A COMPARISON OF MANPOWER FORECASTING METHODS

by

MICHAEL PAUL COHEN

Submitted in Partial Fulfillment
of the Requirements for the
Degree of Bachelor of Science
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
June, 1972

Signature of Author.

Department of Urban Studies
and Planning, May 12, 1972

Certified by.................. Thesis Supervisor

Accepted by. Chairman, Departmental Committee on Theses

Rotch
M.I.T. LIBRARIES
JUL 24 1972
ABSTRACT

This paper discusses employment forecasting for job training and referral programs. The data needs of the forecasting process are considered, and the existing sources are reviewed, along with reasons for their deficiencies. Several series of data are chosen for use in testing the various forecasting methods.

A set of criteria for evaluating the different methods is developed, along with a system for empirically testing forecast accuracy. The more common forecasting techniques are tested and evaluated in the light of these criteria. The techniques include employers surveys, job vacancy projections, naive extrapolations, including auto-regression, comparisons with national projections, and non-naive methods, including linear regression, simultaneous equation models, and input-output matrices. The relative advantages of each method are compared, and a few directions for future research are suggested.
A Short Note of Thanks

The transition from "book learning" to original research is not easy, but it would have been much harder without the help of many of my friends and associates. A large number of people gave advice and assistance, a few of whom deserve special mention.

Professors Arthur Solomon and Aaron Fleisher, and Tony Yeazer, of the Department of Urban Studies and Planning helped greatly with the technical aspects. Charlotte Meisner, of the Massachusetts Division of Employment Security, gave generously of time and information. Dennis During, Leonard Buckle, Suzann Thomas Buckle, Michael Barish, Chuck Libby, and Susan Stewart were also of great help. The Department of Urban Studies and Planning and the Student Information Processing Board provided time on the IBM 360/67 and 370/155 at the M.I.T. Information Processing Center. To all of these go my heartfelt thanks.

I profer the usual waivers of responsibility on their part.

m. r. C.
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>List of Tables</td>
<td>5</td>
</tr>
<tr>
<td>Abbreviations</td>
<td>6</td>
</tr>
<tr>
<td>Symbols</td>
<td>7</td>
</tr>
<tr>
<td>Introduction</td>
<td>8</td>
</tr>
<tr>
<td><strong>I. Data</strong></td>
<td>12</td>
</tr>
<tr>
<td>1. Sources</td>
<td>14</td>
</tr>
<tr>
<td>2. Sample Data</td>
<td>21</td>
</tr>
<tr>
<td><strong>II. Forecasting Methods</strong></td>
<td>24</td>
</tr>
<tr>
<td>3. Criteria</td>
<td>28</td>
</tr>
<tr>
<td>4. Employment Surveys</td>
<td>40</td>
</tr>
<tr>
<td>5. The Job Vacancy Approach</td>
<td>48</td>
</tr>
<tr>
<td>6. Mathematical Techniques:</td>
<td>56</td>
</tr>
<tr>
<td>6A. Extrapolations</td>
<td>58</td>
</tr>
<tr>
<td>6B. Using National Data</td>
<td>68</td>
</tr>
<tr>
<td>6C. Complex Models</td>
<td>75</td>
</tr>
<tr>
<td><strong>III. Conclusion</strong></td>
<td>84</td>
</tr>
<tr>
<td>7. Suggestions for Future Research</td>
<td>87</td>
</tr>
<tr>
<td>8. Additional References</td>
<td>89</td>
</tr>
<tr>
<td>9. Footnotes</td>
<td>91</td>
</tr>
<tr>
<td></td>
<td>Title</td>
</tr>
<tr>
<td>----</td>
<td>----------------------------------------------------------------------</td>
</tr>
<tr>
<td>I</td>
<td>Sample Data and Sources</td>
</tr>
<tr>
<td>II</td>
<td>The Accuracy of the Sample in Forecasting its own Future Employment</td>
</tr>
<tr>
<td>III</td>
<td>Comparison of Vacancy Trends, Boston SMSA</td>
</tr>
<tr>
<td>IV</td>
<td>Simple Extrapolation Models</td>
</tr>
<tr>
<td>V</td>
<td>Empirical Tests of Various Extrapolation Methods</td>
</tr>
<tr>
<td>VI</td>
<td>Formulas for Using National Data and Projections</td>
</tr>
<tr>
<td>VII</td>
<td>Results of Tests of Regression Method</td>
</tr>
<tr>
<td>VIII</td>
<td>Summary of Characteristics of the Various Forecasting Methods</td>
</tr>
</tbody>
</table>
ABBREVIATIONS

BLS  Bureau of Labor Statistics, a section of the U.S. Department of Labor.

DES  Division of Employment Security. The branch of many state governments that deals with employment statistics, unemployment security, and job training and placement. If no state name preceeds the abbreviation, the Massachusetts DES, a branch of the state Dept. of Labor and Industries, is implied.

DOT  Dictionary of Occupational Titles, Published by the Bureau of Employment Security of the U.S. Dept. of Labor, this defines and enumerates the standard set of job titles used in most studies. Unfortunately, this system does not completely agree with the one used by the Census Bureau.

SIC  Standard Industrial Classification. Produced by the U.S. Bureau of the Budget, this is similar to the DOT, but lists industry definitions.
SYMBOLS

\( Y \)
A random variable, it represents the future (unknown) value of a measurement.

\( Y_t \)
The known value of \( Y \) at time \( t \).

\( Y^f_t \)
The forecast of \( Y \) at some future time \( t \).

\( e \)
The forecast error, \( e = Y^f_t - Y_t \).

\( p(Y) \)
The probability density function of \( Y \) (or, if \( Y \) is discreet, the probability distribution). It gives the probability that \( Y \) will be any given value.

\( U \)
The inequality Coefficient, a measure of forecast accuracy. Lower values of \( U \) correspond to greater accuracy. See page 36.

\( \sigma_Y \)
The standard deviation of \( Y \). This measures the width of the distribution of \( Y \). 67% of the area under \( p(Y) \) lies within one standard deviation on either side of the mean.

\( \text{RMS} \)
Root Mean Square. A measure that describes the width of a distribution, and a form of averaging. RMS of \( Y \) is \( \sqrt{\sum Y_i^2} \).

\( \text{E}_Y \)
The expected value of \( Y \), the mean of \( p(Y) \). \( \text{E}_Y = \sum_{i=1}^{n} Y_i \cdot p(Y_i) \) if \( Y \) is discreet, and \( \int Y \cdot p(Y) \) if \( Y \) is continuous.

\( \sum \)
Summation of all following terms.

\( \sum_{i=2}^{2} a_i \cdot Y_i = a_1 Y_1 + a_2 Y_2 + a_3 Y_3 + a_4 Y_4 \)

\( \prod \)
Multiplication of all the following terms, similarly to \( \sum \).
INTRODUCTION

John Q. Public opens his morning newspaper to discover that unemployment has risen another .1%. Several minutes later he is perplexed to discover page after page of classified ads begging for people to fill vacant positions. The principal of a local vocational school is dismayed by the number of his well-trained students who can't find jobs, while the president of a nearby company has to turn down orders because he can't find enough skilled people for a few crucial operations.

These are not uncommon scenes in the U.S. today. For some reason, there is a serious mis-match between the available jobs and the available people. When the match is correct, there are other barriers to bringing together the two parts. The result is a tremendous cost to our society in terms of reduced productive capacity, reduced purchasing power, and government support payments.

Out of the concern over this problem the field of Manpower Planning has grown markedly over the last decade. While there has always been some planning, the increasing mis-match between jobs and workers, plus the rising faith in systematic research and planning, has prompted considerable expenditure by federal and state governments in the field. The outcome has been a proliferation of forecasts and statistics, and a pressure to produce even more, that crowds hard on the available techniques. Under such pressure it is not surprising, but especially dangerous, that there has been relatively little research on the planning techniques themselves.
Manpower planning is a broad field, including occupational training and re-training, collection and interpretation of statistics, and research on educational methods and hiring practices. This paper concentrates on one aspect of it, the forecasting of future levels of employment. By this I mean the estimation of the future number of jobs of a specific type, like the number of drill-press operators in Eastern Massachusetts in 1974. 1974 is referred to as the "target date."

These forecasts may be made by companies to plan their hiring and training programs, by schools to plan their curricula and to counsel students, by economists to predict changes in the economy, or by governments to plan and fund re-training and placement programs. Obviously, each use will impose different constraints and needs on the forecasting process. In this paper I will be concerned only with forecasting to plan training, re-training, and placement programs, like the Massachusetts Division of Employment Security's MDTA program. This fits most state employment-forecasting programs, and some private ones. All remarks in this paper should be taken within this context only.

As the title suggests, this paper critiques and evaluates several common forecasting techniques. For lack of time, no attempt was made to include all known techniques. Rather, those methods most commonly used by groups charged with this type of manpower planning were included. These are generally simpler (though not necessarily less accurate) ones. Evaluation of the more complex ones, and the ones just being developed, has been
left to the economists and researchers who are their main users.

As all forecasting requires data, the first section of this paper will deal with that topic. The types and characteristics of data needed are discussed, followed by a quick sketch of the existing sources in the light of those needs. The sample data used in the empirical testing of the different methods is then introduced.

The section after that discusses the forecasting methods themselves. After a review of the appropriate criteria, the methods are considered in turn, including the results of the tests. The paper then concludes, as all good papers do, with its conclusions about the utility of the different methods and some suggestions for future research efforts.

Before we begin, a few words of caution are in order. First, there is no one right answer, no "best" method. Decisions about any process, including employment forecasting, must be made by balancing alternatives in light of the current situation. The appropriate technique will be different for different groups, and even for the same group at different times. While research like this can help clarify the alternatives, it is not a substitute for personal judgement.

Second, there is no way to theoretically determine the truth. The best forecasting method is the one that works best. The empirical testing in this paper is of necessity limited to a specific class of employment. There is no guarantee that these results will hold for other data, and any group contemplating a major foray into
employment forecasting is strongly urged to conduct its own tests. The value of this paper, it is hoped, will lie as much in its construction of a framework and method for evaluating the techniques as it does in the specific recommendations themselves.
DATA

Any forecasting requires information, and the specific type of forecast sets certain criteria for that data. While information never exists that totally satisfies all the criteria, some data are better than others. In view of the projection techniques to be discussed, the following characteristics seem desirable in employment statistics:

1. Employment must be separated by skill-group within an industry. To prepare proper training programs, etc. the required skills of the available jobs must be known. Currently, the detailed occupational title is taken as a proxy for required skills, but this is not always adequate. It is also useful to know the average or starting wage of an occupation. Wages indicate undesirable, unwanted, or inadequately-paid jobs. The amount of dis-aggregation depends on the final use of the forecast, but 3-digit DOT titles and 2- or 3-digit SIC codes seem about right for planning training and placement programs. An example of a 3-digit occupation is "Flame and Arc Cutting." A 3-digit industry is "Office Machines."

2. A distinction should be made between different labor markets (towns, SMSA's, states, etc.) depending on which is the relevant one for that occupation and industry. While a teacher might seek work all over eastern New England, a custodian would generally not look outside his home city.

3. The number of jobs (filled or vacant) is a better
guide than the number of employed people, since workers may hold several different jobs.

4. Part-time work must be distinguished from full-time, to avoid training workers for under-employment. The concepts of "part-time" and "under-employment" may have to be re-defined in an era of shrinking work weeks and increasing numbers of multiple jobholders.

5. Comparability over time is needed to isolate trends and fit models. Comparability between series of data is useful to check and update them. Comparability between industries permits summing similar skill-groups across industry lines to find total demand.

6. As many observations as possible within the study years are needed to confirm and isolate trends, and remove random effects.

7. The data should come from periods where conditions external to the data are constant, or their changes can be compensated for. In most cases this limits forecasters to post-WW II data, and in some cases to only the past decade.

8. If the universe of interest cannot be wholly questioned accurately, the sample must be of sufficient size and composition that sampling error is minimized.

9. While recent data is always nice, it is only of paramount importance in a few rapidly changing industries. For the rest, the current analytic tools are not sufficiently keen to warrant it. The allowable time lag generally depends on the frequency of the data
and the length of the forecast.

Several government agencies publish employment data. The U.S. Bureau of the Census makes the Census of Population decennially. The 1960 Census reports the employment in 600 occupations by sex, urbanity, and experience for each state, and by sex for SMSA's of over 250,000 people (which is most of them). It also reports employment in 100 occupation groups for 43 industry groups (called the occupational-industry matrix) and wages for 300 occupations for states and these SMSA's. While this is a very useful disaggregation, it is very difficult to compare on Census with another, as occupations are merged and separated from year to year, and titles change. Moreover, even if the 1950, '60, and '70 ones were comparable, there would be only 3 data points since World War II. The number of persons holding jobs is used, not the number of jobs held, and part-time work is not separated. The accuracy varies from Census to Census as the sampling proportion changes, although the latter never drops below 20%.

