

Can King's Ecological Inference Method Answer a Social Scientific Puzzle: Who Voted for the Nazi Party in Weimar Germany?

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Geographers, unlike other social scientists, have not paid much heed to the problem of ecological inference. Since most of the data that geographers access and analyze in their research are aggregate data collected for all units in a pre-defined area (census tracts of a city, counties of the U.S., countries of the world, blocks of a neighborhood, *rayoni* in Moscow, etc.), the main concern has been to avoid the "ecological fallacy" (Robinson 1950). Geographers typically avoid statements such as "the elderly were more likely to vote for the government party in Moscow" by instead noting that the statistical analysis (usually multiple regression) suggests (e.g.) that "the *rayoni* with greater proportions of the elderly in Moscow as well as those awaiting housing were more likely to support the government party" (O'Loughlin et al. 1997: 590); in this way, geographers (including me) skirt the central concern that is implicit in these kinds of statistically based findings.

It is clear from hundreds of aggregate spatial studies of human behavior that geographers have generally not tried to estimate accurately the proportion of groups (elderly, poor, women, middle class, homeowners, etc.) who choose a political party, migrate, commit a crime, or otherwise engage in spatial activity. Using theories that are frequently adopted from economics, political science, or sociology, geographers insinuate the expected individual relationship between

compositional characteristics and spatial activity. Recently, human geographers have increasingly used mixed compositional-contextual approaches that extend the usual social scientific models by recourse to the addition of locational attributes in the equations (Brunsdon et al. 1999; Fotheringham 1997; O'Loughlin et al. 1994). Given that the preponderance of geographic studies of human behavior rely on aggregate data, usually from public records, the linkage of spatial studies to the survey-based work of other social scientists remains elusive. What Gary King (1997) has done in his book, *A Solution to the Ecological Inference Problem: Reconstructing Individual Behavior from Aggregate Data*, is to offer a method for geographers to move closer to the mainstream of the social sciences, while retaining the comparative advantage of their geographic perspective.

King's immediate aim when starting on the project was to improve ecological inference (EI) estimates for electoral choices of whites and African Americans in controversial redistricting cases. King suggests an extension of his methodology to geographic-based analysis in the book (pp. 25, 289) through what he calls "second-stage analysis," thus promoting a new avenue for spatial analysis of human behavior. In response, geographers can visualize the extensions of the EI methodology to contextual analysis and can thus move towards a more convincing common

ground between social theory and quantitative geography. Since Stewart Fotheringham and Luc Anselin offer reviews and critical analysis of the book in this forum, my evaluation of King's methodology will review its main ramifications for geography and provide an empirical example of an extension to a decades-old puzzle—who were the Nazi party voters in Weimar Germany? Using a database collected for earlier study (O'Loughlin et al. 1994; O'Loughlin et al. 1995), I highlight the insights from an application of the King methodology and compare the results to theoretical expectations. The benefits of King's EI approach will, I hope, become evident, and the estimates will indicate its relative value in solving the puzzle of Nazi party voting.

Ecological Inference, Rancorous Debates, and Geographic Methodologies

Thanks to articles in the *New York Times*, *Boston Globe*, and a National Science Foundation (NSF) press release, the 1997 publication of King's book received acclaim that is highly unusual for a social science project. The reason for all the attention was that King claimed to have solved a long-standing problem in social science and was able to generate accurate proportions, with error estimates, of unknowable values for individuals using only aggregate district-level data. According to King, he listened in dismay, as he sat in the courtroom in an Ohio redistricting case, as expert witnesses presented obviously incorrect estimates generated by Goodman's double-regression method. In some districts, the proportion of blacks that voted Democratic was estimated at more than 100 percent. The fact that the most immediate application of King's method was by statistical consultants in courtroom debates in contentious electoral districting cases lent it credibility and immediacy. Though King suggests diverse applications of the method, the examples in his book focus on the racial dimension in voting and districting in the U.S. This focus is perhaps a disadvantage, since the segregated nature of residence by race in the U.S. typically results in skewed distributions, but generates a full range of values (e.g., percent white) for small geographic units from near zero percent to near a hundred percent. Few other aggregate indicators of social charac-

