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Forecasting Traditional vs Blended Retirement System for Individual Service Members

Kevin M. Dwyer

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THESIS

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DEPARTMENT OF THE AIR FORCE
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Wright-Patterson Air Force Base, Ohio

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FORECASTING TRADITIONAL VS. BLENDED RETIREMENT SYSTEM FOR INDIVIDUAL SERVICE MEMBERS

THESIS

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Department of Systems Engineering and Management
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in Partial Fulfillment of the Requirements for
the Degree of Master of Science in Cost
Analysis

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THESIS

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Abstract

Starting January 1, 2018, the Department of Defense new Blended Retirement System (BRS) will go into effect. Military members with less than twelve years of service will have the option to either remain in the current High 3 Retirement System or opt into the BRS. This decision will have a lasting impact on their lives well beyond their military careers. With this in mind, we have developed a Decision Support System that will enable service members to compare the two retirement choices in terms of annual and total lifetime expected value.

There were three phases to the development of the decision support tool. First, we identified Simple Exponential Smoothing Method and Artificial Neural Networks as the most accurate forecasting techniques to predict the Thrift Savings Plan Funds' rate of return. Next, we identified surrogate TSP portfolios based on minimizing downside risk. In the third phase, we identified risk tolerance and the continuation pay multiplier as the key drivers for differentiating between the two systems. Finally, the resulting Decision Support System leverages current time series forecasting techniques, behavioral economic theory, and Bayesian statistics to capture the complexity of this important decision while delivering relevant information to service members in a straightforward manner using an R Studio Shiny Application.

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I would like to thank my Research Advisor, Dr. David Fass, for allowing me to develop my own thesis topic and support throughout the course of this thesis effort. Most importantly I would like to thank my girlfriend for her constant love and devotion throughout the entire process.

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FORECASTING TRADITIONAL HIGH 3 RETIREMENT SYSTEM VS. BLENDED RETIREMENT SYSTEM FOR INDIVIDUAL SERVICE MEMBERS

I. Introduction

1.1 Background

The National Defense Authorization Act (NDAA) for FY 2013 tasked the Military Compensation and Retirement Modernization Commission (MCRCM) with providing recommendations on reforming the Department of Defense military retirement system. Based on the subsequent report provided by the MCRCM in 2015, the NDAA for FY16 authorized changes to the military retirement system from the High Three Retirement System to the Blended Retirement System (BRS), specifically: a reduction in the defined benefit annuity multiplier, a 401(k) style matching program, and a mid-career lump sum payment. Starting on January 1, 2018, and continuing through December 31, 2018, service members with less than 12 years of service will have the option to decide whether they want to opt in to the new BRS.

1.2 Problem Statement

Many service members may make an uninformed decision when assessing which retirement system to choose unless they are provided sufficient education and analytical tools. Currently, the Office of the Secretary of Defense, Department of Homeland Security, Department of Health and Human Services, and the Department of Commerce have been tasked with providing service members with financial education and decision analysis tools. Specifically, the Office of the Under Secretary of Defense for Personnel and Readiness has led the BRS implementation effort to include service member education (*National Defense*

Authorization Act for Fiscal Year 2016, 2015; Office of the Under Secretary of Defense & Personnel and Readiness, 2016). For instance, in January 2017, the Department of Defense provided service members with calculators which rely on the service members inputting their own discount rate.

While some basic, general tools have been developed to aid decision-making, there is a gap in significant research and a lack of investment into preparing individuals for this decision. In contrast, we developed a Blended Retirement System Decision Support System that attempts to make reasonable assumptions for service members and project the expected monetary value of the two potential retirement systems. The Decision Support System is the resulting product from this research to be presented in Chapters 2, 3, and 4. The Decision Support System intends to prepare individuals for making the decision between the two retirement systems by providing service members' a robust, analytical tool to aid their retirement planning. Since the Military Compensation and Retirement Modernization Commission (MCRCM) published its final report and the FY16 NDAA was signed, there has been no comprehensive published research on the Blended Retirement System's effect on service members.

1.3 Research Objectives

The objective of this research is to better prepare military service members for choosing which retirement system is most appropriate for their individual circumstances. To this end, the primary goal is to build an R Studio Shiny Application that gives the service member a visual interactive tool to predict expected monetary value for both the traditional High Three Retirement System and Blended Retirement System. The expected monetary value will be a time-phased expected value of the High Three Retirement System versus the Blended Retirement System based on assumptions and variables tested in this study. The study will use these variables to forecast the rate of return based on an individual's investment risk tolerance and likelihood of remaining in the military for over 20 years. For this study, the individualized retirement system recommendation will be the ultimate utility of the tool.

1.4 Research Questions

In order to adequately provide service members with a representative expected value for their retirement system decision, we must develop a framework for the inquiry.

1. What is the appropriate Thrift Savings Plan fund allocation based on an individual's risk versus return expectations?
2. Based on an individual's Thrift Savings Plan portfolio allocation and contributions, what long-term rate of return can be expected for his or her TSP Portfolio?
3. What variables are the main drivers in differentiating between the High Three Retirement System and the BRS?

1.5 The Way Ahead

Given the scope of the research questions, this thesis will follow a scholarly article, or k-paper model. Chapter 2 will analyze which techniques are appropriate for forecasting the TSP individual fund's rate of return for the retirement decision time horizon. Chapter 3 develops Downside Risk Optimization TSP portfolios based on risk tolerances and analyzes how the developed portfolios perform against current L funds, which are time horizon portfolios composed of individual TSP funds. Chapter 4 identifies which variables are significant in are key drivers in differentiating between the High Three Retirement System and the Blended Retirement System. The tool incorporates a variety of statistical techniques including forecasting techniques, optimization, and Bayesian Inference. Chapter 5 discusses the overall findings from three papers and suggests future research topics.

II. Predicting 50 Year Thrift Savings Plan Rate of Return

2.1 Introduction

The new Department of Defense (DoD) military Blended Retirement System (BRS) will move away from a cliff vesting defined annuity benefit to a Blended Retirement System (BRS) consisting of a reduced cliff vesting defined annuity benefit, a 401(k) defined contribution matching program, and a one-time lump sum payment when a service member is between eight and twelve years of service. The minimum value of the onetime lump sum payment is two and half times an individual's one month pay. The 401(k) style defined contribution-matching program will utilize the current Federal Retirement Investment Board's Thrift Savings Plan (TSP) as the matching program investment vehicle. The new system requires a service member to make a decision to opt in to the BRS (*National Defense Authorization Act for Fiscal Year 2016*, 2015). Important considerations for this decision include the TSP portfolio allocation, the TSP funds' rate of return, and the likelihood that a service member will remain in the military for at least 20 years of service. These inputs have different characteristics and purposes in our Decision Support System. The rate of return is an unknown variable, the portfolio allocation is an input variable, and the likelihood of remaining in the service for 20 years is an input variable. These three inputs along with a service member's individual characteristics such as age, rank, and projected TSP withdrawal data are used to calculate expected monetary values for both retirement systems in the Decision Support System. We explore modeling and forecasting TSP funds' long-term annual rate of return for use in the Decision Support System.

2.2 Background

The Thrift Savings Plan will be the foundation of the new BRS matching program set to take effect on January 1, 2018. All service members with less than 12 years of service will be able to opt in to the BRS or remain in the incumbent retirement system. Note, these service members must make this one-time binding decision between January 1, 2018 and December 31, 2018. Service members who enter the military after January 1, 2018 will automatically be enrolled into the Blended Retirement System. The BRS will automatically deposit an amount equal to 1% of service member's basic pay into a TSP account, will match the first 3% the service member elects to contribute, and will match 50% of the next 2% contributed by the service member. In total, the program will match up to 5% of a service member's pay per month (*National Defense Authorization Act for Fiscal Year 2016*, 2015). The Thrift Savings Plan is composed of five investment funds and five mixed lifecycle funds.

Table 1.Thrift Savings Plan Funds

Fund	Description	Inception Date	Objective
Government (G)	Government Securities	April 1 ,1987	Interest income without risk of loss of principal
Fixed Income (F)	Government, Corporate and Mortgage-backed bonds	Jan 29, 1988	To match the performance of the Barclays Capital U'S Aggregate Bond Index
Common Stock (C)	Stock of large and medium sized U.S. Companies	Jan 29, 1988	To match the performance of the Standard and Poor's 500 (S&P 500) Stock Index
Small Capitalization Stock (S)	Stock of small to medium sized U.S. Companies not included in C Fund	May 1, 2001	To match the performance of the Dow Jones U.S. Completion TSM Index
International Stock (I)	International stocks of more than 20 developed countries	May 1, 2001	To match the performance of the MSCI EAFE (Europe, Australasia, Far East) Index
Lifecycle Funds (L)	Invested in G,F,C,S, and I Funds	Aug 1, 2005	To provide professionally diversified portfolios based on various time horizons, using the G,F,C,S, and I Funds

As shown in Table 1, the investment funds include one treasury fund (G) and four funds with the objective of matching a market index (F, C, S, I). Regardless of portfolio selection, the rate of return must be used in any expected monetary value calculation. It is impossible to predict exact annual returns for the market over the next fifty years. Since the Blended Retirement System is affected by fluctuations in the bond and equity markets (while the High Three is not), a rate of return for the TSP funds must be forecasted. The two cannot be adequately compared without the rate of return because the return is an innate characteristic of the TSP. The return on an individual TSP account will be used to compare the High Three and

BRS cliff vesting multipliers. Using a credible model for market activity over the next half century is essential to helping service members make the correct decision based on their individual situation and preferences. Many decision makers may have a tendency to compare the two retirement systems based upon the mean and standard deviation of the return of the investments over the long term. Unfortunately with this approach the mean will dramatically under or overestimate returns because the market has "fat tails" and standard deviation is insufficient to capture the distribution for the stock market rate of return (Cont, 2001). When the market is highly volatile, the magnitude of negative rate of returns is greater than the magnitude of positive rate of returns (Onour, 2010). The financial market historically moves towards the mean annual return but huge fluctuations in the past have caused significant impacts on accounts. For instance, the mean annual return of the S&P 500 from 1965 to 2015 was 11.01%; however, in 1995 it gained 37% but lost 22% in 2002 and 37% in 2008 (Damodaran, 2016).

To demonstrate the potential hazard of relying on mean rate of return to estimate actual returns, we ran the following comparison. The starting value in each fund is $10,000, and $10,000 is added each year from 1988 to 2015 (note, the S and I funds did not start until 2006) and then comparison between the actual and mean returns is provided in Table 2. We can see that the mean rate of return consistently overestimated the actual returns.

Table 2. Mean vs Actual Rate of Return Comparison

	Actual	Mean	Percent Delta
G Fund	$547,055	$638,567	17%
F Fund	$696,545	$799,456	15%
C Fund	$1,225,109	$1,993,237	63%
S Fund*	$332,506	$347,486	5%
I Fund*	$219,285	$246,880	13%

2.3 Previous Research

Scholars have used many different forecasting methods, including times series, linear regression, and machine learning, to model the performance of index funds (Abu Mostafa & Atiya, 1996; Akgiray, 1989; Altay, 2005; Fama, 1965; Wang, Wang, Zhang, & Guo, 2012). Nevertheless, it has been shown that financial markets are very noisy and difficult to predict based on past history (Abu Mostafa & Atiya, 1996). Market forecasting research tends to fall into one of three categories: statistical methods, artificial intelligence methods, or a combination of the two (Wang et al., 2012). Research based on statistical methods often relies on the Generalized Auto Regressive Conditional Heteroscedasticity (GARCH) model and the Autoregressive Integrated Moving Average (ARIMA) model. Artificial intelligence models focus on using nonlinear artificial neural networks (ANNs) to forecast future returns. More recent research has focused on creating hybrid models between the two classes such as the Wang Hybrid Model using exponential smoothing, ARIMA, and ANNs to capture the strengths of all the methods (Wang et al., 2012).

In this paper, we analyze established forecasting methods and project 10-year time horizons conditioned upon the preceding twenty-two years of data. The purpose of this research is to capture the volatility in the market over large time horizons to provide the Decision Support System with an appropriate starting point for comparing the Blended Retirement System and High Three Retirement System. Specifically, we attempt to characterize the difference between the variable defined compensation aspects of the Blended Retirement System (i.e., the 401(k) and mid-career payment) and the additional .5% per annum for the cliff vesting defined annuity benefit.

Since each TSP Fund has unique characteristics, each fund needs to be separately modeled. Based on previous research, the five investment funds were analyzed using ARIMA, Backpropagation Neural Networks (BPNN), and Exponential Smoothing (Wang et al., 2012). Each fund was analyzed individually using the three techniques with the best performing techniques applied to the Decision Support System. Specifically, Mean Absolute Percent Error (MAPE) and Mean Absolute Deviation (MAD) analyses were used to determine the best technique. Since there is not a consensus in the literature on which accuracy measure is the standard for the stock market, both measures will be used to support the analysis and model.

To train our models, we predict the annual stock returns from 2006-2015 based on the returns from the previous twenty-two years (1984-2006). These time intervals were chosen to reflect a long time horizon. The Decision Support System needs to estimate over a long time horizon due long life expectancy of service members post retirement. Service members average age at retirement is 42.4 years of age and United States life expectancy is currently 78.8 years (Allen & Garcia, 2013; Xu, Murphy, Kochanek, & Bastian, 2013).

2.4 Methodology

Data.

The daily, weekly, and annual rates of returns from inception until July 2016 were obtained for all the TSP funds from the TSP website. The inception dates for each of the funds are provided in Table 3.

Table 3. TSP Fund Inception

TSP Fund	Inception Date
Common Stock	1988
Government	1987
Fixed Income	1988
Small Capitalization	2001
International Stock	2001
Life Cycle Fund 2020/2030/2040	2005
Life Cycle Fund 2050	2012

L Funds are developed based on an efficient frontier used to build portfolios out of the five primary funds with each L fund allocation changing each quarter based on the fund's retirement date(The Federal Retirement Thrift Investment Board, 2016). Prior to inception dates, the data used in this research is based on the index that the TSP funds are attempting to mirror. As a proxy for L Funds historical data, a composite was developed mirroring the L Fund trading strategy going back to 1960. The data for the Thrift Savings Plan was obtained from its website and the index historical data was pulled from Yahoo Finance. Data normalization was completed using the R Studio software program (RStudio Team, 2016).

Autoregressive Integrated Moving Average (ARIMA).