The Census Bureau also conducts Censuses of Business, Manufactures, Transportation, and Government at 4- to 5-year intervals, and an annual report on "County Business Patterns." While several of these contain good series on employment by industry and area, there is no occupational breakdown to speak of.

The Department of Labor's Bureau of Labor Statistics (BLS) reports several series. "Employment and Earnings and Monthly Report on the Labor Force" (monthly data for the U.S. as a whole) and the annual "Employment and Earnings Statistics by States" both list employment by industry, not
occupation, to various levels of disaggregation.

The "Job Openings and Labor Turnover" (JOLT) series, published quarterly, is collected in two parts by the Massachusetts Division of Employment Security (DES) for the Bureau. Labor turnover (separations and accessions) has been collected quarterly from a sample of about 2000 firms throughout Massachusetts since 1958. It does not include occupation, skills, or wage, nor is it broken down by market. Current job openings have been collected quarterly from the 60% of this 2000-firm sample that is in the Boston SMSA since 1969. The series includes occupation, industry, and wage, but its accuracy is limited by the employers willingness to volunteer information about vacancies. The use of an un-structured questionnaire, permitting the employer to use non-standard or ill-defined titles, severely reduces comparability. Both sections have very high (85% - 90%) response rates, primarily because non-respondents are dropped and replaced. This calls into question the randomness of the sample. Problems also arise from the lack of employment data with which to compare vacancies. Neither series accounts for part-time workers.

The Bureau is currently starting a new series, the "Occupational Employment Survey" (OES). This will be conducted semi-annually by the BLS and state agencies. It is envisioned as a 33% sample of manufacturing firms, followed by a smaller one of non-manufacturing ones. The manufacturing questionnaires were distributed to the 3200 Massachusetts firms in October of 1971, and results are currently being compiled. The survey includes industry and occupation, but not wages. The survey is such that reporting by labor
market can be done. The use of a structured questionnaire, with titles and definitions keyed to the Dictionary of Occupational Titles (DOT) will maintain comparability. The use of a staggered sample, in which all the large firms and a portion of the small ones are chosen, will facilitate covering a majority of employees, thus reducing sampling error. As in JOLT, no distinction is made for part-time work. As in all surveys, employees doing two jobs in the same firm are only counted in their "major" role.

While not a regular series of statistics, the BLS has been constantly conducting Industry Wage Surveys since 1946. Only some industries are surveyed, and those that are are done at irregular intervals of several years. The wages and employment for each occupation are given, and the use of DOT titles and constant survey techniques maintains comparability. The surveys are for specific geographical areas that correspond to labor markets, and staggered sampling increases accuracy, but the small number of industries, areas, and observations severely limits the usefulness of this series on a large basis. There is a similar series of Area Wage Surveys, reporting on major industries in an area. The problems are the same.

The Massachusetts Division of Employment Security (DES) collects figures on unemployment insurance taxes, ES-202, but these do not include wage or occupation, and ignore the large number of workers not covered by the program.

The Division's Job Bank, acting as a referral agency, solicits listings of job vacancies from employers and publishes a monthly summary. This series suffers from the same problems as JOLT, above, plus the fact that there is no specific
sample, as anyone can call and list a vacancy.

Several series, with varying degrees of usefulness, are published for specific occupations. Most professional societies, and some unions, publish yearly membership totals by occupation, but these exclude non-members doing similar work, and include non-practicing members which, in fields like nursing, constitute large groups. The U.S. Office of Education publishes yearly data on public elementary and secondary school staff, and estimates of similar figures for non-public schools and schools of higher education. While the accuracy is fairly good, and the series involve almost yearly sampling back to the 1920's, changing definitions and levels of aggregation reduce comparability somewhat.

The reasons for the paucity of data are twofold: First, the accent on re-training programs, and the consequent need for occupational breakdowns, has come only in the past decade. All the older series reflect the previous concern with the "health" of the various industrial sectors of the economy. Therefore, they only contain statistics by industry.

Second, in the end data must be gathered by survey, and surveys take a great deal of time and money to prepare and conduct. For example, the BLS's OES survey was first conceived of in 1963, but it wasn't until late in 1971 that the first questionnaires were mailed. The intervening period contained a continual process of definition and questionnaire development and testing. It takes approximately 2 - 3 man-months to fully develop and test a questionnaire for one industry.
There is also a great deal of work and time involved in getting responses. In the Massachusetts section of the OES survey, conducted by the state Division of Employment Security, questionnaires were mailed to 3200 firms in October, 1971. After several months duplicate questionnaires were sent to the 2000 firms who had not yet replied. In March, 1972, a third set of questionnaires were sent to the 1500 firms still unheard from. Of the 1700 responses, 300 could not be used, due to business failings, product changes, etc. As replies are still coming in, officials would not estimate the final response figure, but they did expect it to continue into the summer.

Of the 1700 responses, 25% required telephone calls from either the employer or DES. Just the process of mailing out forms, and soliciting and checking responses has involved one researcher and two clerks full-time since the summer of 1971. The long time lags also involve a loss of accuracy. Employers were asked to give data pertaining to the week of 12 May, 1971, for compatibility with other surveys. Any follow-up work done now will be asking for data that is nearly a year old, on a subject where few written records are kept. Moreover, in a few industries one or more of the major firms hasn't responded, greatly reducing the sample size, and thus the accuracy.

After the responses are in, additional work remains in the form of coding and editing them, keypunching and punch-validation, writing, testing, and running the data-processing programs, and interpreting and publishing the results. This entire process, with the exception of the original survey development, will have to be repeated every two years to produce a usable series.
There are three main reasons for employers' reluctance to respond to such surveys. First, they don't wish to divulge any operating information, for fear their competitors will learn it, in spite of the collecting agency's promise of strict confidentiality. Second, there is no personal incentive for them to do so, as the final data will be published regardless of any one firm's decision to participate. Therefore, why go to the trouble? The BLS is attempting to rectify this in the JOLT program. In the future, it will compute each firm's turnover rate, and the industry average, and feed them back to the respective firms, thereby providing an incentive to respond. Thirdly, few firms keep records along occupational lines. Most maintain a single, uncat- egorized payroll and, especially the larger ones, have only a rough idea of the number of workers they have in each occupation, as the number is constantly changing. Of those that do keep records, the classifications don't always coincide with the DOT titles used in most surveys.

The situation, though currently poor, is getting better. Because of its occupational structure, use of standard titles, and large sample, the OES survey should, after 6 or 8 years, begin to provide a useful series from which to project. However, there is still room for improvement. The required skills and current wages of each occupation could be included. Unfortunately, inclusion of such data now would require a whole new cycle of development and testing, involving costs that might outweigh the benefits gained. Were the survey being first designed now, questions to obtain this data could be added at little additional cost. The amount of part-time work could be added now, involving primarily problems of definition, but tools and concepts to handle this information will have
More progress could be made towards increasing accuracy and decreasing costs. The Census Bureau system, in which enumerators are sent out April 2 to gather data for April 1, would increase accuracy. Explanatory letters sent several weeks beforehand would encourage participation. A short reply form with these letters would give advance warning of closed businesses, product changes, and recalcitrant firms, thus avoiding later problems and hastening processing.

All but the first of these involve an increase of accuracy with an increase (sometimes quite small) of cost. In cases where the accuracy is quite sufficient, costs can be reduced by states "sharing" the survey. For example, Connecticut, Rhode Island, and Massachusetts would each sample one-third of the industries and pool results, under the assumption that the occupational structure of an industry is the same throughout the region. Absolute figures would come from state-collected industry employment totals. Such an arrangement would decrease operating costs to about 1/3 of previous levels, but if the assumption is true, would reduce theoretical accuracy by $1/\sqrt{3}$ (increase standard error by a factor of $\sqrt{3}$). This would be particularly useful in situations where the uncertainty of the forecasting method far outweighs that of the data.
SAMPLE DATA

A sample set of employment data was gathered for two reasons. First, it was the best way to become familiar with the available data sources and their shortcomings. These were discussed in the preceding chapter. Second, it was necessary to have data in order to conduct empirical tests of the methods themselves, as described on page 20.

In view of the importance of making employment forecasts by occupation, as distinct from by industry, I had originally intended to conduct the empirical tests on occupational employment data. Only one occupation, teaching, had a sufficiently long series of statistics to permit a meaningful test. Since this would not allow much generalization, a substitute had to be found.

Therefore, employment by industry data was used. This involves the definite assumption that results from this type of test are generalizable to occupational forecasting. I have no way of testing whether this assumption is true, but it seems accurate for the precision with which I am reporting my results. It must be stressed, though, that the reader should not assume any greater precision of the comparative accuracy figures, as this assumption does not support it.

Even within the industry employment statistics we are somewhat restricted. In order to compare methods accurately, we would like to be able to use the same sample data on all of them. The method with the most stringent data requirement is the Regression on Independent Variables.

(see chapter 6C). This requires at least 10 observations of each of four variables: wages, employment, capital stock, and value of output. The only source of statistics of these four variables, at any useable level of disaggregation, was the yearly Massachusetts Census of Manufactures, produced by the Massachusetts Department of Labor and Industries. Unfortunately, this limits our data to manufacturing employment, but we have no choice.

The other restriction is on the geographic area covered by the data. Ideally, the forecast area should coincide with the labor market area, which is usually (for urban areas) the Standard Metropolitan Statistical Area, or SMSA. But the Census of Manufactures has no listings for SMSA's, and only has capital stock figures at the city level. Accordingly, the sample data is for the City of Boston, and covers all factories located within the city limits.

The time span of the data should be as long as possible to allow the greatest number of trial forecasts. The obvious economic limits were the end of World War II to the present, since the economy was very different outside this span. However, imperfections and holes in the data series limit the useable span to 1945 through 1969 for employment figures, and 1948 through 1969 for the rest.

The data series used, and their sources, are given in Table I. The industries used are State Census of Manufactures definitions, which may not coincide with SIC definitions. They are:

- Men's and Women's Clothing
- Sausages and processed meats
- Breads and Bakery Products
- Boots and Shoes, except Rubber
- Printing and Publishing
- Electrical Machinery
- Foundary Products
TABLE I

Sample Data and Sources

<table>
<thead>
<tr>
<th>Abbrev.</th>
<th>Series</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>Production Worker Employment</td>
<td>State Census of Manufactures</td>
</tr>
<tr>
<td>K</td>
<td>Total Depreciated Capital Stock</td>
<td>&quot;</td>
</tr>
<tr>
<td>W</td>
<td>Total Wages of Production Workers</td>
<td>&quot;</td>
</tr>
<tr>
<td>X</td>
<td>Total Value of Output, f.o.b. plant</td>
<td>&quot;</td>
</tr>
<tr>
<td>CPI</td>
<td>Consumer Price Index, Boston</td>
<td>BLS, in Statistical Abstract of the U.S.</td>
</tr>
<tr>
<td></td>
<td>(Used to deflate W, X, to constant $)</td>
<td></td>
</tr>
<tr>
<td>KI</td>
<td>GNP Implicit Price Deflator, Producer's Durable Equipment</td>
<td>U.S. Dept. of Commerce, &quot;Current Business&quot;</td>
</tr>
<tr>
<td></td>
<td>(Used to deflate K to constant $)</td>
<td></td>
</tr>
</tbody>
</table>

All figures in current dollars.

All series yearly, 1948 - 1969, except L, which is yearly 1945 - 1969.
Let us now examine some of the more common forecasting techniques. In this chapter I will give a brief description of the types and methods to be discussed. In the next, we will consider the different types of forecasts in greater detail, and the criteria by which they are to be evaluated. The following chapters discuss each method in turn, according to the criteria developed. Where appropriate, the results of empirical tests of the methods will be introduced.

There are several types of forecasts. One is a Point forecast, which predicts that the actual outcome will be a specific value, such as "1000 draftsmen will be employed next year in Boston." These are the most common, as single numbers are the most familiar and the easiest to work with. A second type is the Interval forecast, which specifies a range and a probability that the outcome will be somewhere within this range. For example one might forecast that "There is a 75% probability that employment of draftsmen will be between 800 and 1200 in Boston next year." These forecasts are not common, because users of forecasts dislike working with probabilities and intervals.

The third type, the Distributional forecast, specifies the "a priori," or expected, probability distribution for the unknown value. In other words, it describes the probability of each of the possible outcomes, usually by some mathematical formula. This is never used in
employment forecasting because it is so unfamiliar, so we shall not discuss it further in this paper.

