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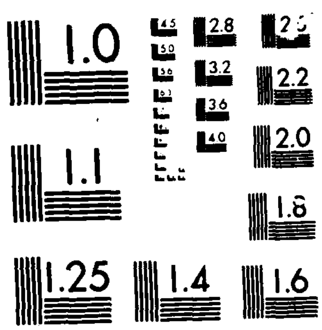

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RECRUITMENT EARLY WARNING SYSTEM
PHASE II

FINAL REPORT

VOLUME I: RESEARCH AND DEVELOPMENT OF THE RECRUITMENT EWS

by

Peter Greenston, Lawrence Goldberg, Sigurd Hermansen, and Sherry Andrews

September 1985

This report was prepared under the Navy Manpower R&D Program of the Office of Naval Research under Contract N00014-85-C-0033.

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The purpose of the Recruitment Early Warning System Project is to provide OSD and the Services with a source of timely, reliable information on the near-term status of the recruiting market. Phase I of the study determined the feasibility of developing and implementing an early warning system for military recruitment; Phase II research has yielded a prototype Recruitment EWS, automated on a microcomputer, which produces monthly forecasts of labor market conditions and enlistments and generates monthly assessment reports.

For each Service, enlistment forecasting models have been developed for two cohorts: 1-3A NPS male HSDG's and seniors, and 3B NPS male HSDG's and seniors. Regression models with an ARMA error structure are used for all Services except the Navy. The typical model is estimated using a non-linear, least-squares estimation

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CHAPTER I

INTRODUCTION AND HISTORY OF THE RECRUITMENT EWS PROJECT

A. The Problem

An enlistment shortfall occurs when a Service cannot meet its recruitment goals in terms of the quantity or quality of accessions. All four Services experienced serious recruiting difficulties or actual shortfalls in FY 1978-79, when the personnel management system failed to recognize and respond to declines in enlistment supply. This study is concerned with preventing a repeat of the FY 1978-79 recruiting experience.

Recruiting difficulties occurred in FY 1978-79 for a number of reasons. There was a sharp, unexpected decline in enlistment supply brought about by declines in relative military pay, unemployment and GI Bill benefits. [Reference 17] Declines in supply were masked by the fact that the ASVAB, the qualification test given to applicants, was misnormed: it appeared to managers that high-quality enlistment supply was relatively fixed when it was, in fact, declining sharply. The Services' Recruiting Commands first recognized these recruiting problems in FY 1978. However, they had difficulty in convincing their own Services that shortfalls were imminent. Delays occurred because credible information was unavailable on recruiting market trends. The delays were aggravated by the distrust among the command levels generated by the Planning, Programming, and Budgeting System (PPBS): gamesmanship is such an integral part of the PPBS that higher levels of command are very suspicious of requests for additional resources. As a result, it was not until FY 1979 that the Recruiting Commands could convince the Services and DOD that more resources were needed.

It took two years from the time difficulties began, in FY 1978, before the PPBS first responded by adding recruiters, in FY 1980. Later, in FY 1981 and in FY 1982, military pay was increased. In FY 1982 GI Bill benefits for Army enlistments were sharply increased through the Ultra VEAP Program. But in FY 1982 the economy, a major factor affecting enlistments, had turned downward: increases in unemployment and slow growth in civilian earnings of youth caused high-quality enlistments to increase sharply in FY 1982-83.

The PPBS solution to the recruiting problem of FY 1978-79 resulted in the creation of resource surpluses in FY 1982-83. The planning and budgeting system was out-of-phase with the recruiting market — not only in FY 1978-82, but throughout the period of the All Volunteer Force (AVF). Since FY 1974, at least, recruiting resources have been cut, while civilian unemployment and enlistments declined.[1] Recruiting difficulties have been exacerbated rather than relieved by the PPBS. Why has this occurred?

In the PPBS, decisions concerning future levels of recruiting resources are based on the previous year's recruiting experience, which in turn depends strongly on the previous year's unemployment level. In projecting enlistment supply, planners implicitly assume that unemployment will be more or less constant over the next three years. Unfortunately, fluctuations in the economy play havoc with this assumption. Without information to alert planners to impending short-term changes in the recruiting market, the long-range planning system cannot respond adequately to recruiting difficulties.

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1 For evidence, see Figure 1, in "A Plan for Implementing the Accession Contingency Planning Process," the final study report of the Accession Contingency Planning Process Project, Economic Research Laboratory and Systems Research and Applications Corporation, September, 1985.

B. A Solution

If future recruiting difficulties are to be avoided, the personnel management system of DOD and the Services must reduce lags in the recognition of changes in the recruiting market. To do so, the Services need a source of timely, objective, credible forecasts of trends in the economy and in enlistments. The Recruitment Early Warning System (EWS), developed in this study, has the capacity to meet this need. The EWS provides monthly forecasts of high-quality enlistments and unemployment for the next 12 months. Forecasts of enlistments are compared with goals to help planners determine whether there will be shortfalls during the next 12 months. The system also includes other data, such as outside forecasts of unemployment, that are useful in assessing trends in the recruiting market.

C. Project History

The Recruitment EWS study has spanned Phases I and II in two years. The project began in September 1983 with a feasibility study. A thorough review of existing early warning systems and forecasting methodologies was conducted. Based on knowledge gained in case studies and an assessment of needs, a precursory design of a recruitment EWS was developed.

Using regression analysis with national-level monthly data (1/76-3/83), preliminary forecasting models of non-prior-service (NPS), male, high-quality enlistment contracts for each Service were estimated in Phase I. High quality is defined as high school diploma graduates (HSDG's) and high school seniors (HSSR's) in mental categories 1-3A and 3B. A univariate ARIMA forecasting model for unemployment was estimated with national-level monthly data (1/72-3/83).

In beyond-sample validation tests for the period 4/83-12/83, the models adequately forecasted enlistments and unemployment nine months ahead; they predicted the declines in enlistments experienced by the Services in late 1983, well before the actual declines occurred. A preliminary design was developed for automating, on a mainframe computer, the generation of forecasts and the production of a monthly recruiting market assessment report.

D. Major Emphases in Phase II

The study moved into Phase II, following conclusions drawn in Phase I that the Recruitment EWS is feasible and recommendations that development be continued. Phase II research has yielded a prototype Recruitment EWS which produces monthly forecasts of enlistments and unemployment, and generates monthly assessment reports including presentation quality graphs and tables. This prototype reflects many research advances made in Phase II.

Recent developments in microcomputer software have enabled us to implement the entire Recruitment EWS on a microcomputer. The system was originally implemented in a mainframe environment using TSO and SAS to produce a monthly assessment report. Now, after considerable research, the tasks of database management, statistical procedures, and tabular and graphic generation have been made operational on a standard microcomputer — the IBM PC XT — and its peripherals, using commerically available software packages. This is a significant achievement which has reduced development costs and will reduce operating costs in the future.

The accuracy of the forecasting models for enlistments is crucial to the success of the Recruitment EWS. In Phase II research has focused on improving the forecasting models: the forecasting window is extended to 12 months; the 1-3A and 3B cohorts are modeled separately; the estimation procedures have been enhanced; the data series have been perfected; more refined measures of some variables have been developed; and additional variables measuring policies and programs have been included.

The successful modeling of unemployment as a function of 15 leading indicators of the economy is another Phase II accomplishment worthy of note. This specification enables us to predict, more accurately, turning points in the economy which result in turning points in recruiting.

E. The Phase II Report

The work of Phase II of the Recruitment EWS study is documented in the two volumes of this final report.

Volume II, System Documentation and User's Manual for the Automated EWS, is devoted to the automated system. To facilitate its use, the volume is written in three parts. Part I, "An Introduction to the Automated EWS for the Project Analyst," provides an overview of the design and capability of the system, and is written for an EWS project analyst. Part II, "Automated EWS Operator's Manual," is a user's manual for the keyboard operator which provides step-by-step instructions for operating the system and producing monthly reports. Part III, "Documentation for the Systems Analyst," presents technical documentation of the system hardware and software for the systems analyst.

The remaining chapters in the current volume, Volume I, document the research and development of the Recruitment EWS:

- Chapter II: "Enlistment Forecasting Models: Description and Estimation."

  This chapter describes the conceptual framework on which the enlistment forecasting models were constructed, and presents the basic model specification. Variable construction, correlations, estimation procedures, and resulting estimates are included.

- Chapter III: "Enlistment Forecasting Accuracy."

  This chapter describes the methodology and the results of out-of-sample forecasting tests conducted to determine the forecasting accuracy of the enlistment models.

- Chapter IV: "Leading Indicator Forecasting of Unemployment."

  Accurate forecasts of unemployment are an essential component in the successful performance of the EWS. The unemployment forecasts are used as a variable in forecasting enlistments and also in forecasting relative military pay, an important determinant of enlistments. Chapter IV is devoted to a description of the research undertaken to develop the significant capability of producing reliable forecasts. Two models were constructed, in which unemployment is modeled as a function of 15 leading indicators of the economy. To evaluate the validity of the models, forecasting tests have been conducted for periods in which there were turning points.

- Chapter V: "The Identification and Remediation of Forecasting Errors Due to Structural Change."

  Because the frequent occurence of changes in the Services' policies and programs reduces forecasting accuracy, a major research effort was undertaken to assess alternative methods of remediating such forecasting errors. This analysis and its results are presented in Chapter V.

- Chapter VI: "Summary and Conclusion."

  The final chapter of Volume I provides a brief summary of the econometric research for the Recruitment EWS, and draws conclusions.

- Appendix A: "Forecasts of Civilian Earnings."

  Appendix A describes the methodology for forecasting civilian earnings which, in turn, is used in the forecasting of enlistments.

- Appendix B: "A Distributed-Lag Enlistment Model."

  An alternative enlistment model using distributed lags to measure the contemporaneous and lagged effects of unemployment is described.

- Appendix C: "Data Series Used in the Recruitment EWS."

  A complete printout of all data series, as they are contained in the Recruitment EWS database is presented.

CHAPTER II

ENLISTMENT FORECASTING MODELS: DESCRIPTION AND ESTIMATION

The usefulness of the Recruitment EWS depends on its capability to provide reliable forecasts of enlistments. In this chapter we describe and analyze the national-level, monthly models used to produce those forecasts. The single-equation model introduced in Section A combines econometric and time-series techniques. In Section A we describe the theoretical approach and specify the forecasting model. Data sources, variable construction, and related problems are discussed in Section B. Section C provides a visual overview of recruiting patterns and the interrelationships of explanatory factors over the last five years. In Section D we discuss the statistical properties of the estimation technique; in Section E we report the estimated coefficients and model statistics, and evaluate the within-sample fit. Alternative specifications and the data series for the enlistment models are presented in the appendices.

A. Enlistment Forecasting Model Specification

1. An ARMA Regression Model

In the EWS feasibility study [Reference 13, Vol. IV] we examined both time-series and econometric forecasting models of enlistments. Univariate autoregressive integrated moving average (ARIMA) models and ordinary least squares (OLS) regression models were estimated and compared in out-of-sample forecasting tests over the April - December 1983 period. Highlights are shown in Exhibit 1. In general, forecast accuracy was higher with the regression model for the HSDG cohort, while the time-series model did somewhat better for the HSSR cohort. In response, we developed a mixed model with an econometric core and an autoregressive moving average (ARMA) error structure.

EXHIBIT 1

COMPARISON OF FORECASTING ACCURACY
UNIVARIATE TIME SERIES MODEL vs OLS REGRESSION MODEL
FORECASTING TESTS (8304 - 8312)

Reported as Root Mean Square Monthly Error
(Percent)

	Army	Navy	Air Force	Marine Corps
HSDG 1-3A				
UTS	23.5	7.9	17.3	28.7
OLS	7.4	14.3	13.0	19.6
HSSR 1-3A				
UTS	10.8	17.9	42.3	12.6
OLS	23.4	30.1	38.3	15.6

UTS = Univariate Time Series Model estimated with data for the period 7601 - 8303.

OLS = OLS Regression Model estimated with data for the period 7601 - 8303.

Source: Reference 13, Volume IV, Exhibit 5.1.

The ARMA model specified in Phase II of the EWS study is a causal regression model upon which time-series techniques have been superimposed. We denote by N(t) the stochastic noise term of a regression model, and let a(t) be white noise — uncorrelated with zero mean, constant variance, and zero covariance. If $N(t) = p_1 N(t-1) + a(t)$, then N(t) is said to follow an autoregressive process of the first order and is denoted by AR(1). An AR(2) process is

$$N(t) = p_1 N(t-1) + p_2 N(t-2) + a(t).$$

If $N(t) = a(t) - q_1 a(t-1)$, then N(t) is said to follow a moving average process of the first order and is denoted by MA = 1. In general, a moving-average process of order r is

$$N(t) = a(t) - q_1 a(t-1) - \ldots - q_r a(t-r).$$

A mixed autoregressive and moving-average process combines the AR and MA models as shown below. The autoregressive process is indicated by the dependence of current noise on prior values, and the moving average error process by the dependence upon current and past random noise components. It is customary to impose some restrictions on the parameters of these processes so that their variances do not explode. For example, in the AR(1) process we assume $|p_1|<1$ and in the MA(1) process we assume $|q_1|<1$. For higher order processes the restrictions are more complicated. [Reference 27, p. 275, and Reference 28, p.422.]

The single-equation, generic ARMA regression model can be formulated as:

$$E(t) = cX(t) + N(t), \text{ and}$$

$$N(t) = [q(B)/p(B)]a(t)$$

where E(t) is the dependent variable, enlistments;
X(t) represents the explanatory variables (discussed below); and N(t) represents combined effects of all other factors influencing E(t); it is modeled as the ratio of moving average — q(B) — and autoregressive polynomials — p(B).[2]

E, X, and N have been appropriately transformed to take care of nonstationary means and variances. The noise term N is comprised of autoregressive (p) and moving average (q) parameters. To take an example, consider an AR = 2, MA = 1 model. Using the backshift operator B, this can be written conveniently as

$$(1 - p_1B^1 - p_2B^2)N(t) = (1 - q_1B^1)a(t)$$

or expanding and rearranging:

$$N(t) = p_1N(t-1) + p_2N(t-2) + a(t) - q_1a(t-1).$$

The estimating equation is derived by substituting the ARMA description of N into the enlistment equation, and rearranging terms:

$$p(B)E(t) = p(B)cX(t) + q(B)a(t).$$

Continuing the AR = 2, MA =1 illustration, the estimating equation would be:

$$\begin{aligned} E(t) = {} & p_1E(t-1) + p_2E(t-2) \\ & + cX(t) + p_1cX(t-1) + p_2cX(t-2) \\ & + a(t) - q_1a(t-1). \end{aligned}$$

2 For a complete, well written, discussion of time series methods see the EWS Phase I Final Report and Makridakis. [Reference 13, Volume IV, pp. 36-39, and Reference 28, Chapters 8-10.]

As can be seen, the autoregressive error process manifests itself as lagged dependent and explanatory variables. The dependence of enlistments on past random noise necessitates an iterative estimation technique.

2. Enlistment Framework and Equations

The number and quality of enlistments can be portrayed within a labor market framework. The interplay of exogenous and controllable factors (from the Service's view) produces a supply of applicants that can be characterized by educational attainment, aptitude for general/specialized training, sex, race, and other personal attributes. To simplify, the demand for NPS enlistments is the difference between overall manpower requirements and the number expected to extend or to re-enlist. It is shaped by prevailing enlistment standards that reflect educational attainment, job aptitude, physical condition, and character requirements.

The Services utilize a variety of policy levers to equilibrate the supply of applicants and the demand for qualified NPS accessions. There are levers to increase (or decrease) the supply of applicants — enlistment options and recruiting policies and expenditures. Furthermore, there are levers that affect the number of applicants considered eligible for a job. These levers are manipulated so as to tighten or loosen quality standards in response to the level of demand. Finally, there are levers to affect the number, type, and timing of job positions to be filled.

We model the outcome of the supply-demand equilibrating process at the contract stage of the enlistment pipeline. We have chosen this point primarily because of the difficulty of collecting sufficient data at earlier points in the enlistment process. At this stage a "supply" of enlistments is observable and comprises the effects of both supply and demand factors into a single reduced-form equation.

The Services are attempting to fill a predetermined number of jobs given wage and unemployment conditions. Recruit quality varies, equating total labor supply and demand. This means that the number of high-quality enlistees is "supply" determined, while the total number of enlistees reflects both supply factors and demand constraints. High-quality enlistees are defined as males with high school diplomas and above average mental aptitude scores. We can draw inferences about high-quality enlistees' responsiveness to the environment because we observe all of them (though not those who declined the invitation to apply). We do not observe the full supply of women, those men without high school diplomas, and those with lesser aptitude, because their presence is currently limited by Service recruiting standards and policies. Hence, we cannot draw correct inferences about the ways in which these groups respond to a changing environment.

Accordingly, the enlistment modeling is focused upon male HSSR-HSDG 1-3A and 3B cohorts.[3] Separate (log-linear) equations are estimated, and we test the hypothesis that 3B enlistments depend upon, among other factors, a 1-3A enlistment gap (between goal and production).

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3 The majority of recent studies confine the estimation of enlistment supply equations to "high-quality" cohorts, for example: Daula and Smith; Goldberg, et.al., Greenston; and Horne [References 11, 15, 17, 19, and 23.] A structural model approach is taken by DeVany and Saving [Reference 12] in differentiating supply and demand phenomena. Brown [Reference 4] examines several cohort aggregations in addition to high-quality cohorts. The study by Ash, Udis, and McNown [Reference 1] illustrates difficulties of analysis and interpretation that occur unless demand and supply-limited cohorts are differentiated.

Economic theories of enlistment — as outlined by Oi (1967) and Fisher (1969) [References 29 and 14] — emphasize that military service is an alternative to either working in the civilian sector or attending school. As a practical matter, present day enlistment supply models assume two choices: working for a wage W_C in the civilian sector, or enlisting for a wage W_M in the military.[4] When the W_M exceeds the sum of W_C and the premium required to compensate for the military lifestyle[5], then the individual is presumed to enlist. In such a model, enlistments depend on the joint distribution of W_C and the premium, as well as W_M. In the model specified here, we utilize the ratio of military to civilian earnings as an explantory variable. This convenient formulation is typical of most recent studies.[6]

Fisher [Reference 14] notes that, to those who are unemployed, the opportunity cost of enlisting may not be reflected by civilian earnings. Thus, the unemployment rate is typically included in enlistment supply equations.

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4 Horne [Reference 23] extends the enlistment model to incorporate the concepts of investment in human capital over the life cycle. He argues that, for a college student, the opportunity cost (W_C) is likely to have little influence on the enlistment decision.

5 Hazards of duty, rigorous training, and loss of some personal freedom constitute negative aspects of the military lifestyle. Some individuals may perceive these to be offset by the sense of adventure and opportunities for travel; others may view these to be offset only by economic advantage.

6 Restricting military pay and civilian earnings to have equal and opposite effects is defensible theoretically if W_C and the premium (i.e., a monetized taste for the military lifestyle) are uncorrelated over the period considered. We have not seen any studies that indicate this assumption is unreasonable.

To sum up, a single-equation, log-linear model is estimated for both 1-3A and 3B cohorts for each Service. Gross contracts is the measure of enlistments. Estimation is confined to high quality enlistees — male, high school seniors and diploma graduates. The explanatory variables consist of 1) those factors that measure a Services's recruiting effort, programs, and policies — number of recruiters, recruiter workload, enlistment incentives and policy changes[7]; 2) those factors that reflect civilian labor market alternatives — the ratio of military pay to civilian youth earnings, and the civilian unemployment rate; and 3) those factors that capture the observed recruitment school-season cycle — a set of seasonal binary variables.

The timing of the effects of these variables differs somewhat across cohorts. With regard to unemployment, earlier bivariate time-series analyses[8] indicated a strong, significant lag of one or two periods. We have undertaken some experimentation with a distributed lag model — a weak parametric specification type that also deals explicitly with serial correlation; the results are described in Appendix B. With regard to relative earnings, we have assumed that prospective enlistees are guided by expected earnings, formed as a five month moving average of past, current and future values (perfect foresight is assumed over the estimation period). With regard to recruiters and recruiter workload, contemporaneous and/or one period lags have been selected. As pointed out earlier, there may be additional lagged terms in the estimating equation due to the noise model selected.

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7 These are described in the data series and variable construction discussion.

8 This work is described in the EWS Phase I Final Report [Reference 13, Vol. IV, pp. 53-61].

B. Data Series and Variable Construction

1. Recruiting Resources

a. Number of Recruiters

This variable is intended to measure the number of recruiters with primary responsibility for contract writing. Some departures from this definition must be taken for the purpose of developing a consistent time series.

The series "production recruiters assigned" (as opposed to authorized) is utilized for the Army; we do not differentiate between recruiters who have zero, half, and full mission assignments. When forecasting we must project this series. USAREC makes four-month projections of total recruiters assigned, and an historically derived 66.6 percent is applied to this series to yield values for production recruiters. Recruiter projections for the following eight months out reflect a USAREC-ERL steady-state approximation. The logarithm of production recruiters assigned (ARECPA) is used in the regression equation. Source: USAREC.

For the Navy the sum of "production" and "fixed overhead recruiters" (i.e., supervisors) is used. "Variable overhead recruiters" are excluded. Since Navy recruiters have had reserve as well as active duty recruiting objectives, we have chosen to weight recruiters by the share of new contract objectives for NPS active-duty males to the total objectives for active-duty and reserve personnel (see below). The logarithm of weighted recruiters (WTNRECT) enters the regression. Both this series and the unweighted production-plus-fixed-overhead-recruiters series (NRECT) can be found in the data appendix of this volume, Appendix C. Source: Navy Recruiting Command.

For the Air Force we are provided a direct measure of NPS production recruiters (FRECPNPS). The logarithm of recruiters enters the regression. Source: Air Force Recruiting Service.

In the Marine Corps models we utilize a series for total "on-board" recruiters (MRECREV). While the number of production recruiters is preferred, it is not available back to the beginning of the estimation period. The measure used includes instructors, MEPS liaison, and other support personnel (in addition to production recruiters). The logarithm of recruiters enters the regression. Source: HQ Marine Corps.

b. Recruiter Workload

For each Service the (logarithm of the) ratio of goals to number of recruiters enters the regression as a measure of recruiter workload. Definition and measurement of goals is described below. A note of caution is in order. Goals are sometimes revised downward after the fact. In constructing a recruiter-workload variable for a specific period, one is not always certain that the reported goals were actually in effect at the time.

A recruiter workload variable is successfully constructed and entered in regression models for the Navy, Air Force, and Marine Corps. For the Army, net missions by sex, education status, and mental category have been set since January 1980. We have available male goals for 1-3A and 3B HSSR's and HSDG's (beginning October 1980), but due to unresolved questions about the accuracy of the data, a recruiter workload variable was not included in the Army models.

For the Navy, total new contract objectives were established in FY 82. These data, plus data on goals for accessions, are used to estimate goals for NPS active-duty males. We assume that the goal for the ratio of male to total

NPS active-duty contracts equals the corresponding goal for accessions (excluding reserves). By applying the active-duty male accession goal percentage to new contract objectives, we estimate a new contracts goal for NPS active-duty males (NMGL). For FY 82-83 we have applied the actual monthly accession goal proportions in estimating monthly goals for new male contracts; whereas for FY 84-85, we use the annual average proportion (i.e., 84.2%).

Prior to 1982, the Navy set only accession goals. For this period we use active-duty male accession goals as a proxy for the nonexistent contract goals.

For the Air Force, NPS male net reservation goals have been established since October 1983 (AFMNRGX). For the FY 79-83 period, the average annual male percent EAD goal is applied to the monthly NPS net reservation goal to derive a male goal.

For the Marine Corps, we have available regular (i.e., active duty) male net new contract goals for the entire period (RMGL).

2. Civilian Labor Market Alternatives

a. Civilian Unemployment Rate

Civilian unemployment rate data are seasonally adjusted and published monthly by the Bureau of Labor Statistics (BLS) in *Employment and Earnings* (Table A-3, recent issue). They are derived from household data collected in the *Current Population Survey*. The rate presently utilized pertains to non-institutionalized male and females, 16-59 years of age (ALLCIVUN).

b. Youth Earnings and Relative Military Pay

Relative military pay is defined as the ratio of first year military pay to average earnings of 16-24-year-old civilian males.

The first year military pay variable is Basic Military Compensation (BMC), assuming single status and three months as an E-1, three months as an E-2, and six months as an E-3. BMC includes basic pay; it also includes the value of subsistence items and housing services provided by the Service (or allowances in place of these goods and services) and the calculated tax advantage of receiving those benefits in-kind. It excludes the variable housing allowance, generally received by personnel who live off base, to compensate for the difference between the basic housing allowances and local housing prices.[9] Since the amount of the housing allowance appears to be zero for those who live on base, the allowance may be ignored by potential recruits when facing the enlistment decision. Therefore, BMC is an appropriate measure for constructing a pay variable to include in the regression model.

The BMC series is smoothed with a five-month moving average, centered on the current month. Given the advance information available on military pay changes, this is a reasonable procedure.

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9 Other items are also excluded from BMC, such as special and incentive pay, and supplemental benefits and allowances, bonuses, payments to retired members, commissary and exchanges, medical care, veterans' educational assistance benefits, and social security contributions. It is unclear how much incentive these "hidden" forms of compensation provide to potential recruits. [Reference 23, pp. 13-14.]

Median weekly earnings of full-time wage and salary workers (not seasonally adjusted) are published quarterly by BLS in Employment and Earnings (Table A-73: January, April, July, October). They are derived from household data collected in the Current Population Survey.

We use quarterly data on 16-24-year-old male earnings to generate a monthly series on civilian youth earnings. Earnings for 16-19-year-olds would be more comparable to first year military pay for NPS enlistees, but a recent revision in BLS methodology prevents creation of such a series (without resort to a special BLS tabulation). The quarterly data are deseasonalized (using OLS techniques), and are interpolated to yield a monthly series. The series is smoothed with a five-month moving average centered on the current month.

In Appendix A we describe the forecasting model that has been developed to generate forecasts of youth earnings. Data requirements are also discussed.

3. Enlistment Incentives and Policy Changes

In the following paragraphs we define the variables that reflect the effects of enlistment incentives and policy changes, and, in order to minimize repetition at a later point, we proceed to discuss the estimated effects. Due to measurement problems of multicollinearity, autocorrelation, and simultaneity, estimates for specific variables may be biased and imprecise.

For the Army we have defined a binary variable (ACF) to reflect the incentive effected by the widespread availability of Army College Fund benefits beginning in October 1981. As expected, a positive coefficient is found with a range of 13-18 percent effect.

We have defined a set of binary variables to reflect the impact of the Army bridge program. This program amounted to approximately $28 million in additional resources to be spent in late FY 84 and FY 85.[10] The program began in August 1984; its effects appear to have peaked in October 1984, reaching a "steady state" in January 1985. The following binary variables were defined to measure the short and long-run effects of the program:

D89 = 1 Aug. - Sept. 1984; 0 otherwise
D10 = 1 Oct. 1984; 0 otherwise
D1112 = 1 Nov. - Dec. 1984; 0 otherwise
BRIDE = 1 Oct. 1984 - present; 0 otherwise

The BRIDE variable measures the effects of the bridge program as well as the catenation of the 1980 reference-population enlistment series (beginning FY 85) to the 1944 reference series (see below). The BRIDE coefficient for the 1-3A cohort is the net impact of a positive bridge effect and a negative slide (i.e., catenation) effect; for the 3B cohort it is the net impact of two positive effects. As expected, the estimated coefficients are positive, and the BRIDE coefficient is larger in the 3B cohort equations due to the slide effect.

For the Navy we have defined a binary variable that reflects restrictions on writing constracts during the June - September 1983 period (NFAT83), a period of recruiting prosperity and end-strength limitations. There were a large number of other policy changes over the estimation period. These include a high school graduation

10 The major components include financial incentives for junior college and vocational school graduates; increased ACF benefits for four-year enlistments; provision of hometown recruiter aides; increase in reserve force recruiters; and increased advertising expenditures.

requirement for relatively low-scoring applicants, which in principle does not affect the supply-limited cohorts; and DEP restrictions upon the number (or share) of non-graduates that can be recruited.

For the Air Force we have defined several variables that reflect major policy and operational changes over the estimation period. In the first place, we have defined a binary variable that reflects the limiting of the number of jobs for sale, relative to goals during the April 1977 - March 1979 period (SCARCE3).

Beginning early in CY 82 the Air Force took a number of steps to limit enlistments. These included capping of the job bank; a shift of recruiting attention from NPS to officer programs; and restrictive job-booking practices. A binary variable (CAP) has been defined to reflect these practices. It is turned on over the February 1982 - November 1983 period. We expect both SCARCE3 and CAP to have negative effects on 1-3A and 3B cohort enlistments.

In addition to the CAP practices, operational mental enlistment standards were increased from G30/C120 to G40/C145, beginning approximately October 1982 — the aim being a reduction in the 3B cohort inflow. We have defined a binary variable (G40EFF) to capture the expected negative impact of the higher standard upon 3B enlistments. The higher operational standard was effectively loosened beginning in October 1984 when a two percent block of the total FY 85 jobs were made available and sold in October through December to those scoring between G30/C120 and G40/C145. By the end of the October - December 1984 period, the ratio of 3B to 1-3A enlistments had returned to its pre-October 1982 level.

In December the two-percent-of-total-enlistments quota allowed at the lower standard was increased to eight percent for the fiscal year. By February the higher standard of G40/C145 was abandoned officially, and a new operational standard of G30/C133 was adopted -- with the aim and effect of increasing the 3B cohort inflow. A return to "normal" presumably occurred in June 1985. To reflect these additional changes, we have defined a binary variable (D1585) that is turned on over the January - May 1985 period; it is expected to have a positive effect on 3B enlistments.

The direction of estimated coefficients of SCARCE3, CAP, G40EFF, and D1585 is in accord with the expected effects. The estimates are all relatively large and statistically significant.

For the Marine Corps we have defined a binary variable that reflects a halt to the writing of contracts during the July - September 1983 period with FY 83 EAD dates (FULL83). This short-lived policy was similar to the one put into effect by the Navy (see NFAT83) over the same period for similar reasons, i.e., end-strength limitations. In a more fully developed structural approach, the theoretically expected negative effects might be more pronounced.

4. Recruiting School Cycle

We have defined (relative to April) seasonal binary variables to capture systematic variation over the year. The estimated coefficients indicate a pattern of considerable contract writing in January - February for seniors, and in the summer for graduates. The seasonal pattern is apparently even more differentiated in the Marine Corps.

5. Enlistment Series Catenation

The dependent variable is a catenation of two DMDC series. The earlier series (from January 1979 through September 1984) is based

on the 1944 reference population metric, while the later series (from October 1984 to the present) is based on the 1980 reference population metric. A comparison indicates a so-called slide effect: under the new metric there are relatively fewer 1-3A's, relatively more 3B's, and relatively more 4's. This is illustrated by a comparison of male HSSR-HSDG Marine Corps enlistments in FY 84 under both metrics (see Exhibit 2).

As of this writing DMDC has not created a pre-FY 85 series calibrated to the 1980 reference population. Even if it had successfully done so, its use would likely confuse rather than improve the modeling because recruiter behavior was geared to the 1944 metric production, and use of a 1980 metric production enlistment series would introduce a serious errors-in-variables problem. Accordingly, we have catenated the two series with a dummy variable (REF44), equal to one from January 1979 through September 1984 and zero from October 1984 onwards. In the 1-3A cohort equation we expect a positive coefficient and in the 3B cohort equation a negative coefficient. In the Army, as mentioned, we cannot disentangle bridge program and slide effects; in the Air Force, we cannot disentagle the "3B programs", i.e., G40EFF and D1585, and slide effects. For the Navy and Marine Corps, the estimated effects are in the expected direction.

C. Time Trends and Descriptive Statistics

A close relationship over time (January 1979 - September 1985) between high-quality Army enlistments and unemployment — not controlling for the effects of other factors — can be seen in the Exhibit 3-6 graphs and the simple pairwise correlations reported in Exhibit 7. This cyclical pattern has been discussed by Gilroy and Dale [Reference 9]. We find an equally strong relationship for Navy enlistments, and a somewhat weaker relationship for Marine Corps enlistments. Interestingly, we do not find the same cyclical pattern in Air Force enlistments; in fact, the

EXHIBIT 2

1944 VS 1980 METRIC
MENTAL CATEGORY COMPOSITION

MARINE CORPS
MALE NPS GROSS CONTRACTS*
HSSR's and HSDG's
FY 1984

Mental Category	44 Metric	%	80 Metric	%
1	886	2.4	1442	3.9
2	11576	31.1	9697	26.0
3A	8387	22.5	6948	18.7
1-3A	20849	56.0	18087	48.6
3B	14783	39.7	16063	43.1
4-5	1608	4.3	3090	8.3
	37240	100.0	37240	100.0

* Source: DMDC

EXHIBIT 3

ENLISTMENT AND UNEMPLOYMENT PATTERNS

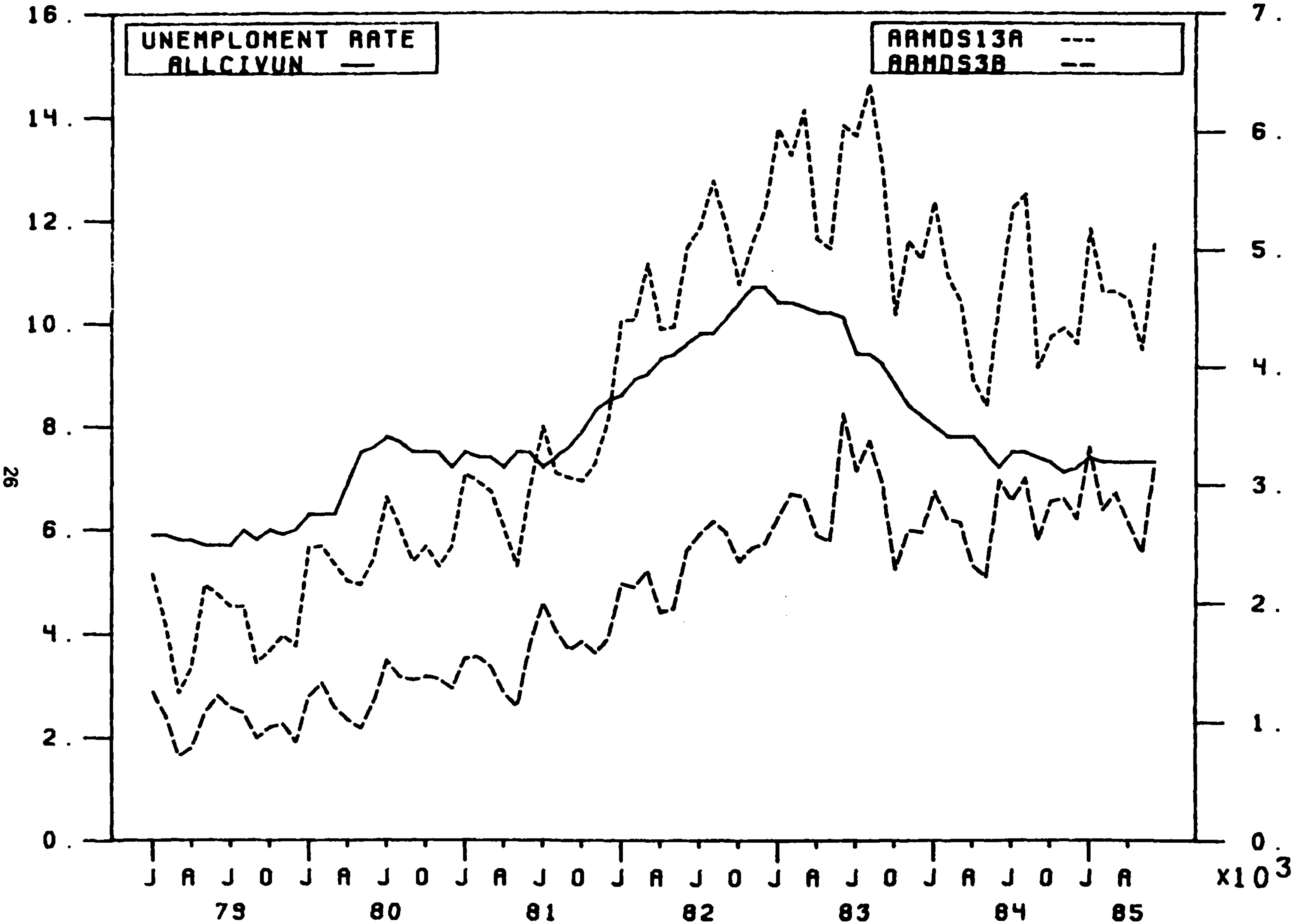

EXHIBIT 4

ENLISTMENT AND UNEMPLOYMENT PATTERNS

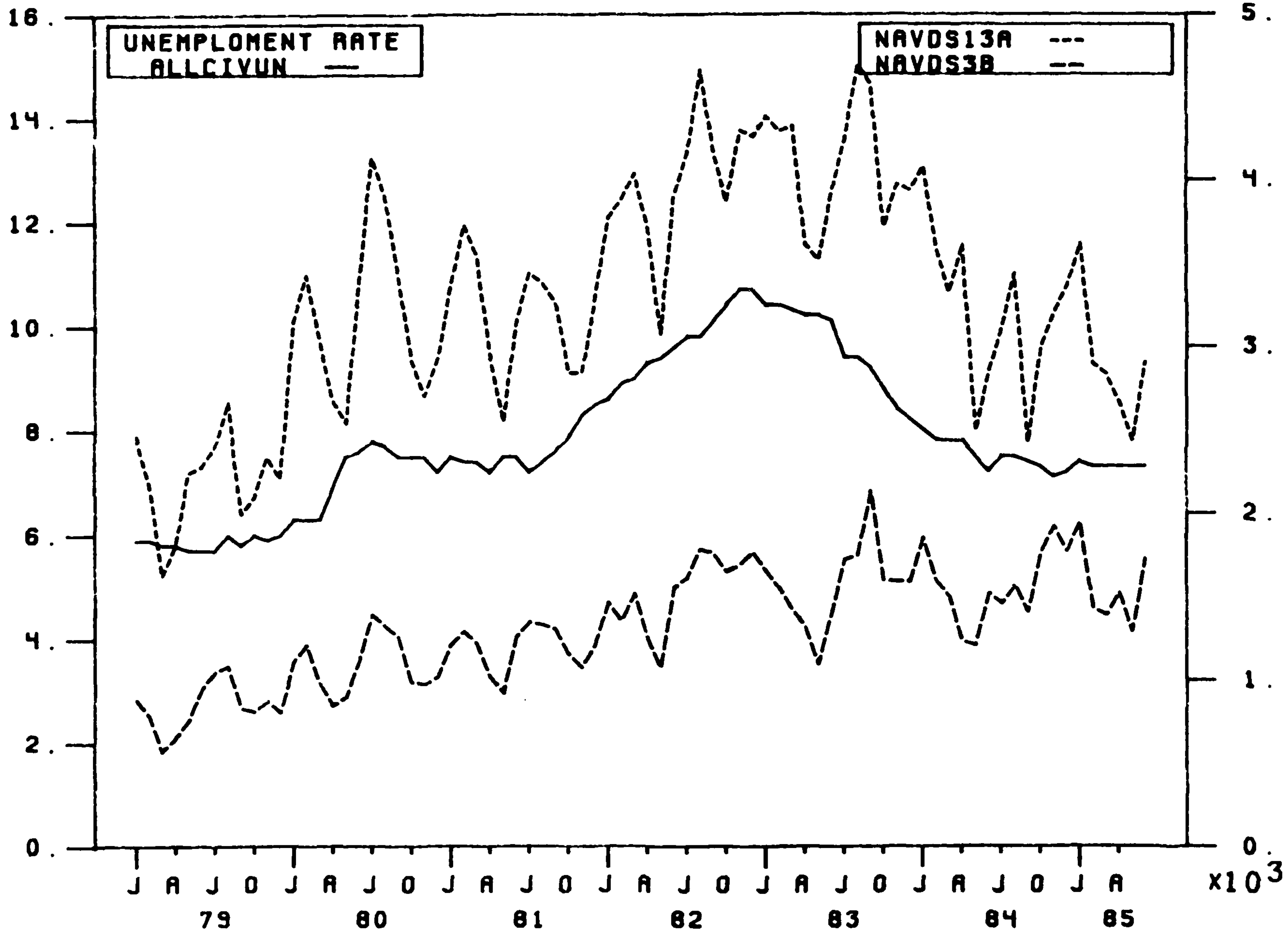

EXHIBIT 5

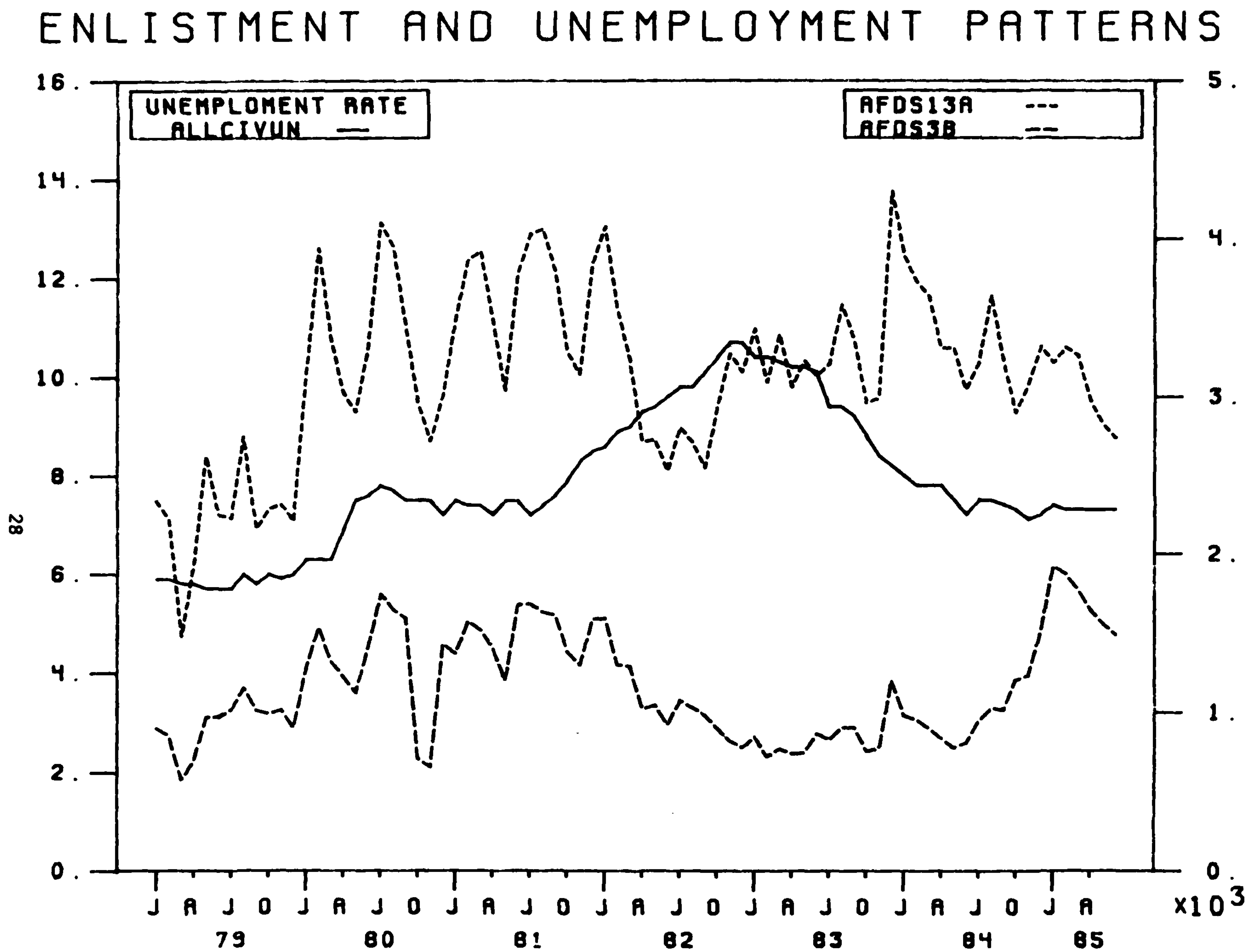
ENLISTMENT AND UNEMPLOYMENT PATTERNS
UNEMPLOMENT RATE
ALLCIVUN —
AFDS13A ---
AFDS3B — —
16.
14.
12.
10.
8.
6.
4.
2.
0.
5.
4.
3.
2.
1.
0.
x10³
J A J O J A J O J A J O J A J O J A J O J A J O J A
79
80
81
82
83
84
85

