Relative Availability and Its Impact on Violent Tendencies Within the African American Community

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A Didactic Application of Multiple Regression

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Abstract

Violence has been a prevalent issue within the African American community for the last two decades. This research study seeks to supplement the plethora of research around this area. Particularly, this study is concerned with what variables impact an individual's tendency to react violently within the African American community. Utilizing structural-functionalist ideology, the hypothesis being tested here is that the more relatives one has to call on for help if needed, and other related variables, the lower tendency that individual will have to violently react. The data was taken from The National Survey of American Life collected through a multi-stage sample design combined a 'core' national area probability sample of households and analyzed using multiple regression techniques. The study ended with confirming the hypothesis that as the number of relatives an individual can call for help increases, the tendency for the individual to react violently will decrease; with stipulations concerning the magnitude of impact. This research can be used to advocate for increased funding and support for

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family strengthening and other related organizations and programs that seek to curtail violent tendencies within the African American community.

Introduction

Violence is one of the primary causes of death worldwide. In 2002 the Centers for Disease Control and Prevention reported that "[e]ach year, about 56,000 violent deaths occur in this country, [and] [v]violence-related death and injuries cost the United States $107 billion in medical care and lost productivity" (CDC). In many cases, these circumstances provide ways for researchers to discover the causes of violent acts to implement effective interventions that will decrease violence, which in turn will decrease violent-related deaths and government spending. In recent years, scholarly discussions pmarily focus on how family violence impacts an individual's propensity to behave violently in other areas of their lives. However, there have been discussions on how available family members can support the individual and impact his or her tendency to be violent. This paper seeks to expand research on that subject, specifically analyzing how the number of family relatives an individual can call on for help will impact one's propensity to act violently, with the hope of garnering support for programs seeking to improve the family unit and its strength, particularly within the African American demographic.

Literature Review

The most current state of knowledge analyzes how drugs, alcohol, social capital, gender, age, religion, and media impact violent behavior. These independent variables are often used as causal entities that influence individuals to make certain decisions that are deemed by society as deviant and violent. The social understanding of deviance and violence plays a huge role in exploring this subject as well. The Mairi Levitt article entitled "Genes, Environment, and Responsibility for Violent Behavior" (2013) assesses how genes, environment, and responsibility may account for violent behavior. Levitt particularly researches whether or not genetic traits can be associated with antisocial and violent behaviors that lead to criminal activity. Levitt's qualitative study looked at participants' explanations as well as the transmission of responsibility for antisocial and violent behavior. The data set that was used contained cases that environmental and or genetic stimuli that were stated by the defending legal teams in court proceedings. Levitt ultimately concluded that genetic factors are not viewed as more applicable or decisive than environmental factors when explaining behavior in court proceedings.

According to Addiction Research Report, methamphetamine which is sometimes referred to as "ice" or "crystal meth" is famous for its relationship with violent behavior. "Violence associated with methamphetamine use is characterized by its capricious and often bizarre nature, this seeming to be fueled by methamphetamine-induced paranoia" (McKetin, 2014). In a research study entitled "Does Methamphetamine Use Increase Violent Behavior" Mcketin looked at this variable in particular, in which he analyzed whether the periods of methamphetamine use increased violent behaviors over time, or if it was the psychotic symptoms induced by the current use of methamphetamine that caused the increase in violent behaviors. A fixed-effect study was conducted using participants' who met the DSM-IV criteria for methamphetamine dependency. The study found that there was a dose-related increase in violent behavior during methamphetamine use that is largely independent of the violence risk associated with psychotic symptoms.

Another article by Calafant entitled "Violent Behavior, Drunkenness, Drug Use and Social Capital in Night Life Contexts" (2011) sought to understand the correlation between drunkenness and drug use, and being threatened and carrying a weapon. It was concluded in this study that young males who abused drugs and are poor were greater predictors of violence in the context of nightlife. Additionally, it was found that these types of young males were particularly more likely to be involved in weapon-related incidents. Table 1 lists literature that studies the effect of peer pressure on one's tendencies to be violent, which would include one's lack of resources and his or her inclination and habit for violent behavior. However, this still does not give insight into how family plays a part in any of this, a topic about which more literature and theory needs to be developed.

Theoretical Conceptualization

The results from the analysis of the number of relatives an individual has to call on and their tendencies to react violently are expected to support the implications from structural functionalism theory that as the number of relatives an individual has to call on for help increases, the tendency to react violently will decrease because a central proposition of structural functionalism theory is that social systems must act as a collective for it to fulfill its social needs. The family plays a key role in preparing an individual to operate properly within society to convey that one contains constructive manners. In other words, structural functionalists believe that individuals in society cannot advance if the society does not operate as a collective, teaching each other societal norms and cultural values. In essence, the more relatives an individual has in their lives, the better they can learn the norms of society and adapt decreasing the impulse to become violent. So, therefore, from a theoretical standpoint, if an individual does not have any available relatives to rely on for help if needed, they are more likely to act in deviance, i.e. violence and deconstructive manners, because they do not have access to a structure central to social equilibrium and cohesion.

In this research study, the number of relatives an individual can call upon for help is determined as the central organizing independent variable as it correlates with one's tendencies to react violently. Additionally, we assess three other independent variables that may impact the dependent variable (see Figure 1). Like our COIV, all of these variables can be supported by implications from the structural functionalism theory. Structural functionalism views neighborhoods as a valuable part of society that ought to provide families with safety for the families to functionally exist as they teach its members specific values and attitudes needed to coexist with others within the same society as well as different ones. In turn, if a neighborhood is unsafe the

Table 1
The Relevant Literature for Tendencies to Violent Reactions

First Author's last name, (years), the title of the article, Journal Name (vol): p. #.	*Exact DV name used in the article*	*Names of IVs in article*	*Theory/ Concep-tualization used in the article*	*Major finding re IVs & DV*
1 Levitt, (2013), Genes, Environment, and Responsibility for Violent Behavior. *New Genetics & Society* (32): P. 4-17	Violent & anti-social nehavior	Genetic traits	Genetics can impact one's likelihood of violent behavior.	Qualitatively focused, looking at participant explanations and assigning of responsibility for violent behavior. Genetic factors were not viewed as deterministically and irrelevant to personal responsibility. Free will and human agency were seen as crucial.
2 McKetin (2014), Does Methamphetamine Use Increase Violent Behavior. *Addiction* (109): p. 798-806	Violent behavior	Meth-amphe-tamine use	Does violent behavior increase during perios of methamphetamine use or is it due to methamphatemine-induced psychotic symptoms.	There was a dose-related increase in violent behavior during methamphatemine use that is largely independent of the violence risk associated with psychotic symptoms.
3 Calafat (2011), Violent Behavior, Drunkenness, Drug Use, and Social Capital in Night Life Contexts, *Psychosocial Intervention* (20, Issue 1); p. 45-51	Violent behavior	Alcohol, drug abuse, gender, age, income, and education	Is there a relationship between violence, social capital, and drug abuse?	Young males prdicted three violent behaviors and held a stronger correlation to violent behavior.

family will become dysfunctional which can lead to the predisposition for violence resulting in the individual(s) displacement from society as a welcome and active member.