teristics record such skewness. Owen and Grofman (1997) show that racially homogeneous precincts make a significant impact on whether the assumptions of ecological inference are met; high racial segregation avoids the fallacies of ecological inference and allows the bivariate linear model to generate reliable estimates of the strength of racial-bloc voting. They are much less optimistic about situations, like the case considered below, where the percentile range is smaller and district heterogeneity is larger. In King's view, armed with his program, social scientists would now be able to provide more reliable numbers to judges and lawyers on the extent of racial-bloc voting, and could even generate microlevel estimates for precincts in an area under scrutiny. Unsurprisingly, the counterargument was not long in coming, especially from those who sit on the other side of the legal challenges to biased districting (Freedman et al. 1991, 1998, 1999). Other researchers have raised questions about the method's accuracy, often by checking the ecological inferential estimates against "truth values" (the proportions given by survey data or from an examination of large numbers of individual records) (Cho 1998; Stoto 1998).

How is King's method a significant improvement over preexisting methods and what are its limitations? King has made the EI computer program available in two versions, *EI* and *EzI*, available on his website (<http://gking.harvard.edu>) and has built dozens of statistical and graphical diagnostic tools into the evaluation of the model's parameters (Benoit and King 1998). Clearly, the method is a significant advance over the limiting assumptions of the homogeneous distribution of parameters across all geographic units that lie at the heart of the Goodman technique (see Fotheringham's review in this Forum for an elaboration). Few geographers are comfortable with this assumption since it challenges the underpinnings of the discipline; Agnew (1996a) has elaborated on the technique's limitations in Italian electoral analysis. The Goodman method is highly unrealistic in most geographic settings. Especially in Western cities, filled with evident geographic disparities, the invariant nature of the Goodman parameters (the stationarity assumption) would require some heroic assumptions about a lack of correlation between socioeconomic status and human behavior, including electoral choices. Freedman et al. (1991, 1998, 1999) adhere to an even less

plausible assumption in their “neighborhood model”—that social characteristics have no influence on human behavior. In their example from Los Angeles, a Hispanic candidate will get the same ratio of votes in each precinct from Hispanic (and non-Hispanic) voters in exact proportion to their relative numbers. If a Hispanic candidate gets 90 votes in a precinct that is one-fifth Hispanic (say, 100 Hispanics and 400 non-Hispanics), the neighborhood model will infer that this candidate gets 18 of the 90 votes from Hispanic voters $\{90 \times 100 / (100 + 400)\}$ (Freedman et al. 1998: 1518). I agree with King (1999) that the Freedman model is not a serious option for analysis of contemporary American race-based issues, including voting and districting.

Consider the problem of electoral turnout, the relative proportion of Nazi party and non-Nazi party voters going to the polls in Weimar Germany. If proportionately more Nazi party supporters vote, the electoral advantage to the National Socialist German Workers Party (NSDAP) could be sizeable, depending on the gap in turnout. Using King’s notation, in the turnout example, the independent variable, X , is the Nazi party vote and the dependent variable is turnout, T . An identity from the modified Goodman formula can be used for combinations of the values for T_i (turnout) and X_i (NSDAP supporters), $T_i = \beta_i^b X_i + \beta_i^w (1 - X_i)$. The purpose of the EI modeling is to estimate β^b (the aggregate turnout rate for Nazi voters for the whole country) as well as the estimates for the individual counties and cities (*Kreisunits*), β_i^b . Combined with information about the bounds for each district, found by projecting the line onto the horizontal (β_i^b , the NSDAP turnout) and vertical (β_i^w , the non-NSDAP turnout) axes, King’s method combines the Goodman approach with the information on bounds. Clearly, the narrower the bounds on the axes, the stronger the chances of a plausible solution to what Anselin, in this Forum, calls an “unobservable” value (p. 587).

While the information from the bounds narrows the range of possible estimates, it is the random-coefficients approach that generates the parameters from a normal distribution. King himself is at pains to emphasize the kinds of situations and data distributions that can produce nonsensical results or cause the computer program to fail. He devotes forty pages in the book to discussion of the problems introduced by aggregation bias, incorrect distributional assump-

tions, outliers, and spatial dependence. Fortunately, the diagnostics available in the computer program and the many sample datasets examined in the book allow identification of possible problems in running the model and caution about the interpretation of the output. By King’s own admission and by comparison of the ecological inferences to the results of other methods and to “truth” (survey data), it is evident that the quality of the ecological inferences is data-dependent. Datasets with many geographical units, relatively low heterogeneity, a proportional distribution across many categories, and a temporal coincidence in the collection of the datasets will assist greatly in generating accurate inferences.