EXHIBIT 6

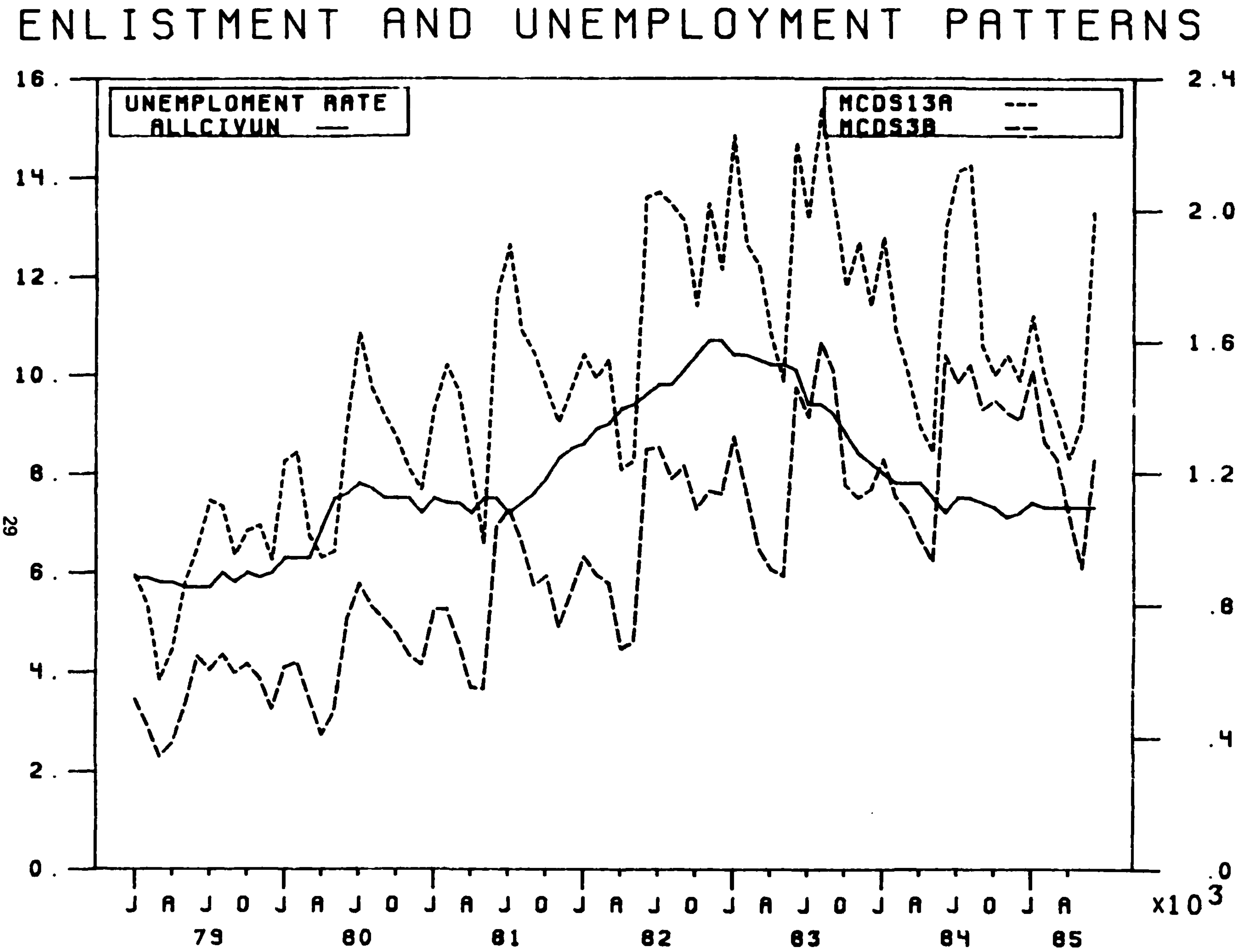
ENLISTMENT AND UNEMPLOYMENT PATTERNS
UNEMPLOMENT RATE
ALLCIVUN
MCDS13A
MCDS3B
16.
14.
12.
10.
8.
6.
4.
2.
0.
2.4
2.0
1.6
1.2
.8
.4
.0
x10^3
J A J O J A J O J A J O J A J O J A J O J A J O J A
79
80
81
82
83
84
85

EXHIBIT 7

UNEMPLOYMENT AND HIGH-QUALITY ENLISTMENT
SIMPLE CORRELATION COEFFICIENTS

(January 1979 - September 1985)

		ALLCIVUN	ALLCIVUN(-8)*	Service 1-3A: Service 3B
1.	ALLCIVUN	—	—	—
2.	ALLCIVUN(-8)	—	—	—
3a.	ARMY 13A	.77	.69	—
3b.	ARMY 3B	.59	.63	.95
4a.	Navy 13A	.81	.51	—
4b.	Navy 3B	.55	.48	.72
5a.	AF 13A	.28	.15	—
5b.	AF 3B	-.25	-.50	.50
6a.	MC 13A	.68	.55	—
6b.	MC 3B	.47	.52	.86

* Lagged eight months.

simple correlations indicate a slight counter cyclical relationship for 3B enlistments. The cyclical pattern of 3B enlistments is somewhat weaker in the other Services as well.

Consider two additional factors that influence enlistments: relative pay and the number of recruiters. The simple correlations are reported in Exhibit 8. Note the relatively strong positive relationship of unemployment with relative pay, Army recruiters, and Marine recruiters. Thus the cyclical enlistment pattern described is partially caused by movements in relative pay and recruiters for these two Services. For the Navy, recruiter movements are related only weakly to unemployment. In the Air Force, we do not observe a strong cyclical pattern for recruiters. This is because the Air Force has implemented counter cyclical policies to some degree.

The interrelationships portrayed in the upper portion of Exhibit 8 are not alarmingly high, but as Maddala [Reference 27, p. 185] points out: in the case of more than two variables, the simple correlations all could be low and yet multicollinearity could be very serious. In such a situation, one looks at the multiple correlation coefficients of each of the explanatory variables with others, i.e., to what extent is each variable a linear combination of the others. These calculations are shown in the lower portion of Exhibit 8 in sets for each Service. These correlations are relatively high and suggest that there may be a problem in disentangling their separate effects upon enlistments.

In Exhibit 7 we also report the simple correlation between enlistments and unemployment lagged eight periods. The slow decline [11] from a contemporaneous effect to a relationship which is still substantial eight periods later, together with the cyclical pattern of enlistments, suggests that a distributed lag model should be investigated. (It may ameliorate the effects of serial correlation.) Preliminary research on such a model is described in Appendix B.

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11 Army and Marine Corps correlations rise to a peak at lags of one or two periods and then decline.

EXHIBIT 8

UNEMPLOYMENT, RELATIVE PAY, AND RECRUITERS CORRELATION COEFFICIENTS

(January 1979 - September 1985)

A. Simple Correlation Coefficients Among Selected Supply Factors

		ALLCIVUN	RELPAY
1.	ALLCIVUN	—	—
2.	RELPAY	.75	—
3.	Army Recruiters	.62	.64
4.	Navy Recruiters	.23	-.17
5.	AF Recruiters	-.47	-.79
6.	MC Recruiters	.59	.78

B. Multiple Correlation Coefficients Among Selected Supply Factors*

ARMY	Army Recruiters	.66
	ALLCIVUN	.76
	RELPAY	.77
NAVY	Navy Recruiters	.54
	ALLCIVUN	.83
	RELPAY	.82
AIR FORCE	Air Force Recruiters	.80
	ALLCIVUN	.76
	RELPAY	.89
MARINE CORPS	Marine Corps Recruiters	.77
	ALLCIVUN	.74
	RELPAY	.85

* For each Service, the MCC of a variable as a function of the other two variables.

D. Estimation of a Forecasting Model in the Presence of Serial Correlation

The task is to estimate the parameters of the single equation log-linear enlistment supply model in which the residuals are serially correlated. Either AR, MA, or ARMA processes are assumed.

Why not ignore serial correlation and simply use the OLS estimation technique? In the presence of serial correlation OLS estimators are unbiased but not efficient. The estimated variances can be seriously understated; thus R^2 as well as t and F statistics tend to be exaggerated. [Reference 27, pp. 281-283.]

Econometrics texts typically describe so-called efficient estimation techniques to be used when residuals follow an AR=1 process. There are iterative two-step procedures (e.g., Cochrane-Orcutt) which first involve estimation of p_1 (i.e., the first order autocorrelation coefficient), then estimation of the other regression parameters. One then solves for a new estimate of p_1, and proceeds iteratively until successive values of p_1 are approximately the same. There are search procedures (Hildreth-Lu) where the value of p_1 is chosen so as to minimize the residual sum of squares. If the number of observations is large, this procedure and the maximum likelihood procedure will produce approximately the same results. [Reference 27, pp. 277-280.]

With one exception, we estimate a more complicated ARMA error structure using a Gauss-Newton non-linear least squares (NLLS) routine.[12] This iterative algorithm operates to minimize the sum of squared residuals.

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12 As implemented in Regression Analysis for Time Series (RATS) — statistical software that operates on the IBM microcomputer. Our own experience is that the Cochrane - Orcutt, Hildreth-Lu, and NLLS procedures yield almost identical estimates for AR = 1 processes.

Before applying the NLLS routine, the ARMA error model must be identified. We follow the Box-Jenkins procedure for fitting an ARMA model of order (p, q) to a time series. It consists of three stages: identification, estimation and testing, and application. [Reference 28, Chapter 8.] In the identification stage, the first step is to obtain a stationary series; otherwise, spurious autocorrelations that have been introduced by trend will hinder identification. In our work, the time series is the residual series from a preliminary OLS regression. It has been found to be stationary without need for transformation (e.g., first differences).

The second step is to examine the autocorrelations and partial autocorrelations. Autocorrelation measures the relationship between current values of the series and past values at specific lags. Partial autocorrelation measures this relationship and also holds constant the effects of lags other than the one in question. From this examination, one determines the process (AR, MA, or mixed) and the appropriate order. Identification requires judgment to deal with the possibility that the direct and partial autocorrelations may not clearly indicate a specific model, or that they may indicate more than one model. Thus, one infers a tentative model, and proceeds to estimate and test it.

In the estimation and testing stage, the goodness of fit is determined by: the residual sum of squares (RSS); the RBAR-squared statistic (the percentage of the dependent variable variance explained by the regression, corrected for degrees of freedom); and the extent to which the estimated model has removed the autocorrelation patterns in the time series and left white noise. The latter is measured by calculation of autocorrelation statistics for the residual time series. The null hypothesis is that the residuals are not (auto) correlated. We choose to examine lags 1 to 24. Correlation is measured by the Box-Pierce Q statistic. The formula is as follows:

$$Q = n \sum_{k-1}^{m} r^2(k)$$

where

n = number of observations;

m = largest time lag considered, e.g., 24;

$r(k)$ = the autocorrelation for time lag k; and

Q is distributed as a Chi-square statistic with $m-p-q$ degrees of freedom

One can determine the probability that, under the null hypothesis, in repeated tests the Q sample value would be as extreme as the observed Q(24) statistic. This probability is indicated by SIGNF in the results tables. Small values for SIGNF indicate small credibility for the null hypothesis. (The range is 0 to 100.)

We conclude this section on a cautionary note. It is convenient to assert that the source of serial correlation in the disturbances can be traced to omitted variables that are themselves autocorrelated. Maddala [Reference 27] points out that to justify the estimation techniques presented as remedies — of which the one described here is a cousin — we have to argue that the autocorrelated omitted variables (that are producing the autocorrelation in the residuals) are uncorrelated with the included explanatory variables. This cannot be readily ascertained. He suggests that:

> "when serial correlation in the residuals is due to omitted variables that are themselves autocorrelated, the question of whether or not the usual procedures of 'efficient' estimation often suggested in textbooks are better than ordinary least squares is a point that needs more careful investigation."
>
> (p. 291)

The implication for our work is to evaluate the ARMA regression model against a basic model estimated with OLS in out-of-sample forecasts tests.

E. Model Results: ARMA and OLS Estimation

Enlistment supply equation results are reported in Exhibits 9-12 by Service for the January 1979 - May 1985 period. A "basic" model that ignores serial correlation has been estimated with OLS, and ARMA models have been estimated with NLLS. Following the procedure described previously, the following ARMA noise structures were selected:

	1-3A	3B
ARMY	MA = 1, 2	MA = 1, 2
NAVY	AR = 1; MA = 10	AR = 1
AIR FORCE	AR = 1; MA = 1	MA = 1, 4
MARINE CORPS[13]	AR = 1; MA = 7, 8, 10	MA = 1

The extent of serial correlation of the residuals is indicated by the Q statistic and its statistical significance (SIGNF) in the basic model. The null hypothesis of zero serial correlation cannot be sustained. The same statistics for the ARMA model indicate that the serial correlation has been reduced or eliminated entirely — especially in the Navy and Marine Corps. It is possible further to reduce serial correlation by introducing additional ARMA parameters. However, this is overfitting which, while producing better fits over the estimation period, results in relatively inaccurate out-of-sample forecasts.[14]

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13 In retrospect, this happened in the case of an Air Force model we were using earlier in the project.

14 For the Marine Corps we estimate two models with differing numbers of lags for selected variables.

EXHIBIT 9

ESTIMATED ENLISTMENT EQUATIONS
NPS MALE HSSR - HSDG COHORTS

ARMY 7901-8505

	ARMA Model++		Basic Model+	
	1-3A	3B	1-3A	3B
Constant	-.768	1.767	-2.594	.759
ARECPA	.861**	.585	1.077**	.715**
RELPAY	1.970**	2.967**	1.986**	3.055**
UNEMP(-2)	.773**	.382**	.777**	.344**
ACF	.178**	.131**	.162**	.125**
D89	.130	.193**	.129	.154*
D10	.247**	.175*	.151	.213*
D1112	.096	.153	.122	.211**
BRIDE	.067	.192**	.075	.165**
SEAS:MAY	.005	.002	.005	.000
SEAS:JUNE	.143**	.287**	.151**	.287**
SEAS:JULY	.231**	.329**	.224**	.324**
SEAS:AUGUST	.176**	.252**	.174**	.255**
SEAS:SEPTEMBER	.014	.117*	.011	.119**
SEAS:OCTOBER	-.105*	.021	-.091	.014
SEAS:NOVEMBER	-.077	.007	-.068	.000
SEAS:DECEMBER	-.045	-.053	-.080	-.073
SEAS:JANUARY	.209**	.205**	.185**	-.199**
SEAS:FEBRUARY	.108	.166**	.127**	.169**
SEAS:MARCH	.071	.096**	.075	.097*
MVG AVGE (-1)	.555**	.448**	—	—
MVG AVGE (-2)	-.575**	-.265*	—	—
SSR	.316	.460	.513	.557
RBAR**2	.97	.95	.95	.95
Durbin-Watson	1.84	2.00	1.66	1.52
Q(24)	22.9	22.7	28.7	34.3
SIGNF	.52	.54	.23	.08

+ Estimated with OLS
++ 1-3A: MA = 1, 2; 3B: MA = 1, 2
* Indicates coefficient is statistically significantly different from zero at 90% confidence level (two tail test).
** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

EXHIBIT 10

ESTIMATED ENLISTMENT EQUATIONS
NPS MALE HSSR - HSDG COHORTS

NAVY 7910-8505

	ARMA Model 1-3A++	ARMA Model 3B+	Basic Model+ 1-3A	Basic Model+ 3B
Constant	-.002	4.580**	1.374	5.397**
NAVDS13A	.365**	.352**	—	—
WTNRECT	.439	.654	.577	.150
WTNRECT (-1)	-.007	-.726	—	—
RELPAY (-3)	.118	1.041**	.450	1.947**
LNGPR (GAP)	.213*	.233*	.204*	.058
LNGPR (GAP) (-1)	-.147	-.127	—	—
UMG	-.033	—	.007	—
UMG (-1)	.041	—	—	—
UNEMP	.432	.125	.690**	.315*
UNEMP (-1)	.065	.173	—	—
NFAT83	.084	.057	.132**	-.011
REF44	.041	-.108**	.088	-.175**
SEAS:MAY	-.121**	-.090*	-.141**	-.106*
SEAS:JUNE	.056	.209**	-.011	.181**
SEAS:JULY	.139**	256**	.114*	.295**
SEAS:AUGUST	.130**	.205**	.141**	.322**
SEAS:SEPTEMBER	-.009	.166**	.005	.317**
SEAS:OCTOBER	.005	.076	-.051	.163**
SEAS:NOVEMBER	.054	.146**	.002	.169**
SEAS:DECEMBER	.078	.164**	.057	-.170**
SEAS:JANUARY	.113*	.248**	.128**	.286**
SEAS:FEBRUARY	.093*	.136**	.112**	.195**
SEAS:MARCH	.074	.080	.071	.115**
MVG AVGE (-10)	-.265**	—	—	—
SSR	.281	.337	.421	.448
RBAR**2	.82	.85	.77	.83
Durbin-Watson	2.05	2.01	1.27	1.26
Q(24)	13.3	13.2	37.0	21.1
SIGNF	.96	.96	.04	.63

+ Estimated with OLS

++ 1-3A: AR = 1, MA = 10; 3B: AR = 1

* Indicates coefficient is statistically significantly different from zero at 90% confidence level (two tail test).

** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

EXHIBIT 11

ESTIMATED ENLISTMENT EQUATIONS
NPS MALE HSSR - HSDG COHORTS

AIR FORCE 7901-8505

	ARMA Model++ 1-3A	ARMA Model++ 3B	Basic Model+ 1-3A	Basic Model+ 3B
Constant	1.853	.134	1.331	1.063
ARDS13A (-1)	.124	—	—	—
FRECPNPS	.272	.743	.569**	.607
FRECPNPS (-1)	.154	—	—	—
FMGPR	.365*	.180	.408**	.206
FMGPR (-1)	-.131	—	—	—
RELPAY	.284	.922	.423	.711
UNEMP (-1)	.742*	.663*	1.047**	.683**
UNEMP (-2)	.155	—	—	—
CAP	-.287**	-.332**	-.320**	-.331**
SCARCE3	-.322**	-.273**	-.343**	-.391**
G40EFF	—	-.324**	—	-.341**
D1585	—	.322**	—	.314**
REF44	.021	—	.016	—
SEAS:MAY	.026	.007	.020	-.000
SEAS:JUNE	.034	.117	.039	.113
SEAS:JULY	.083	.201*	.092	.192*
SEAS:AUGUST	.159**	.231**	.167**	.222**
SEAS:SEPTEMBER	.009	.168*	.023	.162*
SEAS:OCTOBER	-.022	-.008	-.022	-.014
SEAS:NOVEMBER	-.010	-.041	-.024	-.053
SEAS:DECEMBER	.046	.154	.015	.120
SEAS:JANUARY	.145**	.167	.130**	.161*
SEAS:FEBRUARY	.166**	.182*	.178**	.191**
SEAS:MARCH	.090*	.091	.010	.103
MVG AVGE (1)	.507**	.801**	—	—
MVG AVGE (4)	—	-.384**	—	—
SSR	.531	1.013	.731	1.664
RBAR**2	.73	.79	.66	.66
Durbin-Watson	2.04	2.03	1.06	1.14
Q(24)	21.0	23.7	55.1	43.8
SIGNF	.64	.48	.00	.00

+ Estimated with OLS

++ 1-3A: AR = 1, MA = 1; 3B: MA = 1, 4

* Indicates coefficient is statistically significantly different from zero at 90% confidence level (two tail test).

** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

EXHIBIT 12

ESTIMATED ENLISTMENT EQUATIONS
NPS MALE HSSR - HSDG COHORTS

MARINE CORPS 7901-8505

	ARMA Model++			Basic Model+	
	1-3A[a]	1-3A	3B	1-3A	3B
Constant	-3.80**	-5.25**	1.131	-3.118*	.847
MCDS13 (-1)	.103	.044	—	—	—
MRECREV	1.197**	.723	.703**	1.188**	.755**
MRECREV (-1)	—	.708	—	—	—
MCGPR (GAP)	.172*	.101	.021	.164*	.017
MCGPR (GAP) (-1)	—	.168	—	—	—
RELPAY	1.048**	1.079**	2.99**	1.174**	3.01**
UNEMP (-2)	.331**	-.015	.026	.405**	-.018
UNEMP (-3)	—	.342	—	—	—
FULL83	-.056	-.050	.001	-.046	.040
REF44	.112*	.119*	-.176**	.092**	-.184**
SEAS:MAY	.040	.059	.032	.016	.030
SEAS:JUNE	.355**	.409**	.548**	.355**	.566**
SEAS:JULY	.354**	.413**	.549**	.376**	.545**
SEAS:AUGUST	.325**	.347**	.529**	.357**	.525**
SEAS:SEPTEMBER	.168**	.193**	.423**	.221**	.418**
SEAS:OCTOBER	.201**	.190**	.358**	.228**	.361**
SEAS:NOVEMBER	.222**	.255**	.255**	.235**	.256**
SEAS:DECEMBER	.138**	.175**	.205**	.156**	.206**
SEAS:JANUARY	.247**	.303**	.333**	.259**	.335**
SEAS:FEBRUARY	.192**	.202**	.262**	.216**	.264**
SEAS:MARCH	.047	.083	.121**	.071	.122**
MVG AVGE (-1)	—	—	.529**	—	—
MVG AVGE (-7)	-.211*	-.252*	—	—	—
MVG AVGE (-8)	-.331**	-.386**	—	—	—
MVG AVGE (-10)	-.331**	-.346**	—	—	—
SSR	.383	.356	.516	.487	.643
RBAR**2	.92	.92	.95	.90	.92
Durbin-Watson	2.11	2.07	1.93	1.81	1.17
Q(24)	18.8	19.6	12.4	40.9	27.2
SIGNF	.76	.72	.98	.02	.30

\+ Estimated with OLS
++ 1-3A: AR = 1, MA = 7, 8, 10; 3B: MA = 1
* Indicates coefficient is statistically significantly different from zero at 90% confidence level (two tail test).
** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).
a Specification of the AR=1, MA=7,8,10 model in which the lagged explanatory variables are suppressed in the estimating equation.

The fit of the ARMA model over the estimation period is noticeably better than the basic OLS model. This is indicated by the reduction in the sum of squared residuals (SSR). The RBAR**2 statistic, taking into account the additional degrees of freedom used in the ARMA model, indicates a noticeably better fit for the Navy and Air Force.

The suspected presence of multicollinearity makes it difficult to interpret the estimated coefficients as partial effects. As discussed above, the relatively high intercorrelations between unemployment and relative pay, and in certain cases between these and recruiters, may make it difficult to disentangle their separate effects on enlistments. With this caution, we note that for the Army there are strong recruiter, pay, and unemployment effects. For the Air Force there are strong recruiter, recruiter workload, and unemployment effects. For the Marine Corps there are strong recruiter, pay, and unemployment effects (for the 1-3A cohort).

The OLS results for the Navy are plausible, but the ARMA models contain some unexpected signs. We believe the problem is that the Navy enlistment series over the FY 79-83 period is contaminated with reserve enlistees. On an annual basis the proportion varies between 3 and 10 percent, but it is much larger in particular months. DMDC, with the guidance of NRC, is attempting to purge the reservists. When they are successful, we will re-estimate the Navy models (and revise the forecasting equations).

In the 3B cohort models, the goals per recruiter variable (i.e., recruiter workload) is replaced by a measure of the gap between 1-3A goals and production. A positive effect is hypothesized. The measure showed a positive and statistically significant effect in the Navy; it was positive in the Air Force and Marine Corps, but inconsequential in the latter. We did not test for the effect of this variable for the Army, due to the problems in obtaining goal data discussed earlier.

CHAPTER III

ENLISTMENT FORECASTING ACCURACY

A. Introduction

To determine the forecasting accuracy of the Recruitment EWS models, out-of-sample *ex post* forecasting tests are conducted. In this exercise the models are estimated over a subset of the observations; forecasts for a subsequent period (i.e., beyond the estimation period) are generated and compared to the actual values. The known future values of the exogenous factors are employed, with the exception of unemployment for which both forecasted and actual values are used. This procedure closely simulates the situation that actually would have prevailed had forecasts been made at that point in time. The biggest difference is that in the live situation, future values of the exogenous factors would not have been known; except for unemployment, estimated or planning values would have been employed. This is not a serious departure since these factors change slowly, and their trends are generally predicted with reasonable accuracy in the live situation.

The selection of a forecast test period is guided by several considerations. First, a twelve month period is preferred because the EWS is designed to look a year ahead. The more recent the period the more realistic is the test, relative to current capabilities, and the more observations there are for estimation.

The major constraint to selecting a test period is finding one that is relatively free of new policy or program changes not included in the regression model. Such changes occur frequently and they make it difficult to test the "steady state" forecasting accuracy of the EWS. In Chapter VI we describe our exploratory analysis of alternative procedures for forecasting enlistments *after* policies or programs change or new ones are introduced. The results indicate that the ARMA model adapts fairly quickly to the introduction of new dummy variables.

For all the Services, we have selected two periods for out-of-sample forecast testing — FY 84 and one other period. In the Army, the second test is confined to 8502-8506. Effects of the Army bridge programs were first felt in August 1984. By February 1985 the impact of the programs had stabilized to the point where dummy variables fit reasonably well. Accordingly, we estimate the model through 8501, and begin forecasting in 8502. For the Navy and the Marine Corps, the second test covers 8407-8506. The major concern with this period is the recalibration of the enlistment series. Since the estimated model will not include the appropriate dummy variable, the 1-3A (1-3) cohort forecasts may be biased upward (downward). For the Air Force, the second test covers the 8402-8501 period, overlapping the first test. To conduct this test we presume advance knowledge of the change in the G40/C145 operating standard that occurred "officially" in early 1985, but which — for practical purposes — took effect in October - November 1984 and can be measured with a change in an existing mental standards dummy variable. The test period is cut off in January 1985 because it appears that further changes were made (i.e., increasing the availability of 3B jobs) for the January to May 1985 period.

B. <u>Measuring Accuracy</u>

Several measures of forecasting accuracy are reported in the next section. In a given month, the forecasting error is defined as:

$$e(t) = F(t) - A(t),$$

where F and A are forecasted and actual values, respectively. Over a period of n months, the total error is:

$$TE = \sum_{n} e(t)$$

Unless the forecasting model is biased there will be canceling of positive and negative errors and TE relative to total enlistments over the period will be smaller than the monthly error.

The mean absolute error (MAE) and mean squared error (MSE) are useful measures of an average monthly error:

$$\text{MAE} = 1/n \sum_{n} |e(t)| \text{ , and}$$

$$\text{MSE} = 1/n \sum_{n} e(t)^2.$$

The MAE and the square root of the MSE (i.e., RMSE) are reported in percentage form (i.e., with e(t) defined as a percent error).

One attraction of MSE-based measures of accuracy is that they are linked directly to the mean and variance of the prediction error, since

$$\text{MSE} = 1/n \sum_{n} e(t)^2 = 1/n \sum_{n} (e(t) - \bar{e})^2 + \bar{e}^2.$$

The first term is the variance of e and the second is the square of the mean error. Therefore, RMSE is an increasing function of the variance and the mean error, and the larger these are, the more inaccurate are the forecasts.

Following the statistical methods developed by Theil[15], the right hand side of the above equation can be decomposed further into systematic and random components by re-writing as:

$$\text{MSE} = S^2_e + (1/n\Sigma F - 1/n\Sigma A)^2 \quad \text{(where } S^2 \text{ denotes a variance)}$$

$$= S^2_{F-A} = (\bar{F} - \bar{A})^2$$

$$= S^2_F + S^2_A - 2rS_FS_A + (\bar{F} - \bar{A})^2 \quad \text{(by the definition of the variance of the difference of two variables)}$$

$$= (1-r^2)S^2_A + (S_F - r\,S_A)^2 + (\bar{F} - \bar{A})^2 \quad \text{(where } r \text{ is the correlation between the A and F series.}$$

---

15 See Maddala for a summary of Theil methods. [Reference 27, pp. 344-347.]

If we divide each term by the MSE, then the first term is the random disturbance proportion (U^D), the second term represents the regression bias proportion (U^R), and the third term measures the mean bias proportion (U^M).

If U^M is large, it means that the average predicted change deviates substantially from the average actual change (i.e., TE is large). This is a serious error, because we should expect that forecasters must be able to reduce such errors in the course of time. If we consider the regression of actual on forecasted values, i.e.,

$$A(t) = a + bF(t)$$

then U^M will be zero if $a = \hat{o}$, and U^R will be zero if $\hat{b} = 1$. Three cases are illustrated in Exhibit 13.

In addition to reporting U^M, U^R and U^D, we also report the widely-used Theil inequality coefficient, U:

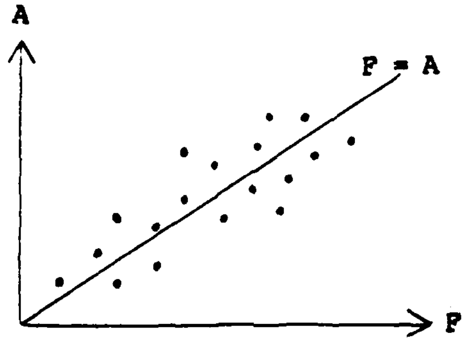
$$U = \sqrt{MSE / \sum (A(t)^2 / n)}$$

It is an RMSE that is standardized for the normal magnitude of the actual outcome during the period under consideration. U is zero only in the case of perfectly accurate forecasts; it rises with inaccuracy, and has no upper bound. U equals 1 for any series of forecasting as inaccurate as a naive "no change" forecast if F and A are redefined as changes.

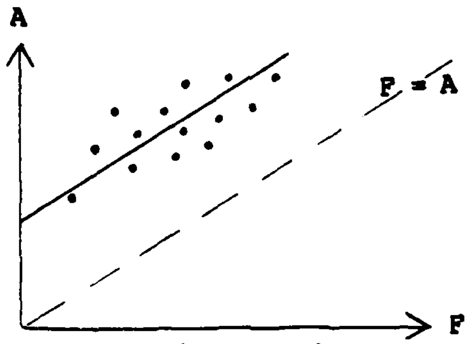
Theil U statistics are calculated for the 1-3A and 3B cohort forecasts, but not for the combined cohort (due to computational difficulties). In addition to the twelve month forecasting tests described above, we carried out a series of subperiod tests: increasing (decreasing) the estimation (forecast) period one month each round so that we made 12 one-month-ahead forecasts, 11 two-month-ahead forecasts, 10 three-month-ahead forecasts, etc. The Theil U statistic summarizes this testing.

EXHIBIT 13

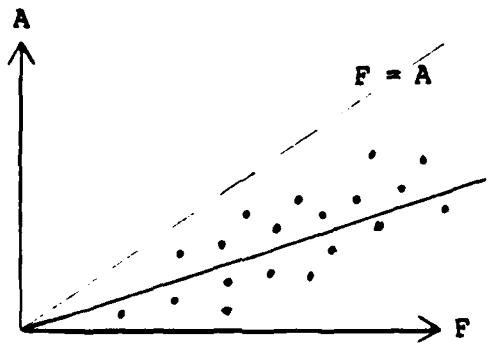
DECOMPOSITION OF FORECASTING ERRORS



(i) $\hat{a} \cong 0$, $\hat{b} \cong 1$



(ii) $\hat{a} > 0$, $\hat{b} \cong 1$
(mean bias)



(iii) $\hat{a} \cong 0$, $\hat{b} < 0$
(regression bias)

C. Out-of-Sample Forecasting Test Results

The results are presented in Exhibits 14-17 by Service. On the first table in each Exhibit, the columns correspond to the accuracy measures described, and the rows represent cohort, periods, and models. The test results reported in the first table are for the 1-3A and 1-3 cohorts. The test for the latter cohort is run on the sum of separate 1-3A and 3B model forecasts. Within cohorts, the ARMA and base models are grouped separately. The second and third tables report the Theil U statistics for 1-3A and 3B cohort forecasting.

1. Army

Average monthly errors (as measured by RMSE or MAE) tend to cluster in the 8-12% range. Over the FY 84 test period we can infer that the error pattern is mixed — both under and overprediction — because the total errors, expressed as percentages, are much smaller than average monthly errors. Indeed, they tend to cluster in the 2-3.5% range. The mixed error pattern and cancelling of errors reflects itself in the low mean bias (U^M). Over the 8502-8506 test period we can infer that overprediction dominates. We do not place too much importance on this test period because it is short and comes soon after program changes which could require additional observation periods to model accurately.

The tests indicate somewhat better forecasting accuracy for the 1-3A than the 1-3 cohort. Forecast errors for 3B's follow the same pattern as those for 1-3A's, but they are disproportionately larger, and cause forecasts for 1-3s to be less accurate than those for 1-3A's. The Theil U statistics also indicate that the 1-3A model is definitely superior to a naive forecast, whereas the same cannot be said for the 3B model beyond a four-month horizon.

