THE WORKSHOP

Statistical Inference in Contextual Analysis

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Political science research in a number of areas is concerned with the effects of contextual explanatory variables. Unfortunately, most past contextual research is seriously flawed by problems of statistical inference that can produce false and misleading results. This paper attempts to equip contextual researchers with a necessary understanding of the main statistical issues involved in contextual analysis. After outlining the basic problems of statistical inference, the paper provides an empirical example that shows strong contextual effects.

Social science research that examines the effect of characteristics of individuals' environments on the individuals' behavior or attitudes has come to be known as "contextual analysis." At first glance, contextual analysis might appear to be primarily a concern of sociologists, and indeed, some of the classics of sociological research (e.g., Durkheim, 1951) investigate the impact of social environment on individuals' behavior. However, the diversity of contextual analyses in the political science literature establishes the importance of contextual analysis within political science.[1] Published research has included contextual analyses of voting, other forms of political participation, partisanship, and local and national political attitudes.[2]

Because of the importance of contextual analysis within political science research, it is critical that researchers increase their understanding of the statistical problems involved in this type of multilevel analysis. Most past research is seriously flawed by one or more problems of statistical inference. In this paper we will attempt to equip contextual researchers with a necessary understanding of the main statistical issues involved in

[1] See Sprague and Westefield (1977) for a fairly comprehensive review of past contextual research in the field of political behavior.

[2] In addition, studies of legislative committees, courts, and other political organizations often involve explanatory variables at several levels and can encounter the same statistical problems as contextual analyses of the behavior of individuals. For example, Atkins and Glick (1976) tried to explain the proportion of different types of cases state courts adjudicate; they included explanatory variables not only for court characteristics but also for political and socioeconomic characteristics of the state.

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contextual analysis. After outlining the basic problems of statistical inference, we will provide an empirical example that shows strong contextual effects and also illustrates several ways that poor analysis can generate spurious effects.

Development of Statistical Methods of Contextual Analysis

Methodological discussions of contextual analysis have appeared primarily in the sociological literature, and only recently have sound statistical methods of contextual analysis been developed. The heavy reliance of modern sociology and political science on survey research for data collection has inhibited the study of contextual effects. Survey research methods are well-suited for collecting data on individual-level characteristics, but not on characteristics of individuals' social and political environments. Some sociologists (e.g., Coleman, 1961) expressed dismay at this individualistic bias, and attempts were made to apply survey research methods to the study of contextual effects, such as the three "climate of opinion" studies published in *Public Opinion Quarterly* (Davis, 1961; Michael, 1961; Levin, 1961). Awareness of contextual analysis as a formal analytic method was stimulated by Blau's (1960) analysis of the job performance of welfare caseworkers as a function of both individual orientations and aggregate work-group orientations. Davis, Spaeth, and Huson (1961), in a manner similar to Blau, formalized a method for examining the independent effects of individual-level and contextual variables.[3] Social science appeared to be progressing in its understanding of how to empirically study the effects of social and political context on individuals' behavior and attitudes.

However, the viability of contextual research soon came under attack. Tannenbaum and Bachman (1964) sharply criticized the cross-tabular techniques of analysis recommended by Blau and Davis et al. and showed that such techniques could easily produce findings of spurious contextual effects. Hauser (1970) illustrated the potential of cross-tabular analysis to produce spurious contextual results and went even further in criticizing the soundness of contextual analysis in general. The Hauser article precipitated considerable debate and comment (e.g., Barton, 1970; Farkas, 1974), including a further indictment of contextual analysis by Hauser (1974).

More recent publications (e.g., Alwin, 1976; Firebaugh, 1979; Boyd and Iversen, 1979) have finally clarified the main methodological issues and eliminated much of the prior confusion. It is now clear that the early methodological criticism of contextual analysis exaggerated the severity

[3] See Boyd and Iversen (1979, pp. 15–19) for a lucid summary and critique of the Blau and Davis et al. approaches to contextual analysis.

and uniqueness of the relevant problems of statistical inference and sometimes created the impression that strong contextual effects do not exist except as artifacts of inadequately controlled individual-level effects. Although contextual analysis does encounter some difficulties not encountered in purely individual-level analysis, valid contextual inference is within the ability of empirical social researchers to understand and execute.

Basic Problems of Statistical Inference in Contextual Analysis

This section outlines and explains the basic statistical issues researchers must understand to undertake valid contextual analyses. For a comprehensive discussion of the methodological details of doing contextual analysis, including an appendix showing computer procedures using the Statistical Package for the Social Sciences (SPSS), researchers should refer to Boyd and Iversen (1979).

The statistical objective of contextual analysis is to estimate the parameters of models of the form:

$$Y = f(X_1, X_2 \ldots X_n, C_1, C_2 \ldots C_m) \qquad \textbf{(Eq. 1)}$$

where:

Y = a dependent variable describing the individual
X_i = independent variables describing the individual
C_i = independent variables describing one or more political or social contexts of which the individual is a member

Note that what distinguishes contextual analysis is the attempt to statistically isolate the effects of contextual variables, independent of individual-level variables.[4] The individual is the unit of analysis, with necessary contextual data appended to the individual-level data.

For data in nonexperimental research the contextual variables are usually statistically associated with the individual-level independent variables.[5] Indeed, the contextual variables of interest may be analogues of in-

[4] A different research objective that should not be confused with contextual analysis is the estimation of individual-level parameters from aggregate data. As Firebaugh (1978) shows, when contextual effects are not present the researcher can compute unbiased estimates of individual-level parameters from aggregate data; similarly, if individual-level effects are not present the researcher can estimate contextual parameters from aggregate data. However, in general, aggregate data confound individual and contextual effects. Recent publications (e.g., Hanushek, Jackson, and Kain, 1974; Burstein, 1978; Firebaugh, 1978; Boyd and Iversen, 1979) have addressed related issues concerning cross-level inference and data aggregation and have corrected the misleading statement of Robinson (1950).

