Violence by Male Partners against Women during the Childbearing Year: A Contextual Analysis

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ABSTRACT

Objectives. Many contextual analyses that bridge the micro-level–macro-level gap in identifying risk factors for adverse outcomes have not used methods appropriate for multilevel data. The purpose of this paper is to illustrate the application of appropriate multi-level analytic methods and discuss their implications for public health.

Methods. A previously published individual-level model of physical violence perpetrated by male partners during the childbearing year was reanalyzed to include variables describing the neighborhoods where the women resided. Logistic regression with estimation methods of the generalized estimating equation was used for the contextual analysis. To assess the advantages of the generalized estimating equation over conventional logistic regression, both were used for the two-level model.

Results. The regression coefficients from the contextual model differed from the betas obtained in the individual-level model. Not only were neighborhood-level variables related to the risk of partner-perpetrated violence, but the presence of these macro-level variables in the models modified the relationships of the individual-level variables to the risk of violence.

Conclusions. Two-level models that include individual- and community-level factors may be beneficial for purposes of explanation in public health research. (*Am J Public Health.* 1995;85:1092–1097)

Introduction

There is increasing recognition in the public health literature of the importance of social factors in influencing individual behaviors and health outcomes.[1–14] Social factors shown to influence health outcomes include poor housing conditions,[5] neighborhoods with high levels of unemployment and poverty, neighborhoods that are racially segregated,[6,7,11] and neighborhoods with high crime rates.[12]

Within the violence literature, especially the research on victimization, the study of neighborhood characteristics is gaining prominence.[2,13] Smith and Jarjoura,[2] for example, studied 57 residential neighborhoods and found that, in addition to individual-level characteristics, household- and community-level characteristics were important predictors of the risk of victimization.

Analyses that include both individual-level data and macro-level information are referred to as "contextual" or "multilevel" models.[15–17,18] Contextual models differ in purpose and analytic technique from unmixed models (i.e., individual-only or ecological models).[8,19] Multilevel models, used often in fields outside of public health,[16,18] are advantageous because they allow for the simultaneous examination of individual- and macro-level risk and outcome factors.[8,16,18,19]

Multilevel models with two or more levels of information should be analyzed with appropriate statistical methods that explicitly acknowledge the different levels of data.[15,16,18,20] The utility of multilevel or ecologic models and the appropriate analytic methods for such models have recently been the topic of considerable discussion.[8,15,18,19,21–23]

An issue that frequently has been overlooked in contextual analysis is the implication of these models for public health policy or intervention development. For example, although such multilevel models may provide a greater understanding regarding the risk factors for a given outcome than individual-level models, how relevant are multilevel models for the development of public health interventions? Will these newer models reveal the neighborhoods in which certain interventions are most needed? How are the results of multilevel models best used by public health practitioners? To what extent can public health interventions or policies be expected to target the macro-level social factors included in contextual analyses? These questions, along with others, must be resolved if public health researchers and practitioners are to maximize the benefits of using the new methods.

The purpose of this paper is to use a specific example of an important public health problem—violence against women—both to illustrate the application of appropriate multilevel analytic methods and to raise the level of discussion about the implications of such an approach for public health practice. In a previously published study, we examined factors that were important individual-level predictors of the risk of interper-

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sonal violence during the childbearing year (i.e., pregnancy and postpartum).[24] For physical violence perpetrated by male partners, being older and having adequate social support from relatives and friends were protective for the outcome. Having greater than a high school education and having a male partner who used drugs were risk factors for experiencing physical violence. That analysis, however, was based primarily on information available about the women's characteristics. We present here an extension of that model that includes a number of social class and environmental neighborhood-level risk factors for interpersonal violence. We expected that low socioeconomic neighborhoods characterized by stressful living conditions (e.g., high crime or poor housing) would increase the risk of partner-perpetrated violence. Low social class status has been associated with higher rates of several types of violence.[25–27] Our measure of overall neighborhood crime was considered an indicator of a stressful living environment. It was hypothesized that higher crime areas would be associated with an increased risk of partner-perpetrated violence. Finally, these neighborhood factors were chosen because they are from routinely available data sources and, thus, can easily be incorporated into future contextual studies on violence.

