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WORKSHOP IN HEALTH ADMINISTRATION STUDIES

AUTUMN, 1988

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"Can Statistical Outlier Analysis Detect Poor Quality Hospitals?"

WORKSHOP PAPER

for

Thursday, October 13, 1988

Rosenwald 405

3:30 to 5:00 p.m.

# EFFICACY OF STATISTICAL OUTLIER ANALYSIS FOR MONITORING QUALITY OF CARE

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## Abstract

Researchers in the federal government and elsewhere have proposed that "outlier" hospitals in distributions of errors of prediction of mortality and other outcome variables have a high likelihood of quality of care problems. Although the technique is being employed in practice to screen for hospitals with quality problems, no theoretical or empirical justification of the approach has been offered. Difficulties in researching the efficacy of the outlier technique are availability of clinical data and direct measures of quality for validating inferences about outlier hospitals. Monte Carlo methods, however, easily overcome these difficulties.

Results of several Monte Carlo experiments to assess the ability of outlier analysis to detect known quality differences in synthetic data suggest that very high proportions of false positives and false negatives are produced under a broad range of possible conditions. One is led to tentatively conclude that without further grounds for developing a-priori expectations about the robustness of the outlier technique or exact conditions generating natural data, the validity of inference from the technique is problematic.

## EFFICACY OF STATISTICAL OUTLIER ANALYSIS FOR MONITORING QUALITY OF CARE

Statistical analysis of mortality and other "outcome" data has been suggested as a way to identify hospitals with quality of care problems (Brook and Lohr, 1987; Duboise, Brook and Rogers, 1987). The proposed approach consists of using regression analysis to control for causes of interhospital variation in mortality due to measured differences in hospital and patient characteristics, and attributing unexplained variation to differences in quality. Using the approach, the Health Care Financing Administration (HCFA) has instituted a policy of publishing mortality rates of Medicare patients compared with rates predicted by regression models (U.S. DHHS, 1987b).

HCFA believes that hospitals with actual mortality rates exceeding the predicted rates by significant amounts are more likely to have quality problems than other hospitals (U.S. DHHS, 1987a). Brook and Lohr (1987) have posited that two-thirds of hospitals identified as "outliers" in distributions of predicted minus actual mortality rates would exhibit quality problems. However, evidence available so far does not suggest that this is the case. In a review of medical records, Dubois, Rogers and others (1987) found no statistically significant difference in quality between treatment of patients in high and low outlier hospitals when objective criteria were used; application of subjective criteria to classify deaths retrospectively as preventable or not preventable revealed a higher rate of preventable deaths in the high outliers but afforded a conclusion of a significant difference with only marginal reliability.

Outlier hospitals on HCFA's 1986 outlier list were analyzed by offerers

responding to the 1986 request for proposals to serve as Peer Review Organization (PRO). In a recent study, the Government Accounting Office (GAO, 1988) interviewed officials of each funded PRO to obtain results of the analyses. GAO found that across all PRO's and 1986 outliers, 13 hospitals were determined to have definite quality problems, six were found to have possible quality problems, and 178 were determined not to have problems. Of the 13 having problems, seven were high outliers, and six were low outliers.

The New York State Department of Health (Hannon, 1988) reviewed 1,373 cases in the 10 hospitals that were positive outliers in the 1987 HCFA mortality data release. In the ten outlier hospitals, quality problems were identified in 0.07 percent of deaths, compared to 1.2 percent of deaths in hospitals from the non-outlier group. The New York study indicated that severity of illness was a significant factor explaining the higher mortality in the outlier hospitals. The HCFA prediction models do not take severity of illness into account. In preparing for the 1988 mortality data release, HCFA has contracted with Mediqual Systems, Inc. to obtain data to study the sensitivity of predicted mortality to inclusion of severity-of-illness indicators.

Empirical research to determine if analysis of statistical outliers can systematically detect poor quality medical care using medical records is very expensive. In the literature produced by proponents of the approach, one detects a high reliance on faith that current applications of the technique are producing useful data, and optimism that the approach will be proved useful in future research.

Proponents of the approach have not offered a theoretical rationale for their belief that the approach is efficacious. Indeed, the usual interpretation of differences between actual values of a variable and values



predicted by a regression model is that they are unexplained errors of prediction which can be characterized only in terms of their underlying probability distribution. To interpret them as estimates of the effect of a particular causal factor (in this case, a measure of "quality") omitted from a prediction model is unusual and would be possible only under particular combinations of very special circumstances. Nevertheless, the notion that unmeasured factors might reveal themselves systematically in errors of prediction seems to have a commonly accepted intuitive appeal.