A forecast can also be Conditional. This means that the future outcome is only expected if some intermediate event occurs. For example, "Employment of Engineers will drop in 1974 if the Viet Nam War has ended by 1973." The user of the forecast must evaluate the probability of this intermediate event himself.

It must be stressed that type, conditionality, and method are merely three non-exclusive descriptors of a forecast. Any method may be used to make any type of forecast, conditional or not. In the rest of this paper, a distinction between types, conditionality, or methods is only made where it affects the matter under discussion.

All the forecasting techniques discussed in this paper are more or less fixed procedures. But economic theory is not yet developed to the point where fixed procedures can be made as sensitive to the nuances of a particular labor market as the judgement of a knowledgeable labor economist. Therefore, the results of all of these methods should only be considered preliminary forecasts. They must be analyzed by someone familiar with the particular labor market to produce the final forecast.

Just as judgement cannot be replaced, it cannot be duplicated in the laboratory. Therefore, none of the following discussion pertains to this judgemental aspect, but only to the preliminary forecasts. References to the need (or lack of need) for economic knowledge also only refer to these forecasts. This is done because a forecaster may wish to divide the work so that less skilled staff,
who may lack this knowledge, prepare the preliminary forecast, and senior staff do the final analysis.

One of the most direct forecasting methods is the Employment Survey. A representative sample of employers is queried about their expected employment at the target date. The result is then inflated proportionally to obtain a forecast for the entire labor market. While it is rarely done, it is possible to survey employment agencies instead, and the procedure is the same.

The Job Vacancy approach uses data on unfilled job openings instead of employment statistics. While any technique could be used to project this data into the future, some form of simple extrapolation is generally used. The data can come from employer surveys of current job openings or from listings with employment referral agencies, like the DES's Job Bank.

Extrapolations are simple mathematical formulae that project past data into the future, usually only requiring a few past observations. There are a large number of such formulae, of varying complexity. A representative sample will be discussed, including auto-regression, a technique which constructs the formula by fitting it to the actual past data.

The paucity of local data, plus the large time and skill costs involved in adding human judgement to mechanical techniques have forced many states to base their projections of the use of National Data. This is not a single technique, but a general approach. In some cases just the past national matrices of occupational employment by industry are used. In others, the local governments use national
projections prepared by the BLS for this purpose.

If the resources and skills are available, it might be preferable to use a more complex method. The important distinction here is that the data on the past that goes into the forecast includes information on more than just employment. This allows the forecaster to utilize the information from leading variables and other indicators. For example, if, in the past, capital investment usually started to drop two quarters before employment did, this variable can be included in the calculations. Then, if capital has just started to fall off, one can expect that employment will start to drop in two quarters. Here, too, there are many techniques, only a few of which will be discussed. Much attention is given to Regression, as it is a component of the other Complex Methods as well. Multi-equation models and input-output analysis, which include the interactions between the independent variables also, are covered briefly.
As in any search, it helps to know, as precisely as possible, what to look for. Accordingly, I will now discuss the criteria by which forecasting methods should be judged.

The criteria fall into three groups: requirements, assumptions, and results of the methods. One of the major requirements is data. Data costs time and money to gather, often far more than that needed to calculate the forecast itself. The amount and quality of data required depends on the method, and on the precision required of the final forecast. For example, a regression over five independent variables requires six observations on each to produce any coefficients, and several more to produce reliable ones. More produce greater accuracy of the forecast. On the other hand, the mechanistic technique of extrapolating from the most recent change only requires two observations. An Employers' Forecast Survey requires no data, as it generates its own. In evaluating existing forecasts, especially ones using previously-collected data, a distinction must be made between the amount and quality of data actually required by the forecast, and the amount and quality collected by the source, for whatever reason.

All of the methods also require a certain amount of skill and knowledge to execute. While the projection of job vacancies only requires simple arithmetic, the Employers' Survey requires a knowledge of surveying techniques, and multi-equation models require an extensive knowledge of economics, econometrics, and electronic data processing. As skilled manpower is usually scarce, this requirement,
Another requirement is time. The more complex a method, the longer it takes, generally, to prepare a forecast. This sets an absolute limit on the frequency of forecasts, and is a large factor in determining costs. Time is closely related to the amount of work (computation, editing, etc.) involved, but there are slight differences. In the data collection phase, much time must be spent waiting for survey returns, such time being determined by the response rate and not by the work load. Work also creates cost in addition to the cost of the time, such as the cost of electronic data processing (EDP).

Different techniques will have different sets of requirements. Some require more time, some more data, and some more of both. There is no single way to order them for all forecasters. However, all of these requirements can be translated into money costs. If a forecasting group has some idea of what its resources cost, it can determine the total cost of doing a forecast using each method, and thereby impose some order on the collection. Obviously, different groups will have different cost structures and a different set of "final costs." It should be remembered that even already-acquired resources, like existing staff and computers, are scarce, and therefore have real costs, in that something else would have to be forgone if they were utilized in forecasting.

The rest of the criteria cannot be so easily fit into a cost structure. The first of these is "What assumptions does the forecast make, either explicitly or implicitly?"
In some cases the forecaster has to explicitly assume future values of variables. A special case is the Conditional forecast (see page ). In calculating the forecast, he will assume the conditions to hold, but in reporting it he will not, and it is up to the user to determine the probability of the conditions coming true. He also must determine what difference (to the forecast) a change in these conditions would make. A good example of this is the Census Bureau's projections of the U.S. population through 1980. It is actually five different projections conditional on five different fertility rates.

In other cases there is only the implicit assumption that the external environment will remain unchanged. Given the current frequency of wars, depressions, etc., this is a questionable assumption. In any case the forecast's accuracy will depend on the accuracy of these assumptions. As such accuracy is not known at forecast time, the assumptions must be judged by their "reasonableness" given the current knowledge. Implicit assumptions are particularly dangerous, as the forecaster might not realize that he is making them.

The result of the application of a forecasting method to data is a forecast. It may be specified in several ways: Interval forecasts are statements that there is such-and-such a probability that the actual value \( Y \) will turn out to be in a certain range. Rightly or wrongly, few agencies make such forecasts, since most people prefer to deal in specific numbers. Instead, they make Point forecasts, which state that the actual value will be a
certain number \( Y_1 \). But the probability of \( Y \) being exactly equal to \( Y_1 \) is small, and no forecaster would consider himself "wrong" if he were only off by a few decimal places, so there is obviously the idea of an interval here too.

One interpretation of point forecasts is that they predict very small intervals, usually specified by the precision to which they are reported. However, most employment forecasts are reported to single units, and few forecasters expect to be that correct. Moreover, few would tell you the probability they associate with so small an interval. Or point forecasts can be interpreted as the mean of a predicted probability distribution for \( Y \). But here, too, few forecasters could describe the implicit distribution, or even its standard deviation. So we must approach the problem from the other direction: We will take the point forecast to be the mean of an unknown distribution, and from examination of the distribution of error in the past, we will determine the actual distribution that can be associated with that forecast.\(^8\)

If the forecaster is a gypsy, gazing into her crystal ball, then we have no reason to assume that the distribution of errors will remain unchanged. But if the forecast comes from a standard mechanical process that will not itself change, we can be confident that the pattern of future errors, and hence the probability distribution of a single forecast, is the same as the existing pattern. The narrower this distribution around the forecast point the smaller the expected error, and the better the forecast
method.

Of course, past error distributions and "a priori" probabilities only coincide when an infinite number of observations are made. As that research is beyond the scope of this paper, we will have to content ourselves with a finite, and unfortunately small, sample. This substitution reduces the accuracy of our tests, and must be compensated for by treating the resulting figures as approximations only.

Having now interpreted the types of forecasts, we must decide what factors we are looking for. A major one is accuracy: How close does the forecast come to being "correct"? We want to be able to find a single measure of accuracy for comparison purposes. To do this, we must compare the forecasts, \( Y^f_i \), with the actual values \( Y_1 \). It is, of course, impossible to measure the accuracy of a forecast whose target date has not yet occurred.

As we want as many observations on each method as possible, we must be able to apply the method to different data series and be able to relate the results of the various series to the single accuracy-of-method term.

Conditional forecasts in which the stated conditions have occurred are judged as regular forecasts. Where the conditions haven't come to pass, no sound judgement can be made. It is not enough to merely substitute the correct initial values and crank through the forecast. In many cases the arrangement of the forecasting method depends on the initial values. Moreover, all forecasts in the real world are tempered by judgement, a process
which cannot be mechanically reproduced and, cranked through.

Similar to conditional forecasts is the problem of policy changes. All forecasts are based on current or expected policy. If that policy is changed, in response, say, to an unattractive forecast, the future conditions will, hopefully, be changed. While this might affect the accuracy of the forecast, it should not count against the forecaster. For example, if the forecaster predicts a shortage of draftsmen, and training programs for draftsmen are accordingly started, they may remove or prevent the scarcity. While the forecast was "wrong," it was still very valuable.

Moreover, the labor market responds to forces of supply and demand. The extra draftsmen may reduce the real wages of the occupation, thereby encouraging more firms to seek draftsmen. Thus, there could still be a scarcity, but at this new equilibrium point, which will be different from the forecast. It is very difficult to sort out these effects, and determine how accurate the forecast would have been in the absence of any policy change, without detailed knowledge of the labor market involved.

For interval forecasts, accuracy is easily measured if the probabilities associated with the intervals are held constant. The fraction of actual values that fell within their predicted intervals, divided by the constant forecast probability, is a ratio that is independent of the actual data being forecast, and is thus comparable
between trials and between methods.

For point forecasts, the problem is more difficult, as we must reduce an entire distribution to a single term. A measurement of accuracy, \( U \), must meet the following criteria:

1. It must account for multiplicative and additive scaling. This means that larger absolute errors can be tolerated when forecasting larger quantities. This is a linear relation. Therefore, let us consider two forecasts \( Y_1^f \) and \( Y_2^f \), and two actual values \( Y_1 \) and \( Y_2 \). If \( Y_1 = kY_2 \) and \( Y_1^f = kY_2^f \) then the accuracy of the two forecasts is equal and \( U_1 = U_2 \). But if \( Y_1 = k + Y_2 \) and \( Y_1^f = k + Y_2^f \) (\( Y_2 \neq k > 0 \)) then \( Y_1^f \) is a closer fit, and \( U_1 \) should be "better" than \( U_2 \). These concepts also apply to two series with different means.

2. \( U \) must be independent of the number of terms in the series being inspected.

3. \( U \) must be order-insensitive. In producing a single measure of accuracy for a series of predictions and errors, it must be immaterial which predictions are evaluated first. Otherwise, identical series, in opposite order from each other (i.e. one ascending and one descending) will generate different \( U \) terms.

4. It must be distortion-free. This means that the best guess of a forecast, given the available data, produces the best quality rating. This is an important, though rarely-investigated, criteria. Consider the forecaster who, after applying his techniques to his data, has arrived at a probability distribution \( p(Y) \). The specific number he will chose as his point prediction should be the expected value.
of $y$, $E_y$, which is the mean of $p(y)$. It is important that this point have the best expected U-value, EU.

To see the effects of a distorting measure, consider a series of actual events $Y_1$ and two sets of forecasts, one always at $E_y$ and the other at EU. Assume further that the forecaster was correct, in his choice of $p(y)$. Over a long series, the mean of $Y$ will be $E_y$; and this will have the smallest average error, but the forecast at EU will have the best overall U-rating. Thus the rating system will give a distorted view of the forecast value. This may seem obvious, but as popular a measure as the absolute percentage error seriously violates this criteria.\(^{10}\)

Having established our criteria, let us consider briefly several common measures of forecast accuracy. Throughout the discussion, let "e" stand for the error between forecast and actual value, $y^f_i - Y_i$. A popular measure is the standard deviation of the errors, $\sigma_e = \sqrt{\frac{\sum (e - E_e)^2}{n}}$.

It is distortion-free, but does not handle multiplicative or additive scaling. As such, it is a good measure for comparing different methods applied to the same single series. The Mean Absolute Percentage $\frac{\sum |e_i|}{n}$ and RMS Absolute Percentage $\sqrt{\frac{\sum (e^2/y_i)^2}{n}}$ are not distortion free, as is not the original version of Theil's Inequality Coefficient $\sqrt{\frac{\sum (E_e/y_1)^2}{\sqrt{\sum y_i^2} \sqrt{\sum (y_i^f)^2}}}$.