The first statistical model used to forecast rates of return on the five investment funds is an ARIMA model. We apply ARIMA models using the three-step Box-Jenkins method to determine which model is best. The ARIMA model assumes that the future value of a series is based on a linear function of past data points. ARIMA models consist of three parts: Autoregressive (AR), Integration (I), and Moving Average (MA). AR, I, and MA are represented in the model by parameters *p, d,* and *q*, respectively, where *p* is the number of autoregressive terms, *d* is the number of non-seasonal differences, and *q* is the number of lagged forecast errors in the prediction equation (Wang et al., 2012). Under the Box-Jenkins methodology, mean and variance stationarity is required. If the data are not already stationary, they can be transformed using logarithmic or power transformations. Stationarity of variance and mean was assessed using the Augmented Dickey-Fuller Test. The Dickey-Fuller procedure tests whether a variable has a unit root that follows a random walk around a trend--i.e., is the unit root a random walk around a trend or is the unit root a trend stationary process? If the data are still not stationary after the transformation, they need to be "differenced." Differencing the data is accomplished using the following equation:

$$\acute{Y}_t = Y_t - Y_{t-k} \tag{1}$$

Y_t is the data at time *t and* Y_{t-k} is the data at time period *t-k*. After the data are stationary, the next step is to examine the autocorrelation and partial autocorrelation functions to identify potential models. The auto correlation function relates different *Y* points with *k* lags using the following equation:

$$r_k = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{2}$$

The partial autocorrelation function removes the effect of other lags in the time series to measure the relationship between Y_t and Y_{t-k}. The partial autocorrelation function equation is

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \cdots \ldots + b_k Y_{t-k} \tag{3}$$

Where b_0 is the intercept, Y_{t-k} is the data at time period *t-k*. In order to determine the appropriate *p* and *q* values in the ARIMA model, the individual models were compared using the Akaike Information Criterion (AIC). AIC is a measure for comparing models by attempting to estimate the relative information loss in the model (Burnham & Anderson, 2004). AIC is calculated by

$$AIC = -2ln(L) + 2k \tag{4}$$

Where *k* is the number of estimated parameters (including the intercept and residual variance) and *L* is the likelihood function. A lower AIC value produces a better model; however, the models can only be compared with the same order of differencing. The model coefficients were derived using an objective nonlinear optimization procedure based on the steepest descent method. Specifically, we used the Marquardt optimization procedure within the R program (Roweis, n.d.). Table 4 shows the p, d, and q values that are used in the ARIMA models.

Table 4. ARIMA Parameters

Fund	AR(P)	I(D)	MA(Q)
C Fund	2	2	4
F Fund	3	0	2
S Fund	1	1	4
I Fund	2	1	5
G Fund	0	2	1

Backpropagation Neural Network.

Artificial Neural Networks (ANN) may be characterized as an advanced pattern recognition technique. Neural Network was chosen because neural network can approximate mappings of input and output without linearity (Rather, 2011). This research used ANNs to forecast time series TSP funds. There are many different types of ANNs but this research will use the Backpropagation training method first introduced by Rumelhart (Rumelhart, Smolensky, McClelland, & Hinton, 1986). The following Backpropagation methodology, as outlined in Neural Network Time Series Forecasting of Financial Markets (Azoff, 1995), is used to predict the future rate of return for each fund.

Table 5. Neural Network Parameters

Fund	AR(P)	K (Hidden Nodes)
C Fund	1	1
F Fund	1	1
S Fund	1	1
I Fund	1	1
G Fund	1	1

Simple Exponential Smoothing Model.

Simple Exponential Smoothing Model allows for forecasting data without a trend. Exponential Smoothing method is was chosen because it can be used with both homoscedastic and heteroskedastic data and does not require stationarity. The technique uses two smoothing equations and a forecasting equation (Hyndman & Athanasopoulos, 2017).

$$\hat{y}_{t+1|t} = \ell_t \quad (5)$$

$$\ell_t = \alpha y_t + (1-\alpha)\ell_{t-1} \quad (6)$$

Equation 5 (the level equation) describes ℓ_t as the weighted average of observation y_t one-step prior in time. Equation 6 (the trend equation) shows the forecasted value at *t+1* is the estimated at time *t*. The coefficients and alpha for the funds are shown in Table 6.

Table 6. Exponential Smoothing Parameters

Fund	Alpha	Coefficient
C Fund	0.092	7.440
F Fund	0.184	3.665
S Fund	0.135	8.912
I Fund	0.033	4.560
G Fund	0.230	2.640

Forecasting Accuracy Tests.

Once the forecasts are developed, accuracy tests are used to identify which forecasting method is most accurate for each individual TSP fund. We identified Mean Absolute Percent Deviation and the Mean Absolute Deviation for our accuracy tests. MAPE was identified because it is the most common measure for forecast error and MAD was identified because it is most useful in measuring forecast error when linked to an independent measure of value ("Mean Absolute Deviation (MAD), Mean Absolute Error (MAE)," 2017). In some cases the MAPE and MAD will yield different results. When MAPE and MAD differ on which forecasting method is most accurate, MAD will be used because MAPE is significantly affected by percent errors near zero. For instance, the mean value will produce a few values with a very low deviation which will skew MAPE downward.

Mean Absolute Percent Error.

Mean Absolute Percent Error (MAPE) is a measure of prediction accuracy; mathematically, it is the average absolute percent error for each time forecast ("Mean Absolute

Percent Error," 2017) –see Equation 7.

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\frac{|F_k - A_K|}{A_k} \quad (7)$$

Where *N* is the number of observations, F_k is the fitted value for observation K *and* A_k is the actual value for observation K.

Mean Absolute Deviation.

Mean Absolute Deviation (MAD) is the average absolute forecast error for a set of observed events ("Mean Absolute Deviation (MAD), Mean Absolute Error (MAE)," 2017) –see Equation 8.

$$\text{MAD} = \frac{1}{N}\sum_{k=1}^{N}|F_k - A_K| \quad (8)$$

Where *N* is the number of observations, F_k is the fitted value for observation *K* and A_k is the actual value for observation *K.*

2.5 Analysis

Common Stock Index Investment Fund Analysis.

The Common Stock Index Investment Fund (C Fund) is the most popular index fund for TSP investors. As of December 31 2015, the C Fund has assets of $142.2B which is second only to the G Fund. The C Fund objective is to match performance of the Standard and Poor's 500 Index which is comprised of 500 large to medium sized United States companies. The C Fund can be characterized as an index fund which tracks the S&P 500 index. The S&P 500 increases and declines in response to negative overall changes in economic conditions in the United States and abroad. The C Fund was analyzed, after the data was adjusted for inflation, using the forecasting methods from section 1.5. Figure 1 shows the summary statistics and distribution for the combination of the C Fund since 1987 and the S&P 500 from 1984-1987.

Summary Statistic	
Mean	0.093346
Std Dev	0.170638
N	32
Variance	0.029117
Interquartile Range	0.240835

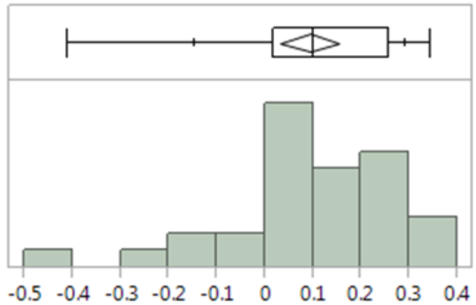

Figure 1. C Fund Summary Statistics and Distribution

Figure 2 shows an example of the how the C Fund actuals compared against ARIMA forecasted values. As seen in Figure 2, the forecasted rate of return for the Common Stock Index Fund varied drastically from year to year. Appendix A has the remainder of the deviation plots and tables for the Common Stock Index Investment Fund.

	Actual	Forecast	Deviation
2006	11.80	-9.93	21.7
2007	3.46	-6.43	9.9
2008	-41.27	9.52	50.8
2009	26.65	14.20	12.4
2010	12.43	-43.96	56.4
2011	0.48	22.26	21.8
2012	13.14	28.16	15.0
2013	30.86	-39.10	70.0
2014	12.20	22.15	10.0
2015	1.55	-26.38	27.9

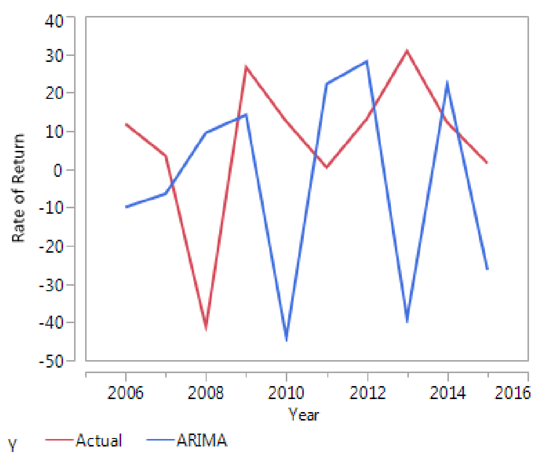

Figure 2. C Fund ARIMA Forecast vs Actuals

After fitting all three models, the Mean Absolute Deviation and Mean Absolute Percent Error were calculated for the C Fund—see Table 7.

Table 7. C Fund Forecast Accuracy Tests

Common Stock Index Investment Fund Deviation			
	ARIMA	Exponential	Neural Network
MAPE	7.61	2.37	2.94
MAD	29.59	12.80	12.37

As mentioned in the methodology, in some cases there will be discrepancies between the forecasting accuracy measures. In this case the Simple Exponential Smoothing Method and Neural Networks perform best on the test data.

Small Capitalization Stock Index Investment Fund Analysis.

The Small Capitalization Stock Index Investment Fund (S Fund) is comprised of a broad group of medium to small companies that are not included in the S&P 500 index. The S Fund objective is to match the performance of the Dow Jones United States Completion Total Stock Market Index. The S Fund, as seen in Figure 3, generally has similar characteristics as the Common Stock Index; the variation is larger though due to the fact that small and medium stock returns have fatter tails historically. When the economy is doing well, small and medium stocks rise at a faster rate and similarly decline at a faster rate when the economy is contracting (Switzer, 2012).

Summary Statistic	
Mean	0.094316
Std Dev	0.196408
N	32
Variance	0.038576
Interquartile Range	0.304825

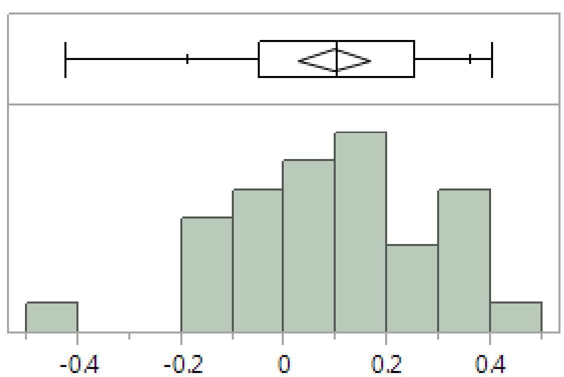

Figure 3. S Fund Summary Statistics and Distribution

Figure 4 shows the difference between the actuals and ARIMA model for the S Fund. Appendix

A has the remainder of the deviation plots and tables for the Small Capitalization Stock Index Investment Fund.

	Actual	Forecast	Deviation
2006	11.31	1.17	10.1
2007	3.41	-5.71	9.1
2008	-42.60	-14.12	-28.5
2009	34.82	16.95	17.9
2010	26.43	-13.91	40.3
2011	-5.01	10.74	-15.8
2012	15.64	-12.01	27.6
2013	36.76	33.31	3.4
2014	6.22	-13.35	19.6
2015	-2.83	-16.43	13.6

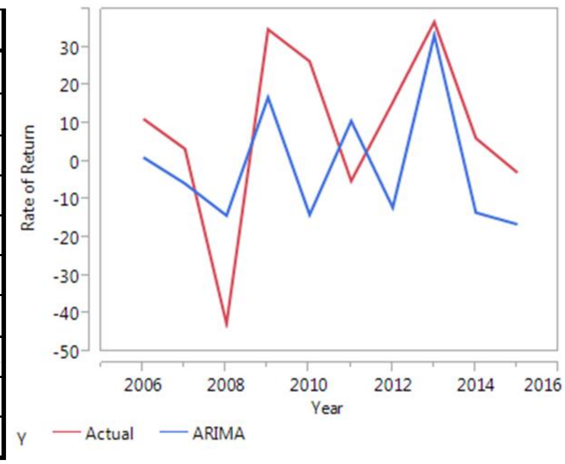

Figure 4. S Fund ARIMA Forecast vs Actuals

After fitting the available three models, the Mean Absolute Deviation and Mean Absolute Percent Error were calculated for the S Fund—see Table 8.

Table 8. S Fund Forecast Accuracy Tests

Small Capitalization Index Investment Fund Deviation			
	ARIMA	Exponential	Neural Network
MAPE	1.92	1.30	1.14
MAD	18.59	16.58	16.64

As with the C Fund, the S Fund results show a discrepancy with the forecasting accuracy measures but the Simple Exponential Smoothing Method and Neural Networks perform best on the test data.

Fixed Income Index Investment Fund Analysis.

The Fixed Income Index Investment Fund (F Fund) objective is to match the performance of the Barclays Capital United States Aggregate Bond Index by acquiring only investment grade securities. The F Fund was initiated in 2006 and can be seen as an alternative for risk adverse investors who want to invest in fixed income investments aside from United States Treasury Bills in the G Fund. As shown in Figure 5, the F Fund has a mean of 4.7% return with a standard deviation of .053; these values are much smaller than either the C or S Fund.

Summary Statistic	
Mean	0.046963
Std Dev	0.053001
N	32
Variance	0.002809
Interquartile Range	0.074375

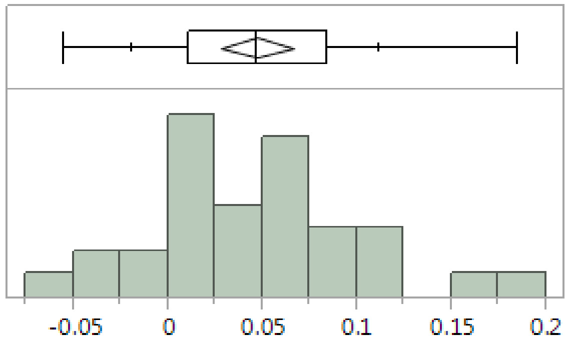

Figure 5. F Fund Summary Statistics and Distribution

Figure 6 shows the deviation between the actuals and ARIMA model for the F Fund. Appendix A has the remainder of the deviation plots and tables for the Fixed Income Index Investment Fund. After fitting the three available models, the Mean Absolute Deviation and Mean Absolute Percent Error were calculated for the F Fund—see Table 9.

	Actual	Forecast	Deviation
2006	0.41	2.30	-1.9
2007	5.01	-3.62	8.6
2008	1.17	3.59	-2.4
2009	5.96	-0.90	6.9
2010	4.08	-3.88	8.0
2011	6.26	-1.84	8.1
2012	1.36	-10.50	11.9
2013	-3.27	-2.62	-0.6
2014	5.15	5.93	-0.8
2015	1.00	2.22	-1.2

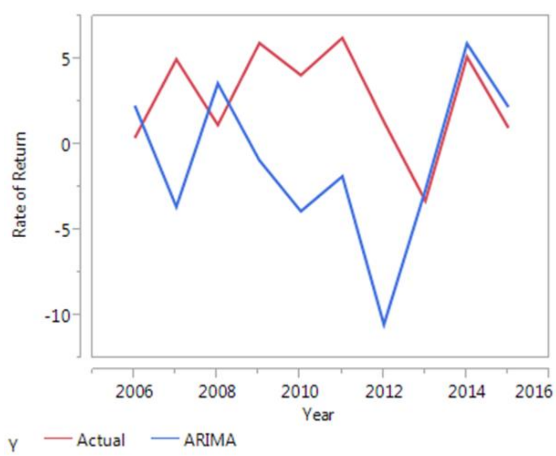

Figure 6. F Fund ARIMA Forecast vs Actuals

Table 9. F Fund Forecast Accuracy Tests

Fixed Income Index Investment Fund			
	ARIMA	Exponential	Neural Network
MAPE	2.31	1.80	2.56
MAD	5.04	2.58	2.82

As shown in Table 9, the Simple Exponential Smoothing Model had the best forecasting accuracy for both accuracy tests.