[5] Typically, only nonexperimental, cross-sectional data are available for analyzing contextual effects, since political scientists and sociologists seldom have the experimental control to randomly assign subjects to different political or social contexts. Occasionally, quasi-

dividual-level independent variables—such as neighborhood racial composition and an individual's race—and therefore tend to be highly statistically related as a result of social segregation. The high correlations often found among independent variables in contextual analysis exacerbate the estimation problems of specification error, measurement error, multicollinearity, and simultaneity.

Specification and Measurement Errors

Assume that we have data that have been generated by a model that is the linear form of the general contextual effects model given in Equation 1:

$$Y = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n + d_1C_1 + d_2C_2 + \ldots + d_mC_m \quad \textbf{(Eq. 2)}$$

Ordinary least squares regression will, in general, produce unbiased estimates of the coefficients (b_i and d_i) of this model only if the independent variables (X_i and C_i) are errorless and are all included in the regression.[6]

If an independent variable in the regression contains random measurement error, then its coefficient estimate will be biased toward zero and we will tend to underestimate its effect on the dependent variable. The larger the error component, the larger will be the bias. In addition, other independent variables that are correlated with the variable containing measurement error will also have biased coefficient estimates. The magnitude of this bias depends on (1) the strength of the effect of the error-containing independent variable on the dependent variable, (2) the amount of measurement error, and (3) the correlations between the imperfectly measured variable and the other independent variables. We can think of this bias as the result of the other independent variables picking up some of the lost explanatory power of the error-containing variable because they are correlated with it and can thus serve as surrogate measures.

If one of the independent variables is not included in the regression, the effect is like an extreme case of random measurement error. The lost explanatory power of the omitted variable biases the coefficient estimates of correlated independent variables. Such omission, and any other incorrect formulation of the regression model, is referred to in the econometrics literature as a specification error.

Like random measurement error, systematic measurement error can

experimental, longitudinal data may be available, such as data on student achievement scores before and after racial integration of schools.

[6] For more detail than provided in the next three paragraphs about the effect of specification and measurement errors, see Kmenta (1971), Wonnacott and Wonnacott (1970), or other econometrics texts.

also create bias. Whereas random errors are statistically unassociated with the variable's true value,[7] systematic errors introduce distortions that cause the actual measure to be nonlinearly related to the true variable. A common source of systematic error results from measuring a continuous variable into discrete values or categories. Systematic measurement error can not only bias the coefficient estimate for the error-containing variable but can also bias coefficient estimates for correlated independent variables by interfering with the predictive power of the error-containing variable.

Specification Error. Researchers interested only in the effects of contextual variables often make the specification error of omitting relevant individual-level variables from their analysis. Omission of individual-level variables that affect the dependent variable will bias coefficient estimates for correlated contextual variables. This prompted Hauser (1970, p. 621) to argue that "it is possible to generate 'contextual effects' at will" and that "their magnitude will be inversely proportional to the adequacy and completeness of the underlying model of relationships among individual attributes." Thus, contextual analysts must carefully consider not only what contextual variables, but also what individual-level independent variables, need to be included in the model.

The political science literature is replete with examples of purported contextual effects that are probably artifacts of inadequate specification of individual-level effects. For example, during the 1950s and 1960s there was a great deal of speculation that the increasing suburbanization of the United States would lead to a Republican majority. This speculation was based upon the assumption that the suburban social and political environment caused conversion to Republicanism. The large suburban majorities won by Eisenhower in the 1952 and 1956 elections provided support for this assumption. Yet when Deborah Hensler carefully analyzed the effect of suburban versus central-city residence on political attitudes, she concluded that

> our failure to find measurable independent locale effects on attitudes, once we have "partialled out" the effects of individual attributes, suggests that the dynamics of attitude formation in urban and suburban populations are the same. The suburban "climate of opinion," while different from that of the city, does not seem to play a significant role in determining individual political orientations. Suburbanites' attitudes are different from those of their urban counterparts because of the kinds of people they are, *not* because of where they live. (Wirt et al., 1972, pp. 129–30)

The differences between suburbanites and central-city residents that had

[7] The most common model of random measurement error considers the measured value the sum of the true value and an uncorrelated error term.

been observed by previous researchers were artifacts of a failure to specify the individual-level effects of social class and ethnicity.

Another type of specification error important in contextual analysis is misspecification of the variable representing a relevant contextual characteristic. Erbring and Young (1979), for example, have criticized the use of contextual variables that are group means. The naive use of group means, or any other contextual variable calculated from an individual-level variable, certainly deserves criticism. Researchers must carefully consider how to best represent the relevant contextual characteristics as variables in the model, and then should strive to develop empirical measures that represent as closely as possible the contextual effects expected according to theory. Some contextual variables of theoretical interest in political science research, in fact, are not derived from individual-level variables but rather are contextual characteristics, such as type and size of government.

When the relevant contextual characteristic does concern the distribution of an individual-level trait in a group in which the individual is a member, the analyst should carefully consider what it is about the distribution of that trait that is relevant. Perhaps what matters is not the central tendency, but rather the spread. For example, a sociologist studying the effect of economic diversity in a group on interpersonal tension might use a contextual measure of heterogeneity, such as the standard deviation of log income.[8] If both the central tendency and the spread have theoretical significance, the researcher might also use a measure of central tendency, such as mean log income. Since the standard deviation across contextual units often has a low correlation with the mean, researchers can quite practically include both as variables in a regression equation.