We were specifically interested in answering the following research questions regarding contextual analyses and interpersonal violence: (1) Does the addition of macro-level data on neighborhoods to models of interpersonal physical violence change the magnitude of the individual-level risk factors? (2) Are there neighborhood-level variables that are related to an increase or decrease in risk of partner-perpetrated physical violence toward women? and (3) Do the findings of a contextual analysis alter the implications for the development of interventions and policies that would otherwise be inferred from an individual-level analysis?

Methods

Sample and Data Collection

The present study involved a reanalysis of a previously published investigation of partner-perpetrated physical violence during the childbearing year.[24] In that study, data from 182 low-income women living in an urban area were analyzed. Among the 182 women included, 157 gave a Baltimore City residential address. This residential address was then coded for census tract. The remaining 25 women either gave a non–Baltimore City address of residence (i.e., one of the surrounding counties or out of state) or gave a post office box as an address and thus had to be eliminated from the present analysis. The 157 women were no different from the total sample on any demographic characteristics, including the rate of partner-perpetrated violence.

Data on physical violence were collected through personal and telephone interviews during the third trimester of pregnancy and at 6 months postpartum. Information on census tracts or neighborhoods was obtained from 1990 census data and from the Maryland Department of Economic and Employment Development. Additional details on the sampling methodology and data collection can be found in the earlier paper.[24]

Outcome Variable

The Conflict Tactics Scale is a widely used measurement tool that provides a systematic method of data collection and a meaningful classification system for differentiating events that range from mild interpersonal conflict to severe violence. We used this scale for the present study and followed the conventional classification system to differentiate those events that have a high probability of causing injury ("moderate and severe violence") from those that do not. The scale items are listed below. In both interviews, respondents were asked whether, in the previous 6 months, "any of the following things happened when you were having an argument with someone else close to you." They were then asked whether someone (1) insulted them or swore at them; (2) made them cry; (3) threatened to hit or throw something at them; (4) threw something at them; (5) pushed, grabbed, or shoved them; (6) slapped them; (7) kicked, bit, or hit them with a fist; (8) hit or tried to hit them with something; (9) beat them up; (10) threatened them with a knife or gun; or (11) used a knife or fired a gun.

Each yes response was followed up with an item that assessed the perpetrator for each occurrence. Up to three different perpetrators could be coded. A woman was considered as experiencing partner-perpetrated moderate or severe physical violence if she responded yes to any of items 4 through 11 and identified her male partner (boyfriend, husband, partner) as the perpetrator. The final sample included women who either had experienced moderate or severe episodes of partner-perpetrated physical violence or had experienced no physical or verbal violence at all. (Women who experienced negative verbal interaction only were eliminated from the previous and present analyses to maximize the contrast between the violence and no-violence groups.)

Individual-Level Independent Variables

Independent variables that were hypothesized to be either risk factors or protective factors for partner-perpetrated physical violence included social support, partner drug use, and selected demographic variables.

Three social support scales were created from individual interview items: (1) friend support (availability of emotional support from friends), (2) family support (availability of emotional support from family members), and (3) instrumental support (availability of instrumental support). Each scale could range from 1 to 4 (4 representing a high degree of support). Cronbach's alpha coefficients were .88 for the friend support scale, .89 for the family support scale, and .73 for the instrumental support scale. A fourth component of social support was the availability of two types of confidants: the woman's male partner or a close relative.

Demographic variables (age, marital status, education, employment status, income, parity, and race) were assessed at the initial interview. Because characteristics of the partner could be equally or more important than characteristics of the woman in explaining risk of interpersonal violence, the partner's drug use was also included in the analysis.

