.g., proportion of delinquent alters in a respondent's personal network) on the delinquency measures, we exponentiate the coefficient multiplied by any given meaningful percentage increase in the proportion of the predictor variable, and then subtract one. For example, if we are reporting on the change in delinquent activity based on a change in an alter's delinquent network of 25 percent (that is, the respondent increases the percent of delinquent alters in his network by 25 percent), we calculate (exp(B*0.25)-1) * 100. For independent variables that represent a change in count (e.g., number of components), we simply calculate (exp(B)-1) * 100 to represent the percent change in delinquent activity that would occur given a one-unit increase in the variable. A positive value for the coefficient (before exponentiating) represents an increase in delinquency, and a negative relationship represents a decrease in delinquency.

Model 1 in Table 20 shows the influence of delinquent peers on respondents' delinquent activity. If the percentage of delinquent members in a respondent's network changes by 25 percent (calculated by dividing the number of delinquent peers by the total number of peers in a respondent's network), that respondent's delinquent activity increases 119 percent ((exp(3.129*0.25)-1)) * 100); if half of the peers in the respondent's network are delinquent, the respondent's delinquent activity increases by nearly 400 percent ((exp(3.129*0.5)-1) * 100). Model 1 also shows that for every additional subgroup the respondent adds to her personal network (i.e., a one-unit increase in the number of components), the respondent's delinquent activity decreases 26 percent ((exp(-0.306)-1) * 100) ($p < 0.05$). Male respondents exhibit 232 percent ((exp(1.18)-1) * 100) more delinquent activity than female respondents. Having parental support for attending school reduces delinquent activity by 49 percent ($p < 0.10$). Likewise, higher levels of the respondent's family cohesion decrease a respondent's delinquent activity by 3 percent (i.e., every additional unit of family cohesion represents a 3 percent decrease in delinquent activity ($p < 0.05$)). Increasing acculturation (read as a one-unit decrease in the separation scale) corresponds to an 18 percent increase in the respondent's delinquent activity ($p < 0.01$). Finally, for every additional year a respondent lives at his/her current address (and, therefore, in the target neighborhood), the respondent exhibits a 4 percent increase in delinquency ($p < 0.01$). Housing stability is associated with a slight increase in delinquency but, as with the binary logistic models, this effect is likely tied to more to the neighborhood context than to housing stability itself. In other words, stability alone is not likely to be associated with increased delinquency, but stability in a negative environment—which, in many ways, the target area is—can have the opposite affect and be associated with increased delinquency.

Model 2 shows the influence of all alters in predicting respondents' delinquent activity. There are very few differences between the results of Model 1 and 2, although Model 2 has a slightly better fit in that the AIC for Model 2 is 481.24 compared to an AIC of 485.22 for Model 1. A comparison of the results of Models 1 and 2 indicates that the coefficient for the proportion of delinquent *peers*, compared to the proportion of delinquent *alters*, is the same. The difference, however, is marginal when used in calculating percent change of the dependent variable: a 25 percent change in delinquent alters would result in a 36.7 percent increase in delinquency whether the peer or alter variable is used. In Model 2, as well (using alter (non-peer) variables), parental support for attending schools is not a significant predictor of overall delinquent activity, and its size is lower than that found in the peer model. The other slight change in the results is that the number of components is less significant in Model 2 (at the $p < 0.10$ level) than it is in Model 1 (at the $p < 0.05$ level); the size of the predictor in both models is almost equal, however. For every additional component the respondent has within his/her personal network, then, the respondent's delinquent activity decreases 26 percent ($p = 0.05$) in the peer variable model and 25 percent ($p = 0.05$) in the alter variable model. Because these two models are so similar, we cannot make a statement about which network measures—peer or alter—best describe the influence of social networks of youth on delinquency in our study.

It is also worthwhile to note that a number of significant relationships found in the bivariate correlations did not remain significant in the regression models. Bivariate analyses (Appendix C) showed a negative correlation between the proportion of nondelinquent alters to whom the respondent would go for advice and the overall delinquency scale ($p < 0.05$); however, this variables was not significant in our regression models.

Table 21 presents the results of the models examining recent (last six months) delinquency. Comparing the two models reveals that there are almost no differences between the models (although the alter model has a slightly better fit). What is notable is that the effect for the variable "alter delinquency" (in Model 2) is larger than the effect for "peer delinquency" (in Model 1) (they were effectively equal in the model of overall delinquency). If delinquency within a respondent's network increases by 25 percent, that respondent's recent delinquent activity increases by 90 percent ((exp(2.560*0.25)-1) * 100); if delinquent peers increase by 50 percent, the respondent's delinquent activity increases 260 percent ((exp(2.560*0.50)-1) * 100). When a respondent's *alter* network increases in delinquency by 25 percent, her delinquent activity increases 97 percent ((exp(2.720*0.25)-1) * 100); if delinquent alters increase by 50 percent, her delinquent activity increases 290 percent. Because the effects are different, having information on relationships other than peers may be very important for understanding delinquency.

Table 20. Negative Binomial Regression Results Predicting Overall Delinquency

	Model 1: Peer Variables				Model 2: Alter Variables			
	Coeff.	S.E.	Exp(B)	*p*	Coeff.	S.E.	Exp(B)	*p*
Intercept	2.00†	1.14	7.42	0.08	0.77	1.11	2.16	0.49
Peer variables								
Proportion delinquent friends	3.13***	0.81	22.86	0.00				
Proportion friends in same neighb.	-0.22	0.39	0.80	0.57				
Proportion go to for advice (not delinq.)	-0.12	0.43	0.89	0.79				
Alter variables								
Proportion delinquent alters					3.13***	0.67	22.79	0.00
Proportion alters in same neighb.					0.46	0.45	1.58	0.32
Proportion go to for advice (not delinq.)					-0.04	0.48	0.96	0.93
Network structure variables								
No. of components	-0.31*	0.15	0.74	0.04	-0.29†	0.15	0.75	0.05
Acculturation								
Separation from U.S. culture	-0.20**	0.06	0.82	0.00	-0.20**	0.06	0.82	0.00
Controls								
Age	-0.01	0.04	0.99	0.79	0.01	0.04	1.01	0.75
Male	1.18***	0.27	3.26	0.00	1.26***	0.27	3.52	0.00
Latino	0.46	0.31	1.58	0.15	0.43	0.31	1.54	0.16
Proportion of peers in network	0.55	0.53	1.73	0.30	0.85	0.54	2.34	0.12
Family member completed HS	-0.29	0.27	0.75	0.29	-0.37	0.27	0.69	0.18
Parent-school encouragement	-0.68†	0.39	0.51	0.08	-0.45	0.39	0.64	0.24
Family cohesion	-0.03*	0.01	0.97	0.02	-0.03*	0.01	0.97	0.02
No. years at address	0.05**	0.01	1.05	0.00	0.04**	0.01	1.04	0.01
Goodness of fit								
Log likelihood	-227.61				-225.62			
Deviance value/df	1.09				1.98			
Pearson chi-square value/df	0.97				0.97			
Likelihood ratio chi-square	51.90				55.88			
AIC	485.22				481.24			

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Note: Proportion variables range from 0.00 to 1.00.

For recent delinquency, the alter model has a better fit than the peer model, and in addition, some of the variables that were not significant in the overall alter delinquency model were significant in the recent delinquency model. Age is marginally significant in the recent delinquency model: for every year older a respondent is, she exhibits 7 percent fewer recent delinquent acts (marginally significant at $p = 0.06$). Parent support for school was not significant in the alter model for *overall* delinquency, but in the *recent* delinquency alter model, having parental support for attending school is associated with a statistically significant decrease in the respondent's recent delinquent activity (by 60 percent; $p = 0.01$).

Table 21. Negative Binomial Regression Results Predicting Recent Delinquency

	Model 1: Peer Variables				Model 2: Alter Variables			
	Coeff.	S.E.	Exp(B)	*p*	Coeff.	S.E.	Exp(B)	*p*
Intercept	3.13†	1.62	22.96	0.05	1.74†	1.75	5.72	0.05
Peer variables								
Proportion delinquent friends	2.56**	0.97	12.94	0.01				
Proportion friends in same neighb.	-0.36	0.52	0.70	0.49				
Proportion go to for advice (not delinq.)	-0.64	0.50	0.53	0.20				
Alter variables								
Proportion delinquent alters					2.72**	0.84	15.17	0.01
Proportion alters in same neighb.					0.60	0.61	1.81	0.49
Proportion go to for advice (not delinq.)					-0.55	0.56	0.57	0.20
Network structure variables								
No. of components	-0.37†	0.20	0.69	0.06	-0.37†	0.20	0.69	0.06
Acculturation								
Separation from U.S. culture	-0.12	0.08	0.89	0.14	-0.12	0.08	0.88	0.14
Controls								
Age	-0.11†	0.06	0.90	0.06	-0.08†	0.06	0.93	0.06
Male	1.15**	0.34	3.14	0.00	1.26**	0.35	3.52	0.00
Latino	0.07	0.38	1.08	0.85	0.04	0.37	1.04	0.85
Proportion of peers in network	0.41	0.73	1.50	0.58	0.76	0.75	2.13	0.58
Family member completed HS	0.04	0.35	1.04	0.91	-0.10	0.35	0.91	0.91
Parent-school encouragement	-1.15**	0.44	0.32	0.01	-0.93**	0.44	0.40	0.01
Family cohesion	-0.03	0.02	0.97	0.21	-0.03	0.02	0.97	0.21
No. years at address	0.07**	0.02	1.08	0.00	0.07**	0.02	1.07	0.00
Goodness of fit								
Log likelihood	-151.49				-149.85			
Deviance value/df	0.82				0.83			
Pearson chi-square value/df	0.91				0.89			
Likelihood ratio chi-square	35.36				38.65			
AIC	332.98				329.69			

† $p < 0.10$; *$p < 0.05$; ** $p < 0.01$; ***$p < 0.001$

Note: Proportion variables range from 0.00 to 1.00.

While a respondent's family cohesion and separation from the United States are significant predictors of overall delinquency, they were not significant predictors of recent delinquency. While there were some differences between the predictors of overall delinquency and recent delinquency, one key network-based variable—the number of components in the respondent's network—was a (marginally) significant predictor of recent delinquency, as it was in the overall delinquency model. The effects of the number of components on recent delinquency, controlling for all variables, was slightly larger than its effect on overall delinquency: in Model 2, each additional component represents a 31 percent decrease in recent delinquent activity (p=0.06).

There were fewer notable differences between the bivariate analyses (shown in the correlation matrix in Appendix C) and the recent delinquency model results (compared to the overall delinquency bivariate and multivariate analyses). As is the case with overall delinquency, having associates to whom you can go for advice is associated with lower delinquency ($p < 0.05$), but this relationship was not reflected in the regression model. While the model for recent delinquency offered some support for exploring the impacts of inclusive alter networks instead of just peer networks, the models are again very similar and overall, the use of neither method appears to offer significant improvement over the other in predicting delinquency.

Table 22 presents the results for the models examining the scale of serious delinquency. Similar to the models for recent delinquency, the alter model (Model 2) has a slightly better fit and the alter delinquency measure has a larger effect than the peer delinquency measure. When delinquency in a respondent's alter network increases by 25 percent delinquent, that respondent's serious delinquent activity increases significantly by 170 percent ((exp(3.980*0.25)-1) * 100); if network delinquency increases by 50 percent, the respondent's delinquency increases by 631 percent (exp(3.98*0.5)). It is important to note that, based on these figures, the existence of delinquent alters in a personal network is a much stronger predictor of *serious* delinquency than overall delinquency or recent delinquency. Other important findings for the model of serious delinquency are that the "number of components" variable and the measure of separation from United States culture are significant. Consistent with the model of overall delinquency, every additional group represents a 34 percent decrease in serious delinquent activity ($p < 0.05$). Also consistent with overall delinquency models, higher levels of separation from the United States (lower acculturation) decrease a respondent's delinquent activity by 20 percent ($p < 0.05$). It is also worth noting the importance of some of the control variables—having a close family member (i.e., parent or guardian) complete high school reduces the respondent's serious delinquent activity by 51 percent ($p < 0.05$). The only other outcome where this variable was significant was for selling drugs (see Table 19 above). The slightly larger effect sizes for the alter delinquency variables suggest that in modeling serious delinquency, there is a benefit to including wider networks beyond simple peer relationships.

Having parental encouragement in school also reduces serious delinquent activity by 58 percent ($p < 0.05$). Over the six models of delinquent behavior, this measure was significant in five, but followed an interesting pattern. When peer delinquent variables were used in the model, the parental encouragement variable was strongly significant. When the alter variables were used in the model, the parental encouragement variable either dropped out of significance (e.g., in overall delinquency model) or dropped in both magnitude and significance. So, the variable is less important in the model when youths' full networks are reported on—not just their peers. While additional investigation into this effect is beyond the scope of this report, an exploration of the parental relationship and its effect on delinquency, it is something worth an additional look in future efforts.

In examining the bivariate analyses (shown in the correlation matrix in Appendix C) and the serious delinquency models, three relationships were notable. As was the case with overall and recent delinquency, the proportion of nondelinquent alters to whom the respondent would go for advice is negatively correlated to the respondent's recent delinquency ($p < 0.05$), but this correlation was not reflected in the regression model.

Table 22. Negative Binomial Regression Results Predicting Serious Delinquency

	Model 1: Peer Variables				Model 2: Alter Variables			
	Coeff.	S.E.	Exp(B)	*p*	Coeff.	S.E.	Exp(B)	*p*
Intercept	1.42	1.36	4.13	0.30	-0.13	1.30	0.88	0.92
Peer variables								
Proportion delinquent friends	3.86***	1.00	47.66	0.00				
Proportion friends in same neighb.	-0.06	0.45	0.95	0.90				
Proportion go to for advice (not delinq.)	-0.33	0.45	0.72	0.46				
Alter variables								
Proportion delinquent alters					3.98***	0.76	53.53	0.00
Proportion alters in same neighb.					0.23	0.52	1.26	0.66
Proportion go to for advice (not delinq.)					-0.28	0.50	0.76	0.58
Network structure variables								
No. of components	-0.46*	0.18	0.63	0.01	-0.42*	0.18	0.66	0.02
Acculturation								
Separation from U.S. culture	-0.22**	0.08	0.80	0.00	-0.22**	0.08	0.80	0.01
Controls								
Age	0.00	0.05	1.00	0.98	0.04	0.05	1.04	0.45
Male	1.66***	0.29	5.27	0.00	1.85***	0.32	6.36	0.00
Latino	0.36	0.36	1.43	0.32	0.33	0.33	1.39	0.32
Proportion of peers in network	-0.16	0.62	0.85	0.80	0.19	0.60	1.21	0.75
Family member completed HS	-0.59†	0.32	0.55	0.07	-0.71*	0.31	0.49	0.02
Parent-school encouragement	-1.07**	0.39	0.35	0.01	-0.82*	0.37	0.44	0.03
Family cohesion	-0.02	0.02	0.98	0.16	-0.02	0.02	0.98	0.23
No. years at address	0.05**	0.02	1.05	0.01	0.04*	0.02	1.04	0.01
Goodness of fit								
Log likelihood	-152.08				-149.49			
Deviance value/df	0.88				0.92			
Pearson chi-square value/df	0.86				0.93			
Likelihood ratio chi-square	63.09				68.27			
AIC	345.80				328.98			

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Note: Proportion variables range from 0.00 to 1.00.

SOCIOCENTRIC DESCRIPTIVE ANALYSES

Demographics of the Whole Network

The first step in the whole network analysis was to explore the characteristics of the individuals who compose the whole network after overlapping the ego and alter data. We first "sliced" the network in two different ways as a method to compare characteristics of the neighborhood-based network—one "full" slice of the whole network comprised all 2,521 unique individuals who were named by any ego, and the other slice involved defining the network so it would comprise only those individuals who were egos or an alter who was named at least twice. Approximately 11 percent of the whole network was named at least twice; the "2+ network" has 369 members. We expect that many of the individuals who were named only once are older individuals (parents or other family members) who may influence one person's network but not multiple youths' networks; if this is true, the 2+ network should comprise more peers. We also examined the descriptive statistics by age group—network members were classified into four distinct age groups (where age was known): kids are under age 14, youth are the target ages—14–21 years, young adults are age 22–30, and adults are over 30 years. We used these groups to determine whether patterns of demographics and delinquent behavior differed by broad age categories.[26] Table 23 provides demographic information for both networks.

[26] We did not provide each measure by age group in the table but note interesting patterns where present in the text. Full statistics by age group are available from the authors on request.

Table 23. Demographic Characteristics of Whole Networks

Individual Measures	Whole Network	2+ Network[1]
Size (count of nodes)	2,521	369
Average age	20 years	19 years
Percent named as parent	3.9	4.6
Percent named as sibling	7.7	20.3
Percent named as friends	69.1	68.5
Percent who live in neighborhood	34.9	72.9
Percent Latino	69.4	78.9
Percent born abroad	43.8	37.1
Percent male	57.6	61.8
Percent who sold drugs[2]	4.2	6.8
Percent who carry a weapon[2]	5.6	5.9
Percent in gang fights[2]	5.7	8.9
Percent who use violence[2]	5.5	7.6
Percent in gang	4.5	9.5
Percent delinquent[3]	7.5	13.8

[1] The 2+ network includes only egos or people who were named at least twice by egos.
[2] Percent of those deemed very likely or somewhat likely to engage in behavior listed.
[3] Percent of those who were very likely to participate in at least one of five delinquent behaviors reported.

Age of Network Members

The average age of the two networks was of interest because it could demonstrate that youth would name individuals not in their peer group, lending support to our decision *not* to conduct a school-based survey. Indeed, we found the average ages to be surprisingly high, considering that our respondents were between the ages of 14 and 21; the whole network had an average age of 20 years and the 2+ network average age was just slightly lower at 19 years. This was higher than the average age for egos alone, which was about 18 years.

The most common ages for the two networks were slightly different, however: the mode of the whole network was 17 while the mode of the 2+ network was 20. Of those in the whole network, ages ranged from newborn to 78 years of age; the range of ages in the 2+ network was slightly smaller, from 7 years old to 68 years old. While the average ages are slightly higher than we might have expected, and the age ranges for each network are very wide, the majority of individuals actually did fall into a much narrower age range, with over 70 percent of the whole network members and over 80 percent of the 2+ network members between the ages of 14 and 21 years. This suggests that the individuals who were named twice are likely peers (or closer in age to the respondents), as we had expected prior to conducting the analysis.

Just about half of the members in both networks were school-age, or between the ages of 13 and 18. Fully half of the individuals in both networks, then, were over age 18, indicating that school-based surveys about delinquent behaviors may be missing a significant portion of the social networks that influence youth. Below, we will discuss how levels of delinquency vary by age to determine whether the older individuals are more likely to be acting as protective factors or negative factors in a youth's life.

Relationship to Egos

The alter questions about type of relationship were ego-specific, meaning that different egos would respond differently about the same alter on the question. As described in an earlier section, because EgoNet outputs the summary statistics for every relationship, we can calculate percentages for types of relationships that would be inclusive for the node (or individual). Table 24 reports on the percentages of individuals who were named as a parent, sibling, or friend (the three most common relationship categories), but one individual could show up in more than one category; the categories of relationship as reported in this table, therefore, are not mutually exclusive.

One interesting characteristic of the 2+ network is the fact that many more of its members were named as siblings than in the whole network; this could be a result of having siblings from the same family take the survey (once one individual took the survey, it was much more likely that his/her siblings would also take the survey) so all siblings would be included in the network as egos regardless of how many times they were named as alters, or it could be that the siblings are part of the same social networks, and so are named by multiple egos. Also interesting is that the number of siblings in the *whole* network seems relatively low.

The relationship variables also reveal that very similar proportions of both networks were named as parents and/or as peers; while our analyses revealed that the average age of the 2+ network is lower, suggesting that it probably contains more peer relationships, the proportions of parents and peers in each network, at least, are relatively similar (3.9 and 4.6, respectively, for parents and 69.1 and 68.5, respectively, for peers). In addition, a very small proportion of individuals were named as parents, but this is not surprising given the way the whole network is calculated when egos most likely only have a maximum of four parents to list as possible alters out of 20.

Geography of the Network

One measure with dramatically different proportions was the “live in neighborhood” variable; only approximately 30 percent of the members of the whole network live in the neighborhood while nearly three-quarters of the members of the 2+ network live in the neighborhood. While not wholly unexpected—it is more likely that those who are named by (and thus known by) more than one ego are peers who live nearby than individuals who live farther afield—it does suggest that the core social network for the youth who are most well-connected or well-known in the area are neighborhood based, another sign of support for the design of the survey. This could have implications for the influence of the individuals in the neighborhood versus those from outside the neighborhood; such a finding warrants further investigation, which will be discussed below. In order to more fully explore those who live in the neighborhood versus those who live outside the neighborhood, we divide nodes into those two categories and look at their characteristics separately, below.

Other Demographic Characteristics

For each network, the majority of members were Latino, with the 2+ network having a slightly higher proportion of Latino members at nearly 80 percent, very similar to the percentages for egos only. Members of the 2+ network were born abroad at a similar rate to egos, but members of the whole network were slightly more likely than the egos and the 2+ network to have been born abroad. At the network level, gender appeared divided similarly to egos only, where slightly less than two-thirds of the egos were male in both networks. But more interesting patterns emerged when we looked at gender by age group for each network. Among adults in the whole network, the gender pattern reversed, with slightly more adult females (54 percent) than adult males. In the 2+ network, the gender ratio (about 2:1) was similar to the egos across all age groups. This indicates that when egos named adults, they were more likely to name women as individuals that they saw frequently or spent time with, but when they nominated peers, egos were more likely to nominate males. This pattern likely did not hold for the 2+ network because again, there were fewer adults in the 2+ network. If youth named mothers, aunts, or other adult females they were likely only influential for one individual in the network, and not several.

Delinquency/Criminality of Network Members

We explored the delinquency of the network members by looking at the five main delinquency measures individually (weapon use, sold drugs, in gang fight, in gang, and use violence)[27] and together via the overall delinquency measure.[28] While not shown in Table 23, for these measures, we also considered delinquency for different age groups in the data, described above; we wanted to assess whether older individuals might be acting as risk or protective factors based on their levels of delinquency.

[27] As mentioned in the measures section of the report, we use the term delinquency and criminality interchangeably in that many of the alters are not under 18.

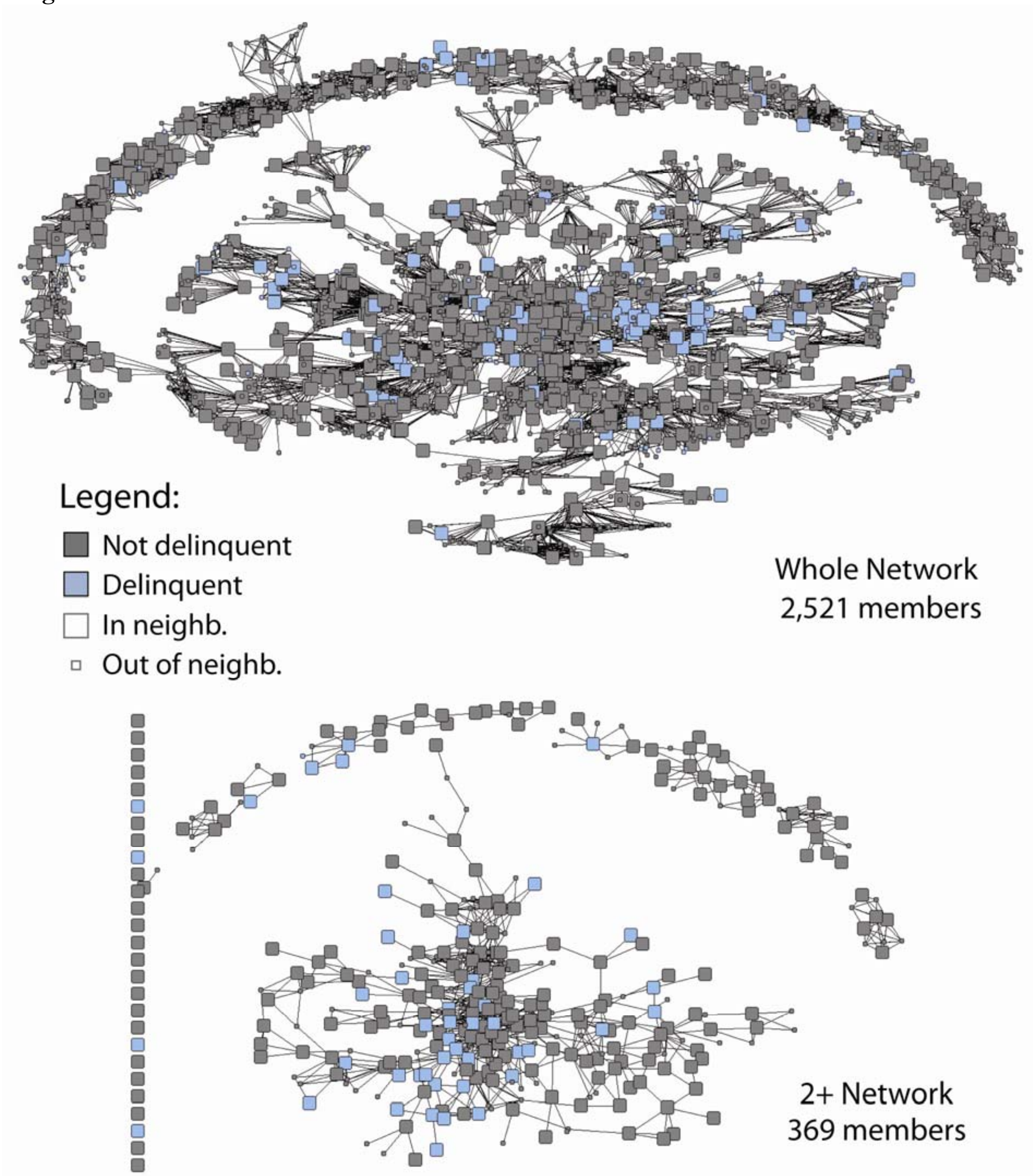
[28] An individual is considered delinquent if he/she was very likely to participate in at least one of the five delinquency measures.

