The Performance of Stock Portfolios formed Using Fuzzy Logic

Andrew J. Jacob[1], Amit K. Sinha[2*]

[1] Information Analyst at Caterpillar, United States

[2] Bradley University, United States, asinha@fsmail.bradley.edu

ABSTRACT

Expert systems, a type of artificial intelligence that replicate how experts think, can aide unskilled users in making decisions or apply an expert's thought process to a sample much larger than could be examined by a human expert. In this paper, an expert system that ranks financial securities using fuzzy membership functions is developed and applied to form portfolios. Our results indicate that this approach to form stock portfolios can result in superior returns than the market as measured by the return on the S&P 500. These portfolios may also provide superior risk-adjusted returns when compared to the market.

Keywords: Expert Systems; Stock Returns; Portfolios; Fuzzy Logic; Sharpe Ratio; Treynor Ratio

JEL Classification: C8, G1, G11

1. Introduction

Expert System technology has seen its application in wide variety of disciplines including medical sciences, engineering, agriculture, and stock selection (Kamley, R S, and Jaloree 2015; Markic, Tomic, and Pavlovic 2009). The form of expert systems and artificial intelligence technology that has seen a wide application in finance is related to Fuzzy Logic (Chen *et al*. 2017; Cheung and Kaymak 2008; Chourmouziadis and Chatzoglou 2016; Korol 2014; Malagoli, Magni, and Mastroleo 2007; Nedović and Devedžić 2002; Nguyen 2016; Xidonas *et al*. 2009; Zhou and Dong 2004). These expert systems do a very good job of replicating how financial experts think, but when it comes to choosing the best investment opportunities, expert systems offer new opportunities and new ways to analyze not just one security, but all of the securities in a given universe. Furthermore, through use of fuzzy sets, all securities in a universe can be compared relative to each other and the best investment opportunities can be selected, given what investment opportunities are available. This manuscript contributes to the ever growing literature of the application of artificial intelligence, expert systems, and specifically, fuzzy logic to group US stocks into portfolios.

This manuscript differs from the other application of fuzzy logic to stock selection and portfolio formation in both methodological application and data use. It explores the application of fuzzy ranking and a holistic approach to ratio analysis. We develop composite fuzzy scores by estimating a weighted average using fuzzy values of twenty-two different variables. Standardized beta coefficients as discussed in (Bring 1994) are used for weighting purposes. The fuzzy values are used to form portfolios of stocks for the period between 1994 and 2014. Results indicate that at least one portfolio formed using our methodology provides superior risk-return performance when compared to the market portfolio.

Section 2 provides a brief literature review of overview the application of fuzzy logic in finance, while Section 3 has the methodology. Section 4 is the data section. Section 5 discusses the results while Section 6 has the conclusion.

2. Literature Review

Expert systems in general are well suited to deal with information such as financial ratios, indicators of performance for firms, and are able to draw conclusions in ways that are remarkably similar to the way humans think (Chen et al. 2017; Cheung and Kaymak 2008; Chourmouziadis and Chatzoglou 2016; Korol 2014; Malagoli et al. 2007;

Nedović and Devedžić 2002; Nguyen 2016; Xidonas et al. 2009; Zhou and Dong 2004). Fuzzy systems specifically have been tested and deemed safe and useful for applications in business and finance (Malagoli et al. 2007). 2007; Nedović and Devedžić 2002; Nguyen 2016; Xidonas *et al*. 2009; Zhou and Dong 2004). Fuzzy systems specifically have been tested and deemed safe and useful for applications in business and finance (Malagoli *et al*. 2007).

Our paper differs from (Chen *et al*. 2017; Nguyen 2016) as they both apply fuzzy logic algorithm to *mean-variance-skewness-kurtosis framework* while we mostly focus on using balance sheet, income statement, price ratios, and some market data like stock return, beta and trading volume. While (Chourmouziadis and Chatzoglou 2016; Xidonas *et al*. 2009) apply fuzzy trading system to daily data for stocks listed on the Athens Stock Exchange, we apply our methodology to the US stocks. (Korol 2014) applies a fuzzy logic approach to model and forecast exchange rates. While (Malagoli *et al*. 2007) apply the IF-Then fuzzy logic for rating and pricing firms, we form and evaluate performance of stock portfolios. Our paper also differs from (Nedović and Devedžić 2002) as they survey and discuss a number of expert systems commonly used in different areas of finance[1] while we empirical apply our methodology. (Cheung and Kaymak 2008; Zhou and Dong 2004) apply fuzzy logic to technical analysis while our manuscript is focused on fundamental analysis and portfolio formation.