Neighborhood-Level Independent Variables

Census tract data were used to describe the neighborhoods. Baltimore City has 198 residential census tracts, and women from our study came from 76 of those census tracts. Data obtained from the 1990 census included average per capita income for each of the 76 tracts and the ratio of home ownerships to rentals. Unemployment rates for 1989 for the 76 census tracts were obtained from the Maryland Department of Economic and Employment Development. All three of these variables were used in the analysis

TABLE 1—Characteristics of Women with Neighborhood-Level Information

Factors	Sample
Individual level	
Partner-perpetrated violence, %	38
Age, %	
18–20 y	32
20–24 y	31
25–30 y	25
>30 y	17
Employed, %	25
Married, %	10
Education, %	
Less than high school	41
High school	51
Greater than high school	8
Other children, %	71
African American, %	93
Male partner as confidant, %	9
Other relative as confidant, %	72
Drug-using partner, %	11
Family support score, mean (SD)	3.2 (0.46)
Friend support score, mean (SD)	2.7 (0.50)
Instrumental support score, mean (SD)	3.3 (0.43)
Neighborhood level	
Per capita income, %	
<$8000	48
$8001–$11 000	33
$11 001–$13 500	11
≥$13 500	8
Per capita crime rate, mean (SD)	0.13 (0.20)
Unemployment rate, mean (SD)	9.5 (3.7)
Ratio of home owners to renters, mean (SD)	1.0 (1.15)

Note. Data were available for 157 women in 76 neighborhoods.

as measures of neighborhood social class. More than one measure was desirable because each of these indicators may have captured different aspects of well-being or deprivation. Multicollinearity was not a problem because the correlations between these three indicators ranged from .25 to .40. Since the effect of income was not likely to be a linear one, a categorical variable was created for average per capita income. This was accomplished by dividing the average per capita income for the city as a whole into four equally sized categories of approximately 49 census tracts each. The per capita income cutoffs for these quartiles are presented in Table 1. Unemployment rates and ratio of home owners to renters were kept as continuous variables. Per capita crime rates were based on 1990 data from Baltimore City's Division of Planning. Six categories of reported crime were aggregated to create an indicator of overall crime: robbery (both armed and unarmed), homicide, theft, burglary, rape, and aggravated assault. Overall crime was hypothesized to be an indicator of environmental stress.

Statistical Analysis

Results for the individual-level model were obtained from our previously published analysis of factors associated with risk of partner-perpetrated physical violence during the childbearing year.[19] This analysis involved multivariate logistic regression of several individual-level risk factors for partner-perpetrated moderate or severe physical violence during the childbearing year. For the multilevel model, we supplemented our individual-level data with information on the neighborhood (census tract) where the woman resided. For the two-level analyses, we then performed both conventional logistic regression and logistic regression using estimation methods of the generalized estimating equation.[28] Model-building techniques were used for the generalized estimating equation logistic regression. Only those neighborhood-level variables that were statistically significant were retained in the model. Once this "best-fit" model was identified, the same model was fit with conventional logistic regression estimation methods. These models are shown in Table 2.

A central assumption in contextual analyses is not only that environments can influence individual-level outcomes but that people from similar environments or neighborhoods will be more alike than people from different neighborhoods.[18] The reasons for the similarities—sometimes called unobserved shared environmental factors—between people from the same neighborhoods are not fully captured by macro-level covariates in regression models. These unobserved factors are the source of correlation between women from the same census tract (i.e., autocorrelation).[28] When autocorrelation is present, the independence assumption of conventional regression techniques is violated. To account for this potential lack of independence in our data, we used estimating methods of the generalized estimating equation, which was originally developed for use with family and longitudinal studies in which high correlations between family members or longitudinal observations caused problems in parameter estimation. Use of the generalized estimating equation for data with natural clustering is advantageous even if the data involve relatively low levels of autocorrelation, as ours do. It should be noted that, given the nature of our data (i.e., lack of independence due to the presence of several women from the same neighborhood), the estimates of the confidence intervals for the conventional logistic regression method are incorrect. The reason is that autocorrelation affects the estimates of the standard errors of the betas.[28] These confidence intervals are presented in Table 2 for comparison purposes only. The final two-level models were compared to determine whether the estimates of betas from the two methods would differ and to determine the degree of autocorrelation. If no autocorrelation was operating for our independent or dependent variables, then the beta estimates for the two methods should be virtually identical.