Theoretically, the same implications can be applied when assessing the independent variable, neighborhood amenities. Hypothetically, if a family has to worry about where they will receive their next meal or how to give their children an education of quality, it won't be afforded the opportunity to effectively implement societal norms and rules to its members. This is especially troubling considering the family is viewed as the backbone of society and whose very purpose is this vital implementation, according to structural functionalists. The family must provide its members with sex, socialization, procreation, and economics; thus, it is more than imperative that we work towards providing the family with all the support it needs to successfully master its tasks, which will indisputably decrease individuals' propensities to react violently.

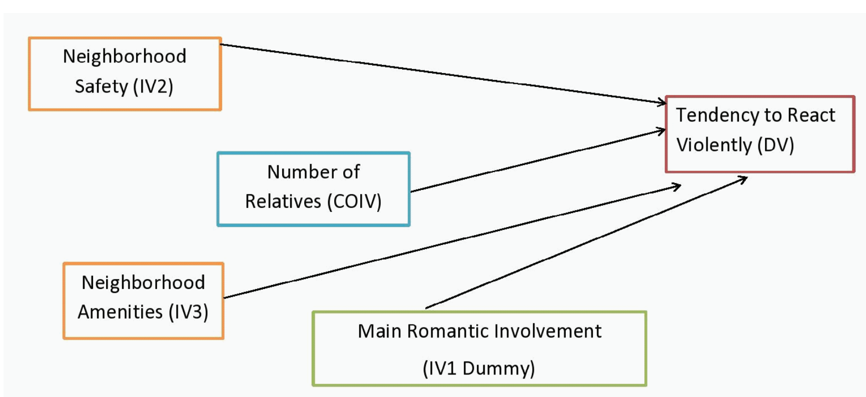
Research Questions/Hypotheses

The following are the hypotheses for the research:

Alternative Hypothesis 1: We hypothesize that one's tendency to react violently regresses significantly on the number of relatives one has to call upon for help if needed even when accounting for the effect of neighborhood amenities, neighborhood safety, and main romantic involvement.

Null Hypothesis 1: We hypothesize that one's tendency to react violently does not regress significantly on the number of relatives

Figure 1
Analytical Model of the Relationships Among Number of Relatives and Tendency to React Violently and Other Related Variables



one has to call upon for help if needed even when accounting for the effect of neighborhood amenities, neighborhood safety, and main romantic involvement.

Alternative Hypothesis 2: We hypothesized that the variance in the tendency to violently react can be explained by the number of relatives available to call upon for help, acting additively (cumulatively) with neighborhood amenities, neighborhood safety, and main romantic involvement.

Null Hypothesis 2: We hypothesized that the variance in the tendency to violently react cannot be explained by the number of relatives available to call upon for help, acting additively (cumulatively) with neighborhood amenities, neighborhood safety, and main romantic involvement.

Alternative Hypothesis 3: We hypothesized that the number of relatives available to call upon for help is relatively more important than neighborhood amenities, neighborhood safety, and main romantic involvement in explaining the tendency to violently react.

Null Hypothesis 3: We hypothesized that the number of relatives available to call upon for help is not relatively more important than neighborhood amenities, neighborhood safety, and main romantic involvement in explaining the tendency to violently react.

Alternative Hypothesis 4: We hypothesized that the number of relatives available to call upon for help produces the tendency to violently react, especially for those that do have main romantic involvements, and that this interactive effect significantly extends understanding of the tendency to violently react beyond that of the addictive model.

Null Hypothesis 4: We hypothesized that the number of relatives available to call upon for help does not produce the tendency to violently react, especially for those that do have main romantic involvement, and that this interactive effect significantly extends understanding of the tendency to violently react beyond that of the addictive model.

Data Source

The data for the study was derived from the *Codebook for the National Survey of American Life* (NSAL), 2001-2003. The *National Survey of American Life* (NSAL) is a study designed to explore racial and ethnic differences in mental disorders, psychological distress, and informal and formal service use. This NSAL is within the context of a variety of presumed risk and protective factors in the African-American and Afro-Caribbean populations of the United States as compared with White respondents living in the same communities. The NSAL is part of the Collaborative Psychiatric Epidemiology Surveys (CPES) data collection which was initiated in recognition of the need for contemporary, comprehensive epidemiological data regarding the distributions, correlations, and risk factors of mental disorders among the general population with special emphasis on minority groups. CPES joins together three nationally representative surveys: the *National Comorbidity Survey Replication* (NCS-R), the *National Survey of American Life* (NSAL), and the *National Latino and Asian American Study* (NLAAS).

There are seven collaborating principal investigators for the NSAL. They include James S. Jackson (Principal Investigator, University of Michigan, Survey Research Center), Harold W. Neighbors (Co-Principal Investigator, University of Michigan, Research Center for Group Dynamics), David R. Williams (Co-Principal Investigator, University of Michigan, Survey Research Center), Robert J. Taylor (Co-Principal Investigator, University of Michigan, Research Center for Group Dynamics), Cleopatra H. Caldwell (Co-Investigator, University of Michigan, Research Center for Group Dynamics), Steven J. Trierweiler (Co-Investigator, University of Michigan, Research Center for Group Dynamics), and Randolph M. Nesse (Co-Investigator, University of Michigan, Research Center for Group Dynamics). The NSAL was funded by the National Institute of Mental Health, with supplemental support from the Office of Behavioral and Social Sciences Research (OBSSR) at the National Institute of Health (NIH), and the University of Michigan.

The sample for the NSAL consisted of primary sampling units selected with probabilities proportional to size. The NSAL multi-stage sample design combined a ‘core’ national area probability sample of households with a special supplemental sample of households in areas of higher Afro-Caribbean residential density. The NSAL Supplement design served solely to augment the sample size from the Afro-Caribbean survey population in a cost and statistically efficient manner and did not contribute to the representative samples of the NSAL’s African-American and White survey populations.

The Survey Research Center (SRC) 1990 National Sample of U.S. households was the starting point for NSAL sample selection. To adapt the sample to be optimal for a national study of the African-American survey population for NSAL, some modification to the primary stage of the basic 1990 SRC National Sample design was needed. The definitions of the primary sampling units in the primary stage frame for the SRC

National Sample remained unchanged, but measures of the size used in the PPS selection of PSUs were changed from 1990 census counts of total occupied households to African-American occupied households. Some reorganization of 1990 'A' National Sample strata were also required to transform the design from one that was optimal for surveys of all U.S. households to one that emphasized precision for samples of African Americans.

Using CPES, the NSAL sample of Afro-Caribbean households was identified through samples selected from two overlapping area probability sample frames. The first sample source for Afro-Caribbean respondents was from the screening of households in the nationally representative NSAL Core sample. As described above, all sample housing units in this national probability sample were contacted and a screening interview was conducted with each eligible, cooperating household. In total, 266 Afro-Caribbean adults were successfully interviewed in the NSAL Core national sample. Therefore it was necessary to supplement the NSAL Core sample to achieve the original NSAL target sample size of 1,600 Afro-Caribbeans.

