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Erratum: The byline for the following article should read:
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THE ECONOMICS OF TEACHER TRAINING: An Exploratory Data Analysis

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Despite reports of a teacher shortage in rural areas, 56 per cent of a sample of recently trained teachers were unemployed. Nonetheless, only 31 per cent would even consider a rural job. The teacher shortage was a structural, rather than an aggregate, phenomenon. It was also a feminist issue, as sex affected the chances of being employed more than did "merit" and most newly trained teachers were women. Policymakers might consider (a) reducing the number of Karachi-trained teachers, and increasing rural-based training; (b) raising tuitions; and (c) requiring graduates to take rural jobs.

I. Introduction

Pakistan's shortage of teachers is said to be severe, especially in rural areas. Yet little is known about the supply of new teachers. What are the costs of teacher training? What has been the employment experience of newly trained teachers? How many have jobs, what are the salaries, and what is the length of job search? How many teachers would be willing to consider rural employment? What demographic, personal, and educational characteristics affect these aspects of teacher employment? These questions are addressed in this study of Karachi's experience in the mid-1970's.

The research reported here, and in our longer monograph on the subject,[1] also has methodological and pedagogical interest as an example of exploratory data analysis. Readers interested solely in the policy questions may skip directly to section IV; those interested primarily in the statistical issues should concentrate on section II (procedures) and III (data and analysis).

[1] Same authors (1977).

II. Notes on Statistical Procedures

This section constitutes an informal justification for the statistical methods employed in analyzing the teacher training data. Its objectives are: (1) to outline the "philosophy" behind the exploratory techniques utilized in the study; (2) to comment on how to interpret the results from regression equations chosen through exploratory data analysis; and (3) to outline the differences between ordinary least squares regression and logit analysis, in the case of a binary dependent variable.

An Exploratory Philosophy

We may search for hypotheses, or we may try to confirm hypotheses already held. The second disposition has dominated much of statistics and econometrics. Models are posited, often on the basis of a theory; and statistical tests are carried out, based on assumptions about underlying frequency distributions.

In many cases, we have neither a well-specified model nor a rationale for distributional assumptions. Although it is easy and conventional simply to assume a certain model (e.g., linear additive) and a certain multivariate distribution (e.g., normal), there is often no convincing reason for doing so. Even when a microeconomic model is appropriate as the basis for statistical work, real life almost always introduces complications: for example, the errors stemming from missing data and proxy variables. And of course microeconomic theory itself is replete with assumptions, as its most distinguished practitioners freely advertise.

Thus in many real-life settings, we lack a convincing model or a hypothesis. We must search rather than confirm. In these situations a different "philosophy" of data analysis is useful. Following John Tukey, we may call this philosophy "exploratory data analysis."

> The processes of criminal justice are clearly divided between the search for the evidence – in Anglo-Saxon lands the responsibility of the police and other investigative forces – and the evaluation of the evidence's strength – a matter for judges and juries. In data analysis a similar distinction is helpful. Exploratory data analysis is detective in character . . . . Unless the detective finds the clues, judge or jury has nothing to consider . . . . *Exploratory data analysis can never be the whole story, but nothing else can serve as the foundation stone – as the first step.*[2]

We will use statistical tools to try to uncover "what the data seem to be saying."

[2] See Tukey (1977, pp. 1-3).

An example may be useful. Often in statistical and econometric studies, the analyst employs linear regression analysis. The ordinary least squares technique (OLS) may assume, in the simple case of one dependent variable Y and one independent variable χ, a particular specification:

$$Y_i = b_o + B_1 \chi_1 + e_i$$

where b_o and b_1 are constants. The error term e_i is assumed to fulfil three assumptions:

$$E(e_i) = 0$$

$$E(e_i e_j) = 0 \quad \text{if } i \neq j$$

$$= \sigma^2 \quad \text{if } i = j$$

where σ^2 is a constant.

There may well be departures from these assumptions in real life. The specification of the model may be incorrect. Perhaps an additional independent variable should be included. The variables may need re-expression; for example, perhaps X should be transformed to logarithms. We may need to discriminate among the individual observations: we may weight certain observations less, or we may remove wildly deviant observations from the analysis.

If the OLS assumptions are met, then well-known statistical tests can be used to confirm or reject prior hypotheses. But if those assumptions cannot be supported, then there is no guarantee that the theoretically optimal statistical tests actually test anything in the real world. The computed regression coefficients and confidence intervals are similarly cast into limbo.

In our case of teacher training, we are worried about several matters. First, we do not have an *a priori* model of how our variables concerning teachers' demographic, educational, and personal characteristics affect various dimensions of teachers' employment experience (unemployment, salary, months of job search, willingness to take a rural job). We do not even know which variables we should include in our model. We do not know the proper functional form of the regression equation.

Second, we have differing numbers of nonresponses on the different variables. A teacher who reported her wage may not have answered the question about her intermediate division; another teacher may have answered all the questions except the one about mother tongue. We cannot conveniently assign a value to the missing answer. Nor can we eliminate all teachers who failed to answer any question, for we would have a drastic

reduction in sample size.[3]

As a result of these problems, we have adopted a variety of exploratory techniques. We examine variables in pairs, looking for clues about which variables are most important and which may require transformations. We fit simple regressions and then examine plots and tables of residuals vis-a-vis a string of other variables, with the nonresponses included. We try a number of complicated multiple regressions, paying particular attention to residuals and to the stability of regression coefficients. We report a variety of results, not just one, so that the reader can draw some of his or her own conclusions about what the data reveal.

The Interpretation of Exploratory Regression Results

With the approach we have adopted, our resulting regression equations cannot be interpreted in the strict sense of "confirmatory" data analysis. When the inclusion or exclusion of variables in the nth regression is based on the statistical significance of variables in the n-1th regression, the sampling distribution of estimators in the nth regression is affected. In particular, the t-statistics and F-statistics cannot be used in exact tests of hypotheses about the regression coefficients or the regression equation as a whole.