The 2+ network had higher levels of delinquency than did the whole network on every measure; only weapon use was similar across the two networks.[29] The difference was greatest for percent in a gang; only 4.5 percent of the whole network was in a gang, but nearly 10 percent of the 2+ network was. Ten percent is a relatively small number of individuals, but it is an indication that gang members who were named in the network tended to be named more than once, as opposed to being named as influential for just one ego. In addition, among the delinquency measures, "in gang" was highest for the 2+ network, but "gang fight" was highest for the whole network. Overall, nearly 14 percent of the 2+ network was delinquent, while just over 7 percent of the whole network was delinquent. This means that 14 percent of members in the 2+ network were judged to be *very likely* to engage in one of the delinquent behaviors of interest. This is lower than the rate of delinquency for the egos only (20 percent of egos were delinquent), indicating that on the whole, egos were attributing more delinquent behavior to themselves than to members of their networks. Overall, the levels of delinquency found among network members for both networks were relatively low, given our local knowledge of the neighborhood.

Figure 2 provides a picture of both networks, combining each node's delinquency status and in- versus out-of-neighborhood status. From these figures, we can see that both networks have clearly defined and large central clusters of members, and that the delinquent members (the light colored nodes) tend to be located in this central cluster. The pictures also reveal, not surprisingly, that the in-neighborhood nodes appear to be more centrally located within the network while the out-of-network members appear more peripheral and seem to have fewer connections. Finally, the 2+ network has a large number of isolates, nodes who are not connected to anyone else, likely the result of dropping a large number of nodes.

[29] Because the 2+ network is a subset of the whole network, we cannot perform t-tests to statistically compare the differences between the two networks.

Figure 2. Sociograms of Whole Network and 2+ Network, Displaying Node Delinquency and "In-Neighborhood" Nodes



The Neighborhood Network

Because one of the main goals of the research was to explore the accuracy and utility of defining a social network using geographic boundaries, we also investigated the characteristics of those individuals residing in and outside the neighborhood. Those characteristics are presented in Table 24. The in-neighborhood group is significantly smaller, at nearly half the size of the out-of-neighborhood group. We performed t-tests to determine whether the two groups were significantly different, and every measure was significant. Other than for average age, for most measures, the differences between the two networks are stark; in-neighborhood nodes were more likely to be parents and siblings; out-of-neighborhood nodes were more likely to be friends. More in-nodes are Latino while more out-nodes were born abroad. In addition, the table demonstrates clearly that the in-nodes have significantly higher levels of delinquency for every measure examined. Table 24 indicates that there are likely some systematic differences between the two groups that are manifested in higher levels of delinquency for in-neighborhood nodes.

Table 24. Demographic Characteristics of Networks Within and Outside the Neighborhood

Individual Measures	Live in Neigh.	Live out of Neigh.
Size (count of nodes)	879	1,642
Average age	21 years	20 years
Percent named as parent	8.9	1.2
Percent named as sibling	15.0	3.9
Percent named as friends	59.0	74.4
Percent who live in neighborhood	100.0	0.0
Percent Latino	76.5	65.6
Percent born abroad	51.3	61.4
Percent male	62.3	55.1
Percent who sold drugs[1]	8.4	3.8
Percent who carry a weapon[1]	9.7	4.8
Percent in gang fights[1]	10.3	5.0
Percent who use violence[1]	8.8	5.5
Percent in gang	7.1	3.1
Percent delinquent[2]	11.5	5.4

[1] Percent of those deemed very likely or somewhat likely to engage in behavior listed.
[2] Percent of those who were very likely to participate in at least one of five delinquent behaviors reported.
Note: All differences between networks significant at $p < 0.05$ level.

Cohesiveness and Centrality of the Networks

As discussed in the analysis plan above, there are many different network measures that can be employed—with different results—to identify both how cohesive and centralized a network is and how central individual members are, based on such things as ties to others, distance to all nodes in the network, and centrality of nodes an individual is connected to. We employ one cohesion measure (density) and four centrality measures for this work, to compare the findings across measures and to provide a comprehensive understanding of connections between nodes in the two networks under study. Table 25 provides the cohesion and centrality measures for each network.[30]

Table 25. Cohesion and Centrality Measures

Network Measures	Whole Network	2+ Network
Size (count of nodes)	2,521	369
Avg. number of nominations per node	1.17	2.14
Number of ties between nodes	16,552	1,810
Density		
Density	0.0026	0.01
Effective density[1]	0.33	-
Degree centrality		
Mean	6.57	4.91
Mean, normalized degree	0.26	1.33
Network centralization index (%)	2.04	5.48
Betweenness centrality[2]		
Mean	3,860.93	341.14
Mean, normalized betweenness	0.12	0.51
Network centralization index (%)	9.19	6.75
Closeness centrality[3]		
Mean	6.13	5.26
Mean, normalized closeness	34.06	35.08
Network centralization index	436.86	347.95
Eigenvector centrality		
Mean	0.004	0.02
Mean, normalized eigenvector	0.63	3.01
Network centralization index (%)	42.58	41.06

[1] Effective density is calculated using a network size that accounts for the number of people respondents were asked to name.
[2] Freeman node betweenness score is reported.
[3] Calculated using the Valente-Foreman average of reversed distances.

[30] Centralization measures are calculated at the network level, while centrality measures are calculated at the individual (node) level.

Cohesion

As noted earlier, the whole network contains 2,521 nodes while the 2+ network has 369 nodes. The whole network contains far more ties (because it contains far more nodes) than the 2+ network. Density is the most basic and commonly used measure of cohesiveness and is simply the proportion of actual ties relative to all possible ties; it ranges from 0 to 1. As the size of the network increases, density typically decreases, and we can see that effect with the whole network and the 2+ network used here. The whole network has a density of effectively 0 while the 2+ network has a very slightly higher density at 0.01. Both densities, then, are very low, indicating loosely connected networks with sparse ties. Especially in the case of the whole network, this finding is not very surprising; respondents' family members who were included in the whole network were unlikely to be tied to anyone but the ego naming them, and thus there are many nodes with only one tie.

For networks based on nomination data, Valente (2010) suggested a modified version of density that takes into account the size of the personal networks used to make the whole network. In other words, the density measure is adjusted for the number of alters each ego was asked to name. In this case, each ego named 20 individuals. Valente's "effective density" measure, taking into account the 20 alters for each ego, resulted in a higher density for the whole network of 0.33, indicating that about one-third of the possible ties actually existed. While still relatively low, this density value is similar to those reported by Kreager, Rullison, and Moody (2011) and Snijders and Baerveldt (2003) in their studies of delinquent groups, and higher than the density of Natarajan's (2006) drug distribution network. Because the 2+ network does not include all members of an ego's personal network, with a size of 20, but instead only those alters that were named by two or more individuals, the effective density is not appropriate for that network.

Degree Centrality

Like density, degree—the number of direct ties between nodes—is another very standard network measure that is commonly reported in whole network studies and is used as a measure of network structure in predictive models. Table 25 reports the mean degree, or the average degree for each member of the network; this is calculated at the node level. While the raw mean degree is higher for the whole network, the normalized degree is adjusted for the size of the network, allowing that measure to be compared across networks. The normalized degree is higher for the 2+ network, indicating that members in that network have more direct ties to other nodes. This result is not surprising; everyone in that network was either an ego (with an automatic 20 ties) or was nominated at least twice.

As described above, the centralization index is akin to a standard deviation of the centrality measures, and lower centralization values indicate a less centralized network while higher values indicate a more centralized network (Hanneman & Riddle 2005; Knoke & Yang 2008; Valente 2010). Even though the degree centralization index for the 2+ network is more than twice as large as that of the whole network, the values for both networks are extremely low, indicating that neither is especially centralized.

Betweenness Centrality

We calculated betweenness centrality using the Freeman node betweenness method. The normalized betweenness measure for the whole network is more than four times the value for the 2+ network, but both values are very small. The standard deviations for both measures are high relative to the normalized mean values (0.59 and 1.13, respectively), suggesting that there is a lot of variation of betweenness scores among actors in both networks. The betweenness centralization values, however, are very low, indicating that the level of centralization in both networks overall are very low. These low levels of betweenness centralization for both networks suggest that there are few members who have high betweenness scores and rather that most members have similar, low betweenness scores. This may be an indication that there are few people who act as "bridges" or brokers (e.g., of information, drugs) between groups within each network.

These low values for betweenness centralization are surprising given the low degree values; those values suggested that a small number of network members were directly connected to a large number of nodes. Given the degree scores, we expected to find a small number of central players connected to many nodes and many nodes connected to very few other nodes—in other words, a loosely structured network with high betweenness centrality. The first two measures of centrality, however, suggest that both networks have similarly low levels of centralization, low levels of ties between members, and few individuals to act as brokers or "go-betweens" for different subsections of each network.

Closeness Centrality

We next examined closeness centrality of both networks. Closeness is a measure of the distance between each node and every other node.[31] The normalized closeness of both networks is very similar at around 35, even while the closeness centralization index is much higher for the whole network. This may be a function of the whole network being significantly larger than the 2+ network, so a node must go farther in order to reach every other node. On the whole, these measures indicate that the number of nominations received does not appear to have a great effect on the levels of closeness for each actor; those with at least two nominations have virtually the same levels of closeness to other actors as those with only a single nomination.

Eigenvector Centrality

The 2+ network has a much higher mean eigenvector centrality than the whole network, even while the values themselves are relatively low. The standard deviations for the mean

[31] We used Valente and Foreman's (1998) reverse distances measure to calculate closeness.

eigenvector centrality measures for both networks are high (2.75 and 6.72, respectively), indicating that there is a high amount of variability in individual eigenvector measures, and in turn, that centrality is not evenly distributed across network members but is instead high for some members and low for others. This finding is supported by the eigenvector centralization value for each network, which for both networks is just over 40 percent. The centralization value suggests a substantial amount of centralization in both networks. The individual- and network-level values together support the finding that the networks are both centralized.

We also, however, examined the eigenvalues for each factor in each network. The eigenvalues of the first factor are extremely low, explaining just 2.5 percent and 0.6 percent of the variability in the whole and 2+ networks, respectively. Combined with the pattern of eigenvalues across each factor, we conclude that the eigenvector centrality measure should not be regarded as accurate for these data. Therefore, although the eigenvector centrality measure suggested the highest levels of centrality of the all four measures examined, we do not consider it to have produced useful findings in this situation. In addition, it produced measures of centrality that were much higher than what we found with the other three centrality measures, further calling into question the validity of the measure as applied to these specific networks.

Similarity of the Centrality Measures

We ran correlations of the four different centrality measures to assess how similar the measures were across individuals. Table 26 and Table 27 provide the results of the correlation analysis. The results indicate that the measures are not very similar; in other words, they are likely measuring very different structural characteristics of the networks. Degree centrality is the most closely related to every other measure (its correlation with betweenness is the highest of all comparisons for both networks), but even the degree correlation coefficients are relatively small. Thus, the use of multiple centrality measures is warranted, and these tables reiterate the importance of selecting the correct centrality measure for the construct to be studied. While not shown, we also investigated the correlations of the centrality measures with the five delinquency measures of interest; the correlations, while significant, were all extremely low (i.e., less than 0.01).

Table 26. Correlation between Different Measures of Centrality, Whole Network

	Degree	Betweenness	Closeness	Eigenvector
Degree	1.00	0.51**	0.03	0.47**
Betweenness	0.51**	1.00	0.13**	0.34**
Closeness	0.03	0.13**	1.00	0.14**
Eigenvector	0.47**	0.34**	0.14**	1.00

Table 27. Correlation between Different Measures of Centrality, 2+ Network

	Degree	Betweenness	Closeness	Eigenvector
Degree	1.00**	0.63**	0.41**	0.80**
Betweenness	0.63**	1.00**	0.36**	0.47**
Closeness	0.41**	0.36**	1.00**	0.41**
Eigenvector	0.80**	0.47**	0.41**	1.00**

Table 28. Centrality of Networks Within and Outside the Neighborhood

Network Measures	Live in Neighb.	Live out of Neighb.
Size (count of nodes)	879	1,642
Average number of nominations	1.33	1.08
Number of ties between nodes	4,682	4,246
Density		
Density	0.0061	0.0016
Effective density[1]	-	-
Degree centrality		
Mean	5.33	2.59
Mean, normalized degree	0.61	0.16
Network centralization index (%)	3.27	1.12
Betweenness centrality[2]		
Mean	874.22	6.07
Mean, normalized betweenness	0.23	0.00
Network centralization index (%)	8.79	0.03
Closeness centrality[3]		
Mean	3.98	0.03
Mean, normalized closeness	26.56	0.45
Network centralization index (%)	366.28	11.71

[1] Effective density is calculated using a network size that accounts for the number of people respondents were asked to name.

[2] Freeman node betweenness score is reported.

[3] Calculated using the Valente-Foreman average of reversed distances.

Cohesion and Centrality of the Neighborhood Network

Table 28 presents the network structural measures for the neighborhood networks (in-neighborhood vs. out of neighborhood). Despite having only about half of the *nodes* of the out-network, the in-network has more *ties*, and, accordingly has a higher level of density as well. As was the case with the whole networks presented above, however, the density measures overall are very low, indicating loose structures for both in- and out-networks. The in-network also demonstrates higher levels of centrality based on all three measures employed (eigenvector centrality was excluded based on the results of the whole network analysis above). The centrality of the in-network may contribute to the levels of delinquency observed; consequently the "live in neighborhood" variable will be included in the predictive models presented below, allowing a more sophisticated test of its relationship to delinquency.

Identifying Central Actors in the Network

The four main centrality measures examined—degree, betweenness, closeness, and eigenvector—produced pictures of the two networks under study as loosely connected nodes with few ties between them and few central players either playing a brokering or bridging role between different subgroups in the data. Despite the fact that the networks overall have low levels of centrality, we can still identify specific actors who are the most central in both networks based on the four centrality measures. For this portion of the analysis, central players in the whole network were those who were in the top 1 percent for at least one of the centrality measures; for the smaller, 2+ network, we examined the top 5 percent of individuals for at least one of the centrality measures. Table 29 presents a comparison of summary statistics for the whole network for those central players as identified using the degree, betweenness, and closeness measures.

Table 29. Summary Demographic Characteristics and Centrality of Whole Network Members with High Centrality Values

Central Actors[1]	Whole Network	Degree	Between.	Closeness
Size (count of nodes)	2,521	29	26	28
Avg. number of nominations	1.17	5.0	4.1	4.8
Percent who are egos	5.83	93.1	74.1	46.4
Average age	20 years	17 yrs.	17 yrs.	16 yrs.
Percent named as parent	3.9	0.0	0.0	0.0
Percent named as sibling	7.7	34.5	29.6	21.4
Percent named as friend	69.1	96.6	88.9	96.4
Percent in neigh.	34.9	96.6	85.2	78.6
Percent Latino	69.4	89.7	81.5	92.9
Percent born abroad	43.8	27.6	22.2	28.6
Percent male	57.6	86.2	85.2	96.4
Percent who sold drugs[2]	4.2	13.8	16.0	7.7
Percent who carry a weapon[2]	5.6	20.7	14.8	10.7
Percent in gang fights[2]	5.7	20.7	23.0	11.5
Percent who use violence[2]	5.5	10.3	3.7	0.0
Percent in gang	4.5	10.3	11.1	7.1
Percent delinquent[3]	7.5	20.7	25.9	17.9
Average of centrality measure	-	1.6	4.7	0.14

[1] For the whole network, we used the top 1 percent of the centrality values.
[2] Percent of those deemed very likely or somewhat likely to engage in behavior listed.
[3] Percent of those who were very likely to participate in at least one of 5 delinquent behaviors reported.

More of the high degree individuals were egos, an intuitive finding because egos are automatically connected directly to 20 individuals (their alters); far fewer of those with high closeness values, however, were egos (46.4 percent and 68.4 percent for the whole and 2+ networks respectively). These findings indicate that the closeness centrality measure may be less biased given the structure of our data, where not everyone was a survey respondent and egos (who *did* complete the survey) by definition have at least 20 direct connections. Instead, closeness measures the "distance" between each node and every other node. Those who can reach more nodes over a shorter "distance" have lower closeness values (or are closer to each other). Therefore, while egos have more direct connections (higher *degree)* on average than non-egos, they aren't necessarily more closely connected to others in the network, with easy access (or short distance) to many other nodes in the network.

The average age of the node groups varies as well, with the central players actually younger than the average whole network by three to four years. Not surprisingly, no central players were named as someone's parent (in other words, none of the central players was an ego's parent) but a much higher percent of central actors were named as siblings and friends than in the whole network. Central actors are also more likely to be male and Latino but not as likely to have been born abroad than less central members of the whole network; the central actors thus demonstrate higher levels of acculturation than noncentral actors. Central actors are also more likely to live in the neighborhood.

Delinquency among the central players appeared much higher than for members of the whole network on average, with most measures of delinquency significantly higher for central actors than for the whole network. Central players who have high betweenness scores are the most likely to sell drugs, participate in gang fights, and be considered delinquent using our overall delinquency scale. Less central, or "between" actors are not as involved in delinquent behaviors. At the same time, those with high betweenness scores were also *less* likely than noncentral members to use violence to get what they need. This seeming contradiction in results will be explored in more detail in the discussion section.

Table 30 provides the same summary statistics for the 2+ network. As with central actors in the whole network, those in the 2+ network are more likely to be egos, and are a few years younger than the average 2+ network member. Also similar to the whole network's central players is the higher frequency with which central players were named as siblings and friends. In the 2+ network, central actors were also more likely to be Latino and male, and less likely to have been born abroad. These findings on acculturation support the hypothesis that individuals with higher levels of acculturation are more likely to be delinquent than those who have lower levels of acculturation.

Table 30. Summary Demographic Characteristics and Centrality of 2+ Network Members with High Centrality Values

Central Actors[1]	2+ Network	High Degree	High Between.	High Closeness
Size (count of nodes)	369	19	19	19
Avg. number of nominations	2.1	6.3	5.2	6.2
Percent who are egos	39.8	78.9	78.9	68.4
Average age	19 years	16 yrs.	16 yrs.	16 yrs.
Percent named as parent	4.6	0.0	0.0	0.0
Percent named as sibling	20.3	21.1	31.6	21.1
Percent named as friend	68.5	100.0	94.7	100.0
Percent in neigh.	72.9	94.7	94.7	94.7
Percent Latino	78.9	94.7	89.5	94.7
Percent born abroad	37.1	26.3	36.8	26.3
Percent male	61.8	100.0	89.5	100.0
Percent who sold drugs[2]	6.8	10.5	11.1	11.1
Percent who carry a weapon[2]	5.9	15.8	10.5	15.8
Percent in gang fights[2]	8.9	21.1	16.7	16.7
Percent who use violence[2]	7.6	0.0	0.0	0.0
Percent in gang	9.5	5.3	10.5	5.3
Percent delinquent[3]	13.8	21.1	21.1	21.1
Average of centrality measure	-	5.3	4.6	57.1

[1] For the whole network, we used the top 1 percent of the centrality values.
[2] Percent of those deemed *very likely* or *somewhat likely* to engage in behavior listed.
[3] Percent of those who were *very likely* to participate in at least one of five delinquent behaviors reported.

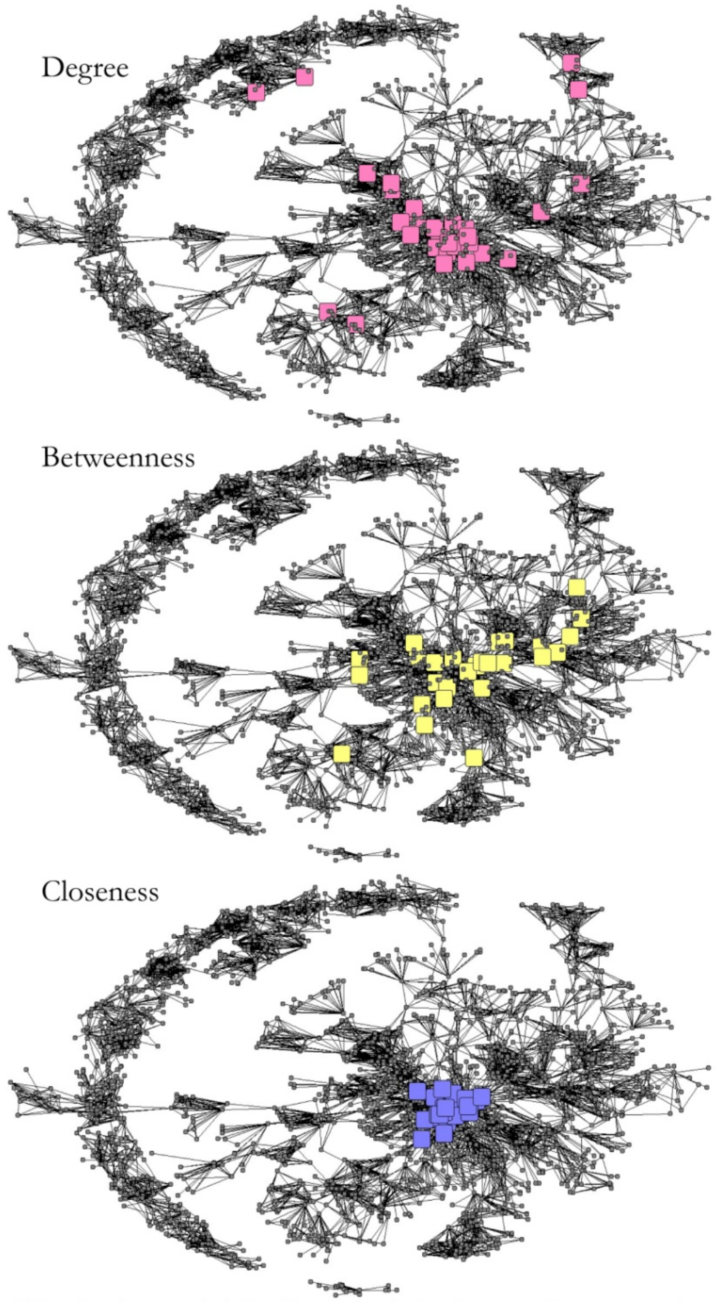
Delinquency among the 2+ networks central actors was higher than among noncentral network members, but the difference with the average network member was not nearly as dramatic as it was with the whole network's central actors. About one-fifth of central actors participate in some kind of delinquent activities. No central players, however, use violence; this is similar to the whole network findings where the use of violence was very low among central players.

