Risk Behavior in Public Pension Funds

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Abstract

This study analyzes how fund characteristics and state economic and political ideological factors influence risk (measured by equity allocation) in public pension funds in the United States. The researcher builds a predictive model of equity allocation using three categories of data from three separate sources (one on pension management, one on state economics, and one on state ideological cohesion) to build multiple tree-based models and a neural network. This study finds that a random forest model is the most predictive way to represent this data. All three categories (fund characteristics, economics, and ideological cohesion) play a role in the models and lower the error rate. Further, higher homogeneity in politics is generally associated with higher equity allocation.

keywords: Pension management, political polarization, investment risk.

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1 Introduction

According to the Organisation for Economic Co-operation and Development (OECD), in 2016 the U.S. had the largest pension market in OECD countries, with assets worth 25.1 trillion USD (OECD (2017)). U.S. public pensions are extremely underfunded. In 2016, the median funding ratio (assets available for payments to retirees) was 71.1% (Meisler (2017)). According to Mooney (2017) at the Financial Times, in 2017 US public pension funds lacked approximately "$3.85 [trillion dollars] that they need[ed] to pay the retirement benefits of current and retired workers." Thus, it is essential to understand the factors that influence pension fund risk and return to better understand how to meet the crisis of underfunding. This paper analyzes the variables that influence risk-taking (measured by equity allocation) in public pension funds in the United States. The factors considered include fund characteristics (such as accounting assumptions, funding ratio, and performance), state political ideological polarization, and measures of state economic factors (such as tax rate and budget surplus). *I ask whether and how these characteristics can be used to predict equity allocation in public pension funds.*

The current literature on pension management covers topics such as fund performance and its relationship to asset allocation and active management (Brown et al. (2010), Aglietta et al. (2012)), accounting practices and liability measurement (Pennacchi and Rastad (2011), Brown and Wilcox (2009), Novy-Marx and Rauh (2009)), and political and social factors that influence pension board management behavior (Bradley et al. (2016), Hochberg and Rauh (2013), Pennacchi and Rastad (2011)). Though the literature on pensions is vast, I did not encounter any research that tried to find a relationship between political ideology and polarization of the broader government to pension fund performance. Thus, my research would add to the current body of pension research by asking whether state political ideology and cohesion influences risk-taking behavior in pension funds. However, as I add to the existing literature, I will attempt to take previous findings into account by including factors that have been shown to influence fund risk and return, such as accounting practices and other fund characteristics. Additionally, I will test whether state economic factors, such as taxes and budget surpluses, influence equity allocation in pension funds.

This research analyzes factors that influence pension risk-taking using data from three difference sources: (1) the Public Plans Data of pension characteristics and performance, (2) the Correlates of State Policy Project, which includes state economic and political variables, and (3) the Shor-McCarthy State Legislative Aggregate Ideology Data, which includes estimates of state political ideological cohesion. I theorize that equity allocation can be modeled as an interaction of many of these variables, but the relationship will be highly complicated and nonlinear. Thus, I have chosen to model the relationship between the variables and build a predictive model of fund risk using decision trees, a random forest model, and a neural net. These models likely work better than simple linear models because they account for many types of interactions between variables and multiple layers.

I find that these models work fairly well. The random forest model performs the best out of all the models, with a mean squared error rate of 0.003. Further, analysis of multiple decision trees yields some interesting results, such as a positive relationship between political cohesion and equity allocation. Further results will be discussed in Section 5: Analysis and Results.

This paper is structured as follows. First, I will discuss previous theory on pension fund management and how it influences my variable selection and the models I use to try to predict equity allocation. Second, I discuss my data sources and present summary statistics for key variables. Third, I outline my methodological approach and discuss its relevance to my research question. Fourth, I discuss the results of my analysis. The paper will end with a conclusion that will summarize my findings and discuss opportunities for further study.