Consider the problem facing the researcher in electoral geography of estimating the relative importance of the factors that lie behind the rise to power of the Nazi party (NSDAP) in Weimar Germany. In the absence of any survey data, we have to rely on aggregate statistics for inferring the bases of NSDAP support. But it is not enough to produce national-level estimates since it is well-known that there were dramatic regional differences in the NSDAP support, even after differences in regional socioeconomic conditions are controlled (O’Loughlin et al. 1994). Faced with the double problem of making both national and local inferences, five research methodologies are now on offer.

First, the typical OLS (Ordinary Least Squares) approach, still used widely in Geography, adopts a multivariate explanation and selects key variables for the analysis on the basis of causal explanations of why certain groups supported the NSDAP. While starting from a causal modeling perspective is certainly advantageous, the multivariate approach, focused on compositional categories, does not consider “space” to enter the explanatory framework. The inclusion of dummy variables suggests an awareness of regional idiosyncrasies that might be significant in understanding political behavior; typically, national election surveys will have a regional code. It is highly unlikely, however, that this regional dummy is sufficient to capture the complexity of geographic effects, which are usually both regional (spatial heterogeneity) and local (spatial dependence) (Anselin 1988). Few, either geographers or others, check the diagnostics of the OLS model carefully for evidence of bias and correlation of the error terms, partly because the most popular statistical programs have no ready

made modules for this purpose. Specific software for the analysis of aggregate spatial data, especially Anselin's 1999 *SpaceStat* program (www.spacestat.com), is gaining in users. The generation of spatial lag matrices and GIS-related displays are still surprisingly rare, however, despite two decades of calls to the strong probability of inefficient and biased estimators in OLS analyses of geographic data.

A second set of methodologies can be classified generally as spatial analysis. These methods include spatial econometrics (Anselin 1988), the spatial expansion method (Jones and Cassetti 1992), and geographically weighted regression (Brunsdon et al. 1996). Common to these three approaches is the equal treatment of location with structural characteristics as explanatory variables in quantitative analysis, and the resulting equations have been termed spatial-structural models by O'Loughlin and Anselin (1991). While the spatial econometrics method begins with OLS modeling, the calibration of the final models depends on the nature of the geographic heterogeneity (regional) and spatial dependence (local effects) in the dataset. Final models often contain spatially lagged dependent variables as independent predictors and/or structural regimes, with separate models fitted for different regions. Both the expansion and the geographically weighted methods adjust the structural variables (socioeconomic status, etc.) to account for the location of the geographic cell relative to other units, as explained in Fotheringham's (2000) article in this forum. All three of the methodologies are explicitly multivariate in their modeling approach.

King's ecological inference methodology offers a fifth alternative to the analysis of aggregate geographically based data. Unlike OLS modeling, the ecological inferential method moves beyond aggregate causal modeling but at least in the initial stages, the relationship is a bivariate one. The key development from a geographic perspective of King's EI method is the ability to combine the advantages of a mixed spatial/structural causal modeling framework with the local emphasis of King's "second-stage" analysis. In his book, King (1997: 164–68) treats spatial dependence as a special case of aggregation bias and shows, using a Monte Carlo simulation, that spatial dependence will not significantly affect the ecological estimates if there are many geographic units. He suggests the incorporation of spatial dependency variables (residential mobil-

ity, interconnected transport networks, frequency of commuting, etc.) among the independent covariates to model the spatial autocorrelation that remains after conditioning by the independent predictor.