Government Securities Investment Fund Analysis.

The Government Securities Investment Fund (G Fund) is invested in short term United States Treasury securities specially issued to the Thrift Savings Plan. The principal and interest payments are guaranteed by the United States Government and thus there is no credit risk. The G Fund is the largest TSP Fund as of 31 December 2015. This is most likely due to the number of retirees on fixed income salaries who are looking to protect their assets and individuals who are risk averse and looking to preserve their retirement accounts. As shown in the summary statistics and distribution, the G Fund has a mean return of 3.6% with a standard deviation of .053. These values are much smaller than either the C or S Fund. Interestingly, it has a lower mean rate of return than the F Fund with approximately the same standard deviation.

Summary Statistic	
Mean	0.036541
Std Dev	0.053148
N	32
Variance	0.002825
Interquartile Range	0.031325

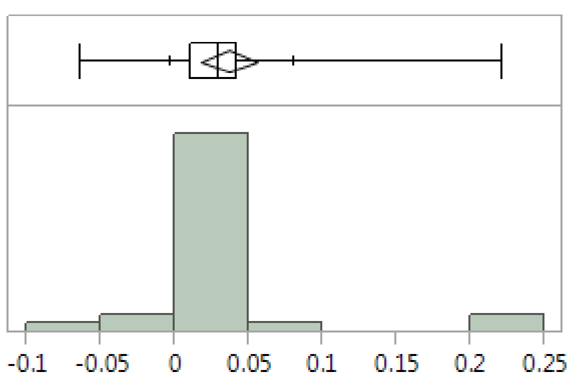

Figure **7.** G Fund Summary Statistics and Distribution

Figure 8 shows the deviation between the actuals and ARIMA model for the G Fund. Appendix A has the remainder of the deviation plots and tables for the Fixed Income Index Investment Fund.

	Actual	Forecast	Deviation
2006	0.94	15.85	-14.9
2007	2.79	-10.73	13.5
2008	-0.53	3.79	-4.3
2009	2.94	-4.10	7.0
2010	0.18	0.09	0.1
2011	0.82	-1.83	2.6
2012	-1.46	-7.11	5.7
2013	0.30	4.71	-4.4
2014	0.73	3.92	-3.2
2015	2.13	-0.08	2.2

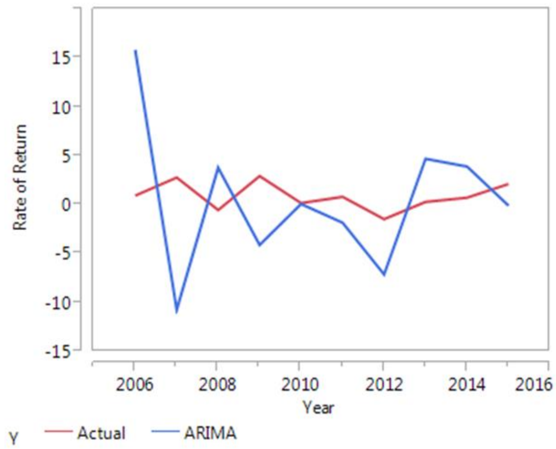

Figure 8. G Fund ARIMA Forecast vs Actuals

After fitting the three models, the Mean Absolute Deviation and Mean Absolute Percent Error were calculated for the G Fund—see Table 10.

Table 10. G Fund Forecast Accuracy Tests

Government Securities Investment Fund			
	ARIMA	Exponential	Neural Network
MAPE	5.90	3.73	4.82
MAD	5.80	1.85	2.44

As shown in Table 10, the Simple Exponential Smoothing Model had the best forecasting accuracy for both accuracy tests.

International Stock Index Investment Fund Analysis.

The International Stock Index Investment Fund (I Fund) invests in stocks in developing countries outside the United States. The objective of the International Fund is to match the MSCI EAFE (Europe, Australasia, and Far East) Index. The I Fund is by far the most volatile fund of the five investment funds; its mean return is below S and C fund which track market indexes within the United States.

Summary Statistic	
Mean	0.073766
Std Dev	0.227556
N	32
Variance	0.051782
Interquartile Range	0.280165

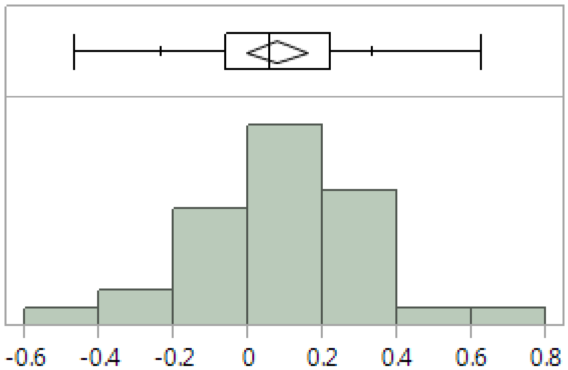

Figure 9. I Fund Summary Statistics and Distribution

Figure 10 shows the deviation between the actuals and the ARIMA model for the I Fund. Appendix A has the remainder of the deviation plots and tables for the Fixed Income Index Investment Fund.

	Actual	Forecast	Deviation
2006	22.33	-34.34	56.7
2007	9.35	6.26	3.1
2008	-46.71	-26.49	-20.2
2009	30.01	24.25	5.8
2010	5.31	-8.50	13.8
2011	-13.44	71.61	-85.0
2012	15.69	-15.51	31.2
2013	20.54	-3.55	24.1
2014	-6.85	-19.76	12.9
2015	-0.42	-3.53	3.1

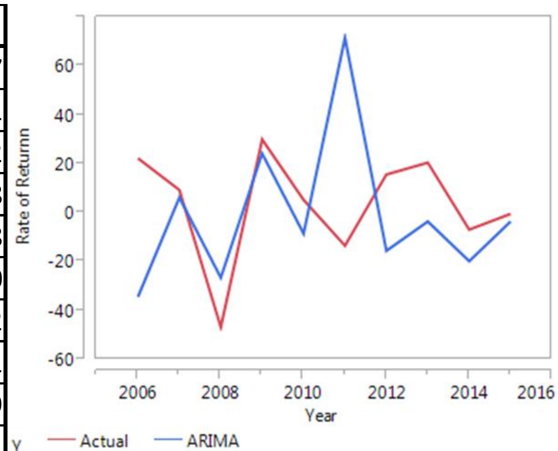

Figure 10. I Fund ARIMA Forecast vs Actuals

After fitting the three models, the Mean Absolute Deviation and Mean Absolute Percent Error were calculated for the I Fund—see Table 11.

Table 11. I Fund Forecast Accuracy Tests

International Index Investment Fund Deviation			
	ARIMA	Exponential	Neural Network
MAPE	2.49	1.98	2.15
MAD	25.59	16.15	16.00

As with the C Fund and S Fund, the I Fund results show a discrepancy with the forecasting accuracy measures but the Simple Exponential Smoothing Method and Neural Networks perform best on the test data once again.

2.6 Discussion and Conclusion

Based on the chosen forecasting accuracy measures, the Neural Network and Simple Exponential Smoothing Model consistently outperformed the Autoregressive Integrated Moving Average model. The results show that ARIMA models do not forecast as well with limited amount of data compared to Simple Exponential Model and Neural Network Model. The results show that low variability in the data does not necessarily mean future returns will be any more accurately predicted than highly volatile indexes in terms of Mean Absolute Percent Error. For instance, the G Fund has a standard deviation of .053 and the best MAPE was 3.73 in comparison to the S Fund which had a standard deviation of .196 but the best MAPE was 1.14. In the case of Mean Absolute Deviation, our results indicate that volatility of the index may have an association with the magnitude of MAD. In this case G Fund had a MAD of 1.85 in comparison to S Fund with a MAD of 16.58. The results from this study will now be used to simulate the rate of return for the Decision Support System. In particular, the Neural Network method will be used for the Common Fund and International Fund; Simple Exponential Model will be used for Small Capitalization Fund, Fixed Income Fund, and the Government Fund. The rates will be bounded using confidence intervals; this will provide service members a reasonable range of rates to compare the two retirement systems.

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III.Thrift Savings Plan Downside Risk Optimization Portfolio Selection

3.1 Introduction

The National Defense Authorization Act for Fiscal Year 2016 (FY16 NDAA) outlined changes to the Department of Defense (DoD) service member's retirement program. The changes require service members to choose between remaining in the traditional cliff vesting defined benefit annuity system (High-Three) or converting to the Blended Retirement System (BRS). The BRS includes both a reduced defined benefit and a new defined contribution component with a 401(k) style-matching program. The 401(k) style-matching program will be coordinated exclusively through the Federal Retirement Investment Board's Thrift Savings Plan (TSP). In order to compare the two systems, individuals need returns based on assumed TSP portfolio to forecast the return of the TSP defined contribution. To support the comparison between the two systems in follow on research, this paper explores using downside risk to develop TSP Portfolios.

In most theoretical models, equity portfolio selection contains two components: risk and return. Fishburn's (1977) model showed that maximum expected utility occurred when all returns were above target value. Researchers have also found that individual investors tend to value protection from losses more than the opportunity for large gains -- implying that most people are risk averse (Kahneman & Tversky, 1979). Conversely, the *downside risk framework* considers the "safety first rule" which measures the likelihood of an outcome falling below the target return (Roy, 1952). Beck (2010) developed downside risk optimized (DRO) TSP portfolios that provided the same level of return as TSP lifecycle (L) funds with less downside risk. This paper extends Beck's research to show whether a DRO portfolio is superior to TSP L funds at conserving assets at different risk tolerances when the economy contracts.

Hypothesis: *Downside Risk Optimization portfolios provide increased conservation of assets compared to TSP L Funds.*

3.2 Background

The FY16 NDAA modified the military retirement system which will take effect on January 1, 2018. All service members who enter military service after January 1, 2018 will automatically be enrolled into the new Blended Retirement System. Current service members with less than 12 years of service as of December 31, 2017 can choose to stay in the High Three system or change to the BRS. The BRS was underpinned by the FY2013 NDAA which established the Military Compensation and Retirement Modernization Commission (MCRMC) to recommend ways to "modernize and achieve sustainability for the compensation and retirement systems for the Armed Forces and the other Uniformed Services for the 21st Century" (Military Compensation and Retirement Modernization Commission, 2015).

In civilian sectors, pension reform has swept the country in both the public and private sectors over the last three decades. The lack of sufficient funding for defined benefit annuity pensions and the decreased returns for pension funds in the decade since the Great Recession has left many private and public pensions underfunded. These decreased rates of return and persistent underfunding have put the onus on municipal leaders, state leaders, and taxpayers to decrease pension shortfalls. According to a 2013 Pew Charitable Trusts report, United States gubernatorial pension plans had a combined $968 billion shortfall which leaves state pensions funded at only 72%--down from 74% funded in 2012 ("The State Pensions Funding Gap: Challenges Persist," 2015). State pension funding levels for future liabilities range from an abysmal 40% in Illinois to 100% in Wisconsin ("The State Pensions Funding Gap: Challenges

Persist," 2015). Within the private sector, many corporations have stopped offering defined benefit pension plans. Table 12 illustrates the changes in the private sector between 1979 and 2013 (Employee Benefit Research Institute, 2016).

Table 12. Changes in Private Sector Retirement

Retirement Type	1979	2013
Defined Benefit Only	28%	2%
Mixed	10%	11%
Defined Contribution Only	7%	33%
None	55%	54%

The United States Congress' decision to change from a cliff vesting defined annuity plan to a blended retirement system reflects the shift over the last three decades for organizations to transition from defined benefit to defined contribution retirement plans. Hustead (1998) showed the reason for most private and public shifts from defined benefit to defined contributions plan is the cost savings associated with the defined contribution plans. He also found that defined benefit administrative costs are upwards of 100% more expensive for small businesses than defined contribution administrative costs. Finally, employers do not need to take into consideration increased longevity with defined contribution plans (Hustead, 1998).

Currently 17% of service members receive some form of retirement benefit after their service. The new Blended Retirement System, in contrast, is expected to provide 85% of service members with a retirement benefit (Military Compensation and Retirement Modernization Commission, 2015). The main difference between the change to the Blended Retirement System and comparative changes in the private sector is that the primary motivation is not to save money but rather to distribute retirement benefits more equitably compared to the current High Three Retirement System. According to the MCRMC recommendations, the Department of Defense will save $6.1 Billion during FY16-20 while achieving $1.9 billion annual savings by 2046

(Military Compensation and Retirement Modernization Commission, 2015). The Congressional Budget Office estimated a $5.3 Billion savings from FY16-20 on the FY 16 NDAA H.R. 1735, Section 631-635, as cleared by the Congress on October 7 2015 (Congressional Budget Office, 2016). To put the savings in context, the Department of Defense retirement obligations for FY2015 were $56.49 Billion (Allen & Garcia, 2016).

The United States Internal Revenue Service (IRS) puts retirement plan options offered to employees into four categories: profit-sharing plans, defined benefit plans, money purchase plans, and employee stock ownership plans. For this research, only defined benefit and profit-sharing plans are considered. The IRS defines a Defined Benefit Plan as "a fixed, pre-established benefit for employees retirement" ("IRS_DefinedBenefitPlan," n.d.). Defined contribution plans fall under the IRS's profit sharing plans. A 401(k) plan is "a feature of a qualified profit-sharing plan that allows employees to contribute a portion of their wages to individual accounts under the plan." Within the 401(k) plan structure, employers may match contributions for employees who contribute to their own 401(k) plan ("Topics for Retirement Plans," n.d.). The Department of Defense matching program in the Blended Retirement System will reflect the 401(k) structure.

The current High Three Retirement System is a cliff vesting defined benefit annuity that vests at 20 years of service. For each year of service, service members accrue 2.5% of their basic pay, but the benefit is held in abeyance until 20 years of service. After 20 years of service, members receive 50% of their base pay per month for life. Service members who depart the service prior to 20 years of service receive no retirement benefit. Conversely, the Blended Retirement System is composed of a reduced defined benefit annuity, a lump sum continuation bonus, and a monthly TSP matching contribution. The multiplier for the annuity portion is reduced from 2.5 to 2 percent. The lump sum continuation bonus occurs at approximately 8-12 years of service and is valued at a minimum of two and one half months of basic pay. Finally, the plan includes a matching contribution on behalf of the member to his or her TSP account based on his or her personal contribution. Specifically, the DoD will automatically contribute 1% basic pay after 60 days of service and will begin matching personal contributions after two years. Figure 11 displays a comparison between the two retirement systems (*National Defense Authorization Act for Fiscal Year 2016*, 2015).