2 Theory and Model

I theorize that pension fund risk can be modeled as an interaction between fund characteristics and state political and economic factors. Equity allocation is a commonly used simplified construct for risk-taking behavior due to asset allocation?s place in modern portfolio theory (which originated with Markowitz (1952)). This theory suggests that when constructing an optimal portfolio, investors must balance the individual portfolio risk contributed by each investment with the expected return of the investment. Thus, previous literature has used allocation as a risk measure (Lucas and Zeldes (2009), Weller and Wenger (2009)) and suggested that fund characteristics, such as funded ratios and previous performance, influence allocations in funds. For example, the level of fundedness might cause investors to change their risk allocation in order to chase returns, or in order to avoid risk that might further diminish funds' abilities to meet their liabilities. These conflicting hypotheses come from previous research, such as that by Weller and Wenger (2009) that asked whether investors are likely to engage in imprudent behavior when funds are low and that by Lucas and Zeldes (2009) that hypothesizes the opposite, that funds engage in less risky behavior when funds are low. Similarly, a low one year investment return might prompt an increase in risk behavior (chasing returns to make up for loss) or a decrease in risk taking ("cutting one's losses"). Drawing from this research, I include funded ratio and previous year investment return in my model variables. (Note: Though I was initially concerned that funded ratio might be highly correlated with investment return, a preliminary scatter plot and regression analysis indicated that it is not (R^2 of 0.004)). Additionally, I included other fund characteristics such as employee type, cost structure, coverage of social security, employer type, and total membership in my model to control for any variation in these variables that might influence the outcome.

Other previous research suggests that accounting approaches, such as the Government Accounting Standards Board (GASB) actuarial approach, can influence investment decisions, understandings of risk, and pensioner's feelings of obligation to contribute to their funds (Pennacchi and Rastad (2011), Brown and Wilcox (2009), and Novy-Marx and Rauh (2009)). Thus, my model accounts for GASB assumptions, such as the return assumption and funded ratio (which are influenced by liability assumptions), and cost method.

Additionally, economic factors in a state might influence risk behavior. Thus, I control for two state economic factors: taxes as a percent of Gross State Product (GSP) and state budget surplus (also % of GSP). Taxes (% of Gross State Product) represent two main concepts in this data: (1) conservativeness and (2) level of government fundedness. State budget surplus (% of Gross State Product) is a measure of risk tolerance for the broader political and governmental sphere. It may directly (through greater funding of pensions) or indirectly (through political or economic policy) influence the risk behavior of a fund.

Lastly, literature suggests that political bias in investment behavior on pension boards and by individual investors influences risk-taking behavior. Bradley et al. (2016) and Hochberg and Rauh (2013) have looked at political bias and its influence on risk in pension funds. Similarly, Pennacchi and Rastad (2011) looked at bias in board composition and how it influences risk in the form of tracking error. Work on political bias by Bonaparte et al. (2017) shows that individual investors perceive less risk and are more willing to invest in risky assets in investing when their preferred political party is in power. My research draws on this previous research that suggests that political bias and affiliation might influence risk behavior by using measures of state ideology and polarization to try to predict fund risk-taking behavior.

I model the relationship between these selected variables using decision trees, random forest models, and neural nets. I chose to use these models because, though initial regressions do not find any significant relationship between allocation and the key variables, I hypothesize that there are hidden linear and non-linear partitions or interactions in the data that may show a stronger relationship between my independent and dependent variables. These models are useful for modeling these non-linear combinations of relationships.

3 Data

The data for this study came from three primary sources. First, the data containing pension fund information came from the Public Plans Data pension database. The data is produced and maintained by the Center for Retirement Research at Boston College in partnership with the Center for State and Local Government Excellence (SLGE) and the National Association of State Retirement Administrators (NASRA). It is available for direct download in .csv format at the Public Plans website. This database contains annualized details about 170 large pension plans in the United States (114 state and 56 large local plans), which covers 95% of public state and local plans in the U.S. The data covers the years 2001-2016. There are over 150 variables that include information topics including, but not limited to, funding, accounting assumptions and methods, allocation, returns, and fund characteristics. These data were collected from information available in the most recent Comprehensive Annual Financial Reports (CAFRs), actuarial valuations (AVs), and the Public Fund Survey and are updated regularly by the NASRA. Previous research using the Public Plans Data includes a study by Mohan and Zhang (2014) that looked at risk behavior in defined benefit pension plans. Additionally, researchers have looked at the funding status of pension plans using this data (Munnell et al. (2011)).