Even if the researcher decides a measure of central tendency is theoretically appropriate, the mean may not be the best measure. For example, suppose a political scientist wishes to study the relationship of neighborhood income level to political participation. Mean income would probably have a very skewed distribution and be nonlinearly related to social status, and it would also be highly sensitive to outliers. Median income, log mean income, or log median income might therefore be preferred.

If the contextual effect being studied results from a process of social influence, then the use of a mean (or log mean) value contextual variable may imply unrealistic influence processes, as Erbring and Young (1979, pp. 400–402) argue. For influence-mediated contextual effects, using a

[8] Using the standard deviation of the logarithm of income would probably be preferable to using the standard deviation of income, since the standard deviation of income tends to naturally increase with income.

mean value contextual variable implies that the individual is influenced by all other individuals in the contextual unit for which the mean value is computed. However, as Sprague (1975) points out, the units for which contextual data are available often differ from the theoretically desired units. For example, census tract data may be used instead of data on individuals' immediate neighborhoods. Thus, the totality of individuals in the contextual unit of observation in such cases may not correspond to the individuals causing the contextual effect. For practical purposes of research, this divergence is serious only if the relevant individuals are highly unrepresentative of the total population in the contextual units of observation. When enough social segregation exists to create fairly homogeneous contexts, then the mean values for the observational units, even for units as large as census tracts, may be so strongly correlated with the mean values for the relevant individuals that the practical difference for research is negligible.

In some analyses a mean value contextual variable may not represent an influence-mediated contextual effect, but rather a contextual effect resulting from another mechanism. For example, contextual effects may result from perceptions of different political and social environments, which we term perception-mediated contextual effects. Erbring and Young (1979, p. 403) suggest, as an example of another type of contextual effect mechanism that is essentially a specification error, that mean socioeconomic status of a school may be related to school resources that affect students' educational performance. Thus, mean value contextual variables may be proxies that represent the true causal variables, and their observed effects would disappear if the true causal variables were measured and included in the regression equation along with the mean value variables.

Using mean value variables that are proxies does not distress us as much as it does Erbring and Young (1979). Many variables in social science research are not clear, simple measures, but rather indicators of one or more underlying variables. Common individual-level variables like race or age, for example, serve as proxies for differences in socialization, cultural background, developmental experiences, and other factors. Even experimental research is not immune to the problem of interpreting observed effects, since disagreement often exists about what was really manipulated that caused the observed effect. In contextual analysis, as in all social research, the researcher must either (1) obtain measures of the true variables, or (2) recognize that the measured variables are proxies and try to understand what the observed effects of these variables represent. Since measurement problems often preclude obtaining direct measures of the theoretically desired variables, proxy variables play a vital role in research. Contextual research using mean value proxy variables can yield important findings and stimulate further research to clarify the mechanism through which the observed effects operate.

An alternative to estimating the effects of explicit quantitative contextual variables is to use dummy variables to estimate the net contextual effect for each context.[9] The first approach yields estimates of the independent effects of each contextual variable, whereas the second approach confounds the contextual effects in single estimates of the net effect for each context. Nonetheless, the dummy variable method does offer the advantage of feasibility when the contextual component of the model cannot be well specified because (1) data on the contextual variables are unavailable, (2) the appropriate contextual variables are unknown, or (3) there are too few contexts.[10] Implementing the dummy variable approach requires only the relevant individual-level data, and knowledge of the context in which the individual is a member. Therefore, the dummy variable approach can be a useful exploratory tool when limitations of data or theory prevent fully specifying a contextual model.

Measurement Error. Contextual analysts often create needless measurement error and resulting statistical bias by categorizing continuous independent variables.[11] Much of the published contextual analysis in the political science literature suffers from this problem because of the use of cross-tabular (contingency table) analysis and other analytical techniques requiring categorization (e.g., Orbell and Uno, 1972). Tannenbaum and Bachman (1964) have demonstrated how categorization and cross-tabulation can produce apparent but erroneous effects at both the individual and contextual levels. Also, since cross-tabular analysis severely limits the number of independent variables the analyst can include at one time, it is likely to produce specification errors through omission of relevant explanatory variables. Contextual researchers, therefore, should usually

[9] Given n contexts, the analysis would include $n - 1$ dummy variables, representing $n - 1$ contexts, allowing one context to be the reference. Alwin (1976), Firebaugh (1979), and Boyd and Iversen (1979, p. 11) contrast this dummy variable approach to the use of explicit quantitative measures, referring to them as covariance analysis and contextual analysis, respectively.

[10] As we shall discuss later, the number of contexts limits the number of contextual variables that can be included in the model. Given n contexts, the model can include no more than $n - 1$ contextual variables, regardless of the number of individuals from each context, because n or more contextual variables will be linearly dependent.

[11] Since even truly continuous variables can be measured in practice only with finite accuracy, some discontinuity inevitably exists in the relationship between a true continuous variable and its actual measure. Researchers should try to measure continuous variables with fine enough categories to make the categorization error small compared to other sources of measurement error.

avoid cross-tabulation and instead use multiple regression.[12] Continuous individual-level variables (e.g., income) that have strong correlations with the contextual variables and may have strong effects on the dependent variables should be measured with high precision, not with just two or three categories.[13] Code values should be assigned to appropriately represent such variables' effects in the model, and existing code values in survey data sets should be scrutinized to avoid gross transformation errors due to inappropriate coding schemes.[14]

In order to minimize measurement error due to inappropriate contextual units of observation, researchers should attempt to obtain data for units that correspond as closely as possible to the theoretically desired units. For contextual effects resulting from processes of social influence, contextual units of observation smaller than such typically available units as census tracts are desirable, so as to better correspond to the individuals causing the influence-mediated contextual effect. On the other hand, contextual effects resulting from different perceptions of one's environment might require larger units of contextual observation. For example, a study of factors affecting citizens' evaluations of how desirable their city is as a place to live should use city-level contextual variables. The desirable contextual unit of observation for perception-mediated contextual effects therefore depends on the perceptual referent.