The correlation between $Y^f_i$ and $Y_i$, and the ratio of variances $\frac{\sigma_{y_i}^2}{\sigma_{y_i^f}^2}$ do not handle scaling. Moreover, they will produce equal
U-values for any series with the same variance, regardless of the actual errors involved. \( \frac{\sum e}{\sum y} \) does not scale.

No measure was found that fitted all the criteria perfectly. The closest one was the adjusted standard error, \( U = \sqrt{\frac{\sum e_i^2}{\sum y_i^2}} \). It meets all the criteria, with the following exceptions:

1. It is not totally distortion-free, although it is far more so than absolute percentage. In the terminology of footnote 10, if \( y = y_1 \) then \( \sum y_1^2 \) is less than if \( y = y_2 \), so \( U_1 > U_2 \). But the difference falls off very quickly after the first few forecasts are made, so \( EU \approx EY \).

2. While scaling between series is handled, scaling between terms within a series is not. Thus, errors on values above \( EY \) count for as much as the same size errors on smaller \( Y \). This was considered bearable here because all but two of the series are grouped tightly around the mean, and because no other measure could correct this without introducing a more serious problem itself.

The adjusted standard error, also known as the inequality coefficient, has the advantage of including the popular economic concept of "quadratic loss." This concept says that large errors are so bad they are more than proportionally worse than small errors. For example, an error of four is not twice as bad as one of two, but four times as bad. Quadratic loss considers "badness" as a function of the square of the error \( (4^2 = 4 \cdot 2^2) \).
A second aspect of accuracy is bias, that is the difference between $EY$ and $EY^f$. Ideally, the forecasts should be evenly grouped around the actual values, so that the mean error is zero. But if the forecasts are consistently or predominantly too low or too high, then the distribution of errors will be "lopsided." Then $EY^f \neq EY$ and $Ee \neq 0$. In such a case the point forecasts should be interpreted as only the forecaster's incorrect estimate of the mean of $P(Y)$. In interval forecasting such an error will show up as a reduced percentage of "correct" forecasts, not as a specific bias, but the compensation for it is the same. Note that, while the forecasts are still "wrong," this is a very different problem from that of the forecasts being too widely distributed around the actual values. It is also more easily solved. If all forecasts $Y^f_i$ are corrected by a series correction factor, the entire distribution of forecasts is shifted, and a new series of forecasts $Y^f_{i}'$ is generated. The forecasts are now more accurate, and a new set of standard errors and U-terms are generated. If such a correction is applied to future forecasts, they will be improved, too. Obviously, the correction factor will be different for different series. The factor can be additive, $Y^f_{i}' = Y^f_{i} + (EY - EY^f)$, or multiplicative, $Y^f_{i}' = Y^f_{i} \cdot (EY/EY^f)$, or both. If both terms are desired, they are best determined by a regression of $Y^f$ on $Y$. However, in most cases the bias will be very small, and can be ignored.

To find the bias, merely add up all of the errors, including their signs, and divide by the number of errors.
(Bias = \sum_{i=1}^{n} \frac{e_i}{n})$. To compare different series, divide the bias by the standard deviation. If the bias is only a small fraction of $\sigma_y$, the forecast can be considered unbiased.

In determining accuracy, the question remains as to which series to measure. While the level of employment is what is usually reported in a forecast, it is generally the change in employment that is of interest to planners. Moreover, the amount of change from year to year varies far more than the actual level. Therefore, it is the projected change that should be tested for accuracy. In this paper I have used the methods to forecast both variables, where possible, and have tested both forecasts.

The third aspect of the resulting forecast is its precision. This is very different from accuracy, and refers to the specificity of the projection. It is quite possible to have a very precise forecast that turns out to be highly inaccurate. Conversely, the less precise the forecast, generally, the greater the chance that it will be correct, but the less useful it will be.\footnote{None of these methods have any specific inherent precisions. They all will produce numbers down to the units digit. But the useable precision is limited by the precision and accuracy of the input data, and the effective accuracy of the method itself. Any greater precision reported only creates a false sense of security. Bearing in mind the trade-off between precision and accuracy, it is generally best to report the lowest acceptable precision for the use to which the forecast is being put.}
Obviously, accuracy, bias, precision, and assumptions cannot be easily translated into money terms. This would require a knowledge of the effects of manpower policy that we currently lack. However, bias can be compensated for, and precision, accuracy, and assumptions are inter-related. Therefore, the best way of deciding which forecasting method to use is often to assume fixed resources, and choose the one with the greatest accuracy, or to target a given precision and accuracy, and choose the one with the least cost. Beyond this, a subjective balancing of costs and results is required that is beyond the scope of this paper.

There is one more aspect of forecasting that is far too often forgotten. Throughout the forecasting process the questions must be repeatedly raised: "Does this forecast tell us what we want to know?" and, if so, "Will it help to solve the problem at hand?". If the answer to either question is "No", then the best forecast in the world is a waste of time and resources, at best, and a negative policy aid at worst.
SURVEYS

One method of estimating future employment is to ask employers whom they plan to hire. This can be part of a survey of current employment, or a separate project. In either case the technique is the same: a representative sample of employers is generated, a target date in the future is selected, and the employers are asked to estimate their employment at that date, by occupation, including new job categories. The sample totals are then inflated to the universe by multiplying each sub-total by its appropriate scaling ratio. For example, if the sample of firms currently employing 25 to 100 employees is estimated to include one-fifth of the total employment in industries of this size, the expected employment for each occupation in the group is multiplied by 5. The result is the estimated employment, by occupation, for all firms of that size. Due to their importance, large firms (over 50 or 100 employees) are usually sampled 100%. This is efficient, covering the greatest number of workers with the fewest questionnaires.

The requirements of this method are different from those of other techniques. In the first place, there are almost no data requirements, as the method generates its own data. It is more efficient, in terms of questionnaire size, to have an approximate idea of the occupations that will have large surpluses or shortages of workers. This data, though, can be easily and informally gathered from employment agencies, etc.
Surveying does require certain skills, particularly the ability to construct a questionnaire that is unambiguous and easy to complete. This will encourage responses from busy employers. Also, since a survey of any reasonable-sized labor market will generate several hundred or even several thousand questionnaires with 20 to 100 items each, it is rather impractical to tabulate the results manually. Therefore, keypunching and programming skills are needed. However, since no knowledge of the labor market is necessary for this task, it can be sub-contracted out. For example, in the OES survey (see page 15), the Mass. DES is interpreting the responses, but the BLS is tabulating them by computer.

Time is probably the stiffest requirement. It takes months, sometimes years, to develop a comprehensive, unambiguous questionnaire. This involves designing one, testing it on a small sample of employers, evaluating the response, and re-designing it. It also takes a long time, often half a year, between the first distribution of the questionnaires and the returns of the stragglers. While some of this time can be utilized in processing the early returns, much of it is spent answering respondents' questions and waiting. The interpretation and tabulation of the returns, even by computer, can also take many weeks, since the results must be keypunched and verified before the computer can read them.

In addition, there are several miscellaneous costs which, for a large survey, are not insignificant. There is the printing and mailing of up to several thousand
questionnaires, and the writing and distribution of many follow-up letters to non-respondents. Moreover, there is a considerable amount of staff time involved in answering employers' questions and tracking down non-respondents.

Very few specific assumptions are made by this method. The only important one is that the sample accurately reflects the entire labor market. While there is no way of testing this assumption, without constructing an entire second survey, this can be minimized by using as large a sample as possible. However, the individual respondents do make all sorts of implicit assumptions. They assume the future state of the economy and their market, they generally assume that the labor force will not change, etc. The worst part about this is that first, many employers are not sufficiently knowledgeable about the economy to make reasonable assumptions, and second, that the assumptions are not reported. Being unknown, they cannot be evaluated or corrected for, thereby introducing an unknown error into the forecast.

The problems are the same as those involved in "current employment" surveys (see page 19). Furthermore, many employers are unable to project their employment, or are unwilling to divulge the information, so there are fewer responses. There is a greater chance of new jobs, not in the DOT, being created and listed, thereby increasing processing time and reducing comparability.

It is difficult to test the employment survey empirically. The conduction of even one such survey is beyond the scope of this paper, not to mention the
number necessary to be able to generalize. The lack of real data by occupation also makes it very difficult to test past surveys. However, some idea of the potential accuracy of surveys can be gotten from a Rutgers University study of the Newark Occupational Training Needs Study. This was an employers survey conducted by the New Jersey DES in Newark in 1963.14

The 1963 survey asked employers to forecast their September, 1965 and 1968 employment. In October, 1965, the Rutgers group distributed questionnaires to 604 of the 811 employers who had responded to the original survey. These questionnaires listed the employers' forecasts from the 1963 survey and asked them to list their actual September, 1965 employment and to attempt to explain any differences from the forecast.

Before we discuss the results of this study, a note of caution is in order. First, since not all of the employers responded to the follow-up survey, only 77% of the employees covered by the 1963 survey were involved in the re-survey. Thus, it is not certain how much the 1965 results are representative of the actual value of the original survey.

Second, we are still only discussing a single employment forecasting survey. There are many aspects of the 1963 survey, such as sample size and type, nature of the questionnaire, etc, that may have affected its accuracy. Having no way to control for these factors we have no way to generalize the results of this study to other employment surveys. We can only get a general idea of the usefulness of such surveys.
There are two aspects of survey accuracy to test: How representative of the entire labor market was the sample, and how accurate was the survey in predicting the future employment of the sample? To answer the first one, Rutgers compared the actual percentage increase in employment of the sample with the percentage increase in employment of the entire labor market, on an industry-by-industry basis. The results were fair. The best correlation was in Manufacturing, where a 2.8% increase in the sample almost matched a 3.5% increase in the market as a whole. The worst was in Retail Trade, where the sample suffered a 2.9% decline while the market as a whole rose 6.5%.

To a large extent, errors of this type were due to small sample size, permitting the characteristics of a single firm to bias the sample, and thence the projection. Retail Trade was only sampled 6.8% while Manufacturing was sampled 17.8%. This must not be the only reason, however, since the third worst industry was sampled 41%.

As a general rating of sample representativeness, we can use the inequality coefficient described on page 36. This says, in effect, "Even if the survey had predicted the change in the sample perfectly, how good would the forecast of the market as a whole have been?" As such, it is comparable with the results of empirical tests of other methods. The inequality coefficient was .94, which is fairly good for forecasting changes in employment.
There was no way to compare the forecasts of levels of employment, as the study gave no such information.

To evaluate the ability of the survey to predict the sample employment, it was necessary to compare the 1963 predictions with the actual figures for the sample in 1965. The Rutgers study reports the two sets of figures for 9 occupational classes (Managerial, Clerical, etc.) and several industries. The resulting inequality coefficients, representing the average value of the predictions for all the occupations in a given industry, are shown in Table II. The first coefficient is for predicting the 1965 level of employment, and the second is for the change from 1963 to 1965. The "total" line is the RMS average of the industry coefficients.

TABLE II
The Accuracy of the Sample in Forecasting its own Future Employment.

<table>
<thead>
<tr>
<th>Industry</th>
<th>( U_{\text{level}} )</th>
<th>( U_{\text{change}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing</td>
<td>.03</td>
<td>.63</td>
</tr>
<tr>
<td>Construction</td>
<td>.22</td>
<td>.83</td>
</tr>
<tr>
<td>Transportation</td>
<td>.01</td>
<td>1.14</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>.13</td>
<td>2.63</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>.07</td>
<td>.85</td>
</tr>
<tr>
<td>Finance and Real Estate</td>
<td>.06</td>
<td>.86</td>
</tr>
<tr>
<td>Services</td>
<td>.09</td>
<td>1.01</td>
</tr>
<tr>
<td>Total</td>
<td>.11</td>
<td>1.30</td>
</tr>
</tbody>
</table>

"\( U_{\text{level}} \)" reflects the accuracy of predicting the 1965 employment levels.

"\( U_{\text{change}} \)" reflects the accuracy of predicting the 1963-1965 absolute change.
With the exception of the Wholesale Trade industry, the results are quite good. However, the overall usefulness of the method depends on how well the sample reflects the market, as well as the ability to predict the sample's future. There is no mathematical way to combine the two, but the .94 U-value of the former seriously weakens the good U-values of the latter.

Also, there are only nine occupational classes. With the much greater detail necessary for manpower planning, the accuracy would be less, as errors would then appear that, at higher levels of aggregation, would cancel each other out. Unfortunately, the Rutgers study did not report its results in sufficient detail to permit an investigation of this.

These results are quite different from the experience of the Massachusetts DES. They did some informal follow-up work on the Boston College Manpower Skills Survey which indicated that it had not been a good predictor. Also, they used to conduct short-term (2 and 4 months ahead) surveys, but they discontinued them for the same reason.