Our manuscript also uses a unique approach to obtain a composite fuzzy score. While financial data can be fuzzified by applying fuzzy logic, financial variables while important, may differ in their significance for consideration. Additionally, the relative importance of these variables could also change from year to year. To address this issue in an unbiased manner we apply standardized beta coefficient approach as discussed in (Bring 1994) to appropriately weight our fuzzy values and calculate a weighted average fuzzy score for all the stocks. Portfolios are formed by using these fuzzy scores.

3. Methodology

An important step in the fuzzification of financial data, is the identification of minimizing and maximizing factors. Minimizing factors are factors that have an inverse relationship with return, meaning that a factor is better in terms of return when it is smaller. Maximizing factors have a direct relationship with return and are better when maximized. Whether a factor should be minimized or maximized was determined by applying traditional fundamental valuation logic. For example, if a price to earnings ratio is low relative to companies in a universe, the company is considered to be undervalued. Therefore, the price to earnings would be a minimizing factor assuming a lower price to earnings ratio is preferable to a higher one.

The next step in the process is the identification of the largest and the smallest values of the variables in consideration. The smallest value of the minimizing variables is assigned a value of 1, while the largest value is assigned a value of 0. For the maximizing variables, the smallest variable gets a value of 0, and the larges a value of 1. A fuzzy value is estimated for each value in between the highest and lowest values of each variable using the following membership function:

$$
f(x) = \begin{cases} \frac{1}{\max-\min}(x) + b \text{ ,if maximizing factor} \\ \frac{1}{\min-\max}(x) + b \text{ ,if minimizing factor} \end{cases}
$$

$$\text{where}$$

$$
b = \begin{cases} 1 - \frac{1}{\max-\min}(\max), \text{ if maximizing factor} \\ 1 - \frac{1}{\min-\max}(\min), \text{ if minimizing factor} \end{cases}
$$

(1)

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[1] For example, PORT-MAN is used in banking and management, INVEX is used in investment advisory, FAME in financial marketing, and DEVEX for currency exchange.

After having obtained fuzzy values for all factors, multiple regressions were run on annual data to obtain the standardized beta coefficients. (Bring 1994) provides a good overview about the estimation of standardized beta coefficients. Consider the following equation with dependent variable y, and several independent variables x_i. The usual assumptions regarding multiple regressions apply.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_3 + \ldots + \beta_k x_k + \varepsilon \tag{2}$$

The typical interpretation of the coefficients of this equation, especially if the coefficients are significant, is that a change on 1 unit in x_i changes y by β_i. This interpretation, however, does not provide any information about the relative importance of the explanatory variables. The approach to standardize regression coefficients, although not without controversy[2], allows the determination of the comparative magnitude of the independent variables in the regression model.

While (Bring 1994) discusses two approaches to estimating standardized variables, the process used in this manuscript is one where the standardized regression coefficient is obtained by dividing a parameter estimate by the ratio of the sample standard deviation of the dependent variable by that of the independent variable. Accordingly, the standardized parameter coefficients for parameter estimates in equation 2 are as below.

$$B_i = \frac{\hat{\beta}_i}{\left(\frac{\sigma_y}{\sigma_{x,i}}\right)} = \hat{\beta}_i (\sigma_y / \sigma_{x,i}) \tag{3}$$

The standardized parameter estimates obtained in equation 3 is converted to relative weights by using the following equation.

$$w_i = \frac{abs(B_i)}{\sum_i^n abs(B_i)} \tag{4}$$

The absolute value of each standardized coefficient is divided by the sum of the absolute value of all the standardized coefficients. This allows the coefficients to be converted into weights based on the relative significance of each independent variable. Using the weights from equation 5 and fuzzy values from application of equation 1, a weighted average fuzzy score is obtained for each stock using the following equation.

$$FS_i = \sum w_i b_i \tag{5}$$

This score is the security's fuzzy score relative to the other securities. As all factors are now on the same scale, they can be weighted and combined into a meaningful aggregate fuzzy score.