Parameter estimates obtained from the generalized estimation equation for binary outcomes are straightforward in their interpretation, which is equivalent to the interpretation for the beta and standard errors derived in logistic regression. Thus, one can obtain odds ratios and confidence intervals from the equation.

Results

The demographic and risk characteristics of the women included in our analyses are presented in Table 1. The average family support score for women in our sample was 3.2 ± 0.27 (SD) (on a scale ranging from 1 to 4). For friend and instrumental support, the average scores were 2.7 (±0.50) and 3.3 (±0.43), respectively. Because our sample was a low-income population, 48% were from neighborhoods in the lowest quartile of per capita income (<$8000). However, 11% and 8% were from neighborhoods that had per capita incomes in the second highest and highest quartiles of income, respectively. The average unemployment rate in the census tracts where the women in our sample resided was 9.5% (±3.7%), in comparison with the city average of 6.7% (±4.37%). In our sample, the average proportion of renters was equal to the proportion of homeowners, whereas the city rate was higher (1.43 ± 1.32). The

TABLE 2—Odds Ratios (ORs) and Confidence Intervals (CIs) for the Models Used

Characteristic	Logistic Regression Individual-Level Model[a] OR (95% CI)	Two-Level Logistic Model (Generalized Estimating Equation) OR (95% CI)	Two-Level Conventional Logistic Model[b] OR (95% CI)
Individual			
Age	0.326* (0.156, 0.680)	0.405* (0.246, 0.667)	0.398* (0.226, 0.703)
Employment	0.417 (0.139, 1.252)	0.930 (0.408, 2.123)	0.923 (0.321, 2.653)
Marital status	1.624 (0.296, 8.903)	1.372 (0.301, 6.257)	1.624 (0.296, 8.903)
Education	2.535* (1.115, 5.765)	1.916*** (0.932, 3.942)	2.064*** (0.918, 4.641)
Parity	0.871 (0.535, 1.417)	1.357 (0.801, 2.299)	1.279 (0.824, 1.986)
Race	0.341 (0.065, 1.785)	9.387* (1.827, 48.226)	7.216** (1.097, 47.455)
Confidant: male partner	0.211 (0.041, 1.073)	0.711 (0.133, 3.802)	0.705 (0.135, 3.683)
Confidant: relative	0.294* (0.098, 0.882)	0.641 (0.208, 1.978)	0.762 (0.253, 2.298)
Family support	0.204 (0.025, 1.683)	0.946 (0.358, 2.502)	0.405 (0.098, 1.684)
Friend support	0.253** (0.066, 0.976)	0.401* (0.220, 0.733)	0.375** (0.145, 0.966)
Other instrumental support	1.938 (0.229, 16.400)	1.655 (0.622, 4.400)	1.829 (0.457, 7.315)
Partner drug use	24.778* (4.149, 148.00)	14.620* (3.774, 56.643)	12.498* (2.630, 59.397)
Neighborhood			
Ratio of home owners to renters[c]	. . . . .	1.785*** (0.939, 3.391)	1.937*** (0.967, 3.881)
Unemployment rate[d]	. . . . .	3.423* (1.305, 8.979)	4.785* (1.586, 14.435)
Per capita income less than $13 500	. . . . .	4.405** (1.064, 18.182)	4.902 (0.356, 66.667)

Note. Data were based on 76 neighborhoods. Reference groups for the seven indicator variables are as follows: not employed, not married, African American, male partner not a confidant, other relative not a confidant, no partner drug use, per capita income of $13 500 or more.