From a geographic perspective, there are two problems with King's EI model that undermine any easy extension to the domains of spatial analysis. First, King's simulation of spatial dependency is very simple and does not begin to account for the complexity of geographic autocorrelations; unidirectionality of autocorrelation, as in time-series analysis, when only past events can influence later developments, is plainly limiting and unrealistic as an analogy for the two-dimensional world that geographers study. Issues of the choice of spatial weights measures, distance of the spatial lag effects, territorial structure of the geographic units and related scale-dependent problems (the Modifiable Areal Unit Problem [MAUP]), and whether dependence should be incorporated in the initial models (the spatial expansion and geographically weighted regression approach) or included only if initial OLS estimates show spatial autocorrelation in the residuals (the spatial-econometrics approach) continue to plague spatial analysis. Given these difficulties, King's spatial-dependency simulations are unconvincing. Though he recognizes the complexities of spatial autocorrelation (p. 255), King argues that the conditional probabilities are not changed with different areal combinations since the basic distributions are built from the normal in the ecological inference model. But this "solution" avoids the real MAUP issue of the effects of different kinds of aggregation on spatial behavior, including electoral geography. As the debate between Agnew (1996a, b) and King (1996) made clear, there is still an enormous gap between the geographer's nuanced notions of context and the cartographic construct to which King reduces context (and MAUP). As Gould (1970) pointed out thirty years ago, the specific problems of geographic data analysis require a different mode of thinking from that usually found in inferential statistics.

The second problem that might inhibit the adoption of King's methodology by geographers is the limiting feature of one independent variable as the explanation of human spatial behavior. Though the basic 2×2 table can be extended, King (p. 276) accepts that the graphical limitations of display in greater than two dimensions will severely limit any extension to multi-

variate analysis. The alternative is to proceed by making the ecological estimates for a key causal variable and then using the estimates as dependent variables in a structural-spatial model using Anselin's (1988) methodology. To illustrate the King methodology and to suggest some answers to the puzzle of NSDAP voting, I present the results of some multiple runs of the *EzI* program for the Weimar Germany dataset, for the 1930 and July 1932 elections, with estimates prepared for key independent predictors.

Ecological Estimates of NSDAP Voting and the Odds of Being Wrong

Aggregate data for Weimar Germany are available in a large databank that has been corrected and reorganized under the direction of Jürgen Falter, a leading analyst of political behavior in the Nazi period (Falter 1991; Falter et al. 1986; Falter and Zintl 1988; Lohmöller et al. 1985). The archive contains 1925 and 1933 census data, election results from 1920 to 1933, 1927 housing figures, occupational data from 1933, and unemployment data from 1930–1932. Because of territorial and administration restructuring, however, the geographic units (more than 4000 in all) are not directly compatible across elections and census years, so that territo-

rial matching is necessary for most analyses (Falter and Gruner 1981; Hänisch 1988). In the examples presented in Table 1 and in Figures 1 and 2, estimates are presented for the NSDAP in their breakthrough election of 1930 and for the July 1932 election, when the Nazi party vote jumped significantly. The choice of the covariates for the Nazi and Communist party votes was based on the many theories that have been suggested to explain the rise of the Nazi party, including the effects of economic crisis (unemployment data), class status (occupational variables), political confessionalism (religion), mass protest party (turnout), and mass society (women in the labor force). Reviews of the theories and their specific measures can be found in Brustein (1996); Falter (1991); Falter et al. (1986); Flint (1995); and O'Loughlin et al. (1994).

Summary displays of the relationship between turnout and the NSDAP proportions in the 1930 election are shown in Figure 1. In the turnout example, the independent variable, X_i , is the Nazi party vote and the dependent variable is turnout, T_i . By examining this ecological relationship using aggregate data and inferring the turnout rates for Nazi (and non-Nazi) voters in 1930, possible distortions introduced by temporal gaps and mismatching of geographic units are avoided. The scatter of the 1016 points is shown in Figure 1 (top-right), with the $E(T_i | X_i)$

Table 1. Estimated NSDAP Ratios by Ecological Group in the 1930 and July 1932 Elections in Weimar Germany

Predictor Variable	1930 Election (NSDAP = .183)			1932 July Election (NSDAP = .373)		
	Over- (+) or Under-representation	Proportion of Population	% Voting ^a for NSDAP	Over- (+) or Under-representation	Proportion of Population	% Voting for NSDAP
Turnout ^a	+.047	.811	.858 ^a (.014) ^b	+.085	.830	.915 ^a (.005)
Protestant	+.041	.620	.224 (.016)	+.091	.620	.464 (.003)
Workers	+.016	.388	.199 (.021)	-.089	.380	.284 (.020)
Unemployed workers	N/A			-.139	.291	.234 (.023)
Unemployed white-collar	N/A			-.032	.133	.341 (.039)
Total unemployment	+.145	.121	.328 (.015)	-.179	.138	.194 (.034)
Manual industrial	-.016	.322	.167 (.014)	N/A		
Females in labor force	N/A			+.143	.372	.526

^a The ratios in this column represent the ratio of the respective socioeconomic groups voting for the NSDAP. These ratios should be compared to the national average (18.3 in 1930) to see the relative advantage or disadvantage that the NSDAP obtained from each socioeconomic group.