I joined this data with state-level data from two data sources. The first was the Correlates of State Policy Project at the Institute for Public Policy and Social Research (IPPSR) at Michigan State University. This dataset contains over 900 variables for each state from 1900-2016. The variables cover many topics, including, but not limited to, policy, demographics, economic and fiscal policy, eduction, election information, government, public opinion, partisanship, and ideology. The data is available in excel, .csv, Stata, or R on the IPPSR website. The data has been collected, cleaned, and combined over the years by scholars and students who combined multiple smaller datasets. The specific economic variables I use in this model (budget surplus as a percent of state GSP and taxes as percent of state GSP) came from Carl Klarner's State Economic Data database published in 2013.

The last dataset I joined was the Shor-McCarthy State Legislative Aggregate Ideology Data. This data was originally part of research by Shor and McCarthy (2011) and was updated in 2018 to include data through 2016. It can be found on the American Legislatures website. It contains 26 variables for each state on political ideology and polarization from 1993-2016, which covers 2,025 chamber years of data. The scores for ideology and polarization are developed based on individual-level ideal point estimates using Shor and McCarthy's NPAT common ideological space model. A full description of the model can be found in Shor and McCarthy (2011). The data is available in .dta format from the Harvard Dataverse website.

For this research, the data were downloaded from the above websites in .csv and .dta files. Each database was loaded into a pandas dataframe. Variables of no interest were removed and the dataframes were then joined by year and state so that each fund/year combination had all the data. The dataframe was cleaned of missing values, making sure that missing values occurred either random or not random in a way that could be dealt with, such as more recent or older years being subtracted from the data. In this specific case, our data ended up only covering 2001-2010 because the State Policy dataset did not have more recent years. Then, non-numerical variables (such as state, employee type, and cost structure) were changed to numerical variables using pandas factorize. The final dataframe was used in analysis as outlined in Section 4: Methods.

Table 1 shows the summary statistics for some of the main variables of interest in this study. These variables are presented from 2001-2010 with all the missing values removed, but prior to normalizing the variables.

Table 1: Summary Statistics for Key Variables

Key Variables	Mean	Standard Deviation	Minimum	Maximum	25%	50%	75%
Total Equity	0.561	0.103	0.000	0.814	0.512	0.577	0.630
Prev Year Inv Return	0.049	0.119	-0.307	0.314	-0.048	0.088	0.140
Funded Ratio	0.867	0.193	0.191	1.974	0.753	0.867	0.971
Inv Return Assumption (GASB)	0.080	0.004	0.060	0.090	0.078	0.080	0.083
Total Membership	145,870	215,374	2,627	1,621,906	20,663	68,339	173,343
Taxes (% GSP)	5.387	1.244	3.263	17.754	4.648	5.361	5.965
Budget Surplus (% GSP)	-0.069	1.008	-8.454	14.301	-0.470	-0.083	0.265
Sen Dem Heterogeneity	0.340	0.117	0.082	0.937	0.255	0.342	0.419
House Dem Heterogeneity	0.353	0.116	0.107	0.602	0.278	0.358	0.437
Sen Rep Heterogeneity	0.271	0.113	0.069	0.887	0.182	0.258	0.330
House Rep Heterogeneity	0.283	0.094	0.060	0.579	0.223	0.283	0.330
Distance b/w Party Medians (Sen)	1.650	0.620	0.410	3.010	1.193	1.596	1.920
Distance b/w Party Medians (House)	1.671	0.630	0.463	3.017	1.221	1.553	2.048

Note: Other variables of interest not included above are Employee Type, Social Security Covered, Cost Structure, Employer Type, Accounting Cost Method (GASB), Avg. Distance b/w Individual Senate Members, and Avg. Distance b/w Individual House Members. In total, 20 variables were used in the models to predict Total Equity allocation. For more information on the additional variables, please see the Analysis jupyter notebook in the MethodsResults section of the github for this project.

4 Methods

To select my variables, I used principal component analysis (PCA) to see which variables had similar loadings on my first two components. The outcome of this PCA is shown in Figure 1.

I considered removing variables with similar loadings (such as *hou_rep*, which has a similar loading to *sen_rep*, and *hou_dem*, which has a similar loading to *sen_dem*) so that there was only one variable to represent each loading. However, upon further analysis (as shown in Figure 2) less than 50% of the variance in the data is described by the first two components.