It is also useful to consider the location, or position, of the central nodes within the whole network as determined via the three centrality measures employed here. Figure 3 presents the whole network with the central nodes highlighted—the central nodes for each measure are larger and shaded a light color. Those nodes that had high degree values and high betweenness values were similarly located; with a central cluster at the center of the whole network, and some central members in less-central clusters. Those more distant nodes in the degree and betweenness sociograms, however, were not the same nodes, representing some differences between the two measures. Perhaps most interesting, however, is the level of clustering demonstrated among nodes with high closeness values. This isn't surprising; the nodes with high levels of closeness have the shortest connections to all other nodes in the network, so it is intuitive that they are central in the sociogram. The interesting point is that all three measures indicate some type of centrality, yet nodes that are high on closeness are the ones that do appear to be the most central nodes.[32]

To explore the centrality and delinquency connection in more depth, we present a small subgroup of network members in Figure 4 as an example. This group of individuals was chosen simply by selecting one node with high values on all three centrality measures (we selected node 394) and all of the nodes to whom node 394 is connected. The sociogram includes all ties between all nodes in the diagram (not just those between 394 and other nodes). The most central actor, 394, is a Latino male, age 16, who lives in the neighborhood. He was not a survey respondent but was named by 11 egos. He is also not delinquent, but a number of the other central actors are, including actors who named node 394. In addition, node 394 appears to be playing a brokering role between two distinct clusters of individuals, as reflected by his high betweenness value. Several other highly central actors are included here by virtue of their connection to node 394. These individuals are not simply central within their own group of connections but are central in the larger network, and are connected to other central individuals. These individuals, then, form almost a central subnetwork within the larger whole network, and are not simply operating as lone central individuals.

[32] One note of caution: the sociogram is not drawn in a way that indicates anything about the true centrality of the nodes. The program used for visualization, NetDraw, uses an algorithm to determine the best layout of nodes for any given network, but nodes can be moved manually and the algorithm does not take into account any node attributes (e.g., what the node's centrality measures are) but simply positions the nodes into a visually coherent layout. That said, the nodes that are at the center of the network *are* those that have the most ties to other nodes, and the sociograms shown in Figure 3 are the same but for the changing colors to indicate the central nodes for each measure.

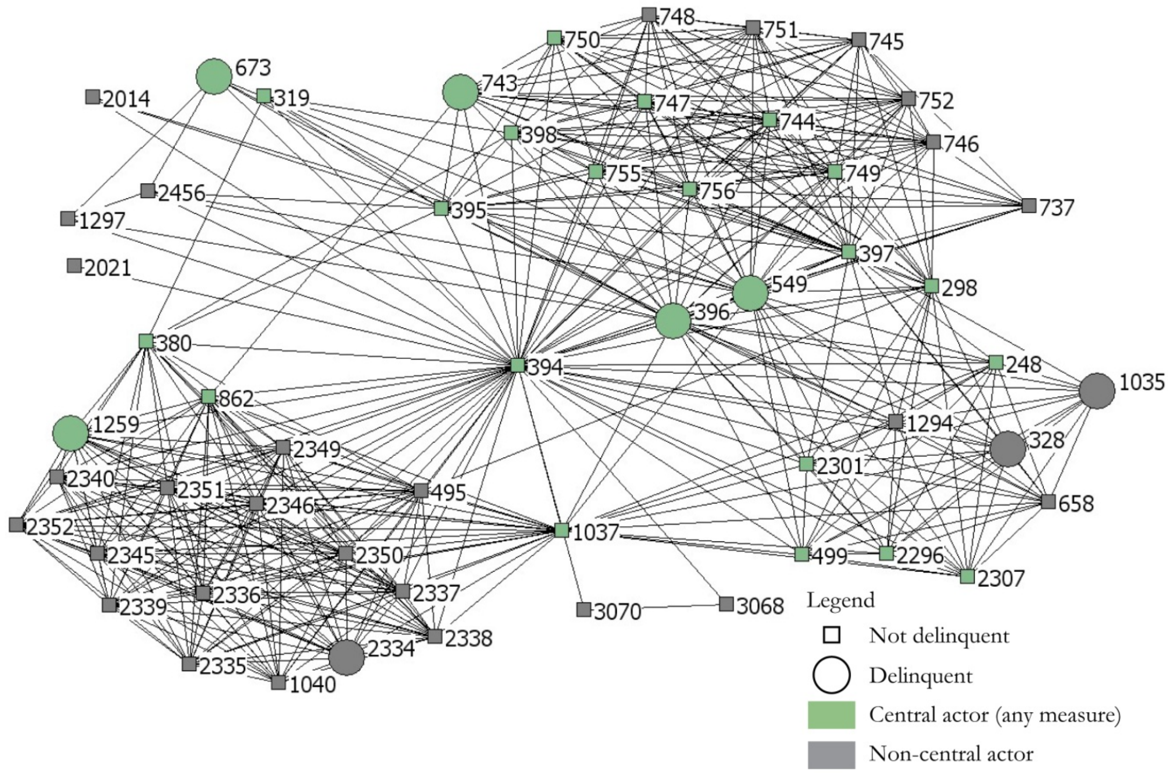
Figure 3. Comparison of Central Nodes via Three Centrality Measures



Light colors, larger symbols identify central nodes based on centrality measure used.

While this subgroup of network members was arbitrarily chosen to provide an example of node centrality, the ability to divide a large network, such as we are using here, into smaller, coherent groups has utility for more closely examining the different characteristics of the network, how

Figure 4. Ego-Network of a Highly Central Individual (node 394)



groups are related to one another, and how nodes are nested within the network. The next section describes this process and its results.

Identifying Community Structure within the Network

While there are several methods that can be used to divide networks into different, coherent groups based on a number of different criteria,[33] we used Girvan and Newman's methods as implemented in UCINet. Girvan and Newman (2002), in discussing the division of nodes in a network into different subgroups, described the subgroups that make up a whole network as "communities." While not used in the same way as the word "communities" is traditionally defined, we use the word here as Girvan and Newman did. The technical term used for the subgroups identified by the algorithm is "partition." We assessed the community structure of the whole network only.

[33] Nodes can be classified into groups based on attributes and ties, or simply ties. We use ties only to classify nodes.

The Girvan-Newman (G-N) iterative algorithm identified 25 partitions in the whole network. The networks had range of sizes, from 20 members to 1,792 members. Several (17) of the partitions appeared to be simply ego networks (i.e., networks surrounding a survey respondent and including only or mostly alters she named) but they did display differences in centrality and in delinquency levels. For each partition, we calculated the same demographic and delinquency measures as presented for the overall whole network above (Table 23). We also examined the three main centrality measures[34] identified above for each faction. Of the 25 factions, we selected six to present in the text that shed light on the research questions guiding this study. To simplify the discussion of the factions, we named each faction based on its characteristics. The demographic and delinquency measures for the six factions are presented in Table 31.

The first faction is included simply to demonstrate the different sizes and forms of partitions that are created through the G-N algorithm. This one, termed Everyone Else appears to be a catchall of nodes that were not included in other partitions. This partition is by far the largest, with over 1,700 nodes. Its characteristics echo those of the whole network. The second partition is termed The [Latino] Outsiders. Members of this group have low levels of acculturation; all are Latino, and all were born abroad. The average age of the group is slightly higher than for the whole network at 23 years, and less than 20 percent live in the neighborhood. None of the members is delinquent, supporting the hypothesis that lower levels of acculturation are associated with lower levels of delinquency.

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[34] We excluded the fourth measure, eigenvector centrality, based on the results from the whole network analysis.

Table 31. Demographic and Delinquency Summary Measures for Selected Girvan-Newman Partitions

Measures	**Subgroups**					
Subgroup Name	Everyone Else	The [Latino] Outsiders	No "Aging Out" Here	The [Latino] Insiders	A Thug in Charge	A Tale of Two Brothers
Subgroup Description	Catchall	Low acculturation, older, outside neighborhood	Non-Latino, older, delinquency	Low acculturation, younger, inside neighborhood	Latino, gang members, delinquency	Brothers, younger not delinquent, older delinquent
Individual (node)-level measures						
Size (number of nodes)	1,792	21	21	21	20	40
Average age	19	23	24	18	23	21
Percent Latino	73.5	100.0	4.8	100.0	90.0	25.0
Percent named as friends	72.0	61.9	66.7	4.8	75.0	75.0
Percent named as family members	25.1	23.8	28.6	0.0	15.0	10.0
Percent born abroad	41.1	100.0	0.0	85.7	20.0	25.0
Percent male	58.5	66.7	66.7	100.0	80.0	72.5
Percent who live in neighborhood	35.9	19.0	52.4	95.2	55.0	35.0
Percent in gang	5.5	0.0	9.5	0.0	15.0	15.0
Percent in gang fights[1]	6.4	0.0	4.8	0.0	15.0	10.0
Percent who use violence[1]	6.3	0.0	0.0	0.0	5.0	5.0
Percent delinquent[2]	8.6	0.0	9.5	0.0	40.0	15.0

[1] Percent of those deemed very likely or somewhat likely to be in gang fight/use violence.

[2] Percent of those who were very likely to participate in at least one of five delinquent behaviors.

The partition termed No "Aging Out" Here has one of the highest average ages of all factions at 24 years old, but also demonstrates a moderate level of delinquency; its members do not appear to be "aging out" of delinquent behaviors as they get older. In addition, few are Latino and none were born abroad. The [Latino] Insiders is similar to The Outsiders except that its members are, on average, a few years younger, and most live *in*side the neighborhood instead of outside the neighborhood. Similarly, most members of the partition named A Thug in Charge are Latino (90 percent) and male (80 percent). This faction, however, has the highest level of delinquency of all factions, with 40 percent of its members having participated in at least one delinquent behavior and

Table 32. Cohesion and Centrality Measures for Selected Girvan-Newman Partitions

Measures	**Subgroups**					
Subgroup Name	Everyone Else	The [Latino] Outsiders	No "Aging Out" Here	The [Latino] Insiders	A Thug in Charge	A Tale of Two Brothers
Subgroup Centrality Description	Low connected-ness	Low density but highly centralized, star shaped network	Average connected-ness	Extremely dense, no central players, flat structure	Low density but highly centralized, star shaped network	Two connected networks, several central actors
Network-level measures						
Number of ties	11,994	40	206	420	38	164
Size (number of nodes)	1,792	21	21	21	20	40
Density						
Density	0.004	0.1	0.5	1.0	0.1	0.1
Effective density[1]	0.3	0.1	0.5	1.0	0.1	0.2
Degree centraliz.						
Mean	6.7	1.9	9.8	20.0	1.9	4.1
Normalized mean	0.4	9.5	49.1	100.0	10.0	10.5
Centralization index	2.9	95.0	53.0	0.0	94.7	52.3
Betweenness centraliz.[2]						
Mean	5,411.3	9.1	5.1	0.0	8.6	24.6
Normalized mean	0.3	4.8	2.7	0.0	5.0	3.3
Centralization index	18.1	100.0	15.4	0.0	100.0	71.0
Closeness centraliz.[3]						
Mean	12.0	1.1	1.5	1.0	1.1	1.7
Normalized mean	66.4	54.8	74.2	100.0	55.0	58.0
Centralization index	281.4	100.0	56.3	0.0	100.0	92.0

[1] Effective density is calculated using a network size that accounts for the number of people respondents were asked to name.
[2] Freeman node betweenness score is reported.
[3] Calculated using the Valente-Foreman average of reversed distances.

fully 15 percent in a gang. Finally, A Tale of Two Brothers is a partition made up of two adjoining networks, one surrounding an older brother and one surrounding a younger brother. These adjoining networks are connected by the brothers and by a handful of others who are associated with both brothers. This partition has a moderate amount of delinquency, most of which is found on the older brother's side of the network. In addition, this network has a relatively small number of Latino members (only a quarter are Latino) and a small number of people who live in the neighborhood.

While these statistics point to similarities across the networks in terms of the characteristics of people, an examination of each faction's network structure reveals that structure and node characteristics do not always match up in the same way. Table 32 provides summary cohesion and centrality measures for each of the six selected partitions. The table also provides a brief description of the centrality of each partition. The Outsiders and A Thug in Charge provide classic examples of star-shaped networks, where one central actor (the ego) is connected to all other nodes, but the other nodes are only connected to the ego, and none to each other. This kind of network is highly centralized—there is only one central figure—but it is not very dense because, except for the central figure, nodes are connected only to one other node. Figure 5 provides the sociograms for these two networks, displaying the egos, delinquent nodes, and in- versus out-of-neighborhood status. These two networks, despite having very similar densities and centrality measures, display very different delinquency characteristics. A Thug in Charge, as the name suggests, is centered on one delinquent individual, a 19-year-old Latino male who is gang involved. No members of The Outsiders, on the other hand, are delinquent; the central player is also a 19-year-old Latino male, but one who is unlikely to use violence or to participate in delinquent behaviors. He also spends less time with others from the neighborhood than the individual at the center of "Thug." The sociograms in Figure 5 demonstrate the hierarchical nature of these networks, their one-node centrality, and the variations in delinquency across the network structures.

The [Latino] Insiders partition, while similar demographically and delinquency-wise to The [Latino] Outsiders, reveals a very different network structure, one where nodes are highly connected and ties are very dense. In fact, this faction has the maximum density possible, meaning that all nodes are connected to all other nodes. The structure is thus very flat, without an obvious hierarchy or central figure. The mean degree is also the highest possible, while betweenness and closeness are extremely low; there are no nodes that are on more paths between nodes, or could reach a node over a shorter distance, than any other node. The sociogram for this partition is shown in Figure 6.

The last partition highlighted here is A Tale of Two Brothers. This partition is larger than the others highlighted because it contains two connected ego networks. The partition has a moderate level of overall density, but because it has a few very central actors (each brother and a handful of others connected to both brothers), the partition's centrality measures reveal a hierarchical network structure. The centrality measures of this partition are more similar to those of the star-networks than those of the dense, flat network. In fact, the sociogram for this partition, in Figure 7, reveals that one brother's network is dense and well-connected while the other brother's network is akin to the star-shaped network. The faction thus displays multiple types of structures within one network. In addition, the sociogram reveals that the older brother, with higher levels of delinquency, also spends more time with individuals from within the neighborhood while the younger brother is more outwardly focused in his social network. Finally, the sociogram identifies the four central nodes connected to both brothers and the two brothers themselves (the two egos in the sociogram) as central actors.

Figure 5. Star-Shaped Networks

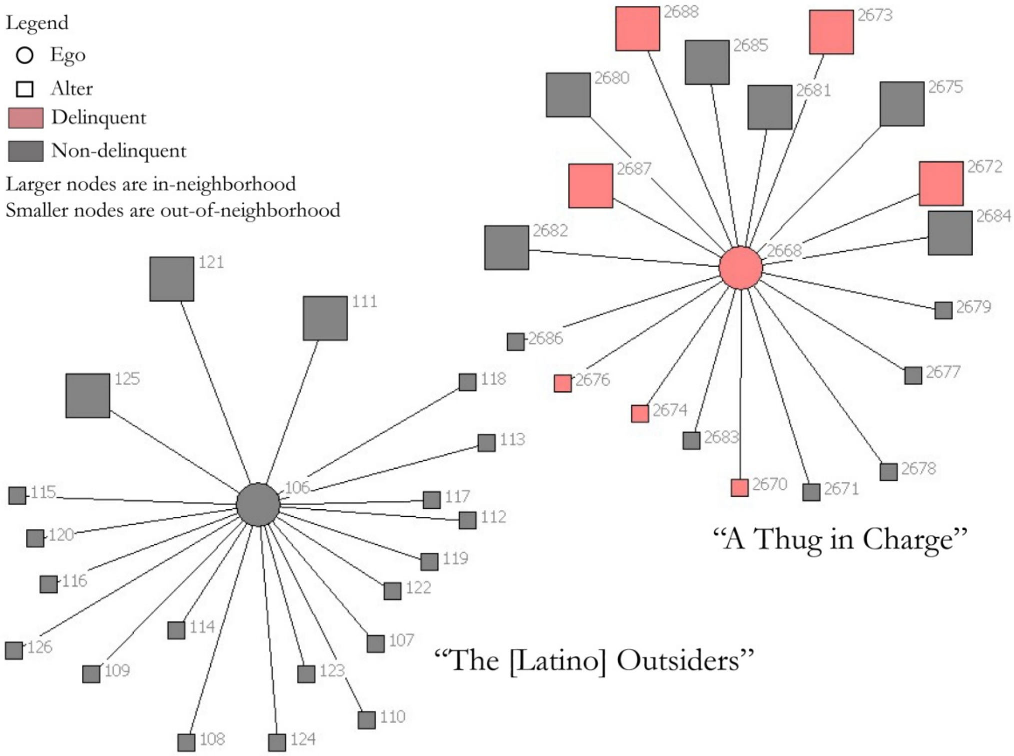


Figure 6. Dense Network with Low Centrality

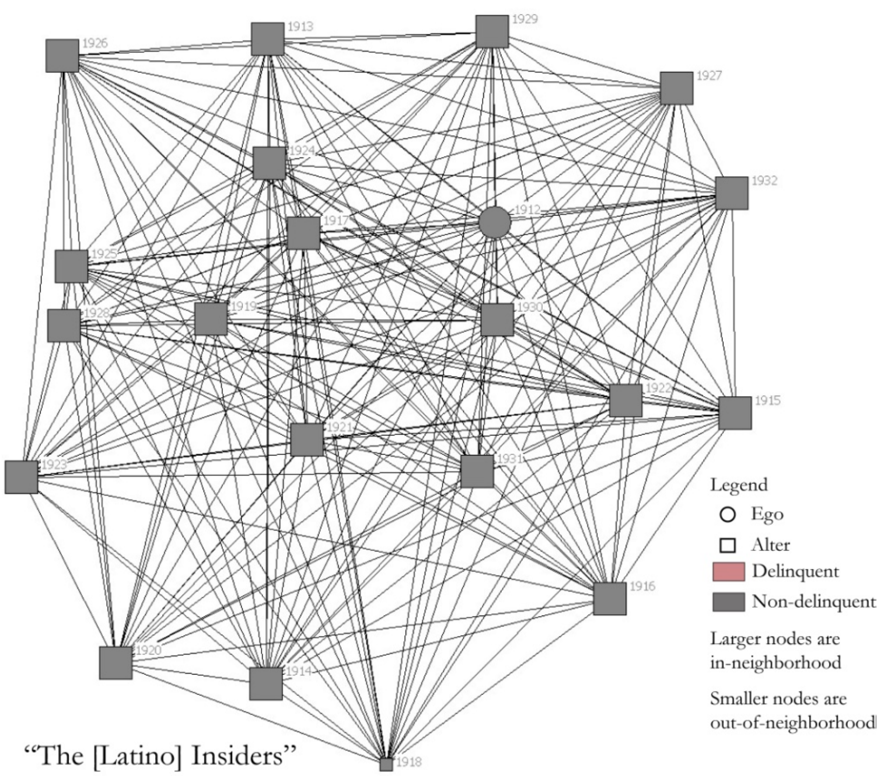
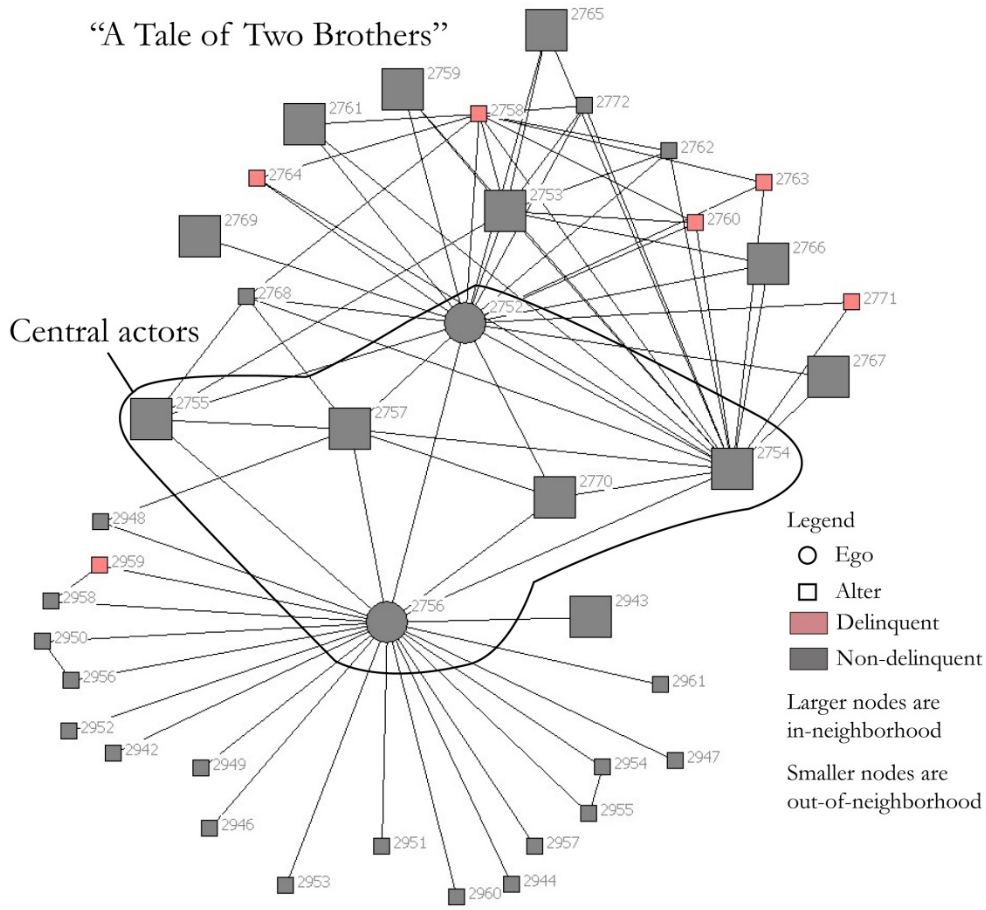


Figure 7. A Two-Ego Network



PREDICTIVE MODELS, WITH NETWORK MEASURES

Ego-Level Regression Models with Sociocentric Network Measures

And last, we turn to our third research question that asks whether the addition of whole network positional measures are important predictors of delinquency and related outcomes. Thus, we ran the same regression models (both logistic regression and negative binomial regression models) as specified in the ego-level findings sections but included two additional network structure variables: the respondent's betweenness centrality to the whole network (which assesses the respondent's "brokerage" across all egos and alters in the network) and whether the respondent is an "isolate" in the whole network, which means that the respondent is not named by anyone else in the network and his/her alters are not egos (survey respondents).

Tables 33(a–f) provide the results of the binary logistic models for each of the individual delinquency measures and Table 34 provides the negative binomial results for the overall delinquency scale measure.[35] While the Cox & Snell R^2 figures are relatively low, this is typical for binary logistic regression models (Hosmer & Lemeshow 2000). The figures are useful, however, for comparison purposes with the previous models that did not include network measures, and such a comparison reveals no change in the Cox & Snell R^2 figures. Therefore, the network structure variables do not appear to be adding explanatory power to the overall models.

At the individual variable level, betweenness centrality was a significant predictor of only one dependent variable—selling drugs. For every additional unit of betweenness centrality to the entire network, the respondent's odds of selling drugs increased one time. However, in the bivariate analyses, we saw correlations that were not reflected in the binary logistic regressions. The respondent's betweenness centrality to the whole network was positively correlated to the respondent's overall delinquency, carrying a weapon, and being in a gang fight ($p < 0.10$), but was not significant in either regression model. The variables also are not significant predictors in the models for recent delinquency and serious delinquency (not shown). We also tested the use of the closeness centrality measure and the degree centrality measure, and found neither that differences in the overall explanatory power of the model from the models without network measures, nor did we find either measure to be significant in for any of the delinquency measures.

[35] As mentioned earlier, the Cox & Snell R^2 figures are provided but should be interpreted with caution.

Tables 33a–f. Binary Logistic Regression Results Predicting Delinquency Measures, Including Network Structure Variables

Table 33a. Binary Logistic Regression Results Predicting **Overall Delinquency**, incl. Network Measures.