The Massachusetts DES felt that the inaccuracies are due to the lack of manpower planning in most firms.

With the exception of a few large firms, employers wait until someone resigns or is fired, and then promote employees, accept applicants, or recruit. Expansion, contraction, and changing product mixes are handled in the same way. Moreover, few employers have a sufficient understanding of the economy or of their own product and


labor markets to be able to forecast much of the future. This last reason is born out by the Rutgers study. When asked to list reasons for their forecast errors, the majority of employers reported that business was better or worse than expected.

Faced with such contradictory evidence, it is hard to reach a conclusion on the accuracy of this method. In the absence of further data I am inclined to give greater weight to the Rutgers study, as it was more systematic and complete. But the acceptance of the Employment Survey as a forecasting tool is made reservedly, and future research on the matter is obviously called for.
THE JOB VACANCY APPROACH

If we are planning training or referral programs, the actual item of importance is the unfilled job into which the trainee can go. It has therefore been suggested that the appropriate statistics to use are the number of job openings in each occupation. Although this approach is not now used, for reasons which we will come to later, it has some strong points that merit consideration.

The basic idea is to collect figures on current job openings through surveys of employers (like the current JOLT program, see page 15) or employment agencies (the Boston Job Bank, run by the state employment agency, publishes monthly summaries of its current listings). Over time these series will, hopefully, show a pattern which can be extrapolated out to the target year. While any extrapolation method could be used, a simple curve-fitting, like linear regression against time, is usually envisioned.

The method appears to have several good points. In the first place, it is direct: the item being dealt with is the item of concern, namely the openings for unemployed people. It is not necessary to make the time-consuming calculation of separation and retirement rates, nor to make any assumptions that such rates will not change in the future. As these assumptions are only based on the decennial census, they are rather dubious, and a method which does not require them is that much stronger. There is the assumption that the net result of these rates will continue to move in the same way, but this is a more general assumption, with a greater chance of being correct.
The process of data collection is also much easier. Employers are much more aware of the jobs they are actively trying to fill than the number of employees they have, since an unfilled job usually presents an urgent problem. Moreover, in seeking to fill the job, the employer has already had to define it rather specifically. All of this makes the completion of a survey questionnaire very easy for the employer, promoting a high response rate and good accuracy. This is one reason why the JOLT survey has an 85% - 90% return rate month after month, with only one call-back, while it took the Boston College Manpower Survey (an Area Skill Survey) two mailings and a telephone call to achieve this figure just once.

If a government referral service, like the DES Job Bank, already exists, the task is even easier, as no data has to be gathered from employers. It is only necessary to sum the service's listing by occupation. Data on length of time listed (to indicate persistent trends), wages, and (sometimes) skills needed are all available in the same way. As the collection and sorting of data often take up 70 - 90% of the time and money of a research project, the cost savings here are tremendous. Even if one includes the cost of setting up the collection part of the job bank (as distinct from the referral part) it is cheaper than surveys, as there is little in the way of call-back and solicitation, and no questionnaire development and decoding. Moreover, employers have a definite incentive to provide the information, namely the hope of getting applicants for the post.

The only assumption inherent in this approach is that
there are no major changes in the external environment, like wars, depressions, etc. This assumption, though dubious, underlies all naive forecasting methods, whether they deal with employment, job vacancies, or any other economic variable, and the forecast is accurate to the extent that such an assumption is true. There is also the assumption, in the case of referral service data, that the service accurately represents the spectrum of available jobs. This is discussed on page 54, where I compare the two data collection methods.

Unfortunately, there are several problems with the job vacancy approach. A major one is an uncertainty about just what is being reported as a vacancy. If an employer is asked to list everyone he currently employs, that is fairly well understood, and is concrete. But when you start counting employees that don't exist, which is what vacancies are, things become less well-defined and less understood. Does it mean the number of jobs once filled but not now filled? Then what about expansion and contraction? If we define it as the number of new employees "actively" sought, the question arises as to when. Many employers are "actively," indeed sometimes desperately, recruiting now for jobs that won't be available for several weeks or months, because employees are hard to find. If the definition revolves around "willingness to begin paying now" we run into problems of the market: If two people applied for a job, each willing to work for half the salary, would the employer hire both? And how many vacancies would that be? Suppose each would settle for 3/4 of the
offered salary? And what is meant by "willingness to pay"? If a good enough man came along, at a low enough price, any employer would hire him, regardless of whether the employer had considered the post vacant or not. Conversely, if there aren't any sufficiently good applicants for an advertised post, the employer might consider substituting another type of worker. For example, if the employer advertised for an engineer, and got none he liked, he might consider hiring a technician for the job. Is this an engineer vacancy, a technician vacancy, or what?

Of course, it is possible to come up with a definition of vacancy that seems sound, but it is very hard to come up with one nearly as unambiguous as the definition of "employee." And even if one were conceived, the data would still be unreliable, because the employer's definition would be unknown. Even including the definition within the questionnaire's detailed instructions wouldn't help much, as many employers would continue to use their own, unknown definitions. In the case of a state employment service, which is so attractive because it offers the greatest cost savings, this uncertainty is even larger, as there isn't even a good way to instruct the employer as to what definition is being used. This problem of unknown definitions also applies to the job titles themselves, since different employers may include different tasks and skill requirements under the same job title, and there is often no way for the forecaster to know what they are. This is usually much more true for employer surveys than Job Banks.

In addition to this confusion over definition, a serious bias is introduced by the hiring practices of
American business. While vacancies appear in all jobs due to retirements, expansion, promotion, etc. not all of them are open to outside applicants. Because of union rules, management policies, or the nature of the work itself, most vacancies are only filled by promotion of other members of the firm, thus creating a separate internal labor market. As employees are promoted as soon as the previous occupant leaves the post, employers do not even think of a vacancy as having existed, and will not recruit for the spot. Therefore, all of these positions will be excluded from all sources of job vacancy data. The jobs that will be listed are those that serve as "points of entry" to the internal labor market, often the lowest-paying, least-skilled jobs.

This situation would not be serious if the goal of manpower planning were merely to find jobs for people. This situation could then be viewed as two independent labor markets. an internal one of existing employees, and an external one of "entry-point" jobs and the currently unemployed. Employment forecasters would operate in the external market only, training the unemployed for the expected available jobs in that market. Many forecasting/training programs operate in just this manner.

But the goal of manpower planning is not just to find jobs for people, but to find jobs that lead to other jobs, and more challenges, more status, and higher wages. And this can be done because the two labor markets inter-act, and, once hired by a firm, workers are eligible for promotion from entry-point jobs to other ones, thereby entering the internal labor market. Yet because this market is excluded from job vacancy data, little would be known about it. It therefore becomes difficult to equip the unemployed
with the skills necessary to pass beyond the entry-point. Thus entry-point jobs, which could otherwise lead to better positions, become dead-end jobs, returning us to a position little better than before.

The ambiguity created by these problems of definition and internal labor markets prevents this approach from predicting future changes in employment caused by current changes in other variables, like capital investment. This is because this ambiguity has greatly hindered the development and testing of the economic theory necessary to relate vacancies to other variables. All that can be made are simple models relating future openings to past ones. As such, not all the information we have about the future can be used, and the forecast suffers.

Job vacancy data also excludes the self-employed, since there is no position to be vacant when such a person goes out of business. With 6.2 million people self-employed in the U.S. in 1963, this is a sizeable omission. Not only does self-employment create jobs directly for the unemployed, but as other workers leave their jobs to "become their own boss" they create vacancies in their old jobs. While this second set of vacancies will show up on surveys, etc, it cannot be predicted because the causal variable, self-employment, is unmeasurable.

Vacancy data is made even more unreliable by its dependence on the method by which it is gathered. Several occupations were picked at random, and their data, as reported from the Boston Job Bank (a state employment service), was compared with that from the JOLT program (a quarterly survey). As the JOLT survey isn't inflated
to the universe, the absolute values aren't comparable, but the short-term trends are. They are shown in Table III. It can be seen that not only are the trends of different magnitudes, they are often of different sign:

TABLE III
Comparison of vacancy trends, Boston SMSA, total non-farm vacancies, % change

<table>
<thead>
<tr>
<th>Occupation</th>
<th>JOLT</th>
<th>Job Bank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Listed 30</td>
</tr>
<tr>
<td></td>
<td>Listings</td>
<td>Days or More</td>
</tr>
<tr>
<td>Sewing Machine, Garment</td>
<td>+10%</td>
<td>+10%</td>
</tr>
<tr>
<td>Bookeeping Machine Work</td>
<td>-85%</td>
<td>-90%</td>
</tr>
<tr>
<td>Commercial Art</td>
<td>-80%</td>
<td>0</td>
</tr>
<tr>
<td>Arc Welding</td>
<td>-90%</td>
<td>-100%</td>
</tr>
</tbody>
</table>

JOLT trend is from August to November, 1971
Job Bank figures cover Sept. - Nov. 1971
Source: Mass. Division of Employment Security

There are several reasons for this. In the first place, the Job Bank listings represent openings that employers cannot fill by other means, and that they feel apply to the people looking for work through the Job Bank. For example, very unskilled labor may be constantly presenting itself to the company for work, while very specialized skills may be found more easily through trade publications, etc. Neither of these examples would be listed with the Job Bank, while both might show up in JOLT. Since the decision to list vacancies is based on the employer's personal perception of the nature of the job and the Job Bank applicants, and different employers (with different perceptions)
have vacancies at different times, short-term fluctuations can be introduced irrelevant of actual business conditions.

In the second place, listings remain in the Job Bank for 60 days unless the employer notifies the bank otherwise. According to the staff, "over 50%" of employers notify the bank when an opening is filled. This still leaves a large number of reported vacancies that have been filled but are still listed, which shows up in the predominantly smaller magnitudes for the Job Bank in Table III. The 60-day lag is particularly serious, since it has a disproportionately greater effect on the "30 days or more" listings which, because they indicate longer trends, are often considered the true indicators of labor shortages.

In the third place, the continual surveying of the JOLT program requires a sample that is willing to answer questionnaires repeatedly. Such a sample has been obtained, but this requirement casts doubt on its randomness and its representativeness. While this seems like a small inaccuracy, it cannot be assumed away, since the actual biases introduced are unknown.

So in the end problems of definition, internal labor markets, and collection-method effects wipe out the advantages of the job vacancy approach. However, it is quite possible that advances in data collection techniques and economic knowledge will someday reduce these problems to a level which will permit forecasters to utilize the advantages of this method.
MATHEMATICAL MODELS

We now turn to the area of mathematical models. These are algebraic formulae, called algorithms, which operate on past data, or projections of future data, to predict future employment. They range from simple linear extrapolations of recent changes to simultaneous, multi-equation simulations.

In the next chapter, we will discuss various forms of extrapolations of past trends in employment data. In the chapter after that, we will consider the application of these techniques to national data. Both of these approaches are called "naive" models because they use only employment data as inputs. The term is not necessarily a reflection on forecasting utility. It merely refers to the absence of any consideration of the processes which cause employment and employment changes.

In the last chapter of this section, we will discuss non-naive, or "complex" models. These may use past values of external variables, like capital investment, or predictions of their future values, or both. Unfortunately, it is not possible to discuss all the complex models for two reasons. First, there is an almost infinite number of them, as variations and improvements can always be made. Second, the construction and testing of any one of the more elaborate ones is beyond the scope of this paper, requiring several months. Therefore, the simpler techniques will be tested, and tentative conclusions about the others made from these tests.

The algorithms are called models because they represent the processes that actually occur, just as a plastic boat
represents a real one. For example, "L = aX" represents
the thousands of individual decisions by employers to hire
more workers when their output increases. However, no model
can be an accurate representation of all the aspects of the
employment-generating process. Only as much is included
as time, resources, and economic knowledge permit. But
the relationships contained in the algorithm must be consist-
tent with current knowledge of the actual process. Otherwise,
one is reduced to the frustrating position of playing with
numbers until a pattern is found, with no reason to assume
that the pattern will hold in the future.
EXTRAPOLATIONS

The simplest group of mathematical models is the direct extrapolations. These are very simple algorithms involving past levels of employment only. The specific formulae are given in Table IV. In addition to their use in forecasting, they are often used as standards against which to judge other forecasting methods.\(^{17}\) These techniques are particularly noteworthy because of their low requirements. Following the plan of this study we will discuss these requirements first, then the assumptions and accuracy of the individual techniques.