Is there an objective way of developing a-priori expectations about the efficacy of this unproven but optimistically promoted approach? A technique which can be implemented at minimal expense, and results of several examples of its application are described in the remainder of this paper. The technique is generally known as the "Monte Carlo" technique which is a method of generating and using synthetic data to examine the performance of statistical techniques applied to them.

#### THE MONTE CARLO TECHNIQUE

The manner in which mortality rates among hospitals are affected by differences in quality of care is unknown. This poses special problems for statistical analysis of mortality data since the distributional assumptions of the statistical techniques employed may not be satisfied, rendering inference invalid. Thus, it is important to know the particular processes generating the data (Mosteller, 1987). If we cannot know the process, then we need to know how results of applying a statistical technique are affected by applying it to data generated by the several or perhaps, the many, possible processes that could be generating the actual data. For, inference may be possible if one process generates the data but invalid if another process generates the

data. By generating synthetic data from models of a variety of possible processes that could be generating the data in nature, and by then applying the statistical technique in question to the data, one can observe the ability of the technique to discern the known properties of the processes and thereby develop expectations about the efficacy of the technique in real world applications.

In the case of mortality data generated by what are presumed to be both good quality and poor quality hospitals, the question for investigation is whether "outlier" residuals obtained from particular varieties of regression analysis contain an acceptable proportion of the poor quality hospitals in one's sample. To examine this question, one can produce synthetic data in which the poor quality hospitals as well as the processes - including the explanatory variables and their exact weights - generating the observed mortality rates are completely known. Then, one can apply the techniques under investigation to the data to see if the techniques achieve the objective of the analysis. In this case, the objective is to have the known poor quality hospitals appear in the positive tail of the distribution of the errors of prediction. Furthermore, one would prefer that no good quality hospitals appear in the positive tail.

Since all aspects of the process generating the synthetic data are known, deficiencies of the applied analytical technique can be examined in terms of their impact on reliability. In the case of analysis of mortality data to infer quality, several issues of deficiency are primary. First, since in practice hospitals cannot be distinguished a priori in terms of quality differences, explicit measures of quality will not be available for inclusion in the analysis. (If such measures were available, then the approach under discussion of inferring quality indirectly would be unnecessary.)

Consequently, if variation in quality does cause variation in mortality, any analysis such as regression analysis will produce biased estimates of population parameters and biased predictions of conditional expectations of mortality rates due to a misspecification of omitting explanatory variables from the prediction equation. The effect of omitting explanatory variables is a key issue in the efficacy of the approach under discussion. For example, it is featured in the criticism of the omission of "severity of illness" measures in the HCFA method.

Second are the implications of drawing sample hospitals from different populations rather than the same population. If in nature poor quality hospitals come from different populations than good quality hospitals, then inference based on assumptions that they all come from a single population is invalid. The practical effect on the distribution of prediction errors of mixing sample observations from different populations can be observed directly in a Monte Carlo experiment.

Any other departure from the full ideal conditions of the applied technique may produce bias in the errors of prediction. Some of primary interest include departures from the form of the distribution of the errors assumed by the technique; errors of measurement of the dependent or independent variables; and using a functional form for estimating population parameters different from that which generated the data. The impact of these ways of misspecifying one's predictive model can be investigated by Monte Carlo methods either singly or jointly.

## TWO PLAUSIBLE MODELS OF QUALITY VARIATION

How does "quality" effect patient care outcome variables like mortality? In the following are considered two different but equally likely (as far as is



known about how quality differences may be manifested) models. The first model (Model I) postulates that every hospital's mortality rate is governed by the same parameters with a linear add factor determining its deviation from the normal expected mortality rate. In this model, there is one population of hospitals, and a single equation generates the data for all of them; thus, a single equation is appropriate to estimate the regression parameters. The second model (Model II) postulates that there are two populations of hospitals: regular hospitals and killer hospitals. The two populations are characterized by different population parameters so that estimation of the parameters requires that separate samples be drawn and separate regression models be estimated.

In practice, regular and killer hospitals cannot be distinguished a-priori. Consequently, no matter which model is the true model, any attempt to estimate the population parameters necessarily involves a single equation omitting explicit measures of the levels of quality produced by sample hospitals. Nevertheless, one hopes that killer hospitals will be revealed as outliers in a regression analysis that takes into account as many explanatory factors as possible.