Source. Logistic regression individual-level model data are reproduced from Table 5 of Gielen et al.[24], copyright 1994, with permission from Elsevier Science Ltd, The Boulevard, Langford Lane, Kidlington OX5 1GB, UK.

[a]Adjusted for locus of control and personal income, neither of which were statistically significant.

[b]The beta estimates are the only valid estimates; confidence intervals cannot be correctly estimated through conventional logistic regression methods. These confidence intervals are presented for comparison purposes only.

[c]The odds ratios are for a census tract with a ratio of 1.43 in comparison with 1.0.

[d]The odds ratios are for a census tract unemployment rate of 12% in comparison with 6%.

*$P < .01$; **$P < .05$; ***$P < .10$.

average annual per capita crime rate was 13 events per 100 persons.

Individual-Level Model vs Two-Level Generalized Estimating Equation Model

Table 2 presents the results for risk of interpersonal violence from the individual-level and two-level regression models. We focus here on comparing the results from the individual-level model with those from the two-level generalized estimating equation model. Many of the odds ratios for individual-level factors changed with the addition of neighborhood-level factors in the model. The effects of the individual-level variables on the risk of partner-perpetrated violence, with the exception of race, were diminished with the addition of the neighborhood-level variables. For example, when the neighborhood-level variables were added to the model, the protective effect of age was reduced by 21% [1 − (0.40 ÷ 0.33)]. Similarly, the risk associated with increasing education was reduced by 32%. The risk associated with having a partner who used drugs was reduced substantially by 41%. The most dramatic change occurred with the race variable. With the addition of the neighborhood variables, the risk associated with being White changed from a nonsignificant risk to a statistically significant odds ratio greater than nine.

Certain neighborhood-level characteristics increased the risk of partner-perpetrated physical violence. Living in neighborhoods in the lowest percentile of per capita income involved a risk more than four times that of living in neighborhoods in the highest percentile of per capita income. It should be noted that this effect was independent of individual-level income. When individual-level income was included in the models, it was not significant. On the other hand, the risk of partner-perpetrated violence also increased as the ratio of home ownership to rental units (and presumably social class) increased; this relationship was not significant, however, at the $P = .05$ level. Living in neighborhoods with high unemployment increased the risk of partner-perpetrated violence. The odds ratio was 3.4 for neighborhoods with an unemployment rate of 12% relative to neighborhoods with an unemployment rate of 6%. The per capita crime rate was the only neighborhood-level variable that was not statistically significant in our model. Interactions in our model between individual- and macro-level variables were explored, but none were detected.

Conventional Logistic Regression vs Generalized Estimation Equation Logistic Regression for Analysis of Two-Level Models

The only valid comparisons that could be made between the two methods involved the estimates of beta, because the standard error estimates in conventional logistic regression require that the observations be independent. There were observable differences between the beta estimates and confidence intervals for the two methods. For many variables (e.g., marital status, race, family support, unemployment, and per capita income), parameter estimates differed noticeably by method of estimation. Also notable were the differences seen for per capita income; this variable was statistically signifi-

cant in the generalized estimating equation model but was not significant in the logistic regression two-level model.

Discussion

Our findings indicate that, for our previous individual-level model of partner-perpetrated physical violence, the extent of confounding by contextual-level variables was selective in that only 3 of the 11 variables were affected. Having a relative as a confidant, which was statistically significant in the individual-level-only model, lost significance in the mixed model. The reason for this confounding is not readily apparent. However, it suggests that the neighborhood characteristics in our two-level model affected the relationship between confidant and risk of partner-perpetrated physical violence.