Simple extrapolations have the advantage of being easy and cheap. They require very little data. With the exception of Auto-regression (method 7), only two previous observations are required, and auto-regression with four variables only requires six observations. Of course, for the averaging methods (3, 5, and 6) and the auto-regression, the more observations the greater the accuracy. Moreover, the only variable required is employment itself, instead of determiners like capital stock and output value. This makes it easy to fit such forecasts into an ongoing employment statistics program.\(^{18}\)

These extrapolations also require little in the way of special skills. No knowledge of economics or econometrics is needed beyond the ability to graph points and recognize trend lines. Auto-regression does require the ability to run a least-squares regression, but there are many stock computer programs to do this. The forecaster need only be
### TABLE IV
Simple Extrapolation Models

1. No Change
   \[ Y_{t+2} = Y_t \]

2. Latest Increment
   \[ Y_{t+2} = Y_t + \frac{2(Y_t - Y_{t-1})}{n} \]

3. Average Increment
   \[ Y_{t+2} = Y_t + 2 \left( \frac{\sum (Y_i - Y_{i-1})}{n} \right) \]

4. Latest Ratio
   \[ Y_{t+2} = Y_t \cdot \left( \frac{Y_t}{Y_{t-1}} \right)^2 \]

5. Average Ratio
   \[ Y_{t+2} = Y_t \cdot \left( \frac{\sum (Y_i / Y_{i-1})}{n} \right)^2 \]

6. Link Relative
   \[ Y_{t+2} = Y_t \cdot \left( \frac{1}{\sqrt{n}} \left( \frac{Y_t}{Y_{t-1}} \right) \right) \]

7. Auto Regression
   \[ Y_{t+2} = a_1 + a_2 Y_t + a_3 (Y_t - Y_{t-1}) + a_4 (Y_t - Y_{t-2}) + a_5 (t+2) \]

where \( a_i \) is a constant generated by the regression and unique to the specific forecast.

the subscripts denote the number of the observation.
told how to enter the data.  

Methods 1 through 6 also require no specialized equipment, although a slide-rule or desk-calculator is handy. While auto-regression, method 7, could be done on a calculator, it is much more easily done on a computer. Here, too, the smallest computer would probably be adequate.

Extrapolations are also fast. All that is necessary to choose the type of extrapolation is a rough plot of the data. Once the choice is made the calculation, even by hand, takes only a few seconds. If a computer is available, it can plot, choose, and project even more quickly, but unless the data already exists in machine-readable form the added keypunching time will wipe out any saving in computation time. Lastly, there is no waiting time as there is with surveys.

All of these low requirements mean that extrapolations are cheap. As such, they can be done often, like on a monthly basis, and for a large number of series, permitting very disaggregative forecasts.

There are, however, several implicit assumptions in this approach. Like all naive methods, extrapolations assume that the world will continue to exist up to the target date in much the same fashion as it has previously. For example, the methods ignore any present indicators of coming changes (i.e. recessions) because they only consider employment data. But some extrapolations are particularly naive. Numbers One, Two, and Four are only based on the 1 or 2 most recent observations. As such, they ignore any earlier information on longer-term trends, particularly cyclical. On the other hand, methods 3, 5, and 6, which calculate average
change factors, give as much weight to changes many years ago as they do to current ones. For any industry or occupation responsive to a changing environment, the implicit assumption here is false.\textsuperscript{20}

There is a technique, called "exponential Smoothing." that considers all past terms, but weights the recent ones more heavily. The general form is

\[ Y_{t+2} = (1-a) + (1-a)^2 Y_t + (1-a)^3 Y_{t-1} + \ldots + (1-a)^n Y_{t-n-2} \]

This method is considerably more costly than the other extrapolations, as "a" must be chosen to fit the individual series. Pre-written computer programs to do this are far less widely available than for regression, however, so it is usually done by trail-and-error convergence. This requires programming skill and a moderately fast computer. It also requires the not-inconsiderable time necessary to write, test, and run the calibration program and then make the forecast.

Unfortunately, this additional time made it impossible to test the method for accuracy. However, when calibrating the auto-regression, it was found that terms earlier than \( Y_{t-2} \) were not statistically significant. We can therefore feel confident that their inclusion would not significantly improve forecast accuracy. Since the auto-regression is also easier and cheaper, we can effectively disregard exponential smoothing. Thus, auto-regression seems to be a compromise between the two assumptions, considering more than just the recent past, but still providing different weights for each term.

The only way to determine accuracy is empirically.
Towards this end a series of forecasts was created and tested by a testing routine on a computer in the following manner:

Our sample data consists of several series of observations \( Y_{ji} \), where "j" denotes one of the 7 industries and "i" denotes the year of the observation. Now, given all of the data \( Y_{ji} \) (i=1 to n) use a specific method, k, to forecast \( Y_{jf} \). Compare this with the actual value \( Y_{jn+2} \) and note the error. Now assume as given all \( Y_{ji} \) (i = 1 to n+1) and forecast \( Y_{jf} \). The process is repeated until the most recent year is forecast. The next industry is treated in a similar fashion. This process is done completely for each forecasting method.

In other words, pretend it is 1950. Using all the data for a particular industry up to 1950, forecast 1952. Now pretend it is 1951, and forecast 1953 similarly. Keep going until the most recent data is forecast. Now repeat the process for the next industry. Since the only input data to the forecasts are the recorded past values, each forecast is independent of the others. This approach thereby provides many independent tests of each method, using actual data. It also does so efficiently, as we get almost as many forecasts as we have data points. Lastly, it ensures compatibility and comparability because the same data is used to test all the methods.

The resulting series of predictions, real values, and errors can be amalgamated into a single accuracy rating through any suitable measure. In this case the measure used was the inequality coefficient, U, as described on page 36. This procedure was applied to each industry's series of
forecasts \( (j) \) for each method \( (k) \), resulting in a single measure of accuracy \( U_{k,j} \) for each industry-method combination. These were combined, using the root-mean-square method, \(^{21}\) to produce a single rating, \( U_k \), for each method of extrapolation.

Table V summarizes the test results. The first column of figures is the inequality coefficient for forecasting the level of employment from the last known data. The second is the coefficient for forecasting the change in employment level. The third is the average bias-to-standard-deviation ratio for the different industries over which the method was tested. The last number is the total number of test forecasts made with that method.

You will notice that, regardless of the method used, much better accuracy is obtained regarding the future level of employment than the future change. This should not be surprising, since the level rarely fluctuates more than 10\%, while the amount of change may fluctuate several hundred percent. The difference in accuracy is not due, as might be thought, to the fact that the formulas explicitly predict levels. The formulas can be changed to explicitly predict the change in employment, without changing their mathematical meaning, by subtracting the present value of employment from both sides. Since the mathematical meaning is not changed, the accuracy remains the same.

The other results are somewhat surprising. Method 1, which says that the future value will be the same as the present one, was the best. This implies that the past history of employment is relatively less related to its future level than the present level is. A look at the data explained this. All of the industries in the sample had pretty much stopped growing by the fourth year of the
<table>
<thead>
<tr>
<th>Method</th>
<th>U_{level}</th>
<th>U_{change}</th>
<th>Bias</th>
<th>No. of forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. No Change</td>
<td>.15</td>
<td>1.00</td>
<td>.35</td>
<td>147</td>
</tr>
<tr>
<td>2. Latest Increment</td>
<td>.29</td>
<td>1.75</td>
<td>.11</td>
<td>147</td>
</tr>
<tr>
<td>3. Average Increment</td>
<td>.22</td>
<td>1.44</td>
<td>.54</td>
<td>147</td>
</tr>
<tr>
<td>4. Latest Ratio</td>
<td>.33</td>
<td>2.01</td>
<td>.18</td>
<td>147</td>
</tr>
<tr>
<td>5. Average Ratio</td>
<td>.26</td>
<td>1.81</td>
<td>.54</td>
<td>147</td>
</tr>
<tr>
<td>6. Link-Relative</td>
<td>.25</td>
<td>1.70</td>
<td>.56</td>
<td>147</td>
</tr>
<tr>
<td>7. Auto-regression</td>
<td>.15</td>
<td>1.28</td>
<td>.31</td>
<td>98</td>
</tr>
</tbody>
</table>

\[ U = \sqrt{\frac{\sum (y_i^f - y_i)\hat{i}^2}{\sum (y_i)\hat{i}^2}} \]

\[ \text{Bias} = \frac{\sum \left| \frac{\sum (y_i^f - y_i)}{N} \right|}{\sqrt{\frac{\sum (y_i^f - y_i)\hat{i}}{N}} \cdot M} \]
While there were sometimes large changes from year to year, the overall trends were quite flat. The changes were basically random fluctuations around this trend, and as such had little forecasting value. That is also why the Average Increment, Method 3, was a better forecaster than the most recent change, Method 2, as the averaging reduces the effect of the random component.

That all industries had very limited growth gives a serious bias to the sample data. Unfortunately, the State Census of Manufactures only publishes complete data for the major industries in a city. These industries, almost by their nature, have ceased growing rapidly.

If the industry were growing or declining at a noticeable rate the "no change" method would not be optimal, since it would consistently over- or under-estimate. The best technique would depend on the nature of the trend. If the trend were linear, then the absolute change from year to year would be relatively constant, and either Method 2 or 3 would be optimal.

If the trend were exponential (i.e. a 10% gain each year), then the absolute increments would not be fixed, but the ratio of successive years would be. In such a situation methods 4, 5, or 6, which utilize this ratio, would be most accurate. The Link-Relative technique is merely the geometric average of all past ratios. As such, it is very similar to method 5, as shown by the test results. While a geometric average is slightly more consistent with an exponential series, being totally multiplicative, the arithmetic average is considerably easier to calculate if a computer is not available.
The auto-regression, though linear in form, can handle almost any type of trend, including polynomial curves, by varying the coefficients \((a_1, a_2, \text{ etc.})\) of the variables. The fourth variable is just a linear trend over time. The importance of regression is that the coefficients are chosen to fit the past data of the specific series by a "Least Squares Regression" computer program. Then these coefficients are used to extrapolate a forecast according to the formula shown in Table IV. In the tests, the auto-regression did as well as the "no-change" method in forecasting employment levels, and slightly poorer in forecasting changes. Since it costs considerably more than method one, though, it is less preferable in this situation.

The choice between average and most recent change factors (2 vs. 3 and 4 vs. 5 and 6) depends likewise on the data. Average factors will produce forecasts closer to the trend, as they even out the random component of the series. If the trend has changed significantly in the past, however, the average factors will not be indicative of the current trend, and should not be used.

The important point is that the choice of method depends on the characteristics of the individual industry. Of course, few series fit trend lines perfectly. The forecaster must separate the trend from the random variation, and then decide what trend it is. Skill at this comes from experience. There are also standard computer programs to do this but, here again, if the data is not already in machine-readable form little time will be gained.
If the forecaster is not able to discern the trend, or if it is unclear what type of trend it is, there are two options open to him. He can use auto-regression, which automatically fits a formula to the trend. While this is sometimes slightly poorer than one of the trend-specific methods, it is almost as good, and is relatively easy to carry out. It does, however, require an electronic computer and machine-readable data.

Alternatively, the most promising method can be chosen empirically through the same technique as used here to test the methods. Since it will be necessary to choose separately for each industry (all the trends will not be alike) the problem of comparing accuracy between different series vanishes, and the standard deviations of error can be used directly. This procedure will generally produce the optimal extrapolation technique. However, in addition to requiring a computer it requires programming skills, as there are no standard programs to do this.
THE USE OF NATIONAL DATA

The collection of raw data is a costly process, often accounting for over half the budget of a research project. Yet, as we saw in Chapter 1, there are few available sources of data for states and areas. To circumvent this problem, many states have used data for the country as a whole to predict local employment.

Toward this end the U.S. Bureau of Labor Statistics has published\textsuperscript{24} industry total employment and occupation-by-industry employment statistics for the U.S. in 1960. It has also projected and published similar figures for 1975. The occupation-by-industry figures are arranged in a matrix, with one side being about 150 occupations and the other being 160 industries. The entries in the matrix are the proportion of total employment in that industry represented by that occupation. For example, in 1960, motor vehicle mechanics accounted for 3.37% of total employment in the trucking industry nationwide.