Thus, though I originally planned to scale down my number of variables using PCA, I decided to use all the variables in my models in order to avoid potentially

Figure 1: PCA of Key Variables

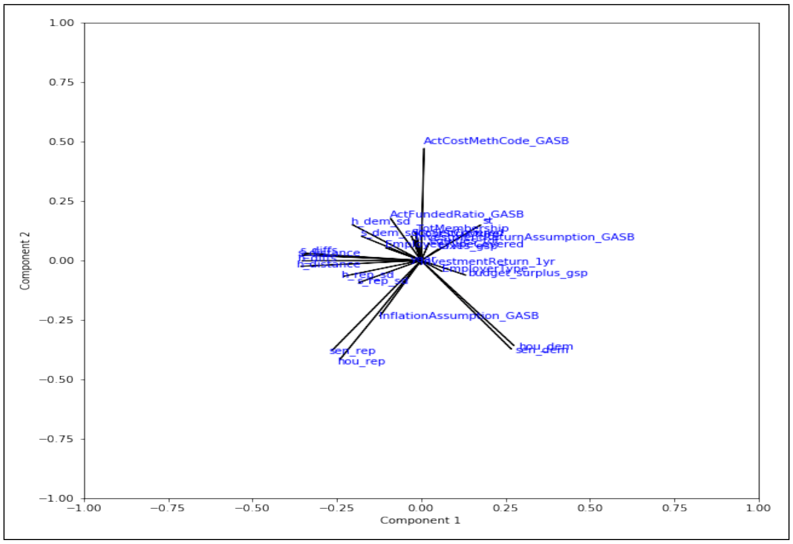
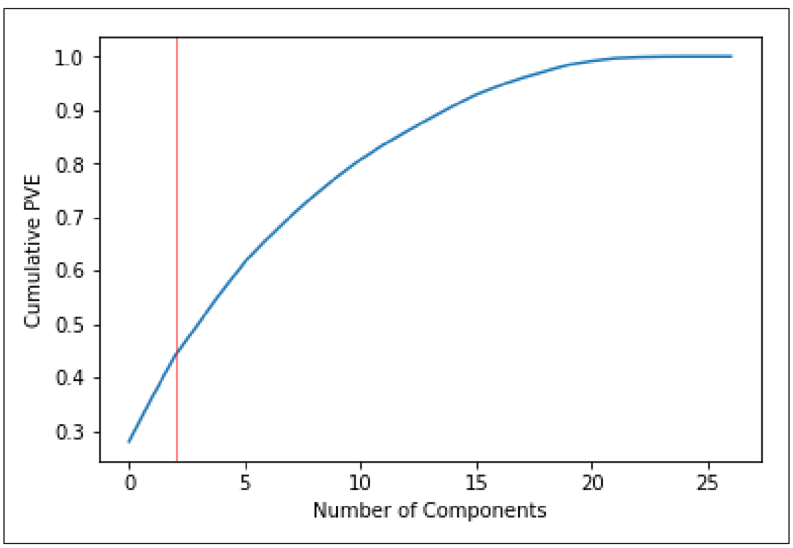


Figure 2: Percent Data Variation Explained by Component



losing information about interactions between variables that were not represented in the first two components. As further support for this decision, I removed variables with similar loadings and ran my models to see if the error rate differed. The error rate for my models with the reduced number of variables was higher for every model, suggesting that these variables are still useful in modeling total equity.

This brings me to my modeling methods. My first methodology was to compare two different models to predict my dependent variable, total equity: a neural network (specifically, the scikit-learn neural net regressor package in python) and four tree-based methods: a decision tree (depth=4) for interpretability, a decision tree (depth=100) to analyze feature importances, a bootstrapped decision tree, and a random forest model. All these models used the scikit-learn package in python.

Before I ran these models, I removed the observations from 2011-2016 (1,020 observations) because I did not have state data on these observations and also removed any additional missing values, which were missing at random. This took my data set from the original set of 2,692 observations of 16 years to the final dataset of 1,233 observations. For my neural net, I then scaled all the variables to have mean 0, standard deviation 1 because neural nets are very sensitive to unscaled variables. However, for my decision trees and random forest models I left the variables unscaled for greater interpretability since these models are not as sensitive to unscaled variables.