Also, in the two-level model, the risk of partner-perpetrated physical violence for White women was nine times the risk for African American women. In the individual-level-only model, this relationship was nonsignificant, suggesting that the absence of neighborhood-level variables results in substantial confounding. These findings must be interpreted with caution because the odds ratios were based on relatively small numbers of White women, resulting in a wide confidence interval. Furthermore, race is a complex variable capturing a wide array of social factors.[29] Future studies might undertake a more careful conceptualization and measurement of factors related to race.[29]

The confounding effect of the neighborhood-level factors was also apparent for the partner's drug use variable, although again there were relatively few women with drug-using partners. The odds ratio associated with partner's drug use was reduced from almost 25 to 15 by the addition of the neighborhood-level variables to the model.

Including neighborhood-level information substantially improved the explanatory model for partner-perpetrated risk, as evidenced by the statistically significant relationships of the contextual variables in the mixed model. Three of the four neighborhood-level factors—ratio of home owners to renters, high per capita income, and unemployment rates—were significantly associated with risk of partner-perpetrated violence in the generalized estimating equation two-level model. All of the significant neighborhood-level factors were indicators of social class. This finding is consistent with other reports in the literature indicating that economic strain may contribute to an increased risk of domestic violence.[30] Including several indicators of social class may be advantageous in building better explanatory models. Our study focused on data that are routinely available so that such indicators might easily be incorporated into future studies. However, including information on other types of neighborhood attributes and processes not routinely available might be useful. Information on the availability of services for women in battering situations, as well as the availability of such services in churches, community groups, or social networks, may further enhance our understanding of risk and protective factors for partner-perpetrated violence.

Per capita crime rates were not associated with partner-perpetrated violence. It may be that overall crime is a poor indicator of environmental stress. Furthermore, partner-perpetrated violence, determined to a large degree by interpersonal factors, may be less influenced by the environmental factors that contribute to high overall neighborhood crime. Alternatively, environmental stress, as measured by overall crime rates, may not increase the risk of partner-perpetrated violence.

Although our data show that macro-level factors are associated with an increased risk of partner-perpetrated violence, further research is needed to better understand the mechanisms by which neighborhood-level factors affect individual outcomes. For example, it is not clear whether the stress of unemployment is a causal factor in male-perpetrated violence or a proxy for other macro-level or individual-level factors in the pathway to domestic violence.

Differences between the beta estimates for conventional two-level logistic regression and the generalized estimating equation two-level model were notable for selected variables. These differences were observed despite the relatively low level of autocorrelation in our data. Thus, use of the generalized estimating equation was advantageous even for our data. For cluster data in which higher levels of autocorrelation are expected (e.g., data on an outcome such as an infectious disease within a cluster), differences in results between logistic regression estimates and the generalized estimating equation should be even greater.

Our particular example suggests that the performance of a contextual analysis, relative to that of an individual-level-only analysis, would not substantially alter implications for the design of individually targeted interventions. On the other hand, the finding that neighborhood-level variables made a substantial contribution to the risk of partner-perpetrated violence suggests that targeting individual-level factors without consideration of social conditions may minimize the effectiveness of the effort. In our data, the individual-level findings suggest that enhancing women's social support might be an effective intervention strategy. While this factor remained important in the multilevel models, the significance of unemployment and low income suggests that such an intervention strategy could be enhanced by including efforts to increase employment opportunities.

Finally, neighborhood-level information in contextual analyses could be used to identify communities with different risks for partner-perpetrated violence. Moreover, when intervention resources are scarce, neighborhoods involving a higher risk of partner-perpetrated violence could be more heavily targeted with appropriate interventions. In our example, neighborhoods experiencing high economic deprivation (as indicated by high unemployment rates), in particular, might be targeted for interventions. Thus, contextual analyses not only are useful for improving on our explanatory models but might be used in future needs assessments for the planning and implementation of public health programs. □