If we knew exactly how the estimators were affected by adopting a particular "regression strategy," we could make allowances. For example, we might hope that the bias of coefficients and of t-tests could be analyzed *given* a certain multi-stage selection procedure for the included variables. Then adjusted tests could be used.

Researchers have tried to do this. Unfortunately for practical work, estimates of bias depend on the unknown true values of the coefficients, as well as on the distribution of underlying error terms. The data analyst is left in limbo.[4]

One solution is to test the final equation we choose on another set of data. With large data sets, one may set aside half the observations and choose a preferred equation using the other half, later testing that result on the first half. In the case at hand, we did not have enough observations to afford this luxury.[5]

We must therefore be cautious in interpreting the coefficients and

[3] We cannot, therefore, use the brute force, exploratory regression techniques proposed by Daniel and Wood (1971), which analyse the results of regressions on every possible combination of independent variables and some of their transformations.

[4] See, for example, Larson and Bancroft, (1963, pp. 462-479), Draper and Smith (1966), and Bancroft (1964, pp. 427-442).

[5] For an example of this technique, based on a different data set from Karachi's secondary schools, see Klitgaard, Dadabhoy, and Litkouhi (1981, pp. 99-113).

summary statistics of our regressions. They may be biased upwards: we are likely to have a higher $\bar{R}^2$, for example, than our model "really" deserves.[6]

OLS Explorations with a Binary Dependent Variable

When we are trying to predict whether a recently trained teacher has a job or not, or whether he or she would consider a rural job or not, the variable of interest is binary. Such dichotomous variables can cause statistical problems, especially in the context of regression studies like ours.

For example, consider the simple function

$$R_i = \alpha_o + \alpha_1 A_i + e_i,$$

where R = would consider a rural job (1 = yes, 0 = no), and A is age. We estimate α_o and α_1 using the data at hand. It is possible that the sum $\alpha_o + \alpha_o A_i$ might take values greater than 1 or less than 0, depending on A_i. R_i, on the other hand, must equal 0 or 1. Therefore, e_i given A_i can only take two values: $-(\alpha_o + \alpha_1 A_i)$ and $1 - (\alpha_o + \alpha_1 A_i)$. Now according to OLS assumptions, $E(e_i) = 0$ for any A_i. Therefore,

$$P[e_i=(\alpha_o + \alpha_1 A_i)] = 1 - (\alpha_o + \alpha_1 A_i) \text{ and } p[e_i=1 - (\alpha_o + \alpha_1 A_i)] = \alpha_o + \alpha_1 A_i.$$

But since $\alpha_o + \alpha_1 A_i$ may be negative or greater than one, but a probability cannot, the OLS specification has a serious problem.

Researchers have shown that OLS estimators in such cases are inefficient and, if the independent variables are dummy variables, inconsistent.[7] Some scholars have therefore recommended the use of "logit," "probit," and other specifications, instead of OLS.

These other specifications, however, are not without their own shortcomings. Some are statistical. It is true that the logit specification is relatively simple, symmetrical, convenient in handling grouped data, and mathematically attractive because under certain assumptions a maximum likelihood estimator can be derived.[8] But these mathematical reasons are un-

[6] When the analyst considers many alternative specifications and chooses according to a criterion like "smallest residual variance," his resulting estimate of that variance will on the average be below the true figure.

[7] See, for example, Nerlove and Press (1973), Halperin, Blackwelder, and Verter (1971, pp.125-158).

[8] For a comparison of the logit specification with other models, see Bishop, Fienberg, and Holland (1975, Chapters 2 and 3, pp. 366-372). They summarize: "Lest the reader conclude that the only problem remaining is to make an intelligent choice of existing methods, we now indicate the urgent need for the development of further methodology . . . Much remains to be done, particularly when the data base is large and consists of mixed variables, and measurements are unevenly replicated" (p.371).

related to the issue of the appropriateness of the logit specification for the data at hand. Furthermore, the maximum likelihood estimates may not exist in certain cases.[9]

Other shortcomings are computational. Computer programs for logit analysis did not exist in Pakistan when we carried out this research. In general, logit programs take much more time to run than OLS programs, and therefore the many runs necessitated by our exploratory techniques would have been extremely costly.

We can, however, adopt a strategy like the one used in this paper. We use OLS and other techniques to select a set of independent variables, on the assumption that *t*-tests for OLS regression coefficients are roughly accurate indicators of what MLS would show. If one assumes multivariate normality and equal covariance matrices among the independent variables, the OLS approach provides exact *t*-tests concerning the independent variable.[10] In our applications, which contained dummy independent variables, one cannot assume multivariate normality. Some research, however, has shown that the OLS-based estimates of the logit parameters agree closely with the MLE estimates, even with dummies as independent variables.[11]

III. Data and Analysis

Programs for teacher training vary greatly in Pakistan. Brief refresher courses for experienced teachers have become more widespread. Such courses usually last less than a year and sometimes only a few weeks. They may try to teach the teachers new technical or vocational skills (for example, in agriculture), or they may attempt to recharge the teacher's battery of basic subjects (such as reading and arithmetic).

Traditional degree programs, on the other hand, put both fresh graduates and experienced teachers through at least one year's training that results in a formal degree and imparts the basic skills of the profession. Several programs exist. The "highest" degree is the Master of Education (M.Ed.); the "lowest" is the Primary School Teachers' Certificate (P.T.C.). Falling somewhere in between are the degrees of Bachelor of Education (B.Ed.) and Certificate of Teaching (C.T.). The Drawing Teacher's Certificate (D.T.C.) and Oriental

[9] If the same linear combination independent variables for teachers with $R_i = 1$ are all larger or smaller than the corresponding values for teachers with $R_i = 0$, the maximum likelihood estimates for the logit parameters will not exist.

