Air Force Officer Attrition: An Econometric Analysis

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Introduction

The Retention Problem

- Personnel management is a concern for any organization
- The Department of Defense (DoD) in particular is concerned with retention as it must grow its leadership from the bottom
- The military places unique stressors on its members and their families, who play a significant role in individual retention decisions (Fugita and Lakhani 1991)
  - These stressors can also help create highly desirable skill sets (Kane 2012)
- Civilian labor markets can offer competitive compensation (Kane 2012)

Econometric Approach

- Saving, et al (1985) find evidence that civilian wages and unemployment could be related to retention patterns
- Schofield (2015) uses logisitic regression to identify key demographic factors affecting non-rated attrition
- Franzen (2017) applies similar methods to the rated officer corps, primarily focusing on demographic variables, and also finds evidence of economic influence
- Jantscher (2016) utilizes correlation analysis to identify economic indicators correlated with retention, and attempts to model retention with a regression model

Assumptions and Limitations

- We assume that there exists at least one economic indicator that inform an individual member's retention decision
- Standard assumptions associated with regression modeling and forecasting are made

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Methodology Overview

Prerequisites

- Regression modeling utlizes exogenous variables (predictors) to predict a separate variable (response)
  - Assumes predictor variables are independent of each other
  - Assumes errors are normally and independently distributed with a mean of zero and constant variance
  - Seeks to explain variance in response using predictors

Prerequisites

- Times series modeling relies on the relationship between a variable and previous observations of itself, known as autocorrelation
- Stationarity refers to the mean and variance of a time series variable
  - A stationary variable's value does not depend on the time at which it is observed
- Differencing is one method for treating non-stationary variables

$$y'_t = y_t - y_{t-1}$$

Prerequisites

- Backshift notation is often used when defining time-series models

$$B^k y_t = y_{t-k}$$

- Specifying a model often involves splitting the data into at least two sections, training and validation
- The training set is used to estimate parameters of the theorized model
- The validation set is used to assess model performance

Prerequisites

- Model performance and fit is assessed by the behavior of the residuals, and several criteria:
  - Corrected Akaike Information Criteria (AICc) estimates information loss
  - Training and Validation root mean square error (RMSE) summarizes the discrepancy between predicted values and observed values

Data Composition

- The Strategic Analysis branch of the Force Management Division of Headquarters Air Force (AF/A1XDX) provided monthly observations of voluntary separations from the officer corps from October 2004 to September 2017
  - Data are retrieved from the Military Personnel Data System (MilPDS)
  - Data input is a mix of manual contributions by trained personnelists and automatic updates
  - Total of 157 observations across 67 AFSCs

Data Composition

- Federal Reserve Bank of St. Louis maintains a freely accessible economic database, FRED
- Historical data on several economic indicators were retrieved: unemployment (seasonally adjusted and not), labor force participation, job openings (adjusted and not), job quits, labor market momentum, real gross domestic product per capita, and the consumer price index
- Job indicators are from the nonfarm sector, and all indicators have been seasonally adjusted unless otherwise specified
- Missing values, date modification, data merging

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Analysis and Results

Initial Exploration

- Significant spikes during 2005, ’06, ’07, and ’14 and no obvious seasonality

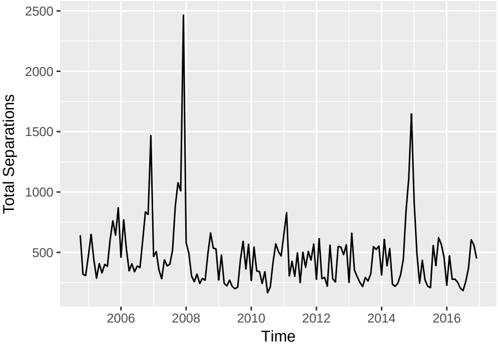


Figure 1: Total Attrition

Initial Exploration

- Separating by year reveals seasonality in response

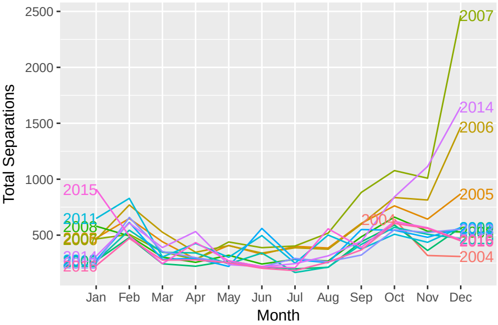


Figure 2: Seasonality Plot

Initial Exploration

- We know from the data provider that the spikes in attrition were most likely due to special programs designed to incentivize attrition
- Opt to replace outliers with the average of the corresponding months
  - e.g. November 2006, '07, and '14 are replaced with arithmetic mean of November observations in all other years

