

1 testify and make this declaration based on my personal knowledge and the files and records
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3 in this matter.

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5 2. Pursuant to the Court's ruling of May 2, 2005, WSDCC hereby submits the
6
7 report of WSDCC's expert Christopher Adolph, Ph.D.

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9 3. Due to the late disclosure of various supplemental reports by Petitioners'
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11 experts and supporting and related materials, and because the Court may reject certain
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13 categories of allegedly invalid ballots or challenges to individual allegedly invalid ballots,
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15 Respondent WSDCC reserves the right for its experts to apply the basic approaches set forth
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17 in their reports to the evidence submitted at trial.
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21 SIGNED at Seattle, Washington, this 12th day of May, 2005
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25 *s/ David J. Burman*

26 DAVID J. BURMAN
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Report on the 2004 Washington Gubernatorial Election

Christopher Adolph

May 12, 2005

1 Qualifications

I am an assistant professor of political science at the University of Washington, Seattle. I am also a core faculty member of the Center for Statistics and Social Sciences, and an adjunct assistant professor of statistics. I have been hired by legal counsel as a private individual for my relevant expertise, and do not represent the university.

I have an extensive background assisting consultants and expert witnesses in conducting statistical analyses of voting behavior relevant to numerous legal proceedings on legislative re-districting and Voting Rights Act challenges. I have published several scholarly articles on ecological inference, the key statistical issue in this lawsuit. I also conduct research, teach courses, and advise graduate students in the broader field of quantitative political methodology.

I received my Bachelor of Arts degree from Rice University, and my Master of Arts and Doctor of Philosophy degrees, both in political science, from Harvard University. My curriculum vitae is provided as an appendix to this report.

2 Introduction

I have been asked by legal counsel to evaluate the claims in the expert reports of Jonathan Katz and Anthony Gill, and to assess the ability of statistical techniques to uncover the vote choices of invalid voters in the 2004 Washington gubernatorial election.

The 2004 Washington gubernatorial election was extraordinarily close, with Democratic candidate Christine Gregoire narrowly defeating Republican Dino Rossi by 129 votes in the final manual recount, out of 2,810,058 votes cast (0.005 percent).¹ The petitioners argue that the outcome of the election would have been different if 1,183 ballots which they allege to be invalid were not counted. Petitioners claim the invalid ballots consist of those cast by disenfranchised felons, the deceased, people who voted in multiple states or precincts, non-citizens, and people casting invalid provisional ballots. It is important to remember that invalid ballots comprise a very small fraction of the total votes cast (0.042 percent, if we consider the petitioners' 1,183

¹Figures in this paragraph rely on data from the Washington Secretary of States office, and do not include votes for write-in candidates, under- and over-votes, or spoiled ballots.

invalid ballots). In their reports, both Gill and Katz claim that it is possible to say how this small minority of voters cast their secret ballots, that a substantial majority of them cast ballots for Gregoire, and that the election outcome would have been different had these ballots not been counted.

I have reviewed the reports and data used by Gill and Katz, as well as new data provided by the respondents. Based on my own analyses of these data, I have three main conclusions:

- Neither Katz nor Gill employ currently accepted methods for solving the problem at hand, known in social science as the *ecological inference* problem.
- Application of currently accepted methods of ecological inference would inform us that the behavior of invalid voters in this election cannot be inferred from the aggregate data Katz and Gill use, or indeed, from any data currently available.
- Even if one accepts the (flawed and non-standard) methods used by Gill and Katz, their own methods find the election outcome would not change, once problems with their data are corrected.

The issues in this case turn on subtle but important—and in many cases, very long recognized—social science and statistical concepts. To help the court wade through these issues, I will proceed through my review of Gill and Katz, and my re-analysis of the problem, in three stages. In each of these three stages, I illustrate a different fatal problem in these experts' work. Each of these problems completely undermines the results offered by Katz and Gill. Rather than stop after the first issue, in each section, I ask “If the previous issues were somehow corrected or ignored, would Gill and Katz’s findings still stand?” In each case, I find it would not.

The three independent problems in Gill and Katz reports are:

1. Use of a non-random, non-representative, and incomplete sample of invalid votes, which is useless for answering questions about the net effect of all invalid votes on the state-wide election outcome.
2. Use of a flawed and error-prone method of ecological inference. Modern, accepted methods would provide strong warnings to the researcher that ecological inference in this case is impossible.
3. Combination of flawed methods and unrepresentative data. Applying Katz and Gill’s methods to more complete data results in no change in the election outcome from excluding invalid votes.

As I show below, correcting *any* of these flaws would show that invalid ballots cannot be found to have affected the election outcome with any certainty.

3 Serious flaws in the petitioners' data undermine their claims

The methods adopted by Katz and Gill will almost surely fail to produce accurate estimates unless applied to a full census, random sample, or representative sample of invalid ballots. For example, if there were a systematic bias in the collection of their data, such that invalid ballots were more likely to be included if they were in certain counties or precincts, then we would say that their sample is not representative, nor randomly drawn, nor a complete census. It would be systematically biased, and that bias would carry over to their results. In particular, Gill's and Katz's estimates of the likely impact of invalid votes, and Katz's confidence intervals, require an unbiased sample to produce meaningful results. (Of course, an unbiased sample does not guarantee meaningful results by itself, as we shall see below when we consider the virtues of Gill and Katz's methodology.)