As an example of the implementation of our methodology, let's assume that the returns of the five firms in **Table 1** Panel A are dependent on two variables: var1 and var2. The variable var1 is a maximizing variable while var2 is a minimizing variable. As var1 is a maximizing variable, its value of 8.05 for firm2 is assigned to have a value of 1, and its value of 2.56 for firm5, is assigned to have a value of 0. As var2 is a minimizing variable, its lowest value and highest values are assigned values of 1 and 0 respectively. Fuzzy maximum and minimum variables are in Panel B of Table 1.The following fuzzy membership function applied.

$$f(x) = \begin{cases} \dfrac{1-0}{max-min}(x) + b, & if\ maximizing\ factor \\[2ex] \dfrac{1-0}{min-max}(x) + b, & if\ minimizing\ factor \end{cases}$$

where b is estimated as

$$b = \begin{cases} 1 - \dfrac{1}{max-min}(max), & if\ maximizing\ factor \\[2ex] 1 - \dfrac{1}{min-max}(min), & if\ minimizing\ factor \end{cases}$$

As var1 is a maximizing variable, its value of 8.05 for firm2 is assigned to have a value of 1, and its value of 2.56

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[2] Some manuscripts raising objections to the use of standardized regression coefficients are(Achen 1982), (Darlington 1990), (Greenland, Schlesselman, and Crigui 1986), (Hanushe and Jackson 1977), (Kim and Ferree 1981), (King 1986), and (Pedhazur 1982).

for firm5, is assigned to have a value of 0. As var 2, is a minimizing variable, its lowest value and highest values are assigned values of 1 and 0 respectively.

Plugging values in Eq. 1a, we obtain values of b as show below:

$$b = \begin{cases} 1 - \dfrac{1}{8.05 - 2.56}(8.05) = -0.4663 & if\ maximizing\ factor \\ 1 - \dfrac{1}{0.98 - 5.62}(0.98) = 1.2112 & if\ minimizing\ factor \end{cases}$$

Appropriately applying values of b to values of var1 and var2 for all firms, fuzzy values are obtained. Panel C in **Table 1** provides the fuzzy and crisp values both variables var1 and var 2.

The next in the process, requires running the following multiple regression equation shown below to get standardized beta coefficients. The regressions are carried out on the fuzzy values. Similar to variables var1 and var2, the return is fuzzified as well. The regression output is in Panel D of **Table 1**.

$$return_i = a_0 + b_1 var1_i + b_2 var2_i + \epsilon_i$$

The relative weights of the standardized beta coefficients are estimated by using the equations below.

$$w_1 = var1_{sb\_w} = \frac{abs(0.8457)}{abs(0.8457) + abs(-1.1340)} = 0.4272$$

$$w_2 = var2_{sb\_w} = \frac{abs(-1.1340)}{abs(0.8457) + abs(-1.1340)} = 0.5728$$

The fuzzy score (f_s) for each stock is estimated as the weighted average of the fuzzy values.

$$f_s = w_1 var1_f + w_2 var2_f$$

After fuzzy scores for all the variables are estimated, the 50th percentile value for the fuzzy score is used to group stocks into two portfolios. Portfolio 1 is made up of stocks below the 50th percentile value, and portfolio 2 is made up of stocks above the 50th percentile value. Panel E in **Table 1** presents the fuzzy score, 50th percentile and portfolios.

Panel A: Crisp values of variables

Firm	Variable		
	Return	var1	var2
Firm 1	8.12%	3.16	2.83
Firm 2	7.01%	8.05	5.62
Firm 3	12.25%	6.23	0.98
Firm 4	8.21%	2.98	1.92
Firm 5	7.23%	2.56	2.21

Panel B: Fuzzy values for the best and worst crisp values

Firm	Variables			
	var1 (Crisp)	var1 (Fuzzy)	var2 (Crisp)	var2 (Fuzzy)
Firm 1	3.16		2.83	
Firm 2	8.05	1.00	5.62	0.00
Firm 3	6.23		0.98	1.00
Firm 4	2.98		1.92	
Firm 5	2.56	0.00	2.21	

Panel C: Crisp and Fuzzy values

Firm	Variables			
	var1 (Crisp)	var1 (Fuzzy) var1$_f$	var2 (Crisp)	var2 (Fuzzy) var2$_f$
Firm 1	3.16	0.1093	2.83	0.6013
Firm 2	8.05	1.0000	5.62	0.0000
Firm 3	6.23	0.6685	0.98	1.0000
Firm 4	2.98	0.0765	1.92	0.7974