[10] See Kshirsagar (1972, p. 213).

[11] Halperin, Blackwelder, and Verter, *op. cit.*, unpublished work by Gus Haggstrom and others at the Rand Corporation; and some of the examples analyzed in Nerlove and Press, *op. cit.*, who, nonetheless, argue in favor of MLE estimators. The logit parameter α_1 is estimated by multiplying the OLS regression coefficient by n/SS_e, where SS_e is the residual sum of squares.

Teacher's Certificate (O.T.C.) refer to those specific skills.[12] In this paper, we focus on B.Ed., P.T.C., and C.T. programs.

The Costs of Teacher Training

How much does it cost to train a teacher? Surprisingly few data are publicly available. "Development costs" and "recurring costs" are often distinguished, although the line between them is hard to draw. The Planning Commission's working papers for the 1975-80 plan estimated "recurring expenditure per trainee per annum" at Rs. 200. Was this accurate for Karachi's teacher training programs?

We collected detailed cost and environment information for six of Karachi's colleges and institutes that trained teachers. This arduous exercise and its results are detailed in our monograph. Space permits only a few major findings:

1. Recurring costs per student varied by a factor of six. We could not attribute much of these variations to different accounting rules. The average recurring cost across all schools was more than double the Planning Commission's projection.
2. Costs were lower in schools with more rapid expansion. The rank correlation between growth in enrollment from 1970 to 1975 and growth in average per pupil operating costs over the same period was -0.77. Real costs had declined over that period. Officials told us that the quality of training had also gone down, as enrollments were increasing by 10 to 60 per cent per year.
3. Students paid only a small part of the costs of their training. The proportion varied greatly, but a rough average figure would be a fifth or less of the total recurring expenditure per student.

The Sample Survey

We surveyed June 1974 graduates from Karachi's four largest teacher training schools. We excluded experienced teachers and looked only at those classified as "fresh" graduates by the schools. After enumerating the graduates *via* a careful examination of each school's records, we drew a stratified random sample of 400 graduates, representing 55 per cent of B.Ed. graduates. We designed a questionnaire and pretested it on a small, indepen-

[12] Admission requirements for these degree programs help describe who participate in each:

	Age	Academic Qualification
M.Ed.	none	B.Ed., D.P.E.
B.Ed.	none	Bachelor's degree
P.T.C.	16-22	Matriculate (secondary)
C.T.	19-22	Intermediate (higher secondary)

dent random sample of the graduates. The pretesting convinced us to change some questions and to delete others, including questions about parents' income and education.

Revised questionnaires were sent by registered mail to the stratified sample in June 1975, thirteen months after our respondents had graduated. Follow-up letters were sent to non-respondents in August. By September about 240 responses had been returned. We randomly selected 32 of the non-respondents and interviewed them personally. All of them were available and willing to respond; many said that they had posted their answers despite our not having received anything. Non-respondents did not significantly differ from respondents in salaries or months to first job, so we have some confidence that our sample is "representative."[13]

Nonetheless, not all respondents answered every question. As a consequence, our data analysis strategy was hampered by incomplete information on our respondents – a common problem in research using sample surveys.

Before we get to the data analysis, consider first some basic facts about the respondents. Table 1 gives a summary, and there are many surprises. Perhaps the most astounding result is the *unemployment rate* of 55.7 per cent. *Despite the "shortage" of teachers, over half of our sample were jobless thirteen months after graduating from teacher training school.* (Of those who had jobs, 7 per cent were not employed as teachers.) As we shall see later, the job openings were in *rural* Pakistan, not in urban areas like Karachi. In short, we see a problem of structural unemployment.

How many in our sample would be *willing to work in rural areas?* The answer was somewhat discouraging: only 31 per cent of those responding to the question said they would. Fully 30 per cent of the subjects who returned questionnaires did not answer this question. This is a higher rate of nonresponse than for almost any other question, and we suspect that many of those who did not respond meant to say "no." (More on this below.)

Nonetheless, our respondents say that they *want to work.* Fully 93.2 per cent are classified as participating in the labor force. Of the unemployed, 94 per cent are seeking work. Remarkably, of those already holding jobs, 51 per cent responded affirmatively that they were now seeking work.

As noted above, our sample included only students classified as "fresh" by the teacher training schools, a term which refers not to personality but to teaching experience. Nonetheless, fully 25 per cent of our "fresh" respondents said they held a *teaching job before entering teacher training school.* Only 43 per cent hold a job *after* finishing teacher training school. The enhancement of employability does not seem to be monumental.

[13] No general rules of thumb exist about the likely size or distribution of nonresponse bias. "There is now ample evidence that these biases vary considerably from item to item and from survey to survey, being sometimes negligible and sometimes large" (Cochran 1963, p.389)

TABLE 1

Some basic information on newly trained teachers

Variable	Response Rate	Statistics
Age	100%	Avg. 23.2 yrs. s.d. 3.7
Sex	99%	Men 13%; Women 87%
Married	99%	Yes 14%; No 86%
Religion	100%	All were Muslims
Native tongue	95%	Urdu 91%; Punjabi 3%; Bengali 3%; Sindhi 2%; Pushto 1%; English <1%; Baluchi 0%; Other 0%
Matriculate division	99%	I 17%; II 49%; III 32%; Pass 1%
Intermediate division	73%	I 2%; II 53%; III 43%; Pass 2%
Graduate division	52%	I 2%; II 67%; III 31%; Pass 0%
Degree type	100%	B.Ed. 47%; M.Ed.<1%; C.T. 22%; PTC 1%
Held job before t.t.	98%	Yes 25%; No 75%
More study soon[1]	99%	Yes 85%; No 15%
Employment status	97%	Employed as teacher 40%; Employed in other job 3%; Unemployed 55%; In school 2%
Rate of labor force participation[2]	94%	95.3%
Unemployment rate[3]	94%	55.7%
Seeking work[4]	n.a.	Yes 77%; No 68.6%
Would work in rural	70%	Yes 31%; No 69%

[1] The question was: "Do you plan to study more in the near future?"