3.1 Petitioners' data are a non-random sample

Are the petitioners' data a census, a random sample, or a representative sample of invalid ballots? Neither Gill nor Katz claim they are. This omission is unusual and conspicuous. The first thing another scholar would ask about these reports is "Where did the data come from? Are the data a valid sample?" Unless the petitioners can make and support the claim that these data are a representative sample of invalid ballots across the whole state, it will be impossible to make even minimally valid scientific claims regarding the likely effect of these alleged invalid ballots on the election outcome. In particular, if petitioners over-sampled precincts that voted overall for Gregoire, then their method will tend to produce biased results suggesting, perhaps incorrectly, that Gregoire benefited from the inclusion of invalid votes.

To see if the petitioners' data appeared to be a representative sample, I first divided Washington voting precincts into four categories: those voting heavily for Gregoire (i.e., where Gregoire's margin over Rossi was at least 23 percentage points), those moderately favoring Gregoire (i.e., where Gregoire's held a margin of less than 23 percentage points), those moderately favoring Rossi (i.e., where Rossi held a margin less than 18 percentage points), and those heavily favoring Rossi (i.e., where Rossi's margin was greater than 18 points). Each of these categories roughly corresponds to a quartile of Washington voters.

Table 1 shows that the large majority of petitioners' invalid ballots were found in pro-Gregoire precincts, and especially in heavily Gregoire precincts. By itself, this is not *prima facie* evidence of cherry picking, since we do not know the true distribution of invalid votes. However, because the petitioners have an interest in finding invalid ballots precisely where they did find them, and because their experts resolutely refuse to vouch for the data, we should proceed cautiously.

The easiest way to check whether petitioners have systematically over-sampled invalid ballots from Gregoire precincts is to look for missing invalids in Rossi precincts. Legal counsel have provided me with a list of 743 felons, omitted from the petitioners' list, who appear to have cast ballots in the 2004 Washington gubernatorial election.² Most of these felons cast ballots in

²The total number of invalid ballots, and the standards for what constitutes an invalid ballot, appear

Precincts ranked by margin	% of ballots cast	Invalid ballots found by petitioners	Invalid ballots overlooked by petitioners
Gregoire by 23% or more	24.8 %	541	2
Gregoire by less than 23%	27.8	308	7
Rossi by less than 18%	22.7	251	234
Rossi by 18% or more	24.6	83	498

Table 1: Petitioners’ invalid vote sample appears skewed towards precincts voting heavily for Gregoire. Petitioners found far more invalid ballots per ballot cast in precincts that voted heavily for Gregoire. Such a distribution is *a priori* possible. However, respondents have found large numbers of invalid ballots in precincts which Rossi won, strongly suggesting that the petitioners’ data are neither a random sample, nor a representative sample, nor a census of invalid ballots. (The column for respondent data is missing two Benton County ballots for which I lack precinct voting data).

precincts leaning towards Rossi.

Adding these new data helps balance the petitioners’ skewed dataset. For what it is worth, the combined data appear roughly uniformly distributed across the precincts. But we still cannot be confident that the data gathered collectively by both sides is either a census or representative of the whole state. As a result, we should view with skepticism any claims that the election might have turned out differently, had invalids been excluded, based on these data.

3.2 Petitioners’ methods fail when applied to a non-random sample

Gill and Katz’s methods assume that invalid votes were cast in the same proportion as other votes in a given precinct. Thus if we had a complete statewide census of invalid votes, but excluded from the analysis invalid votes cast in precincts won by Dino Rossi, the Katz-Gill method would conclude that Gregoire benefited from the inclusion of invalid votes. On the other hand, if precincts Christine Gregoire won were excluded, it would appear that Rossi benefited from the invalid votes, as Gill illustrates when he excludes King County from his analysis. Only a complete statewide census, or a random or representative sample, has any hope of offering an unbiased estimate of the effect of invalid votes.

To the extent we are unsure that the petitioner’s data is truly complete or representative—or, to put it another way, to the extent the petitioners have cherry-picked invalid votes in Gregoire country—we should strongly discount the conclusions of the Gill and Katz analyses. Only if the Rossi campaign put as much effort into searching for invalid votes in precincts they won (where, by their own logic, finding such votes would hurt them) as in precincts they lost, can we begin to trust their experts’ reports.

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to be evolving as the case progresses. All the methods in this report can be re-run with no essential changes on revised data as they become available.

		Voting Decision			
		Gregoire	Rossi	Other	
Individual Ballots	Invalid	?	?	?	1,926
	Valid	?	?	?	2,808,132
		1,373,361	1,373,232	63,465	2,810,058

Table 2: The Ecological Inference Problem applied to invalid voters. The goal of ecological inference is to infer from the marginal entries (each of which is the sum of the corresponding row or column) to the cell entries. It is in general a very difficult problem. To succeed, we will need either tight deterministic bounds, or strong assumptions. (Voting data above are from the Washington Secretary of States office, and do not include votes for write-in candidates, under- and over-votes, or spoiled ballots. These ballots could easily be lumped in with the Other category, however. Invalid ballots are the sum of those claimed by petitioners and respondents.)