	Overall delinquency						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	2.77	2.68	15.94	0.301			
Alter variables							
Proportion delinquent alters[1]	7.72**	2.70	1.47	0.00	1.21	0.10	21.30%
Proportion alters live in same neighb.[1]	1.28	0.99	1.07	0.20			
Proportion go to for advice (not delinq.)[1]	0.06	0.90	1.00	0.95			
Personal network structure variables							
Number of components	-0.83*	0.42	0.43	0.05	0.66	0.21	-34.06%
Isolate	0.79	0.68	2.21	0.24			
Betweenness centrality	0.00	0.00	1.00	0.17			
Acculturation							
Separation from U.S. culture	-0.39**	0.14	0.68	0.01	0.82	0.10	-17.51%
Controls							
Age	0.00	0.10	1.00	0.98			
Male	2.20***	0.62	8.98	0.00	3.00	0.50	199.67%
Latino	1.16†	0.70	3.20	0.10	1.79	0.28	78.87%
Proportion of peers in network[1]	-0.24	1.07	0.99	0.82			
Family member completed HS	-0.48	0.52	0.62	0.36			
Parent-school encouragement	-0.17	0.88	0.84	0.84			
Family cohesion	-0.09*	0.04	0.91	0.01	0.96	0.02	-4.50%
No. years at address	0.07†	0.04	1.07	0.06	1.04	0.02	3.56%
Goodness-of-fit measures							
Cox & Snell R Square			0.34				
Cox & Snell R Square (model with peer vars)			0.34				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in *p* is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 33b. Binary Logistic Regression Results Predicting **Carrying a Weapon**, incl. Network Measures

	Carried a Weapon						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	-2.30	3.07	0.10	0.45			
Alter variables							
Proportion delinquent alters[1]	7.64**	2.28	1.47	0.00	1.21	0.21	21.06%
Proportion alters live in same neighb.[1]	1.52	1.17	1.08	0.19			
Proportion go to for advice (not delinq.)[1]	0.52	1.04	1.03	0.61			
Personal network structure variables							
Number of components	-0.77†	0.46	0.46	0.09	0.68	0.32	-32.09%
Isolate	1.22	0.76	3.38	0.11			
Betweenness centrality	0.00	0.00	1.00	0.86			
Acculturation							
Separation from U.S. culture	-0.09	0.16	0.91	0.55			
Controls							
Age	-0.01	0.11	0.99	0.95			
Male	3.38**	1.13	29.25	0.00	5.41	4.41	440.87%
Latino	-0.19	0.76	0.82	0.80			
Proportion of peers in network[1]	-0.68	1.20	0.97	0.57			
Family member completed HS	-0.28	0.63	0.76	0.66			
Parent-school encouragement	0.49	1.17	1.64	0.67			
Family cohesion	-0.05	0.04	0.95	0.20			
No. years at address	0.06	0.04	1.07	0.12			
Goodness-of-fit measures							
Cox & Snell R Square			0.30				
Cox & Snell R Square (model with peer vars)			0.27				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in *p* is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 33c. Binary Logistic Regression Results Predicting **Drug Selling**, incl. Network Measures

	Sold Drugs						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	-15.14†	8.00	0.00	0.06			
Alter variables							
Proportion delinquent alters[1]	16.30**	5.51	2.26	0.00	1.50	0.20	50.30%
Proportion alters live in same neighb.[1]	-4.25	3.01	0.81	0.16			
Proportion go to for advice (not delinq.)[1]	-0.50	2.62	0.98	0.85			
Personal network structure variables							
Number of components	0.34	0.82	1.40	0.68			
Isolate	-0.33	1.48	0.72	0.82			
Betweenness centrality	0.00†	0.00	1.00	0.07	1.00	0.00	0.00%
Acculturation							
Separation from U.S. culture	-0.34	0.44	0.71	0.45			
Controls							
Age	0.56	0.35	1.75	0.11			
Male	4.95†	2.59	141.60	0.06	11.90	0.84	1089.95%
Latino	-1.04	1.78	0.35	0.56			
Proportion of peers in network[1]	-1.12	2.66	0.95	0.67			
Family member completed HS	-2.88†	1.66	0.06	0.08	0.24	0.62	-76.30%
Parent-school encouragement	-4.91*	2.06	0.01	0.02	0.09	0.84	-91.42%
Family cohesion	0.09	0.09	1.09	0.29			
No. years at address	0.16†	0.08	1.17	0.06	1.08	0.04	8.06%
Goodness-of-fit measures							
Cox & Snell R Square			0.29				
Cox & Snell R Square (model with peer vars)			0.27				

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in *p* is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 33d. Binary Logistic Regression Results Predicting **Attacking Someone**, incl. Network Measures

	Attacked Someone with Intent							
	Coeff.		**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	-3.46		4.27	0.03	0.42			
Alter variables								
Proportion delinquent alters[1]	5.13	**	2.27	1.29	0.02	1.14	0.06	13.68%
Proportion alters live in same neighb.[1]	-0.22		1.61	0.99	0.89			
Proportion go to for advice (not delinq.)[1]	-3.05	†	1.58	0.86	0.05	0.93	0.04	-7.33%
Personal network structure variables								
Number of components	-0.24		0.60	0.79	0.70			
Isolate	-0.74		1.05	0.48	0.48			
Betweenness centrality	0.00		0.00	1.00	0.15			
Acculturation								
Separation from U.S. culture	-0.13		0.22	0.88	0.54			
Controls								
Age	0.07		0.17	1.07	0.69			
Male	3.12	†	1.60	22.65	0.05	4.76	0.65	375.88%
Latino	0.53		1.04	1.70	0.61			
Proportion of peers in network[1]	-1.19		1.55	0.94	0.44			
Family member completed HS	-0.42		0.86	0.66	0.63			
Parent-school encouragement	-0.33		1.22	0.72	0.79			
Family cohesion	0.01		0.05	1.01	0.82			
No. years at address	-0.03		0.06	0.97	0.62			
Goodness-of-fit measures								
Cox & Snell R Square				0.18				
Cox & Snell R Square (model with peer variables)				0.15				

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in *p* is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 33e. Binary Logistic Regression Results Predicting **Being in a Gang Fight**, incl. Network Measures

	Been in a Gang Fight						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	3.30	3.19	27.11	0.30			
Alter variables							
Proportion of alters *in a gang fight*[1]	18.3**	6.05	2.50	0.00	1.58	0.22	58.01%
Proportion alters live in same neighb.[1]	-0.3	1.23	0.99	0.81			
Proportion go to for advice (not delinq.)[1]	0.57	1.16	1.03	0.62			
Personal network structure variables							
Number of components	-0.43	0.49	0.65	0.38			
Isolate	-1.13	1.16	0.32	0.33			
Betweenness centrality	0.00	0.00	1.00	0.92			
Acculturation							
Separation from U.S. culture	-0.28	0.19	0.76	0.14			
Controls							
Age	-0.15	0.13	0.86	0.25			
Male	1.59*	0.80	4.90	0.05	2.21	0.38	121.44%
Latino	0.77	0.92	2.16	0.40			
Proportion of peers in network[1]	0.66	1.46	1.03	0.65			
Family member completed HS	-0.82	0.65	0.44	0.21			
Parent-school encouragement	-2.20*	1.00	0.11	0.03	0.33	0.50	-66.71%
Family cohesion	-0.04	0.04	0.96	0.35			
No. years at address	0.09*	0.04	1.09	0.04	1.05	0.02	4.60%
Goodness-of-fit measures							
Cox & Snell R Square				0.24			
Cox & Snell R Square (model with peer vars)				0.24			

† $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in *p* is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 33f. Binary Logistic Regression Results Predicting **Gang Membership**, incl. Network Measures

	Gang Member							
	Coeff.		**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δ*p*[4]**	**Δ*p* (%)[5]**
Constant	0.25		4.43	1.28	0.96			
Alter variables								
Proportion of alters *in a gang*[1]	21.19	**	6.11	2.88	0.00	1.70	0.26	69.85%
Proportion alters live in same neighb.[1]	-0.42		1.70	0.98	0.81			
Proportion go to for advice (not delinq.)[1]	2.63		1.80	1.14	0.14			
Personal network structure variables								
Number of components	-0.96		0.72	0.38	0.18			
Isolate	1.49		1.20	4.41	0.22			
Betweenness centrality	0.00		0.00	1.00	0.39			
Acculturation								
Separation from U.S. culture	-0.35		0.25	0.71	0.17			
Controls								
Age	-0.10		0.18	0.91	0.60			
Male	-0.02		0.91	0.98	0.98			
Latino	2.31		1.62	10.10	0.15			
Proportion of peers in network[1]	3.97		2.74	1.22	0.15			
Family member completed HS	-1.13		1.01	0.32	0.27			
Parent-school encouragement	-2.38	*	1.17	0.09	0.04	0.30	0.53	-69.55%
Family cohesion	-0.09		0.06	0.91	0.12			
No. years at address	0.13	*	0.06	1.13	0.03	1.06	0.03	6.45%
Goodness-of-fit measures								
Cox & Snell R Square				0.25				
Cox & Snell R Square (model with peer vars)				0.22				

† p <0.10; *p < 0.05; **p < 0.01; ***p < 0.001

[1]Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by dividing the high probability by the low probability, given the OR for the variable and an initial probability of 0.05 (the center of the possible range for the dependent variable).

[4] The change in p is the difference between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

[5] The change in p (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical probability of 0.5.

Table 34. Negative Binomial Regression Results Predicting Overall Delinquency

	Model 1: Peer Variables				Model 2: Alter Variables			
	Coeff.	S.E.	Exp(B)	*p*	Coeff.	S.E.	Exp(B)	*p*
Intercept	2.02†	1.16	7.55	0.08	1.89	1.21	6.61	0.12
Peer variables								
Proportion delinquent friends[1]	3.21***	0.87	24.69	0.00				
Proportion friends in same neighb. [1]	-0.22	0.41	0.80	0.58				
Proportion go to for advice (not delinq.)[1]	-0.12	0.43	0.89	0.78				
Alter variables								
Proportion delinquent alters[1]					3.27***	0.72	26.33	0.00
Proportion alters in same neighb.[1]					0.50	0.46	1.65	0.28
Proportion go to for advice (not delinq.)[1]					-0.05	0.48	0.95	0.91
Network structure variables								
No. of components	-0.32*	0.15	0.73	0.04	-0.32*	0.15	0.73	0.04
Isolate	0.00	0.34	1.00	1.00	0.05	0.35	1.05	0.89
Between. centrality	0.00	0.00	1.00	0.87	0.00	0.00	1.00	0.46
Acculturation								
Separation from U.S. culture	-0.20**	0.06	0.82	0.00	-0.20**	0.06	0.82	0.00
Controls								
Age	-0.01	0.04	0.99	0.77	0.01	0.04	1.01	0.89
Male	1.20***	0.27	3.32	0.00	1.31***	0.28	3.71	0.00
Latino	0.47	0.31	1.60	0.13	0.46	0.30	1.58	0.13
Proportion of peers in network[1]	0.59	0.55	1.81	0.28	0.99	0.56	2.69	0.08
Family member completed HS	-0.29	0.27	0.75	0.29	-0.37	0.27	0.69	0.17
Parent-school encouragement	-0.66†	0.40	0.52	0.10	-0.41	0.40	0.67	0.31
Family cohesion	-0.04	0.02	0.97	0.02	-0.04*	0.02	0.97	0.02
No. years at address	0.05**	0.02	1.05	0.00	0.05**	0.02	1.05	0.00
Goodness of fit								
Log likelihood	-227.815				-225.915			
Deviance value/df	1.02				0.991			
Pearson chi-square value/df	0.895				0.851			
Likelihood ratio chi-square	59.25				63.051			

† p <0.10; *p < 0.05; **p < 0.01; ***p < 0.001

[1]Proportion variables range from 0.00 to 1.00.

Node-Level Regression Models with Sociocentric Network Measures

In order to more fully answer our third research question on the effects of network structural measures on delinquency, we developed two sets of binary logistic models at the network level: one predicting the binary delinquency outcome for members of the whole network, and one for members of the 2+ network. While these models benefited from larger sample sizes than the ego models (2,521 and 369 network members compared to 147 egos), they were restricted by the amount of data that were collected on alters (17 items about each alter). Only a handful of the same predictors could be used in the whole network model, but we did include network centrality measures to examine more broadly the effects of a person's position in the network on whether he/she was delinquent. We created three models of serious delinquency (binary), each including a different centrality measure, for each of the two networks. We did not include all measures in one model because of multicollinearity issues among the centrality measures.

The results of the models are presented in Table 35 to 37. The tables are presented in the same format as the binary logistic models developed at the ego level: the results include the risk ratios for all significant predictors and the hypothetical change in probability assuming a 50 percent initial delinquency level. All probability calculations, including change in probability, are based on this initial 50 percent level. While the goodness of fit for all six models is extremely low, this is typical for binary logistic regression models, so the significance of certain predictors therefore still warrants mention (Hosmer & Lemeshow 2000). Because the Cox and Snell R^2s were very low, we also examined the Hosmer-Lemeshow test. That test indicated that the betweenness model was a good fit (the Hosmer-Lemeshow test was not rejected) but that the models including closeness and degree did not have good fits. This is interesting because the betweenness measure was not significant while the closeness and degree terms were. This may be an indication that, as we found in the ego-level models, the addition of network structural variables does not improve explanatory power of our models.

In all of the whole network models, being an ego was significant, but this was not the case in the 2+ network models. Being an ego in the whole network is associated with a higher probability of delinquency. Age, however, follows the opposite pattern: it is significantly negative, and only in the 2+ models. The effect of age on delinquency is also smaller than the effect of being an ego. The "live in neighborhood" term is significant across all six models, and increases the probability of delinquency for members of both networks, although the effect is much larger in the 2+ network: individuals residing in the neighborhood are over two times more likely to be delinquent than those not in the neighborhood.

Of the centrality measures, only two are significant, and in the whole network only; no centrality measures are significant in the 2+ network, and betweenness centrality is not significant for either network. At the whole network level, closeness centrality is highly significant and has a large positive effect, increasing one's probability of delinquency. Given that we were unable to control for other measures (such as we used in the ego-level models) and that the models have extremely low goodness of fit levels, though, we are hesitant to give the large effect size much weight. Degree centrality is significantly negative in the whole network model, indicating that individuals who are more directly connected to many others have a lower probability of being delinquent. This supports the hypothesis that individuals who are connected to many groups may find their behavior more restricted, and may therefore have a lower probability of being delinquent. While these models are certainly restricted in terms of the availability of measures pertaining to network members, they do shed light on the effects of centrality measures. The very different results obtained for the three different centrality measures, while all else was held the same, is further support for the notion that centrality cannot be treated as one single construct, and that different measures of centrality are appropriate given different research hypotheses. The significance of the live in neighborhood term also lends weight to our selection of neighborhood, and suggests that there is something about having stronger ties within the neighborhood that is associated with higher levels of delinquency.

Table 35. Binary Logistic Regression Results Predicting Overall Delinquency at Network Level, Incl. *Betweenness Centrality*

	Whole Network							2+ Network						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**	**Coeff.**	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	-3.47***	0.39	0.03	0.00				-2.24*	1.12	0.11	0.05			
Network structure variables														
Betweenness centrality	0.13	0.09	1.14	0.17				-0.04	0.12	0.96	0.75			
Closeness centrality	-	-	-	-				-	-	-	-			
Degree centrality	-	-	-	-				-	-	-	-			
Controls														
Ego	0.53†	0.28	1.70	0.06	1.30	0.13	30.28%	0.17	0.34	1.18	0.63			
Age	0.01	0.01	1.01	0.58				-0.10*	0.05	0.91	0.04	0.95	0.02	-4.78%
Male	0.79***	0.19	2.20	0.00	1.48	0.19	48.44%	0.81*	0.38	2.25	0.03	1.50	0.20	49.86%
Latino	-0.16	0.20	0.85	0.41				-0.31	0.38	0.74	0.42			
Born in U.S.	0.18	0.20	1.20	0.36				0.52	0.36	1.69	0.15			
Live in neighborhood	0.69***	0.19	2.00	0.00	1.41	0.17	41.41%	1.72**	0.65	5.59	0.01	2.36	0.41	136.32%
Goodness-of-fit measure														
Cox & Snell R Square			0.03							0.09				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 36. Binary Logistic Regression Results Predicting Overall Delinquency at Network Level, Incl. *Closeness Centrality*

	Whole Network							2+ Network						
	Coeff.	**S.E.**	**Exp(B) (OR)**[2]	***p***	***RR***[3]	Δp[4]	Δp *(%)*[5]	**Coeff.**	**S.E.**	**Exp(B) (OR)**[2]	***p***	***RR***[3]	Δp[4]	Δp *(%)*[5]
Constant	-4.49***	0.48	0.01	0.00				-2.96*	1.20	0.05	0.01			
Network structure variables														
Betweenness centrality	-	-	-	-				-	-	-	-			
Closeness centrality	8.96***	2.45	7,820.32	0.00	88.41	0.98	8741.13%	0.01	0.01	1.01	0.10			
Degree centrality	-	-	-	-				-	-	-	-			
Controls														
Ego	0.71**	0.25	2.04	0.01	1.43	0.18	42.69%	0.26	0.34	1.30	0.45			
Age	0.01	0.01	1.01	0.33				-0.08†	0.05	0.93	0.09	0.96	0.02	-3.73%
Male	0.79***	0.19	2.21	0.00	1.49	0.20	48.59%	0.73†	0.37	2.08	0.05	1.44	0.18	44.12%
Latino	-0.26	0.20	0.77	0.20				-0.46	0.39	0.63	0.24			
Born in U.S.	0.13	0.20	1.14	0.52				0.47	0.37	1.61	0.19			
Live in neighborhood	0.70***	0.19	2.01	0.00	1.42	0.17	41.62%	1.71**	0.65	5.51	0.01	2.35	0.40	134.78%
Goodness-of-fit measure														
Cox & Snell R Square			0.04							0.09				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

Table 37. Binary Logistic Regression Results Predicting Overall Delinquency at Network Level, Incl. *Degree Centrality*

	Whole Network							2+ Network						
	Coeff.	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**	**Coeff.**	**S.E.**	**Exp(B) (OR)[2]**	***p***	***RR*[3]**	**Δp[4]**	**Δp (%)[5]**
Constant	-3.39***	0.40	0.03	0.00				-2.23*	1.13	0.11	0.05			
Network structure variables														
Betweenness centrality	-	-	-	-				-	-	-	-			
Closeness centrality	-	-	-	-				-	-	-	-			
Degree centrality	-0.82*	0.37	0.44	0.03	0.66	0.20	-33.60%	-0.02	0.11	0.98	0.84			
Controls														
Ego	1.25***	0.36	3.50	0.00	1.87	0.30	87.01%	0.16	0.34	1.17	0.65			
Age	0.01	0.01	1.01	0.54				-0.10*	0.05	0.91	0.04	0.95	0.02	-4.73%
Male	0.84***	0.19	2.32	0.00	1.52	0.21	52.35%	0.80*	0.38	2.23	0.03	1.49	0.20	49.18%
Latino	-0.12	0.20	0.89	0.56				-0.30	0.39	0.74	0.44			
Born in U.S.	0.21	0.20	1.23	0.30				0.52	0.36	1.69	0.15			
Live in neighborhood	0.76***	0.19	2.14	0.00	1.46	0.19	46.37%	1.72**	0.65	5.58	0.01	2.36	0.41	136.32%
Goodness-of-fit measure														
Cox & Snell R Square			0.03							0.09				

† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

[1] Proportion variables range from 0.00 to 1.00.

[2] The OR, or Exp(B) for the proportion variables is multiplied by 0.05 to put it in scale of *count* of alters, instead of *proportion* of alters. Each ego has 20 alters; 1 alter out of 20 is 5 percent.

[3] RR is calculated by taking the square root of the OR.

[4] The change in *p* is the difference between the hypothetical high and low probabilities, calculated using the RR and a hypothetical initial probability of delinquency of 0.5.

[5] The change in *p* (%) is the percent change between the high and low probabilities given the OR for the variable and a hypothetical initial probability of 0.5.

CHAPTER 4

SUMMARY AND DISCUSSION

This study set out to examine the importance of social networks in understanding delinquent and criminal behavior of youth living in a high-risk neighborhood. We used innovative network methods to overlap personal networks—creating a "whole" network— and to understand how the structure and composition of subgroups, as well as an individual's position within the neighborhood network, might be important factors shaping delinquency and criminal behavior. In addition to conducting egocentric analyses aimed at identifying key predictors of delinquency and criminal behavior, we used the whole network to explore the features of the neighborhood network via sociocentric measures and techniques. Combining egocentric and sociocentric analyses within one study provided greater insight into the potential importance of neighborhoods as the frame for learning and socialization with regard to delinquency, or as frameworks for prevention and intervention efforts. Below we briefly review and discuss the findings following the research questions laid out in the introduction of this report.

DELINQUENCY AT THE EGO-LEVEL

Research Question 1: Are network/structural variables important predictors of delinquency and gang membership (beyond the traditional set of risk factors) across ego networks?

To answer this research question, we relied on a risk factor framework to model the likelihood that a youth/young adult would be involved in a variety of criminal behaviors, given the network characteristics and the youth's individual position and connectedness within the network, and controlling for important risk and protective factors identified in the criminological literature. We attempted to predict the extent of involvement by modeling delinquency both as a binary measure (delinquent/not delinquent) and as a scale (number of delinquent acts). The network measures are those measures related to personal networks that characterize or quantify relations between a respondent and his/her 20 nominated alters. The sample for these ego-level models included only those 147 individuals who responded to the survey.

The Influence of Delinquent Alters

Not surprisingly, for ego networks, the proportion of relations (alters) who are delinquent is highly significant across all binary outcomes where it is included in the model: serious delinquency, carried a weapon, sold drugs, and attacked someone. For instance, for every additional delinquent alter in an ego's network, the ego's probability of selling drugs increases by 38 percent. We find similar results when we examine the proportion of alters in a gang fight or in a gang, respectively. Individuals who named an individual in a gang fight are 1.6 times more likely to be in a gang fight themselves. Thus, having delinquent/criminal relationships appears to be a key factor in shaping an individual's likelihood of delinquency and gang membership.

The Youth Network, Beyond Friends

Because the current study asked respondents to nominate people—both other youth and adults—who were influential to them, this study also had the opportunity to assess whether relationships beyond those with peers are associated with delinquency and gangs. Instead of examining nested models, in order to compare models, we examined effect sizes and model fit between sets of negative binomial models. Two sets of models were created for each dependent variable: one set that included the proportion of *peer* delinquency and one set that included *alter* delinquency (see Table 20, Table 21, and Table 22). The results from these comparison models showed that although both models fit the data well, the "all alters" models fit significantly better and the effect of the variable measuring the proportion of delinquent/criminal alters on delinquency was slightly larger in each model than the effect of the peer delinquency term. This finding is important, and one that we hope to expand upon with future analyses and larger sample sizes, because the overwhelming majority of network-based studies on delinquency focus only on peer networks.

Within high-risk areas rife with intergenerational gangs, assessing the importance of all relationships to delinquency and gang membership becomes particularly salient. In our study, over 40 percent of respondents named at least one parent as an alter, 61 percent named at least one aunt or uncle, and one-third of the respondents named at least two siblings as alters. Larger sample sizes would enable future research to examine whether characteristics of these family relations (e.g., whether the respondent would go to the family member for advice, or whether the family member is delinquent or criminal) serve as protective or risk factors over and above relationships with non-relative peers. These avenues have not been explored—mostly because studies of this kind (i.e., widening the network to all types of relations) have not been conducted before. Typically, researchers would use networks to examine peer relationships but then examine parental relationships and institutional attachments (as suggested by bonding theory) through the typical survey items based on self-report, not as attributes of network relations.

Future research could more appropriately test the tenets of bonding theory related to familial relations via network-based surveys and resultant measures. The findings from our study that non-peer criminal influences may be just as important or influential with regard to delinquency as peer influences will hopefully advance research in this field by widening our focus to go beyond simply studying peers within a network framework. There are unlimited possibilities for research in this vein. A social network framework could be used to examine how adult role models facilitate maintenance of or help delinquent youth desist from crime or leave gangs. Although this study did not explicitly ask respondents to include their parents or caregivers future research could set the network frame to cast a wider net over specifically pro-social relations.

Replication of this research with larger sample sizes would also provide the opportunity to explore the influence of teachers on the delinquent behaviors of those who name teachers as alters—almost 10 percent of respondents named a teacher in our study. Research has suggested that teachers acting as positive role models within and outside the classroom setting can reduce the delinquent behaviors of students (Gottfredson 1987).