A particularly insidious type of measurement error unique to contextual variables results from their estimation from sample data. For example, suppose a researcher has interview data for 1,000 respondents from 100 city blocks with a fixed cluster size of ten. The researcher might estimate the mean years of education for each block by computing the average years of education for the ten respondents in each cluster, and then proceed to regress an individual-level dependent variable on the respondent's years of education and the estimated mean years of education of the block in which the respondent lives.

Although estimating contextual values from sample data is a convenient method of obtaining contextual data, it produces sampling error in the contextual variable that is correlated with the individual-level variable. This in turn leads to violation of these basic assumptions of the linear regression model: (1) the disturbance (error) term for any observation

[12] Logit, probit, and discriminant analysis provide analogous methods for dichotomous and polytomous dependent variables.

[13] Assuming a rectangular (even) distribution of the true variable, categorization error variance as a proportion of the true variance can be shown to be $1/n^2$, where n is the number of categories. Therefore, as a rough rule of thumb about five categories are needed to limit the categorization error to less than 4 percent of the variable's variance.

[14] See Hensler and Stipak (1979).

is uncorrelated with the disturbance for all other observations, and (2) the disturbance is uncorrelated with the independent variables.[15] Violation of these assumptions results in inefficient, biased, and inconsistent estimates of the parameters of the model (Kmenta, 1971, pp. 269–78, 499–508; Wonnacott and Wonnacott, 1970, pp. 136–40, 149–53). The fewer cases there are in a cluster, the more sampling error there is in the cluster estimate, and the worse the violation of the statistical assumptions. The contextual analyst can eliminate the problem of correlated error by excluding each case from the estimation of its value of the contextual variable.[16] In the above example, the analyst would compute separately for each case the mean years of education for the other cases in the cluster and use this value as the estimated block mean years of education for the case. However, this approach is only palliative, since it does not eliminate sampling error, and contextual analysts should use more reliable contextual data from independent sources whenever possible. If the analyst does plan to estimate contextual variables by aggregating individual-level independent variables, enough cases should be sampled from each context to reduce the sampling error to the level of other sources of measurement error.

Multicollinearity

Perfect multicollinearity will result if the analyst attempts to estimate as many contextual effects as there are contexts. To understand why, recall that n variables are linearly dependent over n or fewer cases, and that the number of explanatory variables in a model must be less than the number of independent observations from which their effects are estimated. This seldom poses a problem in purely individual-level analysis, since survey data sets typically have a large number of cases. However, in contextual analysis the number of contextual units of observation, not the number of cases, limits the number of contextual explanatory variables, because individual cases within a context have the same values on the contextual variables and are not independent observations. Therefore,

[15] The error of estimate of the contextual independent variable (mean block years of education) is correlated with the individual-level independent variable (the respondent's years of education) because a respondent with more years of education than the true block mean contributes a positive error to its estimate, and a respondent with fewer years of education than the true block mean contributes a negative error. Since errors of measurement become part of the disturbance term in the linear regression model (Wonnacott and Wonnacott, 1970, p. 165), the disturbance for a given case is correlated not only with both the individual-level and contextual independent variables for that case but also with the disturbances for all other cases drawn from the same cluster.

[16] This procedure prevents the value of the individual-level independent variable for a case from contributing to the error of estimate of the contextual independent variable for that case.

in order to avoid perfect multicollinearity the number of contextual units of observation in the data must exceed the number of contextual independent variables in the model.

Because perfect multicollinearity will result from attempting to estimate as many contextual effects as there are contexts, the contextual analyst has limited ability to disentangle the effects of different contextual variables if there are only a few contexts. In the case of only two contexts, one contextual variable serves as well as any other, since there is no empirical basis for choosing one variable over another as an explanation of the intercontext difference. Unless the analyst obtains data for more contextual units, multivariate contextual analysis is not possible, and the contextual component of the model is not likely to be well specified or tested. In such cases the analyst may have to resort to an exploratory analysis using the dummy variable approach described earlier.

Multicollinearity can also pose problems for contextual analysis when independent variables are highly intercorrelated, even though not perfectly collinear. High multicollinearity among the independent variables increases the standard errors of the coefficient estimates and creates intercorrelations among the coefficient estimates of the independent variables (Kmenta, 1971, pp. 387–89; Wonnacott and Wonnacott, 1970, pp. 257–59). The greater the multicollinearity among the independent variables, the less precisely can the analyst estimate their separate effects, and the more highly correlated will be the deviations of their coefficient estimates from the true population values. Since high cross-level correlations often exist between individual-level and contextual explanatory variables, contextual analysis often suffers from relatively less precision of estimation due to multicollinearity, in addition to spurious transfers of estimated effects between individual-level and contextual variables. For example, assume that an individual-level variable has a strong positive effect and a very highly positively correlated contextual variable has no effect. Because of the high intercorrelation, one sample might produce coefficient estimates showing no individual-level effect and a positive contextual effect, whereas another sample might instead show an overly strong positive individual-level effect and a negative contextual effect, and a third might produce roughly correct coefficients. However, because multicollinearity also increases the estimated standard errors for the coefficients, the contextual analyst is not any more likely to make an incorrect statistical inference. High multicollinearity simply entangles the effects of the explanatory variables and decreases the researcher's ability to separate the effects of contextual variables from highly correlated individual-level variables, but it does not increase the likelihood of inferential error.

Contextual researchers should avoid creating artificial problems of multicollinearity by including in a regression equation several contextual variables that are alternative measures of the same underlying variable. For example, mean log housing value and mean log family income of census tracts are for most purposes simply alternative measures of economic affluence. Including both as independent variables in a regression equation would result in much larger standard errors for their coefficient estimates, compared to including either one variable or the other. In such cases the contextual analyst can combine the alternative measures of the single explanatory variable to form a single measure to enter into the model, thus avoiding artificial multicollinearity and minimizing measurement error.