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References

1. Collins JW Jr, David RJ. The differential effect of traditional risk factors on infant birthweight among blacks and whites in Chicago. *Am J Public Health.* 1990;80:679–681.
2. Smith D, Jarjoura G. Household characteristics, neighborhood composition and victimization risk. *Social Forces.* 1989;68:621–640.
3. Haan M, Kaplan G, Camacho T. Poverty and health: prospective evidence from the Alameda County Study. *Am J Epidemiol.* 1987;125:989–998.
4. Feldman J, Makuc D, Klineman J, Cornoni-Huntley J. National trends in educational differentials in mortality. *Am J Epidemiol.* 1989;129:919–933.
5. Smith S. Health status and the housing system. *Soc Sci Med.* 1990;31:753–762.
6. Laveist TA. Segregation, poverty, and empowerment: health consequences for

African Americans. *Milbank Q.* 1993;71(1): 41–64.
7. Peterson R, Krivo L. Racial segregation and black urban homicide. *Soc Forces.* 1993;71:1001–1026.
8. Susser M. The logic in ecological: I. the logic of analysis. *Am J Public Health.* 1994;84:825–829.
9. Gould J, LeRoy S. Socioeconomic status and low birth weight: a racial comparison. *Pediatrics.* 1988;82:896–904.
10. Brewster K, Billy J, Grady W. Social context and adolescent behavior: the impact of community on the transition to sexual activity. *Soc Forces.* 1993;71:713–740.
11. Palisi B, Ransform H. Effects of urbanism, race, and class on happiness and physical health. *Sociol Spectrum.* 1987;7:271–295.
12. White M, Kasl S, Zahner G, Will J. Perceived crime in the neighborhood and mental health of women and children. *Environment Behav.* 1987;19:588–613.
13. Miethe T, McDowwall D. Contextual effects in models of criminal victimization. *Soc Forces.* 1993;71:741–759.
14. Crane J. The epidemic theory of ghettos and neighborhood effects on dropping out and teenage childbearing. *Am J Sociol.* 1991;96:1226–1259.
15. Von Korff M, Keopsell T, Curry S, Diehr P. Multi-level analysis in epidemiologic research on health behaviors and outcomes. *Am J Epidemiol.* 1992;135:1077–1082.
16. Bryk A, Raudenbush S. *Hierarchical Linear Models.* Newbury Park, Calif: Sage Publications; 1992.
17. Iverson G. *Contextual Analysis.* Newbury Park, Calif: Sage Publications; 1991.
18. Hox J, Kreft I. Multilevel analysis methods. *Sociological Methods Res.* 1994;22:283–299.
19. Schwartz S. The fallacy of ecological fallacy: the potential misuse of a concept and the consequences. *Am J Public Health.* 1994;84:819–824.
20. Rashbash J. *ML3 Software for Three-Level Analysis.* London, England: Institute of Education, University of London.
21. Poole C. Ecologic analysis as outlook and methods. *Am J Public Health.* 1994;84:715–716. Editorial.
22. Piantadosi S. Ecological biases. *Am J Epidemiol.* 1994;139:761–764.
23. Cohen B. In defense of ecologic studies for testing a linear-no threshold theory. *Am J Epidemiol.* 1994;139:765–768.
24. Gielen A, O'Campo P, Faden R, Kass N, Xue N. Determinants of interpersonal violence during the childbearing year. *Soc Sci Med.* 1994;39:781–787.
25. Reiss A, Roth J, eds. *Understanding and Preventing Violence.* Washington, DC: National Academy Press; 1993.
26. Rosenberg M, Fenley M, eds. *Violence in America: A Public Health Approach.* New York, NY: Oxford University Press Inc; 1991.
27. Stokols D. Establishing and maintaining healthy environments: toward a social ecology of health promotion. *Am Psychol.* 1992;47:6–22.
28. Zeger S, Liang KY, Albert P. Models for longitudinal data: a generalized estimating equation approach. *Biometrics.* 1988;44: 1049–1060.
29. Williams DR, Lavizzo-Mourey R, Warren RC. The concept of race and health status in America. *Public Health Rep.* 1994;109:26–41.
30. Gelles R, Cornell C. *Intimate Violence in Families.* 2nd ed. Newbury Park, Calif: Sage Publications; 1990:110.