The possibility that some invalid ballots are missing in a non-random way directly undermines a key thesis of Gill’s report. Gill claims that there are “a sufficient number of uncontested invalid ballots in King County alone to believe the 2004 Washington State gubernatorial election may have resulted in a victory for Mr. Dino Rossi had those invalid ballots not been cast . . .” (Gill, Supplemental Report, page 2). Because Gill’s own method is to deduct a proportion of invalid ballots from the candidates’ totals based on their precinct-wide support, the net change in the statewide margin of victory will depend, again according to Gill’s method, on the number of invalid ballots cast in each and every precinct in the state. Because Gill provides no evidence or even any assurance that his data are complete, we cannot discount the possibility that further invalid ballots may be discovered outside of King County, and in particular in precincts won by Dino Rossi. Under Gill’s own method, such discoveries would mitigate or overwhelm the effects of invalid ballots cast in King County. For Gill to suggest that conclusions on statewide outcomes may be drawn solely on the basis of King County is intuitively and statistically preposterous. Furthermore, this is not merely a hypothetical point: the data used by Gill appear to have systematically missed invalid ballots cast in precincts won by Rossi, and inclusion of these ballots would change the results of his analysis, as we shall see below.

So far we have seen that the petitioner’s data are suspect. In the next section, we will see that their methods are equally dubious.

4 Petitioner’s experts commit the ecological fallacy

The statistical problem in this case can be illustrated with a simple table. Table 2 shows what is known and unknown. From the final recount, we know the total number of ballots cast for Gregoire, for Rossi, or for other candidates. Setting aside our doubts about the completeness of the data, we “know” the number of ballots which were invalid or valid. These numbers form the

row and column sums, or marginals, of a 2×3 table, the interior cells of which are unknown. The *ecological inference problem* concerns making inferences from the marginal totals to the contents of the cells. It has long been recognized as a very difficult problem.

Unfortunately, it is the problem we face. The question is simply which candidate got the most valid votes, or in terms of the diagram, which box in the lower row of “?”’s is largest. Therefore, the scientific problem before us is intrinsically the ecological inference problem, and any method failing to solve the ecological inference problem will give a dubious and scientifically unacceptable estimates of the election outcome.

Rather than face the ecological inference problem head on, Gill and Katz assume it away. At the core of the reports of Gill and Katz is a single, critical assumption: that the vote choices of any sub-population within a voting precinct can be assumed to be the same as the average vote choice in the precinct as a whole. This assumption is strong, implausible, and unwarranted. Moreover, it flies in the face of decades of warnings from social scientists and statisticians to avoid committing the “ecological fallacy”.

In this section, I first explain the ecological fallacy and efforts to overcome it. I then apply modern methods to the problem of inferring the voting behavior of Washington’s invalid voters, and show that the aggregate data used by Katz and Gill cannot reveal individual voters’ choices. Finally, I address the impact of the ecological inference problem on the specific methods used by Gill and Katz.

4.1 Examples of the ecological fallacy

Since the publication of a landmark paper by William S. Robinson in 1950, social scientists have recognized the hazards in making inferences about a particular individual’s behavior using only information about the average behavior of groups (Robinson, 1950).³ Indeed, it is only in desperation at a lack of individual data that one would attempt ecological inference, and it is intuitively obvious that such inferences will very often be badly wrong. This danger is known as the *ecological fallacy*, and it is at the heart of this case.

An example will help illustrate the fallacy. Suppose you were asked to estimate the batting average last season of a particular Seattle Mariner, Ichiro Suzuki, but you know only that the team as a whole had a batting average of 0.270 in 2004. If we were to leap from the fact that 0.270 was exactly the American League average to the conclusion that all Mariners had mediocre seasons at the plate, we would make a badly mistaken inference. In fact, Ichiro Suzuki batted 0.372, the highest average of anyone in the American League.⁴

The study of voting is rife with examples of the ecological fallacy. We need look no further

³ Robinson’s paper is one of the most cited in all social science, and the second most cited in the history of the *American Sociological Review* (Jacobs, 2005). Robinson noted that at the aggregate level, the number of immigrants and the number of literate residents in a state appear to be correlated. This might lead a researcher to mistakenly infer that immigrants are more likely to be literate than those born in the US, when at the time the reverse was known to be true from surveys of individuals.

⁴Data taken from www.espn.com.

than the 2004 presidential election. After the election outcome was announced, some commentators in the mass media noted that the so-called “red” states—which voted, on average, for President George W. Bush—tend to have lower average incomes than the “blue” states—which voted, on average, for challenger John Kerry. These commentators were puzzled by this aggregate behavior, because it seemed to contradict the well-known tendency of individual high-income voters to be more likely to vote for Republican candidates. Some wondered whether the aggregate pattern implied that the connection between income and partisanship had broken down, or even reversed itself.