Enlistment forecasting accuracy with forecasted unemployment turns out to be approximately the same as with actual unemployment. Monthly errors are about two percentage points higher with the

EXHIBIT 14
page one

OUT-OF-SAMPLE FORECASTING TESTS
1-3A and 1-3 COHORTS

ARMY

	RMSE	MAE	Total Error No.	Total Error Pct.[+]	Error Decomposition (%) U^M	U^R	U^D	
1-3A								
8310-8409[a]	10.9	8.9	-1069	-1.9	1.1	22.3	76.6	ARMA[1]
8310-8409[f]	12.7	10.8	990	1.8	3.5	30.8	65.7	ARMA[1]
8502-8506[a]	6.0	4.8	756	3.3	NR	NR	NR	ARMA[1]
8310-8409[a]	10.7	8.4	- 779	-1.4	0.6	160	83.4	Base**
8310-8409[f]	12.5	10.4	1295	2.3	5.0	24.0	71.0	Base**
8502-8506[a]	7.7	6.7	1326	5.7	NR	NR	NR	Base**
1-3								
8310-8409[a]	10.2	8.1	-6093	-6.9	36.8	5.1	58.1	ARMA[2]
8310-8409[f]	9.8	8.0	-3047	-3.4	8.9	15.8	75.3	ARMA[2]
8502-8506[a]	10.3	9.0	3307	8.9	NR	NR	NR	ARMA[2]
8310-8409[a]	9.8	7.8	-5186	-5.9	28.7	3.2	68.1	Base**
8310-8409[f]	9.5	7.6	-2156	-2.4	4.7	10.8	84.5	Base**
8502-8506[a]	11.8	10.5	3866	10.4	NR	NR	NR	Base**

+ Total error as percentage of actual enlistments over the period
1 MA = 1, 2
2 1-3A: MA = 1, 2; 3B: MA = 1, 2
** OLS estimation
a With actual unemployment
f With forecasted unemployment
NR Not reported due to too few observations for the calculation

EXHIBIT 14
page two

THEIL U STATISTICS
FOR ARMY 1-3A COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409		
1	.67	.76	12
2	.71	.67	11
3	.55	.58	10
4	.62	.64	9
5	.72	.74	8
6	.75	.75	7
7	.68	.69	6
8	.52	.54	5
9	.46	.51	4
10	.50	.53	3
11	1.35	1.42	2
12	.01	.04	1
	Forecast Period: 8502 - 8506		
1	.75	.55	5
2	.66	.63	4
3	.53	.52	3
4	.44	.53	2
5	1.19	1.84	1

EXHIBIT 14
page three

THEIL U STATISTICS
FOR ARMY 3B COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409		
1	.79	.80	12
2	.99	.83	11
3	.67	.68	10
4	.76	.75	9
5	1.11	1.11	8
6	1.30	1.29	7
7	1.08	1.07	6
8	.72	.72	5
9	1.27	1.26	4
10	1.10	1.09	3
11	3.18	3.11	2
12	1.23	1.19	1
	Forecast Period: 8502 - 8506		
1	.72	.70	5
2	.81	.68	4
3	.83	.72	3
4	.74	.74	2
5	4.90	4.88	1

EXHIBIT 15
page one

OUT-OF-SAMPLE FORECASTING TESTS
1-3A and 1-3 COHORTS

NAVY

	RMSE	MAE	Total Error No.	Total Error Pct.+	Error Decomposition (%) U^M	U^R	U^D	
1-3A								
8310-8409[a]	22.9	19.2	2353	5.8	12.6	44.9	42.5	ARMA[1]
8310-8409[f]	24.3	20.5	4396	10.8	29.8	36.6	33.6	ARMA[1]
8407-8506[a]	16.9	12.1	3749	10.4	47.3	0.9	51.8	ARMA[1]
8310-8409[a]	17.6	13.9	-2332	-5.7	6.1	35.5	58.4	Base**
8310-8409[f]	14.9	13.3	-540	-1.3	0.0	30.4	69.6	Base**
8407-8506[a]	19.6	15.5	4775	13.3	57.3	1.2	41.5	Base**
1-3								
8310-8409[a]	23.9	18.9	5128	8.7	19.6	53.1	27.3	ARMA[2]
8310-8409[f]	23.1	19.2	6472	11.0	30.2	43.5	26.3	ARMA[2]
8407-8506[a]	13.9	10.4	2823	5.1	16.9	3.6	79.5	ARMA[2]
8310-8409[a]	15.5	12.2	-2378	-4.0	3.5	41.4	55.0	Base**
8310-8409[f]	12.3	10.5	-1367	-2.3	1.4	30.0	68.6	Base**
8407-8506[a]	15.3	12.6	3581	6.5	21.1	6.6	72.3	Base**

+ Total error as percentage of actual enlistments over the period
1 AR = 1; MA = 10
2 1-3A: AR = 1, MA = 10; 3B: AR = 1 (with GAP)
** OLS estimation
a With actual unemployment
f With forecasted unemployment

EXHIBIT 15
page two

THEIL U STATISTICS FOR NAVY 1-3A COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409[f]		
1	.79	.87	12
2	.91	.90	11
3	.86	.83	10
4	1.03	.92	9
5	1.00	.80	8
6	1.03	.81	7
7	1.14	.90	6
8	1.06	.79	5
9	1.22	.88	4
10	1.18	.81	3
11	1.07	.72	2
12	.63	.38	1
	Forecast Period: 8407 - 8506[a]		
1	.79	.91	12
2	.85	.89	11
3	.91	.93	10
4	.73	.75	9
5	.90	.98	8
6	.92	1.04	7
7	1.03	1.18	6
8	1.50	1.70	5
9	.84	.90	4
10	.83	.95	3
11	.91	1.18	2
12	5.12	6.95	1

[a] With actual unemployment
[f] With forecasted unemployment

EXHIBIT 15
page three

THEIL U STATISTICS FOR NAVY 3B COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409[f]		
1	.75	.73	12
2	.76	.63	11
3	.84	.60	10
4	1.07	.72	9
5	1.28	.77	8
6	1.36	.84	7
7	1.25	.72	6
8	1.29	.73	5
9	1.97	1.02	4
10	1.64	.73	3
11	1.61	.59	2
12	1.11	.20	1
	Forecast Period: 8407 - 8506[a]		
1	.96	.90	12
2	1.12	.97	11
3	1.00	.87	10
4	.70	.66	9
5	.86	.74	8
6	.84	.61	7
7	.96	.68	6
8	2.96	1.84	5
9	1.26	.82	4
10	2.37	1.66	3
11	1.08	.68	2
12	1.30	1.00	1

---

a With actual unemployment
f With forecasted unemployment

EXHIBIT 16
page one

OUT-OF-SAMPLE FORECASTING TESTS
1-3A and 1-3 COHORTS

AIR FORCE

	RMSE	MAE	Total Error No.	Total Error Pct.[+]	Error Decomposition (%) U^M	U^R	U^D	
1-3A								
8310-8409[a]	10.5	6.9	-1711	-4.1	13.5	1.4	85.1	ARMA[1]
8310-8409[f]	11.1	9.6	-22	0.0	0.5	6.7	92.8	ARMA[1]
8402-8501[a]	7.4	6.2	1751	4.4	32.8	13.3	53.9	ARMA[2]
8310-8409[a]	12.3	10.0	-25	0.0	0.4	15.4	84.2	Base**
8310-8409[f]	15.5	14.2	2268	5.5	7.9	25.9	66.2	Base**
8402-8501[a]	14.8	13.2	5055	12.8	70.7	11.3	18.0	Base**
1-3								
8310-8409[a]	11.2	7.9	-3224	-6.2	24.1	0.2	75.7	ARMA[3]
8310-8409[f]	11.3	9.3	-1359	-2.6	6.7	4.1	89.2	ARMA[3]
8402-8501[a]	9.1	7.2	-1209	-2.3	5.0	42.8	52.3	ARMA[4]
8310-8409[a]	12.0	8.7	-1679	-3.2	8.2	7.9	83.9	Base**
8310-8409[f]	13.9	12.6	924	1.8	0.3	20.6	79.1	Base**
8402-8501[a]	13.3	12.0	3045	5.8	17.8	52.3	29.9	Base**

\+ Total error as percentage of actual enlistments over the period
1 MA = 1 (AR = 1, MA = 1 model could not be solved over this period)
2 AR = 1, MA = 1
3 1-3A: MA = 1; 3B: MA = 1, 4
4 1-3A: AR = 1, MA = 1; 3B: MA = 1, 4
** OLS estimation
a With actual unemployment
f With forecasted unemployment

EXHIBIT 16
page two

THEIL U STATISTICS FOR AIR FORCE 1-3A COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
Forecast Period: 8310 - 8409[f]			
1	.73	1.07	12
2	.77	.90	11
3	.66	.84	10
4	.52	.82	9
5	.57	.91	8
6	.58	.90	7
7	.66	1.04	6
8	.69	1.21	5
9	.35	.69	4
10	.36	.61	3
11	.73	.26	2
12	2.32	.87	1
Forecast Period: 8402 - 8501[a]			
1	.73	1.10	12
2	.57	.71	11
3	.57	.72	10
4	.67	.87	9
5	.64	.85	8
6	.62	.83	7
7	.50	.69	6
8	.42	.51	5
9	.43	.50	4
10	.50	.52	3
11	.62	.68	2
12	.65	.97	1

---

a With actual unemployment
f With forecasted unemployment

EXHIBIT 16
page three

THEIL U STATISTICS
FOR AIR FORCE 3B COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409[f]		
1	.84	1.09	12
2	.82	.87	11
3	.70	.71	10
4	.54	.56	9
5	.64	.65	8
6	.90	.81	7
7	1.36	1.05	6
8	1.07	.80	5
9	.79	.71	4
10	1.02	.98	3
11	1.30	1.27	2
12	3.08	3.03	1
	Forecast Period: 8402 - 8501[a]		
1	1.50	1.92	12
2	1.34	1.46	11
3	1.25	1.37	10
4	1.15	1.29	9
5	1.10	1.25	8
6	1.02	1.14	7
7	.98	1.07	6
8	1.02	1.09	5
9	1.11	1.18	4
10	1.15	1.20	3
11	1.16	1.12	2
12	1.08	1.03	1

---

a With actual unemployment
f With forecasted unemployment

EXHIBIT 17
page one

OUT-OF-SAMPLE FORECASTING TESTS
1-3A and 1-3 COHORTS

MARINE CORPS

	RMSE	MAE	Total Error No.	Total Error Pct.+	Error Decomposition (%) U^M	U^R	U^D	
1-3A								
8310-8409[a,f]			— Not Estimated —					ARMA[3]
8407-8506[a]	12.8	11.5	1132	5.8	29.6	13.3	57.1	ARMA[1]
8407-8506[a]	18.3	16.5	2207	11.3	49.3	20.1	30.6	ARMA[2]
8310-8409[a]	11.5	9.6	1503	7.2	47.5	12.3	40.1	Base**
8310-8409[f]	12.6	10.5	1732	8.3	52.0	12.5	35.5	Base**
8407-8506[a]	9.6	8.2	675	3.5	20.5	3.3	76.2	Base**
1-3								
8310-8409[a,f]			— Not Estimated —					ARMA[3]
8407-8506[a]	7.4	6.4	-992	-2.9	4.9	57.3	37.8	ARMA[4]
8310-8409[a]	6.3	4.9	-1243	-3.5	23.1	3.8	73.1	Base**
8310-8409[f]	6.0	4.5	-739	-2.1	6.9	7.6	85.5	Base**
8407-8506[a]	8.1	6.8	-1361	-3.8	10.4	51.4	38.1	Base**

\+ Total error as percentage of actual enlistments over the period
1 AR = 1, MA = 7, 8, 10 (unlagged form)
2 AR = 1, MA = 7, 8, 10 (lagged form)
3 Both lagged and unlagged ARMA cannot be solved as specified; autocorrelations are noisy, but without strong pattern
4 1-3A: AR = 1, MA = 7, 8, 10 (unlagged form); 3B: MA = 1
** OLS estimation
a With actual unemployment
f With forecasted unemployment

EXHIBIT 17
page two

THEIL U STATISTICS
FOR MARINE CORPS 1-3A COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409[f]		
1	NA	.53	12
2	NA	.43	11
3	NA	.38	10
4	NA	.43	9
5	NA	.52	8
6	NA	.48	7
7	NA	.49	6
8	NA	.45	5
9	NA	.80	4
10	NA	.53	3
11	NA	1.11	2
12	NA	.49	1
	Forecast Period: 8407 - 8506[a]		
1	.54	.55	12
2	.44	.44	11
3	.43	.38	10
4	.48	.40	9
5	.57	.47	8
6	.48	.42	7
7	.45	.39	6
8	.33	.31	5
9	.32	.25	4
10	.24	.21	3
11	.17	.07	2
12	1.13	.55	1

---

a With actual unemployment
f With forecasted unemployment
NA Not Available

EXHIBIT 17
page three

THEIL U STATISTICS
FOR MARINE CORPS 3B COHORT

Steps Ahead	ARMA Model	Base Model	No. of Observations
	Forecast Period: 8310 - 8409[f]		
1	NA	.80	12
2	NA	.70	11
3	NA	.64	10
4	NA	.64	9
5	NA	.78	8
6	NA	.87	7
7	NA	.81	6
8	NA	.71	5
9	NA	1.11	4
10	NA	1.33	3
11	NA	2.36	2
12	NA	3.80	1
	Forecast Period: 8407 - 8506[a]		
1	1.19	1.58	12
2	1.59	1.58	11
3	1.39	1.37	10
4	1.20	1.19	9
5	1.25	1.22	8
6	1.09	1.07	7
7	.86	.85	6
8	.65	.65	5
9	.57	.58	4
10	.48	.51	3
11	.42	.48	2
12	1.00	1.13	1

[a] With actual unemployment
[f] With forecasted unemployment
NA Not Available

forecasted values, while total errors almost coincide for 1-3A's. In the 1-3 cohort tests, the errors turn out to be smaller with the forecasted values.

What can be said about the comparative accuracy of the ARMA and base models? For the 1-3A cohort, the ARMA model forecasts have a slight edge, whereas, for the 1-3 cohort, forecasts of the two models are about the same.[16]

At this point we would recommend selection of the ARMA model. While on forecasting accuracy alone it is difficult to choose, the ARMA has done better during the most recent test period. This may be a good indicator of current capability. As discussed earlier, the ARMA model does fit somewhat better, and has a more plausible recruiter elasticity.

2. Navy

More distinctions can be drawn in the forecasting test results for the Navy than can be for the Army. At the same time, we know that the enlistment series are inconsistent and the results must be viewed with caution.

The forecasting errors for the Navy are larger than those for the Army. Average monthly errors fall between 12-22%, but there is a fair amount of cancellation over the year period. Total error measures tend to fall below 10 percent, though the decomposition analysis reveals more mean and regression bias (vis-a-vis the Army). Forecast accuracy for the 1-3A cohort is similar to the 1-3 cohort.

16 This is not surprising because there is no direct effect of the MA parameters on the forecasts beyond two periods into the future. This corresponds to the way univariate MA model forecasts quickly dampen to the mean.

The base model appears more accurate than the ARMA model (see also the Theil U statistics for support), and we recommend its implementation until a revised enlistment series is available and new tests can be conducted.

3. Air Force

It is more difficult to generalize about the Air Force results. Forecasting test accuracy is similar to that found for the Army: moderate average monthly errors, and a mixed error pattern that results in relatively low total error over the twelve-month period. Errors cluster in the 0-6% range. Unlike the Army results, forecasts for the 1-3 cohort are generally no less accurate than those for the 1-3A cohort. This is due to offsetting 1-3A and 3B errors rather than to a better 3B cohort model. This is evidenced by the tendency toward overprediction of the 1-3A cohort and the underprediction of the 1-3 cohort, as well as by the Theil U statistics for the 3B model.

Based on performance over the more recent test period, the ARMA model is unambiguously preferable to the base model. Over the FY 84 period, the base (ARMA) model accuracy is relatively better with actual (forecasted) unemployment. Accordingly, we recommend implementation of the ARMA model.

4. Marine Corps

We were not able to estimate the 1-3A ARMA model (as specified) over the 7901-8309 period[17], and did not produce forecasts for the subsequent FY 84 period. Accordingly, the base vs. ARMA model comparisons are confined to the 8407-8506 test period.

17 The algorithm aborts when a non-invertible moving average is encountered. In this case, the model is probably over-parameterized.

The monthly errors are moderate, and they are somewhat lower for the 1-3 cohort. There is some cancellation over time, producing reasonably low total errors in the 4-8% range for the 1-3A cohort and the 2-4% range for the 1-3 cohort.

The forecasting errors for the 1-3 cohort are lower due to offsetting 1-3A against 3B errors, rather than particularly accurate 3B forecasts. This is evidenced by the 1-3A overprediction and the 1-3 underprediction, and the 3B model Theil U statistics.

The basic model performed better in forecasting 1-3A enlistments, while the ARMA model performed better in forecasting 1-3 enlistments. In this situation we opt for the ARMA model, preferring to address, rather than ignore, the serial correlation.

CHAPTER IV

LEADING INDICATOR FORECASTING OF UNEMPLOYMENT

A. Introduction

In Phase I of the project we faced the question of what "outside" forecasts of unemployment would be most appropriate for use in the Recruitment EWS. The EWS requires a current forecast that is made available at nominal cost in a timely manner. Several sources were identified: Bureau of Economic Analysis (BEA), Blue Chip Economic Indicators (BCEI), and the Economic Forecasting Project at Georgia State University (GSU). These sources produce quarterly forecasts; BEA updates their forecasts every six weeks, BCEI updates monthly, and GSU every three months. We could have made due with these, but were uncomfortable with their forecasting track records, and believed they could be improved upon. Therefore, we developed a univariate ARIMA forecasting model for unemployment. In out-of-sample forecasting tests for CY 83, this model proved its superiority to the three outside forecasters. [Reference 13, Volume 4.]

The major shortcoming of the ARIMA model was its inability to predict turning points. To respond, in Phase II of the project we focused on the development of leading indicator models for the forecasting of unemployment. The EWS now includes such a model and generates unemployment forecasts each month, for the next 12 months. These forecasts are used in the forecasting of enlistments. For comparative purposes we still collect forecasts produced by outside sources, and include them in the monthly report.

At present, EWS forecasts of unemployment are generated by a model which includes 15 indicators of the economy. Initially we followed the approach developed by our consultant, Professor Richard A. Holmes of Simon Fraser University [Reference 22]. Holmes constructed a composite leading indicator and used it in a transfer function for the prediction of unemployment. The distinguishing feature of the approach is a weighting scheme (for aggregating the component leading indicator series) which is tailored to the series being forecast and to the length of the forecast period. Research led us to choose a related approach which uses leading indicator series individually in an ARMA regression model.

In the work sponsored by ERL, Holmes demonstrated the feasibility of forecasting turning points in unemployment time series. He analyzed a seasonally unadjusted series of civilian male unemployment data. Using leading indicator time series identified by ERL, a composite leading indicator was constructed to predict the cyclical variability of unemployment. The effect of the indicator was estimated within a transfer function model framework that captures seasonality and systematic noise. Performance in several out-of-sample forecasting tests confirmed that the model does forecast turning points accurately. This work is documented in a study report by Holmes and Ross Neill. [Reference 21.]

In contrast to Holmes' work, we have modeled a seasonally adjusted civilian (both male and female) unemployment series. This modeling is implemented on a microcomputer using RATS software for which a transfer function and multiplicative seasonal parameters are not yet available: hence our decision to use a seasonally adjusted series and a multivariate regression model in this phase of the work.

In this chapter we describe the methodology for constructing the composite leading indicator, the preparation of the leading indicator series, the specification and estimation of both the composite leading indicator and individual leading indicator regression models, and the forecasting tests carried out to validate the approaches and select a model for the EWS.

B. Constructing the Composite Leading Indicator

It is convenient to view a time series (O) as comprised of trend (T), seasonal (S), cyclical (C) and irregular (I) components — linked together in multiplicative fashion:

$$O = T \times S \times C \times I.$$

In creating a composite leading indicator, we isolate the cyclical component of the unemployment series and that of each of the (explanatory) leading indicator series, and then construct a cyclical composite leading indicator that fits the cyclical component of the unemployment series. Variation in unemployment due to trend and seasonality are modeled separately in a multivariate regression equation.

During the first step in the process of isolating the cyclical components, seasonal factors are estimated using the Census II ratio-to-moving average decomposition techniques. The original series is divided by the estimated seasonal factors to yield:

$$O' = T \times C \times I.$$

Since we chose to work with a seasonally adjusted series, we begin by regressing O' against a constant and trend. The residuals represent variation apart from trend, to which the mean of the series is added. This results in a de-trended series:

$$O'' = C \times I.$$

This series is smoothed to reduce the presence of the irregular component by calculating a weighted average of current and lagged values:

$$O_t''' = .7 \times O_t'' + .3 \times O_{t-1}''.$$

The resulting series O"' approximates the cyclical component. The series is divided by its standard deviation to insure that the composite is not dominated by the most volatile series.

In the second step weights are derived with which to sum the individual leading indicator series into a composite. Since we have a requirement for a twelve-month forecast, the weights were selected to reflect the strength of the correlation between the cyclical variation in unemployment and the cyclical variation in each leading indicator series lagged twelve months. For each leading indicator, an OLS regression

$$UCy(t) = a + bLICy(j,t-12) + u(t)$$

is calculated, where

UCy = cyclical variation in unemployment series;

LICy = cyclical variation in leading indicator series, j = 1, 2, ... m;

u = disturbance term.

From the bivariate regressions, the R-square (R^2) scores — proportion of variance explained by the regression — are used to form the weights W(j):

$$W(j) = R^2(j) \;/ \sum_j R^2(j).$$

Thus, the weights vary directly with the bivariate association and are scaled to add to unity.

The composite leading indicator (CLI) can be expressed as

$$CLI(t) = \sum_{j} W(j) * LICy(j,t-12).$$

Operationally speaking, we calculate percentage change leading indicator indexes, and construct a percentage change composite which is sequentially applied to generate a level index.

C. Leading Indicator Series

From a broad spectrum of economic processes, we identified a set of candidate indicators for use in constructing a composite leading indicator of unemployment. The candidates represent the spectrum and were selected because they have tended to lead aggregate economic activity. They are listed in Exhibit 18 along with their median lead times at peaks and troughs. As can be seen, unemployment itself has been a leader at peaks though it has lagged at troughs. (There has been variability in the relationship between turning points in unemployment and overall economic activity; see the discussion in the EWS Phase I report. [Reference 13, Vol. II, pp. 97-101.])

Exhibit 18 also reports the estimated aggregation weights (i.e., the W(j) described above) — as of April 1985 — for the fifteen leading indicators selected for inclusion in the composite. We included "new private housing units started" but did not include the building permits index since the two are closely related. The manufacturers' inventories series had to be excluded because there is a delay of an extra month in availability of the series. This is unfortunate because changes in this series have had relatively long lead times at troughs and hence might be especially useful in predicting unemployment peaks.

EXHIBIT 18
page one

CYCLICAL INDICATORS: AVERAGE TIMING AT PEAKS, TROUGHS, ALL TURNS AND ESTIMATED WEIGHTS IN THE CLI MODEL

Series No.		Median Timing At Peak	Troughs	Turns	Weight (percent)
	A. Composite Indexes				
910	Index of Twelve Leading Indicators	-10	-2	-5	12.9
	B1. Employment and Unemployment				
1	Avg. weekly hours, prod. workers, mfg.	-11	-1	-4½	8.0
21	Avg. weekly overtime hours, prod. workers, mfg.	-13	0	-4½	8.3
5	Avg. weekly initial claims, State unemployment insurance (inverted)	-12	0	-5½	6.9
46	Index of help-wanted advertising in newspapers	-7	+2	-2½	3.0
43	Unemployment rate (inverted)	-5	+3	-½	NA
	B2. Production and Income				
74	Index of industrial production, nondurables	-1	-1	-1	4.0
	B3. Consumption, Trade, Orders, and Deliveries				
7	Manufacturers' new orders, durables	-8	-1	-3	4.0
8	Manufacturers' new orders, consumer goods	-12	-1	-4½	6.7
96	Manufacturers' unfilled orders, durables	-5½	+2	0	5.4
75	Index of industrial production, consumer goods	-2	-1	-1	6.9

EXHIBIT 18
page two

	B4. Fixed Capital Investment				
20	Contracts and orders for plant and equipment	-8	-1	-3½	0.8
27	Manufacturers' new orders, nondefense capital goods	-9	-2	-4½	0.6
28	New private housing units started	-13	-2	-9½	17.9
29	Index of housing starts authorized by local building permits	-13	-3	-9½	NI
	B5. Inventories and Inventory Investment				
78	Manufacturers' inventories, materials and supplies on hand and on order	-2	+3	+1	NI
	B6. Prices, Costs, and Profits				
19	Index of stock prices, 500 common stocks	-9½	-4	-5½	2.6
	B7. Money and Credit				
106	Money supply M2	-20	-9	-15½	12.1

Note: NI = not included; NA = not applicable

Sources: Series taken from Business Conditions Digest, Bureau of Economic Analysis, Department of Commerce. Median timing taken from 1984 Handbook of Cyclical Indicators (Table 8). Weights taken from ERL's own calculations.

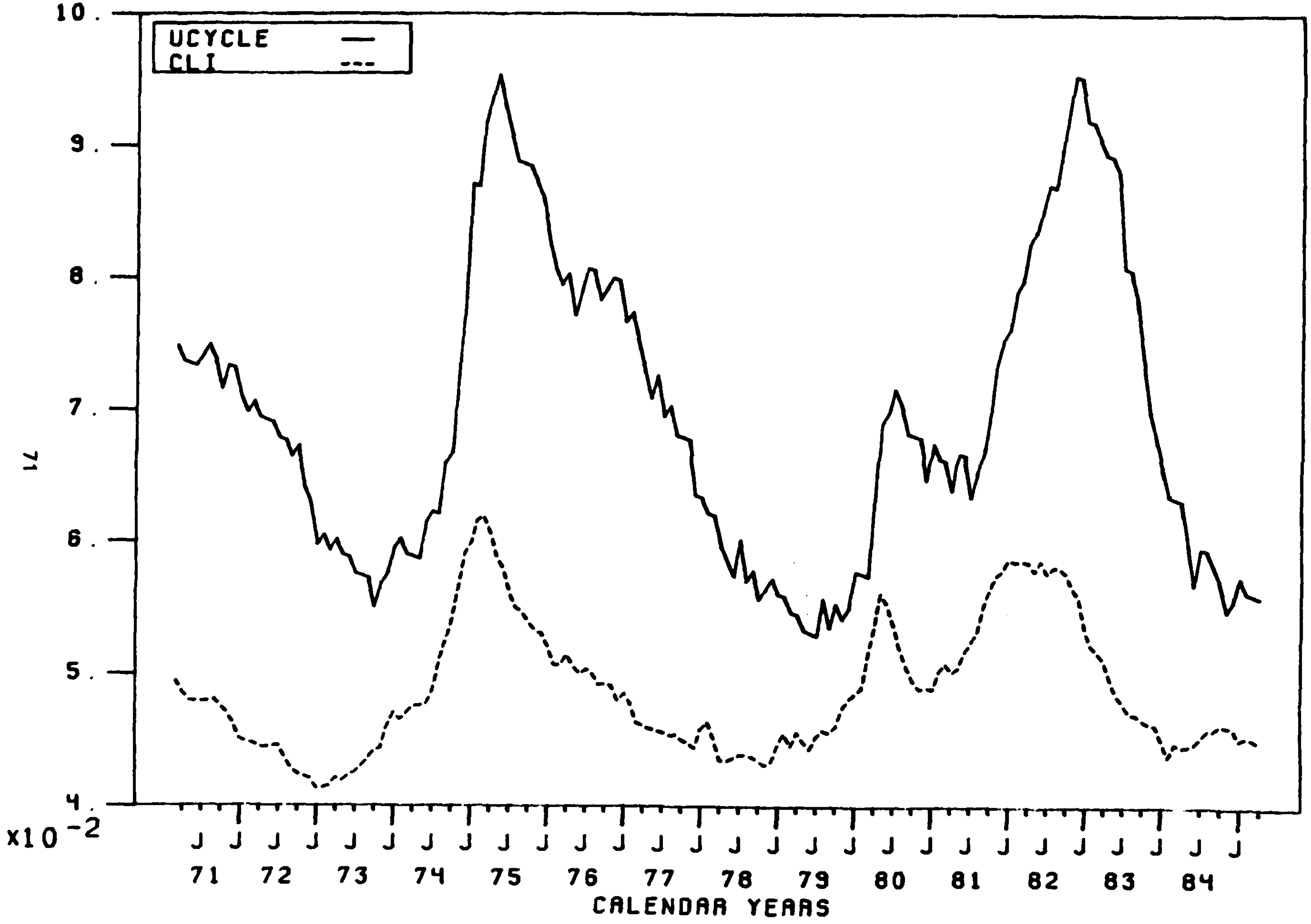
The leading indicator series extend back to January 1970. Each month the series are updated; periodically they are revised by the source agency. In Exhibit 19 we graph the cyclical component of unemployment (UCYCLE) and the composite leading indicator (inverted) as estimated with data for the period 7001-8504. The peaks and troughs of UCYCLE and the corresponding extrema for the CLI are as follows:

	CLI (Inverted)		Holmes' USULI12-C
UCYCLE	Peak/Trough CLI Timing	Difference	Difference
T = 7310	T = 7302	-8	-8
P = 7505	P = 7502	-3	-2
T = 7906	T = 7811	-8	-11
P = 8007	P = 8005	-2	-2
T = 8107	T = 8101	-6	-8
P = 8211	P = 8203	-8	-9

At the unemployment troughs the CLI has lead by 6-8 months; while at the unemployment peaks the lead has been smaller and more variable (ranging from 2 to 8 months). The lead times produced by Holmes' composite leading indicator are also shown in the table; he is able to attain slightly longer leads. [Reference 21, pp.13-14.] Some of the same difficulty of finding indicators that lead unemployment peaks or overall economic activity at troughs — as indicated by the median timing information in Exhibit 18 — is manifested in the composite. Nevertheless, the composite does track all turning points in advance of their occurence.

EXHIBIT 19

LEADING INDICATORS OF CYCLES



D. Specifying and Estimating the Leading Indicator Models

1. Composite Leading Indicator (CLI) Model

Civilian unemployment was regressed against the CLI — both variables transformed to first differences. An ARMA error structure

$$AR = 1,2; \; MA = 2,12$$

was found to work well over the observation period. The estimated coefficients and other statistics are reported in Exhibit 20. The coefficient of the first-differenced CLI is significantly different from zero, and is negative — as expected because unemployment varies inversely with overall economic activity. Serial correlation in the residuals is minor as evidenced by the Durbin-Watson statistic and the significance level of the Box-Pierce Q statistic (see Chapter II, Section D). The first-difference regression explains almost 40 percent of the variation in the dependent variable. When the equation is transformed to levels, the regression explains almost 90 percent of the variation (adjusted for degrees of freedom).

2. Individual Leading Indicator (ILI) Model

Civilian unemployment was regressed against the cyclical components of the fifteen leading indicators in a multivariate regression. The indicator series were lagged twelve months to enable forecasting with a twelve-month horizon. There was extensive serial correlation. Therefore, the dependent variable, lagged one period, was introduced to turn the serial correlation into explanatory power; also an MA = 4 error term was introduced further to reduce the serial correlation. The estimation results over the 7205-8504 period are presented in Exhibit 21.

EXHIBIT 20

CLI UNEMPLOYMENT FORECASTER
ESTIMATED ARMA REGRESSION MODEL

7205-8504
Dependent Variable = ALL1

Variable	Estimated Coefficient
Constant	.003
ALL1 (-1)	.031
ALL1 (-2)	.789**
LIDIFF1	-.033**
MVG AVGE (-2)	-.737**
MVG AVGE (-12)	-.206**
SSR	4.55
RBAR**2	.39
Durbin-Watson	2.16
Q(36)	25.1
SIGNF	.91

Definitions:

ALL1 = civilian unemployment (ALLCIVUN), first differenced
LIDIFF1 = composite leading indicator (CLI), first differenced

** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

EXHIBIT 21

ILI UNEMPLOYMENT FORECASTER
ESTIMATED ARMA REGRESSION MODEL

7205-8504

Dependent Variable = ALLCIVUN

Variable	Estimated Coefficient
Constant	.088
ALLCIVUN(-1)	.989**
IND1 (-12)	-1.105
IND5 (-12)	-.069
IND7 (-12)	-3.896**
IND8 (-12)	4.018**
IND19 (-12)	.095
IND20 (-12)	-.143
IND21 (-12)	-.056
IND27 (-12)	.051
IND28 (-12)	-.645*
IND46 (-12)	.278
IND74 (-12)	4.563
IND75 (-12)	-2.832
IND106 (-12)	-3.552
IND910 (-12)	-1.122
IND96 (-12)	2.997
MVG AVGE (-4)	.274**
SSR	5.86
RBAR**2	.98
Durbin-Watson	1.65
Q(36)	33.5
SIGNF	.59

Definitions:

ALLCIVUN = civilian unemployment rate

IND1, ... IND96 = leading indicator series; deseasonalized, detrended, and smoothed; see Exhibit 18 for identification

** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

The indicators as a group are highly inter-correlated, making it impossible to evaluate the individual significance of any particular indicator. As a group they do make a statistically significant contribution to reducing the unexplained variation (i.e., the sums of squared residuals).[18]

E. Testing the Leading Indicator Forecasting Models

Out-of-sample forecasting tests are especially important in this task because the key capability is the prediction of turning points. Within-sample fits cannot be used to infer this capability.

As shown in Exhibit 19, civilian unemployment begins a gradual fall in May 1975 and eventually bottoms out in June 1979. It then rises to a mini-peak at July 1980 and reaches a mini-trough as quickly in July 1981, before climbing rapidly to a November 1982 peak. The rate has fallen since late 1982 and has been flat over the last several months.

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18 An F-test was used to compare the unrestricted SSR with the restricted SSR. The latter was calculated from a regression that excluded the leading indicators: a regression of ALLCIVUN against a constant and ALLCIVUN(-1). The test indicated rejection of the null hypothesis that the leading indicator coefficients are zero:

$$F = \frac{(RSSR - USSR)/r}{USSR/ndf} = \frac{(7.812 - 5.858)/15}{5.858/138} = 3.07$$

compared to $F_{.95}(15, 120) = 1.75$.

We have conducted out-of-sample forecasting tests for the five periods between these turning periods with the CLI and individual leading indicator (ILI) models. For the first four tests, the estimation period is cut off nine months before the known turning point, and the models are used to forecast the next twelve months. The testing determines whether and when the models predict the turning point, and the size of the forecast errors. For the fifth forecasting period (8310-8409), there is no turning point and the concern is solely with forecasting accuracy. The first two columns of Exhibit 22 indicate the forecast period and the date of the actual peak/trough in unemployment.

For both models we employed the same ARMA error structure that was developed over the full observation period (i.e., 7106-8504). This was a way to control a natural inclination to make changes in the error structure that would improve forecast accuracy in the test periods.

As indicated in Exhibit 22, the CLI misses the mini-peak in July 1980 and the November 1982 peak. Additional tests (not shown here) extended the forecast horizon on both ends, but still did not reveal a turning point; hence, these were unambiguous misses. The ILI model also missed the mini-peak. The timing of the predicted turning points vary from eight months premature (ILI:A) to two months late (CLI:A). The mean absolute errors (MAE) and root mean squared errors (RMSE) are respectable: below one point for seven (out of ten) tests and below 0.5 point for five tests. These errors are comparable to those made by Holmes' model (shown in Exhibit 22), although the ILI model appears to have equal or better MAE's and RMSE's — except for test D.

F. Conclusions

The CLI and ILI forecasting models are substantial improvements over the ARIMA forecaster that was developed earlier in the EWS project. In their current versions the ILI did better than the CLI in predicting turning points. Their forecast errors are comparable, though the CLI model's predictions are more accurate for FY 84.

EXHIBIT 22

OUT-OF-SAMPLE TESTS
CLI AND ILI
UNEMPLOYMENT FORECASTING MODELS

Test	Forecast Period	Actual Unempl. Peak/Trough	CLI Model Predicted Peak/Trough	CLI Model Forecast Error MAE	CLI Model Forecast Error RMSE	ILI Model Predicted Peak/Trough	ILI Model Forecast Error MAE	ILI Model Forecast Error RMSE	Holmes CLI[1] Transfer Function Model 2 Forecast Error MAE	Holmes CLI[1] Transfer Function Model 2 Forecast Error RMSE
A.	7810-7909	T = 7906	7908	.58	.64	7810	.31	.35	.66	.76
B.	7911-8010	P = 8007	misses	1.00	1.16	misses	.47	.54	.46	.58
C.	8011-8110	T = 8107	8102	.22	.28	8107	.30	.35	1.28	1.49
D.	8203-8302	P = 8211	misses	.76	.92	8207	1.10	1.29	.27	.32
E.	8310-8409	None	—	.47	.52	—	1.04	1.15	NC	NC

1 Holmes and Neill, p. 25.
NC = Not calculated.

It is difficult to choose between the CLI and ILI models on the basis of the forecasting tests.[19] We have selected the ILI as the unemployment forecasting model for the EWS at this time, because its current forecasts (FY 85-86) seem more plausible. The comparison is shown in Exhibit 23. The CLI forecasts are trending upward from mid FY 85 to mid FY 86, whereas the ILI forecasts are approximately level. These ILI forecasts resemble outside forecasts more closely, and are preferred.

In choosing between the CLI and ILI models, it is also instructive to examine how well the composite, per se — as distinct from the ARMA model in which it is imbedded — predicted turning points. The composite, in fact, predicted all four turning points in the out-of-sample tests. It also tended to be premature in the turning: T = 7902, P = 7911, T = 8105, P = 8201.

Based on Holmes' success, both the CLI and ILI models should forecast more accurately within a transfer function framework. The capability of the composite per se to predict all of the turning points bodes well for the more sophisticated transfer function model. The construction of an ILI index variable — created from a regression of the cyclical component of unemployment against the leading indicators — and its use in a transfer function may produce a more accurate forecaster.

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19 On theoretical grounds, the CLI avoids the related nature of the indicators by weighting and combining them without regard for their inter-correlations. The working assumption is that a properly weighted average will be a more stable predictor than a collection of individual indicators. Indeed, the reweighting each month ensures that the composite incorporates any changes in the relationship between unemployment and the component indicators. In contrast, the indicators in the ILI model are allowed "to fight it out." As a consequence, there may be a question about the stability over time of the index so produced. However, stability is facilitated by having a large enough number of indicators to reflect broad coverage. The forecasting equation, reflecting the multicollinearity, is not pleasing to those who would like to see something more than a forecasting equation.

EXHIBIT 23

A COMPARISON OF CLI AND ILI OUT-OF-SAMPLE UNEMPLOYMENT FORECASTS*
May 1985 - April 1986

MONTH	ACTUAL Civilian Unemployment	CLI Forecasts	ILI Forecasts	BCEI Forecasts
8505	7.3	7.3	7.4	7.2
6	7.3	7.3	7.4	7.2
7	7.3	7.3	7.5	7.1
8	7.0	7.3	7.5	7.1
9	?	7.4	7.5	7.1
10	?	7.5	7.5	7.1
11	?	7.6	7.4	7.1
12	?	7.6	7.4	7.1
8601	?	7.7	7.3	7.1
2	?	7.8	7.3	7.1
3	?	7.8	7.2	7.1
4	?	7.8	7.2	7.2

* Models are estimated with observations through April 1985.

** Blue Chip Economic Indicators; concensus forecasts, May 10, 1985
(Quarterly forecasts reported by month)

CHAPTER V

THE IDENTIFICATION AND REMEDIATION OF FORECASTING ERRORS DUE TO STRUCTURAL CHANGE

One of the pitfalls in forecasting is the sudden change in market structure. A model that closely approximates the behavior of a system throughout its recorded history may generate wretched forecasts: a change in market structure changes the patterns of behavior in the system and leads to forecasting errors. This circumstance, called a "regime change," haunts every economic forecaster.

Regime changes occur in the recruitment market as a result of program and policy changes by the Services. Introduction or alteration of programs and policies are the Services means of adjusting, in the short-term, to fluctuations in the economy which effect recruiting. These regime changes can cause serious forecasting errors.

The EWS study team has undertaken exploratory research to assess methods for forecasting enlistments in the face of regime changes. The results of this research has led to the development of diagnostic procedures for identifying regime change, a better understanding of the speed with which the EWS can adapt to regime changes, and refinements in the EWS forecasting models. We have found that, when advance warning is given and evidence is available on the effects of the policy shifts being enacted, expert judgement can yield reasonable preliminary forecasts. Forecast accuracy can be regained over time by respecifying the models to include dummy variables measuring the effects of the regime change. With the addition of three to six months of observations following the regime change, respecified forecasting models resume their pre-change level of forecasting accuracy.

Our research has focused on remedies for the effects of regime changes that occur prior to the forecasting period. Assume a scenario in which the EWS forecaster believes that a significant policy change is occurring. After one month, the forecaster has a "sample" of one observation under the new regime, and must produce monthly forecasts of enlistments for the next twelve months. How does the forecaster use information from the prior regime, together with limited data from the new regime, to generate accurate forecasts?

We begin by providing evidence that, whenever estimations overlap distinct regimes, an increase of observations does little to improve either parameter estimates or forecasts. To forecast accurately, another alternative must be found. We have examined three approaches: respecification with dummy variables, Kalman filtering, and the application of expert judgement. In each of three case studies, we have identified the occurence of a regime change, produced forecasts with the alternative approaches, and compared their forecasting accuracy. The results are reported in this chapter.

A. Identifying Structural Change in the Market for Enlistments

The forecaster's first task is to determine whether or not a regime change has occured. This can be done by examining beyond-sample forecasts. Advance information of the occurrence of policy change would cue the forecaster to look for the appearance of systematic forecast errors following the change. Lacking the assurance of advance information, the analyst must constantly assess beyond-sample forecasting errors to determine if there are systematic patterns.

A complementary approach is to determine whether there are acute changes in parameter estimates as new observations are added. Typical forecasting methods treat parameters as constant. Increasing the size of a sample should not, in theory, affect the levels of parameter estimates. [Reference 24] In practice, the combination of collinearity among variables and measurement errors does lead to some variability of parameter estimates, but instability tends to decrease as the size of the sample increases. A pattern of increasing stability (i.e., a convergence of sorts as the set of observations grows) followed by a sudden change in the parameter estimates, as the forecaster adds new observations to the estimation, points to a regime change.

To illustrate the use of forecasting error analysis and parameter estimate analysis in diagnosing and adjusting to regime change, we use three cases. In each case, a model is specified to reflect the market as we knew it to be at a given time; the model does not reflect a distinct regime change which — we now know — took place. Therefore these cases give us an opportunity to examine what the forecasting errors would have told us in the live situation.

In the first case we consider, the Air Force changed recruiting policies, beginning officially in November 1983 (and effectively as early as August), to relax previous constraints on the demand for enlistees. These changes included releasing a cap on the job bank, shifting recruiting attention from officer programs back to non prior service, and releasing restrictions on job-booking. Naturally these policy changes would increase the flow of enlistments. But without knowledge of the change, forecasts based on the prior market structure would necessarily underpredict enlistments.

The second case involves Air Force expansion of applicant eligibility beginning effectively in October 1984 and officially adopted as an operating standard in February 1985. In this change, the operational mental enlistment standard, a minimum ASVAB test score of G40/C145, was loosened first, and then lowered to G30/C133. The purpose was to increase the flow of 3B enlistments, and thereby, the flow of total enlistments.

The third case involves an increase in recruiting resources made available to the Army, beginning in late FY 84, under the so-called "bridge" program. The major components included financial incentives for junior college and vocational school graduates, increased Army College Fund benefits for four-year enlistments, provision of hometown recruiter aides, increase in reserve force recruiters, and increased advertising expenditures. The program began officially in October 1984, and approximately $28 million was provided for expenditure through FY 85.

The forecasting models used in each of the cases are single-equation ARMA models with regressors, as discussed in Chapter II, and focus on the 1-3 cohort for each Service. Projections of unemployment, civilian pay, policy variables, and lagged errors enter the computation of the forecasts. Since, for this exercise we are focusing on the issue of model stability rather than EWS forecasting accuracy per se, actual values rather than forecasts are used as independent variables in the out-of-sample periods.

For the analysis of each case, we assumed a constant specification and successively re-estimated the models as we added observations (first for three months, then one month at a time). For each new set of estimates we generated monthly forecasts for the remainder of the time period through 8409, and compared them with actuals. The forecasting errors appear in Exhibits 24, 25, and 26.

EXHIBIT 24

DETECTION OF POLICY CHANGES: CASE I - AIR FORCE REMOVAL OF DEMAND CONSTRAINTS

OUT-OF-SAMPLE FORECASTING ERRORS (ex post)
Percentage Error

FORECASTS FOR	ESTIMATION THROUGH: 8303	8306	8309	8310	8311	8312	8401	8402
8303	—	—	—	—	—	—	—	—
8304	4	—	—	—	—	—	—	—
8305	- 3	—	—	—	—	—	—	—
8306	- 0.7	—	—	—	—	—	—	—
8307	- 0.4	0.5	—	—	—	—	—	—
8308*	-17	-16	—	—	—	—	—	—
8309	-22	-21	—	—	—	—	—	—
8310	-16	-15	- 2	—	—	—	—	—
8311**	-22	-22	-15	-14	—	—	—	—
8312	-37	-37	-34	-34	-29	—	—	—
8401	-30	-29	-21	-21	-17	- 7	—	—
8402	-19	-18	-12	-12	- 8	- 1	- 5	—
8403	-26	-26	-18	-18	-15	- 8	- 4	- 6
8404	-31	-31	-23	-23	-20	-14	-10	-18
8405	-30	-28	-22	-22	-18	-11	- 7	- 9
8406	-26	-24	-16	-16	-13	-10	- 4	- 5
8407	-31	-29	-22	-22	-20	-18	-12	-14
8408	-36	-35	-24	-24	-22	-18	-14	-15
8409	-38	-37	-26	-26	-26	-22	-19	-20
Average MAE after 8311	30.4	29.4	21.8	21.8	18.8	12.1	9.4	12.4

* Suspected start date of policy change.
** Official start date of policy change.

EXHIBIT 25

DETECTION OF POLICY CHANGES:
CASE II - AIR FORCE EXPANSION OF ELIGIBILITY

OUT-OF-SAMPLE FORECASTING ERRORS (ex post)
Percentage Error

FORECASTS FOR	ESTIMATION THROUGH: 8401	8404	8407	8410	8411	8412
8401	——	——	——	——	——	——
8402	23	——	——	——	——	——
8403	15	——	——	——	——	——
8404	7	——	——	——	——	——
8405	10	1	——	——	——	——
8406	20	6	——	——	——	——
8407	2	- 5	——	——	——	——
8408	2	- 5	- 4	——	——	——
8409	- 2	- 7	- 8	——	——	——
8410*	-10	-15	-15	——	——	——
8411	- 8	-15	-14	- 7	——	——
8412	-14	-15	-14	- 9	- 6	——
8501	-11	-13	-13	- 8	- 6	- 4
8502**	1	- 9	- 7	- 3	- 2	- 0.4
8503	- 7	-14	-14	-11	- 9	- 8
Average MAE after 8409	8.5	13.5	12.8	7.6	5.8	4.1

* Month in which implementation of policy change began.
** Official start date of policy change.