^b Numbers in parentheses and italics represent standard errors.

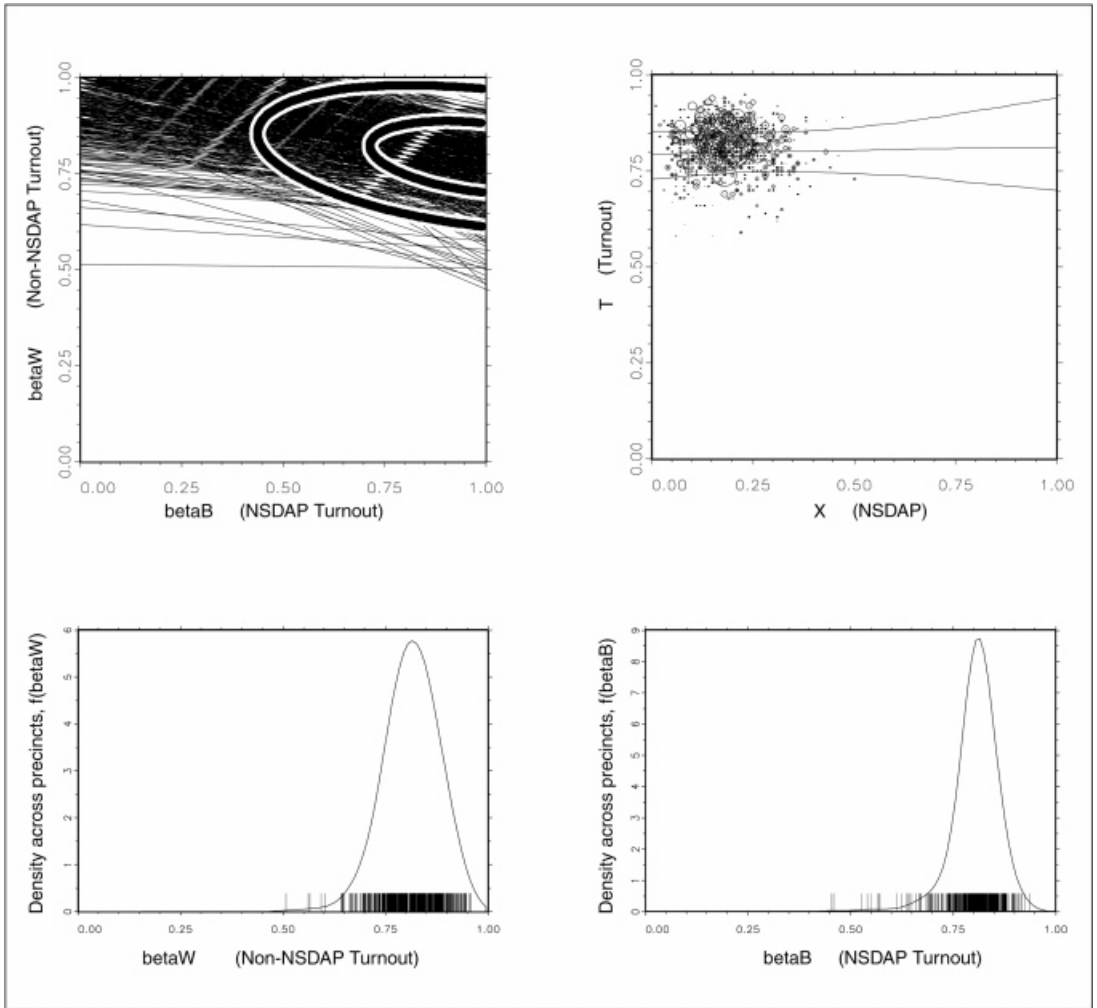


Figure 1. Summary displays of the relationship between turnout and the NSDAP proportions in the 1930 election in Germany.