I also ran simple linear regressions on many individual variables and combinations of the normalized variables for greater interpretability of the effect of each variable. These regressions did not yield significant results, so I will leave them out of my discussion of results. Instead, I used variance importance measures and the splits in multiple trees to interpret the meaning of my results.

For further information on my methodology or to reproduce my code, please visit the github page for this research. If you have questions, feel free to leave a comment on the "Issues" page.

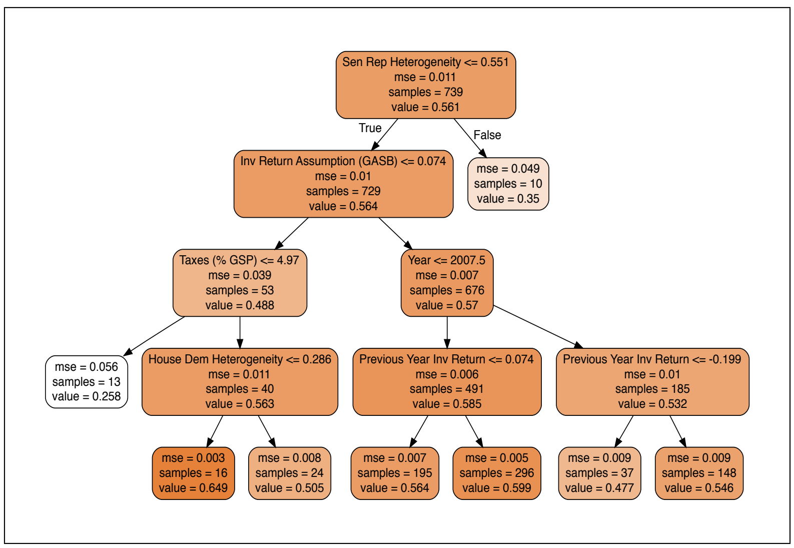
5 Analysis and Results

Initially, I ran simple linear regressions for individual variables and combinations of variables to see if equity allocation could be described with a linear combination of variables. However, I did not get significant results with these regressions. The lack of significant results in my simple regressions suggests that the significance in these models comes from interactions between these variables or combinations of linear and nonlinear relationships.

To test this theory and attempt to build a predictive model, I ran the decision tree model using all the variables in my cleaned dataset (see Table 1 for details). For the first decision tree, I divided the 1,233 observations in my cleaned dataset randomly into a training and a testing set, and ran a tree with four layers and a minimum of ten samples per leaf. I reached these layer and leaf size parameters by systematically testing different combinations of each. This combination of parameters gave me sufficient predictive power without losing much interpretability.

The decision tree generated is visualized below in Figure 3. The "value" at each stage is the predicted value for total equity, and the "mse" is the mean squared error for that prediction.

Figure 3: Decision Tree Model of Total Equity (MSE = 0.0084)



This model has a mean squared error of 0.0084, which at first glance seems very good. However, this gives a mean error rate of approximately 0.0916, which is a little less than one standard deviation (0.103) away from the mean equity allocation. Thus, this model is not very predictive. Part of this error could be due to sensitivity to the training and testing set. Thus, in order to create a more predictive model, I tried using a bagging regressor, which randomly draws many training sets from the data, estimates the trees for each set, and then finds the bagging decision tree as the average predicted x across all the trees. This performed better, with a mean squared error of 0.0070 and average error of 0.0838. However, this model was still not predictive enough, so I ran a random forest model (RFM) using the typical number of features as the square root of the total number of features. Random forest models also use bagging regressors, but they add an additional level of randomization by using different groups of features in each sample. This reduces the correlation between the trees built from each training set. The final result averages each tree together to find the predicted value. This performed the best, with a mean squared error of 0.0035 and an error of 0.0590.

An analysis of the feature importances on a the decision tree with with depth of 100 (MSE = 0.0075, Error = 0.0865) suggest that the following variables are the most important in predicting this model: Year, Accounting Cost method (GASB), Account Funded Ratio, Previous Year Investment Return, Avg. Distance b/w Individual Senate Members, Sen Rep Heterogeneity, Budget Surplus (% GSP), and Taxes (% GSP). Thus, all three factor categories (fund characteristics, state economics, and political cohesion) played a role in partitioning the data.