EXHIBIT 26

DETECTION OF POLICY CHANGES:
CASE III - ARMY INCREASE IN RECRUITING RESOURCES

OUT-OF-SAMPLE FORECASTING ERRORS (ex post)
Percentage Error

FORECASTS FOR	ESTIMATION THROUGH: 8401	8404	8407	8409	8410	8411	8412
8401	——	——	——	——	——	——	——
8402	3	——	——	——	——	——	——
8403	- 6	——	——	——	——	——	——
8404	3	——	——	——	——	——	——
8405	12	6	——	——	——	——	——
8406	- 1	2	——	——	——	——	——
8407	- 6	- 6	——	——	——	——	——
8408*	-17	-17	-16	——	——	——	——
8409	- 6	- 5	- 7	——	——	——	——
8410**	-25	-25	-25	-27	——	——	——
8411	-24	-24	-24	-24	-10	——	——
8412	-24	-23	-24	-23	-28	-26	——
8501	-13	-14	-13	-11	-12	-14	- 3
8502	- 1	- 3	- 2	2	- 0.4	0.3	- 1
8503	-15	-13	-14	-14	- 8	- 8	- 6
Average MAE after 8409	17.0	17.0	17.0	16.8	11.7	12.1	3.3

* Suspected start date of policy change.
** Official start date of policy change.

1. Analysis of Systematic Forecasting Errors

Case 1 illustrates the persistence of forecasting errors despite increases in the sample size. Estimated with data through March 1983 (column 1), the model certainly loses its predictive power after November of 1983, the "official" date of the policy change (and probably as early as August). Adding observations, from November on, reduces the errors somewhat (see columns 5-8). However, even with three months of additional data, the mean average error (MAE) is still 9.4 percent (see column 7), and the model consistently underpredicts enlistment in each month.

The forecasts in Case II are produced by a respecification of the model used in Case I. The model has been modified to include a dummy variable for capturing the effects of the regime change that occurred in November 1983; accordingly, the forecasting errors for several months following that change stabilize and the signs are positive. However, the magnitude of the errors increases sharply and persistently beginning in October 1984. This would lead one to suspect that another regime change is taking place. Although the errors decline as new observations are added after October, the sign of the errors remains consistently negative in the period of the apparently new regime. The strong indication of an October regime change provided by this analysis was substantiated subsequently by Air Force personnel who informed us that the policy change, "officially" adopted in February 1985, began to be implemented operationally in October 1984.

Case III shows a similar pattern of forecasting errors. From October 1984 on, the error is unusually large and the series of errors is persistently negative. We know now that the Army bridge program "officially" was begun in October with the beginning of the fiscal year. The error for August 1984 is also unusually large, leading one to suspect that the policy change actually began taking place at that time. In fact, there has been unofficial indication that this is so.

In each of these cases, structural change precipitated by the occurrence of policy shifts is reflected strongly by the greater magnitude and persistent signs of forecasting errors. Increases in the samples do not diminish the forecasting errors. The problem is not one of statistical precision; rather, the models are mis-specified.

2. Analysis of Patterns in Parameter Estimates

The pattern of parameter estimates, generated by one-step-ahead estimations, gives us further evidence of structural change. Adding one month of data to estimations of the same model reveals the instability of parameter estimates in the vicinity of policy changes. Exhibits 27 through 32 present graphs which show the time profiles of selected parameters for the model used in Case I. The evidence confirms our suspicion that implementation of the policy changes began in August 1983.

The data for Case I span the interval from early 1979 to the dates shown on the horizontal axes of the graphs. We would expect to see a certain degree of instability in the time profile of parameter estimates, since the variables are estimated using a small sample, some data are collinear (e.g., pay, unemployment, and recruiters), and some are measured with error (e.g., civilian pay and policy variables). In addition to this general instability, the graphs reveal relatively large shifts in parameter estimates, beginning in August 1983, with increasing magnitude in November 1983 and after. The estimated value of the constant more than doubles from October of 1983 to January of 1984. The estimated recruiter effect falls into the theoretically absurd negative range some five months after the policy shift. The relative military pay effect varies erratically, and the unemployment estimate drifts downward. The parameter estimate for a policy dummy variable increases noticeably, as does the the estimate for the August seasonal dummy effect.

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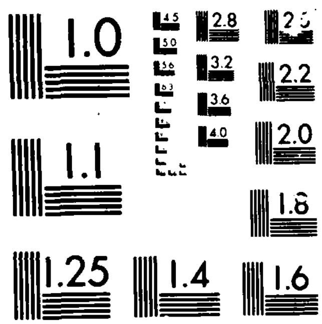


MICROCOP CHART

EXHIBIT 27

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

CONSTANT

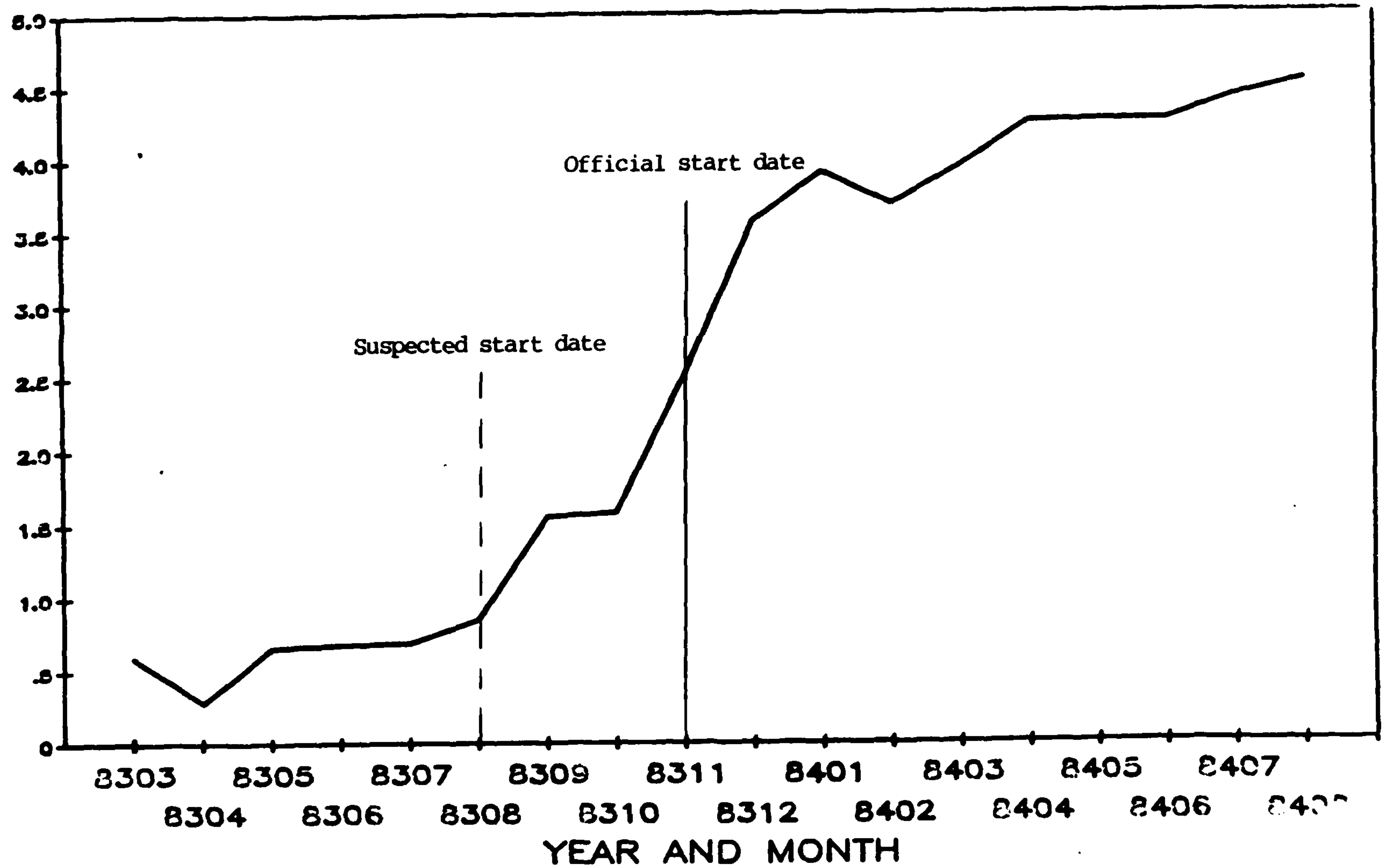


EXHIBIT 28

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

RECRUITERS

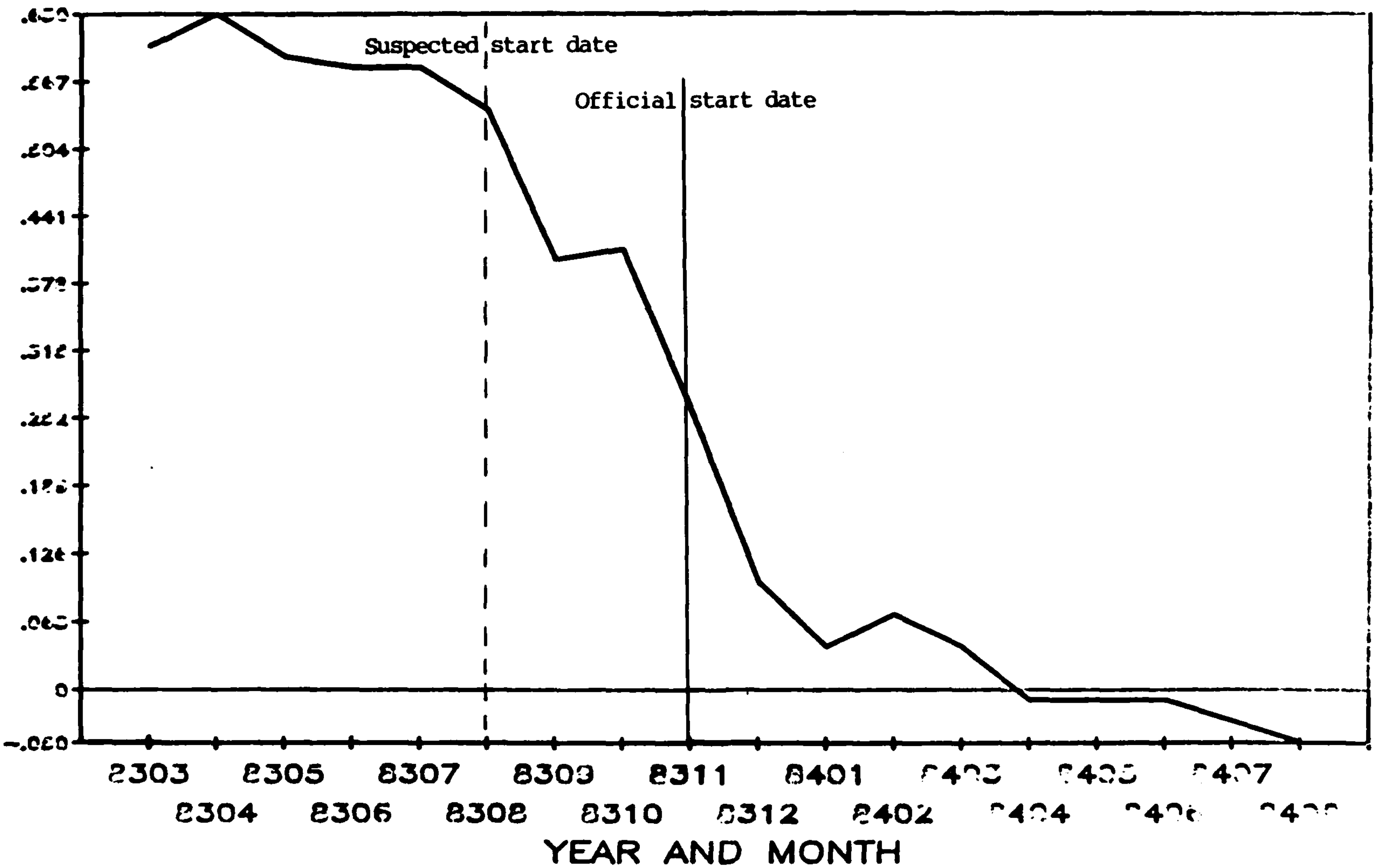


EXHIBIT 29

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

RELATIVE MILITARY PAY

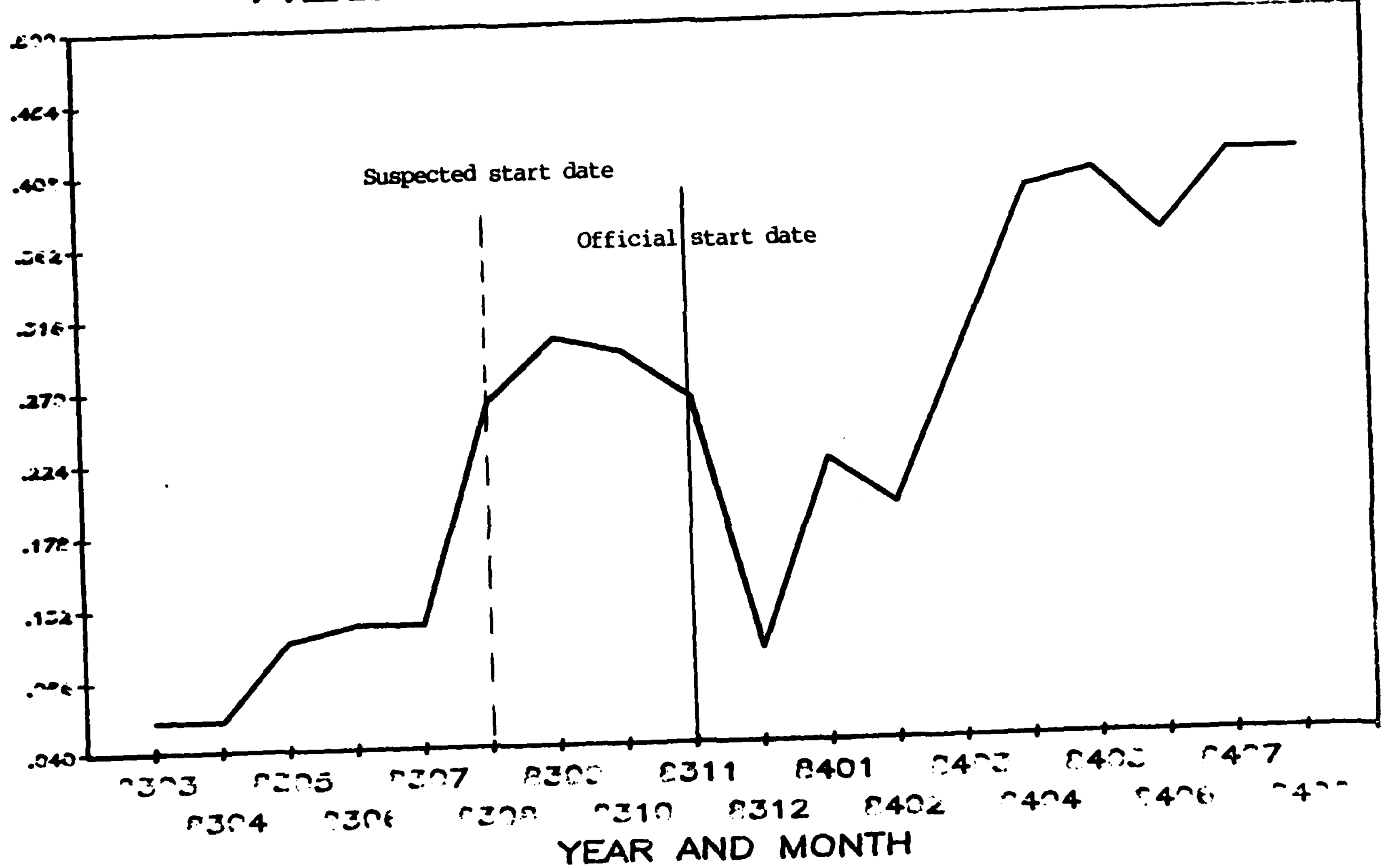


EXHIBIT 30

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

UNEMPLOYMENT

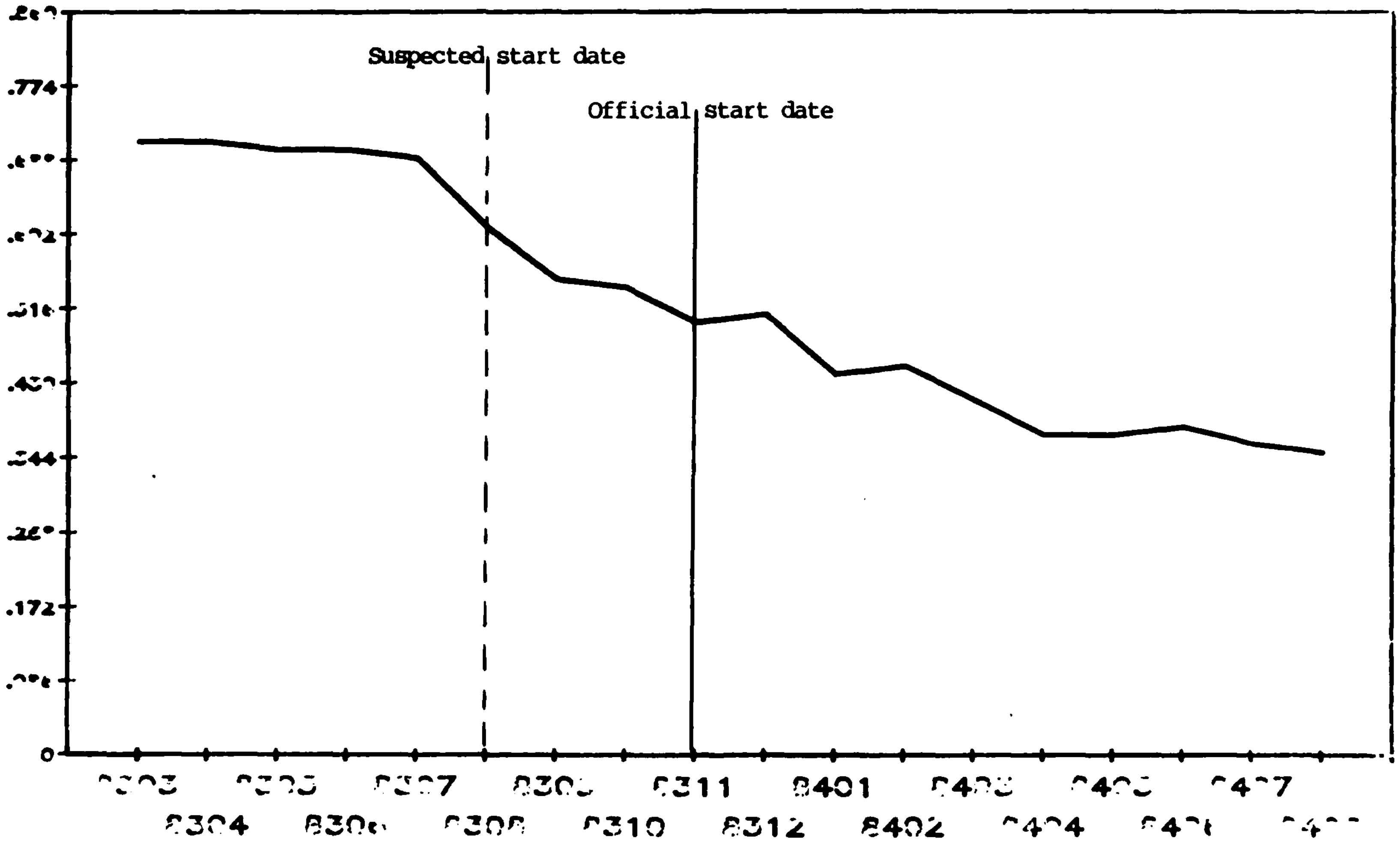


EXHIBIT 31

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

DEMAND RESTRICTIONS

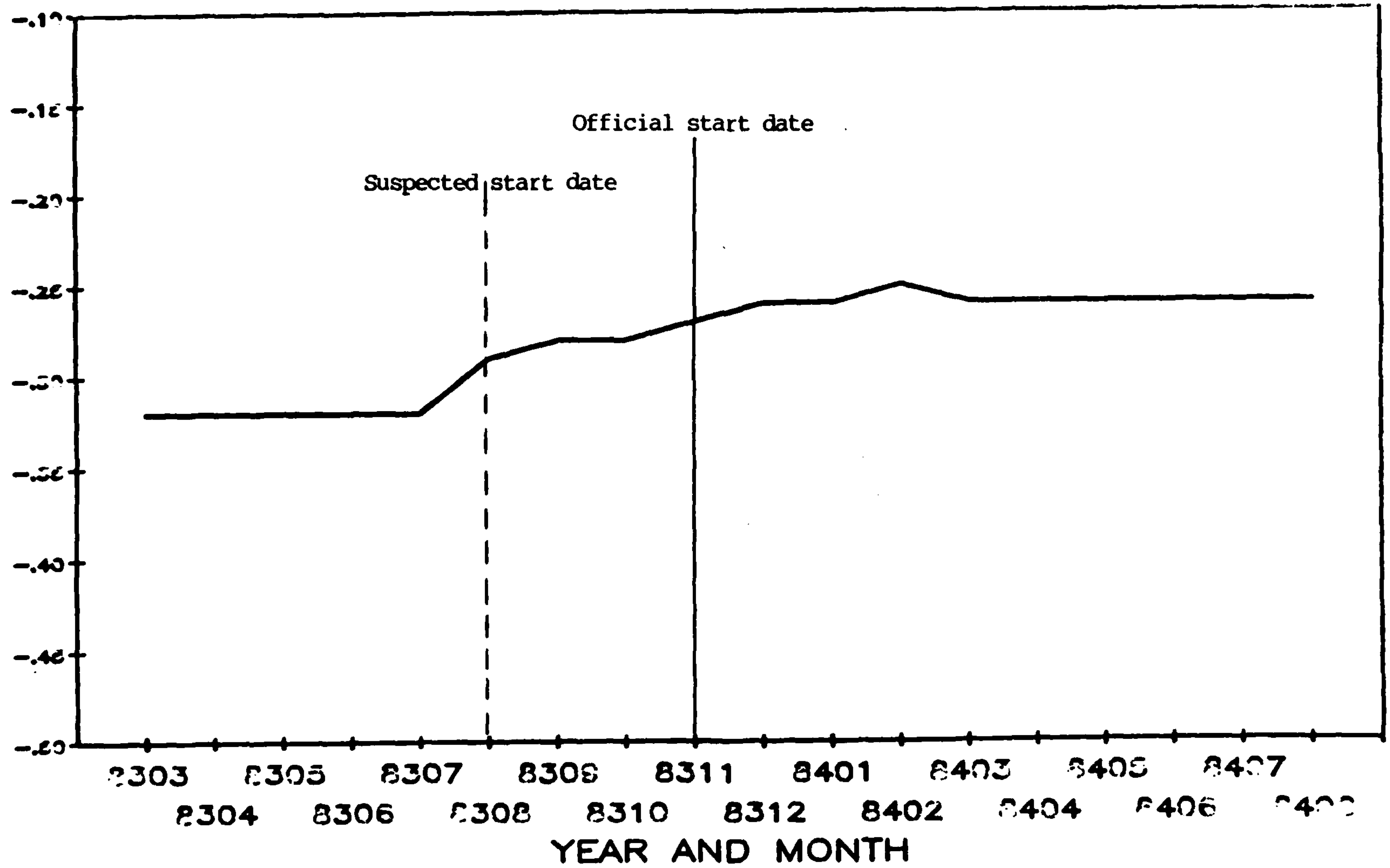
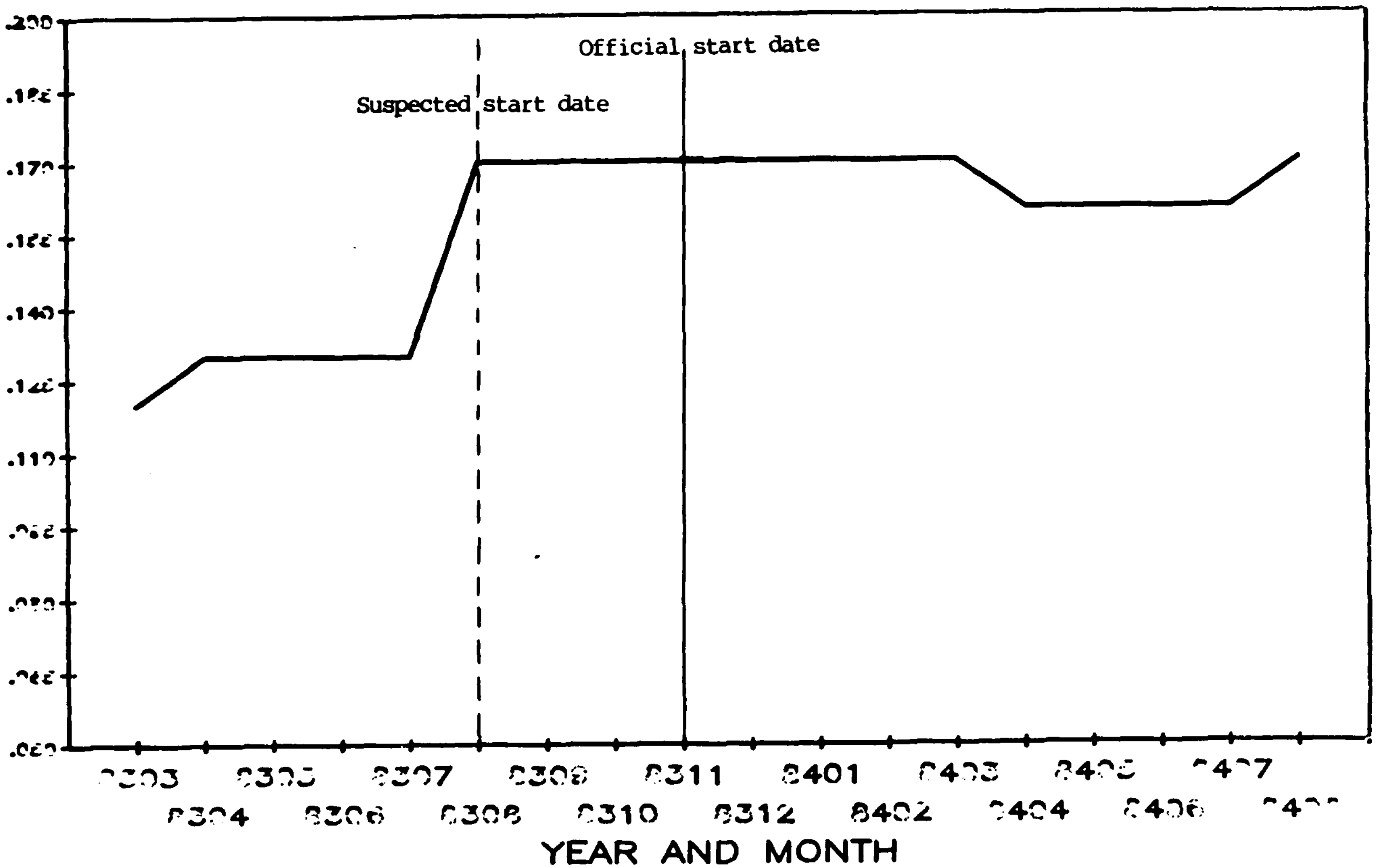


EXHIBIT 32

Parameter Estimate Convergence

Case 1: Air Force Removal of Demand Constraints

SEASONALITY: AUGUST



In Case II, a dummy variable measuring the effects of the November 1983 policy shift of Case I has been added to the specification. Time profiles of some of the parameters are shown in Exhibits 33 through 37. The parameter estimate for the constant falls sharply after the Case I policy shift, and then stablizes somewhat as the estimate of the policy dummy includes more observations. The acute climb of the constant estimate in the first quarter of FY 85 is an indication of the operational implementation of the policy shift officially adopted in February 1985. However, the effect of this policy shift on parameter estimates is much less dramatic than in Case I. With the exception of the constant, the estimates reveal only a slight downward shift.

Case III involves program changes and a dependent variable measurement problem as well. See Chapter II, Section B. Exhibits 38 through 40 show the time profiles of parameter estimates. The parameter estimate for the constant shows an erratic pattern around an upward trend until October of 1984. At that point the constant estimate drops sharply. The recruiter parameter estimate drifts upward to a level approaching constant returns to scale. The relative military pay estimate, which is very large relative to estimates of the analogous parameter for the other Services, increases to even higher levels. Here again, the data suggest that a policy change took place in October 1984, but the evidence is not as strong as in Case I.

It appears that analysis of the stability of individual parameters can lead only to tentative conclusions. In these reduced-form enlistment forecasting models, the individual parameter estimates are unstable to some degree because of measurement problems. Nevertheless, analysis of parameter stability can be useful in identifying the timing of regime change.

EXHIBIT 33

Parameter Estimate Convergence

Case 2: Air Force Expansion of Eligibility

CONSTANT

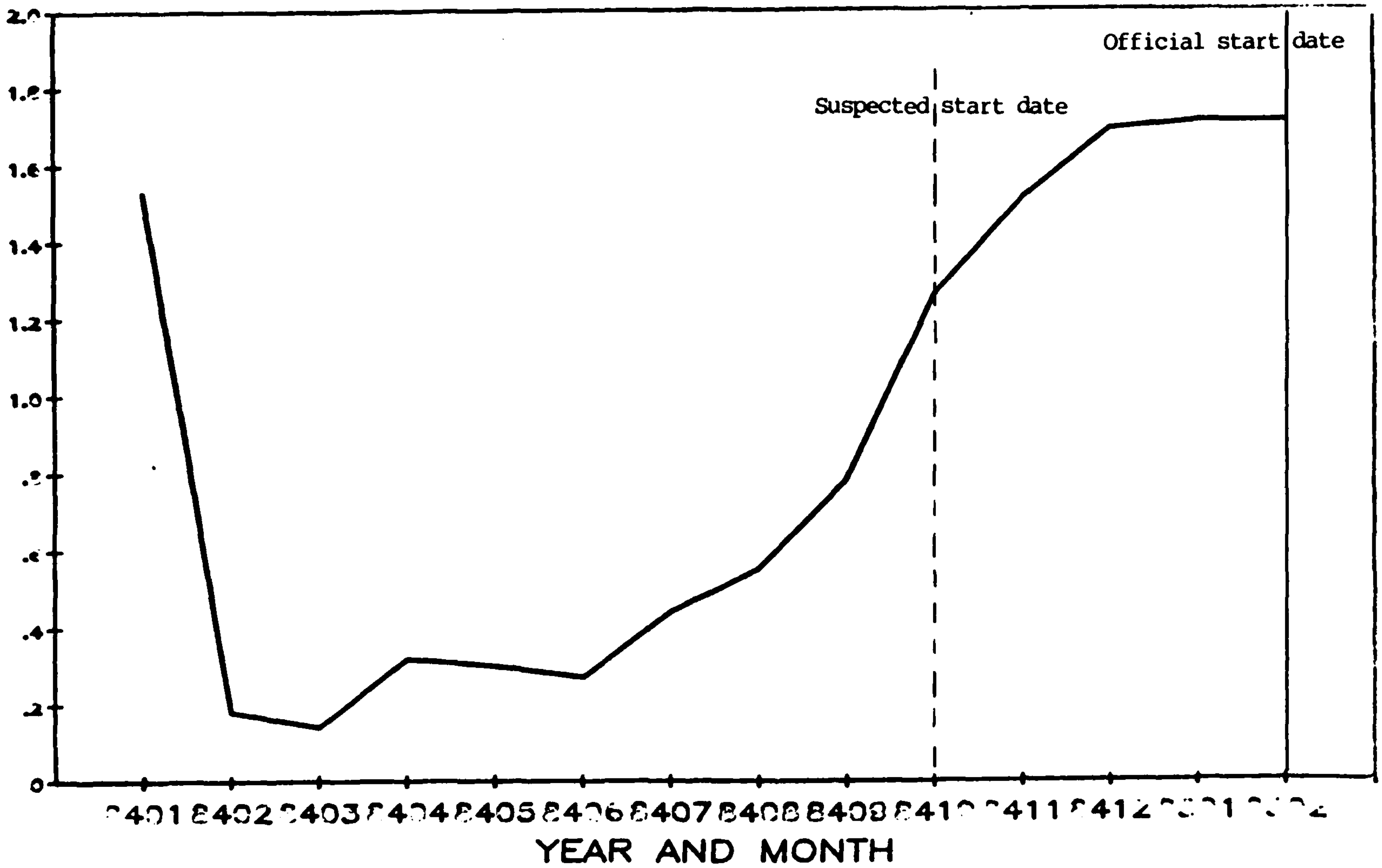


EXHIBIT 34

Parameter Estimate Convergence

Case 2: Air Force Expansion of Eligibility

RECRUITERS

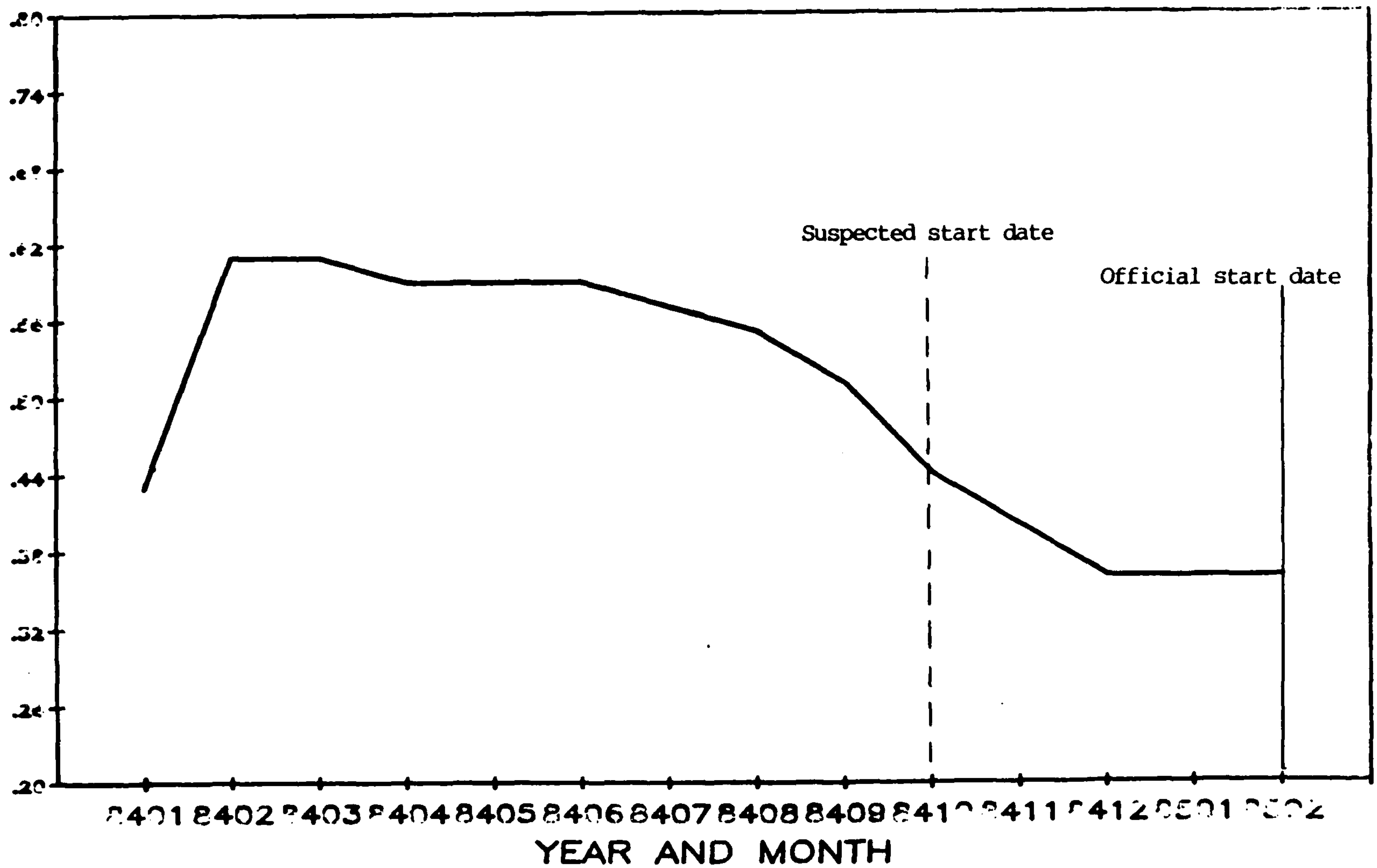


EXHIBIT 35

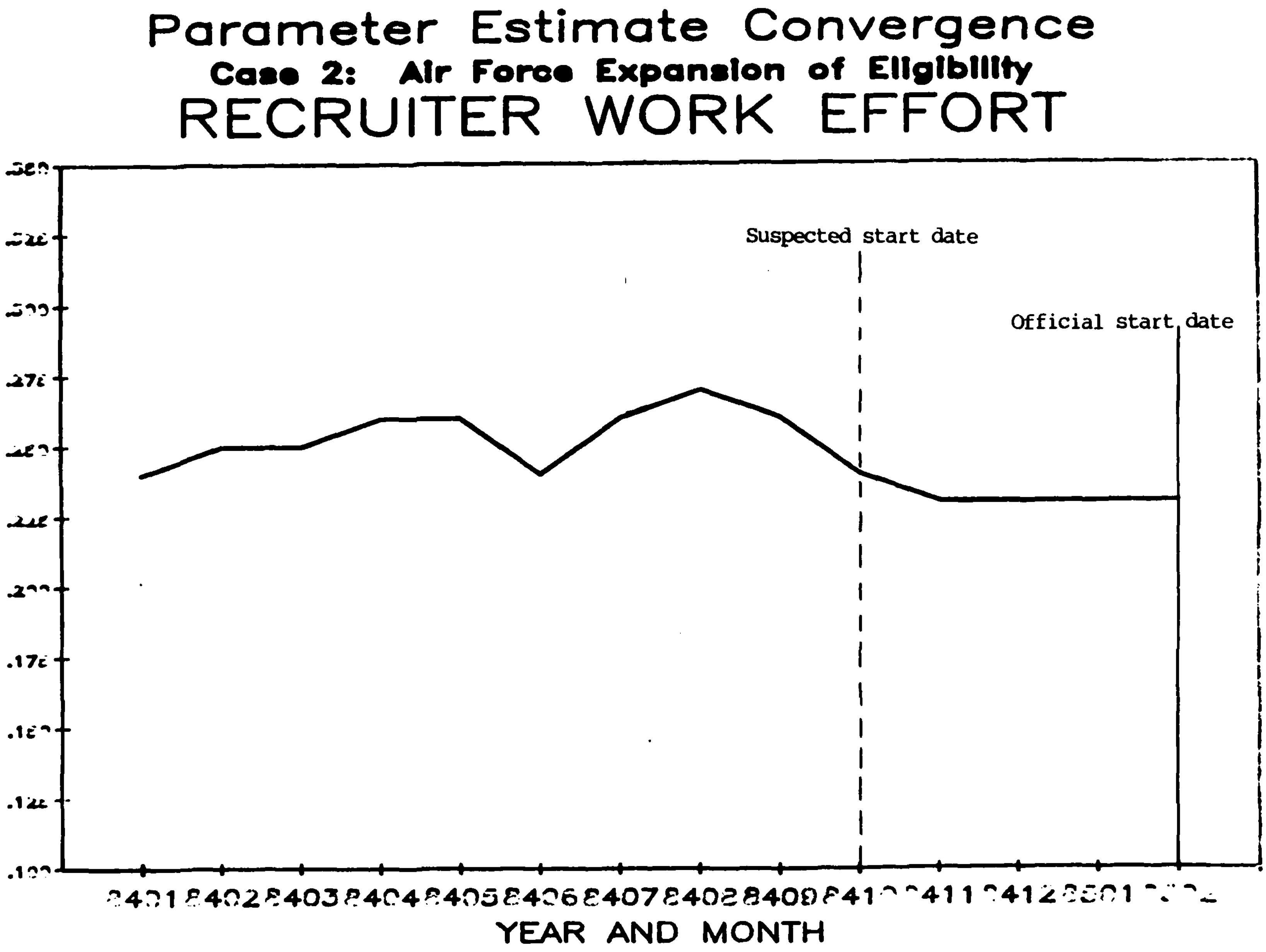

Parameter Estimate Convergence
Case 2: Air Force Expansion of Eligibility
RECRUITER WORK EFFORT
Suspected start date
Official start date
YEAR AND MONTH