We should not overestimate the severity of the problem generally posed by multicollinearity in contextual analysis. Two independent variables must have a correlation over .75 to increase the standard errors of their regression coefficients by as much as 50 percent over what they would be if the variables were uncorrelated.[17] Thus, serious problems with multicollinearity are generally encountered only when correlations among the independent variables exceed this level. In our experience, individual-level and social context variables are usually not so strongly correlated.

The only solution for contextual analysts facing real problems of high multicollinearity is to obtain more data because the basic problem is the lack of sufficient statistical information to differentiate the effects of the independent variables. For example, an analyst studying racial issues may want to differentiate the effect of a respondent's race (black versus white) from the effect of the proportion black in the respondent's neighborhood. Since the individual-level and contextual race variables are probably correlated very highly, the analyst must either obtain a large sample or else sample so as to overrepresent whites in black neighborhoods and vice versa.

Simultaneity

In some contextual analyses the individual-level dependent variable may possibly affect the context in which the individual is a member. Hauser (1974, pp. 373–74) refers to this as selection on the dependent variable. For example, educational researchers might want to estimate the effects of school characteristics on students' educational performance; however, Hauser (1974, pp. 373–74) warns that a simultaneous effect of

[17] In the trivariate regression model with two explanatory variables, the variances of the coefficient estimates are inversely proportional to one minus the squared correlation between the two explanatory variables (Kmenta, 1971, p. 388).

the dependent variable on the independent variable might be present if low-income parents of gifted children choose their residence to allow their children to attend the presumedly better schools serving higher income families. Armor (1972, p. 112) similarly warns about the difficulty of contextual inference when self-selection is present—such as families of high-achieving students choosing to live in integrated neighborhoods—and argues that self-selection may account for the Coleman study's finding (Coleman et al., 1966, pp. 29, 331) that integrated black students had higher achievement than segregated students.

Simultaneous causal relationships like these can bias coefficient estimates (Wonnacott and Wonnacott, 1970, pp. 155–58), resulting in false contextual findings. To use Hauser's example, estimating a single-equation model that regresses educational achievement on family income, a school-level measure, and other predictors, could spuriously attribute effects to the contextual income measure that in reality result from the selection process. If the contextual analyst thinks the dependent variable may have a substantial simultaneous effect on a contextual independent variable, perhaps as a result of individuals' locational decisions, then the analyst must use a simultaneous equation model rather than a single-equation regression model.

Overview

We have attempted to outline the basic problems of statistical inference in contextual analysis and to suggest ways analysts can avoid or minimize these problems. Realistically, these types of problems exist to some degree in all nonexperimental social research. It would be foolhardy to declare a model free of specification and measurement error. Since some multicollinearity almost always exists in nonexperimental data, specification and measurement errors tend to bias parameter estimates throughout the model. Specification and measurement errors can easily create false apparent effects for contextual variables when correlated individual-level variables have strong effects, and false individual-level effects can result when correlated contextual variables have strong effects. Contextual researchers should therefore view suspiciously weak estimated contextual effects for variables that correlate highly with explanatory variables showing stronger effects. Through awareness of these problems of statistical inference, contextual researchers can attempt to minimize bias and avoid being misled by the inevitable bias that does occur.

Empirical Illustration

To illustrate some of the issues concerning statistical inference discussed above, we will present an analysis of the effect of neighborhood social characteristics on residents' evaluations of their neighborhoods. This example shows strong, unambiguous contextual effects. It also demonstrates that when strong contextual effects exist, spurious individual-level effects can result from inadequately accounting for contextual variables in the analysis.

The analysis uses a data set of merged survey and census data for the Los Angeles metropolitan area. The survey data are from the Los Angeles Metropolitan Area Survey (LAMAS), conducted by the UCLA Institute for Social Science Research in 1972. LAMAS employs a stratified, area probability sample of Los Angeles County, and the sample size in this analysis is 1,017. Census data from the 1970 Census of Population and Housing, fourth count data, were merged with these survey data. Thus, for each case (respondent) the data set contains both survey data about the respondent and census data about the respondent's census tract.

The dependent variable is a four-item scale measuring residents' evaluations of their neighborhoods. A factor analysis of a large set of items, all concerning perceptions of the respondent's neighborhood, showed that four neighborhood evaluation items were strongly associated with one principal component. The four items obtained evaluations of the respondent's neighborhood in terms of (1) safety for the respondent and his family, (2) available recreational facilities, (3) the quality of the public schools, and (4) an overall evaluation of the neighborhood as a place to live.[18] Because these four items empirically define a single dimension, and because they tap different aspects of perceived neighborhood quality, they were combined to form a general neighborhood evaluation scale. The estimated scale reliability (Cronbach's alpha) is .65, indicating that about 35 percent of the scale variance results from random error. The summated scale was divided by four to return it to the original five-point scale units of its component items.[19]

Table 1 presents the estimation results for three different regression equations.[20] The first equation regresses the neighborhood evaluation scale on sociodemographic characteristics of the respondent: the logarithm (base ten) of the respondent's family income,[21] the respondent's

[18] The Appendix provides the exact item wording.

[19] The five response categories for each were coded with rank-order numbers from one for least positive to five for most positive.

[20] The estimated standard errors in Table 1 are only approximations, since they assume simple random sampling. However, judging from Frankel's (1971) findings about design effects for partial regression coefficients, these approximations are probably reasonable.