Benefit System	HI-3	BRS
Multiplier	2.5% per YOS	2% per YOS
Continuation Bonus	-	Min 2X Monthly Base Pay
TSP Matching	-	Up to 5%*

Your Contribution	DoD Auto Contribution	DoD Matches	Total DoD Contribution
0%	1%	0.0%	**1.0%**
1%	1%	1.0%	**2.0%**
2%	1%	2.0%	**3.0%**
3%	1%	3.0%	**4.0%**
4%	1%	3.5%	**4.5%**
5%	1%	4.0%	**5.0%**

Figure 11. High Three vs Blended Retirement System

3.3 Previous Research

Modern portfolio management was introduced by Markowitz with Modern Portfolio Theory (MPT). Markowitz attempted to create the optimal investment strategy by using the expected return-variance rule to guide portfolio selection (Markowitz, 1952). Markowitz's *mean variance optimization* method maximizes portfolio returns based on a pre-determined level of risk as measured by the variance. Markowitz computed portfolio expected return as:

$$E = \sum_{i=1}^{N} X_i U_i \tag{9}$$

Where X_i is the percentage of the portfolio allocated to asset *i*, N is the number of assets in the portfolio, E is the expected return of the portfolio, and U_i is the expected return of asset *i*. The assumed level of risk (i.e., variance) is computed by the following equation:

$$V = \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_{ij} X_i X_j \tag{10}$$

Where V is the variance of the portfolio, σ_{ij} is the covariance of the of assets *i* and *j*, and X_i and X_j are the percentages of the portfolio allocated to assets *i* and *j*. Based on MVO, Markowitz was able to create an efficient frontier wherein an investor would achieve the highest expected return based on his or her level of risk along the frontier created by the portfolio mix (Markowitz, 1952).

A natural extension to Markowitz's Modern Portfolio Theory is the Capital Asset Pricing Model (CAPM). CAPM is a model used to determine the rate of return required on an asset to compensate for the systemic risk taken by the investor. CAPM was developed in the 1960's by Treynor (1961, 1962), Sharpe (1964), and Lintner (1965). Specifically, Sharpe (1964) contended that under certain market conditions, mean variance optimization would lead to unsatisfactory prediction of behavior. CAPM attempts to compute the relationship between risk and required expected return in the pricing of risky securities. CAPM computes the expected return of an asset in a portfolio as the rate of a risk free asset plus a risk premium. The expected rate of return for the asset is:

$$E(R_i) = R_F + \left[E(R_m) - R_f\right]\beta_{iM} \tag{11}$$

$$\beta_{iM} = \frac{cov(R_i, R_M)}{\sigma^2(R_m)} \tag{12}$$

$$\sigma^2(R_m) = Cov(Rm, RM) = \sum_i^N x_{iM} * \mathrm{Cov}\,(R_i, R_M) \tag{13}$$

$E(R_i)$ is the expected is return of asset or portfolio i, R_F is the risk free interest rate, R_m is the market risk, and β_{iM} is a risk premium.

A further extension of MPT and CAPM is Arbitrage Pricing Theory (APT). APT posits that an asset's expected returns are linearly related to loading factors. Unlike the other methods, APT considers additional random variables such as Consumer Price Index, politics, or turmoil in different parts of the world (Ross, 1976). APT was developed by Ross in 1976 and research has shown that APT outperforms both CAPM and MPT (Ross, 1976; Sharpe, 1964). The key to APT is to find the underlying factors that account for the relationship between specific assets and then using those factors to exploit the difference between the price of the stock and its "true" underlying value (Huberman & Wang, 2005).

Since much of the progression of portfolio optimization research does not seem to fit department of defense retirement options, we looked to behavioral economics and other portfolio management constructs to build the portfolios. For instance, CAPM and APT were not used in this analysis because the TSP's policies violate some of their explicit assumptions such as unlimited trades, short selling, etc. Research has repeatedly shown that previous wealth is correlated with risk tolerance; for example, as one's wealth increases, absolute risk aversion decreases (Guiso et al., n.d.; Riley & Chow, 1992). In addition, risk tolerance has been shown to be related to generations and also time periods. Younger generations are shown to take on more substantial risk and all generations take on more or less risk during certain time periods (Riley & Chow, 1992; Yao, Sharpe, & Wang, 2011).

Downside Risk Optimization (DRO) is used to select a portfolio of assets (in this case TSP funds) to minimize risk at a specified minimum acceptable rate of return. The DRO framework makes two assumptions concerning the investor utility function which have been supported in previous research: risk aversion and skewness preference (Foo & Eng, 2000; Harlow, 1991; Harlow & Rao, 1989). Under the downside risk framework, the left side of the distribution is used in the calculation of risk, or semi-variance, in contrast to mean-variance optimization in which the entire distribution is considered. Additionally, DRO does not have limiting assumptions such as normality that could confound interpretation of calculations. For the downside risk framework, risk is captured in Low Partial Moments (LPM) and Co-Lower

Partial Moments (C-LPMs). LPM is a general group of measures that identifies below target risk measures including below target semi-variance (Bawa & Lindenberg, 1977). The LPM uses risk tolerance to describe below target risk through the following equation:

$$LPM_n(\tau, x_i) = \frac{1}{T-1} \sum_{t=1}^{T} Max\,[0, (\tau - \sum_{t=1}^{N} R_{it})]^n \tag{14}$$

where T is the number of observations, x_i is the target return of asset *i*, τ is the degree of the lower partial moment, R_{it} is the return of asset *i* during time period *t*, and *n* identifies the degree of the moment: 0 being the probability of loss, 1 the probability of target shortfall, 2 the probability of target semi-variance, and 3 the probability of target skewness. For *n*, 0 and 1 may mistakenly appear to limit risk, but it was shown that LPM of 0 and 1 only apply to the most risk seeking individuals (Fishburn, 1977). According to Harlow (1991), *n* must be above 1 in order for risk aversion to be considered important in the decision making processIn 1974, the semi-variance (i.e, *n*=2) was extended to the CAPM model creating the co-semi-variance concept which quantified the risk between the a risky asset and the efficient market portfolio (Hogan & Warren, 1974). The theory was generalized in 1977 for any n^{th} degree.

The application of portfolio optimization theory on the Thrift Savings Plan started in 2004. Blanchette (2004) created a Decision Support System in Microsoft Excel applying Markowitz modern portfolio theory to create TSP portfolio mixes that were along the efficient frontier. Prior to Blanchette, research on service members' Thrift Savings Plan compared High Three and Redux Military Programs and the impact that putting the Redux lump sum payments into a TSP fund would have on comparing the two military retirement programs (Shafer, 2000). At the time of Blanchette's research, the Federal Retirement Thrift Savings Board had not introduced the Lifecycle Funds to the Thrift Savings Plan. This is important to note because the Lifecycle Funds used strategies similar to Blanchette's to create the efficient frontiers for the L

Funds. After applying Modern Portfolio Theory, Blanchette created a simulation of long term results for a range of service members based on 13 portfolios he created; note, the model could be tailored to any custom TSP portfolio mix. Another part of Blanchette's research used linear programming techniques to achieve two objectives: 1) limit downside return, and 2) maximize upside return. The investment model was defined by the objective function:

Maximize:

$$\sum_{i=1}^{n} S_i \,(W_D \, P_{iD} \; + W_U \, P_{iU} \,) \tag{15}$$

Subject to

$$\sum_{i=1}^{n} S_i \, = 1 \tag{16}$$

where *i* is the portfolio alternative; *n* is the total number of alternatives; S_i is a binary variable used to select an alternative *i*; W_D and W_U are the individual weights for the downside and upside returns, respectively; and P_{iD} and P_{iU} are the probabilities of investment *i* achieving the upside and downside returns (Blanchette, 2004). The model assumed linear increases to the objective function and portfolio mix was based on a minimum acceptable return by the investor.

Within the first three years of the L Fund introduction, three of five TSP funds (C, S, and I Funds) lost over a third of their value during the Great Recession with three of the four recently created L Funds losing over 20% of their value (L 2040, L 2030, L 2020). The massive losses during the 2008 recession not only affected individual funds but also the Lifecycle Funds. This prompted Beck in 2010 to explore whether a different optimization technique could improve the L Funds conservation of assets in the future. Beck applied Downside Risk Optimization to historical Thrift Savings Plan Funds and benchmarks to create new DRO portfolios based on a minimum acceptable return (MAR) and compared them against a portfolio created by mean variance optimization. The analysis and simulations showed DRO TSP Portfolios protected TSP members' assets better during the recession and subsequently outperformed current L Funds annualized returns when modeled with Modern Portfolio Theory (Beck, 2010).

3.4 Methodology

Data Collection and Verification.

For this research, we used historical prices for all the Thrift Savings Plan Funds and selected benchmarks from open source information. Monthly returns from inception through August 31, 2016 are used for all TSP funds. For returns prior to specific TSP funds inception dates, we use objective indices as a proxy measurement (for instance we used the S&P 500 index for the Common Stock Fund). Note, all rate of return results have been normalized for inflation. Table 13 provides a summary of the TSP Investment funds.

Table 13. Thrift Savings Plan Funds

Fund	Description	Inception Date	Objective
Government (G)	Government Securities	April 1 ,1987	Interest income without risk of loss of principal
Fixed Income (F)	Government, Corporate and Mortgage-backed bonds	Jan 29, 1988	To match the performance of the Barclays Capital U'S Aggregate Bond Index
Common Stock (C)	Stock of large and medium sized U.S. Companies	Jan 29, 1988	To match the performance of the Standard and Poor's 500 (S&P 500) Stock Index
Small Capitalization Stock (S)	Stock of small to medium sized U.S. Companies not included in C Fund	May 1, 2001	To match the performance of the Dow Jones U.S. Completion TSM Index
International Stock (I)	International stocks of more than 20 developed countries	May 1, 2001	To match the performance of the MSCI EAFE (Europe, Australasia, Far East) Index
Lifecycle Funds (L)	Invested in G,F,C,S, and I Funds	Aug 1, 2005	To provide professionally diversified portfolios based on various time horizons, using the G,F,C,S, and I Funds

Data was collected through the following five sources:

-Thrift Saving Plan Website

-Federal Reserve website for 90- day Treasury Bill (T-Bill) returns

-Morgan Stanley website for Europe, Australasia, and Far East (EAFE) returns

-Barclays website for Barclays Capital US Aggregate Bond Index

-Google Finance for Standard and Poor's 500 Stock Index

Optimization Model Limitations.

Alternative techniques such as CAPM and APT violate some assumptions when applied to the TSP. The Capital Asset Pricing Model (CAPM) assumes an individual has access to unrestricted borrowing at the risk free interest rate and the opportunity to engage in unrestricted short selling (Fama & French, 2004). TSP investors do not have access to unlimited borrowing at a risk free rate to contribute to their TSP portfolio nor do service members have unrestricted short selling abilities within their TSP portfolios. As of 2016, the maximum an individual can contribute for the calendar year is $18,000 which includes both a Roth and Traditional IRA (The Federal Retirement Thrift Investment Board, 2016). With regards to applying APT to a Thrift Saving Plan portfolio, the TSP is comprised of funds made up of a basket of assets versus individual assets. Another issue is that TSP investors are only able to make trades twice per month—the one exception to this rule is that members may make unlimited transfers into the G Fund. The purpose of this exception is to allow investors a mechanism to protect against losses in the case of a stock market crash. The G Fund is composed of United States Treasury Bonds sold specially to the Federal Retirement Thrift Investment Board for the Thrift Savings Plan G Fund (The Federal Retirement Thrift Investment Board, 2016).

MAR (τ) Selection for Investor Preference.

For DRO models, we assume a minimum acceptable return (MAR) to construct the five portfolios. The MARs range from 2.5% to 10% --Table 14 shows the five portfolios' MAR values for the DRO developed portfolios.

Table 14. Risk Tolerance and MAR (τ)

Risk Tolerance	MAR (τ)
Very Low	2.5
Low	5
Neutral	6.5
Above Average	8
High	10

Optimization Design.

Once the returns are normalized for inflation, Downside Risk Optimization Lower Partial Moments are used to develop the portfolios. In the case of LPM, n=2 was used with each of the five risk tolerance values in Table 14. The five portfolio constructs were computed in R Studio using the PARMA package and benchmarked against the L Fund target allocation results.

The portfolio mixes were constructed using historical return data. First, the historical risk premium was computed and the risk-free rate of interest was obtained (90-Day Treasury Bill Return). Next, the expected mean return was calculated for all of the funds based on their historical returns dating back to 1984. Once the expected returns were calculated, the risk measures for Lower Partial framework were calculated using the following equations:

Minimize x_i in $LPM_n(\tau, x_i)$

$$\frac{1}{T-1} \sum_{t=1}^{T} Max\,[0, (\tau - \sum_{t=1}^{N} R_{it})]^n \tag{17}$$

Subject to n = 2

$$C_1(x_i) = \sum_{i=1}^{N} x_i\, R_i - R_P \tag{18}$$

$$C_2(x_i) = \sum_{i=1}^{N} x_i - 1 \tag{19}$$

$$x_i \geq 0, i = 1,2, \dots, N. \tag{20}$$

Note, the resultant portfolio mixes can be used as surrogate portfolios in follow-on research.

Model Comparisons.

The Downside Risk Optimization portfolios were developed using the available data from 1984 to 2005; the portfolios were then compared to L Fund returns from 2006 to 2015 to determine if the Downside Risk Optimization portfolios provide better conservation of assets. The L Funds are updated quarterly based on a proprietary efficient frontier model. The analysis benchmarks were used to identify which portfolios maintain asset value during recession and slow growth periods. Since investors historically take assets out of the market when the markets contract, gains are often not fully realized. Therefore, we compare the five different Downside Risk Optimization Portfolios against annual returns of the L Fund and all other individual funds from 2006 to 2015. The comparisons are based on common contribution strategies employed by investors such as dollar cost averaging over the long term and constant contribution increases over a ten-year period. Key years we wanted to explore in the study were during the most recent recession, four years after the recession, and the most recent results. The year of the Great Recession was analyzed to see which portfolios lost the least amount of value. Four years after the recession represented a recovery period in which an economy expanded at an unremarkable pace. The expected values in 2015 were used to compare against the most recent data available.

3.5 Analysis

The portfolios constructed using Downside Risk Optimization in the PARMA package are shown in Table 15.

Table 15. Downside Risk Optimization Portfolios

	Risk Tolerance				
Fund	Very Low	Low	Neutral	Above Average	High
Min Return	2.5%	5.0%	6.50%	8%	10%
C Fund			21.5%	50.7%	92.9%
F Fund	26.7%	26.7%	58.2%	49.3%	7.1%
G Fund	69.2%	69.2%	19.7%		
S Fund					
I Fund	4.1%	4.1%	0.6%		

The Thrift Savings Plan restricts investment strategies in that it takes a month to implement any changes to contribution amounts and limits annual contributions to $18,000. After constructing the DRO portfolios based on annual returns from 1984 to 2005, the DRO portfolios' annual returns were compared against the TSP Funds' annual returns across three different investment scenarios: dollar cost averaging over 10 years, increased contribution over 10 years, and dollar cost averaging mixed with a market timing strategy. The dollar cost averaging contribution strategy is shown in Table 16.