A group of scholars, led by statistician/political scientist Andrew Gelman, point out that this “inference” is simply the ecological fallacy, still rearing its head 55 years after its discovery (Gelman et al., 2005). Gelman et al first note that the aggregate Republican vote share appears strongly inversely related to average state income; see, for example, the cases of Mississippi, Ohio, and Connecticut in Figure 1A. On the basis of this aggregate relationship, careless observers made inferences about the behavior of individual voters. However, by analyzing individual level data from exit-polls, Gelman et al found that, in each state, higher income voters were more likely to vote for Bush, compared to lower income voters, as the upward sloping lines in Figure 1B show. But because the *average* voter in Mississippi was more likely to vote for Bush than the *average* voter in Connecticut, the aggregate data masked this clear and strong individual-level relationship (Figure 1C).

The lesson is clear: if we eschew or lack individual level data, and attempt to make inferences from aggregates, we risk being badly wrong; even completely backwards in our conclusions. To be sure, the recognition of the ecological fallacy in 1950 did not completely stop unwitting social scientists, journalists, courts, or ordinary folks from making unwarranted inferences about individual behavior from aggregate data, and it would not be difficult to find news articles, legal opinions, or even articles published in prestigious journals which commit the ecological fallacy. Still, it is a fallacy, and when recognized in scholarship, tends to be fatal to the publication prospects of a scientific study.

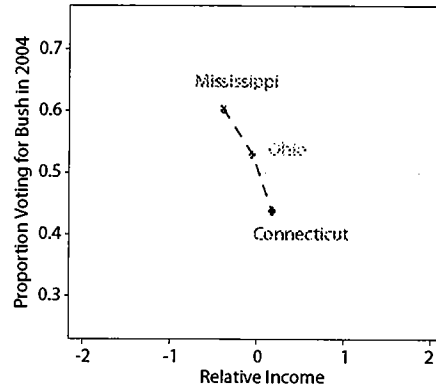
4.2 Early methods of ecological inference

After Robinson identified the ecological fallacy, the race was on to find methods of ecological inference that would avoid or overcome it. Until the late 1990s, there were two competing methods, neither particularly satisfactory. The first, known as the method of bounds (Duncan and Davis, 1953), noted that ecological data sometimes place logical limits on the range of individual data. To understand the method of bounds, it helps to have an example.

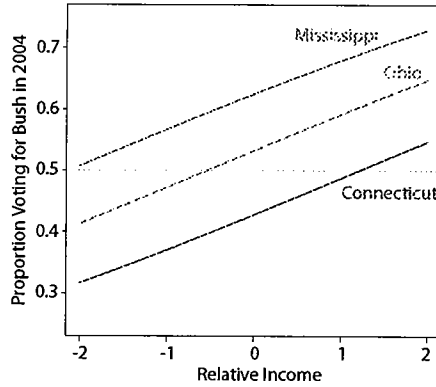
Suppose we were studying racial patterns of voting in a electoral district with a voting age population consisting of 40,000 black adults and 60,000 non-black adults. Suppose further than 80,000 people turned out to vote. Can we say what proportion of black and non-black adults voted?

Not with any precision. But we can state a logical range bounding the possible answers to the question. We start with the following accounting identity, which is mathematically true no

A. State-level averages of income and vote choice, and apparent inverse relationship between income and votes for Republican candidate Bush



B. Individual-level data on income and vote choice, and the actual *positive* relationship between income and votes for Republican candidate Bush



C. The ecological fallacy revealed: Aggregate data are consistent with, but give no obvious indication of, the true individual level data & relationship

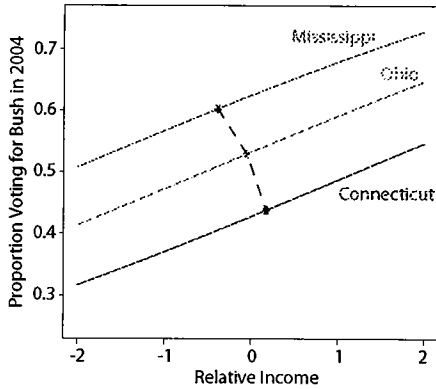


Figure 1: An illustration of the ecological fallacy from the 2004 presidential election. The essence of the ecological fallacy is that aggregate data often are a very misleading guide to underlying relationships. Source: Hierarchical logistic regression from Gelman et al. (2005).

matter what for each precinct:

$$\begin{aligned} \text{Overall turnout rate} &= \text{Black turnout rate} \times \text{Black fraction of VAP} \\ &+ \text{Non-black turnout rate} \times \text{Non-black fraction of VAP} \end{aligned}$$

or in symbols

$$T_i = \beta_i^B X_i + \beta_i^N (1 - X_i) \tag{1}$$

We can use this equation to figure out the black turnout rate if we are first given the white turnout rate. In other words, we can use this equation to find the minimum and maximum mathematically allowed black turnout rate, simply by plugging in the maximum and minimum possible white turnout rate. Hence, if all 60,000 non-black adults had voted, it follows logically that only 20,000 blacks voted. On the other hand, it is logically possible that all 40,000 blacks voted, in which case exactly 40,000 non-blacks must have turned out.

To summarize, the logically possible range of black turnout rates lies between 50% and 100%, while the logically possible non-black turnout rates lies between $66\frac{2}{3}\%$ and 100%. Any values outside these bounds are mathematically impossible. Unfortunately, we are left with rather large ranges. The method of bounds by itself does not tell us any more precisely what the turnout actually was; only what it could be. Still, we have gathered some information that helps narrow the ecological inference problem.