The BLS recommends two methods of forecasting area employment using this data.\textsuperscript{25} Both methods require that the locality obtain its own employment-by-industry 1960 statistics and 1975 projections. This can be done by any of the methods described in this paper. Alternatively, the ratio of state industrial employment to national industrial employment can be plotted over time, and then extrapolated to 1975. The result is then multiplied by the BLS projections of national 1975 industrial employment to obtain the corresponding state figures.
TABLE VI
Formulas for Using National Data and Projections

Method A:

\[
L_j(75) = \frac{f_{ij}(75) \cdot L_i(75)}{f_{ij}(60) \cdot L_i(60)} \cdot L_j(60)
\]

Method B:

\[
L_j(75) = \sum f_{ij}(75) \cdot L_i(75)
\]

and

\[
F_{ij}(75) = \frac{f_{ij}(75)}{f_{ij}(60)} \cdot F_{ij}(60)
\]

where

- \(L_i\) is local employment in industry \(i\).
- \(L_j\) is local employment in occupation \(j\).
- \(F_{ij}\) is the local fraction of total employment in industry \(i\) working in occupation \(j\).
- \(f_{ij}\) is the same, but on a nation-wide basis.

and the numbers in parenthesis refer to the year.
BLS method A also requires state employment-by-occupation figures for 1960. A proxy for local occupational employment is constructed by multiplying the national industry-occupational matrix by the local industry employment on a cell-by-cell basis, and summing the results over all industries. This is done for 1960 and 1975, and the resulting ratio for each occupation is multiplied by the actual 1960 local occupational employment to obtain the 1975 occupational employment projections. Thus change ratios based on national matrices and local industrial employment levels are applied to present local occupational figures.

Method B requires that the state develop its own 1960 occupational-industry matrix. Then the cell-by-cell national change factors are applied to this matrix to produce a local 1975 one. The 1975 matrix is then multiplied by local 1975 industrial employment and summed by industry, to produce forecasts of occupational employment.

Method B avoids having to assume that the national industry-occupation matrix is the same as the national one. In an area with many specialized sections of firms, like Route 128's R & D establishments or New York City's corporate offices, this assumption is a highly questionable one. But the freedom from this assumption is purchased at the cost of constructing a local matrix, a cost not entailed by method A.

The national projections are made by a complex process of linear regression, input-output analysis, and extrapolation. Several sets of projections are made by different techniques,
and their differences analyzed and resolved. In addition to the sophisticated technique, the forecasts are analyzed and corrected by skilled economists familiar with the individual industries.

A major advantage of the use of national data is low requirements. The only data are a series of industry employment statistics, and the 1960 employment by occupation. (Method B requires the 1960 occupational-industry matrix instead of the latter.) Not only are these data needs low, they are easily satisfied by existing data series, the former from BLS data and the latter by the 1960 Census. Thus the only data costs are those involved in making Census figures comparable with BLS ones.

Skill requirements are also low, as much of the economic judgements have been made by the BLS in preparing the national data. No econometrics need be used by the local forecaster, and even much of the final judgemental analysis has been done for him. It is even possible to do the computations manually, though this would be impractical if more than a few industries or occupations were involved. Moreover, the national statistics are already available in machine-readable form.

All of these points make the time requirements fairly low. There is no waiting time, no data collection time, and little equation-fitting time, so that only time required is for computation, and the reconciling of different data series.

The major assumption here is that the national data is a good substitute for the local data. While trends in the
industry-occupation matrices may be similar, as assumed by method B, method A's assumption that the actual matrices are farther less likely to be. With the growth of nation-wide corporations and the increasing ease of long-distance communication, more and more firms are separating their functions geographically according to the availability of markets, skilled workers, raw materials, and cheap labor. Thus the industry structure, and hence the matrices, will be quite different between regions. Moreover, regionally oriented industries often have different product mixes, with correspondingly different employment characteristics.

There are several other drawbacks to this approach. One involves the assumptions used in making the national projections. A 3% unemployment rate and a level of military spending similar to that of 1955 – 1965 were assumed for the 1960 – 1975 period. Both of these assumptions have turned out to be wrong, and the national projections are accordingly in error.

Also, only one set of national projections has been made, so only 1975 conditions can be forecast. While conditions before 1975 can be approximated by interpolation, that does us very little good now. Hopefully the BLS will issue new projections soon. This will probably await the reporting of the 1970 Census, however, which may not come until early 1973.

It is difficult to test these methods empirically, primarily because the process of making the various data series comparable is only worth doing when done on a scale far beyond that of this paper. However, the BLS did test method A on Ohio data for 1950 and 1960. This was
not a test of the entire method, but only of the substitution of the national matrix and matrix trend for the local one. The national projections and the local industry employment ones were assumed to be correct, so the actual target year data was used for them. The rest of the test followed method A, predicting 1960 from 1950 data.

The results were extremely good. It was found that detailed occupations, like "Bank Tellers," were considerably less accurately forecast than occupational groups like "Clerical and Kindred," having inequality coefficients of .07 and .03, respectively, for prediction of employment levels, and .33 and .07 for prediction of changes in employment. This is not too surprising, since there is much more substitution, both in workers' choice of jobs and employers' hiring, than between general groups. Also, since the detailed figures are combined to create group totals, errors in individual occupations will tend to cancel each other out when summed.

The inequality coefficients given are not the rating of the entire method, but only show that the national matrix can be a very good substitute for the local one. This test must be repeated on states with different industrial and occupational structures than Ohio (i.e. New York and Alabama) before the results can be generalized. If this result does turn out to be generally true, then it is doubtful that method B could be much more accurate, and the extra cost of compiling a local matrix would probably eliminate it from consideration. Unfortunately, the BLS did not test method B.

There are two other factors that affect the accuracy
of this approach. The first is the accuracy of the national projections. This is probably quite high, due to the simultaneous projections and comparisons used to create them, and the skill, knowledge, and time put into their final analysis. It is, however, biased by the faulty assumptions mentioned on page

The projection of local industry employment will be less accurate. Its accuracy will depend on the method used, which will probably be one of the other methods discussed in this paper. Thus, the National Data approach cannot be more accurate than the best of the other methods. However, what is an alternative for forecasting industrial employment may not be able to forecast occupations directly, due to data shortages. Thus, it may be possible to use auto-regressions for the industry projections, but, if national data were not used, be necessary to use a "no-change" extrapolation of occupation, where the trend might be steeply rising.

So the major advantage of the National Data approach is that, with very little loss in accuracy, it is possible to make industry employment forecasts, which are easy and for which data already exists, and come out with occupational employment projections, which might otherwise be difficult or impossible to get.
COMPLEX METHODS

All of the mathematical methods described so far have been "naive." This is a technical term for methods which predict future values of a variable based only on its own history. All of the methods have used employment statistics alone as inputs. But in the real world employment is determined by many other factors. For example, the decision to hire workers in the automobile industry is based on expected sales, available machines, the available applicants for jobs, prices, wages, the cost of capital, union contracts, etc. Of course, these things also affected employment in the past, so to some extent they are considered by the naive models.

But there are two reasons to explicitly include these relations. First, any assumptions about the form of the relation will be visible. Being visible they can be compared with existing data and current economic knowledge. This should increase the accuracy of the model.

Second, these variables often have value as predictors. A decrease in the cost of capital will generally increase investment, since it becomes cheaper. This investment can purchase new machines which might replace workers. Thus, dropping interest rates may be a predictor of falling employment. However, due to the delays involved, the time lag could be several years. Thus current interest rates, which we know, tell us something about future employment, which we don't know. If this relation is found to be true, it can be incorporated into a model. This model then makes use of information ignored by the
naive models.

Non-naive models, called "complex" ones, are created to fit the specific situation. First the variables and the types of relations (linear, log, etc.) are chosen, based on economic theory and previous models. This specifies the form of the equation. Then the individual coefficients are chosen by a regression program to fit the historical data, in the same way as the auto-regression (chapter 6A) was calculated. The resulting formula is then applied to the proper data series to produce a forecast.

There are many kinds of complex models. The simplest is the Linear Regression. This is a single expression relating future employment to past employment and to past and future values of independent variables. An example is:

1) \[ L_{t+2} = a_1 + a_2 K_{t+1} + a_3 L_{t+1} + a_5 L_t + a_6 \log X_{t+1} \]

where \( L \) is employment
\( K \) is capital stock
\( X \) is value of output

Regression forms the basis for most of the other complex models, so it will be discussed in depth.

A more advanced model is the simultaneous-equation model. This consists of several equations like 1) above. Large models of the entire economy might have 300 equations. In addition to the relationships between independent and dependent variables, the model states the relations between the various independent variables. These are fitted in the same way. By taking into account these additional relations the model is a closer approximation to reality and, hopefully, more accurate. If it is done
properly, a set of initial conditions, (i.e. present prices and employment) and the model's equations will uniquely determine the value of all the variables.

Another form of complex model is the input-output model. This concentrates on inter-industry flows. Let's say it takes a ton of steel to produce a car, and two tons of coal to produce the steel. If mining requires two miner-days per ton, steel requires 3 man-days per ton, and autos 5 man-days per car, then a demand for 10 cars will require 50 man-days in the auto factory, 30 at the steel mills, and 40 at the mine. A table can be constructed involving all the transfer ratios and the resulting employment requirements of every combination of industries. Then, by just knowing consumer demand, the corresponding employment requirements can be predicted. Consumer demand is often easier to predict than employment.

The data requirements of complex models are usually quite stiff. You need a data series for each variable. Moreover, you need one more observation per variable than the total number of coefficients. For example,

\[ L_t = a_1 + a_2 K_t + a_3 X_t \]

would require 4 observations of each of the 3 variables. The more observations, the more reliable the coefficients. Any model with more than a few equations requires an enormous amount of data.

Input-output models need inter-industry supply ratios and worker-output coefficients. If 100 industries were involved, this would require 10,000 ratios and coefficients. In addition, 100 final demand figures, which
might come from projecting 100 series, and several hundred initial conditions would be needed.

The skill requirements are also high. Since the model must be compatible with current economic knowledge, a good grasp of economics is important. While regressions can be calibrated fairly mechanically, multi-equation models require very involved techniques that call for a thorough knowledge of econometrics and linear algebra.

All of these models require computers, both for calibration and projection. They also require programming skills and machine-readable data.

These methods also take time, although not as much as surveys do. The construction, testing, fitting, and use of even a 10-equation model may take several months. It took several years to make the Brookings Institution's 300-equation model, and that only involves 9 industry groups.

Simple regressions take less time, but one still has to work out the economics of the model. Even after I had settled on the form of the equation, the testing, calibration, and forecasting of the test regression took several days for only five industries.

A major advantage of these methods is that they require almost no unsupported assumptions. While the form of the models are assumed, they are checked by the degree to which they can be fit to past data. The main assumption is that the equations which were fitted to the past observations will hold for the next one, too. This is obviously a fairly safe assumption if the model is backed by accepted economic theory. While some models
require the assumption of future values of independent variables, these can often be supplied by accepted projection techniques. All assumptions are explicit, so the forecaster knows what uncertainty exists. This is not true with other methods.

The regressions were checked empirically using the same method as was used to test the extrapolations (see page 62). Since more data is required for the regressions it was only possible to make eight forecasts per industry. Data imperfections also prevented testing the Boot and Bread industries.

Creating any complex model, even a single regression equation, calls for much economic knowledge, both of the specific industry and the economy as a whole. This knowledge was not available to the author, nor was the time necessary to study the sample industries. In lieu of this, a recently published model, Phoebus Dhrymes' addition to the Brookings Institution's Quarterly Econometric Model, was used.\textsuperscript{26} The form of this model is

\[ L_t = a_1 + a_2 V_t + a_3 V_{t-1} + a_4 X_t + a_5 X_{t-1} + a_6 L_{t-1} + a_7 L_{t-2} + a_8 K_{t-1} + a_9 K_{t-2} \]

where:  
\( L \) is production worker employment  
\( V \) is average yearly wages  
\( X \) is total yearly output f.o.b. plant  
\( K \) is depreciated capital stock  
and all values are constant dollars.

Dhrymes' original model was slightly different, being log-log instead of linear. However, Dhrymes gave no reason for his choice of log-log over linear, and an
excellent fit was obtained with a linear form, so it was retained. To avoid problems of auto-correlation, the phrase "\( a_{i1}Y_i + a_{i2}Y_i \)" where "\( Y_i = Y_i - Y_{i-2} \)" was substituted for \( a_{i1}Y_i + a_{i2}Y_{i-1} \) for each variable \((V,X,L, \text{and } K)\). In developing the coefficients, this form usually explained 90 to 96% of the variance in \( L \).

As the tests forecast two years into the future, most of the independent variables would not be known at forecast time, and would have to be predicted themselves. The quality of the forecast can be expected to depend heavily on the quality of these predictions. Therefore, two forms of the model were tested. The first involved the actual values of the independent variables. This represents the best possible case, when all the predictions were perfect. While this would never happen with real predictions, it represents a theoretical limit.