[2] Nonparticipans include those now in school and those who are both unemployed and not seeking work.

[3] Defined as (No. unemployed and seeking)/Number in labor force.

[4] Includes respondents who were already employed.

A final surprising result concerns the percentage who say they plan to study more in the near future: 85 per cent. Our graduates do not believe they have finished their formal education, even in the short run.

These surprising facts piqued our curiosity. What attributes of these newly trained teachers were associated with their chances of being employed?

With their salaries if employed? With the number of months it took to get a job? With their willingness to work in rural areas?

Employment

We have no *a priori* model that tells us which combination of attributes predicts whether a newly trained teacher will be employed or not. We may suspect that teachers who did better in school will be more likely to be employed, that men will be more likely to have jobs than women, and so forth. But we have no theory that specifies how these and other attributes interact in a situation like ours.

We therefore adopt an exploratory approach. Our first step is to look at two-way tables, which may give us hints about differences and causes within our sample.

To demonstrate our general procedure, consider the relationship between unemployment and sex. Let us construct a two-by-two table between unemployment and sex. For convenience, we only consider the 252 respondents who were not in school and who responded to questions about employment status, age, and sex. Only 30.3 per cent of the males were unemployed compared to 60.2 per cent of the females. Thus, sex seems importantly related to the probability of getting a job.

TABLE 2

Unemployment and sex

	Male	Female	Total
Unemployed	10	132	142
Employed	23	87	110
	33	219	252

Might this result be a fluke, a result of sampling error? We can never be sure. But we can assess the probability that a difference as large as the one we observed could have occurred if, in fact, the true probabilities of being unemployed were the same for men and women.

Suppose the probabilities of being unemployed were equal. Assuming that sex and employment status were statistically independent, our best guess of this probability is the actual percentage unemployed, or 142/252 = 56.3 per cent. Since there are 33 males, we would expect that 33 x 142/252

= 18.6 or 19 males would be unemployed, instead of the 10 unemployed males actually observed. We can create a table of expected counts under the assumption of independence in a similar fashion:

TABLE 3

Expected counts if unemployment and sex were independent

	Male	Female	Total
Unemployed	18.6	123.40	142
Employed	14.4	95.60	110
	33.0	219.00	252

We may now compute the chi-square statistic χ^2. Let O_{ij} be the observed value for row i and column j in Table 2, and E_{ij} be the expected values in Table 3. Then

$$\chi^2 = \sum_{i,j} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

is distributed as a chi-square distribution with one degree of freedom. For a two-by-two table, the Yates continuity correction "is easy to use and often improves the agreement between the distribution of χ^2 and its asymptotic χ^2 distribution under the null hypothesis."[14] The revised statistic for a two-by-two table is

$$\chi^2_{2 \times 2} = \Sigma \frac{(O_{ij} - E_{ij} - \tfrac{1}{2})^2}{E_{ij}}$$

For the case at hand, the computed $\chi_{2 \times 2}$ is 9.30. Checking a table of chi-square distribution, the probability that a χ^2 variable with one degree of freedom would exceed 9.30 is less than one per cent. Therefore, with 99 per cent confidence we can reject the hypothesis that recently trained male and female teachers have the same chance of being employed.

We applied the same test to see how a number of other variables, taken one at a time, were related to unemployment. Some of the tests involved

[14] See, Bishop, Fienberg and Holland (1975, p.124).

two-by-three tables. Table 4 summarizes the results. In our monograph, we examined these findings in detail, as clues to the next steps of analysis. Here only one result can be noted: the lack of relationship between a teacher's academic record and being employed. Only the teacher's Matriculate

TABLE 4

Results of Chi-square tests for the independence of unemployment and eleven other variables taken one-by-one

Significant $p < 0.01$	Significant $p < 0.05$	Insignificant $p > 0.05$
Sex: Teaching job before t.t. (yes, no); Language (Urdu, non-Urdu); Would work in rural (yes, no, nonresponse)	Matric Division (I, II, III).	Would work in rural (yes, no); Intermediate Division (I, II, III); Graduate Division (I, II, III). Degree type (B.Ed., C.T., P.T.C.); Has children (yes, no); Lived with parents after graduation (yes, no).

Division – the results of a test taken at the end of the tenth grade – was significantly related to unemployment at the $p < 0.05$ level ($\chi^2 = 8.53$, 2 d.f.). Most of the chi-square came from first divisioners, the best students, of whom only 37 per cent were unemployed, compared to 58 per cent of the second divisioners and 69 per cent of the third divisioners. No significant differences emerged by later performance at either the Intermediate or Graduate levels. The unemployment rates by degree type were: B.Ed., 56 per cent; C.T., 50.9 per cent; and P.T.C., 61.5 per cent. These differences proved not to be statistically significant at the $p < 0.05$ level.

Only 43 per cent of this group was employed.[15] Figure 1 summarizes some interesting facts about the employed teachers. Since 94 per cent were teaching all subjects – rather than only science and mathematics, for example – specialization in teacher training school may be less functionally important than commonly believed. Also, it is noteworthy that 10 per cent of the employed teachers held an additional job.

Tabular analysis revealed interesting patterns among the employed teachers. Proportionally more women became primary school teachers than men, but there are no statistically significant differences between sexes on type of school (government, nationalized, or exempted) or language of

[15] This calculation includes the 262 who gave answers about employment status, sex, and age; it includes those in school as jobless.

school. Proportionally more women held an additional job; proportionally more men would consider a rural job (62.5 per cent vs. 30.2 per cent).