EXHIBIT 36

Parameter Estimate Convergence

Case 2: Air Force Expansion of Eligibility

UNEMPLOYMENT

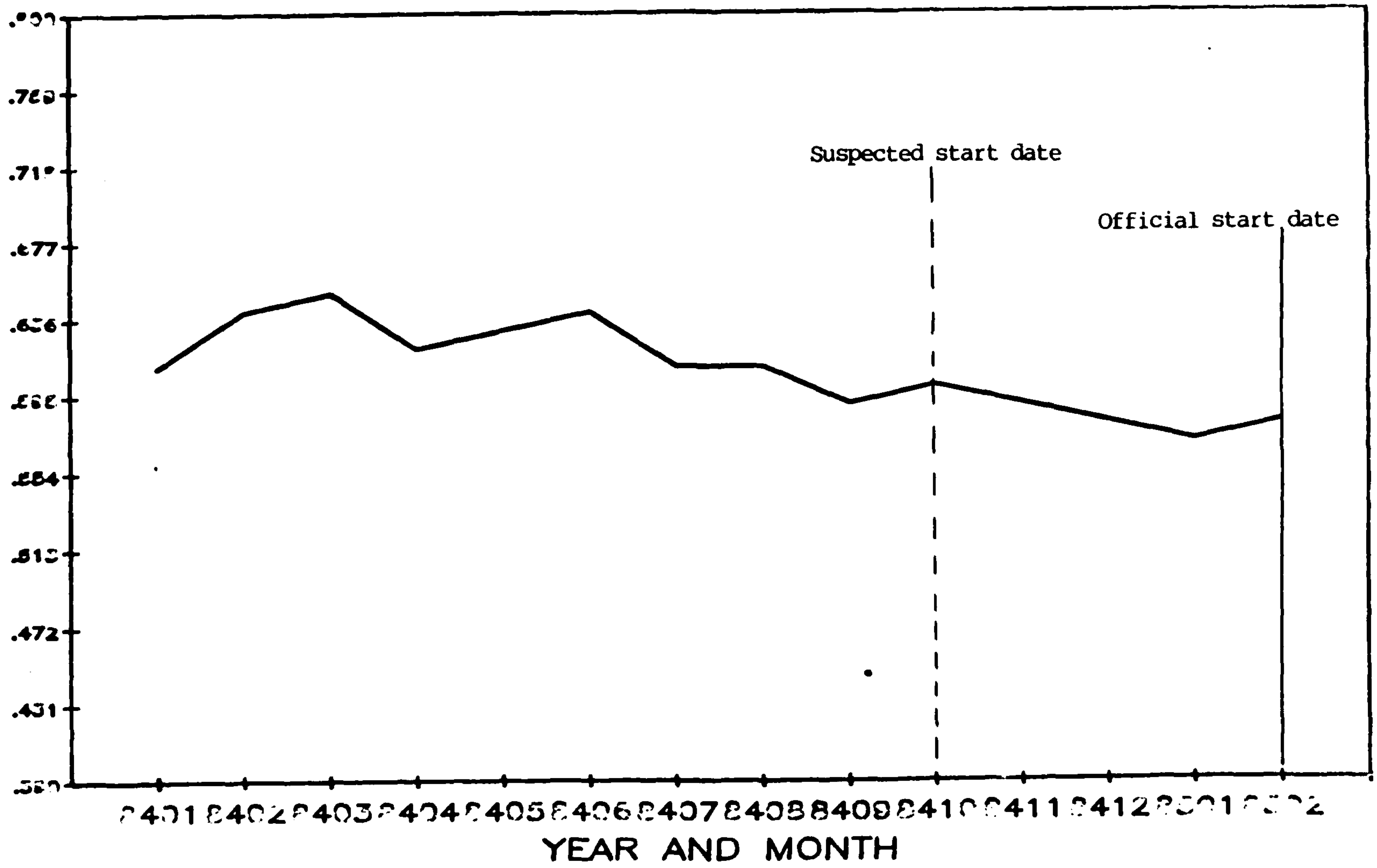


EXHIBIT 37

Parameter Estimate Convergence

Case 2: Air Force Expansion of Eligibility

DEMAND RESTRICTIONS

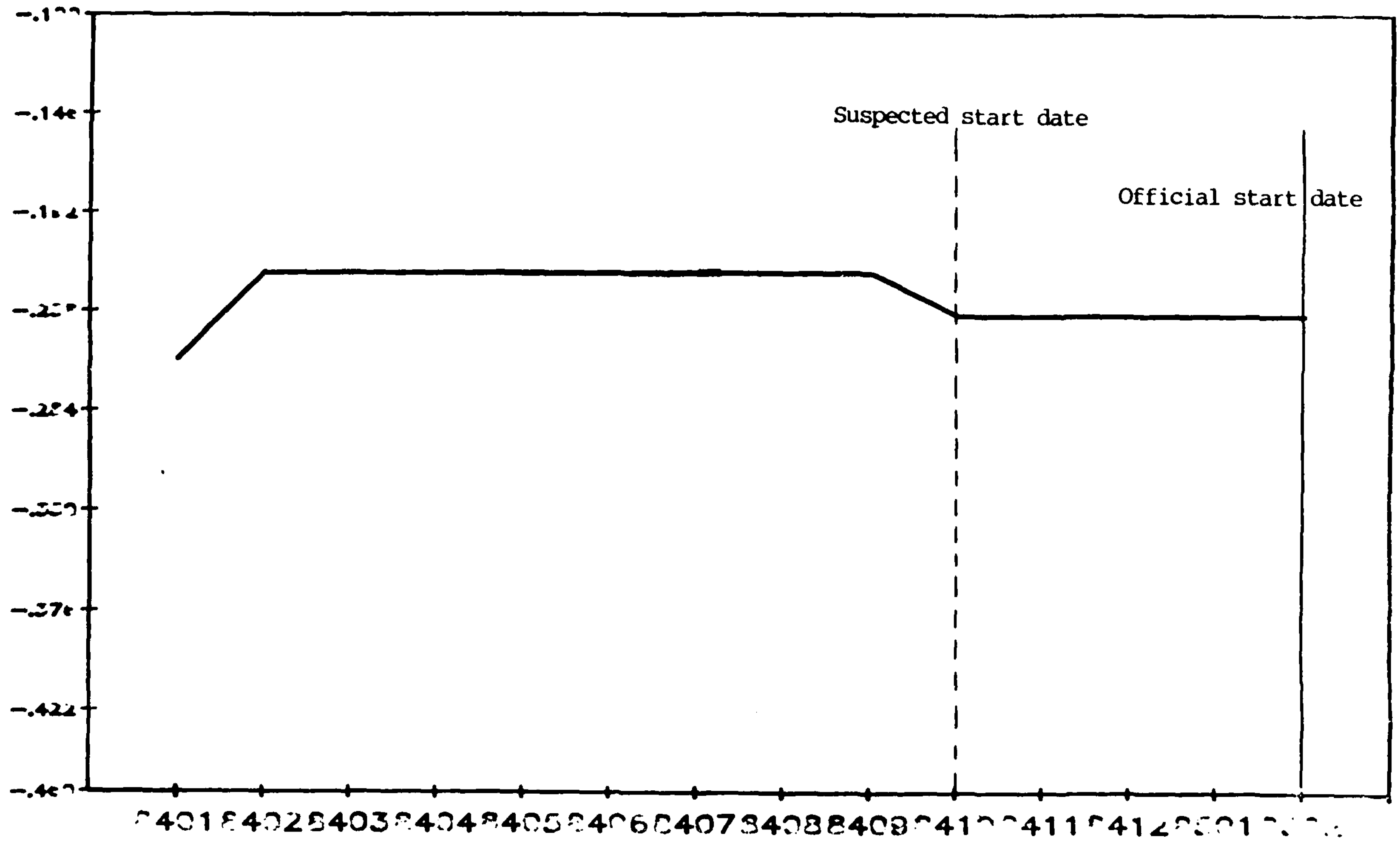


EXHIBIT 38

Parameter Estimate Convergence

Case 3: Army Increase in Recruiting Resources

CONSTANT

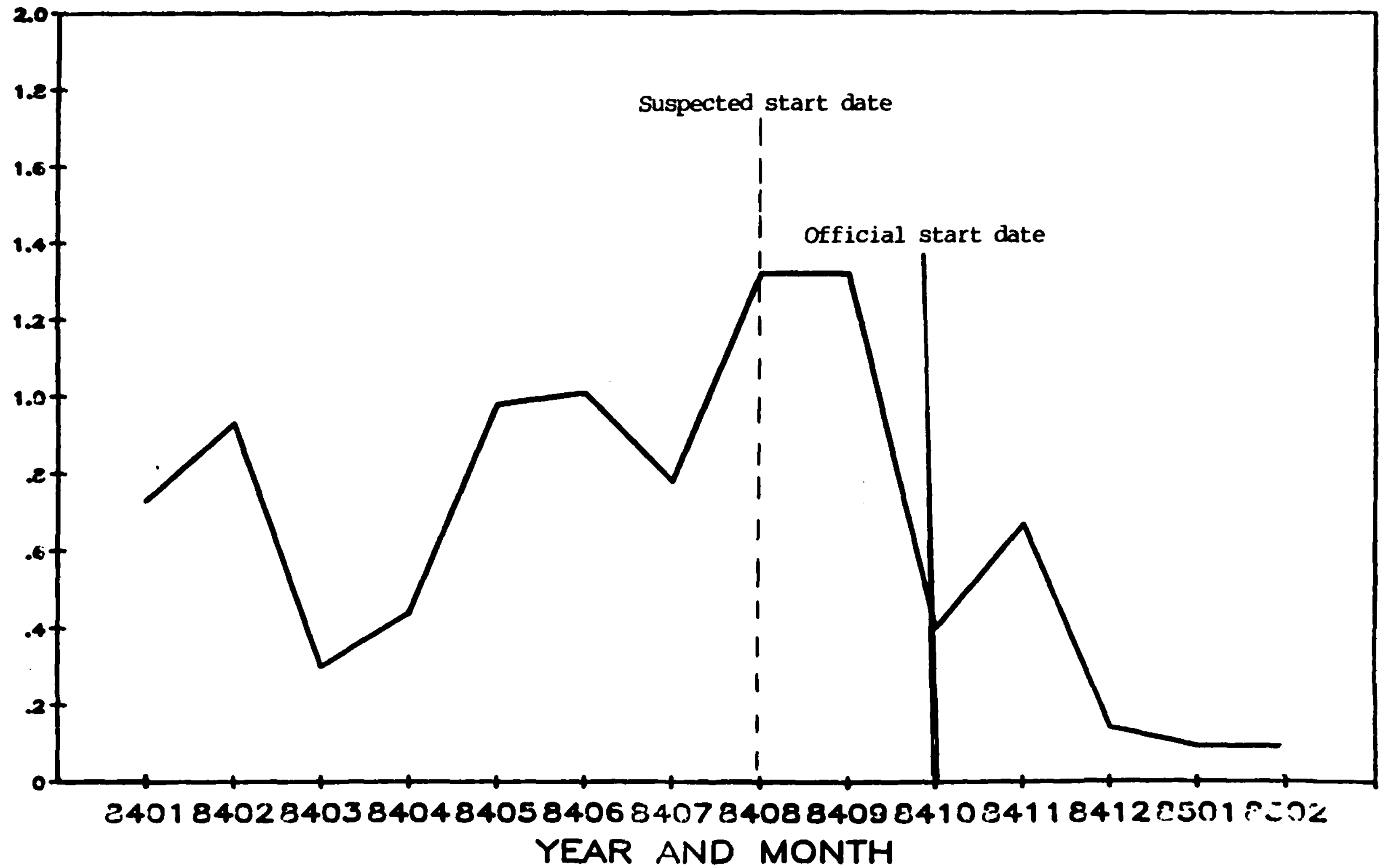


EXHIBIT 39

Parameter Estimate Convergence

Case 3: Army Increase In Recruiting Resources

RECRUITERS

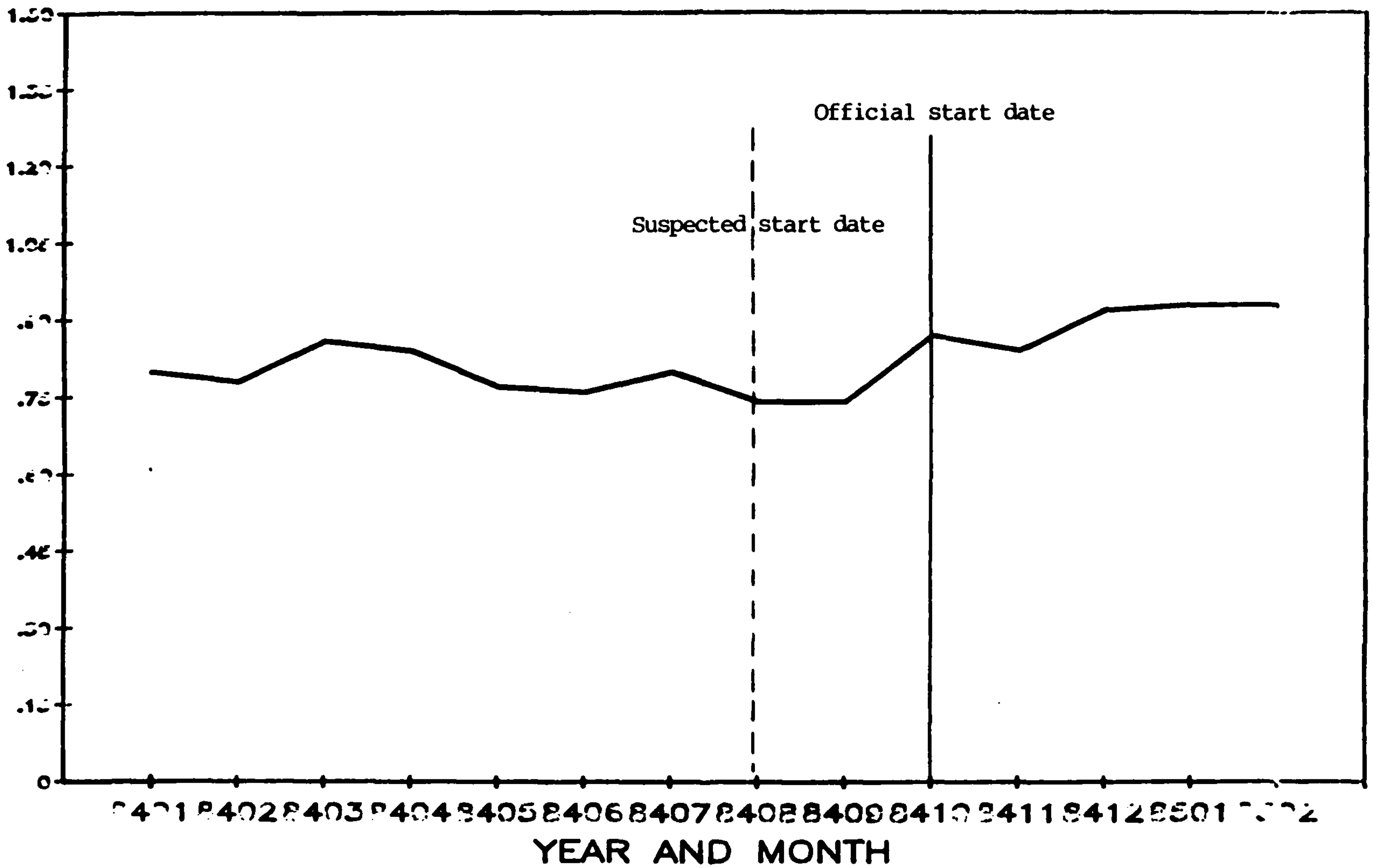
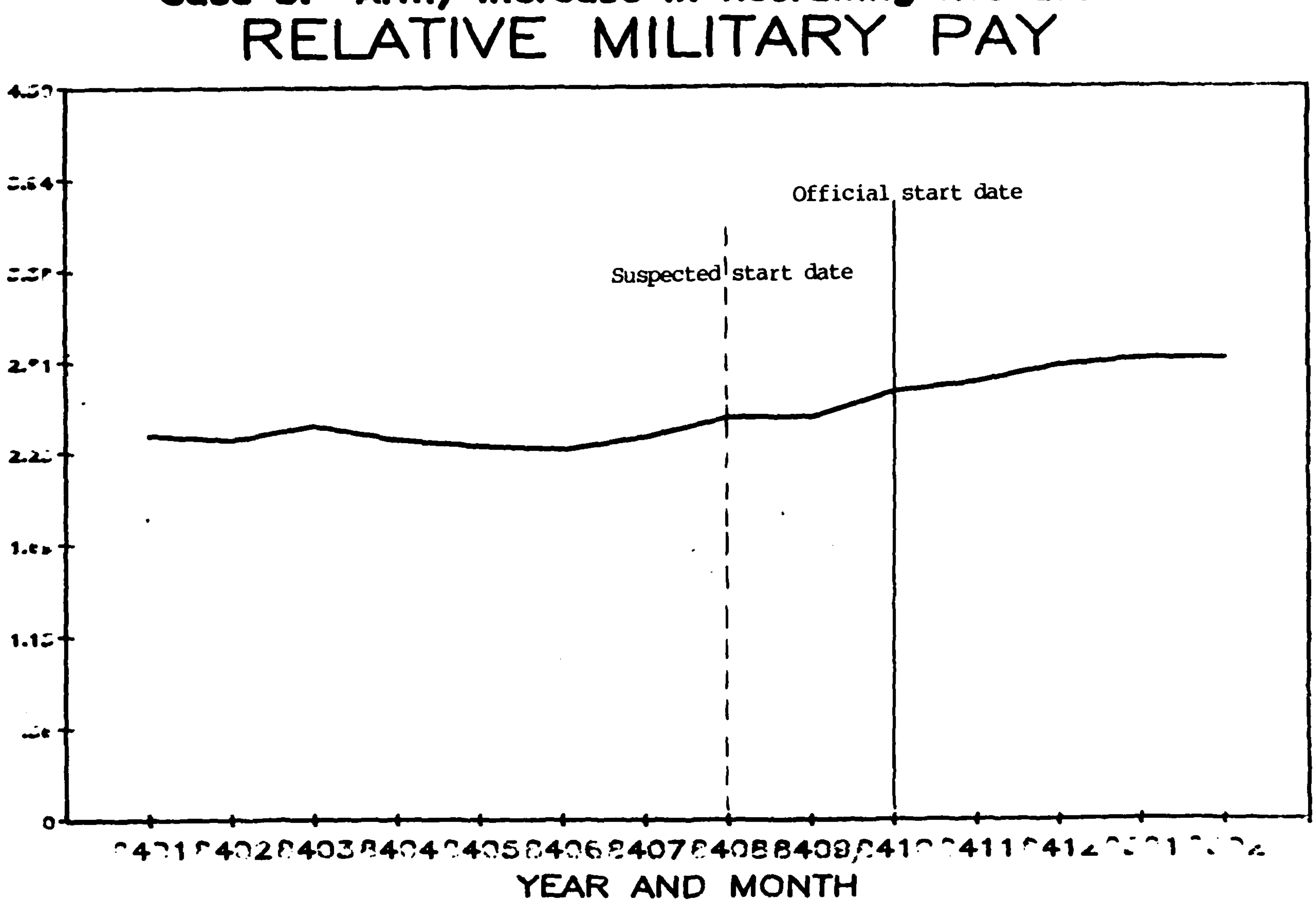


EXHIBIT 40

Parameter Estimate Convergence

Case 3: Army Increase in Recruiting Resources



The analyst must consider all the evidence in deciding whether or not there has been a significant structural change. The presence of systematic forecasting errors, supplemented by the instability of parameter estimates, provides strong evidence. But ideally, these methods should merely augment a regular flow of communication between the EWS forecaster and the Services. When advance information and appropriate analysis techniques are combined, regime changes can be identified and properly modeled within a relatively short time interval.

B. Remedies for Systematic Forecasting Errors Due to Structural Changes

We consider three general types of remedies for the effects of structural changes on forecasts and parameter estimates: respecification with dummy variables, Kalman filtering, and the application of expert judgment. To the extent possible, we reconstruct the information that was available for intervals before and after the policy and program changes. We compare two or more of the methods for each of the cases.

1. Respecification to Include Policy Dummies

The first alternative is respecification of the forecasting model so that it includes a dummy variable representing the change in market structure. Dummy variables measure shifts in the constant due to policy or program changes such as demand restrictions, advertising, and education benefits. Continuous measures would be preferred, but these are seldom available for the full estimation period and difficult to project through the forecasting period.

We are interested in one issue primarily: How many observations are required for the accurate estimation of the effects of the dummy variable. At least one observation is required, in theory, but in practice collinearity and other measurement problems necessitate more observations in order to obtain precise estimates and accurate forecasts.

The basic dummy variable approach — respecification with one dummy variable — is appropriate when the steady-state effect of regime change is felt immediately upon occurrence of the change. However, if in addition to the long-term effects, the change causes short-term effects (i.e., temporary adjustments), this approach will not accurately reflect reality. The more complicated situation requires respecification with multiple dummy variables measuring both short-term and long-term influences. The multiple dummy variable approach is explored in Case III.

2. <u>The Kalman Filter</u>

The Kalman Filter is the general case of a number of adaptive forecasting methods. It combines information from prior states of a system with information contained in the latest observation. The method treats parameter estimates as stochastic variables, thereby allowing for disturbances or measurement errors that disrupt the estimates. It weights the measured effects of changes in variables according to the prior distributions of the parameter estimates. [References 25, 26, and 32.]

We use a simple version of the Kalman Filter as a standard of comparison with the other methods of dealing with structural change. Because our implementation of the Kalman Filter procedure does not allow us to estimate moving average terms, we cannot match the pre-regime specifics of the ARMA models. Instead, we use approximations of the parameter estimates and their variances from pre-regime estimates of the ARMA model. With these estimates as priors, we can update recursively the parameters of the Kalman Filter beginning just prior to the alleged change of regimes.

Approximating the priors turns out to be a bit tricky. For some estimation periods and some parameters, estimates were not stable. In other cases, estimates did not seem reliable in light of theoretical and other prior information. To avoid an awkward mixing of model specifications, yet resist the temptation to make the priors purely subjective, we adopted the following decision rules:

If "old regime" parameter estimates are:

a) Reliable and not likely to be affected by regime change, use old estimates and small variances;

b) Reliable and likely to be affected by regime change, use old estimates and larger variances;

c) Unreliable, use a priori values and relatively large variances.

In addition, where information was available, i.e., Cases I and II, we changed the prior on the constant when updating to reflect the direction and likely magnitude of changes.

In effect we are allowing certain parameter estimates to "float" more rapidly than others. Recursive updating of the model adds more and more observations from the new regime to the data set. While the initial conditions specified in the priors definitely affect the speed of convergence to a reliable set of parameter estimates, small variations in the priors have little effect. The latitude in selecting priors naturally has its limits; priors that are inconsistent with the data from the new regime may lead to a divergence of the filter, so that the one-step-ahead estimates it produces from prior information diverge more and more from actual observations.

The recursive system used to update the Kalman Filter appears in Exhibit 41.

3. Adjustments of Forecasts by Experts

Both the respecification with dummy variables procedure and the Kalman Filter procedure require at least one observation within a new regime. Structural changes within the forecast period quite obviously cannot be estimated with historical data. Yet, if we know that a major policy change will take effect in the next month, we are able to include an approximation of its effect in the forecasts the same month in which it begins. Expert judgement can provide an estimate of the effect *a priori*.

In deriving a forecast, experts must assess how the policy change will affect the forecasting model. In particular, what will be the effects of old and new variables. In estimating effects:

1) The timing of the policy change has to be known with a high degree of certainty;
2) The impact of the change has to be inferred from analogous situations and theory;
3) Side effects of the change have to be considered, including anticipatory and speculative behavior;
4) The effects of other structural changes occurring simultaneously have to be assessed.

Expert adjustments of forecasts normally begin with the forecasts of a model specified for the current regime. Assessing the weight of evidence on the nature of the change, the forecaster applies an adjustment factor to the forecasts.

EXHIBIT 41

A SIMPLE KALMAN FILTER ESTIMATION SYSTEM

$$
\begin{aligned}
B_{t:t-1} &= GB_{t-1} \\
A_t &= GC_{t-1}G^{1}
\end{aligned}
$$

$$
\begin{aligned}
R_t &= A_{t:t-1} = M_t \\
C_t &= R_t - R_tX^{1}{}_t(X_tR_tX^{1}{}_t + N_t)^{-1}X_tR_t \\
B_t &= B_{t:t-1} + C_tX^{1}{}_tN^{-1}{}_t(Y_t - X_tB_{t:t-1})
\end{aligned}
$$

where t:t-1 means the value at t-1 after transformation during the update at t.

For G = I (the primary case considered in this study):

$B_{t:t-1} = B_{t-1}$ and $A_t = C_{t-1}$.

and B_o = a vector of parameters

C_o = an initial covariance matrix

M_t = a matrix of disturbance which represent innovations at t.

C. Comparisons of Forecasts

We use out-of-sample forecasting errors — shown in Exhibits 42 through 46 — as a basis for comparing alternative estimation methods. In Cases I and II, we compare two methods: 1) respecification with a single dummy variable (DV), and 2) Kalman filtering (KF). In Case III we look at the third alternative method, application of expert judgment, as well as the KF and DV methods. Also in Case III, we expand the DV method to include multiple dummy variables, and examine an additional specification of the KF model. The columns in the exhibits indicate the number of monthly observations after the month in which the policy change took place; they represent successive rounds of estimation and forecasting for the months shown in the column on the far left.

In Case I, the Kalman Filter performs better than the dummy variable method during the first two months of the test period after the policy change). This clear advantage disappears thereafter. Mean absolute errors (MAE) for the DV method dampen quickly, while those for the KF forecasts remain almost constant. With the DV method, the MAE of 8.0 percent in the second month is similar to the magnitude of error found for the 1-3 HSDG cohort of the Air Force in forecasting tests for FY 84. (See Exhibit 16.) Thus, with respecification, forecasting accuracy appears to return to its pre-change level following the addition of two months of new-regime data to the model.

In Case II, the dummy variable method dominates the Kalman Filter method in virtually every respect. While the KF errors are not much worse than those obtained in Case I, the much lower errors for the DV method make the KF errors in Case II seem large by comparison. The larger set of observations for the prior regime used in Case II (7901 - 8310), as compared to Case I (7901 - 8310), may account for the different results in the two cases. However, we suspect the real reason is that in Case II the regime change effect is modeled by a properly timed single dummy variable; the dummy is "turned on" in November 1984, the first full month affected by the actual implementation of the change, rather than February 1985, the "official" date of the change. In Case I we turned on

EXHIBIT 42
page one

COMPARISON OF OUT-OF-SAMPLE FORECASTING ERRORS:
D.V. AND KALMAN FILTER MODELS
Percentage Error

CASE I: AIR FORCE - REMOVAL OF DEMAND CONSTRAINT
Regime Change Assumed to Occur in November 1983

FORECASTS FOR	ESTIMATION AND FORECASTING ROUNDS AT SUCCESSIVE MONTHLY OBSERVATIONS AFTER CHANGE								
	1	2	3	4	5	6	7	8	9
ARMA REGRESSION WITH D.V.									
8401	30.6	----	----	----	----	----	----	----	----
8402	49.1	20.9	----	----	----	----	----	----	----
8403	40.7	12.0	- 0.1	----	----	----	----	----	----
8404	32.4	5.1	- 5.4	- 5.0	----	----	----	----	----
8405	35.4	8.5	- 1.9	- 1.6	1.8	----	----	----	----
8406	43.8	9.1	0.9	1.3	4.2	3.5	----	----	----
8407	31.7	- 1.4	- 9.2	- 8.9	- 6.1	- 6.6	- 8.2	----	----
8408	29.3	- 0.9	- 9.3	- 9.0	- 6.7	- 7.1	- 8.1	- 4.6	----
8409	22.0	- 5.9	-13.6	-13.3	-11.2	-11.5	-12.6	- 9.9	- 7.9
MAE	35.0	8.0	5.8	6.5	6.0	7.2	9.6	7.3	7.9

continued

EXHIBIT 42
page two

COMPARISON OF OUT-OF-SAMPLE FORECASTING ERRORS:
D.V. AND KALMAN FILTER MODELS
Percentage Error

CASE I: AIR FORCE - REMOVAL OF DEMAND CONSTRAINT
Regime Change Assumed to Occur in November 1983

FORECASTS FOR	ESTIMATION AND FORECASTING ROUNDS AT SUCCESSIVE MONTHLY OBSERVATIONS AFTER CHANGE 1	2	3	4	5	6	7	8	9
KALMAN FILTER MODEL									
8401	13.8	----	----	----	----	----	----	----	----
8402	13.5	13.4	----	----	----	----	----	----	----
8403	1.6	1.6	1.6	----	----	----	----	----	----
8404	9.5	9.5	9.4	9.4	----	----	----	----	----
8405	12.6	12.5	10.0	10.0	9.9	----	----	----	----
8406	10.6	10.6	12.5	12.5	12.5	12.5	----	----	----
8407	6.3	6.2	10.6	10.6	10.6	10.6	10.5	----	----
8408	- 0.8	- 0.8	6.3	6.3	6.3	6.3	6.2	6.2	
8409	- 2.2	- 2.2	- 0.8	- 0.8	- 0.8	- 0.8	- 0.8	- 0.9	- 0.9
MAE	7.9	7.1	7.3	8.3	8.0	7.5	5.8	3.5	0.9

EXHIBIT 43

COMPARISON OF OUT-OF-SAMPLE FORECASTING ERRORS: D.V. AND KALMAN FILTER MODELS

Percentage Error

CASE II: AIR FORCE - EXPANSION OF ELIGIBILITY
Regime Change Assumed to Occur in October 1984

FORECASTS FOR	ESTIMATIONS AND FORECSSTING ROUNDS AT SUCCESSIVE MONTHLY OBSERVATIONS AFTER CHANGE 1	2	3	4
ARMA REGRESSION WITH D.V.				
8412	- 0.2	——	——	——
8501	1.6	2.1	——	——
8502	7.5	8.1	6.9	——
8503	- 0.7	- 0.2	- 1.1	- 4.5
MAE	2.5	3.5	4.0	4.5
KALMAN FILTER MODEL				
8412	-15.1	——	——	——
8501	- 4.4	- 4.5	——	——
8502	- 2.0	- 2.0	- 2.0	——
8503	-14.3	-14.2	-14.2	-14.3
MAE	9.0	6.9	8.1	14.3

EXHIBIT 44

COMPARISON OF OUT-OF-SAMPLE FORECASTING ERRORS:
EXPERT JUDGEMENT, DV, AND KALMAN FILTER MODELS
Percentage Error

CASE III: ARMY - INCREASE IN RECRUITING RESOURCES
Regime Change Assummed to Occur in October 1984

FORECASTS FOR	ESTIMATION AND FORECASTING ROUNDS AT SUCCESSIVE MONTHLY OBSERVATIONS AFTER CHANGE 0	1	2	3	4	5
EXPERT JUDGEMENT						
8410	-18.4	——	——	——	——	——
8411	- 7.5	8.4	——	——	——	——
8412	- 4.1	-14.2	-10.6	——	——	——
8501	1.5	3.5	2.0	15.8	——	——
8502	9.0	12.9	13.3	11.9	12.5	——
8503	4.0	7.0	7.4	9.7	9.6	11.7
MAE	7.4	9.2	8.3	12.5	11.0	11.7
ARMA REGRESSION WITH ONE DUMMY VARIABLE (Estimation Starting in 8410)						
8410	NA	——	——	——	——	——
8411	NA	5.8	——	——	——	——
8412	NA	9.5	2.6	——	——	——
8501	NA	25.6	23.5	21.8	——	——
8502	NA	43.6	38.5	40.4	19.1	——
8503	NA	21.6	17.9	17.9	20.7	9.6
MAE	NA	21.2	20.6	26.7	19.9	9.6
KALMAN FILTER MODEL (WITH RESPECIFICATION BEGINNING IN 8410)						
8410	NA	——	——	——	——	——
8411	NA	-16.7	——	——	——	——
8412	NA	-11.6	-8.9	——	——	——
8501	NA	-13.0	-10.7	9.1	——	——
8502	NA	- 3.8	- 1.4	0.3	1.9	——
8503	NA	-15.2	-12.5	-10.7	- 9.5	- 9.7
MAE	NA	12.1	8.4	6.7	5.7	9.7

EXHIBIT 45

COMPARISON OF OUT-OF-SAMPLE FORECASTING ERRORS:
DV, AND KALMAN FILTER MODELS
WITH RESPECIFICATION AND ADDITIONAL OBSERVATIONS
Percentage Error

CASE III: ARMY - INCREASE IN RECRUITING RESOURCES
Regime Change Assumed to Occur in August 1984

FORECASTS FOR	ESTIMATION AND FORECASTING ROUNDS AT SUCCESSIVE MONTHLY OBSERVATIONS AFTER CHANGE 0	1	2	3	4	5
ARMA REGRESSION WITH THREE DUMMY VARIABLES (Estimation Starting in 8408)						
8410	-21.1	——	——	——	——	——
8411	- 4.2	20.9	——	——	——	——
8412	- 4.7	18.3	-13.5	——	——	——
8501	0.0	25.2	6.2	6.6	——	——
8502	5.5	32.1	11.3	10.6	4.5	——
8503	1.5	27.1	7.0	7.1	2.6	- 1.4
MAE	7.4	24.7	9.5	8.1	3.6	1.4
KALMAN FILTER MODEL (WITH RESPECIFICATION BEGINNING IN 8408)						
8410	-17.0	——	——	——	——	——
8411	-17.4	-14.4	——	——	——	——
8412	-12.4	- 9.1	- 5.7	——	——	——
8501	-13.4	-10.9	- 8.0	- 6.7	——	——
8502	- 4.2	- 1.5	1.5	2.9	4.2	——
8503	-15.9	-12.6	- 9.3	- 7.7	- 6.8	- 7.3
MAE	13.4	9.7	6.1	5.8	5.5	7.3

EXHIBIT 46

COMPARISON OF AGGREGATE OUT-OF-SAMPLE FORECASTING ERRORS: ALL ALTERNATIVE METHODS

Percentage Error

CASE III: ARMY INCREASE IN RECRUITING RESOURCES

METHOD	FORECASTING PERIOD 8410-8509	8411-8509	8412-8509	8501-8509	8502-8509	8503-8509
EXPERT JUDGEMENT	2.6	7.6	8.0	13.4	13.3	14.0
SINGLE DUMMY VARIABLE	NA	28.3	22.3	21.9	17.3	14.3
MULTIPLE DUMMY VARIABLES	-0.2	27.2	7.6	8.5	3.6	0.6
KALMAN FILTER 1st Observation at 8410	NA	-9.2	-5.8	-3.5	-1.1	-1.7
KALMAN FILTER 1st Observation at 8408	-10.3	-6.6	-2.4	-0.5	1.7	0.7

the dummy variable in December 1983, when, in fact, the change took place as early as August. The timing of the dummy variable directly affects the speed and accuracy with which the approach can accomodate a regime change.

Timing issues are explored further in Case III, which focuses on Army enlistments. With simple applications of the DV and KF approaches, we obtained enlistment forecasts, using the assumption that the regime change occurred in October 1984, the official date. Then we analyzed more complicated DV and KF models in which we assumed that the regime change occurred in August 1984, the date suggested by the analysis of forecasting errors and confirmed in conversations with Army personnel.

In addition to DV and KF analysis of Case III, we obtained forecasts with an expert judgement approach. The study team separately calculated the effect of each of the numerous components of the policy change collectively referred to as the Army "bridge" program. Estimated elasticities from the ERL time-series cross-section model were used in the calculations, together with outside evidence. The various effects were netted out to yield a 16.9 percent effect on 1-3 HSDG's (and a 13.9 percent effect on 1-3A HSDG's).[20] This calculated factor was used to adjust baseline forecasts generated by the EWS ARMA model, which was estimated with data for the prior regime period (i.e., through September 1984). Since the expert judgement approach uses a priori information, it yielded a forecast for October 1984, as well as the months following. The DV and KF methods require at least one observation after the regime change, so their forecasts begin in November 1984.

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20 For details see the Recruiting Market Assessment Report for the Army, January 1985, page 9 and the Appendix.

Exhibit 44 presents the forecasting results produced in Case III by expert judgement, a single dummy variable respecification, and simple Kalman filtering, all assuming a regime change in October 1984. As a standard of performance, the EWS ARMA model, in out-of-sample forecasting tests for the first half of FY 84, yielded an average monthly MAE of 8.5 for 1-3 HSDG Army enlistments. (See Exhibit 14.) As Exhibit 44 shows, the expert judgment approach initially produced forecasts in Case III that meet this level of accuracy and are more accurate than those produced by the other methods. With two new-regime observations the KF forecasts also have reached the pre-change accuracy level. The DV method's errors are largest; while they eventually dampen, they do not do so as quickly as in Case I. As late as March, six months following the change, the DV method's MAE has declined only to 9.6.

Further research shows that the DV method produced poorer forecasts in Case III because the model was still mis-specified. Although the official date of the policy change was October 1984, actual implementation of the change began in August causing distinct short-term effects. To capture these aspects of the regime change, we constructed a more complicated model. This time the respecification included three dummy variables: one for August and September, one for the spike in October, and one for the long-run effects assumed to begin in August. We also modified the Kalman filter approach, including observations from August rather than from October. Forecast errors yielded by these respecified models are reported in Exhibit 45.

The additional analysis produced dramatic improvements for the DV method: by the December estimation and forecasting round, the MAE has declined to 9.5 (as opposed to 20.6 for the same round with the first specification). This level of accuracy was not achieved in the simpler model until the March round — three months later. Improvements are shown also for the KF method's forecasting accuracy, although the changes are less dramatic. Now the KF method's MAE drops below 10 percent in November rather than in December.

To provide further evidence on the forecasting accuracy of the approaches, we obtained enlistments forecasts for the remaining months in FY 85 and aggregated them. The results, presented in Exhibit 46, illustrate the level of forecasting accuracy for each method when one allows for the cancelling of errors over time. As in the analysis of monthly MAE's, the expert judgement method does well initially, then its aggregate forecast errors steadily increase. The simplistic DV method that uses one variable does the worst, although its forecasts improve gradually over time. Again, respecification to include more dummy variables brings dramatic improvements: the aggregate forecasting error declines to 7.6 percent by the December round. Forecasts produced by the Kalman filter method are the most accurate, and they improve with improvements in the model's specification.

D. Outlook for Forecasting Accuracy in the Face of Regime Change

In this exploration of problems caused by regime change, our prime concern has been the testing of alternative approaches for forecasting in the face of a regime change occurring just prior to the forecast period. We have used two diagnostic approaches to identify regime change, and have tested and compared alternative forecasting approaches in three cases — two for the Air Force and one for the Army.

We have found that persistent forecasting errors caused by regime change can be eliminated by respecifying the EWS ARMA models with dummy variables representing policy shifts, and re-estimating. Provided that the respecification is reasonably correct — i.e., the appropriate number of dummy variables are used and are properly timed — the errors tend to diminish quickly as the number of observations increases. Typically, three to four observations under the new regime are required before forecasting accuracy returns to its pre-change level. This method has been and continues to be used successfully in the Recruitment EWS.

The results of exploratory research using the Kalman filtering method are mixed. The approach sometimes produces better forecasts than the DV method, especially when the model is specified with observations which correctly reflect the timing of regime change. However, the methodology of this approach is not well specified, and implementation requires a great deal of art. Kalman filtering is an interesting and potentially useful method, but more research is necessary before we would have confidence in its use as an operating procedure in the EWS.

Until more reliable evidence can be produced, the application of expert judgement to the adjustment of baseline forecasts may be a necessary and worthwhile method of generating reasonable forecasts immediately following regime changes. ERL researchers were fairly successful in applying expert judgement to yield preliminary forecasts of the effects of the Army's bridge program. Success was possible in this case because the forecasters had a clear understanding of the numerous changes that took place and some evidence of the effect of each change.

However, there is evidence that the success of the expert judgement method in the case of the Army bridge program was due, in some degree, to a matter of luck. We suspect that errors in estimation of individual changes tended to cancel each other out, with the result that our net annual adjustment was reasonably correct. Furthermore, judging from our latest ARMA model results, the long-term effects of the regime change were somewhat overstated by the expert judgement adjustment, while the positive short-term effects were ignored. Again, the net effect was a cancellation of errors in our favor. In circumstances where new policies are introduced for which we have no prior information, the application of expert judgement would be less likely to predict enlistments accurately. Cases I and II are examples of such circumstances, and in these we did not even attempt to use the method.

The results of this research show that thorough information on the timing of regime changes would enable the resumption of accurate forecasts earlier — perhaps two to three months earlier — than would otherwise be possible. There is no doubt that a constant flow of information between EWS forecasters and the Services is necessary for the Recruitment EWS to work at an optimal level of efficiency and accuracy.

CHAPTER VI

SUMMARY AND CONCLUSIONS

The components most critical to a Recruitment Early Warning System are enlistment supply models which forecast enlistments accurately. In this research, ARMA regression models have been developed for forecasting enlistments of 1-3A NPS male HSDG's and HSSR's and 3B NPS male HSDG's and HSSR's, estimated with national, monthly data for January 1979 - May 1985. To assess the validity of the models, we conducted out-of-sample forecasting tests for observations in FY 1984-85. The tests were conducted with known values of exogenous variables, except for unemployment which was forecasted. The results indicate that the models adequately forecast enlistments over 12-month intervals. For each Service, forecasting errors are typically only three percent or less for the 1-3A and 1-3 cohorts, over the entire 12-month period; individual monthly forecasts are subject to larger errors (RMSE's vary from 11.1 to 14.9), but they cancel over the 12-month period.

The forecasting tests covered 12-month periods in which there were no "regime changes", i.e., changes or introduction of programs or policies which affected the market structure. In periods where regime changes occur, we find that forecasting accuracy deteriorates markedly. Since the Services do change programs or policies from time to time, we devoted considerable exploratory research to the remediation of forecasting error caused by regime change. Three cases, two for the Air Force and one for the Army, were analyzed. The results indicate that in three to six months, it is possible to take regime changes into account and restore forecasting accuracy to its high pre-change level. The number of additional observations required depends upon the nature of the regime change and the accuracy of the flow of communication between the Service and the EWS forecaster. If the Service fully implements a program or policy change all at once and the forecaster is informed in advance, the change can be incorporated in three months. If a program is implemented in stages without warning, it may take six months to take the effects into account and restore forecasting accuracy to its previous level. Clearly, good communication between the Services and the EWS forecaster is important, if not critical, for the system to function well.