Initial Exploration

- Data are much better behaved, and appear stationary

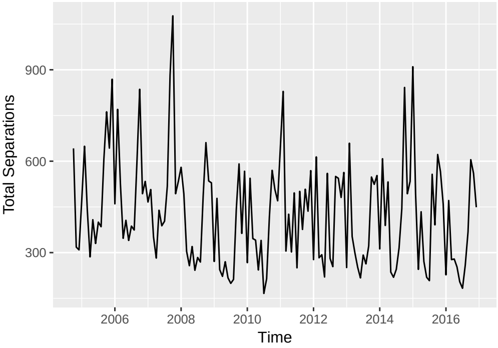


Figure 3: Total Attrition (Imputed)

Initial Exploration

- Seasonality effects are much more pronounced in the imputed data set

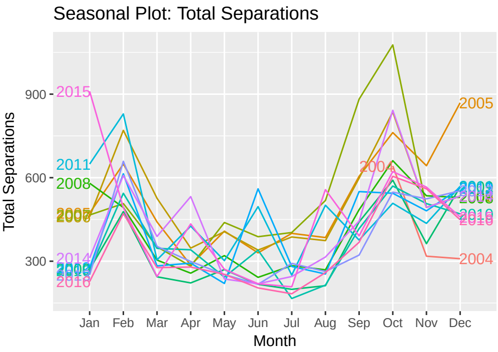


Figure 4: Seasonality Plot (Imputed)

Initial Exploration

- We fit a naive model to both the raw and imputed data to compare the effect on RMSE
- The naive results also provide a baseline to compare later models against
  - If other models perform worse than the naive, then they aren't useful

	Raw Data	Imputed Data
Training	291.791	161.262
Validation	454.288	186.584

Figure 5: Naive Model Comaprison

Dynamic Regression

- Naive models are simple, regression models adequately involve exogenous predictor variables, and time-series models handle autoregressive components of data
- The last two techniques are combined in the dynamic regression model (or transfer function)
  - A multivariate regression is fit using economic indicators as predictors, and an ARIMA model is fit on the errors

Dynamic Regression

- The general formulation of a dynamic regression model with ARIMA(1,1,1) errors is:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \dots + \beta_k x_{k,t} + n_t$$

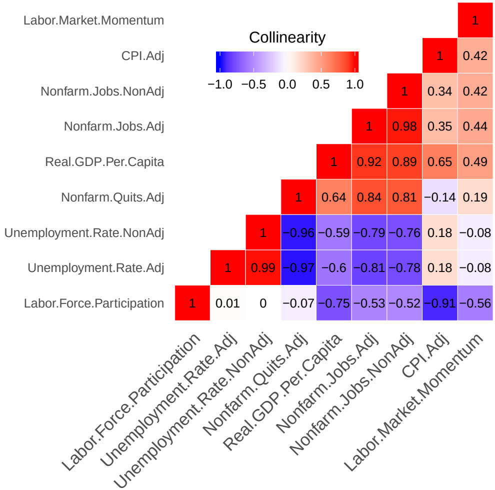
where,

$$(1 - \phi_1 B)(1 - B)n_t = (1 + \theta_1 B)e_t$$

and e_t is white noise.

Dynamic Regression

- A correlation matrix of candidate regressors is generated to help avoid interdependent predictor variables



Dynamic Regression

- Unemployment, labor force participation, and labor market momentum have low correlation and are selected for initial modeling
- Before modeling, we must assess the stationarity of these regressors
    - Dynamic regression requires that the predictor variables are stationary in addition to the response

Dynamic Regression

- Clear evidence of non-stationarity, so we look to differencing

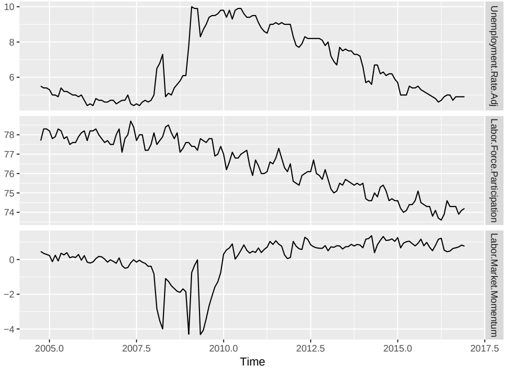


Figure 7: Raw Economic Indicators

Dynamic Regression

- Simple differencing produces desired effects, regressors now show month to month change in indicators

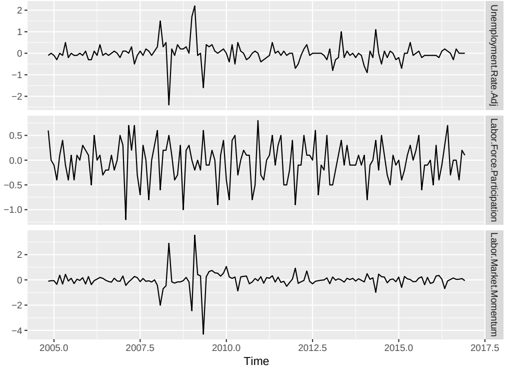


Figure 8: Raw Economic Indicators

Dynamic Regression

- We move to the ARIMA portion of the model
  - Up to six parameters can be specified: the order of autoregression, degree of differencing, the order of the moving average (p, d and q, respectively), and their seasonal counterparts (P, D and Q)
- A range is specified for each parameter, and model is fit for every combination within those ranges
- The model with the lowest AICc is selected
- All subsequent dynamic regression models are selected in this manner, using the ranges/values: $p, q \in [0, 5]$, $d, D = 0$, and $P, Q \in [0, 2]$