Table 16. Dollar Cost Averaging Validation

Year		L Income	L 2040	L 2030	L 2020	G Fund	F Fund	C Fund	S Fund	I Fund	Very Low	Low	Neutral	Above Average	High
2006	$10,000	$10,759	$11,653	$11,500	$11,372	$10,493	$10,440	$11,579	$11,530	$12,632	$10,566	$10,566	$10,708	$11,017	$11,498
2007	$10,000	$21,913	$23,247	$23,035	$22,840	$21,491	$21,889	$22,774	$22,712	$25,219	$21,745	$21,745	$22,022	$22,342	$22,713
2008	$10,000	$30,289	$22,764	$23,950	$25,363	$32,672	$33,627	$20,651	$20,177	$20,275	$32,479	$32,479	$30,653	$27,147	$21,599
2009	$10,000	$43,742	$41,017	$41,583	$42,131	$43,939	$46,240	$38,829	$40,693	$39,370	$44,555	$44,555	$44,709	$43,268	$39,565
2010	$10,000	$56,826	$58,104	$58,020	$57,652	$55,455	$60,014	$56,183	$65,425	$53,290	$56,771	$56,771	$58,943	$59,097	$56,736
2011	$10,000	$68,317	$67,450	$67,809	$67,929	$67,059	$75,538	$67,579	$72,875	$55,816	$68,987	$68,987	$72,707	$72,525	$68,418
2012	$10,000	$82,052	$88,502	$87,621	$86,049	$78,191	$89,208	$90,046	$98,265	$78,071	$81,299	$81,299	$87,957	$90,993	$90,363
2013	$10,000	$98,468	$121,384	$117,301	$111,446	$89,858	$97,541	$132,511	$149,785	$107,561	$92,911	$92,911	$104,312	$116,768	$130,495
2014	$10,000	$112,558	$139,556	$134,608	$127,591	$102,165	$114,779	$162,149	$172,249	$111,365	$106,184	$106,184	$122,655	$139,830	$159,152
2015	$10,000	$124,825	$150,648	$146,112	$139,448	$114,453	$125,914	$174,662	$176,927	$120,746	$118,081	$118,081	$134,304	$151,611	$171,555

As seen in Table 15 and 16, the Very Low and Low risk tolerances result in the same portfolio mix; this portfolio will be referenced as the Low Risk Portfolio in the analysis section. First looking at 2008, the year of the Great Recession, the Low Risk Portfolio provides the best conservation of assets compared to the all other options except exclusive investment in the F and G Fund. Additionally, all of the DRO portfolios conserve assets better than the L Funds except the High Risk Portfolio which had the lowest expected value of all the portfolios. By 2012, The

High Risk Portfolio had the highest overall value of the portfolios; the Low and Neutral portfolio had lower expected values than all three of the time horizon L Funds. The Above Average Risk Portfolio that conserved assets better than the time horizon L Funds still had a greater value in 2012. The trends in 2012 remained the same in 2015 with the High Risk Portfolio outperforming all portfolios, the Above Average Portfolio outperforming all the L funds, and the L Funds outperforming the Neutral and Low Portfolios by a greater margin than in 2012.

The second contribution strategy analyzed was a constant $600/year contribution increase (i.e., an additional $50/month). Table 17 shows the results between the DRO Portfolios, the individual funds, and the L Funds.

Table 17. Constant Contribution Increase Validation

Year		L Income	L 2040	L 2030	L 2020	G Fund	F Fund	C Fund	S Fund	I Fund	Very Low	Low	Neutral	Above Average	High
2006	$5,000	$5,380	$5,827	$5,750	$5,686	$5,247	$5,220	$5,790	$5,765	$6,316	$5,283	$5,283	$5,354	$5,509	$5,749
2007	$5,600	$11,590	$12,267	$12,160	$12,061	$11,375	$11,587	$12,020	$11,989	$13,278	$11,507	$11,507	$11,649	$11,809	$11,990
2008	$6,200	$16,884	$12,645	$13,311	$14,103	$18,234	$18,757	$11,481	$11,219	$11,213	$18,116	$18,116	$17,086	$15,116	$12,011
2009	$6,800	$25,714	$24,343	$24,632	$24,904	$25,777	$27,087	$23,158	$24,299	$23,425	$26,134	$26,134	$26,269	$25,528	$23,553
2010	$7,400	$35,015	$36,152	$36,030	$35,725	$34,110	$36,801	$35,160	$40,910	$33,272	$34,896	$34,896	$36,275	$36,531	$35,430
2011	$8,000	$43,974	$43,728	$43,893	$43,904	$43,141	$48,336	$44,071	$47,257	$36,398	$44,320	$44,320	$46,692	$46,739	$44,525
2012	$8,600	$55,082	$59,795	$59,113	$57,975	$52,502	$59,379	$61,135	$66,230	$53,377	$54,469	$54,469	$58,801	$61,018	$61,217
2013	$9,200	$68,762	$85,023	$82,085	$77,944	$62,868	$67,427	$93,159	$104,357	$76,425	$64,793	$64,793	$72,413	$81,186	$91,559
2014	$9,800	$81,524	$100,721	$97,159	$92,183	$74,347	$82,424	$117,146	$123,061	$81,681	$76,965	$76,965	$88,214	$100,361	$114,818
2015	$10,400	$93,625	$111,932	$108,678	$103,968	$86,475	$93,669	$129,408	$129,564	$91,611	$88,792	$88,792	$99,839	$112,078	$126,998

The Low Risk Portfolio provides the best conservation of assets compared to all other options with the exception of a 100% investment in the F Fund. When comparing the DRO portfolios to time horizon L Funds, all DRO portfolios conserved assets better than the L Funds except the High Risk Portfolio, which had the lowest expected value of all portfolios. By 2012, the High Risk Portfolio had the highest overall value of the portfolios and the Low and Neutral portfolios had lower expected values than the all-time horizon L Funds. The Above Average Risk Portfolio outperformed the L funds but had a lower expected value than the High Risk Portfolio. The neutral funds in 2012 were greater than the L Fund 2020. The trends in 2012 continued in 2015 with the High Risk Portfolio outperforming all portfolios, the Above Average Portfolio outperforming all the L funds, and the L Funds outperforming the Neutral and Low

Portfolios by a greater margin.

The last contribution strategy assessed was lowering an individual's contribution by timing the decrease in the stock market's value and withholding half of his or her annual contribution for the following year as the economy recovered from the Great Recession. Table 18 shows the results from the comparison.

Table 18. Market Timing Contribution Strategy Validation

Year		L Income	L 2040	L 2030	L 2020	G Fund	F Fund	C Fund	S Fund	I Fund	Very Low	Low	Neutral	Above Average	High
2006	$10,000	$10,759	$11,653	$11,500	$11,372	$10,493	$10,440	$11,579	$11,530	$12,632	$10,531	$10,531	$10,707	$11,129	$11,530
2007	$10,000	$21,913	$23,247	$23,035	$22,840	$21,491	$21,889	$22,774	$22,712	$25,219	$21,701	$21,701	$22,145	$22,429	$22,712
2008	$5,000	$25,543	$19,340	$20,325	$21,501	$27,484	$28,355	$17,501	$17,093	$17,397	$27,531	$27,531	$26,911	$21,881	$17,093
2009	$15,000	$44,018	$42,991	$43,267	$43,487	$43,746	$45,952	$41,172	$43,277	$42,129	$44,468	$44,468	$45,374	$43,707	$43,277
2010	$10,000	$57,119	$60,351	$59,914	$59,152	$55,256	$59,706	$58,878	$68,759	$56,268	$56,708	$56,708	$58,807	$60,024	$68,759
2011	$10,000	$68,615	$69,676	$69,698	$69,435	$66,855	$75,206	$70,332	$76,097	$58,442	$69,197	$69,197	$71,673	$73,100	$76,097
2012	$10,000	$82,365	$91,046	$89,747	$87,712	$77,985	$88,861	$93,241	$102,086	$81,186	$81,373	$81,373	$86,024	$92,587	$102,086
2013	$10,000	$98,803	$124,519	$119,856	$113,376	$89,648	$97,200	$136,743	$155,070	$111,365	$92,581	$92,581	$98,409	$122,047	$155,070
2014	$10,000	$112,905	$142,886	$137,310	$129,618	$101,950	$114,415	$166,964	$177,946	$114,969	$106,121	$106,121	$113,077	$146,566	$177,946
2015	$10,000	$125,179	$154,002	$148,842	$141,503	$114,234	$125,547	$179,548	$182,458	$124,332	$118,020	$118,020	$124,294	$158,512	$182,458

For the market timing contribution strategy, similar trends seen in Dollar Cost Averaging and Constant Contribution Increase appeared in Market Timing Contribution Strategy in 2008, 2012, and 2015. In comparison to the other two profiles, it is noted that if an individual was able to time the market to anticipate 2008 losses, the time horizon L Funds reduce the expected value gap in both 2012 and 2015. For instance, the difference between the L2040 Fund and the Above Average DRO Fund was reduced from $2,491 to $1,148 in 2012 and from $932 to outperforming the Above Average DRO by $841 in 2015. For Low Risk investors using DRO portfolios, the timing of the market actually produced a lower return in 2015 compared to Dollar Cost Averaging. The neutral DRO portfolio also performed marginally better in the Market Timing Contribution versus the Dollar Cost Averaging profile. For the time horizon L Funds, market timing had a larger impact on the expected values in 2012 and 2015 compared to DRO portfolios, although they still underperformed the Above Average and High portfolios in both years. The farther out the maturation year of the L Fund, the greater the impact the market timing strategy had on a portfolio's overall expected value.

3.6 Discussion and Conclusion

Individual Thrift Savings Plan members have very limited options for choosing funds and limited ability to move assets between funds in the short term. This paper intended to demonstrate whether Downside Risk Optimization portfolios perform better at conserving assets than the current time horizon L Funds in the short term. The analysis supports the stated hypothesis by demonstrating that DRO portfolios conserved assets better than the time horizon L funds during the Great Recession. The three different contribution strategies showed all Downside Risk Optimization portfolios provided better protection than the time horizon L Funds. In comparison, the Very Low, Low, and Neutral Portfolios started to be outperformed by the L Funds four years after the recession began. The Above Average DRO portfolio with a minimum acceptable rate of 8% did a better job of conserving assets during the recession than the L Funds and outperformed all the time horizon funds over a ten year period except in the timing scenario. The High Risk DRO portfolio (which was composed of only the S Fund) did the worst during the recession and had the highest expected value in 2012 and 2015. The conclusion from the comparisons is to provide the Low, Neutral, Above Average, and High Risk Portfolios in the Decision Support System.

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IV. Evaluating Blended Retirement System Influential Factors

4.1 Introduction

The Department of Defense's new retirement system will take effect on January 1, 2018. The Military Compensation and Retirement Modernization Commission (MCRMC) was commissioned by Congress in the National Defense Authorization Act (NDAA) for FY 2013 to provide recommendations on reforming the Department of Defense (DoD) military retirement system and personnel programs. Service members with less than 12 years of service (YOS) on January 1, 2018 will have the option to opt into the Blended Retirement System. The default preference for all service members will be to remain with the traditional High Three Retirement System (Office of the Under Secretary of Defense & Personnel and Readiness, 2016). The purpose of this paper is to identify which factors are most influential in comparing the expected monetary value of the two retirement systems.

The traditional High Three Retirement System is a defined benefit cliff-vesting pension that vests after 20 years of service. Under the High Three Retirement System, service members who complete 20 years of service earn 2.5 % of their base pay per year. For instance, an individual with 20 years of service earns 50% of his base pay per month for the rest of his or her life. Base pay is defined as the average of a service member's three highest-earning years while serving on active duty. The High Three Retirement System is adjusted for cost of living allowance (COLA) based on the consumer price index (CPI).

The new Blended Retirement System includes three distinct features: a defined benefit cliff-vesting annuity, lump sum continuation pay, and a 401k-style matching program. The defined benefit cliff-vesting annuity multiplier is reduced from 2.5% to 2.0% per year (when compared to High Three) and vests at 20 years (same as High Three). The mid-career continuation bonus, which includes an active duty service commitment, will be a minimum of two months base pay with potential increases based on service personnel requirements. The 401(k) style-matching program will use the Federal Retirement Investment Board's Thrift Savings Plan (TSP) as the investment vehicle to match service member's individual contributions. A comparison between the two systems in shown in Figure 12. In order to identify the most important factors in comparing the two retirement systems, a model of the expected value over a service member's lifetime is used.

Benefit System	HI-3	BRS
Multiplier	2.5% per YOS	2% per YOS
Continuation Bonus	-	Min 2X Monthly Base Pay
TSP Matching	-	Up to 5%*

Your Contribution	DoD Auto Contribution	DoD Matches	Total DoD Contribution
0%	1%	0.0%	**1.0%**
1%	1%	1.0%	**2.0%**
2%	1%	2.0%	**3.0%**
3%	1%	3.0%	**4.0%**
4%	1%	3.5%	**4.5%**
5%	1%	4.0%	**5.0%**

Figure 12. Retirement System Comparison and TSP Matching

4.2 Background

The Military Compensation and Retirement Modernization Committee final report in 2015 presented the major components of the Blended Retirement System with the following recommendations:

1. Defined contributions are TSP-only
2. Automatic monthly 1% contributions occur until 20 YOS
3. Automatic 3% enrollment with participant ability to change
4. Up to 5% maximum matching
5. TSP Vesting after 2 Years
6. Basic continuation pay of 2.5 times one month base pay at 12 YOS
7. 2% per YOS multiplier for defined benefit annuity

8. Lump sum amount at retirement option
9. Secretary of Defense option to modify 20 YOS requirement to correct for manpower

The MCRMC final report borrowed many of these recommendations from RAND's *Analysis of Retirement Reform in Support of Military Compensation and Retirement Commission Progress Report, November 2014* and RAND's Dynamic Retention Model. The Dynamic Retention Model used data drawn from the Defense Manpower Data Center to predict steady state and year-by-year manpower between compensation systems. The RAND Dynamic Retention Model supported its own recommendations for *Concepts for Modernizing Military Retirement* in a March 2014 white paper. In addition, the MCRMC survey conducted between July 1 2014 and October 10 2014 showed that 53.4% of service members preferred an alternative plan. The justification for the change in systems was predicated on the belief that a blended plan would be more equitable because most service members do not reach 20 YOS, and the belief that such a plan would provide services more flexibility in how they shape their future manpower profiles.

The Thrift Savings Plan (TSP) is a federal government administered retirement savings plan similar to 401(k) plans offered to private sector employees (The Federal Retirement Thrift Investment Board, 2016). According to the *Summary of the Thrift Savings Plan:* "The purpose of the TSP is to give you the ability to participate in a long-term retirement savings and investment plan." The Thrift Savings Plan provides both tax-deferred and tax-free earnings options similar to a Traditional IRA and Roth IRA with a variety of withdrawal options. The TSP offers five primary index funds and four portfolio funds based on a fixed time horizon and professionally managed efficient frontier. Table 19 outlines the TSP Fund options available to TSP members. The current expense rate for the TSP funds is a flat rate of .29% for all funds as of April 2016 ("TSP Review April 2016," n.d.).

Table 19. Thrift Savings Plan Funds

Fund	Description	Inception Date	Objective
Government (G)	Government Securities	April 1 ,1987	Interest income without risk of loss of principal
Fixed Income (F)	Government, Corporate and Mortgage-backed bonds	Jan 29, 1988	To match the performance of the Barclays Capital U'S Aggregate Bond Index
Common Stock (C)	Stock of large and medium sized U.S. Companies	Jan 29, 1988	To match the performance of the Standard and Poor's 500 (S&P 500) Stock Index
Small Capitalization Stock (S)	Stock of small to medium sized U.S. Companies not included in C Fund	May 1, 2001	To match the performance of the Dow Jones U.S. Completion TSM Index
International Stock (I)	International stocks of more than 20 developed countries	May 1, 2001	To match the performance of the MSCI EAFE (Europe, Australasia, Far East) Index
Lifecycle Funds (L)	Invested in G,F,C,S, and I Funds	Aug 1, 2005	To provide professionally diversified portfolios based on various time horizons, using the G,F,C,S, and I Funds

4.3 Previous Research

Military retirement research has historically been intertwined with two distinct topics: retention and cost. Military retirement costs have been scrutinized consistently for the past 30 years. By the end of 1983 there were more retired than active military officers paid by the Department of Defense (Gansler, 1989). This trend has only been exacerbated with drawdown in manpower in the last 30 years. At the beginning of Fiscal Year 2015, 383,110 retired officers were collecting a retirement check in comparison to 235,334 officers on active duty (Allen & Garcia, 2015; Office of the Deputy Assistant Secretary of Defense (Military Community & and Family Policy), 2014). Between 1935 and 1989, twelve advisory panels recommended fundamental changes to the military retirement system due to its long-term institutional costs. Future Office of the Secretary of Defense for Acquisition, Technology, and Logistics stated "The military retirement program, though politically loaded, is likely to be forced to change because of cost considerations"(Gansler, 1989).