Neighborhood Ties

Because research has shown that delinquency and gang membership are often rooted in the neighborhood, we also hypothesized that the likelihood that egos are involved in delinquent behavior would increase with an increase in relationships from within the neighborhood (regardless of whether relations were delinquent/criminal themselves). "Proportion of alters who live in the neighborhood" was included in all delinquency models but was not significant in any of the ego models. The results, therefore, did not support this hypothesis. It is likely that sample size could be an issue; fortunately, we also examined this hypothesis using the whole overlapping network and found that in-neighborhood relations were significantly associated with delinquency and criminal behavior. This finding will be discussed in more detail in the appropriate section.

The Strength of Ties

We also assessed the strength of *prosocial* ties by including a variable that measured the proportion of one's network that comprised individuals to whom the respondent would go for advice <u>and</u> who were *not* delinquent/criminal. This measure was found to be significant (approaching significance at $p = 0.05$) in the model predicting "attack someone with intent to harm." In this model, every additional person in a network to whom the respondent would go for advice and who is not delinquent/criminal reduces the probability of attacking someone with a weapon by 7 percent. It is possible that pro-social advice networks are important with regard to a violent outcome (as the other outcomes capture different, less violent behavior) in that having "influential" pro-social relationships puts a damper on a person's willingness to be involved in violent crime. It is also worth noting that we used a variety of measures to capture aspects of tie strength and homophily, but no other measure was found to be significant in initial models (and hence, they were dropped from the final models). Additional research, perhaps using qualitative methods, to dissect whether pro-social advice networks and role models (and other aspects of ties to pro-social individuals) can influence behavior would be an important step in further understanding how certain relationships or characteristics of those relationships help constrain behavior.

Network Structure across Ego Networks

One of the key network structure variables incorporated in the final ego regression models was the number of components that exist in a personal network. The number of components is a network measure that captures the number of subgroups within an ego network that are not connected to other subgroups (i.e., no links exist between any two nodes across components). We hypothesized, following extant network research on constraint and normative behavior (see for example, Krackhardt 1999), that the more "separate" groups of relations one has, the more constraint, and hence, the *less likely* to be involved in delinquent behavior. This hypothesis was confirmed in the negative binomial models for all three scaled criminal behavior outcomes and with regard to two of our binary outcomes (serious delinquency and weapon carrying). In both the peer and the alter models of overall delinquency, one additional component decreases the expected count of delinquency by about one-quarter ($p = 0.04$ and $p = 0.05$). For both the recent and serious delinquency measures, an increase by one component decreases the expected count of delinquency by about one-third ($p = 0.06$ for recent delinquency; $p = 0.01$ and 0.02 for serious delinquency), and by 30 percent and 32 percent for the binary measures of serious delinquency and carrying a weapon, respectively (logistic regression models).

We know of no published delinquency research that has tested this important hypothesis—that the number of components may be an important protective factor against delinquency. Mangino (2009) examined a somewhat similar construct that he called bridges—where an individual is positioned as a bridge between two or more subgroups in a friendship network. He found that being a bridge was associated with reductions in delinquency, and concluded that an individual's association with multiple groups placed constraints on behavior. Our finding of the importance of components in networks is worthy of further exploration as it could have important implications for prevention and intervention. Specifically, this finding suggests that prevention practitioners might find utility in facilitating new pro-social networks for youth that allow them to step beyond their current friends and other networks. Encouraging a new hobby, or new youth group affiliation, or having a local organization start a new club (that has pro-social supervision) could assist in expanding youth networks away from existing delinquent or at-risk groups.

Regardless, future network-based delinquency research should be sure to include a measure of components alongside measures of density and centrality. Past research may have overlooked including a components measure, because the focus has generally been on density of a network, a construct somewhat related to the number of components. A few studies have examined network density as a predictor variable and, for the most part, have found that as density increases, delinquency decreases (see Haynie 2002). However, in the current study, network density was not a significant predictor of any of our outcomes, nor was the interaction term for density and delinquent or criminal relations. (As indicated earlier, these variables were dropped from the final models.)

Ethnic Identity and Acculturation

In addition to the network measures, we were also interested in measuring ethnic identity and acculturation within our sample. The literature generally has been mixed in findings on acculturation; it is often found to be a risk factor for delinquency, but a protective factor with regard to gang membership. In addition, new research has suggested that the inclusion of measures of ethnic identity in survey research can help shed more light on the relationship between culture and antisocial behaviors. Interestingly, our findings revealed that ethnic identity (as measured using the Multigroup Ethnic Identity Measure (Phinney 1992) was not a significant predictor in any of our binary delinquency variables. Our composite variable measuring separation from U.S. culture (which captures place of birth of respondents and of parents and languages spoken at home, with parents, and with friends), however, is a significant predictor of delinquency and serious delinquency in the negative binomial models. A one-unit decrease in the separation scale (read as increasing acculturation) translates into an 18 percent *increase* in the expected count of delinquency and an 11 percent *decrease* in expected count of serious delinquency.

These findings confirm the general literature on acculturation and delinquency. In the current study, separation was not found to be a significant protective or risk factor for gang membership or participation in a gang fight. This null finding could be the result of the small sample size; we suggest that further research is needed here—additional research breaking down the components of separation would be an important addition to the criminal justice field. Are these "separated" youth simply not hanging around delinquent youth because they have few friends or relationships when they first immigrate to the United States? Or do recent immigrants have different norms, morals, or belief systems than individuals who have been in the United States for a number of years?

It would be presumptuous to suggest that programming within Latino communities could benefit from supporting the maintenance of use of the Spanish language. But these findings could be touching on some underlying issues related to parental bonding or acculturation stress; Martinez (2006) suggested that understanding these phenomena is important for understanding the criminal behavior of Latino youth. This type of exploration could help uncover the facets of acculturation and separation that are relevant with regard to delinquency and crime. Martinez suggests that intervention efforts not be targeted to acculturation processes, but to family bonding and parenting. These implications may be directly relevant to our findings, given that, for some outcomes, family cohesion and parent encouragement for school were found to be protective factors (see Table 19a and Table 20).

Other Individual Characteristics

Being male is also a serious risk factor in our models for all delinquent outcomes save for being in a gang. Boys are 14 times more likely to sell drugs than girls, 3.7 times more likely to attack someone with a weapon, and twice as likely to participate in a gang fight. It is not clear why being male was not a significant factor for gang membership when it was a predictor for the other outcomes. Our respondents included the same percentage of girls in a gang as boys in a gang. It could be that recruitment for the survey reached subgroups of girls who were connected through the same gang—a gang that was known to have many (or all) girl members (although responses to open-ended survey data do not bear this out) or it could be that the gangs that exist in the target area simply do not cater predominantly to males. Perhaps our findings represent an underlying characteristic of gangs in the target area—girls are just as likely as boys to self-identify as being part of gangs, but are much less likely to be involved in gang fights.

Another interesting finding, although not central to the current study's research questions, is that a number of other variables used as controls varied in significance across the different outcomes. This suggests that risk and protective factors may act differently for different outcomes. Null findings for some of these variables in extant research should not move researchers and practitioners away from buoying all sorts of supports in the lives of children and youth. For instance, we found that having an adult in the household encouraging a youth to do well in school was highly significant in negative binomial models predicting recent (past six months) delinquency, but not significant in negative binomial models predicting overall delinquency or serious delinquency. Because the implications for prevention are relatively simple and inexpensive to implement—

teaching parents and caregivers the importance of encouraging their children in school could possibly return many benefits—continued research in this area is warranted.

PROPERTIES OF THE WHOLE NETWORK

Research Question 2: What are the properties and characteristics of the sociocentric (i.e., neighborhood-based) network as defined by overlapping egocentric networks? How do these characteristics relate to or influence delinquency and gang membership?

In order to more fully assess the effects of network structure on delinquent behavior, we explored two different networks developed from our data: one comprising all egos and all alters named by any ego in the survey (the "whole network" with 2,521 members) and one comprising all egos and those alters who were named by at least two egos (the "2+ network" with 369 members). Eleven percent of the whole network members were also 2+ network members. The comparison of results for these two networks allowed greater insight into the mechanisms through which network structure can influence behavior for individuals within those networks.

Who Is in the Network?

We first considered the characteristics of the two sociocentric networks, including the demographic characteristics of network members and the relationships (e.g., sibling, cousin, friend) between members of each of the two networks.[36] Not surprisingly, about 70 percent of network members in each of the networks were named as friends by at least one person. There were a significant number of alter members with non-peer relationships to egos, however, and while we expected that the 2+ network would consist of a greater number of peers (because more youth would be named more than once), we actually found that the percentage who were parents was similar to that in the whole network (about 4 percent) and the percentage named as siblings was much higher in the 2+ network—at 20 percent. As further evidence that these networks include important non-peers, the average ages of the whole and 2+ networks were relatively high, at 20 years and 19 years, respectively—higher than the typical high school age range. Because non-peers appear

[36] Remember that these categories are not mutually exclusive; someone can be named as a friend by one respondent and as a sibling by another respondent, thus being counted in two categories. The percentages, then, do not add to 100.

frequently among all alters, capturing these relationships in social network analyses of delinquent behavior is key.

Digging deeper into alter relationships by age and gender revealed some noteworthy patterns. While the majority of both networks were male (at about 60 percent in each network), when we looked at gender by age in the whole network, we found slightly more adult females (54 percent) than adult males. Across the whole network, then, when egos named adults, they were more likely to name women. When they nominated peers, egos were more likely to nominate males. This could be a result of the common trend of young adult males being incarcerated at higher rates than females, thus leaving females as the adult role models in many disadvantaged communities.

While our data cannot confirm that male incarceration rates are the underlying cause of the gender-age trends in our data, this findings warrants further investigation in future research. In addition, prevention and intervention programs that can tap into local strengths—the presence of positive role models, for instance—should be aware that fewer male adults are seen as role models in the neighborhood. More effort may be needed to recruit the help of positive male role models who *are* in the neighborhood, or who are from other areas but can still connect with the youth in the neighborhood. The suggestion that programs try to combat the detrimental effects of missing male role models is by no means new or groundbreaking, but it is consistent with findings from a large body of previous research on mentoring and provides further support for the role of mentoring, and specifically males as mentors, in this specific neighborhood.

As discussed earlier, acculturation and ethnic identity were two key constructs that we sought to measure in relation to delinquent behavior. The findings regarding acculturation's effects on delinquency were minimal at the ego level. At the whole network level, however, we found that a significant number of network members were Latino (although fewer than we expected prior to launching the survey), but far fewer were born abroad. The network members, therefore, likely had overall high levels of acculturation.[37]

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[37] At the alter level, we lacked the data on the acculturation scale used at the ego-level, so we are only able to use born abroad as a proxy for acculturation at the alter level.

Finally, we looked at delinquency among the whole network. On the whole, we found that egos were attributing more delinquent behavior to themselves than to members of their networks—the overall levels of delinquency among alters were relatively low and were lower than those reported for egos alone. Because these whole networks include more adults, such as parents, aunts, uncles, and teachers, it is not surprising that the overall delinquency levels are low. We found that delinquency was slightly higher in the 2+ network, which contained more young people. We also found that gang members who were named in the network tended to be named more than once, as opposed to being named as influential for just one ego. The few gang members in the network, therefore, appear to be relatively central figures. In addition, among the delinquency measures, "in gang" was highest for the 2+ network, while it was lowest for the whole network. Even so, the level of overall delinquency in the 2+ network was only about 14 percent, which is fairly low given our selected neighborhood. Again, this might be an indication that we were unable to interview the more delinquent youth in the neighborhood, or that the levels of delinquency among residents were actually lower than we initially believed.

Sociocentric Measures

Many of the sociocentric network measures are the same as those used at the ego level, but are calculated at the sociocentric level instead of for each personal network. In addition, many of the findings at the whole network level echo the ego-level findings. As with the personal networks, we considered the density of the two sociocentric networks and found both to have very low levels of density, and to have very similar levels of density. We also presented Valente's (2010) effective density measure, which takes into account the number of alters named by each ego (20). These density measures were higher, around 0.33 for the whole network. While still relatively low, this density value is similar to densities reported in previous work on delinquency and criminal networks (Kreager, Rullison, & Moody 2011; Natarajan 2006; Snijders & Baerveldt 2003). The very low densities found in the current study suggest that interventions may be more successful there than in a denser network—it might be easier for an individual to leave a delinquent group if it is only loosely organized, for instance.

On the other hand, networks with sparse connections mean that individuals are freer to act independently (Natarajan 2006); as such, it may be harder to use the network structure to influence the behaviors of its members. In this case, the most appropriate interventions would *not* rely on pro-social, anti-delinquent messages being spread through the network via well placed, influential individuals. The low levels of density also suggest that prevention and intervention strategies that cast a wide net in the area, attempting to reach all youth who need services or assistance, might not be as successful; more targeted efforts to get individuals involved might be required because, again, the message—for instance, that violence will bring law enforcement attention, or that services are available—might not be effectively spread throughout the relatively sparsely connected community. The density of the network, therefore, can have important implications for the selection of an appropriate intervention.

We also explored four measures of centralization at the sociocentric level: degree, betweenness, closeness, and eigenvalue centrality. Initial tests showed that eigenvalue centrality was not appropriate for our data, so we did not continue to use that measure in the analyses. We examined the bivariate correlations between all centrality measures and found that degree centrality was the most closely related to the other two measures, but that even those correlations were relatively low. All of the measures assess the hierarchical nature of the networks and whether there are very central players within the networks. The low correlations between the measures, however, indicate that the three measures explored here do capture different types of centrality, as hypothesized. That said, the centralization values for all three measures were low, indicating that there is little hierarchy or centrality across either sociocentric networks. Based on our centralization analysis, the networks have relatively flat structures and few people enjoy central positions *across the whole network*—to be sure, subgroups within the network have central figures (discussed in the next section) but there are no clear players with strong influence across the larger networks.

Policy suggestions from this finding dovetail nicely with those stemming from the low network density findings: there are few to no central figures who can quickly spread pro-social messages across the network, and extensive efforts to target different, unconnected groups would be required in this kind of social setting. From a law enforcement perspective, removing central figures would be implausible and likely have little effect on the overall delinquency of the neighborhood's social network (as it might were the network dense and hierarchical). As suggested earlier, though, one benefit to this type of social structure is that it may make interventions more successful; without strong leaders enforcing antisocial group norms, the behaviors and attitudes of youth in the area might be more malleable. Police and/or practitioners might find it easier to convince youth to desist from their delinquent or criminal behaviors and redirect their energies into pro-social activities.

<u>Neighborhood as Network?</u>

One of the main concerns with our selected methods was whether it would prove useful to approximate a complete social network using a selected neighborhood—in other words, could we use the neighborhood to define our sample and get a coherent, connected network of individuals? We were able to test this issue because of two study design features: (1) all *respondents* lived in the small, defined neighborhood and (2) one of the alter questions asked whether the individual resided in the neighborhood. Using this information, we could discern who was from within the neighborhood and who was from outside the neighborhood. This is important in terms of policy implications because many anti-gang and anti-delinquency programs are geographically based; they are implemented for a selected geographic area only.

As discussed above, for the ego-level models, we did not find the "in-neighborhood" proportion of alters to be a significant predictor for any of the delinquent outcomes. However, in order to more fully explore the effects of neighborhood context, we also considered the in-neighborhood and out-of-neighborhood status for members of each of the sociocentric networks. Approximately one-third of the members of the whole network live in the neighborhood while nearly three-quarters of the members of the 2+ network live in the neighborhood. This finding is not surprising—it is more likely that those named by more than one ego are peers who live nearby. It also suggests that the core social network of youths is neighborhood based, as the individuals who were named most frequently do indeed reside in the neighborhood.

We also considered differences in demographic and delinquency characteristics and cohesion and centrality measures among individuals who live in the neighborhood and those who live outside. After splitting the whole network into "in-neighborhood" (879 members) and "out-of-neighborhood" networks (1,642 members), we found significant differences on every measure. Notably, all delinquency measures are significantly higher for the in-neighborhood network, with 11.5 percent of in-neighborhood individuals exhibiting delinquent behavior compared to only 5.4 percent of those outside the neighborhood. Examination of the three centrality measures reveal that the in-neighborhood network is more centralized than the out-of-neighborhood network, with the differences in some cases relatively large (e.g., the "in" network degree centrality is more than three times larger than that of the "out" network). Members of the "in" network have more ties on average—and more *direct* ties—to other members and are more tightly connected than are members of the "out" network.

These patterns indicate that there are systematic differences between the groups of people who are neighborhood residents and those who are not. The differences also support the notion that neighborhood context is associated with behavior, and in this specific case, stronger associations with the neighborhood tend to be associated with higher levels of delinquency. Because we lack longitudinal data, we are unable to determine whether this is because of self-selection—where new residents tend to be similar to those who already live there, perpetuating the prevailing attitudes and norms in the area (in this case, to support certain levels of delinquency)—or because of influence—where new residents are eventually influenced by the attitudes and norms of the neighborhood (Johnston & Pattie 2011). But either way, the data and models tested at the whole network level support the idea that having more associations with residents of the neighborhood (i.e., having more friends or contacts in the neighborhood) is associated with higher levels of delinquency for youth.

Our findings on the neighborhood network suggest that geographically based (or neighborhood-based) interventions may be appropriate as long as they take into account the social structure of at-risk and delinquent youth in the neighborhood. If influence is the main mechanism through which new residents become delinquent (or become more delinquent) then reaching those who are not yet deeply embedded in the neighborhood's social norms and attitudes can help stem the spread of delinquency in the area. Any intervention, then, would need to be careful to tailor outreach to those residents who are not well-connected within the neighborhood but could benefit from services as well. Partnering with programs in nearby areas, including sharing information on program participants across different programs—such as those in nearby neighborhoods where an individual may also have connections and ties—can help neighborhood-based approaches to succeed.

In addition, because of the strong association found related to the neighborhood context, programs that seek to broaden youth horizons and explore the vast array of opportunities that exist outside of their neighborhood social structure would likely be successful. These types of programs—like employment skills programs (e.g., Job Corps) or recreational activities that remove them from the negative effects of the neighborhood—can open youths' eyes to pro-social opportunities. Youth who reside in negative neighborhood contexts can benefit from spending time participating in pro-social activities outside of the physical boundaries of their wider neighborhood, and these experiences can help build the protective factors for individual youth that will prevent them from becoming delinquent, or will help them to cease any existing delinquent behavior.

<u>Community Structure within the Whole Network</u>

In addition to dividing up the whole network into in- and out-of-neighborhood networks, we also divided the whole network up into subgroups, here called "partitions," using the Girvan-Newman iterative algorithm. The optimum number of partitions in the whole network was 25, but one large faction was comprised of more than 65 percent of whole network members. Additional analyses not discussed in this report did not reveal any obvious reason why this partition was not divided into smaller subgroups. This is a finding we will explore in more detail in the future. In addition, 17 of the partitions were actually ego networks—they comprised about 21 members that included one ego and that ego's 20 alters. While these were interesting to explore descriptively, the partitioning did not provide us with a large amount of additional insight regarding network embeddedness of subgroups or how or why subgroups might be formed. Only seven factions were some combination of network members beyond just ego networks—several egos and alters together. We chose five factions plus the large catch-all faction to explore in more depth. The factions were chosen based on their varied centrality patterns within the partitions and their different delinquency levels to showcase an array of different subgroups that can exist within the whole network.

The exercise of describing the factions, however, highlighted the fact that even within a whole network, the landscape of ties, density, centrality, and delinquency can vary greatly within different parts of the network. In other words, one-size-fits-all approaches aren't likely to be as successful as those that consider the unique nature of the specific population that is being targeted together with the overall context within which that population is located. For instance, an at-risk Latino group of youth with low levels of both acculturation and delinquency that is embedded in a larger network of more delinquent youth from the same neighborhood would not respond as well to an intervention program that might be successful with the delinquent, acculturated youth.

INTEGRATING WHOLE NETWORK POSITIONAL MEASURES IN EGO ANALYSES

Research Question 3: How does an individual's position and connectedness within the whole network relate to his/her propensity to be involved in delinquent behavior at the individual level? In other words, how does one's position at the sociocentric level relate to behaviors measured and modeled at the egocentric level?

The network technique of overlapping ego networks to develop a whole network provides a unique opportunity to assess the contribution of whole network structural measures to delinquency and other antisocial behaviors. One element of the whole network that we investigated in detail was the position of individuals in the network, and how that position influences delinquency. We created a number of measures derived from one's position within the whole network, including isolates and degree, closeness, betweenness, and eigenvector centrality. We first explored the characteristics of the central players, then used the measures in predictive models at the ego and alter levels.

Who Are the Central Players?

At the whole network level we considered the most central players to be those who had centrality scores on any of the three centrality measures that were in the top 1 percent. For the 2+ network, we looked at the top 5 percent of central members. We found, despite our previous analysis indicating that the centrality measures were *not* highly correlated, that there was a great deal of overlap in the groups: those who were central actors based on degree centrality tended to be high on the other two centrality measures as well.

We found that central players were actually younger than the average whole network member by three to four years—a large difference. In addition, a much higher percent of central actors were named as siblings and friends compared to all members in the whole network. Therefore, in order to get the most central, and thus influential, players involved in any prevention or intervention program, getting an individual's whole family involved is key. While this supports previous (non-social network) research that suggests that parent involvement in a youth's life decreases delinquent behavior, the network perspective provides additional insight. We would suggest that siblings also have an important role to play. Having both older and younger siblings involved can help prevent the spread of delinquent or criminal behavior to a younger generation, provide an important familial support structure for youth in prevention and intervention programs, and help to further spread pro-social messages throughout the network structure.

We also found that the central players in both networks were more likely than those in the whole network to be Latino, but fewer were born abroad. In addition, more than three-quarters (and for degree centrality, nearly 100 percent) of all central players live in the neighborhood. Finally, delinquency levels were significantly higher for central players; one-fifth to one-quarter of central actors were delinquent while only 8 percent of the whole network was. We explore the relationship between centrality and delinquency in the next section.

The Influence of Centrality on Delinquency

As mentioned earlier, having a central role—regardless of the definition of centrality used—may allow a person greater autonomy to act as he wishes; he may have less dependence on any one individual for his needs (e.g., friendship or companionship, economic support, etc.), allowing him the freedom to act as he wishes, including participating in delinquent acts. In this sense, the higher levels of delinquency observed among central players is expected. Previous research has identified central players as more delinquent, especially when drug use and selling are examined (Baron & Tindall 1993; Lee 2004; McGloin & Shermer 2009), and, for the most part, the current work supported the earlier findings from previous research.

There are several possible explanations for this pattern. Those who have high betweenness scores are sources of connection for other nodes; in other words, they frequently lie on the paths between two other nodes. In this way, they can often operate as go-betweens or brokers between two nodes or groups. Indeed, Lee's (2004) work found drug sellers to be at the center of networks, which were typically comprised of drug users. These high betweenness players may also participate in gang fights more often than less central (or less "between") actors, because their centrality may make them targets for competition; they may have to defend their position within the group (whether a gang or other group) through fighting or other means. In addition, according to the "code of the street" where respect is of utmost importance, such central figures might not be able to overlook any sign of disrespect from others, no matter how small the slight (Anderson 1999). They might therefore find themselves involved in more altercations to "save face" or preserve their reputation and the respect others have for them than they would otherwise undertake.

For the predictive models at the ego level, the only network measures we included were betweenness centrality and "ego as isolate," because these measures have hypothesized relationships with delinquency and gang membership. To examine the contribution of betweenness centrality and isolate position to delinquency and related outcomes, we re-ran the same basic logistic and negative binomial regression models from the ego-level analyses and added the two variables to each model. The isolate variable is not statistically significant in any of the models, and betweenness centrality approaches significance at the $p < 0.05$ level only in the model predicting drug selling. The model should be interpreted with caution however, because the effect size is basically zero, and no change of any real magnitude is predicted to take place based on changes in betweenness centrality. With a larger sample, it is likely that the coefficient would be significant and have a large effect size; hence, we believe it is a noteworthy finding.

It is sensible that betweenness—a measure of brokering—is associated with drug dealing because dealers would have many connections, and connections to people who are not connected otherwise. Because selling drugs typically requires getting drugs from a distributor and then having a customer base to buy the product (therefore acting as a connection between distributors and buyers), having many connections between others would facilitate drug selling. In other words, the drug dealer is in a good position to reach many other people and their, perhaps unconnected, groups. Essentially, a node with high betweenness has great influence over what flows (or does not flow) across the network. However, because these data are cross sectional, we are limited in knowing whether a dealer becomes a broker once he starts selling drugs, or he finds his calling because he already is an a position across a whole network that provides ample clients.