Numerous studies have shown that unemployment has a strong effect on recruiting. Given the importance of unemployment, it is desirable that the Recruitment EWS possess the capability of accurately predicting unemployment 12 months ahead. To obtain this capability, we developed unemployment forecasting models which are functions of 15 leading indicators of the economy. Two relationships are estimated with national monthly data for 7205-8504, both within an ARMA model framework. In the Composite Leading Indicator (CLI) model, unemployment is assumed to be a function of a fixed composite of the leading indicators; in the Individual Leading Indicator (ILI) model, indicators are included individually and then effects are measured without constraints. Special attention was given to the question of forecasting accuracy around turning points, a necessary if not sufficient condition for achieving a high degree of overall forecasting accuracy. In five periods, four that included turning points, out-of-sample forecasting tests were conducted. The models predicted turning points at troughs well in advance of the occurrence, but they were less successful predicting peaks. The forecasting accuracy of the CLI and ILI models was similar; over the five test periods, errors averaged 0.62-0.64, i.e., slightly greater than one-half of a point above or below the actual observed value of unemployment. Unemployment forecasting errors of this magnitude are relatively small, and not an impediment to enlistment forecasting accuracy, as evidenced by the enlistment forecasting tests discussed earlier.

The CLI and ILI models performed more or less equally in the forecasting tests. Predictions of employment in FY 1985-86 from the ILI model seem more reasonable, so we recommend choosing it for inclusion in the Recruitment EWS.

The research has yielded relatively accurate forecasting models for enlistments and unemployment. While further improvement is possible, the results provide the critical components needed to develop a credible and useful Recruitment EWS.

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APPENDIX A

FORECASTS OF CIVILIAN EARNINGS

APPENDIX A

FORECASTS OF CIVILIAN EARNINGS

Forecasts of civilian youth earnings are made with a single-equation model based on quarterly time-series data. As discussed in Chapter II, Section B, we focus upon the median weekly earnings of full-time 16-24-year-old civilian workers (WE1624). Short-term forecasts of nominal earnings are produced — typically five quarters out. We include an unemployment variable to capture the wage effects of business cycles and an index of inflation to reflect the lagged effect of price level changes.* Binary variables are included to reflect seasonal variability. We have not carried out an analysis of the factors (such as shrinking youth cohort size) that affect youth wage rates over the longer term.**

OLS estimates of the earnings equation are reported in Exhibit A-1. The observation period extends from 79I through 85II. A linear-in-logs formulation is used: WE1624 is regressed against the civilian unemployment rate (a quarterly version of ALLCIVUN), the CPI (a quarterly version of index no. 320 published in Business Conditions Digest), and seasonal binary variables (relative to the fourth quarter). We found a significant countercyclical effect, a strong lagged effect of price level changes, and a significant seasonal pattern. The fit of the equation is good and serial correlation of the residuals is not pervasive.

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* We have not included variables to capture the wage effects of secular growth in labor productivity. Two such variables might be GNP and civilian labor force. We judged that the uncertainity involved in having to use forecasts of these additional variables would outweigh any increased explanatory power of the earnings equation.

** See Tan, H.W. and Ward, M.P., "Forecasting the Wages of Young Men: The Effects of Cohort Size," The Rand Corporation, R-3115-Army, May 1985.

EXHIBIT A-1

YOUTH EARNINGS FORECASTING MODEL
ESTIMATED OLS REGRESSION EQUATION

1979I - 1985I

Dependent Variable = WE1624

Variable	Estimated Coefficient
Constant	2.929**
Seasonal: QIII	-.042**
Seasonal: QII	.146
Seasonal: QI	.031**
ALLCIVQ	-.054**
CPI(-1)	.459**

Degree of Freedom	=	19
SSR	=	.00489
RBAR**2	=	.94
Durbin-Watson	=	1.88
Q(12)	=	10.94
SIGNF	=	.53

Definitions:

WE1624 = (logarithm of) earnings of full-time civilian youth workers, 16-24 years old

ALLCIVQ = (logarithm of) civilian unemployment

CPI(-1) = (logarithm of) CPI, lagged one period

** Indicates coefficient is statistically significantly different from zero at 95% confidence level (two tail test).

In its forecasting mode, the model is driven by unemployment forecasts produced by the EWS-CLI/ILI forecaster and with CPI consensus forecasts published in Blue Chip Economic Indicators.

The earnings forecasts produced by this model are appended to the historical series, and the entire series is then deseasonalized, using OLS techniques. The quarterly series are interpolated into a monthly series.

To validate the model we conducted out-of-sample forecasting tests. The model was estimated over the 1979I - 1983IV period, and then used to forecast the 1984I - 1985I period. Known values of the exogenous variables were used in the test. In Exhibit A-2 we graph actual youth earnings against fitted values over the estimation period, and against the forecasted values over the test period.

The forecasting tests show that the model predicted very accurately over the five-quarter test period; the MAE and RMSE are $4.02 and $4.47, respectively. In relative terms, the RMSE is a very low 1.9 percent.*

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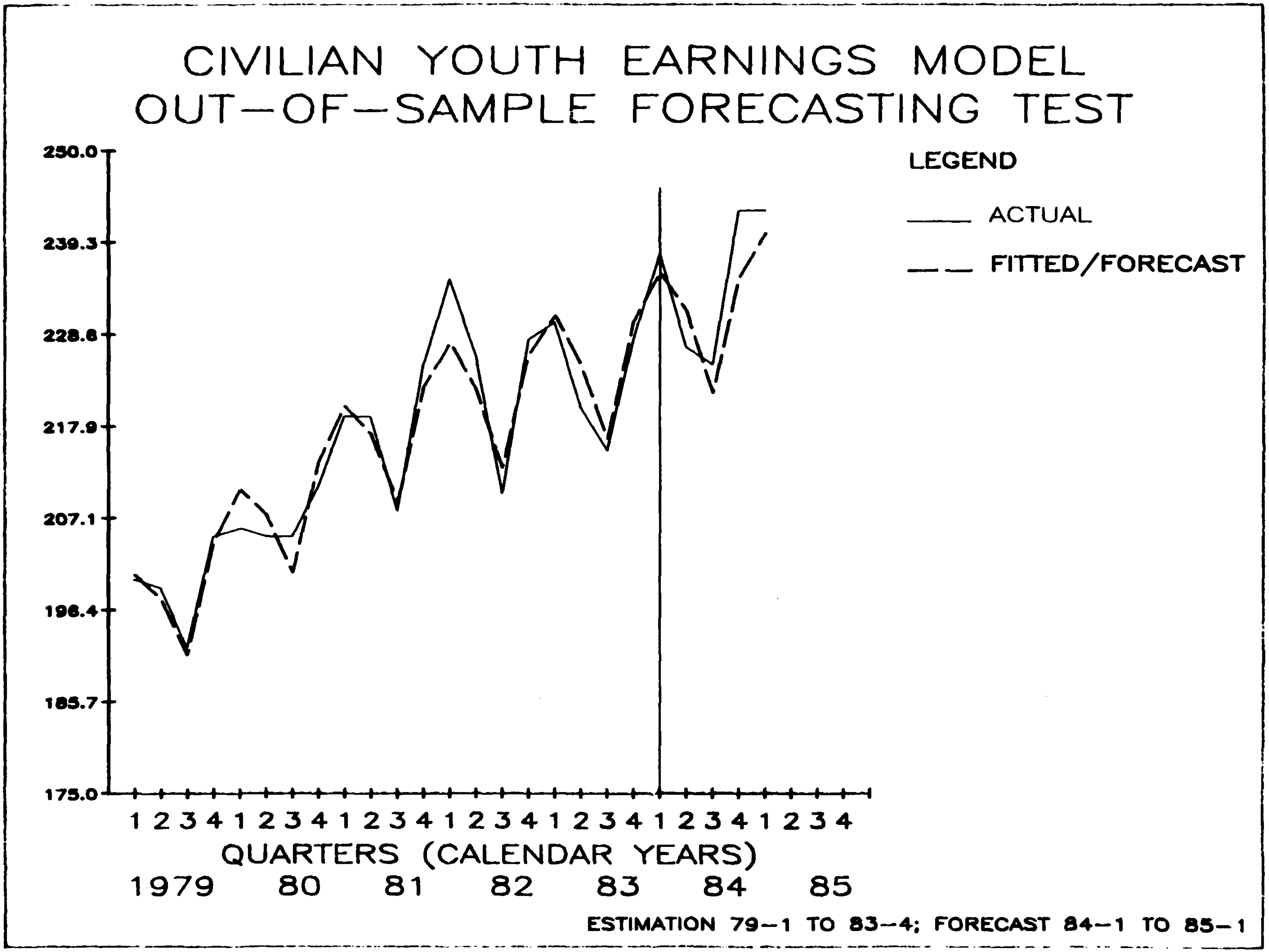
* A model without the CPI variable fits noticeably worse (RBAR-squared = 0.80) and does not forecast as accurately. Out-of-sample forecasting tests over the same period produce a MAE of $22.46; these forecasts are characterized by uniform underprediction.

Exhibit A-2


CIVILIAN YOUTH EARNINGS MODEL
OUT-OF-SAMPLE FORECASTING TEST
LEGEND
ACTUAL
FITTED/FORECAST
250.0
239.3
228.6
217.9
207.1
196.4
185.7
175.0
1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4 1 2 3 4
QUARTERS (CALENDAR YEARS)
1979 80 81 82 83 84 85
ESTIMATION 79-1 TO 83-4; FORECAST 84-1 TO 85-1

APPENDIX B

A DISTRIBUTED-LAG ENLISTMENT MODEL

APPENDIX B

A DISTRIBUTED-LAG ENLISTMENT MODEL

As discussed in Chapter III, it is likely that the effect of unemployment U(t) upon enlistments E(t) is not contemporaneous, but is distributed over time. This implies that E(t) depends on current and past values of U(t). If the effects last k periods, the relationship can be expressed as:

$$E(t) = b_0U(t) + b_1U(t-1) + \ldots + b_kU(t-k) + CZ(t) + N(t),$$

where Z denotes the other explanatory variables in the regression model, and N(t) is the error term. This is known as a distributed-lag regression model.* Use of OLS to estimate the model can result in the loss of a large number of degrees of freedom and imprecise estimates of the b_j's due to collinearity among the lagged values of unemployment.

One solution suggested in the literature has been to put some "structure" on the b_j's. Well-known examples are arithmetic lags, Almon polynominal lags, and Koyck geometric lags. The latter is an infinite lag distribution that decays over time. An attractive feature of this type of distribution is that it avoids the problem of specifying k, the length of the lag.

It has been argued that these specifications impose strong constraints on the lag distribution, often without justification.** No one knows to what extent the results obtained are a consequence of the constraints. Recently there has been a shift to the estimation of distributed-lag models through unconstrained least squares with, possibly, some weak structure imposed on the coefficients.

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* Maddala, G.S., Econometrics, McGraw-Hill, New York, 1977, Chapter 16.

** loc. cit., pp.378-382.

One such estimation technique is known as Hannan's Efficient (HE) Procedure. It is essentially a generalized-least-squares approach where the error term is assumed to follow a stationary stochastic process. In the usual time-series-regression models we assume the errors to be serially independent or to follow a first-order autoregressive process. The advantage of the HE method is that we do not have to make such a restrictive assumption.

In exploratory research we estimated a distributed lag model for unemployment using the HE procedure.* The procedure is complicated and involves a number of steps. We began by transforming the U(t)'s into mutually uncorrelated series. The Nerlove "universal formula" for economic time series was selected:**

$$U^*(t) = U(t) - 1.50U(t-1) + .5625U(t-2)$$

The other variables were transformed in the same manner. Second, an OLS regression was estimated, and residuals computed. Third, the residuals, the dependent variable, and the regressors were sent to the "frequency domain." Fourth, a smoothed estimate of the spectrum of the residuals was computed. Fifth, each of the other series underwent Fourier transformation, were divided by the square root of the residual spectrum, and underwent inverse transformation. Finally, the filtered series were sent back to the time domain and an OLS regression was run. A lag of eight periods was assumed for unemployment.

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* The HE procedure was implemented using the RATS software package. Another method, Hannan's Inefficient (HI) procedure, is most appropriate for distributed-lag models when length of the lag is unknown. Because of difficulty in applying the RATS software, we did not use this approach.

** Loc. cit., p. 380.

In Exhibit B-1, we report the HE estimation results for the Army 1-3A enlistment equation. The basic model results, discussed in Chapter III, are shown for comparison. The unemployment effects sum to 1.123, a large increase over the results from the basic model. There appears to be a contemporaneous effect and strong lagged effects from three to eight periods, judging by the size of the coefficients. However, the effects are not significant and three of the signs are negative.

The other coefficients are more or less similar to those of the basic model, but the estimate of recruiter elasticity is more reasonable (less than unity). Serial correlation is also less serious as evidenced by the SIGNF value for the Q tests.

These results are promising and additional research appears to be worthwhile. The next steps would be to try other lag lengths using the HE method, to try the more general HI procedure, and to undertake forcasting tests to determine if any of the approaches significantly improves forecasting accuracy.

EXHIBIT B-1

ESTIMATED ENLISTMENT EQUATION
DISTRIBUTED LAG MODEL

Army 1-3A HSDG-HSSR Cohort
7901-8504

	Distriubted Lag Model[a]	Basic Model[b]
Constant	-.473**	-2.594
ARECPA	.779**	1.077**
RELPAY	2.358**	1.986**
UNEMP	.183	—
UNEMP (-1)	.004	—
UNEMP (-2)	-.070	.777**
UNEMP (-3)	.487	—
UNEMP (-4)	.197	—
UNEMP (-5)	.574	—
UNEMP (-6)	.580	—
UNEMP (-7)	-.277	—
UNEMP (-8)	-.555	—
ACF	.051	.162**
D89	.137	.129
D10	.090	.151
D1112	.090	.122
BRIDE	.197	.075
SSR	.804	.513
RBAR**2	.95	.95
Durbin-Watson	2.19	1.66
Q(24)	24.1	28.7
SIGNF	.45	.23

NOTE: The variables are in logarithms; seasonal binary variables included in both models, but not reported.

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a Estimated with Hannan's Efficient Procedure

b Estimated with OLS

APPENDIX C

DATA SERIES USED IN THE RECRUITMENT EWS

ARMYD13A
MONTHLY DATA FROM 76 1 TO 85 8
ARMY NPS HSDG 1-3A MALES

76-	1	4601.000000	4087.000000	3885.000000	2434.000000
76-	5	2416.000000	3184.000000	2806.000000	2823.000000
76-	9	2695.000000	2636.000000	3452.000000	5855.000000
77-	1	2359.000000	2205.000000	2336.000000	1839.000000
77-	5	1700.000000	2122.000000	2124.000000	2407.000000
77-	9	1873.000000	1510.000000	1734.000000	1511.000000
78-	1	1795.000000	1592.000000	1527.000000	1106.000000
78-	5	959.000000	1672.000000	1522.000000	1579.000000
78-	9	1274.000000	1092.000000	983.000000	942.000000
79-	1	1640.000000	1311.000000	789.000000	1095.000000
79-	5	1750.000000	1745.000000	1607.000000	1603.000000
79-	9	1207.000000	1227.000000	1259.000000	1159.000000
80-	1	1908.000000	1934.000000	1587.000000	1483.000000
80-	5	1586.000000	2044.000000	2466.000000	2204.000000
80-	9	1901.000000	1825.000000	1508.000000	1582.000000
81-	1	2259.000000	2197.000000	2026.000000	1766.000000
81-	5	1631.000000	2451.000000	2890.000000	2530.000000
81-	9	2481.000000	2285.000000	2174.000000	2422.000000
82-	1	3197.000000	3034.000000	3294.000000	2679.000000
82-	5	3072.000000	3943.000000	4167.000000	4335.000000
82-	9	4191.000000	3413.000000	3483.000000	3444.000000
83-	1	4125.000000	3863.000000	4037.000000	3117.000000
83-	5	3281.000000	4381.000000	4382.000000	4768.000000
83-	9	4145.000000	2739.000000	3020.000000	2686.000000
84-	1	3328.000000	2954.000000	2752.000000	2277.000000
84-	5	2296.000000	2988.000000	3595.000000	3640.000000
84-	9	2708.000000	2442.000000	2347.000000	2328.000000
85-	1	3413.000000	2987.000000	2990.000000	2747.000000
85-	5	2718.000000	3301.000000	3783.000000	3852.000000

NAVYD13A
MONTHLY DATA FROM 76 1 TO 85 8
NAVY EQUIVALENT OF ARMYD13A; AF AND MC FOLLOW

76-	1	4656.000000	3918.000000	4089.000000	2836.000000
76-	5	2438.000000	3330.000000	3525.000000	3593.000000
76-	9	3230.000000	2991.000000	3658.000000	6525.000000
77-	1	2465.000000	2354.000000	2557.000000	2101.000000
77-	5	1969.000000	2527.000000	2573.000000	2885.000000
77-	9	2228.000000	1984.000000	2152.000000	1974.000000
78-	1	2172.000000	2008.000000	2105.000000	1500.000000
78-	5	1482.000000	2009.000000	1937.000000	2080.000000
78-	9	1703.000000	1456.000000	1328.000000	1331.000000
79-	1	1893.000000	1587.000000	1054.000000	1300.000000
79-	5	1739.000000	1933.000000	2084.000000	2304.000000
79-	9	1641.000000	1571.000000	1711.000000	1454.000000
80-	1	2219.000000	2419.000000	1960.000000	1704.000000
80-	5	1882.000000	2767.000000	3495.000000	3282.000000
80-	9	2733.000000	2147.000000	1799.000000	1853.000000
81-	1	2393.000000	2579.000000	2311.000000	1841.000000
81-	5	1762.000000	2484.000000	2852.000000	2731.000000
81-	9	2558.000000	2140.000000	1942.000000	2139.000000
82-	1	2587.000000	2591.000000	2570.000000	2280.000000
82-	5	1994.000000	2962.000000	3371.000000	3738.000000
82-	9	3392.000000	2834.000000	2912.000000	2766.000000
83-	1	3040.000000	2860.000000	2704.000000	2228.000000
83-	5	2321.000000	2820.000000	3109.000000	3374.000000
83-	9	3295.000000	2318.000000	2304.000000	2162.000000
84-	1	2480.000000	2121.000000	1999.000000	1649.000000
84-	5	1606.000000	1924.000000	2114.000000	2267.000000
84-	9	1564.000000	1775.000000	1721.000000	1708.000000
85-	1	2215.000000	1760.000000	1668.000000	1525.000000
85-	5	1535.000000	1911.000000	2218.000000	2156.000000

AFD13A
MONTHLY DATA FROM 76 1 TO 85 8

76-	1	5422.000000	4191.000000	4137.000000	2810.000000
76-	5	2230.000000	2926.000000	2940.000000	3338.000000
76-	9	2450.000000	1975.000000	2946.000000	6386.000000
77-	1	2333.000000	2569.000000	3027.000000	2402.000000
77-	5	2230.000000	2765.000000	2660.000000	2811.000000
77-	9	2163.000000	1808.000000	2214.000000	2207.000000
78-	1	2324.000000	2326.000000	2398.000000	1794.000000
78-	5	1645.000000	2162.000000	1959.000000	2144.000000
78-	9	1778.000000	1594.000000	1552.000000	1526.000000
79-	1	1967.000000	1760.000000	1086.000000	1545.000000
79-	5	2232.000000	2028.000000	2030.000000	2502.000000
79-	9	1966.000000	1965.000000	1848.000000	1698.000000
80-	1	2526.000000	3197.000000	2620.000000	2316.000000
80-	5	2272.000000	2855.000000	3730.000000	3574.000000
80-	9	3069.000000	2477.000000	2044.000000	2175.000000
81-	1	2714.000000	2966.000000	2898.000000	2507.000000
81-	5	2329.000000	3200.000000	3531.000000	3549.000000
81-	9	3287.000000	2744.000000	2395.000000	2843.000000
82-	1	3159.000000	2672.000000	2254.000000	1854.000000
82-	5	1994.000000	1984.000000	2439.000000	2398.000000
82-	9	2223.000000	2582.000000	2752.000000	2422.000000
83-	1	2741.000000	2416.000000	2598.000000	2176.000000
83-	5	2325.000000	2387.000000	2746.000000	3082.000000
83-	9	2976.000000	2347.000000	2278.000000	2971.000000
84-	1	2834.000000	2567.000000	2537.000000	2248.000000
84-	5	2380.000000	2585.000000	2706.000000	2991.000000
84-	9	2658.000000	2056.000000	2061.000000	1988.000000
85-	1	2293.000000	2307.000000	2240.000000	2017.000000
85-	5	2040.000000	2336.000000	2317.000000	2205.000000

MCD13A
MONTHLY DATA FROM 76 1 TO 85 8

76-	1	1723.000000	1324.000000	1245.000000	814.000000
76-	5	767.000000	1316.000000	1004.000000	1026.000000
76-	9	988.000000	968.000000	1080.000000	1828.000000
77-	1	940.000000	900.000000	923.000000	679.000000
77-	5	615.000000	887.000000	883.000000	904.000000
77-	9	592.000000	566.000000	724.000000	662.000000
78-	1	744.000000	685.000000	714.000000	570.000000
78-	5	592.000000	957.000000	863.000000	797.000000
78-	9	645.000000	471.000000	498.000000	444.000000
79-	1	618.000000	529.000000	347.000000	433.000000
79-	5	626.000000	772.000000	851.000000	842.000000
79-	9	685.000000	616.000000	660.000000	581.000000
80-	1	866.000000	875.000000	646.000000	605.000000
80-	5	674.000000	1064.000000	1274.000000	1079.000000
80-	9	938.000000	757.000000	688.000000	662.000000
81-	1	883.000000	991.000000	859.000000	692.000000
81-	5	611.000000	1204.000000	1307.000000	1117.000000
81-	9	1059.000000	859.000000	718.000000	791.000000
82	1	982.000000	857.000000	903.000000	711.000000
82-	5	774.000000	1313.000000	1392.000000	1372.000000
82-	9	1343.000000	937.000000	1204.000000	987.000000
83-	1	1334.000000	1049.000000	955.000000	831.000000
83-	5	852.000000	1167.000000	1028.000000	1301.000000
83-	9	1188.000000	840.000000	1023.000000	862.000000
84-	1	1068.000000	875.000000	775.000000	680.000000
84-	5	673.000000	820.000000	936.000000	1036.000000
84-	9	745.000000	638.000000	694.000000	699.000000
85-	1	913.000000	768.000000	650.000000	594.000000
85-	5	702.000000	897.000000	903.000000	883.000000

ARMYD3B
MONTHLY DATA FROM 76 1 TO 85 8
ARMY NPS HSDG 3B MALES;NAVY, AF, MC FOLLOW.

76-	1	2269.000000	2029.000000	2173.000000	1159.000000
76-	5	1205.000000	1695.000000	1498.000000	1537.000000
76-	9	1464.000000	1417.000000	1885.000000	2755.000000
77-	1	1372.000000	1143.000000	1241.000000	943.000000
77-	5	850.000000	1211.000000	1182.000000	1295.000000
77-	9	962.000000	854.000000	863.000000	755.000000
78-	1	935.000000	764.000000	734.000000	498.000000
78-	5	513.000000	926.000000	872.000000	928.000000
78-	9	794.000000	621.000000	602.000000	511.000000
79-	1	858.000000	674.000000	379.000000	522.000000
79-	5	790.000000	1009.000000	866.000000	869.000000
79-	9	692.000000	677.000000	641.000000	502.000000
80-	1	834.000000	915.000000	640.000000	598.000000
80-	5	628.000000	969.000000	1237.000000	1055.000000
80-	9	1009.000000	867.000000	746.000000	688.000000
81-	1	948.000000	1004.000000	863.000000	720.000000
81-	5	693.000000	1258.000000	1498.000000	1355.000000
81-	9	1193.000000	1139.000000	956.000000	1002.000000
82-	1	1385.000000	1325.000000	1334.000000	949.000000
82-	5	1194.000000	1777.000000	1938.000000	2011.000000
82-	9	2019.000000	1621.000000	1490.000000	1351.000000
83-	1	1643.000000	1750.000000	1557.000000	1370.000000
83-	5	1364.000000	2436.000000	2230.000000	2420.000000
83-	9	2152.000000	1344.000000	1334.000000	1206.000000
84-	1	1528.000000	1427.000000	1392.000000	1140.000000
84-	5	1159.000000	1803.000000	1825.000000	1985.000000
84-	9	1675.000000	1504.000000	1336.000000	1277.000000
85-	1	2009.000000	1604.000000	1621.000000	1334.000000
85-	5	1356.000000	1993.000000	1971.000000	2036.000000

NAVYD3B
MONTHLY DATA FROM 76 1 TO 85 8

76-	1	1229.000000	1029.000000	1061.000000	867.000000
76-	5	770.000000	1230.000000	1162.000000	1199.000000
76-	9	1184.000000	1051.000000	1125.000000	2033.000000
77-	1	929.000000	741.000000	821.000000	662.000000
77-	5	620.000000	930.000000	984.000000	1020.000000
77-	9	743.000000	650.000000	720.000000	640.000000
78-	1	766.000000	652.000000	649.000000	473.000000
78-	5	482.000000	662.000000	759.000000	749.000000
78-	9	655.000000	498.000000	440.000000	440.000000
79-	1	632.000000	521.000000	322.000000	407.000000
79-	5	525.000000	805.000000	862.000000	890.000000
79-	9	685.000000	543.000000	568.000000	486.000000
80-	1	717.000000	783.000000	594.000000	492.000000
80-	5	623.000000	903.000000	1170.000000	1075.000000
80-	9	980.000000	697.000000	617.000000	586.000000
81-	1	825.000000	829.000000	708.000000	560.000000
81-	5	549.000000	938.000000	1051.000000	1038.000000
81-	9	1003.000000	816.000000	676.000000	680.000000
82-	1	890.000000	825.000000	876.000000	698.000000
82-	5	618.000000	1122.000000	1231.000000	1377.000000
82-	9	1397.000000	1116.000000	1079.000000	1024.000000
83-	1	1040.000000	882.000000	781.000000	648.000000
83-	5	634.000000	912.000000	1194.000000	1195.000000
83-	9	1461.000000	922.000000	839.000000	732.000000
84-	1	988.000000	850.000000	795.000000	617.000000
84-	5	619.000000	940.000000	941.000000	988.000000
84-	9	866.000000	929.000000	922.000000	806.000000
85-	1	1057.000000	818.000000	760.000000	719.000000
85-	5	698.000000	1027.000000	1162.000000	1129.000000

AFD3B

MONTHLY DATA FROM 76 1 TO 85 8

76-	1	1235.000000	921.000000	789.000000	689.000000
76-	5	563.000000	712.000000	819.000000	885.000000
76-	9	706.000000	589.000000	785.000000	1866.000000
77-	1	665.000000	876.000000	942.000000	723.000000
77-	5	646.000000	848.000000	883.000000	913.000000
77-	9	735.000000	607.000000	714.000000	717.000000
78-	1	780.000000	724.000000	765.000000	567.000000
78-	5	610.000000	746.000000	693.000000	884.000000
78-	9	746.000000	590.000000	583.000000	589.000000
79-	1	717.000000	633.000000	404.000000	505.000000
79-	5	811.000000	835.000000	937.000000	1060.000000
79-	9	933.000000	837.000000	805.000000	656.000000
80-	1	970.000000	1133.000000	943.000000	867.000000
80-	5	828.000000	1205.000000	1567.000000	1467.000000
80-	9	1375.000000	583.000000	500.000000	959.000000
81-	1	1000.000000	1084.000000	1026.000000	904.000000
81-	5	817.000000	1365.000000	1439.000000	1374.000000
81-	9	1343.000000	1117.000000	950.000000	1027.000000
82-	1	1121.000000	882.000000	788.000000	631.000000
82-	5	685.000000	685.000000	884.000000	863.000000
82-	9	824.000000	761.000000	666.000000	532.000000
83-	1	610.000000	523.000000	523.000000	483.000000
83-	5	476.000000	567.000000	667.000000	757.000000
83-	9	765.000000	559.000000	549.000000	756.000000
84-	1	621.000000	581.000000	553.000000	468.000000
84-	5	471.000000	647.000000	738.000000	809.000000
84-	9	753.000000	782.000000	754.000000	829.000000
85-	1	1203.000000	1191.000000	1052.000000	974.000000
85-	5	970.000000	1201.000000	1121.000000	1187.000000

MCD3B
MONTHLY DATA FROM 76 1 TO 85 8

76- 1	611.000000	510.000000	474.000000	351.000000
76- 5	324.000000	586.000000	481.000000	491.000000
76- 9	507.000000	496.000000	536.000000	833.000000
77- 1	497.000000	425.000000	397.000000	306.000000
77- 5	261.000000	433.000000	442.000000	430.000000
77- 9	280.000000	301.000000	318.000000	327.000000
78- 1	381.000000	330.000000	306.000000	270.000000
78- 5	281.000000	522.000000	458.000000	407.000000
78- 9	400.000000	275.000000	236.000000	246.000000
79- 1	314.000000	266.000000	178.000000	224.000000
79- 5	339.000000	482.000000	439.000000	486.000000
79- 9	413.000000	358.000000	316.000000	272.000000
80- 1	368.000000	393.000000	295.000000	225.000000
80- 5	307.000000	586.000000	647.000000	577.000000
80- 9	493.000000	419.000000	365.000000	309.000000
81- 1	436.000000	457.000000	341.000000	293.000000
81- 5	318.000000	670.000000	739.000000	651.000000
81- 9	493.000000	477.000000	350.000000	370.000000
82- 1	509.000000	460.000000	412.000000	295.000000
82- 5	384.000000	739.000000	811.000000	738.000000
82- 9	741.000000	572.000000	575.000000	540.000000
83- 1	743.000000	532.000000	390.000000	354.000000
83- 5	371.000000	687.000000	620.000000	811.000000
83- 9	793.000000	491.000000	437.000000	452.000000
84- 1	552.000000	497.000000	447.000000	402.000000
84- 5	390.000000	601.000000	656.000000	719.000000
84- 9	641.000000	579.000000	519.000000	508.000000
85- 1	646.000000	558.000000	509.000000	425.000000
85- 5	387.000000	484.000000	478.000000	512.000000

ARMYS13A
MONTHLY DATA FROM 78 10 TO 85 8
ARMY SENIORS 1-3A MALES; NAVY, AF, MC FOLLOW.

78- 10	267.000000	446.000000	570.000000	
79- 1	611.000000	519.000000	458.000000	382.000000
79- 5	413.000000	335.000000	371.000000	380.000000
79- 9	294.000000	385.000000	477.000000	484.000000
80- 1	565.000000	555.000000	742.000000	705.000000
80- 5	577.000000	341.000000	434.000000	440.000000
80- 9	455.000000	659.000000	807.000000	903.000000
81- 1	838.000000	834.000000	924.000000	872.000000
81- 5	684.000000	536.000000	607.000000	568.000000
81- 9	579.000000	746.000000	1005.000000	1142.000000
82- 1	1201.000000	1368.000000	1583.000000	1640.000000
82- 5	1270.000000	1066.000000	1027.000000	1248.000000
82- 9	1010.000000	1297.000000	1568.000000	1914.000000
83- 1	1901.000000	1936.000000	2142.000000	1973.000000
83- 5	1728.000000	1668.000000	1580.000000	1632.000000
83- 9	1573.000000	1714.000000	2062.000000	2231.000000
84- 1	2082.000000	1833.000000	1814.000000	1611.000000
84- 5	1374.000000	1595.000000	1761.000000	1839.000000
84- 9	1292.000000	1824.000000	1993.000000	1877.000000
85- 1	1771.000000	1657.000000	1660.000000	1827.000000
85- 5	1432.000000	1745.000000	1885.000000	2013.000000

NAVYS13A
MONTHLY DATA FROM 78 10 TO 85 8

78-	10	105.000000	248.000000	453.000000	
79-	1	573.000000	600.000000	575.000000	515.000000
79-	5	507.000000	352.000000	316.000000	369.000000
79-	9	361.000000	533.000000	632.000000	757.000000
80-	1	941.000000	1015.000000	1079.000000	974.000000
80-	5	661.000000	589.000000	646.000000	627.000000
80-	9	703.000000	783.000000	910.000000	1076.000000
81-	1	972.000000	1156.000000	1234.000000	1111.000000
81-	5	790.000000	665.000000	592.000000	652.000000
81-	9	707.000000	706.000000	904.000000	1141.000000
82-	1	1188.000000	1290.000000	1469.000000	1434.000000
82-	5	1085.000000	936.000000	796.000000	927.000000
82-	9	778.000000	1034.000000	1388.000000	1494.000000
83-	1	1345.000000	1433.000000	1623.000000	1385.000000
83-	5	1195.000000	1101.000000	1143.000000	1323.000000
83-	9	1284.000000	1402.000000	1668.000000	1778.000000
84-	1	1602.000000	1463.000000	1325.000000	1968.000000
84-	5	885.000000	920.000000	1004.000000	1173.000000
84-	9	862.000000	1227.000000	1488.000000	1656.000000
85-	1	1404.000000	1138.000000	1170.000000	1142.000000
85-	5	899.000000	995.000000	1064.000000	1072.000000

AFS13A
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	103.000000	216.000000	359.000000	
79- 1	376.000000	458.000000	393.000000	403.000000
79- 5	394.000000	224.000000	202.000000	247.000000
79- 9	196.000000	325.000000	474.000000	512.000000
80- 1	602.000000	746.000000	750.000000	712.000000
80- 5	630.000000	467.000000	372.000000	375.000000
80- 9	386.000000	491.000000	676.000000	839.000000
81- 1	778.000000	907.000000	1026.000000	979.000000
81- 5	714.000000	584.000000	498.000000	518.000000
81- 9	510.000000	540.000000	750.000000	1005.000000
82- 1	919.000000	882.000000	983.000000	862.000000
82- 5	736.000000	542.000000	367.000000	314.000000
82- 9	325.000000	353.000000	520.000000	737.000000
83- 1	689.000000	672.000000	800.000000	888.000000
83- 5	903.000000	746.000000	465.000000	501.000000
83- 9	386.000000	610.000000	719.000000	1331.000000
84- 1	1054.000000	1162.000000	1097.000000	1061.000000
84- 5	936.000000	458.000000	508.000000	656.000000
84- 9	569.000000	845.000000	1021.000000	1332.000000
85- 1	925.000000	1009.000000	1022.000000	960.000000
85- 5	788.000000	402.000000	303.000000	740.000000

MCS13A
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	157.000000	252.000000	303.000000	
79- 1	274.000000	272.000000	227.000000	238.000000
79- 5	244.000000	205.000000	267.000000	257.000000
79- 9	267.000000	411.000000	384.000000	358.000000
80- 1	372.000000	391.000000	366.000000	342.000000
80- 5	292.000000	281.000000	356.000000	380.000000
80- 9	441.000000	551.000000	525.000000	489.000000
81- 1	515.000000	540.000000	590.000000	521.000000
81- 5	375.000000	540.000000	589.000000	519.000000
81- 9	509.000000	600.000000	635.000000	667.000000
82- 1	579.000000	632.000000	644.000000	501.000000
82- 5	465.000000	728.000000	663.000000	647.000000
82- 9	626.000000	774.000000	817.000000	834.000000
83- 1	892.000000	847.000000	878.000000	791.000000
83- 5	628.000000	1042.000000	945.000000	1013.000000
83- 9	847.000000	930.000000	883.000000	849.000000
84- 1	854.000000	765.000000	730.000000	658.000000
84- 5	589.000000	1132.000000	1182.000000	1102.000000
84- 9	842.000000	862.000000	866.000000	783.000000
85- 1	767.000000	723.000000	723.000000	651.000000
85- 5	650.000000	1107.000000	1260.000000	1250.000000

ARMYS3B
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	195.000000	314.000000	390.000000	
79- 1	401.000000	382.000000	338.000000	272.000000
79- 5	296.000000	219.000000	265.000000	212.000000
79- 9	177.000000	289.000000	352.000000	333.000000
80- 1	393.000000	420.000000	485.000000	423.000000
80- 5	324.000000	214.000000	286.000000	329.000000
80- 9	349.000000	520.000000	622.000000	600.000000
81- 1	595.000000	553.000000	610.000000	524.000000
81- 5	441.000000	406.000000	510.000000	415.000000
81- 9	416.000000	544.000000	623.000000	710.000000
82- 1	785.000000	811.000000	946.000000	978.000000
82- 5	765.000000	668.000000	648.000000	682.000000
82- 9	578.000000	737.000000	979.000000	1158.000000
83- 1	1085.000000	1175.000000	1340.000000	1205.000000
83- 5	1158.000000	1170.000000	894.000000	953.000000
83- 9	857.000000	950.000000	1284.000000	1396.000000
84- 1	1417.000000	1285.000000	1291.000000	1180.000000
84- 5	1059.000000	1240.000000	1043.000000	1077.000000
84- 9	860.000000	1360.000000	1556.000000	1441.000000
85- 1	1312.000000	1188.000000	1317.000000	1338.000000
85- 5	1070.000000	1188.000000	1139.000000	1111.000000

NAVYS3B
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	46.000000	90.000000	198.000000	
79- 1	255.000000	271.000000	250.000000	252.000000
79- 5	238.000000	153.000000	191.000000	202.000000
79- 9	151.000000	272.000000	313.000000	326.000000
80- 1	398.000000	437.000000	392.000000	359.000000
80- 5	285.000000	217.000000	230.000000	257.000000
80- 9	288.000000	297.000000	365.000000	440.000000
81- 1	395.000000	470.000000	520.000000	468.000000
81- 5	377.000000	327.000000	304.000000	300.000000
81- 9	307.000000	346.000000	406.000000	537.000000
82- 1	579.000000	535.000000	647.000000	563.000000
82- 5	459.000000	440.000000	389.000000	415.000000
82- 9	367.000000	539.000000	619.000000	749.000000
83- 1	622.000000	678.000000	643.000000	680.000000
83- 5	462.000000	498.000000	533.000000	561.000000
83- 9	676.000000	682.000000	755.000000	865.000000
84- 1	868.000000	751.000000	706.000000	621.000000
84- 5	591.000000	585.000000	523.000000	589.000000
84- 9	546.000000	842.000000	1005.000000	971.000000
85- 1	894.000000	616.000000	631.000000	809.000000
85- 5	594.000000	701.000000	692.000000	697.000000

AFS3B
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	36.000000	85.000000	186.000000	
79- 1	188.000000	221.000000	172.000000	200.000000
79- 5	163.000000	139.000000	86.000000	97.000000
79- 9	84.000000	156.000000	215.000000	250.000000
80- 1	311.000000	406.000000	382.000000	362.000000
80- 5	297.000000	214.000000	181.000000	183.000000
80- 9	221.000000	128.000000	157.000000	477.000000
81- 1	373.000000	496.000000	495.000000	505.000000
81- 5	386.000000	318.000000	249.000000	261.000000
81- 9	272.000000	268.000000	351.000000	565.000000
82- 1	477.000000	419.000000	503.000000	391.000000
82- 5	364.000000	237.000000	192.000000	167.000000
82- 9	161.000000	140.000000	155.000000	249.000000
83- 1	239.000000	197.000000	251.000000	258.000000
83- 5	273.000000	304.000000	161.000000	152.000000
83- 9	144.000000	199.000000	229.000000	447.000000
84- 1	359.000000	376.000000	348.000000	370.000000
84- 5	308.000000	164.000000	206.000000	219.000000
84- 9	261.000000	422.000000	480.000000	678.000000
85- 1	722.000000	684.000000	725.000000	675.000000
85- 5	591.000000	288.000000	211.000000	490.000000

MCS3B
MONTHLY DATA FROM 78 10 TO 85 8

78- 10	139.000000	153.000000	195.000000	
79- 1	203.000000	172.000000	166.000000	162.000000
79- 5	159.000000	165.000000	166.000000	167.000000
79- 9	183.000000	266.000000	264.000000	215.000000
80- 1	246.000000	238.000000	226.000000	186.000000
80- 5	174.000000	176.000000	218.000000	220.000000
80- 9	264.000000	294.000000	284.000000	312.000000
81- 1	353.000000	333.000000	344.000000	259.000000
81- 5	230.000000	370.000000	354.000000	341.000000
81- 9	367.000000	413.000000	385.000000	473.000000
82- 1	438.000000	433.000000	454.000000	373.000000
82- 5	307.000000	534.000000	468.000000	446.000000
82- 9	482.000000	519.000000	572.000000	597.000000
83- 1	568.000000	611.000000	581.000000	554.000000
83- 5	517.000000	775.000000	752.000000	790.000000
83- 9	719.000000	672.000000	688.000000	701.000000
84- 1	690.000000	631.000000	634.000000	598.000000
84- 5	542.000000	959.000000	819.000000	812.000000
84- 9	752.000000	844.000000	865.000000	852.000000
85- 1	870.000000	737.000000	732.000000	645.000000
85- 5	524.000000	756.000000	774.000000	752.000000

XMCD13A
MONTHLY DATA FROM 79 10 TO 85 5
MARINE CORPS' SERIES: MCD13A

79- 10	632.000000	635.000000	597.000000	
80- 1	850.000000	812.000000	654.000000	667.000000
80- 5	680.000000	1072.000000	1262.000000	1150.000000
80- 9	1098.000000	764.000000	689.000000	709.000000
81- 1	1037.000000	905.000000	825.000000	718.000000
81- 5	623.000000	1087.000000	1147.000000	982.000000
81- 9	971.000000	807.000000	739.000000	824.000000
82- 1	912.000000	864.000000	975.000000	819.000000
82- 5	723.000000	1241.000000	1326.000000	1314.000000
82- 9	1145.000000	938.000000	1129.000000	1093.000000
83- 1	1301.000000	1068.000000	962.000000	770.000000
83- 5	782.000000	1083.000000	938.000000	1141.000000
83- 9	929.000000	829.000000	998.000000	908.000000
84- 1	1047.000000	902.000000	790.000000	676.000000
84- 5	665.000000	801.000000	885.000000	996.000000
84- 9	765.000000	707.000000	748.000000	751.000000
85- 1	1006.000000	825.000000	718.000000	546.000000
85- 5	847.000000			