At the onset, research on the potential negative effects on retention caused by alteration of the military retirement system was analyzed by the services through federally-funded research institutions, most notably the RAND Corporation. RAND produced a report on the impacts of changes to the retirement system based on a minor change of COLA to the lower of CPI or military pay increases in 1984. The study showed that minor decreases in retirement benefits would not affect pilot retention rates to the same degree as non-rated officers because retirement benefits accounted for a larger percentage of compensation for non-rated officers (Goetz & McCall, 1984). The early 1980's research concluded that retention would be adversely effected if changes were made to the military retirement system. Based on the RAND study, the Department of Defense concluded that changes to the retirement system would have adverse effects on officer retention but would increase man-year accessions to the 15th year of service for the enlisted force (Asch & Warner, n.d.).

The first report to include a hybrid retirement system proposal was delivered to the Office of the Secretary of Defense by RAND in 1998. "Hybrid" refers to offering individuals a retirement program that includes both a defined benefit and a defined contribution component. A National Defense Research Institute commissioned report outlined a military retirement system that was very similar to the Federal Employees Retirement Systems (FERS). The proposal included a defined benefit plan that vests at five years of service, a defined contribution plan in the Thrift Savings Plan that vests at three years and matches up to 5%, and a 7% pay increase. The report ultimately reached the conclusion that reforming the military retirement system would result in a reduction in retention and if the retirement was reduced, current retention levels could only be achieved with a skewed pay increase (Asch, Johnson, & Warner, n.d.). At the turn of the century, Congress and other institutions continued to assert that the military retirement system was costly to the taxpayer, inefficient, inequitable, and did a poor job of shaping the force of the future. At the turn of the century, various sources submitted proposals to the Department of Defense that included defined contribution, gate payments, and defined benefit for the good of the individuals in addition to more flexibility to retain personnel on as-needed basis (Asch & Warner, n.d.; Shafer, 2000). In contrast, the proposed reforms from Warner's (2006) submission to the Department of the Navy did not focus on significant cost savings to the government but rather attempted to address the inequitable nature of the traditional system and provide services with more flexibility. In the High Three Retirement System, approximately 19% of service members receive some retirement benefit. In contrast, the DoD estimates 85% of service members will receive a retirement benefit under the Blended Retirement System.

One major issue that arises with reforming the military retirement system in an effort to constrain costs are the "siren calls" that changes to the retirement benefit will break trust, cut benefits, and open the doors to future cuts. The Blended Retirement System demonstrates a paradigm shift from the goal of cutting costs to the goal of increasing equity and retention. The changes in the private sector along with state government and municipalities over the last three decades provided the Department of Defense some evidence to see which decision most individuals will make in January 2018.

Since 1979, there has been a drastic paradigm shift from defined benefit only plans to defined contribution plans. Pure defined benefit plans have decreased from 28% to 2%, and defined contribution plans have risen from 7% to 33% while blended systems have remained relatively constant from 10% to 11% (Employee Benefit Research Institute, 2016). When the State of Utah's public pension moved from a strictly defined benefit system to a hybrid system it provided the Department of Defense with a meaningful data point to consider for its transition to the Blended Retirement System. One major result Department of Defense Officials and Congress should consider: when Utah offered the choice between a defined benefit only plan and a hybrid plan, 60% did not make an active choice and simply took the default choice of the hybrid plan. This supports the assertion in behavioral economics that individuals will often not make an active choice and rely on the default choice (Teppa & Rooij, 2006). In addition, the study found that individuals under the hybrid system were more likely to leave public service, resulting in higher separation rates (Clark, Hanson, & Mitchell, 2015). In comparison to civilian agency counterparts, the Department of Defense cannot instantaneously replace the loss of skills because there are no current lateral transfers from civilian sectors with the requisite skill sets.

4.4 Methodology

Data Collection.

For this research, we acquired historical Air Force manpower retention figures from the Defense Manpower Data Center (DMDC) broken down by Service, Years of Service, Occupation Code, Fiscal Year, Strength, Retention Count, and Separation Count for both Officer and Enlisted personnel. The data were collected for each year from 1995-2015, resulting in approximately 550,000 data points.

The rate of return assumption has been identified in previous research as a critical variable for determining which retirement system would provide the best expected value (White, n.d.). To date, the literature and models have identified only *rate of return* as a significant factor for comparing what impact different levels of rate of returns will have on the future expected value of the Blended Retirement System in comparison to the High Three Retirement System (White, n.d.). Since there is a reduction in the defined benefit multiplier in Blended Retirement System and the defined benefit annuity is adjusted for inflation in both systems, the comparison between the BRS and High Three Retirement System must address returns accumulated from future TSP matching by the service. Chapter 2, *Predicting 50 Year Thrift Savings Plan Rate of*

Return, identifies which time series forecasting technique is appropriate for forecasting the long-term rate of return for each individual TSP fund. Table 20 shows the forecasting techniques identified to calculate the rate of return.

Table 20. TSP Rate of Return Methodologies

TSP Rate of Return Methodology	
Fund	Methodology
CFUND	Neural Network
FFUND	Exponential Smoothing
GFUND	Exponential Smoothing
SFUND	Exponential Smoothing
IFUND	Neural Network
L Funds	Composed of Other Five Funds

The second input to the model: the TSP portfolio either is obtained from the user or the user may choose the pre-built surrogate portfolios provided based on a risk tolerance survey. Building off research in psychology and behavioral economics, Chapter 3, *Thrift Savings Plan Downside Risk Optimization Portfolio* Selection, shows that TSP portfolios optimized using Downside Risk Optimization historically conserve assets better during recessions and over the long run perform as well as the overall market. In this light, the model provides the user the opportunity to either assume his or her own TSP portfolio or take a survey, which identifies an individual risk tolerance and subsequently provides a surrogate portfolio based on downside risk optimization. Table 21 shows the TSP allocations based on varying risk preferences.

Table 21. DRO Portfolios

	Risk Tolerance				
Fund	**Very Low**	**Low**	**Neutral**	**Above Average**	**High**
Min Return	**2.5%**	**5.0%**	**6.50%**	**8%**	**10%**
C Fund			21.5%	50.7%	92.9%
F Fund	26.7%	26.7%	58.2%	49.3%	7.1%
G Fund	69.2%	69.2%	19.7%		
S Fund					
I Fund	4.1%	4.1%	0.6%		

The third major component was "likelihood of remaining in the military." It is simple to compare the systems and deduce that an individual with 0% chance of remaining in the military should switch to the Blended Retirement System because of the portability of the TSP matching program; however if certainty of leaving the military before 20 years is not the case, the likelihood of remaining in the military is an important consideration. Since the High Three defined benefit annuity requires 20 years of service and the largest portion of the BRS is a defined benefit annuity, the likelihood of completing 20 years of service is an important variable to consider. No research discovered at the time of publication attempted to forecast individual likelihood of meeting the twenty year vesting requirement for either the High Three Retirement System or the Blended Retirement System.

Model.

The two models developed comparing the two systems include three components: defined benefit, defined contribution, and continuation pay. Mathematically, the high-level equation for the traditional High Three Retirement System and the Blended Retirement System are:

$$High\ Three\ Retirement\ System =$$

$$Likelihood\ at\ X * (2.5\% * X * Annual\ Pay * 79 - (Age + X - YOS))^Z \qquad (21)$$

Where X is YOS at Retirement

Z is 0 if X<20 and is 1 if X >20

$$Blended\ Retirement\ System = \ LikelihoodatX\ *$$

$$\left(2.0\% * X * Annual\ Pay * 79 - (Age + X - YOS)\right)^Z + CB + DC + Return \qquad (22)$$

Where X is YOS at retirement

Z is 0 if X<20 and is 1 if X>20

CB is Mid-Career Continuation Bonus

DC is Defined Contribution from the Service

Return is combined Return on Investment from the CB and DC

Input Variables.

The model will test the impact of the input variables used to determine the expected value of the two retirement systems. The following input variables will be based on an individual's specific life circumstances and preferences:

1. Age
2. TSP withdrawal age
3. Years of Service
4. Planned TSP Contribution
5. Rank
6. Career Field
7. Likelihood of Remaining in Air Force 20 Years
8. Individual Portfolio Construction

9. Input Portfolio Allocation manually
10. Based on Financial Risk Tolerance (Assessment Survey provided)
11. Lump Sum continuation pay (Default will be 2.5 months base pay at 12 Year mark)

Individual Decision Support Tool Components.

The one common component of the two retirement systems is the defined benefit cliff-vesting annuity. As stated previously, the High Three Retirement System uses a 2.5% multiplier per YOS service compared to the Blended Retirement System, which uses a 2.0% multiplier per YOS. The two equations to calculate the value of the defined benefit cliff-vesting annuity at any given point in a service member's career are:

$$HighThree\ Defined\ Benefit\ = \quad Likelihood\ (X) * (2.5\% * X * Annual\ Pay * 79 - (Age + X - YOS))^{Z} \tag{23}$$

$$BRS\ \ Defined\ Benefit\ = \quad Likelihood\ (X) * (2.0\% * X * Annual\ Pay * 79 - (Age + X - YOS))^{Z} \tag{24}$$

Where X is YOS at retirement

Z is 0 if X is <20 and is 1 if X is >20

The Annual Pay in the calculation represents the highest three earning years for a service member, which for the majority of retired service members is earned from YOS 18 to 20 at the rank of E-6/E-7 for enlisted members and O-4/O-5 for officers. After retrieving the input variables and rate of return calculations, the likelihood of remaining in the military for 20 years is the remaining component of the model that must be modeled before estimating the expected value of the retirement systems.

The key variable in the calculation is the Likelihood of a service member completing X years of service, which is calculated using Bayesian Updating with Discrete Priors. The likelihood function, Likelihood(X), is the Likelihood of the service member completing X years given the current YOS the service members had completed to date. The methodology requires a set number of outcomes, a Prior Probability and Likelihood. The initial Prior Probability is the individual service member's belief that they will complete X given their current YOS. The Likelihood is the conditional probability an individual reaching X based on the career field. The conditional probability for each career field at each X and YOS is based on the manpower data drawn from the Defense Manpower Data Center. The probability for each year of the career field is calculated as the mean of the retention rates percent for a given YOS from 1995 to 2015. This equation can be best understood using an example of the probability of being in the service at the end of 1 year of service given an individual had completed zero years of service.

Probability of getting from 0 to 20 YOS for Career Field =

$$\frac{\sum \%\boldsymbol{Retention0to1}_{1995} + \%\boldsymbol{Retention0to1}_{1996} + \%\boldsymbol{Retention0to1}_{1997} \ldots \%\boldsymbol{Retention0to1}_{2015}}{\mathbf{21}} \quad (25)$$

The Likelihood of reaching X given the YOS completed is calculated by the following equation

$$\text{P (X|YOS)} = \boldsymbol{P}_{\boldsymbol{X}|\boldsymbol{X}-\mathbf{1}} \times \boldsymbol{P}_{\boldsymbol{X}-\mathbf{1}|\boldsymbol{X}-\mathbf{2}} \times \boldsymbol{P}_{\boldsymbol{X}-\mathbf{2}|\boldsymbol{X}-\mathbf{3}} \times \ldots\ldots \boldsymbol{P}_{\boldsymbol{YOS}|\boldsymbol{X}-(\boldsymbol{X}-\boldsymbol{YOS}+\mathbf{1})} \quad (26)$$

The uncorrected posterior probability for potential events in a given year using Bayesian Updating with Discrete Priors is defined as

$$Posterior = likelihood(x) \times prior \quad (27)$$

Finally, the sequential Prior for each year in the future is defined as the previous year's uncorrected posterior probability.

Simulation.

The strength of the Decision Support System is that each individual can tailor the model to his or her specific circumstances. There are too many combinations of Years of Service, Career Field and Rank to provide significant results applicable to all airmen. Due to this issue, the research team decided to run four simulation profiles through the model and investigate results using sensitivity analysis. The four surrogate Air Force career fields include one rated officer, one non-rated officer, one rated enlisted airman, and one non-rated enlisted airman. The specific simulation profiles are in Table 22.

Table 22. Simulation Profiles

Career Field	Rank	YOS
Security Forces	E-6	11
Financial Management	O-2	3
Aerospace Maintenance	E-5	5
Mobility Pilot	O-3	6

Sensitivity Analysis.

Each Career Field and Year of Service represents a different population in the Air Force. In order to reduce the number of evaluated populations, the four simulations discussed earlier were used to show what conclusions could be drawn from four typical Air Force career paths that will be making a decision between the two retirement systems. One-way analysis was run on seven input variables to identify which variables influenced which retirement system had the highest expected monetary value. Table 23 shows the ranges for the seven input variables.

Table 23. Sensitivity Ranges

Variable	Low	High
Years of Service	1	11
Age	18	44
TSP Contribution	1%	5%
Likelihood of Completing 20 YOS	0.05	0.99
Risk Tolerance	Very Low	High
Bonus Multiplier	1	10
Rank*	E-1	O-4

*Enlisted and Officer Career Fields analyzed only within respective rank structure

4.5 Results

Security Forces.

The first scenario to be analyzed was a Security Forces Technical Sergeant (E-6) who has completed 11 years of service with an average rate of promotion. The additional attributes in the Scenario 1 Base Case are highlighted in Table 24 Scenario 1 Inputs.