A second technique dating from the 1950s is ecological regression, also known as Goodman's regression, after its discoverer (Goodman, 1953). Ecological regression assumes that the black turnout rate in each precinct is exactly identical, and then treats Equation 1 as a regression model. Unlike the method of bounds, ecological regression produces a single answer to ecological inference problems. Unfortunately, this answer is often wrong, and will generally be wrong if the black turnout rate varies across precincts, as it almost certainly does. Indeed, Goodman's regression often produces impossible results: it is not unusual to see ecological regression estimates claiming 130 percent of blacks voted Democratic, or that -30 percent of non-blacks voted Democratic. In general, Goodman estimates fail to respect or take advantage of the logically true information contained in the bounds.

Although at one time, Goodman's regression, or the even cruder proportional analysis used by the petitioner's experts, may have been used to "solve" ecological inference problems, the poor performance of early methods has long been recognized in scholarly work (see, e.g., Achen and Schively 1995), and for the most part scholars long avoided tackling problems of ecological inference because the inherent difficulties seemed insurmountable. Today, these methods are obsolete—to the extent they were ever even accepted—and are not generally accepted solutions to ecological inference problems in scholarly work.

4.3 Recent advances in ecological inference

Scientific progress has been made in recent years on the ecological inference problem. In particular, the new method of King (1997) set off an explosion of work on ecological inference, after decades of neglect. The central insight in this new work is that ecological inference is possible by combining the method of bounds and new statistical techniques (where the latter can be thought of as more sophisticated versions of ecological regression). These new methods work surprisingly well in solving some ecological inference problems in voting, but only when the problem can be broken down into precincts, some of which contain high concentrations of each “type” of voter. From these concentrations, the analyst can calculate tight deterministic bounds on the quantities of interest, and then conduct a statistical analysis within the limits given by these bounds. In this way, every modern method of ecological inference builds on the information in the bounds—and every method of ecological inference fails to produce any useful information when these bounds are universally uninformative.

One of the biggest contribution of King’s approach to ecological inference is the recognition that in some cases ecological inference is practicable, while in other cases it clearly is not. King offers useful tests for whether ecological inference will yield meaningful inferences. These tests do not guarantee success, of course, but when they are negative, failure is almost certain.⁵

The strengths of King’s approach, and the importance of exploiting the information in the bounds, has been recognized in many ways. On one hand, many studies using King’s methods have been published in top journals (Burden and Kimball, 1998; Gay, 2001; Gimpel and Schuknecht, 2002; Liu, 2001; Lublin and Voss, 2002; Voss and Miller, 2001). On the other hand, King’s method serves as the foundation for many new methods of ecological inference (see, for example, Wakefield, 2004; Rosen et al., 2001, and numerous contributions in King et al., 2004). Tellingly, all of these new papers and methods incorporate the deterministic bounds in the manner prescribed by King, and in this critical sense are all variations on his basic model. Finally, King’s method has been used extensively in court cases where racial voting patterns were an issue. A federal judge held that King’s method “is the best method currently available to measure racial bloc voting” (*Mallory, et al, v. State of Ohio, et al.*, USDC Southern District Court of Ohio, case no. C-2-95-381), a view upheld on appeal (*Mallory, et al, v. State of Ohio, et al.*, United States Court of Appeals, Sixth Circuit, No. 97-4425, 4/13/99). Subsequently, King’s method has been used in numerous court cases, and has been accepted everywhere it has been

⁵Other scholars concur in this assessment. University of Wisconsin political scientist Charles Franklin told the New York Times

It’s far better to know that you don’t know as much as you think you do. . . . When the new method fails, it tends to produce evidence that shows you you’re not doing a good job The opposite happens with the older method: it tends to tell you too small a margin of error when it’s doing badly.

See Karen Freeman, “Statistician Builds What May Be a Better Data Mousetrap,” *New York Times*, July 8, 1997, C8. On the importance of having tight bounds in ecological inference, see also Voss (2004) and Adolph and King (2003).

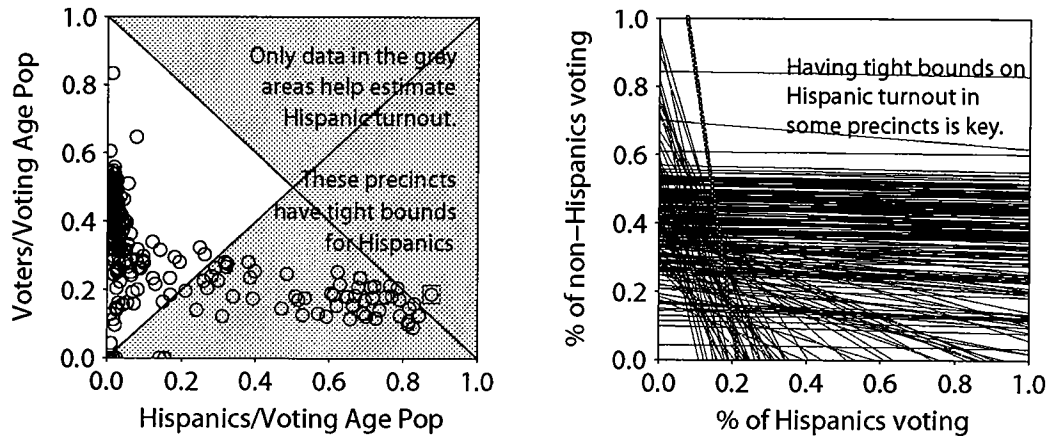


Figure 2: An example of a promising case for ecological inference: The 1990 Pennsylvania State Senate (2nd district) election. The key to successful ecological inference is having some informative precinct-level deterministic bounds on the quantity of interest. Here, the quantity of interest was the rate of turnout among Hispanics. The presence of some precincts with high concentrations of voting age Hispanics allows inferences to be made with modern techniques like that of King. An example of such a precinct is boxed in blue in the left plot. The precinct has bounds shown as a blue line in the right plot. Source: King (1997).