We also conducted binary logistic regression analyses using all members of the whole network to predict overall delinquency. The model was restricted by the availability of data for all alters; the data were not nearly as rich or extensive as those available at the ego level. We did, however, include measures of centrality in the models. This provided an additional test of the relationship between centrality and delinquency across all network members, not just egos, who we knew were more central on average than non-egos. We tested each of the three centrality measures in separate models, with all other predictors the same in each model. We found that living in the neighborhood was significantly associated with higher levels of delinquency; in contrast to our finding at the ego level that peers or alters living in the neighborhood did *not* significantly affect delinquency. We also found, surprisingly, that betweenness centrality is the only centrality measure that is not significant; both degree and closeness centrality were significant for the whole network. Degree, or the number of direct ties an individual has, is associated with decreases in delinquency while closeness was associated with higher levels of delinquency. While these models are more of an exercise in modeling at the whole network level (because we knew at the outset that we lacked sufficient data to replicate the ego-level models), they did further demonstrate the distinctness of the centrality measures and the different results that can be obtained depending on the centrality measure employed.

While the descriptive and regression analyses focused on overall delinquency, we also find that a smaller proportion of central actors are violent than in the whole network or 2+ network. The finding contradicts previous work in this area that suggests, as described above, that central players tend to be more delinquent than peripheral players (Baron & Tindall 1993; McGloin & Shermer 2009). Some very recent work, however (Faris & Felmlee 2011), has suggested that there is a nonlinear relationship between social status and aggression. There is significant support in the literature for the idea that central individuals are likely to be considered popular, and in order to achieve and maintain that status, they use both "antagonistic" (aggressive) and positive behaviors. Faris and Felmlee suggested, however, that once youth reach the "pinnacle" of the social structure, the need for aggression decreases. This lowered aggression is related to the fact that once at the peak of the social structure, there is no higher status to achieve, and those few at the peak thus lose motivation for their aggressive behavior and the frequency of such behavior is greatly reduced.

One alternative explanation to aid in understanding the results here—that “bridgers,” or highly “between” individuals are less *violent*—might be to consider the function of connections to many nodes. The high betweenness individual may feel freer to operate with a certain level of autonomy, able to resist becoming beholden to any one individual because there are many others available to serve a purpose or fill a need. In this situation, violence may be needed less because one can just move on to another individual, instead of resorting to violence. While we are unable to test this hypothesis given our dataset, it is one finding that certainly warrants further investigation.

OTHER FINDINGS

There are other interesting findings that are not directly related to our key research questions, but are important to summarize in this summary report.

Levels of Gang Membership

One obvious and important finding is that only a small proportion of the youth interviewed were involved in gangs (current or past). Only 10 percent indicated they were either currently or had ever been involved in gangs (another 8 percent, however, had been involved in gang fights). When we set out to choose a target neighborhood, we examined a variety of data and talked with community leaders and current and former gang members to determine the particular neighborhoods that had high levels of gang involvement and high-risk youth. Newspaper stories verified a number of gang-related incidents in and around the target area. It is possible that youth were not honest in reporting their gang status or that the words and phrases chosen did not resonate with youth in that they considered themselves to be in a group, but did not view the group as a gang. We feel that this latter possibility, however, is unlikely because we held two focus groups to collect information on phrases and terminology related to gangs and street crime used by youth in the area. We then pretested the survey protocol with at least 10 youth. Youth do report gang activity in their neighborhood—when asked whether there "is a lot of gang activity in the neighborhood," 34 percent said yes, with another 33 percent saying they don't know, and 50 percent said there "was a lot of talk about gangs in the neighborhood." It is possible that there was an underlying bias in who completed the survey; that our survey respondents were telling the truth, and the youth living in the neighborhood who were *not* surveyed were more gang-involved. But given that we know gang status for all the neighborhood-based alters for every respondent and (most of who were not surveyed), it is not likely that we are too far off in estimating the prevalence of gang membership across neighborhood youth. Across the 2,521 youth in the whole network, the prevalence of gang membership (current or past) is 4.5 percent (N = 113).

Gang Members and Delinquency

Although we did not have a large proportion of "gang" youth in our sample, another interesting finding has to do with the relationship between gang membership and criminal behavior—a topic widely studied in criminology. T-tests revealed that youth self-identifying as currently or ever in a gang were three times more likely to carry a weapon, use drugs, or attack someone with a weapon, and four times more likely to sell drugs (differences are statistically significant) than the average youth in our study. These findings are in line with the extant literature that has shown that youth associated with gangs experience an amplification in their offending, or what Thornberry (2003) calls the facilitation effect. Because we do not have longitudinal data or data that would allow us to determine whether crimes reported were committed while a youth was in a gang, we did not conduct additional analyses to examine amplification or facilitation.

Diversity of Network Members

And lastly, an unexpected finding was the extent of diversity in the surveyed population by race and ethnicity as well as the diversity within ego networks and subgroups identified by statistical routines. It is important to remember that populations that appear homogenous on the outside may indeed be very different with regard to a number of factors such as language use, religious affiliation, value systems, and country of birth. In our study, ethnicity (based on country of origin for self or earlier generation) varied greatly in the small community and youth networks contained a wide variety of relations with regard to ethnicity and nativity. In particular, even the few delinquent subgroups identified through network clustering routines included a mix of individuals with regard to whether they were born in the United States or abroad.[38] We did not find any strong results indicating that homophily was an important feature of youth relations with regard to delinquency or gangs. Youth were just as likely to nominate a person of another ethnicity or country of birth/parent country of birth.

LIMITATIONS

Although we hope that we have broken new ground with regard to an innovative data collection method that provides data that can be used to form overlapping networks, we note some important limitations of our research. Overlapping ego networks to create whole networks for analysis is a new technique in the social network field. The method brings with it some limitations (as is typical of any data collection strategy). In the current study, we do not know the level of delinquency/criminal behavior of alters in a network because we do not have self-report data from all alters listed. First, involvement in criminal activities for alters is based on reports from others. For some individuals we have multiple reports (from various egos) on an individual's behavior, providing

[38] We did not collect information on the place of birth of alters; we only have data on whether they were born in the United States or abroad, so we cannot state whether individuals in subgroups represented different nationalities.

some ability to corroborate or verify the information. However, we do not ask the respondents to report on a full set of characteristics on their alters, and as a result, we are unable to capture the level of delinquency. We assume that relations do not know everything about their friends/contacts, and we would not be able to rely on others' reports to gain a comprehensive picture of someone else's criminal activity (nor would it be valid to rely on the ego to report on alter *attitudes*). In addition, the respondent burden would be too heavy if they were required to complete a full list of delinquent acts for each of their 20 alters. Similarly, it was not our intent to interview every alter listed by each of the targeted youth. It would be virtually impossible to reach all alters for an interview, regardless of resources—many lived far away or in another country. Yet, we purposely chose the data collection method and associated analytical techniques because we believed it would provide us the greatest capability to answer our research questions.

Relatedly, it is important to mention underreporting bias as a potential problem. Research has shown that youth are likely to underreport their criminal behavior, and given the nature of our network questions (naming friends and important relationships and then describing their behavior) our respondents may purposely underreport the criminal behavior of people important to them. A similar potential problem is that research has shown that youth will tend to ascribe their own characteristics to those of their friends. However, the frequency distribution of criminal behavior across alters for all of the egos suggests that youth are not readily under-reporting or over-exaggerating alter criminal involvement. Although 31 percent of delinquent egos reported no delinquent or violent behavior for their alters, the remaining two-thirds exhibited typical variation in the proportion of alters who egos reported as having engaged in delinquent/criminal behavior. In other words, the distribution did not raise any red flags (see Table 16). At the outset of our study, we had intended to collect criminal records as a means of validating self-reported information. However, once we determined that the study design would include asking respondents to reveal names of individuals and gangs and any criminal behavior associated with the individuals nominated, we knew we would not engender the trust of the respondents if we additionally asked youth to consent to access criminal records or other law enforcement data. Given the likelihood that few youth would want to complete the survey if we told them we were accessing arrest records or talking to the police, let alone be truthful during administration, we did not collect arrest records (and intentionally told the youth we would not be doing so). Even if we had arrest records or other law enforcement data on gang participation, we would have been only able to validate the criminal behavior of the survey respondents—not the behavior of the alters (unless the alter was an ego).

Another limitation is that this study may have low generalizability. This study involves one network of youth and their relations in one disadvantaged, predominantly Latino community in Maryland. Although specific knowledge gained about these youth and subgroups might not directly generalize to other jurisdictions, we believe that findings regarding problem youth behavior do. Many of the findings related to risk and protective factors mirrored those in the extant literature, lending credence to the methods used for data collection and analysis. Similarly, the findings related to network content and structure, where addressed in previous literature, also were in line with extant research. Even when we examined hypotheses that were new with regard to delinquency, the findings, for the most part, were in the expected direction following past network theory and research.

The cross sectional nature of the study can also be viewed as a limitation. Much of the past and current research on peer effects has attempted to separate peer influence from selection. The research presented here was not intended to address this issue. Longitudinal data is needed to contribute to research in that area. However, endogeneity becomes a methodological issue for the current study: we cannot claim causality for any of our findings. For instance, where we found that a youth's betweenness position in an ego network is associated with selling drugs, we cannot address whether he/she *moved into* a position of higher betweenness *after* he began selling drugs, or whether the nature of his/her high betweenness contributed to his choice (or motivation) to sell drugs. Undoubtedly, future research of this kind that sets out to collect data at more than one point in time to understand the dynamics of networks processes over time, and how these dynamics contribute to delinquency and gang membership, would be a solid contribution to the field.

Finally, as touched upon above, because of the high respondent burden in survey data collection in this study, we had to make difficult decisions about the content of the survey. Adding one alter question results in 20 additional questions for each respondent, and as a result, we only included 19 alter questions, each selected to directly address our hypotheses. We also attempted to keep the ego questions to a minimum, and are aware that that effort resulted in the exclusion of some important constructs. For instance, questions regarding self-control or *unsupervised* time spent with peers were not included. Similarly, as mentioned above, we did not ask egos to report on alter attitudes or beliefs, and thus did not ask egos to report on their own attitudes and beliefs about violence. Some researchers may view the omission of measures of norms and attitudes as a concern; we understand this concern, but chose to rely on *behaviors*, not only because the research method chosen does not support collecting reliable information on attitudes and norms, but because past research has shown that peer behavior has stronger effects on delinquency than do peer attitudes and beliefs (Warr & Stafford 1991).

There were also questions we did not include because we thought youth (in some cases the youngest youth), would not necessarily know the answer or want to report the answer; these included questions regarding socioeconomic status, immigrant status (i.e., legal versus illegal) and home address (or cross streets) for each alter. A related point is that although we purposely surveyed a wide age range of youth (between 14 and 21), this wide range, coupled with our small sample size, makes it difficult to utilize a subset of typical control variables, such as school status, attachment to or involvement in school or school-related activities, or employment status, because many youth were past school age or not of an age where they would be likely to be employed.

We believe these limitations are outweighed by the accomplishments achieved through this study. It is typical that research incorporating new data collection methods and network techniques begins small (in this case, in one site), also testing the efficacy of the method in light of the research questions set forth.

IMPLICATIONS FOR POLICY AND PRACTICE

We have demonstrated that it is possible to collect extensive social network data on sensitive topics from a significant number of youth, and that such work can yield interesting and informative findings with significant implications for policy and practice. Although we have interwoven a discussion of implications throughout the sections above, we believe it is worthwhile to highlight a few below.

- <u>Neighborhoods shape relations</u>. First and foremost, neighborhoods shape relations. Because there may be something particular about neighborhood relations that is associated with delinquency (as shown in whole network regression models), it is important for practice to continue to focus on neighborhood-based programs as a means of intervention and prevention. However, programs that bring delinquent youth together should take care to help youth establish new positive relationships that can be sustained. In addition, neighborhood-based efforts to change the mindset of youth and modify attitudes that support violence or gun carrying via public health model programs like Chicago CeaseFire can help address the culture (or subculture) of violence within a neighborhood setting. Programs that allow youth to have experiences beyond the boundaries of the neighborhood can open their eyes to new pro-social opportunities and provide possible avenues for developing positive relationships outside the community.
- <u>Families should be sources of prevention and intervention</u>. The presence of siblings in the networks present spoke to the importance of peer-aged family support. Including the siblings of delinquent and at-risk youth could increase chances of success for prevention and intervention efforts. Similarly, strengthening the relationship between youth and their parents/caregivers should provide benefits for youth in numerous ways. Special attention should be given to youth who have parents that are incarcerated or have been involved in gangs and the roles these adults play in their children's lives.
- <u>Adult role models should be sources for prevention and intervention</u>. Because one of our key findings suggests that the delinquency/criminality of non-peer alters is associated with

delinquency, it is important for prevention and intervention programs to address the bonds and relationships that youth have with people other than peers. It might be difficult to break up a group of delinquent peers but easier to find or nurture a mentor or new role models for youth. In fact, research has shown that mentoring programs lead to a reduction in delinquency. The findings from this study add to the growing body of research suggesting strong positive relationships matter for youth. To increase the probability of making a difference in the lives of youth, mentor relationships would need to be sustained long enough so that a youth would consider the mentor an important, influential person, someone the youth would turn to for advice, as advice networks appear to be a protective factor when it comes to aggression.

- <u>Pro-social peer networks can be fortified and leveraged</u>. Programs should use strong outreach to appeal to the peer networks of youth already affiliated with existing programs and make an effort to help fortify pro-social peer networks and encourage pro-social activities. Programs that mix delinquent youth with nondelinquent youth could attempt to explicitly reinforce the importance of pro-social behavior and help detach youth from antisocial peers. Our study did not find any strong influences on delinquency related to the amount of time spent with peers or with regard to how close or whether someone was liked; thus, it is possible that practitioners conducting peer outreach can engage a wide swath of peers when recruiting youth for their programming and services.
- <u>Network structure can help determine the most appropriate interventions</u>. Perverse effects can result from even the most well-intentioned programs if neighborhood context and social structure of the targeted area are not understood at the outset. An understanding of youth networks can inform practitioners of the most appropriate interventions, such as whether pro-social messages can be effectively and efficiently spread throughout a network, or if removing key individuals can successfully disrupt a social network's negative behaviors.
- <u>Acculturation's role in delinquency is unclear</u>. Our findings supported prior work demonstrating the link between acculturation and certain types of delinquency. But, given prior work in this area and our findings on the protective roles of family and other pro-social adults, we reiterate Martinez's suggestion that family bonding and parenting should be the focus on intervention effects—not acculturation itself—but we also suggest that making these interventions culturally appropriate is of utmost importance to ensuring community participation and success.

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

The current study provides a much-needed quantitative examination of the network context of youth living in disadvantaged minority communities. It bears emphasizing that the core explanatory concepts in the criminological field refer to social relationships, but few studies examine the social relationship beyond simply the characteristics of individuals. A social network framework provides a theoretically grounded backdrop relevant to the exploration of micro-level social interaction and relations.

Furthermore, collecting network data on youth within a targeted geographic area for all important social relations provided the opportunity to examine how network structure and composition influence aspects of delinquency and related antisocial behavior beyond what has previously been studied in the extant literature. For instance, this study provided us the opportunity to examine how neighborhood-based relations may influence the delinquency of individuals or the formation of subgroups across the neighborhood. Results indicated that youth are very connected to people from the neighborhood—for 30 percent of respondents, at least half of their alters lived in the neighborhood. The majority of peers nominated across respondents resided in the same neighborhood as the respondent, and were not necessarily school-based friends. Although our study did not find that having a larger proportion of in-neighborhood relations was significantly related to delinquency or other antisocial outcomes at the ego level, the measure was significant in regression models that included all nodes in the whole network.

These findings have implications for <u>how</u> network studies collect data from youth. The reliance on peer-based networks to study the processes and risk factors related to delinquency overlooks the importance of non-peer relations as highlighted in our findings. We are able to better examine differential associations among youth simply because of the variety of associations studied, and can additionally utilize information about the strength of ties to assess the quality of associations. In addition, the findings from this study have shown that network *content* alone provides an incomplete picture—an understanding of network structure is also important for advancing delinquency research.

FUTURE RESEARCH

As social network-based research becomes more commonplace in criminology, researchers can continue to articulate a vast range of testable hypotheses related to how social relations shape criminal behavior. We recognize that the current study is only one small step among many new network-based approaches that can help shed insight into the processes and dynamics that shape and reinforce (or buffer against) delinquent and criminal behavior. Below, we provide a few suggestions for future research.

First and foremost, research that attempts to replicate these findings in other Latino neighborhoods, as well as in neighborhoods comprising youth from different minority groups, would provide insight on the reliability of our findings. The findings from this study regarding the "typically studied" risk factors were mostly in line with past research. However, we examined a set of network compositional and structural measures that have not, to our knowledge, been examined in the study of delinquency. It will be important for future research to shed light on how these findings might vary (or not) across different communities. Second, as the cross-sectional nature of this study limited our ability to infer causal relationships, longitudinal research would provide the basis to obtain more insight on the particular aspects of relationships that influence behavior as well as how one's position in a network shapes opportunities to engage in crime. Specifically, longitudinal research in this field will help advance the debate on selection versus influence. Also, because research has suggested that peer networks are rather fleeting, longitudinal research can inform hypotheses related to how changes in relationships impact behavior or influence the criminal career (or gang career), as very little is known about how pro-social or antisocial relationships influence desistance. We admit that tracking high risk youth over time can be very resource intensive and high response rates might be difficult to achieve, but the success would yield a wealth of data that could be used to support a wide range of critical questions that could advance the field. When relying on self-report data, our findings support the idea that widening the framework beyond schools for social network analyses seeking to inform delinquent, criminal, or gang-related behavior would yield substantial benefits for research, policy and practice. Certainly self-report data collected on networks needs further exploration of their validity (and specifically with regard to using overlapping networks), but the point to be made is that exploration of neighborhood-based networks or more broadly, networks not bounded by a specific type of relation, will provide the opportunity to more directly examine core constructs and hypotheses from social learning, bonding, and routine activities theories as well as to test integrated models combining aspects of these theories—as many recent studies have suggested.

While school networks are obviously very important because youth spend a significant portion of their lives in school, the inclusion of non-peers in an analysis of a youth's network sheds more light on the array of influences shaping an individual's behavior. School-based surveys have clear advantages—the network is easily "closed" (all network members are known at the outset and can be included in analysis), and data coding and cleaning can be much easier. In addition, basic logistics of conducting the data collection efforts can be easier in a school-based setting, where youth can be considered a "captive audience," more likely to take the survey. But, analyses that fail to recognize the importance of other, non-peer relationships could suffer from bias and model misspecification.

Admittedly, conducting longitudinal studies of this sort would require ample resources to ensure adequate samples. When we set out with our study, we did not know the exactly how many youth between the ages of 14 and 21 lived in our study site. We began with finite resources and hoped to reach a full "census" of youth to be surveyed. Although we have demonstrated that the data collection strategy we devised can be successful, at least on a small scale, future research should attempt to replicate this study using neighborhoods with large numbers of youth (or perhaps more resources) that would enable recruitment of larger samples of youth. Research conducted simultaneously in more than one neighborhood would also enable some ego-level analyses to be conducted on a combined sample, and at the same time, buoy reliability. These types of studies are resource intensive, but solid planning and valid data on youth populations will enable future studies to make important gains.

It is also important to set aside resources to ensure that serious delinquents and gang members are recruited and represented in a study of this sort. In addition, future network studies seeking to understand delinquency would benefit from adding a qualitative component to the data collection effort, to explore with respondents the structure of their network, the key players, and the relationships between network members. Having respondents reflect on personal network graphics would allow researchers to explore additional hypotheses and follow up on any puzzling or unanticipated findings.

Larger sample sizes and a more comprehensive set of data on alters would also provide new opportunities to examine how non-peers influence youth behavior. This includes testing whether relations other than peers can be protective factors in a youth's life or whether, if these non-peers are delinquent or criminal, their negative behavior is more influential than such behavior among peers. Large samples and data collection methods using different alter nomination strategies would provide new opportunities to test the tenets of current integrated theoretical models as related to familial relations. The level of bonding to adults is also important in understanding how adult role models facilitate maintenance of criminal careers or help delinquent youth desist from crime or leave gangs. Finally, looking in more depth at different types of peer relationships, such as cross-gender friendships and their role as protective or risk factors, will provide a more nuanced view of how delinquent peers influence others' behavior, and in turn offer possible strategies for prevention and intervention.

Although this study uncovered only a handful of delinquent peer groups and gang members, the data collection technique and analyses performed lend themselves easily to gang research. The field of gang research is wide open for network analyses using self-reported data. In gang communities, this type of study could help develop knowledge about delinquent and crew subgroups. The majority of research on gang violence in the past 20 years has been conducted in areas such as Los Angeles and Chicago, where gangs tend to have structure and organization. As such, most current gang prevention, intervention, and suppression strategies, as well as drug market elimination, are developed from efforts that target the behaviors of organized gangs, leaving little room for investigation of how and why less organized criminal groups develop and thrive. Essentially, without precise knowledge of the mechanics of group behavior within the local context, we do not know how to develop strategies to modify norms and behavior. Network research aimed at understanding how loosely based "crew" networks evolve and change over time and how aspects of networks are related to changes in criminal behavior, would greatly assist intervention efforts.

Finally, we would like to conclude with the suggestion that experts in network analyses and network programs continue to devise ways to make network research more practitioner-friendly. One of the ultimate goals of our research, after multiple replications using the same survey instrument, is to determine which particular network-based questions or network routines (in analyses) are the most salient for understanding who (i.e., which individual or group of individuals) should be targeted for different types of prevention and intervention efforts. We recognize that the extensive data collection process we undertook as part of this study is not feasible or practical for most practitioners. But a short risk and network structure assessment instrument (based on our longer instrument) could make such considerations more accessible to practitioners. In this way, they could realistically use social network data to inform the development of an appropriate intervention strategy for individuals and/or entire neighborhoods.

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APPENDICES

Appendix A.

Norms and Networks of Latino Youth
Youth Survey Instrument

Ego:Intro

Welcome to the Youth Survey!

This survey can take up to two hours and includes detailed questions about your friends, people you hang out with or just know on the street, and other people who might be important to you. We will ask about any past or current involvement with general crime, your education, and your relationships with family and other people you name.

You will receive a $50 gift card for completing this survey.

Each question will be asked in this box in **bold**. There may also be directions in this box to help guide you. Please read all questions and directions carefully. In order to answer the question, you will either type your answer in a box below this one or click the dot next to the response that best answers the question. You will only be able to select one response for each question if there are categories listed. Once you answer the question, the **NEXT** button will appear and allow you to move to the next question.

Let's try an example.

Did you read the directions above?

Possible selections:
- Yes (value=1)
- No (value=0)

Ego:Example

Great Job!

Let's try one more!

What is your favorite color?

Type your answer in the box below and then click NEXT.

Ego:Nicknames

You are doing great! Now let's get started.

The first section is going to ask questions about you and where you live. If there are any words or questions that you do not understand, please raise your hand and the interviewer will assist you. Remember, all your answers will be kept private and you don't have to answer any questions that you don't want to. If there is a question that you do not want to answer, please raise your hand and the interviewer will help you skip the question.

Here is the first question: **What are your nicknames or other names that friends and family call you?**

Ego:Birthdate

What is your birth date or date of birth?

NOTE: Enter date as MONTH DAY, YEAR
For example, if you were born on January 1, 2000, type it in the box using the full month, day, and year.

Ego:Gender

Are you male or female?

Possible selections:
- Male (value=1)
- Female (value=0)

Ego:LivingArrangement

<u>WHO</u> do you currently live with?

If you live with more than one group below, please select "other" and specify all those people you live with in the next question.
Possible selections:
- One or both parents (value=1)
- Other relative (value=2)
- Boyfriend or girlfriend (value=3)
- Friend(s) (value=4)
- Other (value=5)

Ego:LivingArrangementOther

Please specify who you live with.

Ego:LivingPlace

<u>WHERE</u> do you currently live?

Possible selections:

- At a parent's home (value=1)
- At a relative's home (other than parent) (value=2)
- At a friend's home (value=3)
- At the home of my boyfriend or girlfriend (value=4)
- At a shelter (value=5)
- At a hotel/motel/rooming house (value=6)
- On the street (value=7)
- Someplace else (value=8)

Ego:LivingPlaceOther

Please specify where you live.