Dynamic Regression

- The first model selected was a regression model with a fourth-order moving average and first-order seasonal autoregression on the errors:

$$y = \beta_0 + \beta_1 x'_{1,t} + \beta_2 x'_{2,t} + \beta_3 x'_{3,t} + n_t$$

where,

$$(1 - \Phi_1 B^{12}) n_t = (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3 + \theta_4 B^4) e_t$$

and,

$$x'_{i,t} = x_{i,t} - x_{i,t-1}$$

Dynamic Regression

- To assess model adequacy, we first look at the residuals

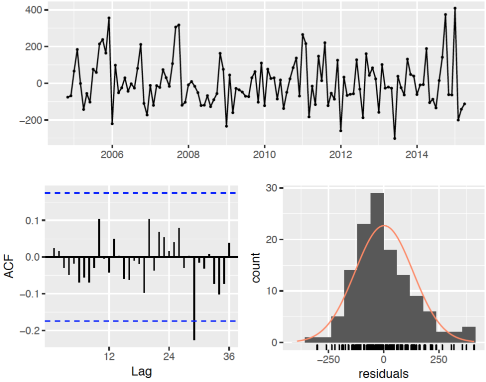


Figure 9: Initial Model Residual Analysis

Dynamic Regression

- Unfortunately, the regression coefficients have high standard errors, implying that none of the economic indicators significantly explain the variance in attrition
- Instead, the ARIMA model handles all the information and regression provides no insight

	θ_1	θ_2	θ_3	θ_4	Φ_1	β_0	β_1	β_2	β_3
Coeff	0.218	0.145	0.336	0.260	0.576	429.875	-13.390	-15.949	-2.819
StdErr	0.087	0.088	0.092	0.092	0.082	47.602	22.286	35.016	11.494

Figure 10: Initial Model Coefficients

Dynamic Regression

- There could be several reasons for the insignficant regression coefficients:
  - Month-to-month changes in economic data are mostly marginal, possibly resulting in minute effects on attrition
  - Economic and personnel data are both aggregated to the national level, and it is possible that the aggregation includes enough noise to mask any effects
  - Indicators currently only show the previous month's change (i.e. regression coefficients express the effects last month's information have on current attrition)

Lagged Indicators

- There are many lag-periods to investigate; to decrease computation requirements, analysis is restricted to 0, 6, 12, 18, and 24 month lag-periods
- A model is generated for every combination of predictor and lag-period, amounting to 125 dynamic regression models
- Models are evelauted on three metrics: AICc, training and validation RMSE
- Top models based on those metrics are identified and further anaylyzed

Lagged Indicators

- We look for models that perform well in all criteria using summary statistics and searching for commonalities
- Three models were identified: when the unemployment rate, labor force participation, and labor market momentum are respectively lagged at (24, 18, 6), (24, 18, 18), and (24, 18, 24)
- All three cases showed similar a similar pattern
  - The unemployment rate is a significant predictor, labor force participation has a large but insignificant effect, and labor market momentum has a small and insignificant effect

Lagged Indicators

- Investigation into the calculation of labor market momentum reveals that it is a combination of many other indicators, including labor force participation
- It might be worthwhile to remove labor market momentum from the model and re-evaluate
- Lagged model analysis is repeated, with only unemployment and labor force participation used as predictor variables
- Models are compared as before, searching for top performers based on AICc, training and validation RMSE

Lagged Indicators

- Only one model is selected as a 'top performer': unemployment and labor force participation lagged at (24, 18)
- Lag periods appear in previous results
- The same pattern holds, as well: unemployment is significant and labor force participation is not
- So far, models have kept to the same subset of regressors, but it is possible that a different subset will yield better results

Alternative Indicators

- Nonfarm job quits and labor force participation have the next lowest correlation coefficient
- Lagged analysis is repeated with these two as predictor variables, and the models are compared in the same fashion
- Again, only one model is identified as a 'top performer': nonfarm job quits and labor force participation respectively lagged at (24, 24)
- This time, however, neither of the regression coefficients were statistically significant

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Conclusion

Insights

- No evidence that recent changes in economic environment (measured by unemployment, labor force participation, and labor market momentum) affect attrition
- The unemployment rate lagged at 24 months show significant effects on attrition in every top model identified
- Dynamic regression models generally exhibited better forecasting performance than naive forecasts

Further Research

- Many economic indicators other than those described are easily available; it is possible that some other combination could uncover evidence of a stronger relationship to attrition
- Only 5 lag-periods were analyzed
- Disaggregation of data could prove useful in revealing stronger relationships
- Analysis could be extended to the enlisted population

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Questions?