XMCS13A
MONTHLY DATA FROM 79 10 TO 85 5
MARINE CORPS' SERIES: MCS13A

79- 10	374.000000	413.000000	351.000000	
80- 1	387.000000	429.000000	355.000000	364.000000
80- 5	284.000000	303.000000	380.000000	366.000000
80- 9	465.000000	468.000000	441.000000	449.000000
81- 1	494.000000	472.000000	491.000000	421.000000
81- 5	277.000000	399.000000	445.000000	429.000000
81- 9	410.000000	529.000000	577.000000	550.000000
82- 1	481.000000	547.000000	553.000000	475.000000
82- 5	399.000000	515.000000	572.000000	545.000000
82- 9	566.000000	715.000000	744.000000	753.000000
83- 1	763.000000	748.000000	779.000000	676.000000
83- 5	535.000000	700.000000	722.000000	729.000000
83- 9	668.000000	743.000000	694.000000	688.000000
84- 1	697.000000	615.000000	584.000000	551.000000
84- 5	507.000000	963.000000	1013.000000	948.000000
84- 9	799.000000	874.000000	890.000000	804.000000
85- 1	771.000000	740.000000	736.000000	660.000000
85- 5	609.000000			

XMCD13
MONTHLY DATA FROM 79 10 TO 85 5
XMCD13 MARINE CORPS SOURCE SERIES, EXCL. 12-6S

79- 10	1313.000000	1271.000000	1136.000000	
80- 1	1534.000000	1526.000000	1219.000000	1159.000000
80- 5	1269.000000	2126.000000	2547.000000	2250.000000
80- 9	2132.000000	1241.000000	1081.000000	1134.000000
81- 1	1648.000000	1408.000000	1268.000000	1096.000000
81- 5	987.000000	1746.000000	1886.000000	1619.000000
81- 9	1523.000000	1332.000000	1165.000000	1287.000000
82- 1	1492.000000	1405.000000	1508.000000	1238.000000
82- 5	1131.000000	2059.000000	2225.000000	2158.000000
82- 9	1909.000000	1594.000000	1775.000000	1791.000000
83- 1	2113.000000	1659.000000	1458.000000	1215.000000
83- 5	1205.000000	1801.000000	1571.000000	2015.000000
83- 9	1589.000000	1388.000000	1591.000000	1481.000000
84- 1	1685.000000	1499.000000	1299.000000	1130.000000
84- 5	1121.000000	1486.000000	1621.000000	1881.000000
84- 9	1454.000000	1364.000000	1291.000000	1335.000000
85- 1	1704.000000	1419.000000	1253.000000	933.000000
85- 5	1342.000000			

XMCS13

MONTHLY DATA FROM 79 10 TO 85 5

XMCS13 MARINE CORPS SOURCE SERIES, EXCL. 12-6S

79- 10	939.000000	965.000000	797.000000	
80- 1	948.000000	927.000000	843.000000	837.000000
80- 5	678.000000	697.000000	825.000000	817.000000
80- 9	1084.000000	834.000000	829.000000	822.000000
81- 1	952.000000	813.000000	905.000000	727.000000
81- 5	554.000000	815.000000	864.000000	806.000000
81- 9	803.000000	1002.000000	1058.000000	1075.000000
82- 1	952.000000	1015.000000	1050.000000	866.000000
82- 5	736.000000	1071.000000	1109.000000	1027.000000
82- 9	1113.000000	1376.000000	1416.000000	1499.000000
83- 1	1467.000000	1482.000000	1453.000000	1305.000000
83- 5	1073.000000	1454.000000	1478.000000	1488.000000
83- 9	1377.000000	1407.000000	1368.000000	1366.000000
84- 1	1392.000000	1267.000000	1252.000000	1166.000000
84- 5	1032.000000	1951.000000	1911.000000	1798.000000
84- 9	1569.000000	1724.000000	1758.000000	1637.000000
85- 1	1656.000000	1503.000000	1498.000000	1331.000000
85- 5	1102.000000			

LEI1
MONTHLY DATA FROM 70 1 TO 85 6
AVERAGE WORK WEEK FOR MANUFACTURING PRODUCTION WORKERS

70- 1	40.400000	40.200000	40.100000	39.900000
70- 5	39.800000	39.900000	40.000000	39.800000
70- 9	39.300000	39.500000	39.500000	39.500000
71- 1	39.900000	39.700000	39.800000	39.700000
71- 5	39.900000	40.000000	39.900000	39.800000
71- 9	39.400000	39.900000	40.000000	40.200000
72- 1	40.200000	40.400000	40.400000	40.700000
72- 5	40.500000	40.600000	40.500000	40.600000
72- 9	40.600000	40.700000	40.800000	40.500000
73- 1	40.400000	40.900000	40.800000	40.900000
73- 5	40.700000	40.600000	40.700000	40.500000
73- 9	40.700000	40.600000	40.700000	40.600000
74- 1	40.500000	40.400000	40.400000	39.300000
74- 5	40.300000	40.200000	40.200000	40.200000
74- 9	40.000000	40.000000	39.500000	39.300000
75- 1	39.200000	38.900000	38.800000	39.200000
75- 5	39.000000	39.200000	39.400000	39.700000
75- 9	39.900000	39.800000	39.900000	40.200000
76- 1	40.500000	40.300000	40.200000	39.600000
76- 5	40.300000	40.200000	40.300000	40.100000
76- 9	39.800000	40.000000	40.100000	40.000000
77- 1	39.700000	40.300000	40.200000	40.400000
77- 5	40.400000	40.500000	40.300000	40.400000
77- 9	40.400000	40.500000	40.400000	40.400000
78- 1	39.600000	39.900000	40.500000	40.800000
78- 5	40.400000	40.500000	40.600000	40.500000
78- 9	40.600000	40.500000	40.600000	40.600000
79- 1	40.600000	40.600000	40.600000	39.200000
79- 5	40.200000	40.200000	40.200000	40.100000
79- 9	40.200000	40.200000	40.100000	40.100000
80- 1	40.200000	40.100000	39.800000	39.700000
80- 5	39.400000	39.200000	39.100000	39.400000
80- 9	39.700000	39.700000	39.900000	40.100000
81- 1	40.300000	39.800000	39.900000	40.000000
81- 5	40.200000	40.000000	39.900000	39.900000
81- 9	39.500000	39.600000	39.400000	39.200000
82- 1	39.500000	39.500000	39.000000	39.000000
82- 5	39.100000	39.100000	39.100000	39.000000
82- 9	38.800000	38.900000	39.000000	39.000000
83- 1	39.400000	39.200000	39.600000	39.900000
83- 5	40.000000	40.100000	40.300000	40.300000
83- 9	40.700000	40.700000	40.600000	40.600000
84- 1	40.800000	41.100000	40.700000	41.000000
84- 5	40.700000	40.600000	40.500000	40.500000
84- 9	40.600000	40.500000	40.500000	41.600000
85- 1	40.600000	40.100000	40.400000	40.100000
85- 5	40.300000	40.400000		

LEI5
MONTHLY DATA FROM 70 1 TO 85 6
AVERAGE WEEKLY INTIAL CLAIMS FOR STATE UNEMPLOYMENT INSURANCE

70-	1	240.000000	256.000000	262.000000	326.000000
70-	5	302.000000	291.000000	273.000000	287.000000
70-	9	319.000000	329.000000	322.000000	299.000000
71-	1	292.000000	286.000000	294.000000	281.000000
71-	5	290.000000	289.000000	285.000000	325.000000
71-	9	307.000000	294.000000	283.000000	265.000000
72-	1	264.000000	262.000000	258.000000	260.000000
72-	5	262.000000	286.000000	272.000000	246.000000
72-	9	245.000000	250.000000	241.000000	236.000000
73-	1	226.000000	223.000000	227.000000	238.000000
73-	5	234.000000	233.000000	232.000000	247.000000
73-	9	241.000000	244.000000	251.000000	284.000000
74-	1	294.000000	315.000000	302.000000	289.000000
74-	5	294.000000	314.000000	294.000000	350.000000
74-	9	374.000000	419.000000	473.000000	494.000000
75-	1	522.000000	532.000000	536.000000	521.000000
75-	5	496.000000	491.000000	442.000000	449.000000
75-	9	447.000000	420.000000	393.000000	364.000000
76-	1	360.000000	340.000000	358.000000	371.000000
76-	5	392.000000	394.000000	393.000000	389.000000
76-	9	410.000000	409.000000	390.000000	361.000000
77-	1	394.000000	427.000000	346.000000	371.000000
77-	5	378.000000	358.000000	370.000000	368.000000
77-	9	363.000000	357.000000	347.000000	342.000000
78-	1	343.000000	381.000000	335.000000	322.000000
78-	5	324.000000	331.000000	347.000000	339.000000
78-	9	321.000000	326.000000	340.000000	347.000000
79-	1	353.000000	352.000000	346.000000	411.000000
79-	5	341.000000	358.000000	377.000000	383.000000
79-	9	378.000000	400.000000	420.000000	428.000000
80-	1	416.000000	397.000000	438.000000	532.000000
80-	5	616.000000	581.000000	510.000000	495.000000
80-	9	488.000000	447.000000	422.000000	420.000000
81-	1	424.000000	410.000000	413.000000	395.000000
81-	5	401.000000	405.000000	395.000000	421.000000
81-	9	483.000000	517.000000	539.000000	551.000000
82-	1	563.000000	514.000000	566.000000	566.000000
82-	5	585.000000	551.000000	533.000000	605.000000
82-	9	653.000000	651.000000	616.000000	531.000000
83-	1	507.000000	478.000000	479.000000	470.000000
83-	5	453.000000	406.000000	380.000000	408.000000
83-	9	387.000000	386.000000	381.000000	378.000000
84-	1	364.000000	345.000000	348.000000	360.000000
84-	5	348.000000	350.000000	365.000000	358.000000
84-	9	368.000000	405.000000	397.000000	386.000000
85-	1	378.000000	402.000000	389.000000	387.000000
85-	5	383.000000	392.000000		

LEI7
MONTHLY DATA FROM 70 1 TO 85 6
VALUE OF MANUFACTURERS' NEW ORDERS, DURABLE GOODS INDUSTRIES,IN 1972 DOLLARS
(BILLIONS OF DOLLARS)

70- 1	30.650000	30.400000	30.020000	29.290000
70- 5	30.150000	30.260000	29.860000	28.950000
70- 9	29.900000	27.050000	27.760000	30.860000
71- 1	31.620000	31.780000	31.290000	30.460000
71- 5	29.950000	30.450000	30.530000	30.190000
71- 9	31.350000	30.640000	31.920000	32.410000
72- 1	32.750000	33.290000	33.410000	33.800000
72- 5	34.560000	34.360000	34.140000	34.810000
72- 9	36.650000	36.450000	37.530000	38.760000
73- 1	40.040000	40.260000	41.210000	40.540000
73- 5	40.630000	40.320000	40.200000	39.990000
73- 9	40.240000	41.630000	42.570000	39.810000
74- 1	41.250000	40.530000	39.690000	39.520000
74- 5	40.790000	39.640000	39.720000	39.860000
74- 9	37.700000	35.080000	34.480000	31.220000
75- 1	30.770000	29.980000	28.440000	30.140000
75- 5	30.000000	29.780000	32.200000	31.650000
75- 9	32.010000	31.230000	31.770000	31.490000
76- 1	32.290000	33.700000	34.890000	35.310000
76- 5	35.600000	35.590000	36.940000	35.500000
76- 9	35.440000	35.370000	36.490000	37.900000
77- 1	37.720000	37.410000	38.590000	38.850000
77- 5	38.870000	40.000000	38.940000	39.230000
77- 9	39.630000	40.850000	40.140000	41.920000
78- 1	39.220000	40.800000	41.710000	42.850000
78- 5	42.860000	42.400000	41.300000	43.400000
78- 9	43.460000	45.550000	45.450000	44.300000
79- 1	44.280000	45.580000	46.330000	42.490000
79- 5	43.720000	42.890000	41.450000	40.990000
79- 9	41.620000	41.020000	40.440000	40.410000
80- 1	41.680000	41.240000	39.090000	37.090000
80- 5	34.300000	34.690000	37.340000	36.320000
80- 9	39.210000	39.740000	39.250000	40.010000
81- 1	38.000000	38.290000	38.390000	39.610000
81- 5	39.620000	39.060000	38.670000	37.880000
81- 9	37.220000	34.970000	34.920000	33.570000
82- 1	33.260000	33.800000	34.310000	33.500000
82- 5	32.930000	32.450000	32.510000	31.120000
82- 9	31.520000	30.760000	30.680000	32.750000
83- 1	35.170000	32.780000	33.570000	34.960000
83- 5	35.040000	37.420000	36.940000	37.260000
83- 9	38.380000	39.930000	40.970000	41.110000
84- 1	41.510000	42.240000	43.180000	40.130000
84- 5	41.650000	40.470000	41.980000	41.850000
84- 9	40.320000	39.650000	42.780000	41.520000
85- 1	43.200000	41.860000	40.580000	40.650000
85- 5	41.880000	42.450000		

LEI8

MONTHLY DATA FROM 70 1 TO 85 6

VALUE OF MANUFACTURERS' NEW ORDERS FOR CONSUMER GOODS AND MATERIAL IN 1972
(BILLIONS OF DOLLARS)

70- 1	28.180000	27.600000	27.460000	27.350000
70- 5	27.600000	28.200000	27.300000	27.020000
70- 9	27.400000	25.510000	25.520000	27.990000
71- 1	29.160000	28.870000	28.060000	28.260000
71- 5	27.960000	27.720000	28.520000	28.210000
71- 9	28.320000	28.700000	29.550000	29.820000
72- 1	30.620000	31.130000	30.970000	31.050000
72- 5	31.260000	31.890000	31.620000	32.760000
72- 9	33.320000	33.700000	34.550000	35.060000
73- 1	36.640000	36.640000	37.060000	35.810000
73- 5	36.110000	35.810000	35.660000	35.440000
73- 9	35.380000	36.180000	36.660000	34.650000
74- 1	35.460000	34.700000	34.280000	34.270000
74- 5	35.170000	34.840000	33.900000	33.130000
74- 9	31.990000	31.270000	30.130000	27.040000
75- 1	27.000000	26.810000	25.990000	27.320000
75- 5	27.540000	27.950000	29.610000	29.550000
75- 9	29.970000	30.150000	30.010000	30.180000
76- 1	30.960000	31.650000	32.320000	32.380000
76- 5	32.800000	32.990000	33.290000	32.700000
76- 9	32.370000	31.770000	33.480000	34.430000
77- 1	35.000000	34.960000	36.310000	35.800000
77- 5	35.750000	36.370000	36.000000	36.190000
77- 9	36.410000	36.120000	36.720000	37.540000
78- 1	36.040000	36.970000	37.310000	39.100000
78- 5	38.480000	38.050000	37.340000	38.720000
78- 9	38.100000	38.980000	39.240000	39.980000
79- 1	39.730000	38.880000	39.400000	37.910000
79- 5	38.780000	37.940000	36.890000	36.340000
79- 9	36.780000	36.450000	35.700000	35.400000
80- 1	36.630000	36.370000	33.950000	31.450000
80- 5	30.180000	29.940000	31.170000	31.930000
80- 9	33.870000	35.110000	34.660000	34.700000
81- 1	33.010000	34.360000	33.970000	34.800000
81- 5	34.970000	34.810000	34.160000	33.190000
81- 9	32.580000	31.370000	30.440000	30.850000
82- 1	29.030000	29.500000	30.480000	29.410000
82- 5	30.460000	29.960000	30.060000	29.240000
82- 9	29.740000	28.240000	28.410000	28.680000
83- 1	31.290000	31.530000	31.610000	32.030000
83- 5	33.060000	33.840000	34.380000	35.020000
83- 9	35.170000	36.320000	37.070000	37.550000
84- 1	38.330000	38.300000	37.210000	37.160000
84- 5	37.420000	36.560000	37.510000	37.390000
84- 9	36.210000	36.980000	37.680000	37.200000
85- 1	39.230000	37.820000	36.920000	37.460000
85- 5	37.880000	37.040000		

LEI19
MONTHLY DATA FROM 70 1 TO 85 8
INDEX OF STOCK PRICES, 500 COMMON STOCKS

70-	1	90.310000	87.160000	88.650000	85.950000
70-	5	76.060000	75.590000	75.720000	77.920000
70-	9	82.580000	84.370000	84.280000	90.050000
71-	1	93.490000	97.110000	99.600000	103.040000
71-	5	101.640000	99.720000	99.000000	97.240000
71-	9	99.400000	97.290000	92.780000	99.170000
72-	1	103.300000	105.240000	107.690000	108.810000
72-	5	107.650000	108.010000	107.210000	111.010000
72-	9	109.390000	109.560000	115.050000	117.500000
73-	1	118.420000	114.160000	112.420000	110.270000
73-	5	107.220000	104.750000	105.830000	103.800000
73-	9	105.610000	109.840000	102.030000	94.780000
74-	1	96.110000	93.450000	97.440000	92.460000
74-	5	89.670000	89.790000	82.820000	76.030000
74-	9	68.120000	69.440000	71.740000	67.070000
75-	1	72.560000	80.100000	83.780000	84.720000
75-	5	90.100000	92.400000	92.490000	85.710000
75-	9	84.670000	88.570000	90.070000	88.700000
76-	1	96.860000	100.640000	101.080000	101.930000
76-	5	101.160000	101.770000	104.200000	103.290000
76-	9	105.450000	101.890000	101.190000	104.660000
77-	1	103.810000	100.960000	100.570000	99.050000
77-	5	98.760000	99.290000	100.180000	97.750000
77-	9	96.230000	93.740000	94.280000	93.820000
78-	1	90.250000	88.980000	88.820000	92.710000
78-	5	97.410000	97.660000	97.190000	103.920000
78-	9	103.860000	100.580000	94.710000	96.110000
79-	1	99.710000	98.230000	100.110000	102.070000
79-	5	99.730000	101.730000	102.710000	107.360000
79-	9	108.600000	104.470000	103.660000	107.780000
80-	1	110.870000	115.340000	104.690000	102.970000
80-	5	107.690000	114.550000	119.830000	123.500000
80-	9	126.510000	130.220000	135.650000	133.480000
81-	1	132.970000	128.400000	133.190000	134.430000
81-	5	131.730000	132.280000	129.130000	129.630000
81-	9	118.270000	119.800000	122.920000	123.790000
82-	1	117.280000	114.500000	110.840000	116.310000
82-	5	116.350000	109.700000	109.380000	109.650000
82-	9	122.430000	132.660000	138.100000	139.370000
83-	1	144.270000	146.800000	151.880000	157.710000
83-	5	164.100000	166.390000	166.960000	162.420000
83-	9	167.160000	167.650000	165.230000	164.360000
84-	1	166.390000	157.250000	157.440000	157.600000
84-	5	156.550000	153.120000	151.080000	164.420000
84-	9	166.110000	164.820000	166.270000	164.480000
85-	1	171.610000	180.880000	179.420000	180.620000
85-	5	184.900000	188.890000	192.540000	188.310000

LEI20

MONTHLY DATA FROM 70 1 TO 85 6

CONTRACTS AND ORDERS FOR PLANT EQUIPMENT IN 1972 DOLLARS

(BILLIONS OF DOLLARS)

70- 1	10.160000	9.740000	9.170000	8.720000
70- 5	8.740000	8.400000	8.700000	8.230000
70- 9	8.430000	7.400000	8.520000	9.300000
71- 1	8.600000	9.300000	9.310000	9.210000
71- 5	8.920000	10.010000	8.230000	9.050000
71- 9	9.600000	8.670000	9.450000	9.710000
72- 1	8.880000	9.360000	10.060000	9.910000
72- 5	10.870000	9.430000	10.500000	9.630000
72- 9	11.010000	10.590000	10.880000	11.060000
73- 1	11.130000	11.750000	11.720000	11.760000
73- 5	12.430000	12.300000	12.580000	12.590000
73- 9	12.490000	13.710000	13.800000	13.090000
74- 1	12.880000	13.120000	13.190000	12.440000
74- 5	13.270000	12.080000	13.820000	12.350000
74- 9	12.490000	11.710000	10.550000	11.250000
75- 1	10.190000	9.440000	9.080000	10.250000
75- 5	10.660000	10.470000	9.780000	10.760000
75- 9	9.250000	9.170000	9.290000	8.790000
76- 1	10.470000	10.350000	10.550000	10.680000
76- 5	9.730000	11.270000	12.080000	10.810000
76- 9	11.640000	11.910000	11.250000	11.480000
77- 1	11.410000	11.470000	10.900000	11.880000
77- 5	12.980000	12.650000	11.290000	12.660000
77- 9	13.370000	12.080000	12.270000	13.500000
78- 1	12.830000	14.520000	13.150000	13.170000
78- 5	14.670000	13.360000	14.300000	14.980000
78- 9	15.380000	17.190000	15.340000	13.600000
79- 1	15.110000	16.570000	18.610000	15.960000
79- 5	14.340000	15.270000	14.890000	14.110000
79- 9	14.630000	14.640000	15.990000	15.270000
80- 1	15.660000	14.320000	13.780000	13.670000
80- 5	12.480000	13.950000	15.110000	13.200000
80- 9	14.130000	13.590000	14.290000	14.900000
81- 1	14.380000	13.690000	14.030000	14.770000
81- 5	14.210000	14.280000	13.910000	14.090000
81- 9	14.150000	13.390000	14.430000	12.830000
82- 1	13.100000	14.600000	13.110000	13.540000
82- 5	11.740000	11.130000	11.630000	11.150000
82- 9	11.960000	11.710000	11.580000	11.580000
83- 1	11.620000	11.770000	12.590000	13.140000
83- 5	13.250000	14.240000	12.890000	13.480000
83- 9	15.200000	14.660000	14.080000	13.870000
84- 1	14.520000	15.550000	15.800000	14.700000
84- 5	16.770000	16.090000	15.360000	15.320000
84- 9	15.800000	14.950000	16.010000	14.050000
85- 1	12.800000	18.560000	15.890000	14.140000
85- 5	14.690000	15.195000		

LEI21
MONTHLY DATA FROM 70 1 TO 85 6
AVERAGE WEEKLY OVERTIME OF MANUFACTURING PRODUCTION WORKERS

70-	1	3.400000	3.200000	3.200000	3.000000
70-	5	3.000000	3.100000	3.000000	2.900000
70-	9	2.700000	2.700000	2.600000	2.700000
71-	1	2.800000	2.800000	2.800000	2.800000
71-	5	2.900000	2.900000	2.900000	2.900000
71-	9	2.900000	2.900000	2.900000	3.000000
72-	1	3.100000	3.200000	3.300000	3.500000
72-	5	3.400000	3.500000	3.400000	3.500000
72-	9	3.500000	3.600000	3.700000	3.700000
73-	1	3.900000	4.000000	3.800000	4.100000
73-	5	3.900000	3.800000	3.800000	3.700000
73-	9	3.800000	3.800000	3.900000	3.700000
74-	1	3.600000	3.500000	3.500000	2.800000
74-	5	3.500000	3.400000	3.400000	3.300000
74-	9	3.200000	3.200000	2.800000	2.700000
75-	1	2.500000	2.400000	2.400000	2.400000
75-	5	2.300000	2.500000	2.600000	2.800000
75-	9	2.800000	2.800000	2.900000	3.000000
76-	1	3.100000	3.100000	3.200000	2.600000
76-	5	3.300000	3.200000	3.200000	3.100000
76-	9	3.200000	3.100000	3.200000	3.200000
77-	1	3.300000	3.300000	3.300000	3.600000
77-	5	3.500000	3.500000	3.500000	3.500000
77-	9	3.500000	3.500000	3.600000	3.500000
78-	1	3.400000	3.700000	3.500000	3.900000
78-	5	3.500000	3.600000	3.600000	3.500000
78-	9	3.600000	3.600000	3.700000	3.800000
79-	1	3.600000	3.700000	3.600000	2.900000
79-	5	3.400000	3.400000	3.400000	3.200000
79-	9	3.200000	3.300000	3.200000	3.200000
80-	1	3.100000	3.000000	3.100000	3.000000
80-	5	2.600000	2.400000	2.500000	2.600000
80-	9	2.800000	2.800000	3.000000	3.100000
81-	1	3.000000	2.900000	2.900000	2.900000
81-	5	3.000000	2.900000	2.900000	2.900000
81-	9	2.700000	2.600000	2.500000	2.400000
82-	1	2.300000	2.500000	2.300000	2.400000
82-	5	2.300000	2.300000	2.300000	2.300000
82-	9	2.300000	2.300000	2.300000	2.300000
83-	1	2.400000	2.400000	2.500000	2.800000
83-	5	2.700000	2.900000	3.000000	3.100000
83-	9	3.300000	3.300000	3.300000	3.400000
84-	1	3.500000	3.500000	3.500000	3.600000
84-	5	3.400000	3.400000	3.300000	3.300000
84-	9	3.300000	3.300000	3.400000	3.400000
85-	1	3.400000	3.300000	3.200000	3.400000
85-	5	3.100000	3.200000		

LEI27
MONTHLY DATA FROM 70 1 TO 85 6
VALUE OF MANUFACTURERS' NEW ORDERS, CAPITAL GOODS INDUSTRIES,
NONDEFENSE, IN 1972 DOLLARS
NEW PRIVATE HOUSING UNITS STARTED

70- 1	7.750000	7.620000	7.270000	6.710000
70- 5	7.230000	6.740000	7.020000	5.700000
70- 9	6.950000	6.460000	7.050000	7.730000
71- 1	7.040000	7.560000	7.520000	7.400000
71- 5	7.380000	8.350000	6.830000	7.220000
71- 9	8.160000	7.380000	7.900000	8.280000
72- 1	7.380000	8.130000	8.450000	8.250000
72- 5	9.170000	7.940000	8.890000	8.280000
72- 9	9.260000	8.950000	9.260000	9.390000
73- 1	9.380000	9.880000	10.170000	10.440000
73- 5	10.610000	10.210000	10.670000	10.410000
73- 9	10.770000	11.550000	11.760000	11.460000
74- 1	11.440000	11.600000	11.760000	11.390000
74- 5	11.100000	10.730000	12.100000	11.090000
74- 9	10.910000	9.630000	9.380000	9.030000
75- 1	9.120000	8.260000	7.820000	8.400000
75- 5	8.180000	7.950000	8.460000	8.290000
75- 9	8.080000	8.150000	8.350000	7.860000
76- 1	8.240000	8.540000	8.350000	9.080000
76- 5	8.940000	8.870000	10.010000	9.140000
76- 9	9.360000	9.760000	9.250000	9.810000
77- 1	9.740000	9.560000	9.540000	9.940000
77- 5	10.140000	10.710000	9.920000	10.240000
77- 9	10.780000	10.910000	10.730000	11.100000
78- 1	10.520000	11.560000	11.230000	11.870000
78- 5	12.290000	11.890000	11.980000	12.720000
78- 9	13.240000	14.060000	13.590000	12.070000
79- 1	12.880000	14.720000	16.480000	13.250000
79- 5	13.230000	13.800000	12.740000	12.860000
79- 9	13.200000	13.070000	14.080000	13.490000
80- 1	14.260000	13.070000	12.360000	12.810000
80- 5	11.470000	12.740000	13.750000	11.920000
80- 9	12.820000	12.110000	12.660000	13.280000
81- 1	13.000000	11.920000	12.330000	13.160000
81- 5	12.520000	12.580000	12.000000	12.770000
81- 9	12.700000	11.680000	12.960000	10.920000
82- 1	11.140000	11.450000	11.300000	12.590000
82- 5	10.230000	9.860000	9.840000	9.470000
82- 9	10.360000	10.530000	9.940000	10.750000
83- 1	10.580000	9.620000	11.090000	12.200000
83- 5	11.630000	13.010000	11.020000	11.820000
83- 9	13.870000	13.480000	12.240000	12.610000
84- 1	13.230000	13.250000	14.060000	13.110000
84- 5	14.820000	14.410000	13.330000	13.530000
84- 9	14.080000	12.890000	14.070000	12.340000
85- 1	11.310000	16.850000	14.060000	12.340000
85- 5	12.920000	13.640000		

LEI28
MONTHLY DATA FROM 70 1 TO 85 6
NEW PRIVATE HOUSING UNITS STARTED

70-	1	1085.000000	1305.000000	1319.000000	1264.000000
70-	5	1290.000000	1385.000000	1517.000000	1399.000000
70-	9	1534.000000	1580.000000	1647.000000	1893.000000
71-	1	1828.000000	1741.000000	1910.000000	1986.000000
71-	5	2049.000000	2026.000000	2083.000000	2158.000000
71-	9	2041.000000	2128.000000	2182.000000	2295.000000
72-	1	2494.000000	2390.000000	2334.000000	2249.000000
72-	5	2221.000000	2254.000000	2252.000000	2382.000000
72-	9	2481.000000	2485.000000	2421.000000	2366.000000
73-	1	2481.000000	2289.000000	2365.000000	2084.000000
73-	5	2266.000000	2067.000000	2123.000000	2051.000000
73-	9	1874.000000	1677.000000	1724.000000	1526.000000
74-	1	1451.000000	1752.000000	1555.000000	1607.000000
74-	5	1426.000000	1513.000000	1316.000000	1142.000000
74-	9	1150.000000	1070.000000	1026.000000	975.000000
75-	1	1032.000000	904.000000	993.000000	1005.000000
75-	5	1121.000000	1087.000000	1226.000000	1260.000000
75-	9	1264.000000	1344.000000	1360.000000	1321.000000
76-	1	1367.000000	1538.000000	1421.000000	1395.000000
76-	5	1459.000000	1495.000000	1401.000000	1550.000000
76-	9	1720.000000	1629.000000	1641.000000	1804.000000
77-	1	1527.000000	1943.000000	2063.000000	1892.000000
77-	5	1971.000000	1893.000000	2058.000000	2020.000000
77-	9	1949.000000	2042.000000	2042.000000	2142.000000
78-	1	1718.000000	1738.000000	2032.000000	2197.000000
78-	5	2075.000000	2070.000000	2092.000000	1996.000000
78-	9	1970.000000	1981.000000	2094.000000	2044.000000
79-	1	1630.000000	1520.000000	1847.000000	1748.000000
79-	5	1876.000000	1913.000000	1760.000000	1778.000000
79-	9	1832.000000	1681.000000	1524.000000	1498.000000
80-	1	1341.000000	1350.000000	1047.000000	1051.000000
80-	5	927.000000	1196.000000	1269.000000	1436.000000
80-	9	1471.000000	1523.000000	1510.000000	1452.000000
81-	1	1588.000000	1279.000000	1305.000000	1332.000000
81-	5	1150.000000	1047.000000	1035.000000	949.000000
81-	9	900.000000	866.000000	839.000000	906.000000
82-	1	843.000000	866.000000	931.000000	917.000000
82-	5	1025.000000	902.000000	1166.000000	1046.000000
82-	9	1144.000000	1173.000000	1372.000000	1303.000000
83-	1	1605.000000	1675.000000	1635.000000	1512.000000
83-	5	1780.000000	1716.000000	1775.000000	1907.000000
83-	9	1677.000000	1696.000000	1748.000000	1704.000000
84-	1	1933.000000	2208.000000	1700.000000	1949.000000
84-	5	1787.000000	1837.000000	1730.000000	1590.000000
84-	9	1669.000000	1564.000000	1600.000000	1630.000000
85-	1	1849.000000	1647.000000	1889.000000	1933.000000
85-	5	1673.000000	1705.000000		

LEI38
MONTHLY DATA FROM 70 1 TO 84 10
LEI38: CHANGE IN STOCKS OF MATERIALS AND SUPPLIES ON HAND AND ON ORDER, MFG

70-	1	-.710000	-.430000	-.170000	-.150000
70-	5	-.230000	-.110000	-.610000	-.380000
70-	9	-.110000	-.280000	.510000	.410000
71-	1	1.040000	.310000	.050000	-.370000
71-	5	-.830000	-1.290000	-.420000	-.050000
71-	9	-.090000	.320000	.300000	.580000
72-	1	.660000	.770000	.460000	.320000
72-	5	.780000	.530000	.990000	1.410000
72-	9	1.290000	.880000	1.420000	1.090000
73-	1	2.520000	2.330000	2.970000	2.240000
73-	5	2.600000	2.290000	1.910000	2.300000
73-	9	2.620000	2.810000	2.540000	2.860000
74-	1	2.840000	3.250000	2.330000	2.720000
74-	5	4.040000	3.700000	3.360000	3.310000
74-	9	1.920000	-.380000	.110000	-.680000
75-	1	-1.610000	-1.720000	-2.880000	-3.200000
75-	5	-1.880000	-1.520000	-.400000	-.560000
75-	9	-.600000	.040000	.460000	-.470000
76-	1	-.240000	-.110000	1.520000	.550000
76-	5	1.050000	.950000	.700000	-.500000
76-	9	.830000	.750000	1.700000	.530000
77-	1	-.750000	.930000	1.300000	1.140000
77-	5	1.220000	.760000	-.040000	1.390000
77-	9	1.340000	1.230000	.670000	2.150000
78-	1	.540000	1.540000	2.100000	1.960000
78-	5	2.990000	3.060000	2.180000	2.970000
78-	9	3.070000	2.930000	3.920000	3.260000
79-	1	4.320000	3.030000	3.420000	3.960000
79-	5	1.390000	2.980000	1.020000	3.110000
79-	9	.920000	2.720000	2.070000	1.160000
80-	1	2.960000	2.760000	1.820000	-.330000
80-	5	-1.640000	-1.240000	1.310000	-.340000
80-	9	.640000	1.490000	.770000	1.260000
81-	1	.510000	.010000	-.610000	.980000
81-	5	1.460000	.790000	.450000	-1.220000
81-	9	.910000	-2.680000	-1.630000	-.530000
82-	1	-2.270000	-2.710000	-1.890000	-1.820000
82-	5	-2.080000	-3.670000	-2.160000	-2.350000
82-	9	-2.200000	-1.720000	-1.810000	-.920000
83-	1	.080000	.970000	.690000	.130000
83-	5	1.160000	1.580000	1.640000	2.920000
83-	9	1.640000	2.470000	1.770000	2.440000
84-	1	2.860000	2.710000	2.420000	2.280000
84-	5	2.550000	-.980000	2.400000	-.510000
84-	9	.370000	-2.980000		

LEI46
MONTHLY DATA FROM 70 1 TO 85 6
INDEX OF HELP-WANTED ADVERTISING

70-	1	110.000000	109.000000	103.000000	100.000000
70-	5	94.000000	92.000000	89.000000	88.000000
70-	9	87.000000	81.000000	81.000000	81.000000
71-	1	78.000000	80.000000	80.000000	80.000000
71-	5	81.000000	84.000000	83.000000	84.000000
71-	9	83.000000	84.000000	86.000000	87.000000
72-	1	91.000000	93.000000	95.000000	96.000000
72-	5	98.000000	99.000000	101.000000	105.000000
72-	9	106.000000	111.000000	113.000000	123.000000
73-	1	126.000000	126.000000	127.000000	125.000000
73-	5	126.000000	127.000000	129.000000	126.000000
73-	9	125.000000	127.000000	126.000000	121.000000
74-	1	117.000000	116.000000	117.000000	120.000000
74-	5	119.000000	119.000000	118.000000	114.000000
74-	9	107.000000	99.000000	91.000000	85.000000
75-	1	75.000000	76.000000	74.000000	74.000000
75-	5	74.000000	81.000000	84.000000	83.000000
75-	9	83.000000	83.000000	87.000000	88.000000
76-	1	87.000000	93.000000	94.000000	91.000000
76-	5	94.000000	96.000000	98.000000	97.000000
76-	9	94.000000	96.000000	99.000000	105.000000
77-	1	105.000000	106.000000	108.000000	109.000000
77-	5	112.000000	114.000000	121.000000	122.000000
77-	9	120.000000	128.000000	133.000000	140.000000
78-	1	138.000000	139.000000	141.000000	146.000000
78-	5	144.000000	147.000000	149.000000	150.000000
78-	9	152.000000	161.000000	161.000000	165.000000
79-	1	161.000000	158.000000	156.000000	155.000000
79-	5	154.000000	153.000000	155.000000	155.000000
79-	9	159.000000	167.000000	158.000000	159.000000
80-	1	154.000000	151.000000	145.000000	122.000000
80-	5	112.000000	115.000000	118.000000	117.000000
80-	9	122.000000	127.000000	134.000000	130.000000
81-	1	128.000000	129.000000	125.000000	118.000000
81-	5	118.000000	121.000000	123.000000	119.000000
81-	9	112.000000	110.000000	111.000000	109.000000
82-	1	106.000000	103.000000	96.000000	88.000000
82-	5	87.000000	85.000000	83.000000	78.000000
82-	9	73.000000	76.000000	78.000000	83.000000
83-	1	83.000000	83.000000	83.000000	81.000000
83-	5	87.000000	92.000000	100.000000	97.000000
83-	9	98.000000	111.000000	114.000000	121.000000
84-	1	123.000000	128.000000	124.000000	124.000000
84-	5	125.000000	134.000000	138.000000	128.000000
84-	9	129.000000	136.000000	137.000000	145.000000
85-	1	139.000000	140.000000	138.000000	131.000000
85-	5	131.000000	138.000000		

LEI74
MONTHLY DATA FROM 70 1 TO 85 6
INDUSTRIAL PRODUCTION,NON-DURABLE MANUFACTURERS

70- 1	112.200000	112.600000	111.900000	112.200000
70- 5	112.300000	112.400000	113.100000	111.700000
70- 9	112.300000	112.400000	111.900000	112.800000
71- 1	113.600000	113.500000	113.500000	114.600000
71- 5	115.100000	116.100000	117.200000	117.000000
71- 9	118.200000	119.500000	120.100000	120.900000
72- 1	122.100000	122.700000	123.700000	125.100000
72- 5	125.100000	125.900000	126.000000	127.500000
72- 9	128.000000	129.000000	129.000000	131.700000
73- 1	130.300000	132.400000	133.300000	132.900000
73- 5	134.400000	133.400000	133.800000	134.500000
73- 9	134.000000	135.000000	135.100000	135.200000
74- 1	135.500000	135.700000	136.800000	136.500000
74- 5	137.500000	137.600000	137.400000	137.200000
74- 9	136.400000	133.600000	128.900000	123.100000
75- 1	119.800000	118.400000	116.100000	118.800000
75- 5	120.800000	125.500000	128.100000	130.500000
75- 9	132.900000	133.600000	136.200000	136.900000
76- 1	138.000000	140.300000	140.600000	140.900000
76- 5	140.400000	141.200000	141.600000	141.400000
76- 9	143.400000	143.900000	144.000000	144.400000
77- 1	146.500000	147.300000	149.100000	149.500000
77- 5	150.500000	151.100000	151.300000	151.600000
77- 9	151.700000	152.300000	152.400000	152.400000
78- 1	152.400000	152.900000	153.800000	155.500000
78- 5	155.800000	157.000000	157.200000	158.400000
78- 9	159.300000	159.500000	160.400000	161.700000
79- 1	161.600000	162.900000	164.000000	162.600000
79- 5	163.600000	163.700000	164.800000	165.200000
79- 9	165.400000	164.800000	165.000000	165.300000
80- 1	166.000000	165.800000	164.300000	161.600000
80- 5	158.100000	155.100000	154.600000	157.600000
80- 9	161.000000	162.100000	163.000000	165.000000
81- 1	165.600000	166.200000	165.300000	165.900000
81- 5	166.400000	165.800000	167.100000	167.300000
81- 9	165.900000	162.800000	160.300000	157.400000
82- 1	155.100000	157.800000	157.300000	156.100000
82- 5	155.000000	155.300000	155.700000	156.900000
82- 9	156.700000	156.200000	155.300000	155.500000
83- 1	157.400000	159.000000	160.700000	163.300000
83- 5	165.400000	167.800000	170.600000	172.900000
83- 9	174.600000	175.600000	174.800000	173.900000
84- 1	175.200000	177.200000	177.600000	179.100000
84- 5	179.900000	181.300000	181.800000	181.700000
84- 9	180.200000	179.400000	179.600000	179.600000
85- 1	179.600000	179.100000	179.400000	179.300000
85- 5	179.700000	180.270000		