Firm 5	2.56	0.0000	2.21	0.7349

Panel D: Parameter Estimates

Variable	Coefs	t-stat	p-value	Standardized betas	R-sq	Adj Rsq	F-value
Intercept	0.0887	11.73	0.0072	0.0000			
var1	0.0074	4.340	0.0492	0.8457	94.70%	89.40%	17.86
var2	-0.0137	-5.820	0.0283	-1.1340			

Panel E: Portfolio based on fuzzy score

Firm	**Fuzzy Score**	**50th percentile**	**Portfolio**
Firm1	0.3911	0.4272	1
Firm2	0.4272	0.4272	1
Firm3	0.8584	0.4272	2
Firm4	0.4894	0.4272	2
Firm5	0.4210	0.4272	1

Table 1. Example

4. Data

The relevance and the economic significance of the methodology is tested by applying it to data extracted from Thompson Reuter's DataStream[3]. Data was initial extracted at an annual frequency for the period between 1973 and 2014. The financial variables extracted from DataStream are common equity (ce), common shares outstanding (cso), dividend per share (dps), earnings per share (eps), fixed assets (fa), market value (mv), net profit (netp), net working capital (nwc), quick ratio (qr), operating profit margin, stock price (prca), sales, total assets (ta), total capital (tcap), total debt (td), and trading volume (vol). To avoid results to be unduly affected by low prices, we only consider stocks that have a price of at least five dollars. Firms with zero or negative equity were excluded from consideration. So were stocks with negative sales. Besides, to minimize the impact of extreme values, variables are windsorizedat the 0.5% and the 99.5% levels, i.e., values less than the 0.5% percentile and greater than the 99.5% percentile are replaced by the 0.5% and 99.5% values. The data was windsorized every year, before the stocks were grouped into portfolios.

Using these extracted variables, the following variables were estimated: self-financing ratio (sfr), financial leverage (fl), capital employed ratio (cer), overall solvency ratio (os), price to sales ratio (ps), total asset turnover ratio (tatr), Tobin's q (tq), payout ratio (pout), price earnings ratio (pe), book to price ratio (bp), profit margin (pm), price to dividend ratio (pdps), sales growth rate (s_g) and dividend growth rate (dps_g). These variables were estimated by using the formulae shown below.

$$sfr = \frac{ce}{tcap}; \; fl = \frac{td}{ce}; \; cer = \frac{(fa+nwc)}{tcap}; \; os = \frac{ta}{td};$$
$$ps = \frac{prca}{(sales/prca)}; \; tatr = \frac{sales}{ta}; \; em = \frac{ta}{ce}; \; tq = \frac{(mv+td)}{ta};$$
$$pout = \frac{dps}{eps}; \; pe = \frac{prca}{eps} \; bp = \frac{(ce/cso)}{prca}; \; pm = \frac{netp}{sales};$$
$$pdps = \frac{prca}{dps}; \; s\_g = \ln\left(\frac{sales_t}{sales_{t-1}}\right); \; dps\_g = \ln\left(\frac{dps_t}{sdps_{t-1}}\right)$$

The S&P 500 index values were also extracted from DataStream while the 3-month T-bill rates were obtained from the website of Federal Reserve Bank of St. Louis. Annual market returns were estimated by taking the natural log of consecutive S&P values. Similarly, stock returns were estimated be taking the natural log of prices from consecutive years.

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[3] The data was for stocks in DataStream seven constituted research lists. These lists include data for stocks that actively traded as well as for those stocks that are not.

$$sktret_{i,t} = \ln\left(\frac{prca_{i,t}}{prca_{i,t-1}}\right); \; mktret_t = \ln\left(\frac{S\&P500_t}{S\&P500_{t-1}}\right)$$

Stock beta were estimated using rolling 20-year rolling window of individual stock returns and return on the S&P 500. Beta is estimated only for those stocks that have at least ten years of return data points during the twenty-year window. The traditional covariance formulae shown in the equation below was used to estimate stock beta. After the beta was calculated, any stock with negative values for beta were eliminated for further consideration during year the year the stock had a negative beta.

$$\beta_i = \frac{Cov(r_i, R_M)}{\sigma_M^2} = \frac{\sum_{i=1}^{n}(r_i - \overline{r_i})(R_M - \overline{R_M})}{\sum_{i=1}^{n}(R_M - \overline{R_M})^2}$$