[21] Using a logarithmic transformation, rather than a linear term, implies that equal proportional changes in income, rather than equal dollar changes, have equal effects on

TABLE 1
Regression of Neighborhood Evaluation Scale on (1) Individual-Level Variables Only, (2) Tract-Level Variables Only, and (3) Both Individual-Level and Tract-Level Variables

Independent Variables	(1)	(2)	(3)
Log Income	.32 (.06)		.04 (.06)
Education	.022 (.007)		.006 (.007)
Black Dummy	-.39 (.07)		.16 (.11)
Spanish Dummy	-.14 (.06)		.12 (.07)
Log Median Income		1.6 (.2)	1.5 (.2)
Median Education		-.01 (.03)	-.01 (.03)
Proportion Black		-.37 (.09)	-.55 (.15)
Proportion Spanish		-.58 (.16)	-.68 (.17)
R	.33	.49	.49

Note: Table entries are the estimated unstandardized partial regression coefficients, with their associated standard errors in parentheses.

number of years of education, a dummy variable for black respondents, and a dummy variable for Spanish-surname respondents.[22] The second equation regresses the evaluation scale on contextual sociodemographic variables corresponding to the individual-level sociodemographic variables used in the first analysis: the logarithm (base ten) of the median family income in the respondent's census tract, the median number of school years completed by adults 25 years of age or older, the proportion tract population black, and the proportion tract population Spanish-surname. The results for both the individual-level only and the tract-level only analyses both reveal strong apparent effects, and all coefficient estimates except for median education are statistically significant (.05 level). However, only a naive researcher would consider these results strong evi-

evaluations. A logarithmic representation of income is generally preferable to a linear representation since, for a number of reasons, income has a diminishing marginal effect on behavior and attitudes. First, economic well-being increases nonlinearly with income because of assistance programs and progressive taxation. Second, utility is usually a nonlinear function of income (e.g., see Hamblin, Clairmont, and Chadwick, 1975). Finally, in our own empirical investigations we have found that the relationship of income to political attitude scales, controlling for other variables, is approximately logarithmic. In contrast, the relationship for respondent education is linear.

[22] The black dummy equals one for blacks and zero otherwise, and the Spanish dummy equals one for Spanish-surname and zero otherwise.

dence of either real individual-level or contextual effects, since both the individual-level variables and the contextual variables must be included simultaneously in the analysis in order to estimate their independent effects.

Before estimating the final regression equation, we tested for interactions between the individual-level and tract-level variables. Perhaps the proportion black residents in a neighborhood affects black respondents differently than white or Spanish-surname respondents. Similarly, perhaps the effect of the proportion of Spanish-surname residents also depends on the respondent's race, and the effect of neighborhood income level may depend on the respondent's income. Tests for these interactions showed no significant interaction effects.[23] The impact of neighborhood racial composition on respondents' neighborhood evaluations appears the same for all racial groups, and the impact of the level of neighborhood affluence does not depend on the respondent's own economic level.

The third regression equation (Table 1) regresses the neighborhood evaluation scale on the individual-level and the tract-level variables. The estimation results show no strong individual-level effects, in contrast to the results for Equation 1, but the coefficient estimates for the contextual variables are about the same as for Equation 2. The apparent individual-level effects found when estimating Equation 1 result from the specification error of failing to include the contextual variables. This specification error allows the individual-level variables to spuriously show false effects due to the correlated contextual variables. Thus, the individual-level income and education variables show effects resulting from the uncontrolled predictive power of contextual income, and the individual-level race variables show effects due to the corresponding contextual race variables.

Since the individual-level variables have little independent effect on the dependent variable, failing to include them in the tract-level only regression does not cause serious bias.[24] However, without estimating the combined individual-level and tract-level regression, the analyst could not know that the individual-level variables had no substantial independent effects.[25] Making contextual inferences solely on the basis of the tract-

[23] Interaction terms were computed for the log income and log median income variables, the black dummy and proportion black variables, and the Spanish dummy and proportion Spanish variables. These interaction terms were entered into the regression equation containing both the individual-level and tract-level variables, and their resulting coefficient estimates were small and not statistically significant.

[24] Whether irrelevant variables (variables having no effect on the dependent variable) are included in a regression equation does not change the expected value of the coefficient estimates for the other explanatory variables but does affect the sampling variance of the estimates (Kmenta, 1971, pp. 396–99; Wonnacott and Wonnacott, 1970, p. 312).

[25] Because the variance explained by the tract-level-only regression greatly exceeds the

level regression would be foolish and, for other analyses, could result in false findings for contextual variables due to omitting relevant individual-level variables.

This example also illustrates the effect of multicollinearity, in addition to the effect of specification error. First, it is because of the high correlations between the individual-level and tract-level variables that misspecifying the model by omitting the contextual variables seriously biases the coefficient estimates for the individual-level variables. Second, high correlations between some individual-level and tract-level variables noticeably decrease the precision in estimating those variables' effects when both individual-level and tract-level variables are included. Because of the high cross-level correlation (.83) between the black dummy and proportion black variables, the standard error for the black dummy variable increases from .07 to .11, and the standard error for the proportion black variable increases from .09 to .15. The next highest cross-level correlation, between the Spanish dummy and the proportion Spanish, is much smaller (.48) and only results in slight increases in the standard errors. Thus, although multicollinearity decreases the precision of estimate, with large sample sizes moderately high cross-level correlations need not decrease precision sufficiently to prevent identifying strong contextual effects.

In this example, the contextual unit of observation is the census tract. A larger unit would probably be less appropriate, since for many respondents even a census tract may be considerably larger than their conception of a neighborhood. In that case, using a larger contextual unit would increase measurement error, resulting in a lower correlation between the contextual variables for the contextual units of observation and the contextual variables for the theoretically desired contextual units (i.e., the perceived neighborhood for each respondent). We explored the consequences of introducing more measurement error of this type by reestimating the combined individual-level and contextual regression model, but replacing the tract-level variables with contextual variables for the respondent's city.[26]

When city-level variables replace the tract-level variables in the regression equation, the multiple correlation drops from .49 to .46. Thus,

variance explained by the individual-level-only regression, the analyst knows that the contextual variables have some substantial effects independent of the individual-level variables. However, determining whether the individual-level variables have substantial effects independent of the contextual variables necessitates estimating both the individual-level and contextual effects simultaneously.