The explanatory factors which could be considered in an analysis of hospital mortality are manifold. For the present purpose, only enough factors need be considered to examine the issues of interest. Therefore, in the following, it is supposed that the number of deaths ( $DEATHS_i$ ) in each hospital  $i$ ,  $i=1, \dots, n$  are related to the number of cases treated ( $CASES_i$ ), the average age of the patients treated ( $AGE_i$ ), an index representing the "complexity" or average cost of a hospital's cases ( $CMIX_i$ ), and an index of the average severity of patients' illnesses at admission ( $SEV_i$ ).



"Quality" is included explicitly as the coefficient of the variable  $Q_{I,i}$  in Model I:

$$(I) \quad DEATHS_i = a_1CASES_i + a_2AGE_i + a_3CMIX_i + a_4SEV_i + a_5Q_{I,i} + e_I$$

where  $e_I$  is a random normal deviate with a mean of 0 and a constant variance. In Model II, quality  $Q_{II,i}$  is a multiplicative factor affecting all the parameters:

$$(II) \quad DEATHS_i = Q_{II,i}(a_1CASES_i + a_2AGE_i + a_3CMIX_i + a_4SEV_i) + e_{II}$$

where  $e_{II}$  is a random normal deviate with a mean of 0 and a constant variance. Samples of data were generated using equations I and II with alternative assumptions about the values of the variables  $Q$ , about the relative proportions of poor quality hospitals in the samples, and about the variance of the random variables  $e_I$  and  $e_{II}$ . These samples were the basis of experiments in which various regressions models were fit to the data to determine if analysis of residuals could isolate poor quality hospitals.

#### THE MONTE CARLO EXPERIMENTS

For each experiment, sample data were generated for five combinations of the independent variables shown in Table 1. Table 2 shows the coefficients of simple correlation between the explanatory variables tabulated in Table 1. The values of the parameters  $a_1, \dots, a_4$  in the models were 0.025, 0.1, 2.0 and 2.0, respectively. The parameter values and ranges of the independent variables were chosen to be roughly consistent with those applicable to the Medicare program and with values of parameter estimates reported in the literature as for example by

Dubois, Brook and Rogers (1987). However, since this was a statistical experiment, the realism of the numbers was not an important issue in determining the values.

For each of the basic models I and II, four experiments designated A through D were performed in which the number and distinguishing character of poor quality hospitals was varied. In experiments A and C, the quality variables  $Q_{I,i}$  and  $Q_{II,i}$  were continuous or "graded," with  $Q_{I,i}$  assigned values of 0, 0.25, 0.5, 0.75, and 1 and  $Q_{II,i}$  assigned values of 1, 1.25, 1.5, 1.75, and 2. In experiments B and D, one hospital was designated a "killer" hospital with systematically higher deaths than the remainder. In experiments IB and ID,  $Q_I$  was assigned a value of 1 for the designated killer and a value of 0 was assigned to the remaining hospitals. In experiments IIB and IID,  $Q_{II}$  was assigned a value of 2 for the designated killer and a value of 1 was assigned to the remaining hospitals. Within each experiment, each hospital in turn was assigned the highest number, with the remainder of the numbers being randomly assigned to the remainder of the hospitals. Thus, each experiment was performed with five data sets.

In experiments A and B, each hospital was sampled 20 times giving a total of 100 observations per sample and 500 per experiment. In experiments C and D, the killer or lowest quality hospital was sampled 2 times while the remainder were sampled 20 times each, for a total of 82 observations per sample and 410 per experiment.

Each set of experiments for each of the models I and II were performed three times with successively larger values for the variance of the error terms  $e_I$  and  $e_{II}$ . The three values were 0, in which case the error is totally systematic due to omitted variables; 1, an error of

moderate size; and 25, a large error relative to error due to omitting the quality variable. In this way, effects of successively larger random error relative to systematic error can be observed on the performance of the regression outlier technique of detecting killer hospitals. The error terms were generated by the SAS random number function NORMAL (SAS Institute, 1985).