fit and the 80 percent confidence bands indicating that the data match the EI assumptions. In 1930, the NSDAP vote was 18.3 percent (non-Nazi vote was 81.7 percent) while the national turnout was 81.1 percent (18.9 percent nonvoters). For each of the *Kreisunits*, the estimated lines are shown on the top-left of Figure 1 in the tomography plot. Most of the lines are flat, indicating high turnout levels in all districts. In Figure 1 (top-left), the bounds are narrower on the non-NSDAP turnout axis (all but 12 projections lie between .75 and 1.0) than on the NSDAP turnout axis (values range between .65 and 1.0). The dark contour lines on the graph lines, representing 50 percent and 95 percent

maximum likelihood intervals, show the truncated bivariate normal distribution of β_i^b and β_i^w , with the center as the mode of the distribution. Further displays of the distributions of the estimates β_i^b and β_i^w are found in Figure 1 (bottom left and bottom right) as histogram plots of the *Kreisunits*. All values are generated via simulation, set at 100 in this case. The narrow distributions of the estimates shown in the histograms, especially for the NSDAP turnout, allow some confidence in the ecological estimates.

Results for a variety of estimates for the NSDAP are presented in Table 1. The values for the turnout variable require some elaboration. In 1930, the election under consideration above,

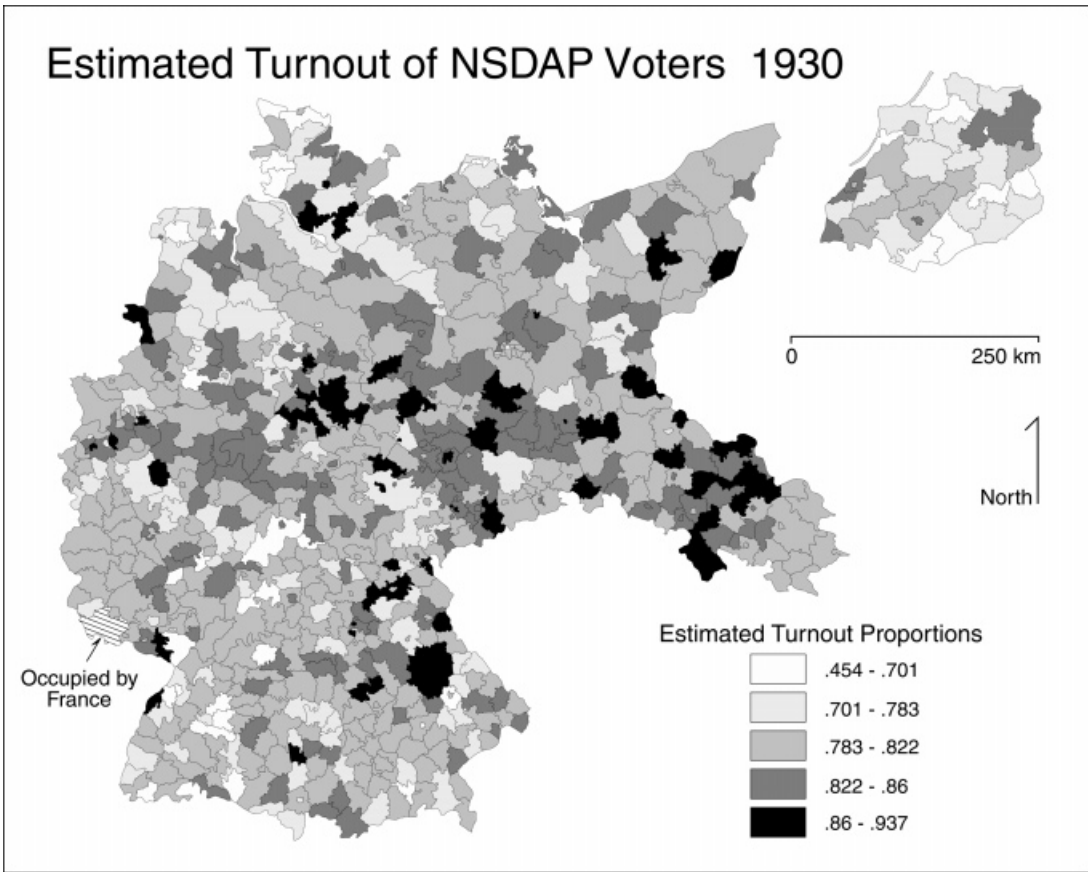


Figure 2. Estimated turnout of NSDAP voters by geographical units in the German elections of 1930.