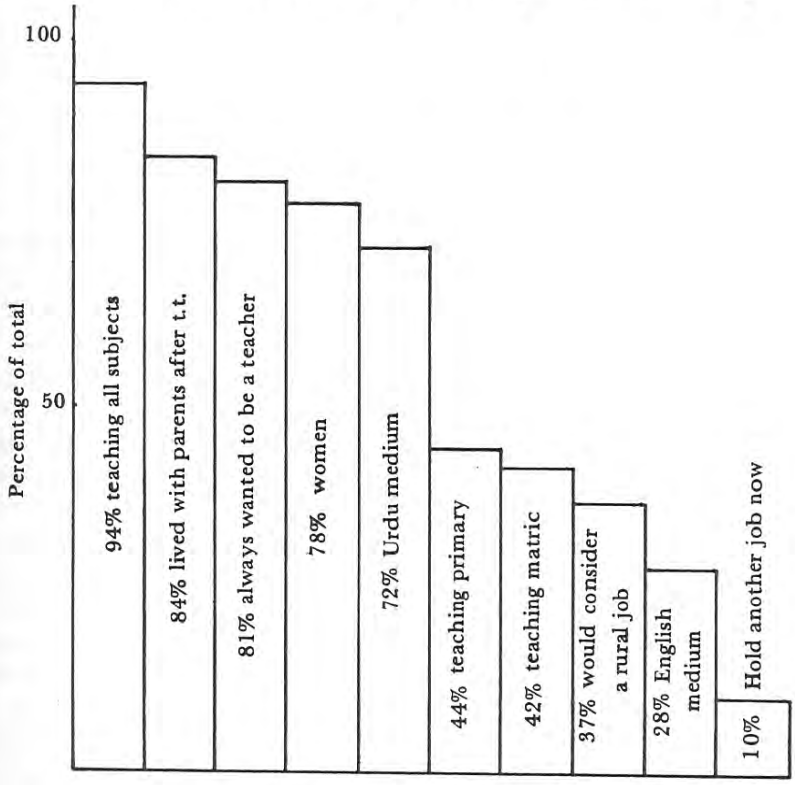

Figure 1

Some characteristics of employed teachers

Note: n = 83, but due to differing percentages of non-response, each question is based on a different number of respondents.

We begin our search for the factors that determine unemployment by noting an important feature of our data set: nonresponses. Many people did not answer every question, and different people left out different answers. We must explore the data, insofar as possible, while leaving in the nonresponses.

As noted above, varying nonresponses on different questions precluded our beginning with several large, preliminary regression equations with all the attributes that we believed had a chance to be significant predictors. If we had eliminated everyone who did not respond to at least one question, our sample size would have been drastically reduced. Our alternative was to

begin with a small equation and to look carefully at the residuals plotted against each variable not included in the equation. Our first equation used age and sex as the independent variables.

$$U = 0.52 + 0.0065\ \text{Age} - 0.28\ \text{sex} \qquad (1)$$
$$\quad (2.10) \qquad (0.75) \qquad (-2.82)$$

$$R^2 = 0.036,\ \text{s.e.est.} = 0.49,\ F = 5.69,\ n = 252$$

(In all regression results reported in this paper, figures in parentheses are t-statistics, and the criterion for "statistical significance," subject to the caveats raised in Section II, is $\alpha = 0.05$.) Sex was statistically significant: Women were less likely to be employed, age held constant. Age was not significant, sex held constant. The percentage of variation explained ($\bar{R}^2$) was very low (3.6%, adjusted for degrees of freedom).

Even with nonresponses, residuals could be usefully plotted against each of the possible predictors. For example, Figure 2 shows the plot of

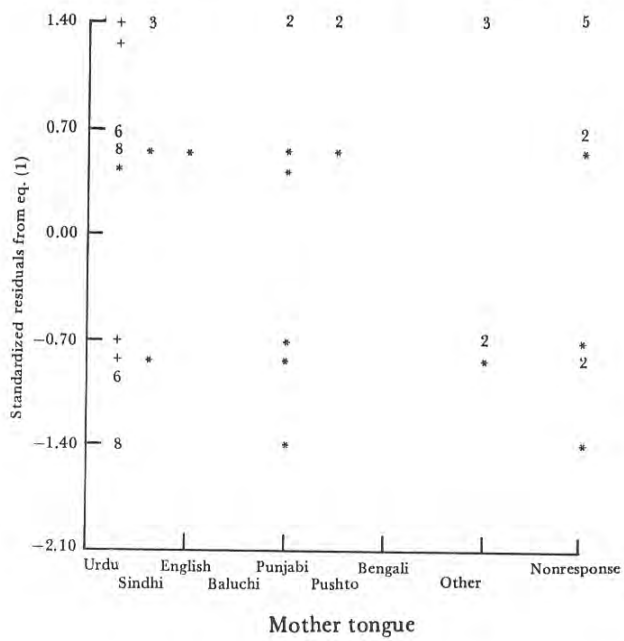

Figure 2

An example of looking at a residual plot

* = 1 observation, + = 10 or more observations

residuals against language spoken in childhood home. Notice that we can simply ignore the nonresponses as we look at the plot. Those with mother tongues other than Urdu tended to have positive residuals—that is, they tended more often to be employed. Only 32 per cent of them were unemployed, well below the percentage for the whole sample. Even after statistically controlling for age and sex, it appears that mother tongue may be a predictor of employment status. Because of the small number of people with non-Urdu mother tongues (22) and because no one language's residuals seemed obviously higher, we decided to use language as a zero-one independent variable in the next step of our statistical exploration (0 = Urdu, 1 = non-Urdu).