To summarize, the intention of the experimental design is to observe the composition of regression residuals under several conditions. These are when the data are drawn from a single and from multiple populations (Model I vs Model II); when quality is a continuum and when low quality hospitals are distinguished sharply from the others (experiments A and C, vs B and D); and when low quality hospitals comprise a large proportion of the total and a small proportion of the total (experiments A and B vs C and D). Finally, the effect of varying the proportion of random error to systematic error was observed by repeating each set of experiments drawing from error term distributions with difference variances. Under each set of circumstances, the interest is in how many "killer" hospitals (hospitals assigned the highest death rates in each experiment) have actual death rates more than two standard deviations above the rate predicted by a regression model.

#### APPLICATIONS OF THE OUTLIER TECHNIQUE

For each experiment, several Ordinary Least Squares (OLS) regression models were fit to the data. With a constant term excluded and then included, the dependent variable DEATHS was regressed on the independent variables CASES, AGE, and CMIX; then the variable SEV was added as an explanatory variable. For each regression, the number of "outliers,"



i.e., residuals exceeding two standard deviations of the predicted values of the dependent variable, were counted and the number of false positives (the number of non-killer outliers) and the number of false negatives (the number of killer observations not appearing as outliers) were noted. The results of the three sets of eight experiments are reported in Table 3 and Table 4.

For each experiment, the results of fitting several different regression models to the experimental data are reported. These are the results of fitting models with the correct functional form (linear functions with the constant terms restricted to zero) but omitting successively the quality variable Q (1 OV) and the variables Q and SEV (2 OV). Then are the results of fitting models with an incorrect functional form (linear functions but including a constant term) and omitting successively the same variables. Table 3 also shows the the results of fitting the "true" model (which includes "quality" as an explanatory variable) to the data.

Since low values of both false negatives and false positives are desirable, one can inspect Tables 3 and 4 for incidences of the joint occurrence of low values. Unfortunately, there are not many. The few that occur are concentrated in the experiments in which killer hospitals comprise a small proportion of the sample hospitals (experiments C and D). Within these experiments, the ability to detect the killers is apparently dependent on the functional form of model used; if the correct functional form is known, the model appears somewhat robust to omitting explanatory variables and drawing data from different populations, but performance is compromised by increasing the proportion of stochastic variation when the data are from a single population.

When killers comprise a larger proportion (i.e., 20 percent) of the sample, ability of the technique to detect killers is not apparent. Uniformly, more than 90 percent of the killers do not appear in the positive tail of the distribution of residuals. With a few exceptions, the majority of residuals in the positive tail are not killers, and the exceptions to this statement do not occur according to a regular pattern.

In summary, the particular experiments performed indicate the technique may have some ability to detect killers when they are a small proportion of the sample; this ability appears sensitive to functional form and to the proportion of random to systematic error. The technique may have no ability to detect killers when they are a larger proportion of the sample. There are no obvious difference in performance when samples are from a single or from multiple populations. Nor is there a difference in performance when quality is a continuous variable compared to when killer hospitals are sharply differentiated from the others. One should not generalize from these particular results unless they are shown to hold up after varying values and assignment of explanatory variables, values of parameters, etc.

It is instructive to examine the residuals and to observe the effect of specification error on their distribution. In practice, inspection of the residuals often provides one way to determine if a model is correctly specified. Figure 1 plots the Studentized residuals of a good performing model with two omitted variables from experiment IC, while Figure 2 is a plot of the true model of experiment IC.

Comparing plots of the residuals for a true model and the misspecified models illuminates the effects of the omitted variable problem on the residuals. The residuals depicted in Figure 2 generated

by the full ideal conditions of the classical linear least squares model are normally distributed about a mean of zero. The residuals shown in Figure 1 of models misspecified due to omitted variables have non-zero means. The dispersions of the residuals about their means are tighter than the dispersions of the residuals in the true model and the relation of the means of the residuals with respect to the explanatory variables is non-linear. The presence of specification error is often evident visually as in Figure 1 and is also detectable under certain conditions by specification error tests such as the RESET and other tests of Ramsey (1969).

#### DISCUSSION

For addressing the question of whether statistical outlier analysis can identify poor quality hospitals, Monte Carlo techniques provide an alternative to the expensive process of abstracting actual patient records. The experiments described above illustrate how the method of using synthetic data to examine the properties of a statistical technique of analysis can be performed. The method is inexpensive and accessible; many personal computer-based spreadsheet programs have the joint capability to perform algebraic calculations, produce random numbers, and perform regression analysis required to undertake a Monte Carlo experiment. If the research community interested in the use of statistical outlier analysis approached the question of its efficacy through the Monte Carlo method, the question might be settled much quicker and with far more precision than if data from natural experiments are employed.