Table 24. Scenario 1 Inputs

Input Variable	Base Case
Years of Service	11
Age	35
TSP Contribution	5%
Likelihood of to Achieve 20 Years	0.99
Risk Tolerance	Neutral
AFSC	3P0
Bonus Multiplier	2.5

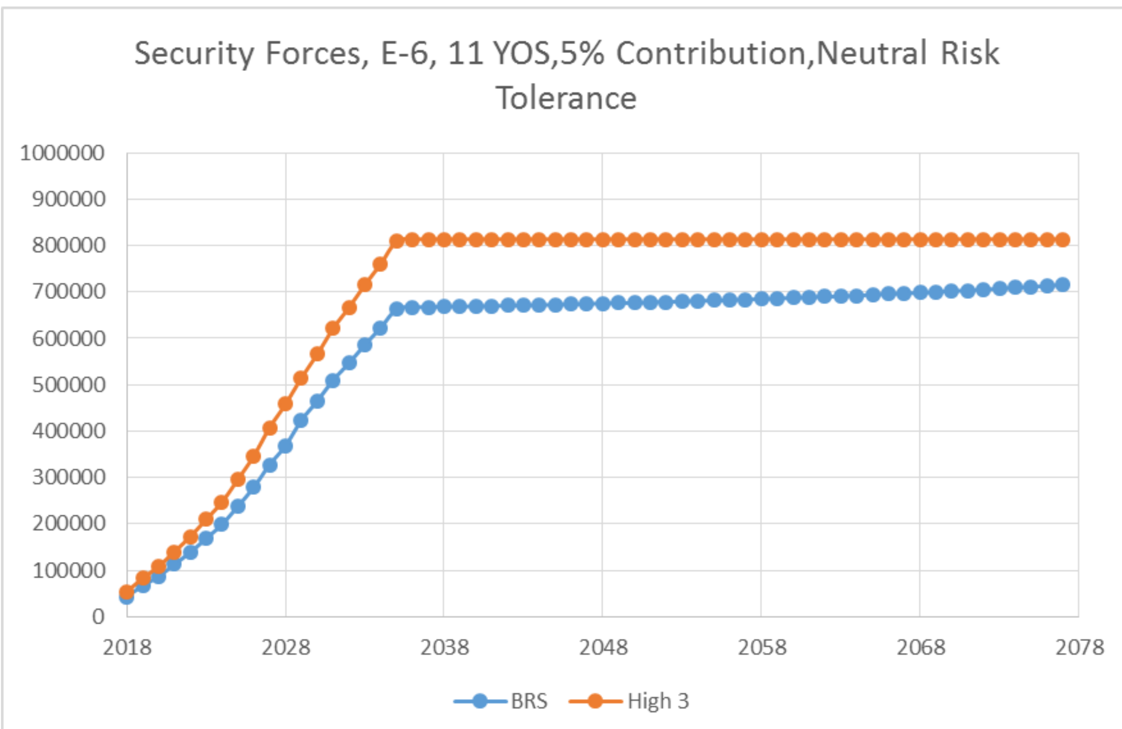

Figure 13. Scenario 1 Results

Scenario one results indicated the High Three Retirement System would have a higher expected value than the Blended Retirement in all years. The sensitivity analysis was conducted to determine if any changes to individual variables would predict the expected value of the Blended Retirement System to be greater than the High Three Retirement System in any year. As shown in Table 25, an increase in Risk Tolerance or Bonus Multiplier above 7 would predict a higher expected value of the Blended Retirement System in comparison to the High Three Retirement System.

Table 25. Scenario 1 Sensitivity Analysis Results

Variable	Base Case Outcome Changes (Values)
Years of Service	None
Age	None
TSP Contribution	None
Likelihood of Completing 20 YOS	None
Risk Tolerance	5
Bonus Multiplier	7-10
Rank*	None

Financial Management Officer.

The second scenario to be analyzed was a Financial Management 1st Lieutenant who has completed 3 years of service with a projected above average promotion rate. The additional inputs in the Scenario 2 Base Case are highlighted in Table 26 Scenario 2 Inputs.

Table 26. Scenario 2 Inputs

Input Variable	Base Case
Years of Service	3
Age	29
TSP Contribution	5%
Likelihood of Completing 20 YOS	0.9
Risk Tolerance	High
AFSC	65F
Bonus Multiplier	2.5

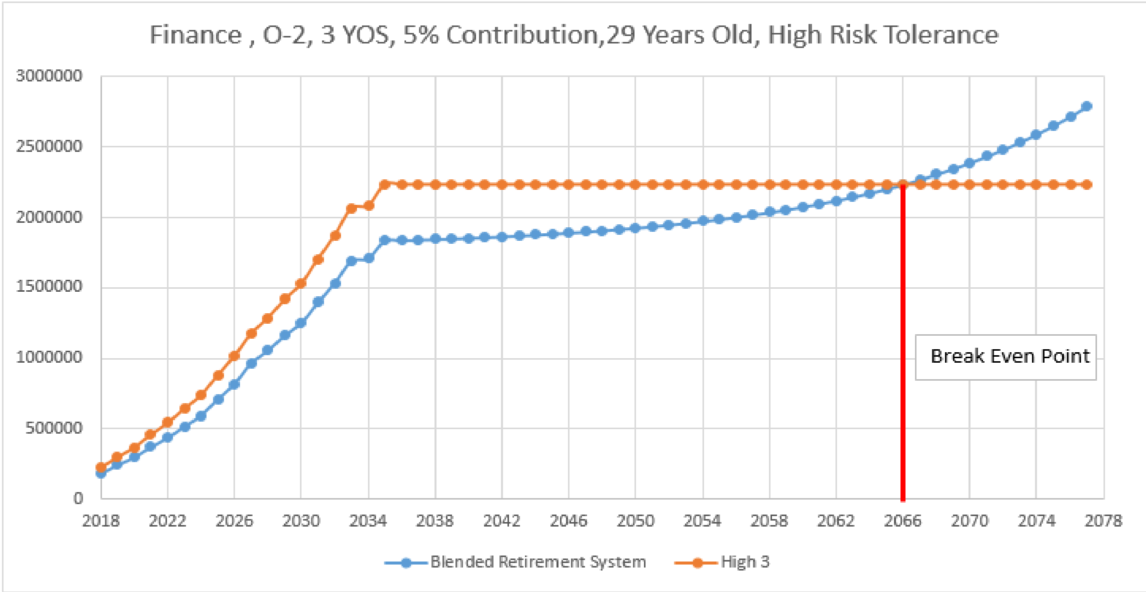

Figure 14. Scenario 2 Results

Scenario two results indicated the High Three Retirement System would have a higher expected value than the Blended Retirement until 2066 and the Blended Retirement System would have a higher expected value from 2067 until death. The sensitivity analysis was conducted to determine if any changes to individual variables would predict either High Three Retirement System or Blended Retirement System was the dominant option across all years. As shown in Table 27, a decrease in Risk Tolerance would provide a dominant option. If the Risk Tolerance for this scenario falls below High, the High Three Retirement System becomes the dominant option.

Table 27. Scenario 2 Sensitivity Analysis Results

Variable	**Base Case Outcome Changes (Values)**
Years of Service	None
Age	None
TSP Contribution	None
Likelihood of Completing 20 YOS	None
Risk Tolerance	Very Low- AboveAve
Bonus Multiplier	None
Rank*	None

Aerospace Maintenance.

The third scenario to be analyzed was an Aerospace Maintainer Staff Sergeant who has completed 5 years of service with a projected average promotion rate. The additional inputs in the Scenario 3 Base Case are highlighted in Table 28 Scenario Inputs.

Table 28. Scenario 3 Inputs

Input Variable	Base Case
Years of Service	5
Age	23
TSP Contribution	3%
Likelihood of Completing 20 YOS	0.4
Risk Tolerance	Above Average
AFSC	2A5
Bonus Multiplier	2.5

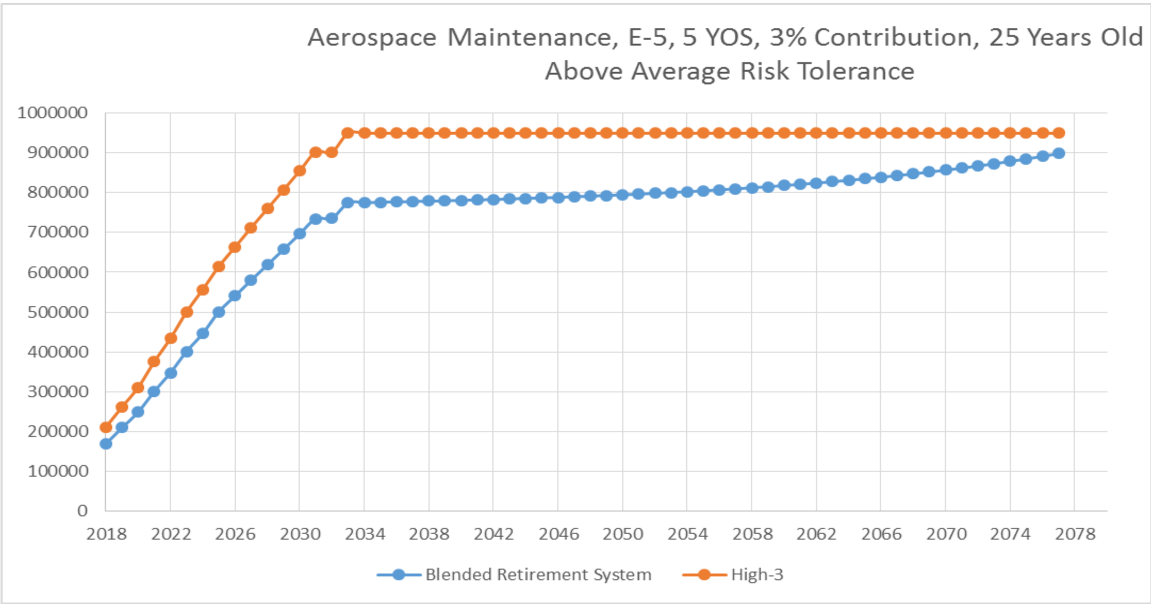

Figure 15. Scenario 3 Results

Scenario three results indicated the High Three Retirement System would have a higher expected value than the Blended Retirement in all years. The sensitivity analysis was conducted to determine if any changes to individual variables would predict the expected value of the Blended Retirement System to be greater than the High Three Retirement System in any year.

As shown in Table 29, an increase in Risk Tolerance and Bonus Multiplier above 4 would predict a higher expected value of the Blended Retirement System in comparison to the High Three Retirement System.

Table 29. Scenario 3 Sensitivity Analysis Results

Variable	Base Case Outcome Changes (Values)
Years of Service	None
Age	None
TSP Contribution	None
Likelihood of Completing 20 YOS	None
Risk Tolerance	High
Bonus Multiplier	4-10
Rank*	None

Mobility Pilot.

The fourth scenario to be analyzed was a Mobility Pilot Captain who has completed 6 years of service with an average rate of promotion rate. The additional attributes in the Scenario 4 Base Case are highlighted in Table 30 Scenario 4 Inputs.

Table 30. Scenario 4 Inputs

Input Variable	Base Case
Years of Service	6
Age	28
TSP Contribution	5%
Likelihood of Completing 20 YOS	0.7
Risk Tolerance	High
AFSC	11M
Bonus Multiplier	2.5

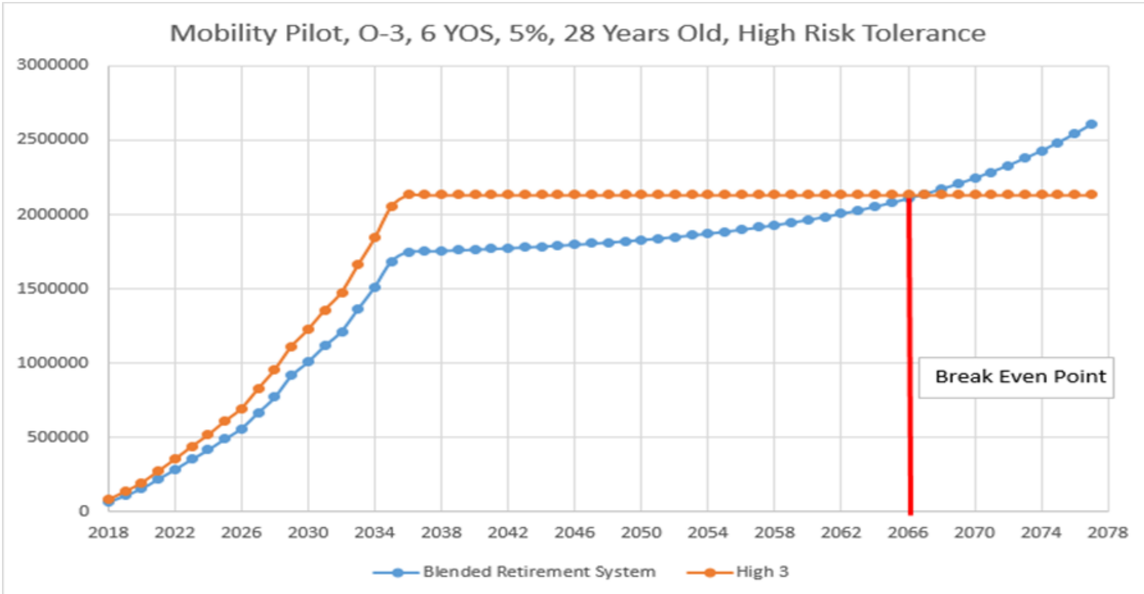

Figure 16. Scenario 4 Results

Scenario 4 results indicated the High Three Retirement System would have a higher expected value than the Blended Retirement in all years up until 2066 and the Blended Retirement System would have a higher expected value from 2067 until death. The sensitivity analysis was conducted to determine if any changes to individual variables would predict either High Three Retirement System or Blended Retirement System was the dominant options across all years. As shown in Table 31, a decrease in Risk Tolerance would provide a dominant option. If the Risk Tolerance for this scenario falls below High, the High Three Retirement System becomes the dominant option.

Table 31. Scenario 4 Sensitivity Analysis Results

Variable	**Base Case Outcome Changes (Values)**
Years of Service	None
Age	None
TSP Contribution	None
Likelihood of Completing 20 YOS	None
Risk Tolerance	VeryLow-AboveAve
Bonus Multiplier	None
Rank*	None

4.6 Conclusion

The four Air Force simulations showed the complexity of the decision even while accounting for all pertinent variables in the decision. An individual's Risk Tolerance repeatedly changes the outcome in the sensitivity analysis and can be characterized as an influential variable for determining whether or not the Blended Retirement System would provide a greater benefit than High Three Retirement System given the service member achieved 20 years of service. Besides Risk Tolerance, the multiple of the continuation pay multiplier was the other factor with potential to increase the expected value of the Blended Retirement System above the expected value of the High Three System. Unfortunately for service members, the Department of Defense did not elaborate on the continuation bonus during FY 2016 but rather requested modification to the continuation pay in the Blended Retirement System. The signed NDAA for FY2017 amended the Blended Retirement System to allow the continuation pay to be offered at no less than eight years of service and no more than 12 years of service. The acceptance of continuation pay incurs an additional 3 years of service commitment. This paper identified Risk Tolerance and the Continuation Bonus Multiplier as key factors in deciding between the two retirement systems. To this end, the Decision Support System provides the user the ability to input his or her specific characteristics and see a side by side comparison.

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V. Conclusions and Recommendations

5.1 Research Questions Answered

The purpose of this thesis was to build an application to better prepare service members for making their decision between the High Three Retirement System and Blended Retirement System. To this end we used our research questions to guide the building of the Decision Support System. First, we used multiple forecasting techniques to identify which forecasting method will be used on each TSP Fund. Neural Networks and Simple Exponential Smoothing Model were identified as the preferred forecasting methods based on the MAPE and MAD. The next step was to develop surrogate portfolios for the Decision Support System. We demonstrated that implementing Downside Risk Optimization yielded TSP portfolios that will conserve assets better than the current L funds and perform on par or better than the L Funds based on an individual's Risk Tolerance. Finally, we endeavored to identify which variables were the main drivers in differentiating between the High Three Retirement and BRS. We found that the service member's Risk Tolerance and the Continuation Bonus Multiplier were the largest differentiating factors for individual service members. The drivers were used to identify which graphs and tables need to be shown and explained in the Decision Support System.

5.2 Limitations

The main assumption underlying the entire thesis was historical data can be used to forecast the future. If this assumption is changed or does not hold, the forecasts and Decision Support System will be do a poor job forecasting the expected value of the Blended Retirement System. A second assumption was that the Blended Retirement System will not have changes before implementation. Future changes to the Blended Retirement System will need to be evaluated to be included in any future version of the tool. The major limitation to this research is the availability of data. Since the Thrift Savings Plan has only been around since 1987 and the newest index only dates back to 1984, some more data intensive techniques were not able to be investigated. The Decision Support System is limited to a one time binding decision for service members during 2018. The tool is not intended to be an all-encompassing financial or retirement planner.