[26] A dummy variable for Los Angeles City, and a variable for the logarithm of city population, were also included.

the measurement error introduced by using a larger contextual unit reduces the predictive power.[27] The proportion black variable no longer shows a statistically significant effect, and some of the lost explanatory power of the contextual variables is spuriously transferred to the individual-level variables. Whereas none of the coefficient estimates for the individual-level variables are statistically significant in Equation 3, the new coefficient estimates for the individual-level log income, education, and black dummy variables are highly statistically significant.[28] Although the magnitude of the coefficient estimates diminishes when the city-level variables are entered, compared to the estimates of the individual-level only regression, they still appear to have substantial, statistically significant effects. Only the use of tract-level variables sufficiently reduces measurement error in the contextual variables to eliminate significant individual-level effects. In short, this example illustrates how measurement error resulting from an inappropriate contextual unit of observation can cause underestimation of real contextual effects and also create false apparent individual-level effects.

Although city-level variables appear less appropriate than tract-level variables for the neighborhood evaluation example, smaller contextual units are not always preferable. Indeed, if the dependent variable were an evaluation of characteristics of the respondent's city, rather than the respondent's neighborhood, city-level contextual variables would seem more appropriate. Since the LAMAS survey included an item asking respondents whether or not they thought their local government was run the way it should be, we regressed this variable on the individual-level and city-level variables. We then compared the results (not presented) to a regression of the government evaluation variable on the individual-level and tract-level variables. The comparison shows that the city-level variables predict better than the tract-level variables. Three of the city-level variables, compared to only one of the tract-level variables, have statistically significant coefficient estimates, and the city-level coefficients have much larger absolute values. Thus, an inappropriate choice of context, whether too large or too small, reduces the predictive power of the contextual variables and biases coefficient estimates.

Interpretation of Contextual Effects

Whether interactions exist between corresponding individual-level

[27] When the equation is estimated for the contextual variables only, the multiple correlation drops from .49 to .36. This decrease occurs despite the inclusion of two new contextual variables, as indicated in the prior footnote.

[28] The new coefficient estimates for the log income, education, and black dummy variables are .26, .021, and -.26, respectively, with corresponding t statistics of 4.1, 2.9, and -3.4.

and contextual variables will sometimes be crucial for interpreting the meaning of contextual effects. For example, a researcher might hypothesize that, due to racial prejudice, people prefer to have neighbors of their own race. Similarly, people might prefer to have neighbors of approximately their own economic level. In such cases, the effect of the contextual race or income variables will depend on the corresponding individual-level variables. However, since this analysis of neighborhood evaluations did not find interaction effects, the effects for the contextual race and income variables do not appear to result from prejudice against neighbors of other racial and economic groups.

This analysis has established that neighborhood attributes do affect residents' evaluations of their neighborhoods and that any effects due to residents' personal sociodemographic characteristics are in comparison very small. Some characteristics of high minority, low income neighborhoods cause more negative evaluations, even for low income, black, and Spanish-surname respondents.[29] Taylor (1979, p. 35) has argued that social disorganization found in black neighborhoods lowers neighborhood satisfaction, and perhaps the contextual black, Spanish-surname, and income variables should be interpreted as indicators of social disorganization and disruption. Alternatively, their predictive power may stem from their empirical relationship to housing quality, density, local amenities, quality of public services, or some other characteristics of low income, high minority areas. Further contextual research could be undertaken to better define the cause of the observed contextual effect. By appending data for measures of social disorganization (e.g., crime rates), housing quality, and other characteristics hypothesized to be important, the researcher could estimate a more fully specified contextual model and could attempt to identify more specifically the neighborhood characteristics causing the contextual effect. Thus, even in areas of contextual research lacking either well-developed theory or ready availability of contextual data, initial findings can both be of interest in their own right and offer direction for further research to clarify the mechanism through which the observed contextual effects operate.

Contextual effects can operate through several types of mechanisms. Most discussions of contextual analysis assume that contextual effects operate through interpersonal influence (e.g., Przeworski, 1974). That is, interacting with other individuals in the context causes behavioral or attitudinal changes in the individual. Such effects are variously termed the

[29] Consistent with the findings of this analysis, survey data have found that most blacks prefer integrated rather than all black neighborhoods (Farley, Bianchi, and Colasanto, 1979, p. 104; Pettigrew, 1973, p. 44).

results of group culture, climate of opinion, or behavioral contagion.[30] However, in contrast to influenced-mediated contextual effects, other contextual effects operate through perceptions of one's environment. Perception-mediated contextual effects occur for dependent variables, such as the neighborhood evaluation scale used in the empirical example, that refer to perceived characteristics of the individual's context.

Influence-mediated and perception-mediated contextual effects differ in the conditions under which strong contextual effects are likely. Strong influence-mediated effects will appear only when strong and mutually reinforcing processes of interpersonal influence operate within the contextual units. Such processes are most likely within small, socially homogeneous, highly integrated primary groups. Under other conditions we expect that influence-mediated effects will be weak, explaining little variance in the dependent variable. Strong perception-mediated effects, on the other hand, are not similary restricted, since they can appear whenever the contextual variables in the analysis are statistically related to perceptually salient aspects of the contextual characteristics to which the dependent variable refers. Moreover, the individual need not be socially integrated within a context, such as a political jurisdiction, in order to have a cognitively well-founded attitude toward that context, and hence for perception-mediated effects to exist.