the estimated turnout for NSDAP voters (β_i^b) was .858, nearly five percentage points above the national average, with the standard error for the estimate equal to .014. The differential turnout (and the subsequent advantage to the Nazis) between NSDAP voters and the national average rate rose 8.5 percentage points by July 1932 (Table 1). King's EI method allows inferences to the individual *Kreisunits*, and these values for NSDAP voter turnout in 1930 are mapped in Figure 2. The individual *Kreisunits* estimates range from .454 to .937, but the geographic pattern is highly localized and not generally understandable in terms of the usual explanatory variables of Weimar politics—regional location, urban-rural differences, size of settlement, or strength of the NSDAP vote. Few clusters of high and low values are evident. Lower Silesia, far East Prussia, Saxony-Anhalt in central Germany, the southern Ruhr cities, and parts of

Westphalia contain small clusters of high NSDAP turnout and, conversely, low turnout values are found generally in East Prussia (an area of NSDAP strength), Lower Saxony, Berlin (a center of opposition to the NSDAP), Schleswig-Holstein and Württemberg. In a brief “second-stage” analysis, using these *Kreisunit* estimates as dependent variables, the strength of the estimated NSDAP turnout is significantly positively correlated with the ratio of employment in white-collar jobs, with women in the labor force, with employment in white-collar jobs in the trade sector and in the civil service, and with the proportion of workers in manual employment. Conversely, NSDAP turnout is significantly negatively correlated with agricultural unemployment. None of the other dozens of independent predictors available in the Weimar Germany data archive showed significant bivariate correlation with the estimated NSDAP turnout, whose pat-

tern is likely to be affected by the relative level of preelection campaigning by the local NSDAP activists, a factor that has been identified in previous studies in explaining the relative gains to the NSDAP across the Weimar elections. The Nazi party, though tightly organized from the center, displayed significant regional variations in activism across the regions and among the localities (Brustein 1996; Freeman 1995).

Estimates of the relative advantage or disadvantage accruing to the NSDAP in the 1930 and July 1932 elections from support among seven socioeconomic groups are also presented in Table 1. All relationships, except possibly that for females in the labor force, support previously established aggregate effects that are based on theoretical considerations. The Nazi party gained 4 percentage points from Protestant voters over Catholic voters in 1930, and this gap had grown to 9 points in July 1932. A slight gain over the national average vote of 1.6 percent in 1930 from working-class voters had switched to a significant deficit of 8.9 percent by July 1932 as the NSDAP ideology became more distinct and the working class reasserted their support for the Social Democratic and Communist parties. Both groups of the unemployed supported the NSDAP less than the national average in July 1932, when unemployment in Germany was near its peak; from a separate ecological inference analysis, it is clear that the unemployed split their support for opposition parties, with the working-class unemployed supporting the Communists disproportionately. It is also clear that the unemployed voters switched from strong support of the NSDAP in 1930 (a gain of 14.5 percent over the national average) to opposition to the Nazi party in July 1932 (a disadvantage of 17.9 percent compared to the national average support). The estimates for the socioeconomic group, females in the labor force (the comparison group is non-working women) for July 1932 are dramatic but not easily connected to the theories. The NSDAP gained more than half of the estimated vote proportion of this population (14.3 percent more from their national average). Whether this high vote is the result of political socialization in the workplace, the differential importance of working women in clerical positions in the civil service and in low-skilled service jobs, or a response to the appeal of the NSDAP leadership is difficult to say in the absence of other survey evidence.

Unlike modern political phenomena, it is next to impossible to collect "truth" data for

Weimar Germany. In the absence of any public opinion surveys, we have to rely on the many, but inconsistent, snippets of information about the activities of the NSDAP in scattered localities across the country. Reliable data are rarely available on the socioeconomic characteristics of individuals who supported this party. In this sense, the estimates presented here using King's ecological inference model are "unobservable" and cannot be disproved or supported in any systematic comparison to individual-level data. Certainly, the estimates are consistent with regression-based causal modeling of the NSDAP vote from many researchers. Like many other spatial distributions, the global-level estimates for the whole country hide significant local variations. Whether these variations are clustered or randomly distributed remains an important way to determine whether the second-stage analysis should carefully probe the spatial dimensions of the ecological estimates.