These results are interesting but are hard to analyze beyond their predictive power. In order to gain more interpretability, I looked at many different tree partitions using different depths, max leaf sizes, and random seeds. In general, higher funded ratios were associated with lower equity allocations, which implies that funds that can take on more risk don't. This is an inconsistent finding that requires further analysis. Higher previous investment returns were associated with higher equity allocations. This makes sense because in a low-risk environment, higher previous investment returns may be due in part to higher equity allocations.

Additionally, higher homogeneity in state politics (within and across parties) was generally associated with higher equity allocations. This suggests that less polarized states tend to have funds with higher risk-taking behavior. I theorize that this finding could be due more cohesive states taking on more risk for three potential reasons: (1) they might have a higher risk tolerance due to greater stability, (2) they may be more likely to have a stronger economic environment in which to take risk, or (3) they may elect or otherwise influence the creation of more cohesive boards that are more comfortable taking risks.

In addition to these decision trees and random forest model, I ran a multilayer perceptron neural network using scikit-learn?s neural network MLPRegressor module in python. This neural net is a machine learning algorithm that creates layers of nonlinear functions of features. I found the best results using the the hyperbolic tan function ($tanh(v) = 2\sigma(2v) - 1$) as my activation function and the quasi-Newton method limited-memory BFGS optimizer as my solver. To extend my data, I used k-fold cross validation, dividing the data randomly into four groups, holding out the k^{th} datasets as my test sets, and training four different models on the additional k-1 datasets. My average mean squared error was 0.0040, which corresponds to an average error rate of approximately 0.0631. This model performs slightly worse than the random forest model and the error rate is still a little high given the distribution of data, but it is somewhat predictive.

Table 2 shows the current results of the three different models.

Table 2: Model Error Rates

Model Type	Decision Tree (4 layers)	Decision Tree (100 layers)	Decision Tree (Bootstrapped)	Random Forest Model	Neural Network (4-folds)
MSE	0.0084	0.0075	0.0070	0.0035	0.0040
Error	0.0916	0.0865	0.0838	0.0590	0.0631

6 Conclusion

Allocation and risk behavior are essential components of understanding investment decisions, performance, and funding outcomes of U.S. public pension funds. This study aims to predict this risk behavior as a function of fund characteristics, state economics, and state political ideology/polarization. It finds that these factors can predict equity allocation with a mean squared error of 0.0035, but this average error represents approximately 1/2 of one standard deviation in the equity distribution. Thus, though the error rate is low and the results are interesting and suggest there is a relationship between the variables, they cannot perfectly predict equity allocation.

More in-depth analysis of the results of the decision trees lead to some interesting takeaways. First, as polarization of state politics decreases, equity allocation tends to increase, suggesting that funds in more cohesive states take on more risk. Also, higher funded ratios are generally associated with lower equity allocations, suggesting that funds that can take on more risk do not, or that funds assume only the amount of risk required to meet their goals. Further research into this finding is necessary to understand the relationship between funded ratio and risk-taking. Additionally, as expected, higher previous investment returns are associated with higher equity allocations.

A significant issue with this study is that the models with the lowest error rates (random forest model and neural network) have low interpretability. Thus, it is difficult to see which variables are playing the largest roles. Further analysis that looks at additional variable importance measures would greatly add to this research.

Future work could use the variables in this dataset to build a deep learning neural network with regularization, which might find more complicated layers between the variables. However, due to the small size of this dataset (1,233 observations), such research may need to occur after more data is collected or use different variables that cover more years. This research did not try to use a deep learning model due to the further lack of interpretability of these models.

Further research is necessary to interpret the cause of the relationships found in this research, such as the relationship between political cohesion and risk-taking. For example, analysis of the relationship between pension board and state political establishments, such as whether funds are elected or otherwise influenced by politicians, could shed light on the inverse relationship between polarization and risk. Board meeting minutes and specific laws and regulations for state pension funds might be fruitful data for this potential work.

Given the computational nature of this research and the specific datasets used, it is difficult to draw any causal conclusions from this study. This research only suggests that there is a relationship between the variables in question, but does not make claims beyond hypotheses as to their specific interaction. Further qualitative research or computational research using natural language (such as interviews with fund managers or politicians) could further elucidate the causal nature of the relationship.

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