Construction of the NSAL Caribbean Supplement sample began with the selection of a stratified sample of eight supplemental primary stage units (PSUs). From these eight PSUs, 86 area segments were selected from the set of qualifying census block groups within the PSUs. To qualify for the Caribbean Supplement, a block group population needed to be at least 10% Afro-Caribbean based on the 1990 census estimates. Once the primary and secondary stage sampling units were selected, field staff visited each area segment to list housing units.

The NSAL White sample was a stratified, disproportionate sampling of non-Hispanic white adults in the U.S. household population. The NSAL White sample was designed to be optimal for comparative descriptive and multivariate analyses in which residential, environmental, and socioeconomic characteristics are carefully controlled in the Black/White statistical contrasts. The original completed interview target for the NSAL White sample was set at n = 1,800. Later in the study period, a decision was made to reduce this target to n = 1,000

White adult interviews were based on survey costs and updated analysis objectives for the NSAL project. By the nature of its equal probability national sampling of all U.S. households, the NSAL Core screening for eligible African-American and Afro-Caribbean households was projected to identify far more eligible White households than required to meet the sample size target. Therefore, subsampling of eligible White adults at the screening stage was employed to bring the sample of interviews with this group in line with the study targets.

The NSAL project yielded 6,199 adult interviews: 3,570 African

American, 1,623 Afro-Caribbean, and 1,006 non-Hispanic Whites. However, the actual number of cases in the CPES data file is 6,082; including 3,570 African American, 1,621 Afro-Caribbean, and 891 non-Hispanic whites. An extremely small sample (n = 115) of White adults who were interviewed in households where the White subsample was less than 10% of the African American density stratum were excluded from the final data set as well as two of the Afro-Caribbean interviews when it was later discovered that they were duplicate cases. The final effective sample size used in my regression analysis was 2670.

As seen in Table 2, females consisted of the majority of the sample accounting for 3796 respondents or 62.4% of the sample. Males accounted for 2286 respondents or 37.6% of the sample. Concerning education, 2136 respondents had completed 12 years making up 35.1 percent of the sample and the majority. 1375 respondents, 22.6 % of the sample, completed between 0 to 11 years of education making. 1468 respondents, 24.1 of the sample, had completed 13 to 15 years of education. Finally, 1103 respondents, 18.1% of the sample, had completed greater than or equal to 16 years of education.

Data Demographics

The age distribution and regional distribution for the sample are as follows. The majority of the population fell within the ages of 31 to 40 years old, consisting of 1418 respondents and 23.3% of the sample. 460 respondents, 7.6%, fell between the ages of 18 to 21; 1080 respondents, 17.8%, between the ages 22 to 30; 1283 respondents, 21.1%, between 41 and 50; 819 respondents, 13.5%, between 51 and 60; 572 respondents, 9.4%, between 61 and 70; 327 respondents, 5.4%, between 71 and 80; and 123 respondents, 2%, were 80 years old and above. The region of the country that consisted of the majority of respondents was the south, holding 3395 respondents or 55.8% of the sample. 1653 respondents, 27.2%, hailed from the northeast; 690 respondents, 11.3%, hailed from the Midwest; and 344 respondents, 5.7%, hailed from the West.

The income distribution for the sample is as follows: the majority of the sample fell in the $20,000 and below annual income range, consisting of 2331 respondents and 38.3% of the sample followed by 1872 respondents, 30.8%, with an annual income between $20,000 and $40,000. In the $60,001 to $80,000 annual income range were 484 respondents making up 8.0% of the sample. In the $80,001 to $100,000 annual income range were 251 respondents making up 4.1 % of the sample. In the $100,001 to $120,000 annual income range were 68 respondents making up 1.1 % of the sample. Finally, in the $120,001 and above annual income range were

150 respondents making up 2.5% of the sample. This sample demographic description is overall representative of the target population.

For NSAL, 11,634 eligible households were identified from 26,495 randomly sampled addresses. The overall response rate for the core NSAL national sample was 71.5 percent. The Caribbean Supplement

Table 2
Demographic Characteristics of Sample

Demographic Characteristics	*Frequency*	*Percent*
Sex		
Female	3796	62.4
Male	2286	37.6
Total	6082	100.0
Education		
0-11 Years	1375	22.6
12 Years	2136	35.1
13 to 15 Years	1468	24.1
Greater than or equal to 16 years	1103	18.1
Total	6082	100.0
Age		
18 to 21	460	7.6
22 to 30	1080	17.8
31 to 40	1418	23.3
41 to 50	1283	21.1
51 to 60	819	13.5
61 to 70	572	9.4
71 to 80	327	5.4
80 and above	123	2.0
Total	6082	100.0
Income		
$20,000 and Below	2331	38.3
$20,000 to $40,000	1872	30.8
$40,001 to $60,000	926	15.2
$60,001 to $80,000	484	8.0
$80,001 to $100,000	251	4.1
$100,001 to $120,000	68	1.1
$120,001 and Above	150	2.5
Total	6082	100.0
Region of Country		
Northeast	1653	27.2
Midwest	690	11.3
South	3395	55.8
West	344	5.7
Total	6082	100.0

sample, which was designed to target areas with high concentrations of persons of Caribbean origin, yielded a weighted response rate of 76.4 percent. These response rates are not problematic for the national representativeness of the data. All in all the preponderance of the evidence from these considerations suggests that the results from this sample can be generalized to fit the target population.

Data Collection

Data collection for the NSAL was conducted in a total of 252 geographic areas or primary sampling units across the U.S.. There were 52 areas unique to NSAL. The NSAL universe included adults in the three target groups: Black Americans of African descent, Black Americans of Caribbean descent, and White Americans, who were aged 18 years and older residing in households located in the coterminous U.S. The interviews took place between early 2001 and the spring of 2003.

The organizational structure of the field and central data collection staff for the NSAL was divided into teams of 6 to 12 interviewers. Each team was supervised by a team leader. Approximately three to four teams formed a workgroup, which was supported by a team leader and coordinator. Each workgroup was assigned to a regional field manager, who was responsible for the work group's interview production efforts, quality control, and personnel management. Whenever possible, teams were comprised of groups of interviewers from the same region. Every effort was made to assign interviewers to teams before training so that interviewers on the same team would be able to work together during training.

The core CPES questionnaire was based largely on the World Health Organization's (WHO) expanded version of the Composite International Diagnostic Interview (CIDI) developed for the World Mental Health (WMH) Survey Initiative, the WMH. The NSAL used a modified version of the WMH-CIDI, which had been developed over a year by an international group of collaborators. The WMH and CPES questionnaires were administered using computer-assisted interviewing (CAI); computer-assisted personal interviews (CAPI) and computer-assisted telephone interviews (CATI). For the most part, interviews were conducted using laptop computer-assisted personal interview methods in the homes of respondents. However, approximately 14 percent of interviews were conducted either partially or entirely by telephone. The instruments were programmed using Blaise, a CAI software package developed by Statistics Netherlands and used by many government statistical agencies and large survey research organizations worldwide. Blaise software is specifically designed to accommodate very complicated questionnaire skip patterns and sub-sampling algorithms. Potential drawbacks of using Blaise include its cost and the requirement for highly trained programmers to write the code for complex surveys. The questionnaire design and testing phase for each project spanned approximately one year.