It is not wise to generalize from a limited number of experiments



such as those described in this paper. However, the experiments do illustrate a well-known fact that bears continuous repetition. This is that misspecification of statistical regression models may severely compromise the validity of statistical inference. It is not wise to base social or industrial policy on conclusions derived from application of such techniques if one has not determined how robust the techniques are in the presence of known errors of specification as well as the possible presence of other errors. Exploration of the performance of the technique on synthetic data generated by the full scope of possible processes generating data in nature will provide a basis for this determination.

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Table 1  
Values of the Independent Variables  
for Hypothetical Hospitals

<u>HOSPITAL</u>	<u>CASES</u>	<u>AGE</u>	<u>CMIX</u>	<u>SEV</u>
1	800	68	1.1	3.0
2	1200	70	1.4	3.5
3	1600	72	1.7	1.5
4	2000	74	0.5	2.0
5	2400	66	0.8	2.5

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Table 2  
Simple Correlations of Independent Variables

	<u>CASES</u>	<u>AGE</u>	<u>CMIX</u>	<u>SEV</u>
CASES	1	0	-0.5	-0.5
AGE		1	0	-0.5
CMIX			1	0
SEV				1

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Table 3: Summary of Outlier Results  
for Experiments with Model I

OUTLIERS

EXPERIMENTS	$\sigma^2=0$		$\sigma^2=1$		$\sigma^2=25$				
	Outliers/ Observ.	%False Pos.	%False Neg.	Outliers/ Observ.	%False Pos.	%False Neg.	Outliers/ Observ.	%False Pos.	%False Neg.
IA: Graded Quality, 20 Killers									
True Model									
Correct Function, 1 0V	0	0	100	2.6	69	96	2.8	71	96
Correct Function, 2 0V	0	0	100	0.6	33	98	2.4	75	97
Incorrect Function, 1 0V	0	0	100	0	0	100	2.0	60	96
Incorrect Function, 2 0V	0	0	100	2.6	69	96	2.8	71	96
IB: Binary Quality, 20 Killers									
True Model									
Correct Function, 1 0V	0	0	100	2.4	75	97	2.2	100	100
Correct Function, 2 0V	0	0	100	0.8	100	100	2.0	80	98
Incorrect Function, 1 0V	0	0	100	0.2	0	99	1.6	38	95
Incorrect Function, 2 0V	0	0	100	2.4	50	94	2.2	100	100
IC: Graded Quality 2 Killers									
True Model									
Correct Function, 1 0V	0	0	100	3.2	69	60	2.4	100	100
Correct Function, 2 0V	2.0	0	20	2.2	11	20	2.4	57	40
Incorrect Function, 1 0V	2.0	0	20	2.0	0	20	2.4	71	60
Incorrect Function, 2 0V	0	0	100	3.7	93	90	2.4	100	100
ID: Binary Quality, 2 Killers									
True Model									
Correct Function, 1 0V	0	0	100	2.4	100	100	2.7	91	90
Correct Function, 2 0V	2.0	0	20	2.9	33	20	3.4	64	50
Incorrect Function, 1 0V	2.4	0	0	2.4	0	0	3.2	38	20
Incorrect Function, 2 0V	0	0	100	2.4	100	100	2.7	91	90
Incorrect Function, 2 0V	1.5	0	40	2.9	42	30	2.7	64	60