We examined 16 residual plots from Equation (1), trying to identify candidates for inclusion into the next regression equation. We selected variables whose residual plots seemed to show nonrandom patterns. For example, we found that those with first division matriculate degrees were more likely to be employed than second or third divisioners, whereas second and third divisioners looked about the same. Again we created a dummy variable for inclusion in the next regression (0 = II, III, or pass; 1 = I). In addition, we ended up including "lived with parents after school,"[16] type of degree, and "had teaching job before t.t. school."[17]

Table 5 presents the results of three of the most interesting subsequent regressions. Three variables were statistically significant and had relatively stable regression coefficients regardless of the other variables in the equation: men, those with first-class matriculate degrees, and those who had teaching jobs before were more likely to be employed, other things equal.

Those with mother tongues other than Urdu were more likely to be employed, but the result was not statistically significant at $\alpha = 0.05$. Age, degree type, and lived with parents did not turn out to be statistically significant, once other factors were held constant.

The importance of the variable "had teaching job before t.t. school" made us worry. Were we truly explaining the unemployment of *fresh* teachers? Would the same results hold if we eliminated from consideration all those who previously held teaching jobs?

To find out, we dropped the previously employed teachers from the sample and painstakingly repeated all our statistical explorations. Some of our findings are given in Table 6. Sex remained significant and the size of the coefficient was about the same. Women were less likely to be employed. Second, the Urdu coefficient stayed about the same size, but the result was

[16] The dummy for "lived with parents" was coded 0 = yes, 1 = no.

[17] To represent degree types, we omitted the one M.Ed. degree holder and created two dummy variables, one for B.Ed. and one for P.T.C. The dummy for "had teaching job before t.t. school," was coded 0 = yes, 1 = no.

Table 5

Some regression results on unemployment

Equation	Regression coefficients											
	Constant	Sex	1 Matric	Job bef.	Urdu	Age	Live w. Par.	PTC	B.Ed.	$\bar{R}^2$	S.e.est.	F
1.	0.36	−0.25	0.17	−0.20	0.20	0.076	0.012	−0.024	0.15	0.096	0.47	3.95*
	(0.94)	(−2.34)*	(2.05)*	(−2.57)*	(1.87)*	(0.65)	(0.10)	(−1.31)	(1.62)			
2.	0.62	−0.29	0.17	−0.22	0.029			−0.024	0.14	0.095	0.47	4.88*
	(4.50)*	(−2.83)*	(2.00)*	(−2.92)	(1.28)			(−1.35)	(1.56)			
3.	0.75	−0.24	0.17	−0.22	0.034					0.093	0.47	6.70*
	(7.17)*	(−2.49)*	(2.00)*	(−2.92)*	(1.49)							

Note: n = 224; figure in parentheses are *t*-statistics; * denotes significance at the $\alpha = 0.05$ level.

TABLE 6

OLS regressions on unemployment, excluding those with prior teaching jobs

Equation	Regression Coefficients									
	Constant	Age	Sex	Urdu	I Matric	C.T.	$\bar{R}^2$	S.e.set.	F	n
(a) Men and women:										
(1)	1.02	−0.019	−0.27	0.028	0.10	−0.044	0.029	0.48	2.04	173
	(2.68)*	(−1.39)	(−2.16)*	(1.14)	(1.05)	(−0.5)				
(2)	0.52		−0.21	0.032	0.12		0.029	0.48	2.74	173
	(4.54)*		(−1.82)*	(1.32)	(1.28)					
(b) Women only:										
(1)	0.98	−0.029		0.027	0.059	−0.071	0.017	0.47	1.65	154
	(2.84)*	(−1.98)*		(1.04)	(−0.55)	(−0.79)				
(2)	0.83	−0.023		0.028	0.072		0.019	0.47	2.00	154
	(2.89)*	(−1.83)*		(1.07)	(0.68)					

Figures in parenthesis are t-statistics.
*Denotes significance at $\alpha = 0.05$ level.

no longer statistically significant. Third, having a first-class matriculate, although still positive in sign, was not statistically significant.[18] Finally, neither age nor degree type (here represented by only a single dummy variable for C.T.) were statistically significant.

We also examined the situation specifically of women who did not have teaching jobs before. In a rather exhaustive exercise, we once again statistically explored the data from the beginning on this sample of 154 female teachers, looking for important variables one-by-one and trying a variety of exploratory regressions. Our "best" results are given in part (b) of Table 6.

Surprisingly, other things equal, the only consistently important predictor of women's employment was *age;* and this variable had a negative sign. Every regression we tried without age included had adjusted $\bar{R}^2$ of less than one per cent. Even with age included, our F-statistics were not impressive. We might be justified in concluding that *none of these variables predicts which newly trained female teachers will get jobs among those who did not have jobs before.*

Other Labor Market Outcomes

Using the same statistical techniques, we studied three other outcomes: teachers' salaries, months of job search between graduation and getting a job, and expressed willingness to work in a rural school. Space only permits the main results; readers may consult our monograph for a full description.

Salaries: Age, months to first job, and type of teaching degree were the only variables to exert a significant effect on salaries (see Table 7). Other things equal, the older one was, the higher one's pay—even in a subsample of teachers without a previous teaching job. Those who found jobs sooner tended to have higher paying jobs. Holders of B.Ed. and C.T. degrees had similar salaries, which were greater than the salaries of P.T.C. degree holders. For example, for a P.T.C. holder who took six months to find a job and who was 22½ years old, the predicted monthly salary from equation (b) is Rs. 197. For a similar B.Ed. graduate, the predicted salary is Rs. 260, and for a similar C.T. degree holder, Rs. 271. Even though degree type was not a significant predictor of employment, it did play a role in determining how well paying the job was. Academic performance and specialization did not affect salaries; neither did one's sex.

Length of job search: A histogram of months between graduation and being hired had several spikes, indicating cyclical hiring. None of our many variables were statistically significant predictors of the length of this job

[18] We hypothesize that first divisioners in matric were more likely to have had a teaching job *before* and *after* teacher training school.