An attempt was made to standardize the interview materials across the studies as much as possible. Nine hundred and forty-six interviewers were recruited and trained based on specific requirements of the project. 329 interviewers for NSAL were chosen particularly matching the interviewer and respondent race. Study-specific training lasted five to seven days, depending on the study and which components were being covered. The training sessions consisted of five main components: (1) instruction on household eligibility and respondent selection procedures; (2) questionnaire training, which included a section-by-section review of each module of the questionnaire, followed by question and answer sessions and two-hour practice sessions; (3) computer training and practice sessions; (4) review of interview procedures and study materials; and (5) mock interviews in which interviewing and administrative tasks were integrated to model realistic interviewing experiences. To better convey the content and to engage the training participants, trainers used a variety of formats, including large and small group lectures, round-robin practice sessions, mock interviews, and one-on-one help sessions. Participants were given homework assignments, which the trainers reviewed to identify interviewers who were having problems with the computer hardware or software.

For the NSAL study training insensitivity to cultural, racial, and socioeconomic diversity that would be encountered while conducting face-to-face interviews were provided. Additional training was also provided on how to interview on sensitive or potentially embarrassing topics. Finally, because some of the questionnaire topics covered subjects that could reveal information about pending harm to the respondent or others, interviewers were trained on their legal obligations and on how to handle these rare but critical situations. Interviewers were provided with initial and ongoing training on the importance of and techniques for reducing non-response, and a wide variety of tools and procedures was developed at the beginning of each project to maximize respondent participation.

Data Measurement

In this study, there are 4 independent variables, 1 constructed interactive variable, and one dependent variable. The descriptive statistics for these variables are found in Table 3. The dependent variable in this study is the tendency to react violently. The tendency to react violently is an ordinal continuous variable constructed using index procedures. There are 14 indicators within this index measured variable, each of them is discrete and nominal true or false questions. Each indicator was coded in the following manner; 1 = True, 5 = False, 8 = Don't Know, 9 = Refused to answer and the missing value codes were 7 through 9. The indicators are as follows:

Indicator 1: Do I go to extremes to keep people from leaving me?
Indicator 2: Do I have tantrums/angry outbursts?
Indicator 3: Do I take chances/do reckless things?
Indicator 4: Have I intentionally damaged others' things?
Indicator 5: Do I argue/fight when people try to stop me from actions?
Indicator 6: Do I get so angry, I sometimes break/smash things
Indicator 7: I'm very moody?
Indicator 8: Can't decide what kind of person I want to be?
Indicator 9: I have never been arrested?
Indicator 10: Do I feel bad when I hurt or upset someone?
Indicator 11: Do I lose my temper and get in physical fights?
Indicator 12: Do I feel uncomfortable/helpless when alone?
Indicator 13: Do I give in to urges that get me in trouble?
Indicator 14: Do I often feel empty inside?

Of these, indicators 1-8 and 11-14 had to be recoded to, 5 = True and 1= False to insure common directionality. These specific 14 indicators and the constructed variable formed by them are reliable valid and form a normal distribution. All 14 indicators were combined because they all assess the respondents' reactions and past actions that could lead to violent situations. The constructed dependent variable (as seen in table 3) had a high/low score range from 66 to 14 and 14 valid values; meeting the ten value qualification and insuring sufficient variation to be considered continuous. The mean for the dependent variable is 23.03 and the standard deviation is 9.21. The dependent variable maintained 4944 valid cases and was missing 1138 cases meeting the required standard.

The central organizing independent variable (COIV) in this study is the number of relatives available the respondent could call upon for help if she needed it. The COIV is a ratio continuous variable found directly in the NSAL codebook. The COIV (as seen in table 3) had a high/low score range from 97 to 0 and 45 valid values; meeting the ten value qualification and insuring sufficient variation to be considered continuous. The mean for the COIV is 8.05 and the standard deviation is 10.53. The COIV maintained 5942 valid cases and was missing 140 cases, meeting the required standard.

The second independent variable in this study, labeled IV1, is the main romantic involvement. Main romantic involvement is a nominal discrete "dummied" variable. This variable was used solely to test the

Table 3
Descriptive Statistics for Model Constructs

Model Constructs/ Variables	*Continuous*								*Discrete (Dummied)*	
	Interval/Ratio				*Ordinal*				*Nominal*	*Ordinal*
	Hi/Lo Score	*# Valid Values*	$\bar{X}$*s*	*s*	*Hi/Lo Scores*	*# Valid Scores*	$\bar{X}$	*s*	*%*	*%*
Independent										
COIV= # of relatives to help N=5942 missing=140	97/0	45 8.	05	10.53						
IV1=Romantic Involvement N= 3703 missing=2379										
1=Yes									37.2%	
5=No									62.8%	
IV2= Neighborhood Safety N=5816 missing=266					15/3	13	9.36	2.67		
I1=Crime frequency						5				
I2= Drugs problem						4				
I3= Neighbor visit freq.						6				
IV3=Neighborhood Amen N=5590 missing=492					40/8	10	28.01	7.42		
I1=Parks						2				
I2=Supermarket						2				
I3=Medical clinic						2				
I4=Bank						2				
I5=Check cashing						2				
I6=Library						2				
I7=Police						2				
I8=Clubs/associations						2				
Dependent										
Y= Violent Reactions N=4944 missing=1138					66/14	14	23.03	9.21		
I1=Go to extremes						2				
I2=Have tantrums						2				
I3= Do reckless things						2				
I4=Damage others things						2				
I5=Argue/fight						2				
I6=Break/Smash things						2				
I7=Moody						2				
I8=Indecisive						2				
I9=Never been arrested						2				
I10=Feel bad						2				
I11= Lose temper						2				
I12=Alone						2				
I13=Trouble urges						2				
I14=Empty inside						2				

interactive effect on the DV when combined with the COIV. IV1 was coded in the following manner; 1 = Yes, 5 = No, 8 = Don't Know, 9 = Refused to answer and the missing value codes were 7 through 9. This variable was recoded to 5 = Yes and 1 = No to insure common direction. In the sample, 37.2 % answered yes and 62.8% answered no. IV1 maintained 3703 valid cases and was missing 2379, meeting the set requirements.