introduced.

Katz himself has used King’s method as an expert witness in legislative redistricting lawsuits—for example, in Texas, *Perry v. Del Rio*, 66 S.W.3d. 239 (Tex. 2001). It is puzzling that he does not employ, or even cite, those methods in his report. Indeed, both examples of ecological inference Katz cites (Burden and Kimball, 1998; Gay, 2001) use King’s method, and it is difficult to imagine these studies would have been published—much less published in the top journal in political science—had they used earlier techniques, such as Goodman’s regression, or dubious methods, like “proportional analysis” or Katz’s “principle of insufficient reason”. Instead, ecological inference is now possible, and on the research agenda, because King’s method provides either good estimates, or clear warnings that good estimates cannot be obtained from a particular dataset.

Although the details of King’s method are quite technical, the general idea and crucial pre-estimation diagnostics can be described in plain English. Figure 4.3 illustrates an example of successful ecological inference using modern methods. The data come from the 1990 Pennsylvania 2nd Senate district general election, and the quantity we wish to infer is the proportion of voting age Hispanics turning out to vote. The two plots shown in Figure 2 are diagnostics introduced by King (1997) to aid researchers in deciding whether ecological inference is feasible for a given dataset.

The plot at left, known as a scattercross plot, graphs the turnout rate for all voters against the proportion of Hispanics in each precinct. The large X divides the plot into four triangles.

Precincts in the top, bottom, and right triangles all have informative bounds on the Hispanic turnout rate. Precincts in the left triangle have so few Hispanics that any turnout from 0 to 100% is possible. As a rule, ecological inference will be fruitless unless some of the precincts have informative bounds. In this case, such precincts exist; one example is boxed in blue.

The plot at right, known as a tomography plot, graphs a line for each precinct. This line contains every possible combination of Hispanic and non-Hispanic turnout rates allowed by the bounds (i.e., every combination of β 's allowed by Equation 1). The bounds and these lines are deterministic in the sense that they rely on no statistical assumptions and are not the least bit uncertain (provided the underlying data are correct). It is logically required that the true turnout rate lie on this line. Steep lines pin down the Hispanic turnout rate in a precinct very precisely. The blue line, which corresponds to the boxed precinct in the left panel, is a precinct where there are enough Hispanics to determine the turnout rate from the bounds alone.

If we find some precincts with informative bounds, we can proceed to the next step, which is applying a statistical model to the distribution of tomography lines; this statistical model would produce estimates of turnout by ethnicity made robust by the information in the bounds. As a rough intuitive guide, note that the estimates of Hispanic and non-Hispanic turnout will tend to cluster near the intersection of the precinct-level tomography lines, though of course the estimates for each precinct will be restricted to lie on the portion of the precinct's tomography line nearest this intersection.

That is what an analyst would do in a good case, and the remarkable thing is we can identify probable good cases from known information (the bounds). On the other hand, if there were no informative bounds—i.e., no precincts outside the left triangle, or with steep tomography lines—then we would stop. In such cases, any effort at ecological inference, under any accepted method, is so dependent on unverifiable assumptions as to be practically useless.

4.4 The deterministic bounds in this case are very wide

Now, let's turn from the Pennsylvania example, where inference is possible, to the 2004 Washington election. We will use plots like those in Figure 4.3 as diagnostics to see whether ecological inference—of any sort—is possible in this case. The data I will consider are the combined invalid votes found by petitioners and respondents; however, the conclusions in this section do not materially change when these two datasets are considered separately.⁶

Recall that without some precincts with substantial invalid voters, there will be no precincts with narrow or informative bounds on invalid vote choice, and hence no possibility of successful inference of invalid vote choice from aggregate data. The scattercross plot for the invalid vote

⁶In his second supplemental report, Katz introduces a “calculated” residual vote total to account for write-ins, under- and over-votes, and spoiled ballots. I have attempted to reconstruct this quantity from data provided by the petitioners, but lack an exact description of the calculation used by the petitioners. Thus, the results given in this section and the next may be slightly different from those used by petitioners. However, I strongly doubt the calculation of residual votes will substantively affect any conclusions, as the findings here are unambiguous.