Table 4: Summary of Outlier Results  
for Experiment with Model II  
OUTLIERS

EXPERIMENTS	$\sigma^2=0$		$\sigma^2=1$		$\sigma^2=25$				
	Outliers/ Observer.	%False Pos.	%False Neg.	Outliers/ Observer.	%False Pos.	Outliers/ Observer.	%False Pos.	%False Neg.	
IIA: Graded Quality, 20 Killers									
Correct Function, 1 OV	0	0	100	0.75	0	96	1.4	57	97
Correct Function, 2 OV	0	0	100	0	0	100	0	0	100
Incorrect Function, 1 OV	0	0	100	2.5	50	94	3.0	80	97
Incorrect Function, 2 OV	0	0	100	5.0	50	99	3.0	53	93
IIB: Binary Quality, 20 Killers									
Correct Function, 1 OV	0	0	100	2.6	33	98	0.10	100	100
Correct Function, 2 OV	0	0	100	0	0	100	0.12	17	95
Incorrect Function, 1 OV	0	0	100	2.8	71	96	2.0	80	98
Incorrect Function, 2 OV	0	0	100	1.4	100	100	2.2	45	94
IIC: Graded Quality 2 Killers									
Correct Function, 1 OV	2.0	0	20	2.0	0	0	2.4	30	30
Correct Function, 2 OV	1.5	0	40	1.2	20	60	1.5	0	40
Incorrect Function, 1 OV	0	0	100	1.8	100	100	2.0	100	100
Incorrect Function, 2 OV	1.0	0	60	1.3	20	50	2.7	64	60
IID: Binary Quality, 2 Killer									
Correct Function, 1 OV	2.0	0	20	2.2	11	20	2.2	11	20
Correct Function, 2 OV	2.4	0	0	2.4	0	0	2.4	0	0
Incorrect Function, 1 OV	0	0	100	1.7	100	100	2.4	100	100
Incorrect Function, 2 OV	0	0	100	1.7	100	100	2.4	100	100
JSH/gS									

FIGURE 1: Plot of RESID\*CASES for Model IC  
 $DEATHS = 0.018CASES + 0.45AGE + 1.91CMIX + e_I$   
 Killer Hospital has 800 Cases

Legend: A = 1 obs, B = 2 obs, etc.

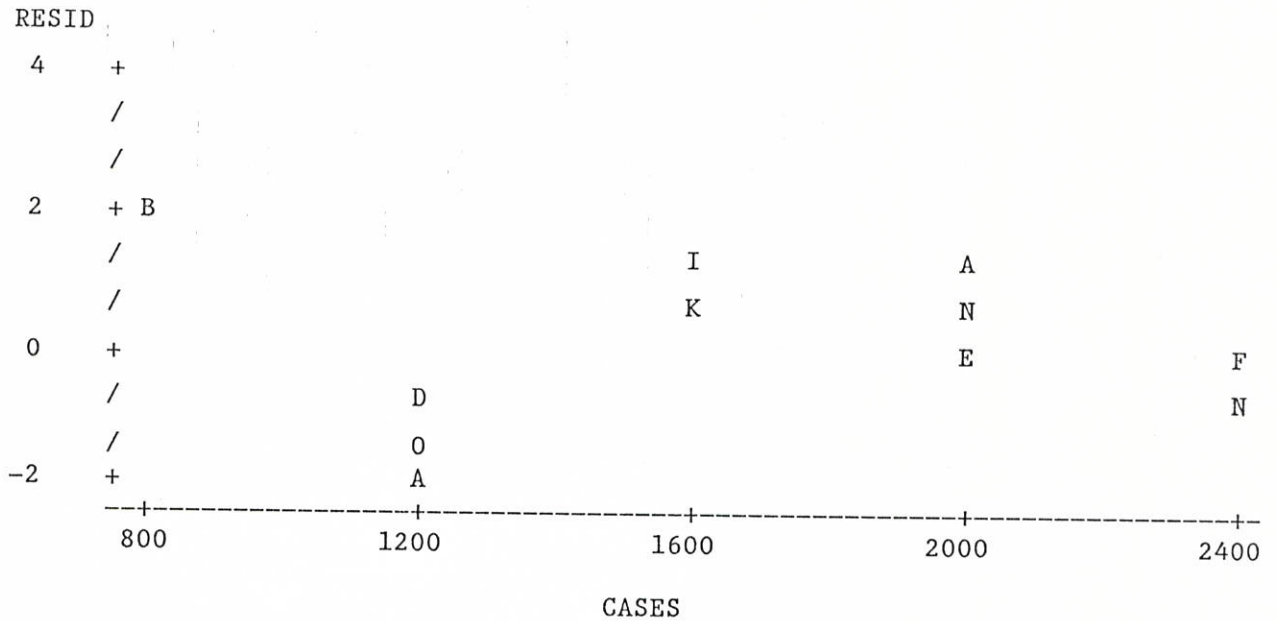
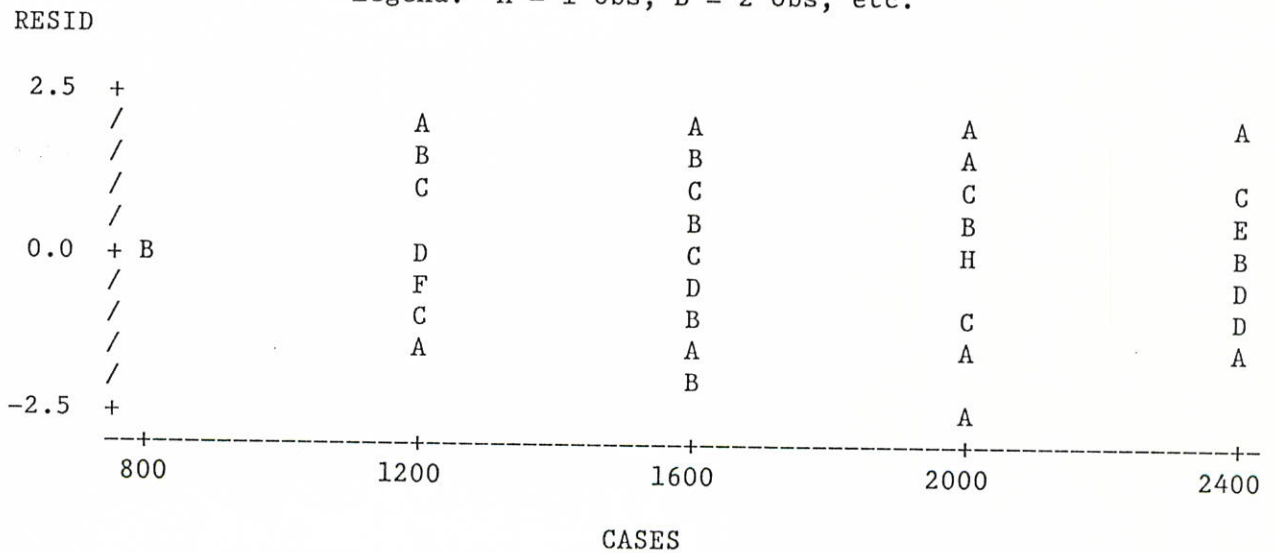