The third independent variable, labeled IV2, in this study is neighborhood safety. Neighborhood safety is an ordinal continuous variable constructed using index procedures. There are 3 indicators within this index measured variable, each of them is discrete and ordinal. Each indicator were coded in the following manner; 8 = Don't Know, 9 = Refused to answer and the missing value codes were 7 through 9. The indicators and its specific coding are as follows:

Indicator 1: Frequency of Crime in the neighborhood
- 1 VERY OFTEN
- 2 FAIRLY OFTEN
- 3 NOT TOO OFTEN
- 4 HARDLY EVER
- 5 NEVER

Indicator 2: Seriousness of drug problems in neighborhood
- 1 VERY SERIOUS
- 2 FAIRLY SERIOUS
- 3 NOT TOO SERIOUS
- 4 NOT SERIOUS AT ALL

Indicator 3: Frequency of visits w/ neighbors
- 1 NEARLY EVERYDAY
- 2 AT LEAST ONCE A WEEK
- 3 FEW TIMES A MONTH
- 4 AT LEAST ONCE A MONTH
- 5 FEW TIMES A YR
- 6 NEVER

Of these, indicators 1 and 2 had to be recoded to insure common directionality. The recodes are as follows:

Indicator 1: Frequency of Crime in the neighborhood
- 5 VERY OFTEN
- 4 FAIRLY OFTEN
- 3 NOT TOO OFTEN
- 2 HARDLY EVER
- 1 NEVER

Indicator 2: Seriousness of drug problems in neighborhood
- 4 VERY SERIOUS
- 3 FAIRLY SERIOUS
- 2 NOT TOO SERIOUS
- 1 NOT SERIOUS AT ALL

These specific 3 indicators and the constructed variable formed by them are reliable, valid, and form a normal distribution. All 3 indicators were combined because they all assess the attributes of the neighborhoods and interpersonal interactions of the respondents in their neighborhoods that can predict, and increase the likelihood or decrease the likelihood of violent situations. This in turn may impact the respondents' need to react violently and/or conditioning to react violently. IV2 (as seen in table 3) had a high/low score range from 15 to 3 and 13 valid values; meeting the ten value qualification and insuring sufficient variation to be considered continuous. The mean for the dependent variable is 9.36 and the standard deviation is 2.67. IV2 maintained 5816 valid cases and was missing 266 cases meeting the required standard.

The fourth independent variable, labeled IV3, in this study is neighborhood amenities. IV3 is an ordinal continuous variable constructed using index procedures. There are 8 indicators within this index measured variable, each of them is discrete and nominal yes or no questions. Each indicator was coded in the following manner; 1 = Yes, 5 = No, 8 = Don't Know, 9 = Refused to answer and the missing value codes were 7 through 9. The indicators are as follows:

Indicator 1: Park/playgrounds/open space in the neighborhood
Indicator 2: Supermarket in neighborhood
Indicator 3: Medical clinic in the neighborhood
Indicator 4: Bank/credit union in neighborhood
Indicator 5: Check cashing outlet in the neighborhood
Indicator 6: Library in the neighborhood
Indicator 7: Police station in the neighborhood
Indicator 8: There are clubs/associations/help groups in the neighborhood

Of these, indicators 1-8 had to be recoded to, 5 = Yes and 1 = No to insure common directionality. These specific 8 indicators and the constructed variable formed by them are reliable valid and form a normal distribution. All 8 indicators were combined because they all assess what available resources are in the neighborhoods in which the respondents lived. IV3 (as seen in table 3) had a high/low score range from 40 to 8 and 10 valid values; meeting the ten value qualifications and insuring sufficient variation to be considered continuous. The mean for the dependent variable is 28.01 and the standard deviation is 7.42. The dependent variable maintained 5590 valid cases and was missing 492 cases meeting the required standard.

The interactive variable COIVIV1 is a combination of the COIV number of relatives available one can call upon for help if need be and the "dummied" variable of main romantic involvement. All in all, the results of the hypothesis that are soon to be discussed are credible because all variables meet the normality, variation, reliability, and validity requirements to conduct accurate and generalizable research.

Data Analysis

Multiple Regression, and its associated statistics (like R^2), constitute the primary statistics used to analyze the NSAL data to test the hypotheses. Multiple regression (MR) allows for the determination of the independent, *relative*, *interactive*, and *collective* effects that multiple independent variables have on a single dependent variable, and these capabilities of regression match well the nature of the questions and hypotheses that the research addresses. As noted when concluding the literature review above, the central and ultimate contribution to the existing scientific literature of our research is the unique hypothesized, *independent*, and *relatively more important* effect of the central organizing independent variable, the number of relatives a respondent could call for help if needed, for understanding our dependent variable, tendency to react violently. Granted the hypotheses of the independent effect of the number of relatives a respondent could call for help if needed is not as unique in the literature as our other hypothesis, it is important to start this research with a hypothesis that gives another perspective to the research outside what is already stated in the literature.

The idea that there is a statistically significant independent effect simply means that we can examine the effect of the number of relatives a respondent could call for help if needed, the central organizing independent variable while controlling for the other independent variables. The structural-functionalist theory, reflected by this central organizing construct, called here our central organizing independent variable, additionally, leads us to the awareness, and thus to hypothesize, that its relationship to the dependent variable, tendency to violently react, depends on the respondent's involvement in romantic relationships. This, of course, is a question of, or hypothesis about, the *interactive* effect of the number of relatives to call for help if needed and main romantic involvement on the dependent variable, tendency to violently react.

MR, also referred to as ordinary least squares linear regression or OLS regression is considered a robust test, as Borhrnstedt and Carter (1971) document, and is based on a linear (straight-line function), least squares [where the criterion of the best estimate of the regression coefficient is if its value is the one that minimizes the difference between the y-observed and y-predicted (y-hat) values for each person in the sample], model that allow researchers to explain or predict how one dependent variable regresses on several independent variables (Allison, 1999). Linearity is going to be important here, as we shall soon see, given that the regression equation is based on a straight-line function, namely: Y = a+b1x1+b2x2+bjxj, or as is more clearly seen in the simple (one independent variable) regression function y = a+b(x). Two of the most widely used parametric procedures are MR and the analysis of variance (ANOVA). Either MR or ANOVA could be considered for addressing the unique type of hypotheses that our theorizing and research uniquely bring to the table on the question of the relationship between the number of relatives one could call on for help if needed and the dependent variable, tendency to violently react. In short, regression seems ideal for statistically summarizing the data that we have that can address the hypotheses that we have.

Multiple regression (MR) was used rather than its close cousin, the Analysis of Variance for several reasons. A reading of Cohen suggests that the conventional analysis of variance model is not the ideal way to analyze the data we have because of MR's ability to look at multiple independent variables, whether discrete or continuous, at the same time while controlling for other independent variables, also either continuous or discrete. Because it can control the influence of other variables, both discrete and continuous, MR is better than ANOVA (the analysis of variance) which can only consider and control for discrete independent variables. This leaves unanalyzed rival continuously distributed independent variables.in accounting for the variance. Cohen also believed that data can be better measured and accounted for using MR to calculate the variance explained in the dependent by the set of independent variables. In particular, the use of R2 was seen as especially efficient, and unique to regression, for doing the calculation of the variance explained in the dependent variable (Cohen, 1983).

Additionally, researchers have found multiple advantages to using MR over ANOVA, chief among them that MR gives you many more statistics than ANOVA, in addition to those provided in the ANOVA summary table, which both MR and ANOVA provide. ANOVA provides a view of whether or not the aforementioned differences are significant and/or due to chance, it offers very little about the nature of that relationship. All that is known, with ANOVA, is whether a significant difference exists between groups. In addition to the residual and regression sum of squares, degrees of freedom, f-statistic, and significance level, Multiple Regression produces standardized and unstandardized regression coefficients, their standard errors, along with the direction of their relationships, confidence intervals for the unstandardized coefficients, zero-order, partial and part correlations and collinearity statistics. MR, in short, tells us if there is a difference, where the differences lie, and we can predict to what degree the group causes changes in the dependent variable. Thus, this study uses MR as it best fits the need of social scientists to account for all possible interactions between the independent variables and dependent variables.