Ego:SupportSelf

Do you now support yourself?

For example, are you responsible for paying your own rent, buying your own food, and paying other bills?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:OnlyAddress

Have you lived at your current address your entire life?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:TimeatAddress

How long have you lived at your current address?

Please type the number of years below.

Ego:LivedBefore

In what city did you live before you lived at your current address?

Ego:LivedUS

Is that in the United States?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:BeforeNeighborhood

Was that house in your current neighborhood?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:BeforeBoundary

Where was your previous home located? For example, what is the name of the most important location that would help us determine where it is, such as the intersection of two streets, the nearest park, or a name that everyone calls that neighborhood?

Ego:Neighborhood

In what neighborhood do you currently spend <u>MOST</u> of your time?

Ego:NeighStreet

Where is that? What is the name of the most important location that will help us determine where it is, such as the intersection of two streets or a park?

Ego:HelpText

You are doing a great job!

This is the first checkpoint, so please raise your hand and an interviewer will come and check the progress of your survey.

Please <u>do not move past this screen</u> without the assistance of an interviewer.

Ego:LastYear

Were you in school at any point during the <u>LAST SCHOOL YEAR</u>?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:CurrentSchool

Are you currently in school?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:CurrentGrade

What grade or year are you in?

Ego:HighSchool

Have you graduated from high school or earned a GED?
Possible selections:

- Graduated from High School (value=1)
- Earned a GED (value=2)
- Neither graduated or earned a GED (value=3)

Ego:LastGrade

What was the last grade in school that you completed?

Ego:CurrentHeld

Have you ever had to repeat a grade in school, for any reason?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:AdultGraduate

Did any adult in your immediate family (mother, father, either grandparent, or older brother or sister) graduate from high school?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:ParentSupported

Did a parent or guardian regularly insist that you go to school and do well?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:ParentSupports

Does a parent or guardian regularly insist that you go to school and do well?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:SchoolSports

The next few questions are going to ask you about the sorts of things you like to do and the kinds of groups you belong to.

In the LAST SCHOOL YEAR were you on any athletic or sports teams at SCHOOL?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:SchoolSportSpecify

What sport(s)?
Possible selections:

- Football (value=1)
- Cheerleading (value=2)
- Basketball (value=3)
- Soccer (value=4)
- Baseball (value=5)
- Volleyball (value=6)
- Track and Field (value=7)
- Multiple sports team (value=8)
- Other (value=9)

Ego:SchoolSportMultiple

Please specify which types of sports.

Ego:SchoolSportOther

Please specify which type(s) of sports.

Ego:SchoolClubs

In the LAST SCHOOL YEAR, have you participated in any SCHOOL groups, clubs, or activities?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:SchoolClubsSpecify

Which SCHOOL groups, clubs, or activities have you participated in during the last school year?
Possible selections:

- Band, chorus, or theatre value=1)
- Dance club (value=2)
- Government (value=3)
- Math, science, art, or chess club (value=4)
- Tutoring or homework help (value=5)
- Cultural or language club (value=6)
- Religious (value=7)
- Multiple groups (value=8)
- Other (value=9)

Ego:SchoolClubsMultiple

Please list which SCHOOL groups or clubs you have participate in during the last school year.

Ego:SchoolClubsOther

Please specify any SCHOOL groups that you participated in the last school year.
Possible selections:

- Yes (value=1)
- No (value=0)
- Refused (value=98)

Ego:CommGroups

In the PAST YEAR, did you participate in any COMMUNITY activities, such as groups at the Y, Boys and Girls clubs, or hobby clubs?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:CommGroupsSpecify

Which <u>COMMUNITY</u> activities have you participated in during the past year?

Possible selections:

- Dance groups or clubs (value=1)
- Sports team(s) (value=2)
- Band, chorus, or theatre (value=3)
- Community center programs (value=4)
- Cultural or language groups (value=5)
- Girls or boys clubs (value=6)
- Multiple groups (value=7)
- Other (value=8)

Ego:CommGroupMultiple

Please specify which community groups or activities you participated in during the past year.

Ego:CommGroupOther

Please specify which community groups you participated in during the past year.

Ego:CommSports

In the <u>PAST YEAR</u>, did you participate in any <u>COMMUNITY</u> sports, such as organized sports or pickup games?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:CommSportSpecify

What sport(s)?

Possible selections:

- Football (value=1)
- Basketball (value=2)
- Soccer (value=3)
- Baseball (value=4)
- Volleyball (value=5)
- Track and (value=6)
- Cheerleading (value=7)

- Multiple teams (value=8)
- Other (value=9)

Ego:CommSportMultiple

Please specify which community sports you participated in during the past year.

Ego:CommSportOther

Please specify which community sport you participated in during the past year.

Ego:Volunteer

Did you participate in any volunteer work during the PAST YEAR?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:FamilyCare

Do you help your family regularly take care of a brother, sister, or cousin?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:JobSchool

Do you currently have a job?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:JobSummer

Did you have a job this past SUMMER?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:YourReligion

What is your religion?
Possible selections:

- Christian (e.g., Catholic, Pentecostal) (value=1)
- Jewish (value=2)
- Buddhist (value=3)
- Muslim (value=4)
- Mormon (value=5)
- Jehovah's Witness (value=6)
- Other (value=7)
- None (value=8)

Ego:YourReligionOther

Please specify.

Ego:Worship

In the PAST YEAR, how often have YOU usually gone to religious services?

Possible selections:

- At least once a week (value=1)
- Almost every week (value=2)
- About once a month (value=3)
- Seldom (value=4)
- Never (value=5)

Ego:WorshipParents1

When you attend religious services, how often do you usually go with your PARENTS or OTHER RELATIVES?

Possible selections:

- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipParents2

When you attend religious services, how often do you usually go with your PARENTS or OTHER RELATIVES?

Possible selections:
- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipParents3

When you attend religious services, how often do you usually go with your PARENTS or OTHER RELATIVES?

Possible selections:
- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipParents4

When you attend religious services, how often do you usually go with your PARENTS or OTHER RELATIVES?

Possible selections:
- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipSchool1

When you attend religious services, how often do you see any of your FRIENDS FROM SCHOOL there?

Possible selections:
- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipSchool2

When you attend religious services, how often do you see any of your FRIENDS FROM

SCHOOL **there?**

Possible selections:

- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipSchool3

When you attend religious services, how often do you see any of your FRIENDS FROM SCHOOL there?

Possible selections:

- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:WorshipSchool4

When you attend religious services, how often do you see any of your FRIENDS FROM SCHOOL there?

Possible selections:

- Always (value=1)
- Sometimes (value=2)
- Never (value=3)

Ego:FamilyKnows

This next section asks questions about your family. Your family can be who you define as family and whatever family means to you.

Read each statement and indicate how much you agree or disagree with that statement about your family.

My family knows what I mean when I say something.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyView

My family and I have the same views about what is right and wrong.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyFeel

I am able to let others in my family know how I really feel.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilySuccess

My family and I have the same views about being successful.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyTalk

I'm available when others in my family want to talk to me.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyListen

I listen to what my other family members have to say, even when I disagree.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyHelp

My family members ask each other for help.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyTime

My family members like to spend free time with each other.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyClose

My family members feel very close to each other.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyActivities

We can easily think of things to do together as a family.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:FamilyCompared

Compared to most families, would you say yours was very close to each other, somewhat close, not very close, or not close at all.
Possible selections:

- Very close (value=1)
- Somewhat close (value=2)
- Not very close (value=3)
- Not close at all (value=4)

Ego:CommHaveEntertain

Now, please think about the neighborhood you LIVE IN and tell me whether each statement is true or false.

There are entertainment places in my neighborhood such as movie theatres and shopping malls.
Possible selections:

- True (value=1)
- False (value=0)

Ego:CommUseEntertain

I use entertainment places in my neighborhood such as movie theatres and shopping malls.
Possible selections:

- True (value=1)
- False (value=0)

Ego:CommHaveRec

There are recreational facilities available in my neighborhood such as gyms.
Possible selections:

- True (value=1)
- False (value=0)

Ego:CommUseRec

I use the recreational facilities available in my neighborhood such as gyms.
Possible selections:

- True (value=1)
- False (value=0)

Ego:Ethnicity

This section asks about you and your family's race and cultural background. Remember to let the interviewer know if there are any words or questions that you do not understand. First you will asked about your Latino descent and then about your race.

Are you of Hispanic, Latino/a, or Spanish origin or descent?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Race

And do you consider yourself to be White, Black/African American, or some other race?

Possible selections:

- White (value=1)
- Black/African American (value=2)
- Other Race (value=3)

Ego:RaceOther

Please specify.

Ego:MotherBorn

What country was your mother born in?

Title: **Ego:FatherBorn**

What country was your father born in?

Ego:BornUS

Were <u>YOU</u> born in the United States?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:TimeOutsideUs

Have <u>YOU</u> lived in <u>ANOTHER</u> country?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:TimeinUS

How many years have <u>YOU</u> lived in the United States?

Ego:TimeinUSforeign

How many years have <u>YOU</u> lived in the United States?

Ego:WhyUS

What is the main reason why <u>YOU</u> came to the United States?
Possible selections:

- For work (value=1)
- To attend school (value=2)
- To be with family (value=3)
- Was studying abroad (value=4)
- Other reason (value=98)

Ego:WhyUSOther

Please specify.

Ego:WhyUSforeign

What is the main reason why YOU came to the United States?
Possible selections:

- Work (value=1)
- School (value=2)
- Family (value=3)
- Other (value=4)

Ego:WhyUSforeignOther

Please specify.

Ego:Speak

What different languages do you speak?
Possible selections:

- Only Spanish (value=1)
- Only English (value=2)
- Both Spanish and English (value=3)
- Other (one language) (value=4)
- Other (multiple languages) (value=5)

Ego:SpeakOtherOne

Please specify.

Ego:SpeakOtherMult

Please specify.

Ego:SpeakMultiple

Do you speak one better than the other?

NOTE:If the languages you speak are not included, please specify the relationship in the OTHER category.
Possible selections:

- Spanish better than English (value=1)

- Both Spanish and English equally (value=2)
- English better than Spanish (value=3)
- Other combination of languages (value=4)

Ego:SpeakMultipleSpec

Do you speak one better than the other?

NOTE:If the languages you speak are not included, please specify the relationship in the OTHER category.
Possible selections:

- Spanish better than English (value=1)
- Both Spanish and English equally (value=2)
- English better than Spanish (value=3)
- Other (value=4)

Ego:SpeakMultiOther

Please specify.

Ego:LanguageHome1

What languages do you usually speak at HOME?
Possible selections:

- Spanish (value=1)
- English (value=2)
- Both Spanish and English (value=4)
- Other (value=3)

Ego:LanguageHOther1

Please specify.

Ego:LanguageHome2

What languages do you usually speak at HOME?
Possible selections:

- Spanish (value=1)
- English (value=2)
- Both Spanish and English (value=4)
- Other (value=3)

Ego:LanguageHOther2

Please specify.

Ego:LanguageFriends1

What languages do you usually speak with your <u>FRIENDS</u>?
Possible selections:

- Spanish (value=1)
- English (value=2)
- Both Spanish and English (value=3)
- Other (value=4)

Ego:LanguageFOther1

Please specify.

Ego:LanguageFriends2

What languages do you usually speak with your <u>FRIENDS</u>?
Possible selections:

- Spanish (value=1)
- English (value=2)
- Both Spanish and English (value=3)
- Other (value=4)

Ego:LanguageFOther2

Please specify.

Ego:Accept1

For the next set of questions, please indicate how much you agree or disagree with each statement about race and culture.

I have spent time trying to find out more about my own ethnic group, such as its history, traditions, and customs.
Possible selections:

- Strongly Agree (value=1)

- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept2

I am active in organizations or social groups that include mostly members of my own ethnic group.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept3

I have a clear sense of my ethnic background and what it means for me.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept4

I think a lot about how my life will be affected by my ethnic group membership.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept5

I am happy that I am a member of the ethnic group I belong to.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)

- Strongly Disagree (value=5)

Ego:Accept6

I have a strong sense of belonging to my own ethnic group.
Possible selections:
- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept7

I understand pretty well what my ethnic group membership means to me.
Possible selections:
- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept8

In order to learn more about my ethnic background, I have often talked to other people about my ethnic group.
Possible selections:
- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept9

I have a lot of pride in my ethnic group.
Possible selections:
- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept10

I participate in cultural practices of my own ethnic group, such as special food, music, or customs.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept11

I feel strong attachment toward my own ethnic group.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:Accept12

I feel good about my cultural or ethnic background.
Possible selections:

- Strongly Agree (value=1)
- Agree (value=2)
- Neither Agree or Disagree (value=3)
- Disagree (value=4)
- Strongly Disagree (value=5)

Ego:TalkGangs

In these surveys, we want to understand the different experiences you may have had at home, in your school, and in your neighborhood. This next section asks questions about how much you think your neighborhood is
affected by gangs.

For instance:

Do people <u>TALK</u> about gangs in your neighborhood?
Possible selections:

- Mostly Yes (value=1)

- Mostly No (value=0)
- Don't Know (value=97)

Ego:GangActivity

Is there a lot of gang <u>ACTIVITY</u> around your neighborhood?
Possible selections:
- Mostly Yes (value=1)
- Mostly No (value=0)
- Don't Know (value=97)

Ego:GangsClose

Are there gang <u>RIVALRIES</u> in your neighborhood?
Possible selections:
- Mostly Yes (value=1)
- Mostly No (value=0)
- Don't Know (value=97)

Ego:PressureGang

Is there <u>PRESSURE</u> on neighborhood youth to <u>JOIN</u> gangs in your neighborhood?
Possible selections:
- Mostly Yes (value=1)
- Mostly No (value=0)
- Don't Know (value=97)

Ego:ImportantGang

Among the youth in the neighborhood, how important is it to be a <u>MEMBER</u> of a gang?
Possible selections:
- Very important (value=3)
- Somewhat important (value=2)
- Not important at all (value=1)
- Don't Know (value=97)

Ego:NeighborsGang

Are any of the people living on your <u>STREET</u> members of a gang?
Possible selections:
- Yes (value=1)
- No (value=0)
- Don't Know (value=97)

Ego:GanginNeigh

Do gang members HANG OUT on your street?
Possible selections:

- Yes (value=1)
- No (value=0)
- Don't Know (value=97)

Ego:ApproachGang

Since you have been living in this area, have you ever been approached to join a gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:ApproachResponse

How did you respond?

Ego:ThoughtGang

Have you ever thought about joining a gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:HurtGang

Are you afraid that someone will hurt you if you don't join a gang?
Possible selections:

- Often Afraid (value=3)
- Sometimes Afraid (value=2)
- Never Afraid (value=1)

Ego:Group

The next set of questions are going to ask you about groups of friends and the reasons why people hang out in groups or gangs.

Is there a group of friends that you hang around with a lot?

It can be any group or even an undefined or informal group of people.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:StreetGang

Do you consider that <u>GROUP</u> to be a street gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:PartGang

Have <u>YOU EVER</u> been a <u>MEMBER</u> of a street gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:StillGang

Are you still?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Affiliation

What other names do you use to refer to this group other than "gang"?

For example, do you just call it a gang or do you use clique, organization, nation, etc. List all names that are commonly used.

Ego:AgeGang1

How old were you when you first began hanging out with your gang?

Ego:FormerAgeGang

Why did you "quit" being a gang member?

Please indicate the proper term below as well if, for example, you call it "deactivate" and not "quit".

Ego:StillHangGang

Do you still hang out with members of your former gang?
Possible selections:

- Yes (value=1)
- No (value=0)
- Refused (value=98)

Ego:GangNameCG

Would you be willing to tell us the name of your gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangNameSpecCG

What is it?

Ego:NumberGangCG

How many people are in your gang?

Ego:GangGirlsCG

How many of these are girls?

Ego:GangYoungCG

How old is the <u>YOUNGEST</u> member of your gang?

Ego:GangOldCG

How old is the <u>OLDEST</u> member of your gang?

Ego:GangTimeCG

How long has your gang been around?

Ego:GangTerritoryCG

Does the gang have a territory it claims as its own?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangStreetsCG

Can you give me the cross streets or names of the streets where the gang hangs out?

Ego:HelpTextCG

You are doing a great job!

This is another checkpoint, so please raise your hand and an interviewer will come and check your progress with the survey.

Please do not move past this screen without the assistance of an interviewer.

Ego:GangNeighborCG

Do most of the members live in your neighborhood?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangClaimCG

What happens when a member goes to prison, do they still claim your gang?
Possible selections:

- Yes (value=1)
- No (value=0)
- It Depends (value=2)

- No Members in Prison (value=3)

Ego:GangPrisonCGy

Are you still in touch with them while they are in prison?
Possible selections:

- Yes (value=1)
- No (value=0)
- It Depends (value=2)
- Not Applicable (value=96)

Ego:GangPrisonCGn

Are you still in touch with them while they are in prison?
Possible selections:

- Yes (value=1)
- No (value=0)
- It Depends (value=2)
- Not Applicable (value=96)

Ego:GangPrisonCGd

Are you still in touch with them while they are in prison?
Possible selections:

- Yes (value=1)
- No (value=0)
- It Depends (value=2)
- Not Applicable (value=96)

Ego:GangReturnCG

What happens when a member of your gang who was in prison comes back to the neighborhood? Are they still in the gang?
Possible selections:

- Yes (value=1)
- No (value=0)
- It Depends (value=2)
- No members in prison (value=3)

Ego:GangNameFG

Would you be willing to tell us the name of the gang you were in?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangNameSpecFG

What was it?

Ego:NumberGangFG

How many people were in the gang?

Ego:GangGirlsFG

How many of those were girls?

Ego:GangYoungFG

How old was the YOUNGEST member of the gang?

Ego:GangOldFG

How old was the OLDEST member of the gang?

Ego:GangTimeFG

How long has that gang been around?

Ego:GangTerritoryFG

When you were in the gang, did the gang have a territory it claimed as its own?
Possible selections:

- Yes (value=1)
- No (value=0)
- Refused (value=98)

Ego:GangStreetsFG

Can you give me the cross streets or names of the streets where the gang hung out?

Ego:HelpTextFG

You are doing a great job!

This is another checkpoint, so please raise your hand and an interviewer will come and check your progress with the survey.

Please do not move past this screen without the assistance of an interviewer.

Ego:GangNeighborFG

When you were in the gang, did most of the members live in your neighborhood?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangClaimFG

When you were in the gang, what happened when a member went to prison, did they still claim the gang?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangPrisonFG

Were you still in touch with them while they were in prison?
Possible selections:

- Yes (value=1)
- No (value=0)
- Not Applicable (value=96)

Ego:GangReturnFG

What happened when a member of the gang who was in prison came back to the neighborhood? Were they still in the gang?
Possible selections:

- Yes (value=1)

- No (value=0)
- Not Applicable (value=96)

Ego:ReasonFriends

Text: Now, please think about the group of friends that you are MOST involved with. Can you think of one?

This can be an informal group of friends. If more than one comes to mind, please choose one.

There are lots of reasons young people HANG OUT WITH THEIR FRIENDS. Considering YOUR GROUP OF FRIENDS, what are the REALLY important reasons you chose your friends?

Title: Ego:ReasonGang

Now, please think about your gang.

There are lots of reasons young people JOIN GANGS. Considering YOUR GANG, what are the REALLY important reasons you chose your gang?

Ego:ReasonFormerGang
Text: Now, think about your former gang.

There are lots of reasons young people JOIN GANGS. Considering YOUR FORMER GANG, what are the REALLY important reasons you chose that gang?

Ego:WhyFriendFriend

Next you will be given a list of other reasons why some people hang out with their friends. Please indicate if any of them were important to you for hanging with your friends.

It is OK if you already included some of them in your previous answer.

Did you select your group of friends, **to make friends?**
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyFriendCG
Next you will be given a list of other reasons why some people join gangs. Please indicate if any

of them were important to you for when selecting your gang.

It is OK if you already included some of them in your previous answer.

Did you select your gang, **to make friends?**
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyFriendFG

I'm now going to read you a list of other reasons why some people join gangs and I'd like you to tell me if any of them were important to you for joining your former gang.

OK. Listen to each and then tell me if it is important for you.

To make friends.
Possible selections:

- Yes (value=1)
- No (value=0)
- Refused (value=98)

Ego:WhyRep

To get a reputation.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyFillup

To fill up empty time.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhySupport

For support and loyalty.
Possible selections:

- Yes (value=1)
- No (value=0)

Eo:WhyImportant

To feel important.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyNoticed

To be noticed.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyBelong

To feel like you belong to something.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyAvoid

To avoid home.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyTrouble

To keep out of trouble.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyProtect

For protection.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyExcite

For excitement.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyIllegal

To get away with illegal activities (such as stealing or breaking into cars).

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyGroup

To participate in group activities.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyOwn

To have a territory of your own.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyRespect

To get your parents' respect.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyMember

Because someone in your family was in the group.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyMeet

To meet guys/girls easily.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyProud

Because the group is one you can feel proud of.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyMoney

To get money or other things.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyFriend

Because a friend was in the group.
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyFamily

To get what you don't get from your family.

For example, to get support or respect.

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:WhyLike

To be with other people like you.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyCool

Because the things they do are cool.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WhyPressure

Because I did <u>NOT</u> have a choice.
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:DamagedProperty

Our purpose is to understand your experiences and activities. We want you to remember that we will <u>NOT</u> hare this information with anyone (including people from Identity and the CYOC) and we will not judge you. Everything that you put in this survey will be kept a secret.

For this next set of questions, please indicate if you have <u>EVER</u> done any of these things.

Have you ever damaged, destroyed, or marked up someone else's property on purpose?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:DamagedPropertyRecent

In the <u>PAST 6 MONTHS</u>, have you damaged, destroyed, or marked up someone else's property on purpose?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:Stolen

Have you ever avoided PAYING for things, like a movie, taking bus rides, or anything else?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:StolenRecent

In the LAST 6 MONTHS, have you avoided PAYING for things, like a movie, taking bus rides, or anything else?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen2

Have you ever tried to STEAL or actually stolen money or things worth $100 or less?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen2recent

In the LAST 6 MONTHS, have you tried to STEAL or actually stolen money or things worth $100 or less?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen3

Have you ever tried to STEAL or actually stolen money or things worth more than $100?

Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen3recent

In the LAST 6 MONTHS, have you tried to STEAL or actually stolen money or things worth more than $100?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen4

Have you ever tried to <u>STEAL</u> or actually stolen a car or other motor vehicle?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:Stolen4recent

In the LAST 6 MONTHS, have you tried to STEAL or actually stolen a car or other motor vehicle?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangFight

Have you ever been involved in a gang FIGHT?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:GangFightRecent

In the LAST 6 MONTHS, have you been involved in a gang FIGHT?
Possible selections:

- Yes (value=1)
- No (value=0)

Ego:UsedDrugs

Have you ever USED illegal drugs such as marijuana, crack, heroine, or

methamphetamine?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:UsedDrugsRecent

In the LAST 6 MONTHS, have you USED illegal drugs such as marijuana, crack, heroine, or methamphetamine?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:SoldDrugs

Have you ever SOLD illegal drugs such as marijuana, crack, heroine, or methamphetamine?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:SoldDrugsRecent

In the LAST 6 MONTHS, have you SOLD illegal drugs such as marijuana, crack, heroine, or methamphetamine?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:Weapon

Have you ever carried a WEAPON such as a gun or knife?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:WeaponRecent

How many times in the LAST 6 MONTHS have you used a weapon or force to get money or things from people?
Possible selections:
- 1 time (value=2)
- 2 or 3 times (value=3)

- 4 or more times (value=4)
- Never (value=1)

Ego:WeaponTimes

How many times in your <u>LIFETIME</u>?
Possible selections:
- 1 time (value=2)
- 2 or 3 times (value=3)
- 4 or more times (value=4)
- Never (value=1)

Ego:WeaponArrest

Have you ever been arrested for this offense?
Possible selections:
- Yes (value=1)
- No (value=0)

Ego:AttackRecent
How many times in the <u>LAST 6 MONTHS</u> have you <u>ATTACKED</u> someone with a <u>WEAPON</u> or with the idea of <u>SERIOUSLY</u> hurting or killing them?
Possible selections:
- 1 time (value=2)
- 2 or 3 times (value=3)
- 4 or more times (value=4)
- Never (value=1)

Ego:AttackTimes

How many times in your <u>LIFETIME</u>?
Possible selections:
- 1 time (value=2)
- 2 or 3 times (value=3)
- 4 or more times (value=4)
- Never (value=1)

Ego:AttackArrest

Have you ever been arrested for this offense?
Possible selections:
- Yes (value=1)

- No (value=0)

Ego:AskInterviewer

Great job!