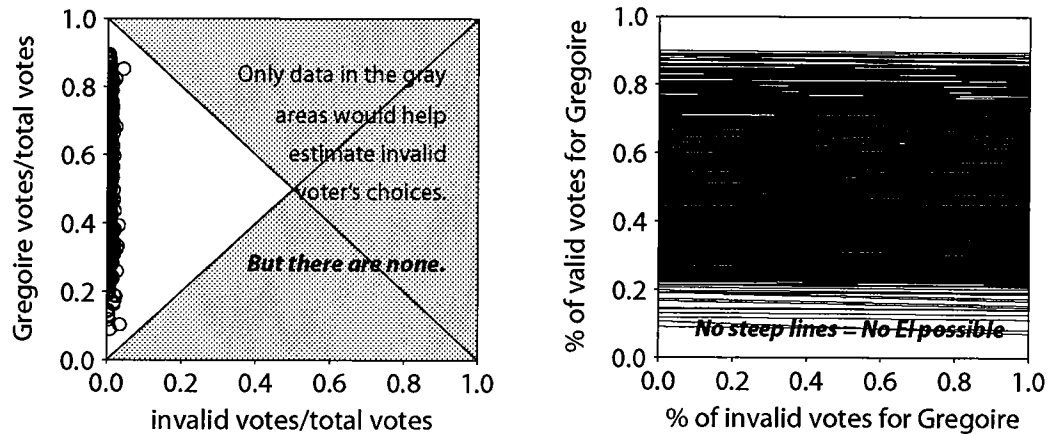


Figure 3: Standard diagnostics show the invalid ballots data are a hopeless case for any form of ecological inference. A key advance in recent work on the ecological inference problem is the ability to diagnose cases where inference is likely to fail. This is one of those cases.

data reveals that prospects for any kind of ecological inference are grim (Figure 3, left panel). It shows that none of the precincts will have informative bounds, a message that is hammered home by the tomography plot, which has no steep lines—meaning any proportions are possible in every any precinct (Figure 3, right panel).

Finally, in Table 3, I list the logically true bounds on the fraction of invalid ballots cast for Gregoire for each of the 1344 precincts which the petitioners or respondents identified as having at least one invalid ballot. *In each and every one of these 1344 precincts, the bounds on the vote choice of invalid voters are very wide. The bounds show it is possible that every invalid vote in every precinct was cast for Rossi. Alternatively, every vote may have been cast for Gregoire—or any combination in between, without contradicting any of the data.* Because there are too many precincts to list in this report, I list only the first and last five of these precincts (ordered by county and precinct number), as well as the two precincts most favorable for the petitioners: the precinct with the largest number of invalid ballots (Pierce County precinct 432, with a mere 8 invalid ballots out of 901 cast), and the precinct with the largest proportion of its ballots considered to be invalid (King County precinct 1595, with 4%). Even in these cases, the fraction of ballots that are invalid is far too small for us to infer anything about the behavior of the invalid voters from these aggregate data.

I have studied racial voting patterns in hundreds of elections using ecological inference techniques, and the statistical problem here is the same, as Katz notes on page 6 of his first report. A crucial step in every analysis I conduct is determining whether the bounds contain sufficient information for inference to proceed. Sometimes, I find that the bounds are simply uninformative, usually because no precincts contain a significant concentration of the group of interest. In such cases, I do not offer estimates, because the only results I could provide would be based on

County	Precinct	Number of invalid ballots, according to petitioners	Total votes cast, from manual recount	% of invalid votes cast for Gregoire		
				Lower Bound	Upper Bound	
Adams	212	1	128	0 %	100	%
Benton	1090	1	65	0	100	
Benton	1400	2	77	0	100	
Benton	1600	1	316	0	100	
Benton	1645	1	151	0	100	
:	:	:	:	:	:	:
King	1595	6	147	0	100	
:	:	:	:	:	:	:
Pierce	432	8	901	0	100	
:	:	:	:	:	:	:
Yakima	4602	2	287	0	100	
Yakima	4606	1	505	0	100	
Yakima	5003	1	720	0	100	
Yakima	5016	2	276	0	100	
Yakima	5020	1	311	0	100	
Statewide bounds on the fraction of invalid ballots cast for Gregoire				0 %	100	%

Table 3: Wide deterministic bounds on the percent of invalid votes cast for Gregoire make this a hopeless case for any form of ecological inference. The above results are based on the combined data of petitioners and respondents. To save space, all but 12 of the 1344 precincts containing invalid votes (according to the petitioners) have been omitted from the table; the full table would run to 32 pages. However, I calculated the bounds for each of these 1344 precincts, and in every case, they range from 0 percent to 100 percent.

pure assumption, rather than the data.⁷

In my experience, I have seldom, if ever, seen a less promising case for ecological inference than the invalid voters of the 2004 Washington gubernatorial election. The precinct-level bounds contain no information whatsoever. If one were to fit a model to these data—whether that model were Goodman’s regression, or “proportional analysis”, or King’s ecological inference method,

⁷To satisfy the reader’s curiosity, I note that when I did press on, naively applying King’s method to these unsuitable data, the method found that on average across the state, invalid voters voted no more Democratic than valid voters. In particular, it found that 49.9 percent of invalid voters voted Democratic, compared to 47.8 percent of valid voters, too small a margin to affect the election outcome. The standard errors for these quantities are less than 1 percent in each case. I emphasize, however, that these results are highly sensitive to model assumptions that cannot be verified, given the lack of informative bounds. The right thing to do in this case is to decline to attempt ecological inference.

or a variant of the same—the results one would find would be highly sensitive to the assumptions made, and there would be no way to check if those assumptions had been validated by the data.