5.3 Recommendations for Future Research

Since this research covered a breadth of research topics, there is opportunity to expand upon all of the research areas covered. For instance, forecasting could be expanded to using monthly or daily data and exploring more data intensive forecasting techniques on the TSP Funds. Downside risk analysis could be expanded to using monthly or daily data or designing additional funds that the Thrift Savings Plan could provide members currently not offered. Finally, future researchers could explore how personnel retention impacts an individual's choice between the two systems and also build a more encompassing military retirement tool for service members.

Appendix A. Forecast vs Actuals Figures

Common Stock Index Investment Fund

	Actual	Forecast	Deviation
2006	11.80	7.44	4.4
2007	3.46	7.44	4.0
2008	-41.27	7.44	48.7
2009	26.65	7.44	19.2
2010	12.43	7.44	5.0
2011	0.48	7.44	7.0
2012	13.14	7.44	5.7
2013	30.86	7.44	23.4
2014	12.20	7.44	4.8
2015	1.55	7.44	5.9

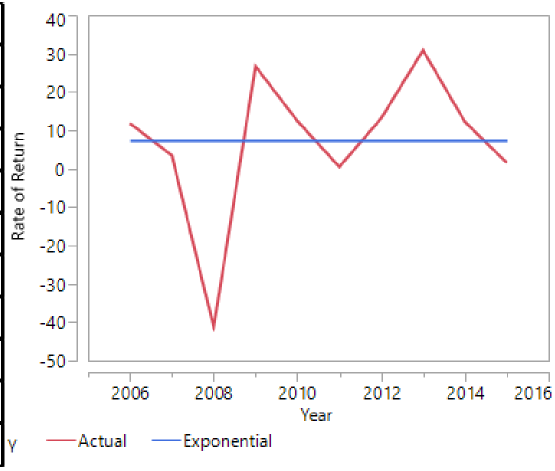

Figure 17. C Fund Simple Exponential Smoothing Model vs. Actuals

	Actual	Forecast	Deviation
2006	11.80	9.59	2.2
2007	3.46	9.59	6.1
2008	-41.27	9.59	50.9
2009	26.65	9.59	17.1
2010	12.43	9.59	2.8
2011	0.48	9.59	9.1
2012	13.14	9.59	3.5
2013	30.86	9.59	21.3
2014	12.20	9.59	2.6
2015	1.55	9.59	8.0

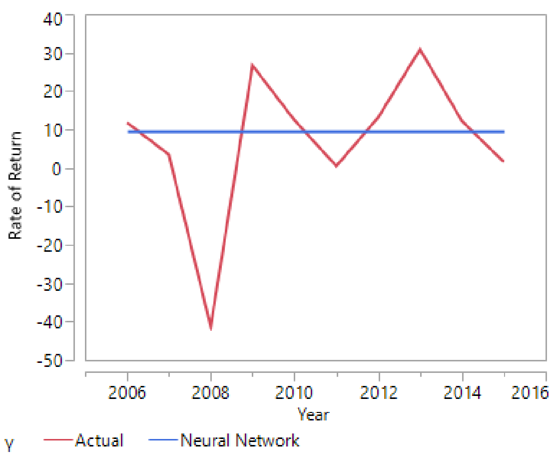

Figure 18. C Fund Neural Network vs. Actuals

Small Capitalization Stock Index Investment Fund

	Actual	Forecast	Deviation
2006	11.31	8.91	2.4
2007	3.41	8.91	-5.5
2008	-42.60	8.91	-51.5
2009	34.82	8.91	25.9
2010	26.43	8.91	17.5
2011	-5.01	8.91	-13.9
2012	15.64	8.91	6.7
2013	36.76	8.91	27.8
2014	6.22	8.91	-2.7
2015	-2.83	8.91	-11.7

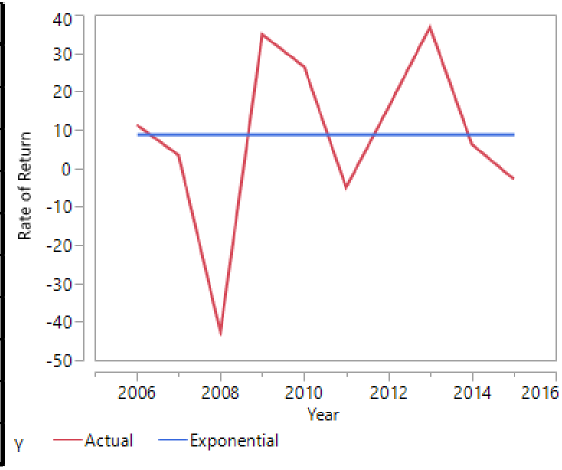

Figure 19. S Fund Simple Exponential Smoothing Model vs. Actuals

	Actual	Forecast	Deviation
2006	11.31	13.22	-1.9
2007	3.41	5.62	-2.2
2008	-42.60	17.86	-60.5
2009	34.82	5.62	29.2
2010	26.43	17.87	8.6
2011	-5.01	5.62	-10.6
2012	15.64	17.87	-2.2
2013	36.76	5.62	31.1
2014	6.22	17.87	-11.6
2015	-2.83	5.62	-8.4

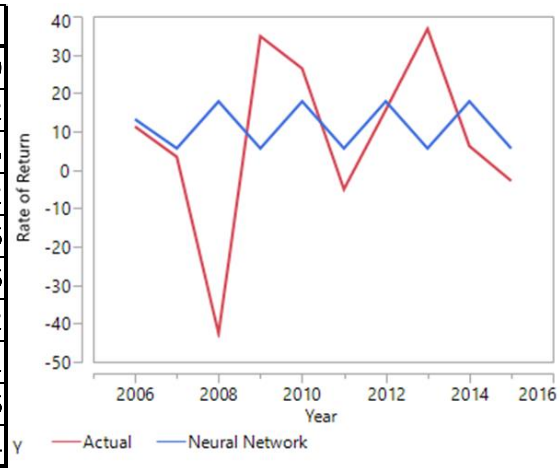

Figure 20. S Fund Neural Network vs. Actuals

Fixed Income Index Investment Fund

	Actual	Forecast	Deviation
2006	0.41	3.67	-3.3
2007	5.01	3.67	1.3
2008	1.17	3.67	-2.5
2009	5.96	3.67	2.3
2010	4.08	3.67	0.4
2011	6.26	3.67	2.6
2012	1.36	3.67	-2.3
2013	-3.27	3.67	-6.9
2014	5.15	3.67	1.5
2015	1.00	3.67	-2.7

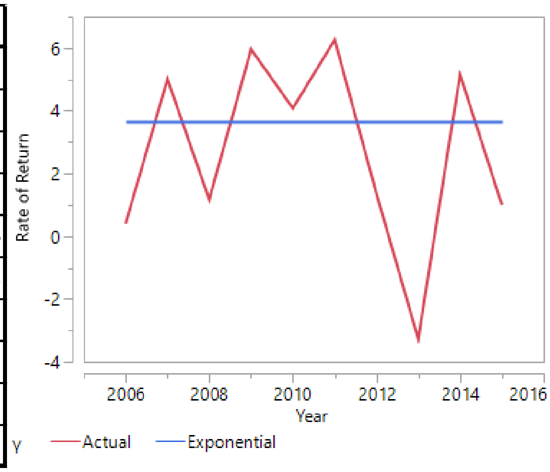

Figure 21. F Fund Simple Exponential Smoothing Model vs. Actuals

	Actual	Forecast	Deviation
2006	0.41	6.08	-5.7
2007	5.01	4.43	0.6
2008	1.17	4.45	-3.3
2009	5.96	4.45	1.5
2010	4.08	4.45	-0.4
2011	6.26	4.45	1.8
2012	1.36	4.45	-3.1
2013	-3.27	4.45	-7.7
2014	5.15	4.45	0.7
2015	1.00	4.45	-3.5

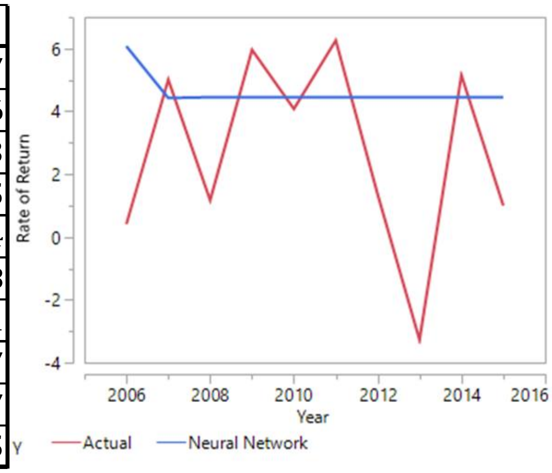

Figure 22. F Fund Neural Network vs. Actuals

Government Securities Investment Fund

	Actual	Forecast	Deviation
2006	0.94	2.64	-1.7
2007	2.79	2.64	0.1
2008	-0.53	2.64	-3.2
2009	2.94	2.64	0.3
2010	0.18	2.64	-2.5
2011	0.82	2.64	-1.8
2012	-1.46	2.64	-4.1
2013	0.30	2.64	-2.3
2014	0.73	2.64	-1.9
2015	2.13	2.64	-0.5

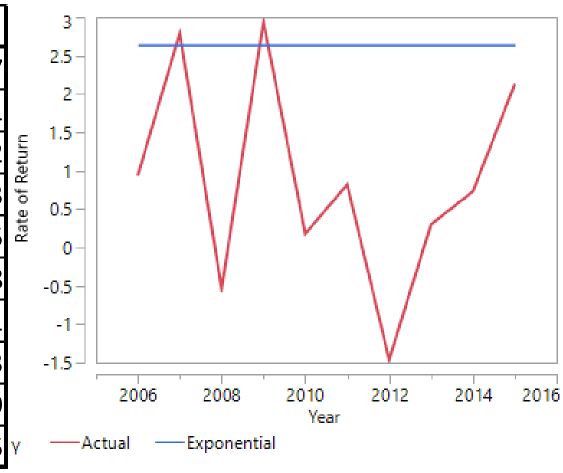

Figure 23. G Fund Simple Exponential Smoothing Model vs. Actuals

	Actual	Forecast	Deviation
2006	0.94	3.31	-2.4
2007	2.79	3.33	-0.5
2008	-0.53	3.33	-3.9
2009	2.94	3.33	-0.4
2010	0.18	3.33	-3.2
2011	0.82	3.33	-2.5
2012	-1.46	3.33	-4.8
2013	0.30	3.33	-3.0
2014	0.73	3.33	-2.6
2015	2.13	3.33	-1.2

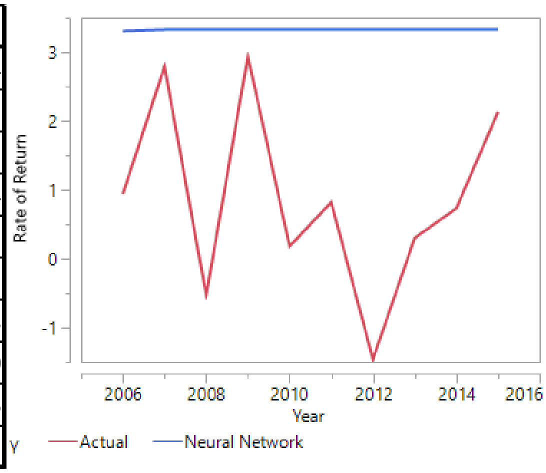

Figure 24. G Fund Neural Network vs. Actuals

International Stock Index Investment Fund

	Actual	Forecast	Deviation
2006	22.33	5.37	17.0
2007	9.35	5.37	4.0
2008	-46.71	5.37	-52.1
2009	30.01	5.37	24.6
2010	5.31	5.37	-0.1
2011	-13.44	5.37	-18.8
2012	15.69	5.37	10.3
2013	20.54	5.37	15.2
2014	-6.85	5.37	-12.2
2015	-0.42	5.37	-5.8

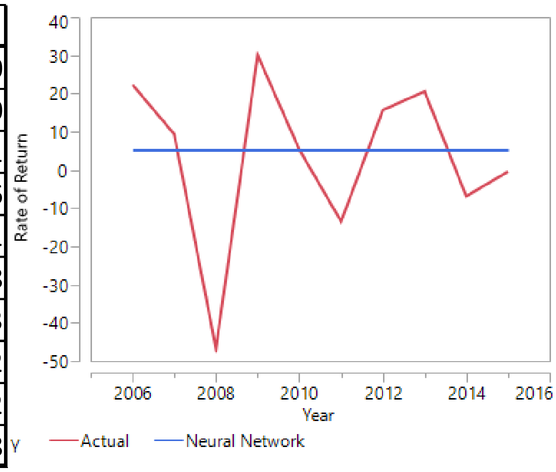

Figure 25. I Fund Simple Exponential Smoothing Model vs. Actuals

	Actual	Forecast	Deviation
2006	22.33	4.56	17.8
2007	9.35	4.56	4.8
2008	-46.71	4.56	-51.3
2009	30.01	4.56	25.4
2010	5.31	4.56	0.7
2011	-13.44	4.56	-18.0
2012	15.69	4.56	11.1
2013	20.54	4.56	16.0
2014	-6.85	4.56	-11.4
2015	-0.42	4.56	-5.0

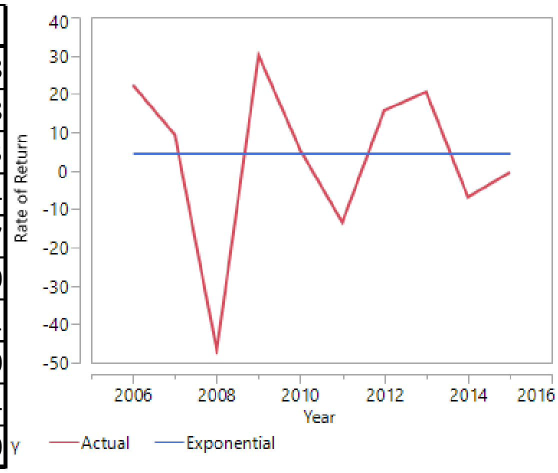

Figure 26. I Fund Neural Network vs. Actuals

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14. ABSTRACT

Starting January 1, 2018, the Department of Defense new Blended Retirement System (BRS) will go into effect. Military members with less than twelve years of service will have the option to either remain in the current High 3 Retirement System or opt into the BRS. This decision will have a lasting impact on their lives well beyond their military careers. With this in mind, we have developed a Decision Support System that will enable service members to compare the two retirement choices in terms of annual and total lifetime expected value. There were three phases to the development of the decision support tool. First, we identified Simple Exponential Smoothing Method and Artificial Neural Networks as the most accurate forecasting techniques to predict the Thrift Savings Plan Funds' rate of return. Next, we identified surrogate TSP portfolios based on minimizing downside risk. In the third phase, we identified risk tolerance and the continuation pay multiplier as the key drivers for differentiating between the two systems. Finally, the resulting Decision Support System leverages current time series forecasting techniques, behavioral economic theory, and Bayesian statistics to capture the complexity of this important decision while delivering relevant information to service members in a straightforward manner using an R Studio Shiny Application.

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