Conclusions

Despite the limitations noted earlier, King's ecological inference methodology offers an important tool for geographers who are interested in going beyond the usual aggregate modeling of OLS. In the specialty area of electoral geography, the combination of ecological inference and second-stage analysis allows more careful dissection of the contextual effects on voting choices. Electoral geographers have argued, against the opinion of King (1996) and others, that where a voter lives has a significant impact on his/her electoral choices. While King (1996: 161) claims that "we need political geography because political scientists don't understand enough about politics," he relegates political geography to the kinds of cartographic display that might only indicate the further direction of political analysis. The usual method of gauging this contextual effect has been through the use of iterative spatial econometric procedures, as in the earlier example of Weimar Germany (O'Loughlin et al. 1994). The problem with this type of aggregate data spatial analysis is that it is very hard to unpack the key causal relationships from their contextual settings and attribute a statistical estimate and significance level to each factor. Using King's methodology, one could examine the extent of contextual effects on racial-bloc voting in the U.S. (his example) or the im-

fact of neighborhood location on support for extremist candidates like Vladimir Zhirinovskiy in contemporary Moscow. From public opinion information, it is relatively easy to check the accuracy of the global (citywide) estimate, say of men aged 18–40. Mapping the estimates thus can indicate some pockets of racial resistance (in the U.S. example) or high unemployment (in the Moscow example), suggesting variables for the second-stage analysis. Agnew (1996b) argues persuasively that adherence to a cartographic mindset misses the point that the political beliefs and choices of individuals are organized geosociologically. A process of contextual framing of political choices cannot be iteratively unpacked by repeated second-stage analyses, and in this debate over context and its determination, King's ecological inferential method will not end the argument. Only careful survey research that incorporates specific contextual questions will resolve the political science-political geography difference of opinion on the nature and significance of context (see Pattie and Johnston 2000).

The title of this commentary asked whether King's ecological inference method could answer a social scientific puzzle: who voted for the Nazi party in Weimar Germany? The honest answer must be that we cannot be sure, in the absence of corroborating information in the form of survey results. Previous checks of ecological estimates against truth data have yielded mixed results, some supporting the methodology (King 1997, 1999) and others challenging its accuracy in contemporary applications (Cho 1999; Freedman et al. 1998, 1999; Stoto 1998). King is to be applauded for the ready access to his program, research papers, and website data, and for his call for a variety of data-collection techniques to make plausible conclusions about ecological inference. Such data are rarely available for historical analysis, but the frequency of surveys and other "truth" sources should persuade geographers and other social sciences to consider ecological inferential estimates as the district-level dependent variables in statistical analyses. This integration offers a way to bridge the aggregate-individual gap that currently separates geography from other social and behavioral sciences.

Acknowledgments

The research on which this paper is based was supported by a grant from the Geography and Regional

Science program of the National Science Foundation. Thanks are due to Colin Flint and Michael Shin who worked on the original project and were responsible for much of the data organization and GIS preparation. Valerie Ledwith helped with the ecological inference estimates.

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Geography, Statistics, and Ecological Inference

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I am grateful for such thoughtful reviews from these three distinguished geographers. Fotheringham provides an excellent summary of the approach offered, including how it combines the two methods that have dominated applications (and methodological analysis) for nearly half a century—the method of bounds (Duncan and Davis 1953) and Goodman's (1953) least squares regression. Since Goodman's regression is the only method of ecological inference widely used in Geography (O'Loughlin), adding information that is known to be true from the method of bounds (for each observation) would seem to have the chance to improve a lot of research in this field. The other addition that EI provides is estimates at the lowest level of geography available, making it possible to map results, instead of giving only single summary numbers for the entire geographic region. Whether one considers the combined method

offered “the” solution (as some reviewers and commentators have portrayed it), “a” solution (as I tried to describe it), or, perhaps better and more simply, as an improved method of ecological inference, is not important. The point is that more data are better, and this method incorporates more. I am gratified that all three reviewers seem to support these basic points. In this response, I clarify a few points, correct some misunderstandings, and present additional evidence. I conclude with some possible directions for future research.

Ecological Inference as Statistical Inference

John O'Loughlin argues that “the specific problems of geographic data analysis require a different mode of thinking than is usually found