FIGURE 2: Plot of RESID\*CASES for Model IC  
 $DEATHS = 0.025CASES + 0.11AGE + 1.83CMIX + 1.94SEV + 19.83Q_I + e_I$   
 Killer Hospital has 800 Cases

Legend: A = 1 obs, B = 2 obs, etc.



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POSITIONS

U.S. NATIONAL INSTITUTES OF HEALTH  
ECONOMIST, OFFICE OF THE DIRECTOR

1986

Advise the Director and Associate Directors on economic positions and information issued by the NIH. Responsible for designing a research agenda to document the contribution of NIH research to medical advances reducing the costs of health care.

U.S. HEALTH RESOURCES ADMINISTRATION  
CHIEF, MANPOWER MODELING AND RESEARCH

1976 TO 1986

Forecast levels of economic activity in the health care industry, prices, employment, and demand for health manpower. Supervised policy research projects for the Bureau Director and Agency Administrator. Contributed extensively to government reports. Served on temporary assignments to Assistant Secretary for Planning and Evaluation.

U.S. CONSUMER PRODUCT SAFETY COMMISSION  
OPERATIONS RESEARCH ANALYST

1975

Assessed cost-benefit of safety standards, regulation of hazardous products and consequences of alternative regulatory approaches.

U.S. SOCIAL SECURITY ADMINISTRATION  
ECONOMIST, OFFICE OF RESEARCH AND STATISTICS

1972 TO 1975

Developed approaches to implement Congressionally mandated changes to Medicare reimbursement; evaluated experimental Medicare prospective payment systems for hospitals and physicians. Developed micro simulation modeling applications for forecasting benefits. Research on costs of graduate medical education related to questions of hospital reimbursement and funding of education.

MICHIGAN STATE UNIVERSITY  
ASSISTANT PROFESSOR, DEPT. OF ECONOMICS AND COLLEGE OF MEDICINE

1969 TO 1972

Taught Microeconomic Theory and Health Economics, supervised thesis and dissertation research.

EDUCATION

Ph.D., Michigan State University, 1969.  
B.B.A., Lamar State College of Technology, 1965.





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September 30, 1988

Professor Ronald Anderson  
University of Chicago

Dear Professor Anderson:

Enclosed is a copy of my paper for the workshop of October 13, "Can Statistical Outlier Analysis Detect Poor Quality Hospital."

I am looking forward to the seminar.

Sincerely,

A handwritten signature in blue ink, appearing to read "J. Hixson".

Jesse S. Hixson  
Director

JSH/gs  
3217v