The second form represented a type of "lowest common denominator." Here the independent variables were predicted by linear extrapolation of their past values, using the Latest Increment algorithm of chapter 6A. This represented the "worst-case" extreme, since it was available even to forecasters with no other knowledge of the independent variables. A condensed form of this equation is:

4) \[
L_t = a_{1t} + a_{2t}V_{t-2} + a_{3t}\Delta V_{t-2} + a_{4t}X_{t-2} + a_{5t}\Delta X_{t-2} + a_{6t}L_{t-2} + a_{7t}\Delta L_{t-2} + a_{8t}K_{t-2} + a_{9t}\Delta K_{t-2}.
\]
The results of these tests are given in Table VII. As was expected, the "best possible" forecast was better than the "worst case" one, although not by all that much. However, for both cases the inequality coefficients are distressingly high for a method this sophisticated, and with such plausible assumptions. A breakdown of the results shows that almost all of this error is found in the "Electrical Machinery" series, without which the first two figures are 1.10 and 1.29, respectively, which are quite good. Checking back, it was discovered that the original regressions, which fitted the forecasting formula to the data, were not able to achieve good fits for this industry, only accounting for around 80% of the variance in employment while fits in other industries usually explained 90 to 95%. It was uncertain what aspect of this industry caused the poor fit. Thus, the coefficient-fitting process provides a good advance indication of the quality of forecast we can expect.

While it was not possible to test the more advanced methods, some conclusions can be drawn from the regression tests. Multi-equation models derive values of non-employment variables from solutions of simultaneous equations and past data. As such, they are somewhere between extrapolations and perfect predictions. Their accuracy should be between the "best case" and "worst case" test results. If they are only used for relations where they can be fitted well, it should approach the "best case" accuracy.

Therefore, the theoretical best that multi-equation models can do is an inequality coefficient of around .10,
### TABLE VII
Results of Tests of Regression Method

<table>
<thead>
<tr>
<th></th>
<th>U level</th>
<th>U change</th>
<th>Bias</th>
<th>No. of forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Best possible</td>
<td>.23</td>
<td>1.54</td>
<td>.55</td>
<td>40</td>
</tr>
<tr>
<td>2. &quot;Worst case&quot;</td>
<td>.36</td>
<td>2.77</td>
<td>.46</td>
<td>40</td>
</tr>
</tbody>
</table>

Without "Electrical Machinery":

<table>
<thead>
<tr>
<th></th>
<th>U level</th>
<th>U change</th>
<th>Bias</th>
<th>No. of forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td>3. Best possible</td>
<td>.10</td>
<td>1.29</td>
<td>**</td>
<td>32</td>
</tr>
<tr>
<td>4. &quot;Worst case&quot;</td>
<td>.17</td>
<td>2.73</td>
<td>**</td>
<td>32</td>
</tr>
</tbody>
</table>

For explanations of column headings, see page 63.
** not available
as indicated by the well-fitted industries of the "best possible" form. It is possible that a better set of variables might do a little better, but it is quite hard to explain more than 90 - 96% of the variance of L, so it is doubtful that much better equations could be obtained. Input-Output analysis might do better, but it makes some far more questionable assumptions. Therefore we can conclude that, if only used for relations that can be fitted well, complex methods are capable of very high accuracy. Used across-the-board, they are only fair. In either case, the costs involved in carrying out the forecasts are quite high.
CONCLUSIONS

This, then, brings us to the end of our comparison of forecasting techniques. As promised, no single "best" method was discovered. Every method has a different mix of requirements, assumptions, and results. The forecaster must choose the appropriate method by balancing these characteristics against his own resources and needs. The different mixes are summarized in Table VIII. Rather than report specific values, the characteristics have been grouped, to emphasize that they are only approximations. Remember that a table cannot convey all the important points of the last 6 chapters. Also, it only gives ordinal ranking, so there is no idea of scale.

Accuracy is listed in two parts. The "general" column gives the expected overall accuracy when the method is used on all series. The "specific" column lists the expected accuracy when the method is only applied to certain series. In the case of Extrapolation, it means choosing the specific extrapolation formula to fit the particular trend. In the case of Complex Models, it means only using the model if a very good regression fit can be obtained. Note that some series may exist for which no formula fits well, and for whom only the "general" accuracy can be expected.

To illustrate the concept of choosing a method to fit the situation, let us consider the appropriate choice for a state employment statistics agency like the DES. Assume that it has limited access to a computer and programming staff, and employs one or two economists. Let us also assume
### TABLE VIII

**Summary of Characteristics of Various Forecasting Methods**

<table>
<thead>
<tr>
<th>Method</th>
<th>Requirements Assumptions</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Data</td>
<td>Skills¹</td>
</tr>
<tr>
<td>1. Survey</td>
<td>very low</td>
<td>high</td>
</tr>
<tr>
<td>2. Job Vacancies</td>
<td>low</td>
<td>low</td>
</tr>
<tr>
<td>3. Direction Extrapolation</td>
<td>low</td>
<td>low</td>
</tr>
<tr>
<td>4. Auto-Regression</td>
<td>mod.</td>
<td>mod.</td>
</tr>
<tr>
<td>5. National Data</td>
<td>low</td>
<td>low</td>
</tr>
<tr>
<td>6. Regression</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>7. Multi-Equation</td>
<td>high</td>
<td>high</td>
</tr>
<tr>
<td>8. Input-Output</td>
<td>very high</td>
<td>high</td>
</tr>
</tbody>
</table>

---

1. Includes equipment requirements.

2. "Specific" means applied only to series where a good fit may be expected. "General" is applied to all series.

3. Depends primarily on technique used to forecast employment by industry. See page
the available data sources are the ones currently existing in Massachusetts, as described in Chapter 1.

If a forecast is needed for occupations in 1975, the choice is between the National Data approach and the Survey. Job Vacancy forecasting has too many problems and weak assumptions, and it is not clear what the result represents. All of the rest require several quarters or years of occupational statistics, which are currently unavailable.

The accuracy of the National Data approach depends primarily on the method used to project industry employment for the target date. A long series of this data exists in the BLS report "Employment and Earnings...1909 - 1967," so it should be possible to forecast this by extrapolation or auto-regression with fairly good accuracy. The National Data approach would be preferable to a Skill Survey because the accuracy lost is small compared to the large cost in savings, although this is a subjective judgement the agency director must make. If the target date is much beyond 1975, the National Data cannot be used, and an Employment Survey must be made.

As time goes on, however, economic theory will improve, and the group will have more economists and more access to computers. At the same time, a series of occupational employment data will become available (i.e. the OES program now starting). After a while, the balance will swing towards the more complex models. The costs of the inputs will go down while the gain in accuracy will rise, until regression models, and possibly multi-equation ones, will become the standard forecasting methods.
SUGGESTIONS FOR FUTURE RESEARCH

Obviously, this paper has barely scratched the surface of Employment Forecasting. Much more work must be done to increase the depth and breadth of our knowledge.

All of the methods discussed here, and several that were passed over, must be tested more fully. Not only must more tests be conducted to reduce sampling error, but the factors that affect accuracy, like data errors and survey format, must be thoroughly investigated. This will permit forecasters to conduct these methods in such a way as to maximize their usefulness. Also, the tests must be run on many different types of data, to see which method forecasts which industries and occupations best.

Work should also be done on the requirements aspects, especially in regard to trade-offs between accuracy, precision, and costs. Ways to reduce requirements could be investigated at the same time.

Lastly, research must continue on evaluation methods and criteria. A measure of accuracy is needed which more closely fits the requirements of chapter 3. A sound mathematical method is needed to combine the accuracy figures for each step of a multi-step method, like the National Data approach, into a single overall rating.

Possibly more important, the users and makers of employment forecasts should be asked what qualities they want in those forecasts and the evaluation process.
changed accordingly.

Of course, this calls for a large research effort. With the current interest in manpower planning, there should be no lack of existing forecasts to test. It is strongly urged that the Federal and state governments allocate some of the money currently spent on forecasts for forecasting research. It is the modest hope of the author that this paper has been of some help in suggesting approaches and methods for this research.
I. Forecasting Methods


6. Institute of Management and Labor Relations; Manpower Forecasting through the Occupational Needs Survey; The State University, Rutgers, N. J. 1966.


II. Forecasts

16. Battelle Memorial Institute; The Michigan Manpower Study; Battelle Memorial Institute, Columbus, Ohio, 1966.


FOOTNOTES

1. The substitution of employment by industry data, for manufacturing only, instead of general occupational employment, is discussed on page 21.

2. The U.S. Bureau of Employment Security's "Dictionary of Occupational Titles (DOT), and the U.S. Bureau of the Budget's "Standard Industrial Classification" (SIC) provide number codes and definitions for several thousand standard occupational and industrial titles, and are the reference for most government agencies.

3. This section is concerned with statistics relevant to Massachusetts. It is possible, though doubtful, that other states may have additional sources.

4. Dr. Grant, of the National Center for Education Statistics, in a private conversation, estimated the accuracy (standard error) at 5%.

5. Estimate by Miss Charlotte Meisner, of the Occupational Research Dept., DES, in a personal interview.

6. \[ \text{Var} (\bar{X}) = \text{Var} (x) \], where \( \bar{X} \) is the average of all x's, and \( n \) is the number of x's in the sample. The standard error \( \sigma_{\bar{X}} = \sqrt{\text{Var} (\bar{X})} \), so multiplying \( n \) by 1/3 increases \( \text{Var} (\bar{X}) \) by 3, and \( \sigma_{\bar{X}} \) by \( \sqrt{3} \) or 1.735.


8. The special case where the forecast point turns out not to be the mean of the actual distribution is discussed below in the section on bias.

9. This is not strictly true. An ideal forecast method improves with use, so chronological order is important. But there is little general acceptance of this, and its introduction here would just create confusion.

10. As an example, consider two points on a symmetrical
distribution \( p(Y) : p(Y_1) \) and \( p(Y_2) \), both equidistant from \( Ey \), with \( Y_1 < Y_2 \). If the forecast is made at \( Ey \), and the actual value turns out to be \( Y_1 \), the accuracy, using "absolute percentage, is \( U = \frac{Ey - Y_1}{Y_1} \). If the actual value is \( Y_2 \), then \( U = \frac{Ey - Y_2}{Y_2} \).

Since \( Y_1 \) and \( Y_2 \) are equidistant from \( Ey \), \( U_1 < U_2 \), yet \( p(Y_1) = p(Y_2) \). This is true for all sets of corresponding points on \( p(Y) \). Thus, higher (and therefore worse) \( U \)-values are associated with \( Y \) falling on the lower side of \( p(Y) \), so \( Ey > Ey \). In other words, the forecaster (to maximize his "score") should shift towards the side with higher penalties, to reduce the size of his errors. This demonstration for "absolute percentage" is less easy for asymmetric \( p(Y) \), but the general proof of distortion in the text still holds then.


12. The lower \( U \) is, the more accurate the method is.

This turned out to be Theil's revised "inequality coefficient." See Theil, H, Applied Economic Forecasting, Page 28.

13. As accuracy is proportional to the area under \( p(Y) \) between \( Y_1 \) and \( Y_2 \) (for interval forecasts), and precision refers to \( Y_2 - Y_1 \), this is not strictly true. For asymmetric or multi-node curves, it is possible to have both factors increase together. But such curves are rare in economic forecasting, and for the usual single-node, symmetric curve the inverse relation holds.

For point forecasts precision determines only the precision of the \( U \)-value calculations, and thus the number of predictions with \( e = 0 \) (and therefore \( U = 0 \)). For this group the comments on interval forecasting hold. The other predictions are unaffected, provided they are rounded to the proper precision instead of being truncated.


15. Personal telephone conversation, March 27, 1972
16. While the extrapolation of job vacancy data (see page 48) uses a mathematical model, it was not included here because the important problems and concepts relate to the data used, and not to the operation performed on it. Given sufficient economic knowledge, any of the methods described here could be used on that data, and the analysis of the following chapters would be equally applicable.

17. See Mincer, Economic Forecasts and Expectations.


19. Of course, the regression package must be maintained by its author, and someone must be available to answer questions on it and fix problems, but many computer manufacturers supply such programs and provide the necessary services.

20. In calculating the auto-regressions, the coefficient of $Y_t$ was always larger than the coefficient of $Y_{t-1}$, indicating the greater importance of the more recent term.

21. While it would have been possible to use the arithmetic mean of $U_j$ (for all $j$), the RMS is more consistent with the quadratic loss function embodied in the inequality coefficient itself.

22. The fact that all the industries fit this description is shown by the point that a "no change" forecast was even superior on an industry-by-industry basis. In other words, for each industry (except Clothing) it was better than any of the other methods. Clothing was an exception because it varied very little, so the Average Increment, number 3, was slightly better.

23. See page 32.


25. The mathematical formulas for both methods appear in Table VI.