Multiple regression is based on and only yields meaningful results when several ideal assumptions are met. These must be reasonably shown to characterize the data. Meeting these assumptions is critical because violations of these assumptions could result in data that is far removed from the type of data on which the advantages of regression are touted. The importance of the assumptions, and that our data meet the assumptions, is critical if we are to obtain the "best linear unbiased estimators, so-called" (BLUE) for the population being studied. That is since the goal of the researcher is to maintain the lowest possible sampling error, meeting the assumptions associated with MR enables one to confidently state that the findings are the "best linear unbiased estimates for the population, which in turn strengthens its reliability and validity. In short, it is critical that the seven ideal assumptions are met so that BLUE regression-related statistics, such as β, are forthcoming, thus lending credibility to the conclusions we draw, and their possible policy or programmatic implications. This section provides a discussion of the BLUE estimators that we seek, and that is guaranteed if we meet the seven ideal assumptions of MR discussed below.

Now mindful of why we want to ensure that our data meet the six ideal assumptions, to generate BLUE estimates, we now consider these assumptions: linearity; error constancy; normality; non-multi-collinearity; independent errors; and adequately specified model. For each assumption, we cover four points. First, we define what the assumption says or means. Second, we tell why the assumption is important, noting the consequence if we violate it. Third, we test to confirm whether or not this study's data meets the assumption and why or why not. Fourth we provide a statement on how the data can be corrected if an assumption is violated.

The first assumption is called the linearity assumption. The linearity assumption is concerned with establishing that a linear relationship between the variables where an increase/decrease in one variable continuously, monotonically, produces increases or decreases in the second variable. This is the straight-line function assumption, following from the straight-line function of the regression equation: $y = a+b(x)$, where we do not expect any curve, in bivariate CONTINUOUSLY DISTRIBUTED data, or downward (or upward) trending error points in multivariate CONTINUOUSLY DISTRIBUTED data. This is an important assumption because we try to fit a model to nonlinear data, we risk getting coefficients that give a model that does not fit the data. STUDENT FINISHES THIS DISCUSSION so that one understands fully why this is an important assumption.

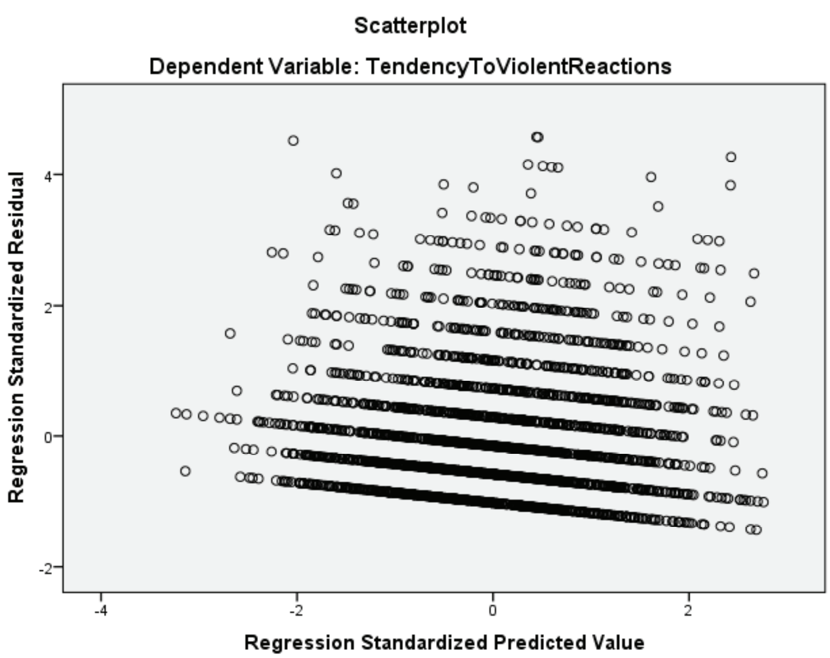
To test this assumption, we construct a residual plot (see Figure 2), a scatterplot of the standardized predicted (ψ) values for the dependent variable, plotted against the standardized residuals (Y- ψ).

Y-hat, of course, represents the linear combination of all of the independent variables, which is reflected in the Y predicted value for each person. Figure 2, is a scatterplot of the standardized residuals for the regression in this analysis, obtained by a subcommand added to the regression SPSS run, called a scatterplot, namely:

*Regression /variables=x,y,z /statistics=all /dep=z /method=enter x, y /scatterplot (*zresid,*zpred).*

Linearity can be established if most of the residuals in the plots fall randomly in or around, or more precisely, within plus or minus two deviations, from the mean. Thus, the mean of these residuals at any, and all, level(s) of y-hat is expected to be 0 (i.e., residual mean = 0 on the horizontal axis of the graph in Figure 2). Here it seems that linearity has been violated due to the appearance of multiple straight lines of data on the scatter plot. In real life, a careful researcher would

Figure 2
Residual Scatterplot of Standardized Residuals (Y- ψ) by ψ from the Regression of DV on IV's



want to possibly go back and attempt to get a better distribution even though all the variables vary with at least 10 values. Doing this might provide another, better distribution for the residuals accomplished by adding more indicators to the constructed dependent variable.

We see that the assumption of linearity is violated. Since, if the imaginary horizontal line at the zero point on the y axis, the spread of scores would not be clustered around the line, but creates a downward triangular shape, but very few plots are 2 standard deviations from the mean, as indicated by Figure 2 most cases are scattered around the horizontal line. Overall, there is a distinct cut of dots around the zero line and indicating that some residuals that fall below or above the zero line are not good predictors of linearity. This type of behavior violates linearity to some degree. However, regression is a robust procedure and can therefore accommodate minor violations (Bohrenstadt, 1971).

Additionally, we note that in correcting a more substantial violation of linearity, one could transform the data using the following equation: y = (a+bx12+bx2+bx3+bx4), which squares the data for x1, if it is determined that x1 is the reason for the nonlinearity (Bohrenstadt and Carter 1971). Also, rather than regressing y (dependent variable) on the independent variables, the syntax could be changed when entering in SPSS and could use the log of y inverse to still meet the BLUE standard (Chatterjee & Price, 2004). Thus, if I did violate one of my assumptions I could simply take the log of y to establish linearity.

The second assumption is that of the assumption of the constancy of errors, also called the assumption of homoscedasticity. This is the assumption that the dependent variable exhibits similar amounts of variance across the range of values for an independent variable. To the extent that there is not the constancy of errors, the standard errors of the regression coefficients (SEb) will be inflated. If SEb is inflated, then when dividing the regression coefficient (b) by its standard error (b/SEb) to see if b is statistically significant, will lessen the chance that we will get significance. That is t, reflecting b/SEb will be less likely to be significant. Thus, we are again missing an accurate representation of the data, and thus not getting BLUE-related regression statistics.