LEI75
MONTHLY DATA FROM 70 1 TO 85 6
INDUSTRIAL PRODUCTION, CONSUMER GOODS

70-	1	108.000000	108.800000	109.100000	109.600000
70-	5	110.100000	110.300000	110.500000	109.200000
70-	9	108.400000	106.900000	106.300000	110.500000
71-	1	112.200000	112.100000	112.300000	113.000000
71-	5	113.200000	113.900000	115.500000	115.100000
71-	9	115.800000	117.000000	117.900000	117.800000
72-	1	119.800000	120.600000	121.500000	122.500000
72-	5	123.000000	123.200000	124.000000	125.500000
72-	9	126.200000	127.500000	128.400000	130.400000
73-	1	129.500000	130.500000	131.400000	131.200000
73-	5	131.100000	131.200000	131.400000	130.200000
73-	9	132.900000	133.100000	132.400000	130.500000
74-	1	128.300000	127.800000	128.500000	129.600000
74-	5	130.300000	131.200000	131.200000	132.200000
74-	9	131.100000	129.700000	126.200000	121.000000
75-	1	117.000000	116.100000	117.000000	119.000000
75-	5	120.400000	124.300000	126.600000	127.500000
75-	9	129.000000	128.700000	131.100000	132.300000
76-	1	133.100000	135.000000	135.500000	136.200000
76-	5	137.100000	137.500000	137.500000	137.800000
76-	9	136.800000	137.500000	139.400000	141.400000
77-	1	141.400000	142.100000	144.500000	144.600000
77-	5	145.200000	146.300000	146.800000	146.500000
77-	9	146.400000	147.100000	146.600000	146.200000
78-	1	143.200000	145.200000	147.500000	149.500000
78-	5	149.000000	149.300000	149.800000	150.600000
78-	9	150.800000	151.200000	151.300000	151.500000
79-	1	151.300000	151.800000	153.400000	149.300000
79-	5	152.200000	152.100000	151.200000	148.700000
79-	9	150.000000	150.000000	149.100000	148.600000
80-	1	147.900000	148.200000	148.000000	145.200000
80-	5	142.100000	141.800000	142.100000	142.900000
80-	9	144.500000	146.300000	148.100000	147.100000
81-	1	146.900000	147.800000	148.300000	148.900000
81-	5	150.700000	150.300000	150.700000	149.600000
81-	9	147.800000	146.500000	144.000000	142.000000
82-	1	139.600000	141.800000	141.500000	142.100000
82-	5	143.600000	144.800000	145.800000	144.100000
82-	9	143.400000	142.200000	141.300000	142.000000
83-	1	143.600000	143.400000	144.300000	147.700000
83-	5	150.400000	152.400000	154.800000	156.300000
83-	9	157.300000	156.900000	156.100000	157.300000
84-	1	159.600000	161.100000	160.200000	161.400000
84-	5	161.700000	163.000000	163.800000	162.500000
84-	9	161.600000	161.600000	162.600000	162.200000
85-	1	162.100000	162.100000	162.600000	162.400000
85-	5	162.400000	162.670000		

LEI96
MONTHLY DATA FROM 70 1 TO 85 6
LEI96: MFRS. UNFILLED ORDERS, DURABLE GOODS INDUSTRIES

70-	1	110.430000	109.360000	108.460000	107.190000
70-	5	106.300000	105.480000	104.480000	103.090000
70-	9	102.420000	101.100000	100.910000	101.570000
71-	1	102.740000	103.620000	103.600000	103.050000
71-	5	101.780000	100.400000	99.640000	99.600000
71-	9	100.550000	100.870000	101.590000	102.120000
72-	1	102.490000	103.160000	103.590000	103.940000
72-	5	104.980000	105.980000	106.610000	107.340000
72-	9	109.730000	110.940000	112.440000	114.720000
73-	1	117.500000	120.330000	124.440000	127.910000
73-	5	131.310000	134.060000	135.860000	138.390000
73-	9	141.180000	144.670000	148.640000	151.500000
74-	1	155.770000	159.520000	162.720000	165.940000
74-	5	170.860000	174.530000	178.800000	184.140000
74-	9	186.810000	185.960000	185.240000	182.920000
75-	1	180.460000	177.820000	174.750000	172.300000
75-	5	170.610000	168.380000	168.420000	167.570000
75-	9	166.730000	165.190000	165.060000	164.140000
76-	1	162.690000	162.540000	163.490000	164.440000
76-	5	165.030000	165.640000	167.350000	166.900000
76-	9	167.900000	169.520000	170.550000	172.270000
77-	1	173.770000	174.250000	174.660000	176.220000
77-	5	177.530000	179.960000	180.870000	182.590000
77-	9	184.610000	188.090000	190.710000	195.010000
78-	1	197.200000	200.310000	204.800000	208.650000
78-	5	213.800000	218.100000	221.410000	226.040000
78-	9	231.120000	238.740000	245.550000	249.460000
79-	1	254.020000	261.190000	267.920000	272.690000
79-	5	275.320000	279.780000	280.750000	281.670000
79-	9	284.580000	285.980000	288.300000	290.750000
80-	1	294.390000	297.370000	298.890000	299.210000
80-	5	296.750000	296.460000	299.920000	301.550000
80-	9	304.720000	307.220000	308.720000	312.560000
81-	1	312.470000	312.890000	312.560000	314.120000
81-	5	316.120000	316.310000	317.100000	316.520000
81-	9	316.570000	313.420000	311.980000	308.770000
82-	1	308.240000	306.890000	306.650000	305.610000
82-	5	302.080000	298.440000	295.200000	290.710000
82-	9	287.490000	285.840000	284.210000	287.010000
83-	1	290.850000	290.470000	290.610000	293.360000
83-	5	294.630000	298.500000	301.300000	303.390000
83-	9	305.940000	311.530000	317.210000	319.300000
84-	1	323.460000	329.510000	337.700000	340.320000
84-	5	344.630000	344.760000	348.060000	349.050000
84-	9	348.780000	346.040000	348.080000	345.440000
85-	1	348.920000	349.670000	347.100000	344.560000
85-	5	344.700000	347.900000		

LEI106
MONTHLY DATA FROM 70 1 TO 85 6
MONEY SUPPLY (M2) IN 1972 DOLLARS

70- 1	651.800000	646.500000	646.100000	644.300000
70- 5	644.800000	646.100000	646.100000	649.300000
70- 9	651.800000	653.500000	657.000000	660.600000
71- 1	665.300000	673.500000	682.500000	690.100000
71- 5	695.600000	698.400000	701.500000	705.600000
71- 9	711.300000	715.600000	721.200000	724.900000
72- 1	730.400000	736.200000	743.800000	747.800000
72- 5	750.800000	755.900000	762.200000	769.500000
72- 9	775.500000	780.900000	785.700000	792.000000
73- 1	796.500000	795.900000	790.700000	788.700000
73- 5	790.700000	793.700000	795.300000	783.500000
73- 9	782.200000	778.000000	778.100000	778.600000
74- 1	773.900000	769.300000	767.400000	764.700000
74- 5	758.900000	756.400000	752.800000	746.500000
74- 9	740.600000	736.900000	735.300000	731.700000
75- 1	729.300000	732.100000	738.200000	743.000000
75- 5	751.000000	758.000000	759.400000	763.800000
75- 9	765.400000	764.200000	767.500000	769.400000
76- 1	774.200000	784.000000	789.400000	795.700000
76- 5	802.700000	802.300000	803.800000	810.500000
76- 9	814.300000	820.500000	827.200000	834.000000
77- 1	838.200000	839.100000	843.000000	845.[illegible]
77- 5	848.600000	850.200000	852.800000	856.800000
77- 9	859.800000	861.700000	862.800000	863.800000
78- 1	864.600000	864.800000	863.800000	861.500000
78- 5	860.200000	858.000000	856.200000	857.500000
78- 9	858.200000	855.300000	854.600000	854.900000
79- 1	850.700000	847.100000	845.600000	843.700000
79- 5	839.500000	839.800000	837.500000	836.400000
79- 9	833.900000	827.000000	819.100000	813.300000
80- 1	808.500000	806.100000	797.000000	787.000000
80- 5	784.900000	786.600000	795.900000	799.100000
80- 9	793.400000	797.700000	795.800000	790.500000
81- 1	787.200000	786.300000	788.300000	793.800000
81- 5	790.900000	788.500000	784.900000	786.400000
81- 9	784.200000	787.900000	792.000000	798.500000
82- 1	802.700000	803.000000	807.500000	810.400000
82- 5	809.200000	805.400000	806.300000	812.800000
82- 9	819.300000	822.900000	830.100000	841.100000
83- 1	857.200000	873.500000	879.700000	880.100000
83- 5	883.200000	887.100000	889.000000	890.600000
83- 9	893.000000	898.000000	900.700000	902.400000
84- 1	902.400000	904.800000	907.100000	908.200000
84- 5	912.400000	916.300000	917.800000	919.000000
84- 9	922.000000	923.700000	932.700000	940.500000
85- 1	949.400000	954.800000	953.300000	949.100000
85- 5	954.000000	963.000000		

LEI910
MONTHLY DATA FROM 70 1 TO 85 5
TWELVE LEADING INDICATORS

70- 1	107.500000	106.600000	105.500000	[illegible]
70- 5	105.100000	105.500000	104.800000	114.7[illegible]
70- 9	104.900000	104.400000	105.000000	[illegible]
71- 1	108.600000	110.200000	111.900000	[illegible]
71- 5	113.700000	113.500000	113.300000	113.7[illegible]
71- 9	114.600000	115.500000	116.500000	[illegible]
72- 1	119.200000	120.700000	122.200000	123.[illegible]
72- 5	122.900000	123.300000	124.400000	[illegible]
72- 9	127.500000	129.400000	130.300000	131.4[illegible]
73- 1	132.400000	134.100000	134.200000	[illegible]
73- 5	133.500000	133.100000	132.700000	[illegible]
73- 9	130.900000	131.000000	131.100000	128.7[illegible]
74- 1	128.700000	128.000000	127.800000	126.100000
74- 5	125.500000	123.800000	123.500000	120.300000
74- 9	116.500000	113.500000	111.200000	109.200000
75- 1	107.700000	107.600000	108.800000	111.000000
75- 5	113.400000	115.800000	118.200000	119.000000
75- 9	120.600000	122.000000	122.400000	122.800000
76- 1	126.100000	128.000000	128.800000	129.300000
76- 5	130.500000	131.600000	132.200000	131.900000
76- 9	132.400000	132.200000	133.500000	134.500000
77- 1	134.500000	136.500000	138.400000	138.5[illegible]
77- 5	138.900000	139.800000	138.500000	140.5[illegible]
77- 9	141.100000	141.900000	141.600000	142.4[illegible]
78- 1	141.000000	142.800000	144.900000	146.3[illegible]
78- 5	146.400000	146.900000	145.400000	146.2[illegible]
78- 9	146.800000	147.900000	147.600000	147.2[illegible]
79- 1	147.700000	147.500000	149.300000	148.4[illegible]
79- 5	147.600000	146.500000	145.200000	144.5[illegible]
79- 9	144.500000	141.700000	140.100000	140.5[illegible]
80- 1	141.400000	140.400000	137.400000	133.4[illegible]
80- 5	130.900000	132.000000	135.100000	138.3[illegible]
80- 9	141.200000	142.400000	143.400000	143.000000
81- 1	142.100000	140.400000	141.700000	144.5[illegible]
81- 5	144.500000	143.200000	142.900000	142.4[illegible]
81- 9	139.300000	136.900000	137.000000	136.2[illegible]
82- 1	135.100000	135.700000	134.700000	136.000000
82- 5	136.200000	135.500000	136.200000	135.100000
82- 9	137.500000	138.600000	139.400000	140.900000
83- 1	145.200000	147.400000	150.200000	152.500000
83- 5	154.500000	157.300000	158.300000	159.000000
83- 9	160.000000	162.400000	162.500000	163.400000
84- 1	164.500000	166.500000	167.200000	168.100000
84- 5	168.200000	166.700000	163.900000	164.400000
84- 9	165.700000	164.200000	165.200000	164.100000
85- 1	166.300000	167.700000	167.600000	166.700000
85- 5	166.900000	168.500000		

FIRSTMIL
MONTHLY DATA FROM 76 1 TO 86 12
ANNUAL MILITARY EARNINGS WITH TYPICAL INCREASES AND PROMOTIONS

76-	1	7108.000000	7108.000000	7108.000000	7108.000000
76-	5	7108.000000	7108.000000	7108.000000	7108.000000
76-	9	7108.000000	7400.000000	7400.000000	7400.000000
77-	1	7400.000000	7400.000000	7400.000000	7400.000000
77-	5	7400.000000	7400.000000	7400.000000	7400.000000
77-	9	7400.000000	7871.000000	7871.000000	7871.000000
78-	1	7871.000000	7871.000000	7871.000000	7871.000000
78-	5	7871.000000	7871.000000	7871.000000	7871.000000
78-	9	7871.000000	8316.000000	8316.000000	8316.000000
79-	1	8316.000000	8316.000000	8316.000000	8316.000000
79-	5	8316.000000	8316.000000	8316.000000	8316.000000
79-	9	8316.000000	8916.000000	8916.000000	8916.000000
80-	1	8916.000000	8916.000000	8916.000000	8916.000000
80-	5	8916.000000	8916.000000	8916.000000	8916.000000
80-	9	8916.000000	10147.000000	10147.000000	10147.000000
81-	1	10147.000000	10147.000000	10147.000000	10147.000000
81-	5	10147.000000	10147.000000	10147.000000	10147.000000
81-	9	10147.000000	11370.000000	11370.000000	11370.000000
82-	1	11370.000000	11370.000000	11370.000000	11370.000000
82-	5	11370.000000	11370.000000	11370.000000	11370.000000
82-	9	11370.000000	11755.000000	11755.000000	11755.000000
83-	1	11755.000000	11755.000000	11755.000000	11755.000000
83-	5	11755.000000	11755.000000	11755.000000	11755.000000
83-	9	11755.000000	11755.000000	11755.000000	11755.000000
84-	1	12033.000000	12033.000000	12033.000000	12033.000000
84-	5	12033.000000	12033.000000	12033.000000	12033.000000
84-	9	12033.000000	12033.000000	12033.000000	12033.000000
85-	1	12537.000000	12537.000000	12537.000000	12537.000000
85-	5	12537.000000	12537.000000	12537.000000	12537.000000
85-	9	12537.000000	12537.000000	12537.000000	12537.000000
86-	1	12913.000000	12913.000000	12913.000000	12913.000000
86-	5	12913.000000	12913.000000	12913.000000	12913.000000
86-	9	12913.000000	12913.000000	12913.000000	12913.000000

AGLM13A
MONTHLY DATA FROM 80 10 TO 86 9
COMBINED SENIORS AND HSDG 1-3A ARMY CONTRACT MISSIONS

80- 10	2487.000000	2472.000000	2389.000000	
81- 1	2249.000000	2010.000000	2146.000000	1894.000000
81- 5	1852.000000	2182.000000	2377.000000	2640.000000
81- 9	2450.000000	2740.000000	3130.000000	2807.000000
82- 1	3447.000000	3459.000000	3965.000000	3766.000000
82- 5	4021.000000	3827.000000	4362.000000	5278.000000
82- 9	4589.000000	3492.000000	4138.000000	3493.000000
83- 1	5102.000000	4612.000000	4839.000000	4982.000000
83- 5	5562.000000	4935.000000	5256.000000	5434.000000
83- 9	5376.000000	4608.000000	4201.000000	3903.000000
84- 1	6103.000000	5357.000000	5453.000000	5167.000000
84- 5	4583.000000	4556.000000	6387.000000	5840.000000
84- 9	5800.000000	5817.000000	4510.000000	5644.000000
85- 1	5052.000000	5075.000000	5211.000000	5171.000000
85- 5	4381.000000	4490.000000	5888.000000	5080.000000
85- 9	5841.000000	5520.000000	4280.000000	5355.000000
86- 1	5367.000000	5391.000000	5536.000000	4861.000000
86- 5	4118.000000	4221.000000	5377.000000	4640.000000
86- 9	5334.000000			

AGLM3B

MONTHLY DATA FROM 80 10 TO 86 9

ARMY NPS MALE HSDG CONTRACT MISSIONS: MC = 3B

80- 10	2719.000000	2683.000000	2536.000000	
81- 1	3016.000000	2612.000000	2832.000000	2168.000000
81- 5	2171.000000	2487.000000	2434.000000	2729.000000
81- 9	2533.000000	1762.000000	1986.000000	1773.000000
82- 1	1702.000000	1702.000000	1960.000000	1978.000000
82- 5	2002.000000	1916.000000	2105.000000	2486.000000
82- 9	2177.000000	1820.000000	2196.000000	1813.000000
83- 1	2378.000000	2124.000000	2243.000000	2356.000000
83- 5	2632.000000	2375.000000	2191.000000	1968.000000
83- 9	2244.000000	2594.000000	2340.000000	2239.000000
84- 1	3057.000000	2665.000000	2703.000000	2674.000000
84- 5	2331.000000	2355.000000	2900.000000	2562.000000
84- 9	2517.000000	2198.000000	1863.000000	1984.000000
85- 1	2798.000000	2797.000000	2914.000000	2825.000000
85- 5	2351.000000	2376.000000	1685.000000	1479.000000
85- 9	1693.000000	2552.000000	2163.000000	2303.000000
86- 1	2789.000000	2788.000000	2904.000000	3096.000000
86- 5	2576.000000	2603.000000	2575.000000	2261.000000
86- 9	2588.000000			

ARECPA
MONTHLY DATA FROM 76 1 TO 86 6
ARMY RECRUITERS (ARECPA IS 66.6% OF ARMYTREC)

76-	1	4801.000000	4315.000000	4364.000000	4339.000000
76-	5	4334.000000	4310.000000	4207.000000	4191.000000
76-	9	4421.000000	4215.000000	4327.000000	4452.000000
77-	1	4525.000000	4544.000000	4561.000000	4536.000000
77-	5	4570.000000	4587.000000	4517.000000	4555.000000
77-	9	4514.000000	4515.000000	4492.000000	4435.000000
78-	1	4396.000000	4345.000000	4296.000000	4344.000000
78-	5	4379.000000	4340.000000	4311.000000	4307.000000
78-	9	4253.000000	4245.000000	4223.000000	4207.000000
79-	1	4151.000000	4136.000000	4104.000000	4255.000000
79-	5	4455.000000	4686.000000	4706.000000	4666.000000
79-	9	4546.000000	4463.000000	4432.000000	4452.000000
80-	1	4603.000000	4618.000000	4771.000000	4987.000000
80-	5	4977.000000	4963.000000	4990.000000	4956.000000
80-	9	4714.000000	4896.000000	4927.000000	4931.000000
81-	1	4600.000000	4621.000000	4624.000000	4616.000000
81-	5	4654.000000	4723.000000	4736.000000	4788.000000
81-	9	4967.000000	4975.000000	5063.000000	5044.000000
82-	1	4983.000000	4922.000000	4853.000000	4772.000000
82-	5	4752.000000	4707.000000	4671.000000	4773.000000
82-	9	4841.000000	4877.000000	5008.000000	5092.000000
83-	1	5017.000000	4949.000000	4926.000000	4917.000000
83-	5	4940.000000	4916.000000	4920.000000	4962.000000
83-	9	5004.000000	5054.000000	5089.000000	5135.000000
84-	1	5105.000000	5010.000000	4858.000000	4900.000000
84-	5	4923.000000	4803.000000	4856.000000	4862.000000
84-	9	4902.000000	4872.000000	4901.000000	4907.000000
85-	1	4991.000000	4842.000000	4839.000000	4878.000000
85-	5	5006.000000	4950.000000	5050.000000	5030.000000
85-	9	5060.000000	5050.000000	4795.000000	4795.000000
86-	1	4795.000000	4795.000000	4795.000000	4795.000000
86-	5	4795.000000	4795.000000		

TADNCO
MONTHLY DATA FROM 84 10 TO 86 9
NAVY TOTAL ACTIVE DUTY NEW CONTRACT OBJECTIVES (NNANMCO/.842)

84- 10	7007.000000	6929.000000	6926.000000	
85- 1	7658.000000	7353.000000	7647.000000	6670.000000
85- 5	6154.000000	7093.000000	7612.000000	7755.000000
85- 9	7773.000000	7238.000000	7032.000000	7402.000000
86- 1	8277.000000	8032.000000	8283.000000	7434.000000
86- 5	6038.000000	6979.000000	7706.000000	7859.000000
86- 9	7720.000000			

NNAMNCO
MONTHLY DATA FROM 81 10 TO 85 12
NAVY MALE CONTRACT OBJECTIVES

81- 10	6189.000000	5941.000000	5481.000000	
82- 1	6971.000000	6850.000000	6877.000000	6341.000000
82- 5	5485.000000	6795.000000	7531.000000	7917.000000
82- 9	7061.000000	5851.000000	6048.000000	5671.000000
83- 1	5787.000000	5905.000000	5811.000000	5465.000000
83- 5	3953.000000	4457.000000	5276.000000	5762.000000
83- 9	6649.000000	5698.000000	5477.000000	5340.000000
84- 1	6015.000000	5797.000000	6159.000000	5597.000000
84- 5	4995.000000	5516.000000	5144.000000	5610.000000
84- 9	5486.000000	5900.000000	5834.000000	5832.000000
85- 1	6448.000000	6317.000000	6526.000000	6099.000000
85- 5	5205.000000	5893.000000	6377.000000	6502.000000
85- 9	6320.000000	6100.000000	6040.000000	6030.000000

ACCNG
MONTHLY DATA FROM 76 1 TO 83 9
NAVY ACCESSION GOALS

76-	1	7460.000000	6200.000000	5899.000000	5639.000000
76-	5	6282.000000	9125.000000	10686.000000	10550.000000
76-	9	10516.000000	9140.000000	7422.000000	5359.000000
77-	1	8467.000000	6577.000000	6085.000000	5594.000000
77-	5	6283.000000	10041.000000	11294.000000	12896.000000
77-	9	12496.000000	7811.000000	6495.000000	4646.000000
78-	1	6657.000000	5146.000000	4725.000000	4538.000000
78-	5	5230.000000	8803.000000	9189.000000	9157.000000
78-	9	8257.000000	7296.000000	6162.000000	4480.000000
79-	1	6243.000000	5222.000000	4998.000000	4829.000000
79-	5	5314.000000	8897.000000	8889.000000	8777.000000
79-	9	8668.000000	7000.000000	5908.000000	4353.000000
80-	1	6588.000000	5820.000000	5609.000000	4866.000000
80-	5	6004.000000	7804.000000	6737.000000	7919.000000
80-	9	8610.000000	7101.000000	5911.000000	4772.000000
81-	1	6835.000000	6067.000000	5799.000000	5091.000000
81-	5	5428.000000	8199.000000	9069.000000	9088.000000
81-	9	8176.000000	6840.000000	5608.000000	3784.000000
82-	1	4186.000000	4596.000000	5156.000000	4940.000000
82-	5	5541.000000	7660.000000	8482.000000	8559.000000
82-	9	7952.000000	5391.000000	6574.000000	4728.000000
83-	1	6182.000000	5086.000000	4598.000000	4518.000000
83-	5	4249.000000	6124.000000	5851.000000	5832.000000
83-	9	7965.000000			

NMRSVGL
MONTHLY DATA FROM 79 1 TO 86 12
NAVY MALE RESERVE GOALS: RM THRU FY83, SAM FY 83-84

79- 1	166.000000	166.000000	166.000000	166.000000
79- 5	166.000000	166.000000	166.000000	166.000000
79- 9	166.000000	166.000000	166.000000	166.000000
80- 1	166.000000	166.000000	166.000000	166.000000
80- 5	166.000000	166.000000	166.000000	166.000000
80- 9	166.000000	170.000000	170.000000	128.000000
81- 1	164.000000	172.000000	172.000000	172.000000
81- 5	172.000000	172.000000	172.000000	172.000000
81- 9	129.000000	166.000000	166.000000	120.000000
82- 1	166.000000	172.000000	173.000000	173.000000
82- 5	175.000000	175.000000	175.000000	174.000000
82- 9	168.000000	190.000000	215.000000	200.000000
83- 1	143.000000	143.000000	221.000000	220.000000
83- 5	199.000000	383.000000	873.000000	958.000000
83- 9	680.000000	1.000000	1.000000	1.000000
84- 1	1.000000	1.000000	74.000000	514.000000
84- 5	537.000000	536.000000	981.000000	931.000000
84- 9	917.000000	1.000000	1.000000	1.000000
85- 1	1.000000	1.000000	1.000000	1.000000
85- 5	1.000000	1.000000	1.000000	1.000000
85- 9	1.000000	1.000000	1.000000	1.000000
86- 1	1.000000	1.000000	1.000000	1.000000
86- 5	1.000000	1.000000	1.000000	1.000000
86- 9	1.000000	1.000000	1.000000	1.000000

NRECT
MONTHLY DATA FROM 76 1 TO 86 9
NAVY RECRUITERS

76-	1	2945.000000	2941.000000	2921.000000	2887.000000
76-	5	2861.000000	2870.000000	2895.000000	2947.000000
76-	9	2975.000000	2935.000000	2959.000000	2936.000000
77-	1	2944.000000	2969.000000	2976.000000	3011.000000
77-	5	3040.000000	3068.000000	3088.000000	3192.000000
77-	9	3173.000000	3117.000000	3091.000000	3094.000000
78-	1	3084.000000	3060.000000	3047.000000	3107.000000
78-	5	3081.000000	3104.000000	3073.000000	3054.000000
78-	9	3027.000000	3014.000000	3044.000000	3036.000000
79-	1	3068.000000	3105.000000	3105.000000	3142.000000
79-	5	3201.000000	3250.000000	3306.000000	3367.000000
79-	9	3420.000000	3463.000000	3520.000000	3498.000000
80-	1	3474.000000	3457.000000	3465.000000	3443.000000
80-	5	3423.000000	3395.000000	3356.000000	3367.000000
80-	9	3413.000000	3476.000000	3469.000000	3480.000000
81-	1	3533.000000	3552.000000	3557.000000	3536.000000
81-	5	3538.000000	3502.000000	3478.000000	3508.000000
81-	9	3477.000000	3397.000000	3382.000000	3327.000000
82-	1	3349.000000	3395.000000	3409.000000	3422.000000
82-	5	3414.000000	3383.000000	3381.000000	3325.000000
82-	9	3326.000000	3364.000000	3404.000000	3407.000000
83-	1	3441.000000	3427.000000	3485.000000	3497.000000
83-	5	3484.000000	3467.000000	3419.000000	3408.000000
83-	9	3396.000000	3331.000000	3283.000000	3224.000000
84-	1	3158.000000	3067.000000	3020.000000	2997.000000
84-	5	2999.000000	3050.000000	3100.000000	3140.000000
84-	9	3200.000000	3197.000000	3234.000000	3265.000000
85-	1	3289.000000	3251.000000	3225.000000	3262.000000
85-	5	3251.000000	3242.000000	3305.000000	3369.000000
85-	9	3433.000000	3496.000000	3530.000000	3520.000000
86-	1	3520.000000	3520.000000	3520.000000	3520.000000
86-	5	3520.000000	3520.000000	3520.000000	3520.000000
86-	9	3520.000000			

AFMNRGX
MONTHLY DATA FROM 76 1 TO 86 9
AIR FORCE GOALS

76-	1	5283.000000	5283.000000	5283.000000	5283.000000
76-	5	5283.000000	5283.000000	5283.000000	5283.000000
76-	9	5283.000000	5219.000000	5219.000000	5219.000000
77-	1	5219.000000	5219.000000	5219.000000	5219.000000
77-	5	5219.000000	5219.000000	5219.000000	5219.000000
77-	9	5219.000000	5256.000000	5256.000000	5256.000000
78-	1	5256.000000	5256.000000	5256.000000	5256.000000
78-	5	5256.000000	5256.000000	5256.000000	5256.000000
78-	9	5256.000000	4920.000000	4920.000000	4920.000000
79-	1	4920.000000	4920.000000	4920.000000	4920.000000
79-	5	4920.000000	4920.000000	4920.000000	4920.000000
79-	9	4920.000000	4737.000000	4737.000000	4737.000000
80-	1	4985.000000	4985.000000	4985.000000	4985.000000
80-	5	4985.000000	4580.000000	5279.000000	4985.000000
80-	9	4985.000000	5644.000000	5644.000000	5644.000000
81-	1	5316.000000	5316.000000	5316.000000	5316.000000
81-	5	5316.000000	5316.000000	5311.000000	5311.000000
81-	9	5311.000000	4570.000000	4570.000000	4570.000000
82-	1	4570.000000	4788.000000	4788.000000	4656.000000
82-	5	3908.000000	3068.000000	3917.000000	3482.000000
82-	9	3917.000000	4479.000000	4479.000000	4479.000000
83-	1	4009.000000	4009.000000	3754.000000	3754.000000
83-	5	3754.000000	3725.000000	3748.000000	3754.000000
83-	9	4095.000000	3885.000000	3919.000000	4531.000000
84-	1	4674.000000	4340.000000	4600.000000	4515.000000
84-	5	4515.000000	4515.000000	4515.000000	4515.000000
84-	9	4515.000000	4250.000000	4303.000000	4569.000000
85-	1	4726.000000	4550.000000	4300.000000	4131.000000
85-	5	3997.000000	4462.000000	4191.000000	4109.000000
85-	9	4082.000000	4384.000000	4439.000000	4713.000000
86-	1	4875.000000	4694.000000	4436.000000	4261.000000
86-	5	4123.000000	4603.000000	4323.000000	4239.000000
86-	9	4211.000000			

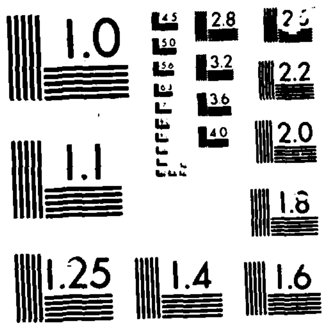
FRECPNPS
MONTHLY DATA FROM 76 1 TO 86 9
AF PRODUCTION RECRUITERS FOR NPS

76-	1	1589.000000	1520.000000	1485.000000	1472.000000
76-	5	1449.000000	1430.000000	1408.000000	1373.000000
76-	9	1374.000000	1422.000000	1482.000000	1535.000000
77-	1	1574.000000	1617.000000	1610.000000	1657.000000
77-	5	1705.000000	1730.000000	1716.000000	1705.000000
77-	9	1699.000000	1683.000000	1661.000000	1656.000000
78-	1	1648.000000	1631.000000	1631.000000	1617.000000
78-	5	1604.000000	1614.000000	1636.000000	1657.000000
78-	9	1677.000000	1733.000000	1738.000000	1763.000000
79-	1	1789.000000	1655.000000	1662.000000	1674.000000
79-	5	1693.000000	1746.000000	1757.000000	1802.000000
79-	9	1803.000000	1802.000000	1794.000000	1796.000000
80-	1	1799.000000	1746.000000	1762.000000	1786.000000
80-	5	1751.000000	1748.000000	1745.000000	1752.000000
80-	9	1771.000000	1772.000000	1795.000000	1786.000000
81-	1	1780.000000	1777.000000	1769.000000	1782.000000
81-	5	1804.000000	1803.000000	1807.000000	1787.000000
81-	9	1787.000000	1767.000000	1759.000000	1770.000000
82-	1	1768.000000	1722.000000	1713.000000	1673.000000
82-	5	1634.000000	1564.000000	1509.000000	1486.000000
82-	9	1464.000000	1430.000000	1410.000000	1398.000000
83-	1	1410.000000	1411.000000	1424.000000	1428.000000
83-	5	1411.000000	1419.000000	1438.000000	1444.000000
83-	9	1439.000000	1404.000000	1397.000000	1409.000000
84-	1	1410.000000	1398.000000	1398.000000	1381.000000
84-	5	1365.000000	1361.000000	1333.000000	1343.000000
84-	9	1348.000000	1330.000000	1337.000000	1356.000000
85-	1	1374.000000	1392.000000	1420.000000	1421.000000
85-	5	1425.000000	1414.000000	1398.000000	1413.000000
85-	9	1399.000000	1414.000000	1418.000000	1460.000000
86-	1	1460.000000	1460.000000	1460.000000	1460.000000
86-	5	1460.000000	1460.000000	1460.000000	1460.000000
86-	9	1460.000000			

RMGL
MONTHLY DATA FROM 76 1 TO 86 9
MARINE CORPS GOALS

76- 1	5419.000000	4936.000000	5258.000000	3970.000000
76- 5	3646.000000	4454.000000	5362.000000	5132.000000
76- 9	4420.000000	4149.000000	3962.000000	4215.000000
77- 1	5132.000000	4238.000000	3604.000000	2870.000000
77- 5	3246.000000	3777.000000	4629.000000	4421.000000
77- 9	3797.000000	3467.000000	3773.000000	4064.000000
78- 1	4111.000000	3645.000000	3668.000000	3131.000000
78- 5	2793.000000	3006.000000	3006.000000	3006.000000
78- 9	3006.000000	3719.000000	3813.000000	3750.000000
79- 1	4011.000000	3598.000000	3884.000000	3200.000000
79- 5	3305.000000	3540.000000	3532.000000	3553.000000
79- 9	3428.000000	3365.000000	3443.000000	3577.000000
80- 1	3960.000000	3387.000000	3752.000000	3129.000000
80- 5	2938.000000	3679.000000	3940.000000	4060.000000
80- 9	3700.000000	2870.000000	2484.000000	2280.000000
81- 1	2974.000000	3077.000000	3000.000000	2529.000000
81- 5	2379.000000	3778.000000	4566.000000	4188.000000
81- 9	3477.000000	3757.000000	3442.000000	3509.000000
82- 1	4427.000000	3697.000000	3922.000000	3421.000000
82- 5	3031.000000	2616.000000	3636.000000	3465.000000
82- 9	3588.000000	4257.000000	3021.000000	3239.000000
83- 1	3837.000000	4491.000000	3613.000000	3054.000000
83- 5	2061.000000	2641.000000	3633.000000	3196.000000
83- 9	3644.000000	2701.000000	2691.000000	2746.000000
84- 1	3540.000000	2900.000000	2750.000000	2369.000000
84- 5	2032.000000	3073.000000	3082.000000	3126.000000
84- 9	3112.000000	2475.000000	2988.000000	2928.000000
85- 1	3251.000000	2869.000000	3430.000000	2668.000000
85- 5	2449.000000	3170.000000	2846.000000	3108.000000
85- 9	2584.000000	2386.000000	2490.000000	2490.000000
86- 1	2699.000000	2285.000000	2699.000000	2075.000000
86- 5	2075.000000	2490.000000	2490.000000	2490.000000
86- 9	2387.000000			

AD-A166 567 RECRUITMENT EARLY WARNING SYSTEM PHASE II VOLUME 1 3/3
RESEARCH AND DEVELOPME..(U) ECONOMIC RESEARCH LAB INC
RESTON VA P GREENSTON ET AL. 30 SEP 85 ONR-85-01-VOL-1
UNCLASSIFIED N00014-85-C-0033 F/G 5/9 NL



MICROCOP' CHART

MRECREV
MONTHLY DATA FROM 76 1 TO 86 9
MARINE RECRUITERS, REVISED SERIES

76-	1	1897.000000	1917.000000	2017.000000	1915.000000
76-	5	1966.000000	1937.000000	2021.000000	2006.000000
76-	9	2015.000000	1750.000000	1800.000000	1819.000000
77-	1	1926.000000	1958.000000	2038.000000	2004.000000
77-	5	2083.000000	2048.000000	3103.000000	2075.000000
77-	9	2134.000000	1747.000000	1778.000000	1763.000000
78-	1	1904.000000	1848.000000	1901.000000	1900.000000
78-	5	1951.000000	1938.000000	1985.000000	1975.000000
78-	9	2032.000000	1666.000000	1703.000000	1715.000000
79-	1	1835.000000	1828.000000	1901.000000	1959.000000
79-	5	2032.000000	2070.000000	2175.000000	2212.000000
79-	9	2297.000000	2086.000000	2139.000000	2178.000000
80-	1	2268.000000	2242.000000	2323.000000	2410.000000
80-	5	2492.000000	2600.000000	2646.000000	2699.000000
80-	9	2691.000000	2495.000000	2500.000000	2535.000000
81-	1	2593.000000	2555.000000	2580.000000	2568.000000
81-	5	2539.000000	2539.000000	2541.000000	2509.000000
81-	9	2532.000000	2354.000000	2407.000000	2433.000000
82-	1	2535.000000	2488.000000	2579.000000	2577.000000
82-	5	2633.000000	2635.000000	2698.000000	2659.000000
82-	9	2688.000000	2506.000000	2562.000000	2541.000000
83-	1	2611.000000	2568.000000	2654.000000	2648.000000
83-	5	2655.000000	2668.000000	2790.000000	2749.000000
83-	9	2827.000000	2679.000000	2750.000000	2756.000000
84-	1	2813.000000	2810.000000	2849.000000	2841.000000
84-	5	2869.000000	2812.000000	2825.000000	2750.000000
84-	9	2786.000000	2786.000000	2796.000000	2756.000000
85-	1	2825.000000	2806.000000	2883.000000	2902.000000
85-	5	2855.000000	2842.000000	2926.000000	2876.000000
85-	9	2950.000000	2800.000000	2800.000000	2800.000000
86-	1	2800.000000	2800.000000	2800.000000	2800.000000
86-	5	2800.000000	2800.000000	2800.000000	2800.000000
86-	9	2800.000000			

ALLCI/UN
MONTHLY DATA FROM 70 1 TO 86 12
ALL CIVILIAN UNEMPLOYMENT

70-	1	3.900000	4.200000	4.400000	4.600000
70-	5	4.800000	4.900000	5.000000	5.100000
70-	9	5.400000	5.500000	5.900000	6.100000
71-	1	5.900000	5.900000	6.000000	5.900000
71-	5	5.900000	5.900000	6.000000	6.100000
71-	9	6.000000	5.800000	6.000000	6.000000
72-	1	5.800000	5.700000	5.800000	5.700000
72-	5	5.700000	5.700000	5.600000	5.600000
72-	9	5.500000	5.600000	5.300000	5.200000
73-	1	4.900000	5.000000	4.900000	5.000000
73-	5	4.900000	4.900000	4.800000	4.800000
73-	9	4.800000	4.600000	4.800000	4.900000
74-	1	5.100000	5.200000	5.100000	5.100000
74-	5	5.100000	5.400000	5.500000	5.500000
74-	9	5.900000	6.000000	6.600000	7.200000
75-	1	8.100000	8.100000	8.600000	8.800000
75-	5	9.000000	8.800000	8.600000	8.400000
75-	9	8.400000	8.400000	8.300000	8.200000
76-	1	7.900000	7.700000	7.600000	7.700000
76-	5	7.400000	7.600000	7.800000	7.800000
76-	9	7.600000	7.700000	7.800000	7.800000
77-	1	7.500000	7.600000	7.400000	7.200000
77-	5	7.000000	7.200000	6.900000	7.000000
77-	9	6.800000	6.800000	6.800000	6.400000
78-	1	6.400000	6.300000	6.300000	6.100000
78-	5	6.000000	5.900000	6.200000	5.900000
78-	9	6.000000	5.800000	5.900000	6.000000
79-	1	5.900000	5.900000	5.800000	5.800000
79-	5	5.700000	5.700000	5.700000	6.000000
79-	9	5.800000	6.000000	5.900000	6.000000
80-	1	6.300000	6.300000	6.300000	6.900000
80-	5	7.500000	7.600000	7.800000	7.700000
80-	9	7.500000	7.500000	7.500000	7.200000
81-	1	7.500000	7.400000	7.400000	7.200000
81-	5	7.500000	7.500000	7.200000	7.400000
81-	9	7.600000	7.900000	8.300000	8.500000
82-	1	8.600000	8.900000	9.000000	9.300000
82-	5	9.400000	9.600000	9.800000	9.800000
82-	9	10.100000	10.400000	10.700000	10.700000
83-	1	10.400000	10.400000	10.300000	10.200000
83-	5	10.200000	10.100000	9.400000	9.400000
83-	9	9.200000	8.800000	8.400000	8.200000
84-	1	8.000000	7.800000	7.800000	7.800000
84-	5	7.500000	7.200000	7.500000	7.5[illegible]
84-	9	7.400000	7.300000	7.100000	7.2[illegible]
85-	1	7.400000	7.300000	7.300000	7.[illegible]
85-	5	7.300000	7.300000	7.300000	[illegible]
85-	9	7.470000	7.520000	7.440000	7.3[illegible]
86-	1	7.300000	7.250000	7.210000	[illegible]
86-	5	7.220000	7.220000	.000000	[illegible]
86-	9	.000000	.000000	.000000	[illegible]

WE1624
QUARTERLY DATA FROM 78 4 TO 86 1

78-	4	190.470000			
79-	1	200.000000	199.000000	192.000000	205.000000
80-	1	206.000000	205.000000	205.000000	211.000000
81-	1	219.000000	219.000000	208.000000	225.000000
82-	1	235.000000	226.000000	210.000000	228.000000
83-	1	230.000000	220.000000	215.000000	228.000000
84-	1	238.000000	227.000000	225.000000	243.000000
85-	1	243.000000	.000000	.000000	.000000
86-	1	.000000			

CPI
QUARTERLY DATA FROM 78 4 TO 86 4

78- 4	201.900000			
79- 1	207.000000	214.100000	221.100000	227.600000
80- 1	236.500000	245.000000	249.600000	256.200000
81- 1	262.900000	269.000000	276.700000	280.700000
82- 1	283.000000	287.300000	292.800000	293.400000
83- 1	293.200000	296.900000	300.500000	303.100000
84- 1	306.400000	309.700000	313.100000	315.400000
85- 1	317.400000	321.500000	325.400000	329.600000
86- 1	334.200000	338.800000	343.500000	348.200000

ALLCIVQ
QUARTERLY DATA FROM 78 4 TO 86 4
ALLCIVQ: MALE & FEMALE CIVILIAN QUARTERLY UNEMPLOYMENT RATES (SEAS. ADJ)

78-	4	5.900000			
79-	1	5.900000	5.700000	5.800000	6.000000
80-	1	6.300000	7.300000	7.600000	7.500000
81-	1	7.400000	7.400000	7.400000	8.300000
82-	1	8.800000	9.400000	9.900000	10.600000
83-	1	10.400000	10.200000	9.300000	8.500000
84-	1	7.900000	7.500000	7.400000	7.200000
85-	1	7.300000	7.340000	7.480000	7.440000
86-	1	7.260000	7.220000	7.220000	7.220000

END
FILMED

5-86

DTIC