You are now ready to start the next portion of the survey. Please raise your hand and an interviewer will come and assist you with the instructions.

Please do not move past this screen without the assistance of an interviewer.

Questions of type: Alter Prompt

Please list 20 people that you hang out with or might see regularly in a typical day. Start by thinking of the people you hang out with every day. Then, think of the people you talk to or see the most- it may be family members, friends, neighbors, or even people you don't like.

NOTE: Please use each person's full name and if you do not know a person's full name, include the first initial of his/her last name or a nickname that will let us know that John and John are two different people. For example,

John Smith
John S
John Smitty

DO NOT MOVE PAST THIS SCREEN. Raise your hand and the interviewer will check your progress once you have entered 20 names.

(1) ____________	(6) ____________	(11) ____________	(16) ____________
(2) ____________	(7) ____________	(12) ____________	(17) ____________
(3) ____________	(8) ____________	(13) ____________	(18) ____________
(4) ____________	(9) ____________	(14) ____________	(19) ____________
(5) ____________	(10) ____________	(15) ____________	(20) ____________

Questions of type: Alter

Alter:Intro

The next portion of the survey will ask a set of about 15 questions for each of the people you just listed.

If you have any questions along the way, please raise your hand and an interviewer will assist you.

Please click NEXT to begin.

[Note: the following questions were asked for each of the 20 alters entered by the respondent.]

Alter:Nicknames

What are ______________’s nicknames or other names that friends and family use to refer to ________?

Alter:Age

How old is ______________?

Alter:Gender

Is ______________ male or female?
Possible selections:

- Male (value=1)
- Female (value=0)

Alter:Describe

Can you name one thing to describe ______________ so that we can tell the difference between this person and another person with the same name?

For example, I have two friends named Sally, but one of my friends, Sally, has pink hair and the other one has her nose pierced. Another example would be if one person has crazy hair or if another is really tall.

Alter:Relationship

Who is ______________
Possible selections:

- Mom (value=1)
- Dad (value=2)
- Sibling (brother, sister, step-brother, step-sister, or half-sibling) (value=3)

- Aunt or Uncle (value=3)
- Grandparent (value=4)
- Cousin (value=5)
- Friend (value=6)
- Neighbor (value=7)
- Teacher (value=8)
- Boyfriend/Girlfriend (value=9)
- Husband/Wife (value=10)
- Other (value=11)

Alter:RelationshipOther

Please specify.

Alter:LiveInNeighborhood

Does _______________ live in your neighborhood?
Possible selections:

- Yes (value=1)
- No (value=0)

Alter:Met

How did you meet _______________?
Possible selections:

- Relative (value=1)
- At school (value=2)
- Hanging out (value=3)
- Through a friend (value=4)
- Through a relative (value=5)
- Church (value=6)
- Neighbor (value=7)
- At a party (value=8)
- Work (value=9)
- Other (value=10)

Alter:MetOther

Please specify.

Alter:Ethnicity

Is _______________of Hispanic, Latino, or Spanish origin or descent?

Possible selections:

- No (value=0)
- Hispanic (value=1)
- Latino/a (value=2)
- Spanish (value=3)
- Other (value=4)

Alter:EthnicityOther

Please specify.

Alter:Birthplace

What country was _______________ born in?
Possible selections:

- United States (value=1)
- Mexico (value=2)
- El Salvador (value=3)
- Guatemala (value=4)
- Honduras (value=5)
- Nicaragua (value=6)
- Other Central American country (value=7)
- Puerto Rico, the Dominican Republic, or other Caribbean country (value=8)
- Peru (value=9)
- Bolivia (value=10)
- Colombia (value=11)
- Other South American country (value=12)
- Other country not listed (value=13)
- Don't Know (value=97)

Alter:BirthplaceCentral

Please specify.

Alter:BirthplaceSouth

Please specify.

Alter:Birthplaceother

Please specify.

Alter:TimeSpent

How much time do you spend each week hanging out with _______________?

Possible selections:

- A whole lot (value=1)
- Some (value=2)
- Not any (value=3)

Alter:PosRelationship

How much do you like _______________?
Possible selections:

- A whole lot (value=1)
- Some (value=2)
- Not at all (value=3)

Alter:Advice

If you needed some information or advice about something, is _______________ someone you could go to?
Possible selections:

- Yes (value=1)
- No (value=0)

Alter:CarriesGun

The next set of questions asks you about the different experiences _______________ may have had with getting into trouble. Our purpose is to understand these activities, and we want you to remember that we will NOT share this information with anyone. Everything that you tell me about _______________ will be kept a secret.

How likely is it that _______________ carries a gun (including in his/her car)?
Possible selections:

- Very likely (value=1)
- Somewhat likely (value=2)
- Not at all likely (value=3)
- Don't Know (value=97)

Alter:SoldDrugs

Has _______________ EVER sold illegal drugs such as marijuana, cocaine, or crack?
Possible selections:

- Yes (value=1)
- No (value=0)
- Don't Know (value=97)

Alter:GangFight

How likely is it that _______________ How likely is it that $$ has been in a gang fight over the LAST YEAR?

Possible selections:

- Very likely (value=1)
- Somewhat likely (value=2)
- Not at all likely (value=3)
- Don't Know (value=97)

Alter:GangTitle

Would you consider _______________ to be in a gang?

Possible selections:

- Yes (value=1)
- No (value=0)

Alter:GangName

Would you be willing to tell me what name _______________ 's gang goes by?

Possible selections:

- Yes (value=1)
- No (value=0)

Alter:GangName2

What is it?

Alter:AlterEgo

Have YOU ever in your life committed a crime WITH _______________? Please think of any crime that you know is against the law.

Possible selections:

- Yes (value=1)
- No (value=0)

Alter:Violence

How likely is ______________ to use violence to get what he/she wants?
Possible selections:

- Very likely (value=1)
- Somewhat likely (value=2)
- Not at all likely (value=3)
- Don't Know (value=97)

Questions of type: Alter Pair

Alter Pair:IndependentContact

[Note: this question was asked for all possible combinations of alters entered by the respondent.]

What is the likelihood that ______________ and ______________ <u>talk to each other</u> or <u>hang out with each other</u> without your involvement or independently of you?

Think about any kind of interaction, even if the two don't get along. Would you say not at all, they might, but not sure, or definitely?

Possible selections:

- Not at all (value=1)
- They might, but not sure (value=2)
- Definitely (value=3)
- Don't know (value=4)

Appendix B. Variable Definitions

Variable	Definition	Used in Final Models?
Dependent Variables		
Ego delinquency scale	Delinquency additive scale: (ever in lifetime) sum of damaged property, stolen goods (four levels), been in a gang fight, sold drugs, used a weapon, attacked with intent to harm (α=.829).	Yes
Ego 6 mos delinquency scale	Delinquency additive scale for activity over last 6 months (α=.824).	Yes
Ego serious delinquency scale	Serious delinquency additive scale: (ever in lifetime) sum of 2 levels of stolen goods, been in gang fight, sold drugs, used a weapon, attacked with intent to harm (α=.770).	Yes
Ego delinquency binary	Respondent is either in a gang, in a gang fight, sold drugs, carried a weapon or attacked someone with intent to harm.	Yes
Ego carry weapon	Respondent has carried a weapon.	Yes
Ego sold drugs	Respondent has sold illegal drugs.	Yes
Ego attack	Respondent has attacked someone with the intent to seriously harm.	Yes
Ego gang fight	Respondent has been in a gang fight.	Yes
Ego gang member	Respondent identifies as ever being a member of a gang or as being part of a group that is a street gang.	Yes
Independent Variables		
Peer delinquency	Proportion of delinquent friends in the respondent's personal network (delinquent is defined as either being a member of a street gang, being in a gang fight, selling illegal drugs, carrying a weapon, or using violence to get what they want).	Yes
Alter delinquency	Proportion of delinquent alters in the respondent's personal network (delinquent is defined as either being a member of a street gang, being in a gang fight, selling illegal drugs, carrying a weapon, or using violence to get what they want).	Yes
Peer in neighborhood	Proportion of friends in the respondent's personal network who live in the same neighborhood as the respondent.	Yes
Alter in neighborhood	Proportion of alters in the respondent's personal network who live in the same neighborhood as the respondent.	Yes

Appendix B. Variable Definitions

Variable	Definition	Used in Final Models?
Peers/friends in network	Proportion of alters in the respondent's personal network who are friends.	Yes
Alter male friends	Proportion of respondent's alters who are male friends.	No
Average alter age	Average age of the alters in the respondent's personal network.	No
Ethnicity scale	Additive measure of the following 12 items that are part of the Multigroup Ethnic Identity Measure (MEIM) as developed by Phinney (1992) (α=.89): • I have spent time trying to find out more about my own ethnic group, such as its history, traditions, and customs. • I am active in organizations or social groups that include mostly members of my own ethnic group. • I have a clear sense of my ethnic background and what it means for me. • I think a lot about how my life will be affected by my ethnic group membership. • I am happy that I am a member of the ethnic group I belong to. • I have a strong sense of belonging to my own ethnic group. • I understand pretty well what my ethnic group membership means to me. • In order to learn more about my ethnic background, I have often talked to other people about my ethnic group. • I have a lot of pride in my ethnic group. • I participate in cultural practices of my own ethnic group, such as special food, music, or customs. • I feel strong attachment toward my own ethnic group. • I feel good about my cultural or ethnic background.	No

Appendix B. Variable Definitions

Variable	Definition	Used in Final Models?
Ego separation scale	Additive scale of respondent being born abroad, respondent parents' being born abroad, proportion of lifetime respondent lived abroad, respondent speaks non-English language, respondent speaks non-English language with friends, respondent speaks non-English language at home (α=.65).	Yes
Alters lot of time spent	Proportion of alters respondent spends a lot of time with.	No
Alters like a lot	Proportion of alters respondent likes a lot.	No
Alters advice support	Proportion of alters respondent would go to for advice.	No
Alters time spent delinquent	Proportion of alters respondent spends a lot of time with and are delinquent.	No
Alters advice support not delinquent	Proportion of alters respondent would go to for advice and are not delinquent.	Yes
Alters advice support delinquent	Proportion of alters respondent would go to for advice and are delinquent.	No
Homophily index	Additive scale of four alter-level variables (aggregated across all 20 alters): number of respondents' alters who are born in the same country; number of respondents' alters who are of the same ethnicity; number of respondents' alters who are of the same age (+/- one year); and number of respondents' alters who are of the same gender. The scale can range from 0 to 80.	No
Num components	The number of subgroups in the respondent's personal network. Components are a measure of separately maintained groups (no link exists between any two nodes of the different groups) within the larger personal network.	Yes
Ego is isolate	Respondent is/is not identified as an alter by another ego in the network <u>and</u> none of the respondent's alters are named by another ego.	Yes
W_betweenness	Betweenness centrality is calculated using overlapping networks of all ego data. The measure is calculated by taking every pair in the overlapping whole network and counting how many times a node can interrupt the shortest paths (geodesic distance) between the two nodes of the pair. For standardization, the denominator is (n-1)(n-2)/2.	Yes

Appendix B. Variable Definitions

Variable	Definition	Used in Final Models?
Ego network density	Number of alters in respondent's network who are connected to one another (export from EgoNet).	No
Family cohesion scale	Additive measure of the following 11 items related to closeness of family; similarity of views and values (α=.90): • My family knows what I mean when I say something. • My family and I have the same views about what is right and wrong. • I am able to let others in my family know how I really feel. • My family and I have the same views about being successful. • I'm available when others in my family want to talk to me. • I listen to what my other family members have to say, even when I disagree. • My family members ask each other for help. • My family members like to spend free time with each other. • My family members feel very close to each other. • We can easily think of things to do together as a family. • Compared to most families, would you say yours was very close to each other, somewhat close, not very close, or not close at all?	Yes
Parent support in education	Response to survey item: Did a parent or guardian regularly insist that you go to school and do well? (binary: yes=1)	Yes
Ego religiosity	Response to survey item: In the past year, how often have you usually gone to religious services? Response categories are: at least once a week (4); almost every week (3); about once a month (2); seldom (1); and never (0)	No
Ego age	Age of respondent as a continuous variable	Yes
Ego male	Gender of respondent (binary: male=1)	Yes
Ego Latino	Ethnicity of respondent (binary: Latino/not Latino)	Yes
Ego time at address	Number of years respondent has lived at his/her current address as a continuous variable	Yes

Appendix B. Variable Definitions

Variable	Definition	Used in Final Models?
Family member completed HS	Response to survey item: Did any adult in your immediate family (mother, father, either grandparent, or older brother or sister) graduate from high school? (yes=1)	Yes

Appendix C. Table C1. Correlation Coefficients of Variables (N=147)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	1																		
2	.71***	1																	
3	.91***	.68***	1																
4	.79***	.50***	.77***	1															
5	.68***	.36***	.72***	.71***	1														
6	.63***	.63***	.74***	.40***	.40***	1													
7	.52***	.42***	.66***	.44***	.40***	.45***	1												
8	.62***	.46***	.71***	.59***	.40***	.50***	.33***	1											
9	.52***	.31***	.57***	.44***	.30**	.37***	.26**	.69***	1										
10	.41***	.30**	.46***	.36***	.39***	.44***	.31**	.41***	.42***	1									
11	.46***	.42***	.52***	.37***	.42***	.47***	.37***	.46***	.43***	.93***	1								
12	-.09	-.04	-.05	-.12	-.10	.04	-.01	.001	-.06	-.13	-.11	1							
13	.13	.10	.10	.14	.16	.05	.02	.05	.05	.19*	.20*	-.85***	1						
14	-.03	-.09	-.12	-.07	-.11	-.16	-.19*	-.07	-.03	-.25**	-.30**	.09	-.11	1					
15	.15	.09	.12	.17*	.13	.01	.05	.09	.05	-.04	-.09	-.14	.09	.67***	1				
16	-.12	-.12	-.07	-.09	-.07	.05	.01	-.11	-.08	-.05	-.05	.08	-.03	-.48***	-.40***	1			
17	.05	.05	.04	-.04	.09	.05	.02	-.06	-.02	.09	.06	-.6	.10	-.10	.01	.14	1		
18	0.19*	-.10	-.18*	-.19*	-.13	-.13	-.10	-.09	-.05	-.20*	-.20*	-.01	.07	.05	.11	.08	-.12	1	
19	.05	.08	.07	.05	.10	.07	.02	.15	.26**	.26**	.25**	-.18*	.19*	-.15	-.21*	.02	.16	-.07	1
20	-.07	-.08	-.09	-.09	-.08	-.02	-.05	-.02	.10	.05	.03	.02	.03	-.10	-.28**	.14	.21*	-.05	.68***
21	-.03	-.03	-.06	-.11	-.02	-.004	-.14	.01	.07	.10	.09	-.05	.07	.06	-.10	.04	.21**	-.01	.49***
22	.39***	.41***	.44***	.31**	.39***	.39***	.33***	.44***	.40***	.82***	.93***	-.12	.21*	-.29**	-.09	-.06	.07	-.15	.32***
23	-.19*	-.19*	-.23**	-.23**	-.17*	-.16	-.26**	-.15	-.08	-.24**	-.29**	-.01	-.003	.17*	-.06	.05	.18*	.06	.38***
24	.40***	.40***	.43***	.30**	.38***	.40***	.31**	.40***	.37***	.86***	.95***	-.11	.19*	-.29**	-.09	-.04	.09	-.17*	.25**
25	-.18*	-.17*	-.23**	-.22**	-.17*	-.15	-.25**	-.15	-.07	-.21**	-.24**	.03	.004	.24**	-.04	-.02	.15	.07	.30**
26	.02	-.03	-.01	.10	.08	-.10	.01	-.08	-.05	-.06	-.07	-.06	.01	.13	.10	-.21*	.04	-.52***	.17*
27	-.12	-.07	-.14	-.18*	-.15	.004	-.07	-.12	-.13	-.09	-.11	-.03	.08	-.04	.01	.02	.08	.09	.09
28	-.06	-.01	-.02	.01	.05	.01	-.01	-.13	-.01	-.08	-.08	.17*	-.13	-.04	-.06	.07	.14	.02	.002
29	.15	.07	.11	.08	.16	.15	-.09	.15	.03	.07	.10	-.11	.16	.11	.22**	-.21*	-.06	-.08	-.06
30	-.09	.03	-.03	.04	-.04	.04	.08	-.03	-.09	-.01	-.01	-.13	.20*	-.13	-.02	.11	.14	-.02	.24**
31	.10	-.07	-.07	-.18*	-.05	-.02	-.05	-.13	-.11	-.07	-.13	-.04	.07	.04	.09	.002	.53***	-.14	.19*
32	-.07	-.19*	-.12	-.03	.05	-.17*	-.06	-.13	-.15	-.02	-.11	-.08	-.01	.15	.17*	-.29**	.20*	-.17*	.08
33	-.03	-.02	-.11	-.05	.01	-.13	-.13	-.15	-.05	-.14	-.15	.07	-.03	.02	-.004	.05	.07	.06	-.002
34	-.06	-.18*	-.05	-.02	-.06	-.02	-.08	-.14	-.08	-.18*	-.23**	.03	-.01	.05	-.05	.44***	.14	.07	-.16
35	.23**	.13	.23**	.29**	.29**	.12	.15	.10	-.04	.06	.01	-.12	.05	.16*	.55***	-.16*	.16	.01	-.13
36	.01	-.02	-.004	.02	-.04	-.06	-.03	.08	.13	-.06	-.06	-.05	.10	.08	.12	-.03	-.11	.53***	.04
37	.17*	.14	.13	.10	.08	.15	-.08	.08	.09	-.08	-.08	-.02	.09	.18*	.17*	-.08	.05	-.09	.16
38	.0009	.02	-.02	.01	.08	-.01	.07	-.02	.02	.21*	.22**	.10	-.08	-.07	-.01	.10	.21**	-.33***	.11

1.Ego delinquency scale
2.Ego 6mosdlelin scale
3.Ego serious delinquency
4.Ego delinquency (binary)
5.Ego carry weapon
6. Ego sold drugs
7. Ego attack binary
8. Ego gang fight
9. Ego gang total
10.Peer delinquency (proportion)
11. Alter delinquency (propor)
12.Peer lives in neighbrhd (propor)
13. Alter lives in neighbrhd (prop)
14. Prp. alters that are friends
15. Prp. alters that are male
16. Average age of alters
17.Ethnicty scale
18.Separation scale
19. Prp lot of time spent w/alters
20.Prp alters R likes a lot
21. Prp of alters go to for advice
22. prp lot of time w/delinq alters
23.Prp go to for advice not delinq.
24. Prp go to for advice delinquent
25.Prp peers advice not delinq
26.Homophily index
27. Number of components
28. Ego is Isolate
29. W_Betweenness
30. Ego network density
31.Family scale
32. Parent supports R's education
33.Religiousity
34. Ego age
35. Ego gender
36. Ego ethnicity
37.Time lived at address
38. Adult in family grad H.S.

Appendix C. Table C1. (Continued) Correlation Coefficients of Variables (N=147)

	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
1																			
2																			
3																			
4																			
5																			
6																			
7																			
8																			
9																			
10																			
11																			
12																			
13																			
14																			
15																			
16																			
17																			
18																			
19																			
20	1																		
21	.64***	1																	
22	.07	.12	1																
23	.61***	.92***	-.26**	1															
24	.07	.17*	.92***	-.22**	1														
25	.53***	.83***	-.22**	.90***	-.19*	1													
26	.06	.02	-.28	.06	-.10	.11	1												
27	.24**	.09	-.08	.12	-.08	.10	-.11	1											
28	-.002	-.08	-.09	-.05	-.08	-.02	-.06	.02	1										
29	-.07	-.01	.11	-.03	.06	-.02	.08	-.03	-.24**	1									
30	.24**	.19*	.05	.18*	.01	.19*	.15	.20	.01	-.17*	1								
31	.24**	.27**	-.06	.31**	-.10	.25**	.18*	-.01	.14	-.04	.21**	1							
32	.04	.07	-.13	.10	-.09	.08	.24**	.07	-.02	.10	.06	.26**	1						
33	.11	.09	-.11	.15	-.16	.17*	.07	.002	.07	-.01	-.03	.14	.06	1					
34	-.05	.02	-.30**	.12	-.26**	.10	-.10	-.06	.15	-.21*	-.02	.03	-.01	-.08	1				
35	-.23**	-.19*	.01	-.18*	-.03	-.24**	.04	.03	.01	.18*	.06	.08	.15	-.04	-.02	1			
36	.07	.07	.01	.08	-.02	.08	-.17*	.01	-.05	.03	.05	-.09	-.11	-.14	.01	.02	1		
37	.07	.10	-.06	.13	-.08	.13	.21**	.01	-.05	.16	.06	.20*	.16*	.13	.13	.03	.03	1	
38	.13	.03	.19*	-.05	.20*	-.01	.13	-.02	.06	-.06	.21*	.17	.08	.08	-.07	.03	-.29**	-.05	1

1.Ego delinquency scale
2.Ego 6mosdlelin scale
3.Ego serious delinquency
4.Ego delinquency (binary)
5.Ego carry weapon
6. Ego sold drugs
7. Ego attack binary
8. Ego gang fight
9. Ego gang total
10.Peer delinquency (proportion)
11. Alter delinquency (propor)
12.Peer lives in neighbrhd (propor)
13. Alter lives in neighbrhd (prop)
14. Prp. alters that are friends
15. Prp. alters that are male
16. Average age of alters
17.Ethnicty scale
18.Separation scale
19. Prp lot of time spent w/alters
20.Prp alters R likes a lot
21. Prp of alters go to for advice
22. prp lot of time w/delinq alters
23.Prp go to for advice not delinq.
24. Prp go to for advice delinquent
25.Prp peers advice not delinq
26.Homophily index
27. Number of components
28. Ego is Isolate
29. W_Betweenness
30. Ego network density
31.Family scale
32. Parent supports R's education
33.Religiousity
34. Ego age
35. Ego gender
36. Ego ethnicity
37.Time lived at address
38. Adult in family grad H.S.

Appendix D. Regression with Full Suite of Covariates

Negative Binomial Regression Results Predicting Overall Delinquency (N=147)

	Original Model			
	Coeff.	S.E.	Exp(B)	*p* =
Intercept	1.121	1.3060	3.069	.390
Alter variables				
Proportion delinquent alters	5.941*	3.0197	380.213	.049
Proportion alters live in same neighborhood	.484	.4757	1.623	.309
Proportion friends	.383	.9281	1.467	.680
Proportion male friends	.621	.9024	1.861	.491
Average age of alters	-.032	.0407	0.969	.437
Amount of time spent with delinquent alters	-4.637	3.0784	0.010	.132
Proportion alters liked very much (delinq.)	5.515†	3.0612	248.318	.072
Proportion alters go to for advice (delinq.)	-3.444	2.1691	0.032	.112
Homophily index for delinquent alters	-.019	.0494	0.981	.701
Network structure variables				
Num. components	-.303†	.1583	0.738	.055
Is ego isolate	-.121	.3579	0.886	.736
Betweenness	.000	.0000	1.000	.332
Ego network density	-.032	.0270	0.968	.236
Acculturation				
Separation from U.S. culture	-.224***	.0630	0.799	.000
Ethnic attachment	.029†	.0170	1.030	.085
Control variables				
Age	.000	.0509	1.000	.997
Male	1.186***	.3171	3.275	.000
Latino	.618†	.3224	1.855	.055
Family member completed high school	-.361	.2809	0.697	.199
Parent-school encouragement	-.405	.3876	0.667	.296
Family cohesion	-.052*	.0202	0.949	.010
Num. years at address	.053**	.0156	1.054	.001
Religiosity	.121	.2518	1.128	.631
Goodness of fit				
Log likelihood	221.782			
Deviance value/df	0.988			
Pearson chi-square value/df	0.832			
Likelihood ratio chi-square	71.316			

†p < .10; *p < .05; ** p < .01; ***p < .001
*Proportion variables range from .00 to 1.00