TABLE 7

Regressions on ℓn salary

Equation	Regression Coefficients											
	Constant	ℓn age	Months	Married	Matric	P.T.C.	C.T.	B.Ed.	$\bar{R}^2$	S.e.est.	F	n
a)	0.63	1.71	−0.033	−0.026	−0.13				0.23	0.37	4.30	45
	(0.40)	(3.42)*	(−1.63)	(−0.13)	(−1.62)							
b)	2.35	1.03	−0.046				0.32	0.28	0.28	0.36	5.31	45
	(1.39)	(1.84)*	(2.33)*				(2.10)*	(1.95)*				
c)	2.80	0.97	−0.040			−0.25			0.21	0.36	4.55	42
	(1.65)	(1.81)*	(−1.89)*			(−1.91)*						

Figures in parentheses are t-statistics.
*Denotes significance at the $\alpha = 0.05$ level.

search. Perhaps thirteen months is too short a time, or perhaps the job search is simply not affected by academic qualifications, age, or sex.

Willingness to work in rural areas: Nonresponses to this question looked, on a variety of other dimensions, like those who answered "no." We hypothesized that the abnormally high nonresponse rate was really a veiled way of answering in the negative. We did the analyses twice: once omitting the nonresponses and once coding them as "no." Table 8 gives some of our results at the end of a great deal of exploring. The findings are fairly consistent. Women are less likely to be willing to work in rural areas, non-Urdu speakers more likely, and those with first division matriculates less likely. Importantly, neither employment status nor "seeking work" had any relationship with willingness to work in rural areas (nor did a host of other variables we investigated).

This concludes the description of our many statistical explorations. Our procedures had two virtues: we could avoid decimating our sample (which a regression on all the independent variables would have done, because of differing nonresponse patterns for different variables) and we made quite sure that we did not miss an association if it were there. We gave our predictors "every chance." Indeed, the exploratory technique of choosing both the regressions' variables and their transformations on the basis of what we saw biases all of the usual statistics toward significance. That certain variables almost never proved significant—educational qualifications, for example — is thus an even more powerful result.

IV. Implications for policy

The labor market for teachers was not working well. Many signs pointed to imbalance and inefficiency. The most striking: the coexistence of a supposed teacher shortage and our sample's 55.7 per cent unemployment rate. A rapid expansion of teacher training in the previous five years had been accompanied by a decline in real costs per student and, we were told, by a drop in the quality of the training. The expansion mostly involved women: in our sample, 87 per cent were female, compared to an estimated 40 to 60 per cent several years before. Perhaps as a result, female teachers had significantly higher unemployment rates.

These problems we uncovered will not be solved simply by training more teachers in Karachi. The teacher shortage was a structural, not an aggregate, phenomenon. The demand was for rural teachers; the supply was of urban ones. In Karachi, the demand was greater for men, but the supply was greater of women.

Our results are also consistent with the proposition that a meritbased labor market was not in operation. Popular wisdom said that connections

TABLE 8

Ordinary least square regressions on "would work in rural"

Equation	Regression coefficients											
	Constant	Sex	Urdu	I Matric	P.T.C.	B.Ed.	Seeking	Unemployed	$\bar{R}^2$	S.est.	F	n
a) Excluding nonresponses:												
(1)	0.57	0.24	−0.051	0.21	0.061	−0.061	−0.0089	−0.07	0.054	0.45	2.25	154
	(3.78)	(2.06)	(−2.20)*	(2.22)*	(1.02)	(−0.61)	(−0.34)	(−0.90)				
(2)	0.52	0.24	−0.053	0.20				−0.083	0.063	0.44	3.57	154
	(4.43)	(2.20)*	(−2.31)*	(2.12)*				(−1.13)				
(3)	0.47	0.26	−0.055	0.19					0.061	0.44	4.32	154
	(4.32)	(2.32)*	(−2.39)*	(2.00)*								
b) Including nonresponses as "no" answers:												
(1)	0.75	0.12	−0.055	0.13				−0.14	0.075	0.39	5.52	224
	(8.94)	(1.53)	(−2.97)**	(1.82)*				(−2.56)*				
(2)	0.86		−0.056	0.11				−0.16	0.069	0.39	6.53	224
	(24.31)		(−3.01)**	(1.64)				(−2.88)**				

Note: The figures in parentheses are t-statistics. The dependent variable was coded: 0=yes, 1=no. Therefore, a negative sign on a regression coefficient indicates that a positive value on that variable tends to imply a greater likelihood of accepting rural job. Sex is coded: 0=male, 1=female; I Matric is coded: 0=no, 1=yes; Unemployment is coded: 0=unemployed, 1=employed; Urdu is coded: 0=Urdu, 1=non-Urdu; Seeking is coded: 0=yes, 1=no.

*Denotes significance at the $\alpha = 0.05$ level.

**Denotes significance at the $\alpha = 0.01$ level.

rather than achievements mattered. We could not disprove this belief.

Sex in the Teacher Market

Our study showed that, holding other relevant factors constant, women have significantly higher unemployment rates than men. Officials of the School Directorate of Education reacted to this finding by offering five explanations:[19]

1. A teaching career is the most popular career choice for educated women, while only a small number of men opt for teaching.
2. There are more boy's schools than girls'; men teach boys and women teach girls.
3. Female teachers are reluctant to serve in coeducational schools, unlike male teachers.
4. Female teachers are more willing than males to teach in rural schools, even those located in the Karachi area.
5. Girls who study science overwhelmingly take the biological/premedical group, in hope of being doctors, which is considered a legitimate profession for women. Those who do not gain entrance into medical school often take up teaching, leading to a glut of female biology teachers and a shortage in the physical/preengineering group.