To test this assumption, one must examine the residual plot (Figure 2 above) and see whether or not the spread of scores or standardized residuals spread evenly across the graph. Graphically this is represented by “the degree of scatter around the regression line is roughly the same” (Allison, 1999). To determine whether or not the data violates homoscedasticity, one must closely examine the scatterplot of the residuals along the x-axis. By looking at the scatter along both the x-axis and the vertical scatter across all points along the x-axis, homogeneity is slightly violated because if the vertical scatter is not the same across all the x values, thus the variance of y at any one level of x is not constant. In the case where the variance of y at one level is not the same across all the x values heteroscedasticity is indicated and it violates this assumption as it influences the standard error of regression coefficients. In the case of this study's data, the spread of scores is constant for the most part, indicating a widespread of non-errors thus revealing a constancy of errors for the most part. To correct this in-constancy, the square root of the dependent variable could be taken (Chatterjee, 1977).

The third assumption, multivariate normality, asks the question if there is a normal distribution when we look at two or more variables at the same time. The significance of this assumption is multivariate normality is a requirement for us to analyze the F and t-tests (Chatterjee, 1977). As such multivariate normality regression is the assumption that there is a normal distribution of errors amongst the linear combination of Xs. However, unlike linearity and constancy of errors—both important assumptions—a violation of normality is not critical and there is little impact when the sample size is large enough (Bohrnstedt & Carter, 1971). We can test the assumption of multivariate normality by looking at the residual plot, above. To achieve multivariate normality, the densest point of residual plots or scores at any level of y that should be at the mean, represented by the zero. Upon observation of the scatterplot in Figure 2, this assumption has not been violated as there is a high density of scores around the mean of zero and away from the mean density, thus indicating multivariate normality. If a violation did exist under this assumption the problem can be resolved by simply increasing the number of cases, assuming you are not working with secondary data.

The fourth assumption, non-multicollinearity, is the assumption that the independent variables are not highly correlated. Rj2 should not exceed the preset limit. This assumption is important because if the independent variables are too highly correlated we are not able, mathematically, to find the inverse of the correlation matrix. Theoretically or substantively, there are also negative consequences in violating this assumption. Namely, a question will arise as to which independent variable is responsible for the change in the dependent variable to test this assumption, we want to ensure that no correlation among or between independent variable exceeds .60. Using the SPSS's regression sub-command for tolerance to examine the collinearity among variables allows us to check this assumption in our data (see Table 4).

In examining Table 4, we see that there is non-multicollinearity. We have not violated this assumption. Especially important, by examining the tolerances, specifically 1 minus tolerance, we can measure the relationship between the independent variables. As noted, tolerances are converted to r^2 (1-tolerance = r^2), at which this study obtained the following values for the independent variables:.07 for the COIV, indicating that only 7 percent of the variance in the COIV, # of relatives that would help if needed, is explained by the other IV's. .013 for main romantic involvement at the time indicating that only 13% percent of the variance in IV1, is explained by the other IVs. For IV2, neighborhood safety the value is .016, indicating that only 16% percent of the variance in IV2, is explained by the other IVs. Finally, IV3, neighborhood amenities, has a value of .013 indicating that only 13% percent of the variance in IV3, is explained by the other IVs. As indicated in Table 4, all these values are less than .60, therefore we can assume that this data meets the assumption of non-multilinearity. If however, this assumption was not met, one solution would be to make an index out of the independent variables that are correlated.

The fifth assumption of the OLS regression is that the procedures that

Table 4
Bivariate Correlation Matrix & Multivariate Tolerances/R2

Variables	*Tendency to violent reactions (DV)*	*COIV # of relatives that would help if needed*	*Main romantic involvement at the time*	*Neighbor-hood safety*	*Neighbor-hood amenities*
Tendency to Violent Reactions (DV)	1	-.044	-.078	-.120	-.033
COIV # of relatives that would help if needed	-.044	1	-.034	.061	.043
Main romantic involvement at the time	-.078	-.034	1	.08	-.076
Neighbor-hood Safety	-.129	.061	.080	1	-.077
Neighbor-hood Amenities	-.003	.043	-.076	-.077	1
Tolerance		.993	.987	.984	.987
R^2 = 1-Tolerance		.007	.013	.016	.013

we are doing and that the conclusions are based on interval/ratio measured variables. In interval measurement, the distance between attributes does have meaning. For example, when we measure temperature (in Fahrenheit), the distance from 30-40 is the same as the distance from 70-80. The interval between values is interpretable. Because of this, it makes sense to compute an average of an interval variable, where it doesn't make sense to do so for ordinal scales. But note that interval measurement ratios don't make any sense—80 degrees is not twice as hot as 40 degrees (although the attribute value is twice as large). In ratio measurement, there is always an absolute zero that is meaningful. This means that you can construct a meaningful fraction (or ratio) with a ratio variable. Weight is a ratio variable. In applied social research most "count" variables are ratios, for example, the number of clients in the past six months. Why? Because you can have zero clients and because it is meaningful to say that "...we had twice as many clients in the past six months as we did in the previous six months."

The assumption is important or significant because the data must be at the interval level when, as in the case, for example, of adding up the scores (or dividing, etc.) to calculate the regression coefficient. That is mathematical computations, like adding, only make sense or can, logically, be performed if there is a reasonably identifiable distance between data points (the values on the variable) from the measurement of the variable. Logically it does not make sense to add nominal data points. For example, the value 1, standing for male on the variable gender, added to 2 standing for female, does not make logical sense. Similarly for ordinal data problems can arise if the data is discrete so distances between data points and therefore certain calculations cannot be determined.

In testing our data to see how well we meet this assumption, we do violate that assumption with IV1, IV2, IV3, and the DV. Nevertheless, even though multiple regression works best with interval/ratio data, a continuously distributed ordinal variable may also be used as well. Continuously distributed ordinal variables allow for a measurable difference in impact to be discerned. Furthermore, nominal variables, sometimes referred to as dummy variables, because they must be changed to dummy variables to make sense of them, are used for interactive tests when combined with the COIV. This allows the researcher to tell whether a combination of variables together impact the DV significantly more than the COIV could by itself. We are also mindful, as it is stipulated, that the dependent variable is not nominal so that accurate, measurable, and valid differences between the impacts of the IVs on the DV can be discerned. As seen in Table 3, in this study the dependent variable, tendency to violently react, is a constructed variable that is continuously distributed ordinal measurement thus meeting the requirements set forth by Borgatta and Bohrnstedt. Additionally, the construction of dummy independent variable, main romantic involvement, is discretely distributed nominal. This meets the requirement set forth by Bohrnstedt and Carter.