Rather than make untenable, untestable assumptions, I find that the best statement of the uncertainty in this case is given by the deterministic bounds. The only confidence interval around invalid voters' behavior that I am comfortable with states that it is possible that none of them voted for Gregoire, or that all of them voted for Gregoire, or any combination in between.

4.5 Gill ignores the ecological inference problem

To see how Anthony Gill's report addresses the problem of ecological inference, we must take a step back. As Gill lays out the problem, there are several things we would like to know to establish that the invalid votes changed the outcome of the election:

- First, we need to know how many net votes Gregoire can afford to lose before her margin is exhausted. This amount, obviously, is 129 votes.
- Second, we might like to know how many invalid votes in each precinct would be enough to overwhelm this margin, *given perfect knowledge of the rate at which invalid votes in each precinct were cast for Gregoire, for Rossi, and for other candidates*. Given such knowledge, the number of invalid votes needed to change the election (Gill's "tipping point") is also very easy to calculate.
- Third, and crucially, we need to know for whom the invalid votes were cast. While items one and two are extremely easy to calculate using basic arithmetic, this final piece of information is extraordinarily hard to estimate. Without this knowledge, items one and two will not avail us in determining the correct election outcome.

Gill devotes the bulk of his report to item two, an easy question. Gill thus focuses attention on a point not really in dispute. On the other hand, he devotes little space to the key issue of the case, which is estimating how invalid votes were actually cast. Gill simply assumes that these votes were cast in the same proportion as the other votes in the corresponding precinct. (Implicitly, Gill assumes that felons and law-abiding citizens in a single precinct are more alike with respect to voting than, say, law-abiding citizens in two different precincts.)

As we have seen, this assumption is a clear example of the ecological fallacy. Yet Gill makes no mention of the ecological inference problem, nor does he acknowledge the long history of scholarship on this difficult problem. Contrary to standard practice, he does not even offer an estimate of the uncertainty of his estimates on the vote choices of invalid voters. On face, Gill seems to suggest that the allocation of invalid votes to the Rossi or Gregoire column is a simple problem that can be solved with little difficulty or doubt.

Instead, there should be great doubt as to whether estimates from the "proportionality method" have any validity or use whatsoever in this case. Using his "proportionality method", not only would Gill conclude that Ichiro Suzuki had a mediocre year in 2004, he would also conclude, erroneously, that nationally, high-income voters vote more Democratic than low-income

voters. But let's give Gill's method a third chance, and ask whether it can correctly identify *known* characteristics of individual invalid voters from the aggregate characteristics of their precincts.

Suppose the statistical problem in this case was to infer, from aggregate data, the sex of the felons claimed by the petitioners to have voted illegally. Let us apply Gill's proportionality method to this problem, where we can verify its performance. We simply assume that the fraction of voting felons who are male matches the fraction of all voters in the precinct who are male. This is exactly how Gill models voting; we have merely applied the technique to gender, in a problem that is the same from a statistical point of view. Applying the proportionality method at the precinct level and summing across the state leads the analyst to conclude that felon voters must have been 46.9 percent male. Unfortunately, this inference is badly wrong. Based on individual level data, we know that the felons who voted were actually 75.3 percent male. The naive assumption of "proportionality" between aggregate and individual level data has led us far astray of the truth.

A basic test of whether a statistical method is valid is whether it produces accurate results under controlled conditions, where the true answer is known and can be compared to the answer given by the method. Judged on this venerable standard, "proportionality analysis" fails, and should be discarded. If the ecological inference problem were so easy to solve, social scientists and statisticians would not have spent half a century wrestling with it.

4.6 Katz fails to solve the ecological inference problem

Katz acknowledges that the problem at issue is one of ecological inference. Yet Katz uses the same method as Gill to allocate invalid votes—he assumes they were cast in the same proportions as the valid votes in the same precinct. Thus, like Gill, Katz's method strikes out swinging in the three examples discussed above.

Unlike Gill, Katz acknowledges the need to give measures of uncertainty for statistical estimates. I applied Katz's method of calculating confidence intervals for proportionality method estimates to the problem of estimating felon gender. Like Gill, Katz would predict that 46.9 percent of illegal felon voters are male. He would also offer a 95 percent confidence interval around this estimate ranging from 43.8 to 50.1 percent. Needless to say, the true proportion of males among the felon voters, 75.3 percent, lies far outside the 95 percent confidence interval.

Why has Katz's 95 percent confidence interval made us so over-confident in a flawed answer? The answer is simple: uncertainty about the *assumptions* of Katz's model is not included in Katz's confidence interval. Katz's confidence interval is valid only if his assumption that invalid voters are the same as valid voters in the same precinct is true. If this assumption is false, Katz's confidence intervals are incorrect, and could lead to dangerous overconfidence in his estimates.

Because the key uncertainty in this case is how invalid voters voted, it is disturbing that Katz and Gill can offer no evidence in favor of their proportionality assumption, nor any estimate of how certain this assumption is to be true. The uncertainty Katz does capture is trivial by comparison, and results from the fundamental variability of binomial (or multinomial) variates.