Our quantitative work tended to support these explanations. We found, however, that if women teachers landed a job, they made as much money as male teachers, other things equal[20] There may not have been wage discrimination in the labor market – or, indeed, any discrimination at all – but there surely was an odd imbalance between the sexes.[21]

We may usefully note the similarity between the employment situation of women in Pakistan and that of oppressed minorities in other countries. Minority group professionals are often able to obtain jobs only "among their own kind": as teachers or doctors or dentists serving others in the minority. Jobs in the majority group are taken by majority group members. A segmented labor market with certain self-reinforcing incentives for training and hiring may be in force.

Most well-educated women who work in Pakistan do so "among their own kind." One choice is to work at home in one's own household. Another

[19] Interviews, January and February 1977.

[20] That is, given equal credentials, ages, and so forth. However, women tended to dominate in the relatively poorly paid C.T. degree program, while most of the men were in the relatively wellpaid B.Ed. program. Other things were not equal.

[21] It is sometimes said that most female teacher training students are not serious about working – that they simply marry upon graduation and do not enter the labor force. Our study does not support this idea. Over 95 per cent of the women were seeking jobs or were employed, and under 10 per cent were marr

is to work as a teacher or a doctor, and almost invariably such choices involve teaching girls or healing women. It is not clear whether this segmentation results from the preferences of men or of the women themselves; and it will probably not be rewarding to insist upon a single cause for what may be a self-reinforcing, though socially non-optimal, equilibrium.[22] What is clear is that few women are willing to accept rural teaching jobs, to work in boys' schools, or to enter the male-dominated employment areas of business, government service, and the professions, except as they may be working with and for women. For policy purposes, the sexual side of teacher supply and demand is critical. Aggregate projections are not enough.

Geography and Teacher Training

Despite reports of shortages of rural teachers, over half our sample of recently trained Karachi teachers were unemployed and looking for work. However, only 31 per cent of the total sample who answered the question said they would consider a rural job – and many of them were already employed.

Language is one problem. Education in rural Sind is mostly in the Sindhi language. Ninety-one per cent of our sample spoke Urdu as a mother tongue: the next most widely spoken first language was Punjabi. Language training in Sindhi or Pushto was not a part of teacher training, nor was mother tongue considered when admitting applicants to teacher training school. Yet in our sample those with non-Urdu mother tongues were significantly more likely to be willing to consider a rural job, other variables held constant.

Several policy issues arise:

1. Should resources allocated to the training of urban teachers be shifted to rural areas?
2. Should admissions policies favour non-Urdu speakers? Should teacher training have a "rural" element, including language courses?
3. Should teachers be required to work two years (say) in rural areas before being considered for urban jobs? Teacher training is heavily subsidized by the State, as we have seen. Could admissions be predicated on a candidate's commitment to accept a rural job after graduation?
4. Are there incentives (salary, quarters, transportation, generous leaves) that could induce more teachers, especially women, to take up rural

[22] In such an euqilibrium the preferences of members of both the dominant and minority groups may lead to an unequal outcome. It may be empirically impossible using data on outcomes to differentiate among the large variety of analytically possible causes. In particular, to lay exclusive blame on employer discrimination in the job market may overlook the deeper structure of inequality. See Becker (1971) and Klitgaard (1972).

jobs? Could experiments and pilot programs be attempted to test these incentives?

5. Could ways be found to improve the job market for rural teachers – such as combining information from the Directorates of School Education in Hyderabad and Karachi, removing "domicile" barriers to hiring, and creating a job bank of unemployed teachers and rural openings?

A Sifarish-Based Job Market?

> At the end of the *ancien regime* in France, the teachers 'paid by the King' *(gages du roi)* were still very few. In the southeastern part of the country, teachers were hired at fairs: a man willing to be hired as a teacher would move around with feathers on his hat while crying *maitre d'ecole:* one feather meant that the man could teach reading, two feathers meant that he could teach reading and writing and three feathers meant that he could also teach arithmetic.[23]

Pakistan's job market for teachers seems equally bizarre, if less picturesque. Many of our findings are consistent with the idea that the teacher job market works on the basis of "sifarish" (connections) rather than qualifications. This disturbing hypothesis raises broad questions of public policy.

First, we may recapitulate that evidence from our statistical analysis. *No dimensions of the teachers' "merit" were significant predictors of which ones get jobs.* For example, there was no evidence that receiving a better B.Ed. division, or having first-division (Intermediate or B.A.) standing, or specializing in science or English, had any significant impact on employability.

Furthermore, *no aspects of a teacher's performance in teacher training school were correlated significantly with salary or with length of job search,* other things equal.

We investigated the procedures for hiring in an effort to explain these results. Officially, teachers are hired according to several criteria. First, their specialty: does it match the opening at hand? Second, their academic record: did they show excellent achievement?

In practice, however, neither mattered. We learned in interviews in the government and the teacher training institutes that in Karachi virtually every teacher hired in the previous year had been accepted on the basis of recommendation from a political or official figure. The custom was to consider only those candidates whose applications had been signed by a Minister or other influential person. Even better was a direct phone call from a Minister, which occurred in our presence during the consideration of one applicant, who was hired on the spot. In fact, the Karachi Directorate had not publicly

[23] See Cipolla (1969, pp.29-30).

advertised for a teaching position for the previous four years.

Anecdotal evidence was consistent with our statistical findings: the job market for teachers in Karachi seemed to work on connections, not necessarily on competence.

Remedies for such problems are difficult to devise, since the difficulty is by no means unique to this labor market. A systematized, publicly accessible register of openings and candidates is a step worthy of detailed study.

A Concluding Observation

In view of the heavy state subsidy of teacher training and the apparent waste of such a large pool of unemployed urban teachers who were unwilling to take rural jobs, policymakers might consider (1) reducing the number of teachers trained in Karachi, in favour of expanded rural training facilities; (2) raising tuitions to cover at least the recurring costs; and /or (3) an agreement by all entering teachers to take a rural job upon graduation, for a specified number of years. In the absence of a radical change in labor market conditions, teacher training policies in Karachi were ill serving teachers, students, and taxpayers.

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