Lastly, the sixth assumption, independent random sample, ensures that any error point for anyone respondent (in calculating Y-y-hat), is not related to any other respondent's errors term, hence the term 'independent errors.' To violate this assumption is to have data that is not like that produced when establishing the distribution of all possible values in calculating, say, the t values for testing the significance of the regression coefficient. If the data from the distribution of getting critical t is based on an independent sample, as it is, then the data for observed t (resulting from the test of b/SEb should also be from independent observations. In testing this assumption for our data, we note that one can conclude that the sample size of 6,082 was randomly selected by a probability sampling (random sampling) method called multi-stage probability sampling. The term probability sampling indicates that there is no bias because everyone in the population had an equal chance of being selected, thus reducing any errors that might suggest that the responses on any one variable are influenced by the responses of another person in responding to the same variable. Generally, independent responses lead to independent residuals from one person's predicted y value to the next person's predicted y value. Due to the probability sampling approach used in the NSAL survey, we can assume that no data point is influencing other data points thus being independent. Even if this assumption had been violated, and as long as we are not trying to make generalizations to the population of persons from whence the sample came, we can assume that the distribution that we do have is a possibly random probability sample.

Results

When looking at the bivariate correlations table it is made clear that the COIV, the number of relatives that can help if needed, has a medium strengthened statistically significant negative correlation to the DV, tendency to react violently at the .05 level; meaning that as the COIV increases the DV decreases. Table 5 displays the results of the regression analysis:

For hypothesis 1, we hypothesize that one's tendency to react violently regresses significantly on the number of relatives one has to call upon for help if needed even when accounting for the effect of neighborhood amenities, neighborhood safety, and main romantic involvement.

According to the results, we reject the null hypothesis and accept the above stated alternative hypothesis. The COIV has an unstandardized regression coefficient of -.034, meaning that DV decreases on average .034 units per 1 unit increase of the COIV, a t-value of -1.973, and the significance level of .049. This falls below the .05 significance level standard meaning the numerical entry occurs by chance and thus has a Type 1 error (α) at 5% or less. Substantively, this Beta or standardized regression coefficient is -.038, meaning that there is an average decrease in the DV of .038 of 1 standard deviation per increase in the COIV.

For hypothesis 2, we hypothesized that the variance in the tendency to violently react can be explained by the number of relatives to call for help, acting additively (cumulatively) with neighborhood amenities, neighborhood safety, and main romantic involvement. According to the results we retain the null hypothesis; the variance in the tendency to violently react is not explained by the IV's combined. The r squared value is .022 meaning that only 2.2 % of the variance is explained well under the 30% criteria needed to reject the null hypotheses and say that a substantial amount of variance is explained by the IV's combined.

For hypothesis 3, we hypothesized that the number of relatives to call for help is relatively more important than neighborhood amenities (IV3), neighborhood safety (IV2), and main romantic involvement in explaining the tendency to violently react. According to the results this we retain the null hypothesis, the number of relatives to call for help is not relatively more important than neighborhood amenities, neighborhood safety, and main romantic involvement in explaining the tendency to violently react. In looking at the statistics it is found that the COIV has a t value

Table 5
Regression Summary Table:
Regression of DV on X1, X2, X3, X4, & X1X2 (NEffective= 2670)

Model	*b*	*SEb*	*T*	*p=Sig*	βb	*R*	R^2_{Adj}	*F*
Additive Model (A)						.152	.022	15.791
X1 = # relatives	-.034	.017	-1.973	.049 -	.038			
X2 = Romantic Invo								
X3 = NSafety	-.432	.068	-6.353	.000	-.123			
X4 =NAmenities	-.021	.025	-.858	.291	-.017			
Interactive (I) (+A)						.153	.022	.667
X1X2	-.007	.009	-.817	.414	-.030			
						$F_{\text{I-A change}}$ [c]		0

of -1.973, significance value of .049, unstandardized coefficient of -.034, and standardized coefficient of -.038. IV2 (X3) has a t value of -6.353, a significance value of .000, an unstandardized coefficient of -.432, and a standardized coefficient of -.123. IV3 (X4) has a t value of -.858, a significance value of .391, an unstandardized coefficient of -.021, and a standardized coefficient of -.017. IV2 meets the less than or equal to .05 significance value criteria and thus the numerical entry occurs by chance and thus has a Type 1 error (α) at 5% or less. So for IV2, it can be said with confidence that DV regression on it is statistically significant. The COIV meets that same criterion as well however, the IV2 has a stronger effect on DV since the DV decreases on average .432 units per unit increase in IV2 and the DV has an average decrease of .123 of 1 standard deviation. IV3 does not meet that significance value criterion of .05, the numerical entry does not occur by chance and thus had a type 1 error at 39.1%. This alone takes it out of contention because we cannot say confidently that the DV regresses statically significantly on IV3. Main romantic involvement is a dummied variable so we do not consider it.

For hypothesis 4, we hypothesized that the number of relatives to call for help produces the tendency to violently react, especially for those that do have main romantic involvements, and that this interactive effect significantly extends understanding of the tendency to violently beyond that of the addictive model. According to the results, the null is retained, the number of relatives to call for help does not produce the tendency to violently react, especially for those that do have main romantic involvements, and that this interactive does not affect significantly extend understanding of tendency to violently beyond that of the addictive model. Statistically, the interactive variable COIVIV1 has a significance value of .414, t value of -.817, unstandardized coefficient of -.007, and standardized coefficient of -.030; not meeting the criteria of less than or equal to .05 meaning that the numerical entry does not occur by chance, and thus has a Type 1 error (α) at 41.4%. This means that the DV does not regress significantly on the interactive variable COIVIV1. Also, the interactive variable COIVIV1 when combined with the other IV's only has an R-squared value of .022; the same value as the IVs acting independently of it. This means that even when including the interactive variable, 2.2 % of the variance in the DV is explained as falling well below the 30% criteria. Also, the F change statistic is zero, showing no change between when the interactive variable is added.

Discussion

Overall, the number of relatives one has to call on for help if needed can explain to some extent one's tendency to violently react. Relatively, the COIV, the number of relatives one has to call for help if needed is not the most important variable in explaining one's tendency to violently react, neighborhood safety is. The interactive variable, the combination of the COIV, # number of relatives one could call for help if needed, and IV1, main romantic involvement does not extend understanding of the DV, tendency to violently react.

The statistics confirm that the theory concerning family availability, utilizing structural-functionalist ideology, does hold some truth concerning its possible determination of whether one will tend to react violently in situations. However, it may not play an important part as the theory would suggest. As the literature review mentioned, drugs already have been known to be connected to violent tendencies and the situations that bring them about. In this research, the variable, neighborhood safety, took account for this and the results supported its already considered importance. The amenities in one's neighborhood were not a significant factor, however, limitations concerning population and the fact that the data was collected in the early 2000s may play a part in this.

Practically, if the U.S. is going to continue to attempt to lower violent incidents within the African American community, it must continue to support and develop, on all governmental levels, helpful programs. Without acknowledgment and addressing factors that may increase the likelihood of violent reactions violence may never decrease. These programs must attempt to address family availability for support as well as the drug issues that are rampant throughout the United States in African American communities. Initiatives such as the African American Family & Cultural Center opened in 2011 as an MHSA funded collaboration between Youth for Change and the Butte County Department of Behavioral Health in California and those similar to it across the nation need more support if any headway is going to be made.

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