Whereas the potential problem of simultaneity can complicate the interpretation of influence-mediated contextual effects, this complication seldom arises for perception-mediated effects. For example, a political sociologist studying political conservatism might investigate whether living in more politically conservative areas increases individuals' political conservatism. However, an apparent finding of an influence-mediated contextual effect due to living in politically conservative areas could potentially be a spurious result of more conservative individuals choosing to move to politically conservative areas. Perception-mediated effects are usually free from such problems of interpretation, since the dependent variable refers to a political or social context in which the individual currently resides, not to a characteristic of the individual that is autonomous of the context and could potentially affect the choice of context of residence.

Political scientists may sometimes want to interpret the significance of contextual effects for public policy.[31] Many types of public policies af-

[30] Some researchers use the term *behavioral contagion* to refer to the effect the behavior of others has on an individual's behavior (e.g., Sprague and Westefield, 1979).

[31] See Stipak (1980) for a discussion of the relevance of contextual analysis to public policy. Stipak shows that the implications of contextual effects for public policy depend not only on the strength of the effects but also on their functional form.

fect the integration of sociodemographic groups in different settings. Undoubtedly the most salient examples in the United States today concern racial integration of schools and housing. Some policy proposals seek to directly use governmental authority to manipulate the social context, partially on the justification that influence-mediated effects exist that affect outcome variables. For example, interschool busing of school children changes the racial composition of schools, on the assumption that influence-mediated contextual effects resulting from school racial composition affect educational performance. The classic Coleman report (Coleman et al., 1966) attempted to estimate the effect of school racial composition on educational achievement, in order to provide information for policy making concerning school integration.

Contextual analyses of perception-minded contextual effects can also address important policy issues. For example, if opposition to housing integration results primarily from pure racial prejudice, rather than perceived characteristics actually existing in higher minority neighborhoods, the argument (Pettigrew, 1973) that integrated housing will erode such opposition may seem more plausible. However, the analysis of neighborhood evaluations presented earlier found that characteristics of high minority areas affect all racial groups the same way, which suggests that housing integration will not change negative evaluations of high minority areas as places to live unless other perceived negative characteristics also change.

Contextual analysis can potentially provide, by investigating the effects of different types of social integration, empirical guidance for progressive public policy. This contrasts sharply with the conservative bias of research purely at the individual level. Research that reports only on the effects of such variables as an individual's attitudes, education, and race —which are difficult or impossible to change—can offer little guidance for social progress. However, by predicting the consequences of changing the organization of people in society, research can potentially have some progressive impact.

Conclusion

Through awareness of the basic problems of statistical inference in contextual analysis, researchers can minimize bias due to avoidable specification and measurement errors. Past critics of contextual analysis have rightly criticized blatant errors like omission of obvious individual-level explanatory variables and the use of cross-tabular analysis and other techniques requiring categorization of continuous variables. Such errors are inexcusable, and any contextual analysis deserving credibility must avoid them.

Researchers should also maintain an appreciation of how easily spurious contextual effects can result. Since contextual analyses almost always need to separate the effects of highly correlated but theoretically distinct independent variables, contextual analysis is generally more methodologically demanding than purely individual-level analysis. False contextual findings and interpretations can result not only from blatant, inexcusable errors, but also from more subtle difficulties, as we have discussed. Through appreciation of these difficulties, astute contextual researchers will not only minimize bias but will also be less easily misled by the inevitable bias that does occur in nonexperimental research.

Methodologically competent contextual analyses can make several important contributions to social research. Contextual analyses can potentially discover strong contextual effects and can direct further research to clarify the mechanism through which the contextual effects operate. Also, contextual analysis can prevent erroneous findings for individual-level explanatory variables. When strong contextual effects exist, as in the case of the neighborhood evaluation example, spurious individual-level effects can result from not including the contextual variables in the analysis. Finally, the results of contextual research can have relevance for public policy and can potentially aid in formulating progressive social policies, in contrast to the conservative bias of purely individual-level research.

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APPENDIX

Text of Survey Items

At the beginning of the interview, the respondent was asked what name he used to refer to his neighborhood.

> The Los Angeles area is composed of many cities, sections, and neighborhoods. What is the name of this neighborhood? (probe: When you tell other people what neighborhood you live in, what name do you usually use?)

In the subsequent questions referring to the respondent's neighborhood, the neighborhood name the respondent provided was used for those respondents who provided it, and the phrase "this neighborhood" was used for respondents who did not provide a name. This choice is indicated below in parentheses.

Safety

Thinking about the amount of crime that occurs in your neighborhood, the type of crime, and the quality of police protection, how safe is (name/this neighborhood) as a place for you and your family to live? Would you say very safe, safe, fairly safe, unsafe, very unsafe?

Recreational Facilities

Think about the number of recreational facilities in (name/this neighborhood) and their quality. Compare these to recreational facilities in other neighborhoods and cities in the Los Angeles area. [Interviewer shows respondent a card with the response categories.] Do you think the facilities in (name/this neighborhood) are better than those in most other neighborhoods, better than those in some other neighborhoods, about the same as those in most other neighborhoods, worse than those in some other neighborhoods, worse than those in most other neighborhoods?

Public Schools

Think about the public schools the children from this neighborhood attend. How would you rate the quality of public education in this neighborhood compared to other neighborhoods and cities in the Los Angeles area? [Interviewer shows respondent a card with the response categories.] Would you say that the quality of public education is better than in most other neighborhoods, better than in some other neighborhoods, about the same as in most other neighborhoods, worse than in some other neighborhoods, worse than in most other neighborhoods?

Overall Evaluation

Thinking about everything in (name/this neighborhood), do you think it is a very good place to live, a good place to live, a fair place to live, a bad place to live, a very bad place to live?

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