The variables considered to maximizing variables are: stock return, stock beta, quick ratio, operating profit margin, self-financing ratio, capital employed, overall solvency ratio, price to sales ratio, total asset turnover ratio, Tobin's q, profit margin, price to dividend per share ratio, lagged stock return, trading volume, sales growth rate, and dividend growth rate. The variables considered to be minimizing variables are: book to price ratio, payout ratio, financial leverage ratio, price to earnings ratio, and market value. The choice of variables defined as maximizing or minimizing is based on the assumption whether these variables are going to have positive or negative impact on stock returns. **Table 2** tabulates the variables and their perceived impact on stock performance. A maximizing variable increases return, while a minimizing variable has a negative impact on stock returns. While effort has been made to use existing finance literature as a guide to decide whether variables are maximizing or minimizing, classification of variables into maximizing or minimizing could be arbitrary.

Variables	Direction
Book to Price Ratio	Maximizing
Capital employed Ratio	Maximizing
Dividend growth rate	Maximizing
Financial Leverage	Minimizing
Market Value	Minimizing
Operating Profit Margin	Maximizing
Overall Solvency Ratio	Maximizing
Payout Ratio	Maximizing
Price to Dividend per share	Minimizing
Price to Earnings Ratio	Minimizing
Profit Margin	Maximizing
Price to Sales	Minimizing
Quick Ratio	Maximizing
Sales growth rate	Maximizing
Self-Financing Ratio	Maximizing
Size	Minimizing
Stock Return and Lagged Stock Return	Maximizing
Stock Beta	Maximizing
Lagged Stock Return	Maximizing
Tobin's Q	Maximizing
Total Assets Turnover ratio	Maximizing
Volume	Maximizing

Table 2. Variable Direction

This table shows the variables used in the manuscript. It also tabulates the direction of the impact of the variable. A

maximizing variables is considered to have increase future returns, while minimizing variables are considered to decrease future returns. Based on the direction of the future impact, the raw values of the variables are converted into fuzzified variables using the following equation:

$$f(x) = \begin{cases} \frac{1-0}{max-min}(x) + b, & if\ maximizing\ factor \\ \frac{1-0}{min-max}(x) + b, & if\ minimizing\ factor \end{cases};$$

where

$$b = \begin{cases} 1 - \dfrac{1}{max-min}(max), & if\ maximizing\ factor \\ 1 - \dfrac{1}{min-max}(min), & if\ minimizing\ factor \end{cases}$$

Our methodology to apply fuzzy logic requires variables considered to be classified into maximizing and minimizing variables. We selected stock beta to be a maximizing variable, as it measures systematic risk. Empirical tests (Kandel and Stambaugh 1987, 1989, 1995; Lintner 1965a; Miller and Scholes 1972; Roll 1977; Roll and Ross 1994) of the risk-return relationship as hypothesized by the Capital Asset Pricing Model (Lintner 1965b; Mossin 1966; Sharpe 1964) show that *risk premia will be proportional to exposure to systematic risk* (Bodie, Kane, and Marcus 2018).

We consider quick ratio to be a maximizing variable, as a higher quick ratio indicates a better ability of the firm to meets its liquidity needs. Like current ratio, quick ratio measures a firm's ability to bills using its most liquid assets (Bodie *et al*. 2018), but is often preferred to current ratio(Reilly and Brown 2009). We consider the total asset turnover ratio as a maximizing variable because as per (Bodie *et al*. 2018), it indicates efficiency of use of a firm's asset to generate sales. We consider Tobin's Q to be a maximizing variables as firms that have Tobin's Q value greater than one have greater incentive, which should result in higher returns to shareholders (Brainard and Tobin 1968; Lindenberg and Ross 1981; Tobin 1969).

As higher profit margin (pm) boosts potential for growth using less external funds (Brigham and Daves 2013) we consider profit margin as a maximizing variable. We also consider operating profit margin a maximizing variable, as it relates a firm's performance to its operations (Brigham and Daves 2013) and accordingly, a higher number is more desirable than a lower number. We consider the payout ratio (pout) to be a minimizing variables, because a lower and steady payout policy invariably lowers the cost of equity thereby maximizing stock price (Brigham and Daves 2013).

We consider self-financing ratio and overall solvency as maximizing variables, while we consider financial leverage to be a minimizing variable. A higher value of the self-financing ratio means more equity in total capital, thereby allowing the firm to invest in riskier projects without having to access the external capital markets. High equity also indicates a higher capacity for accessing the debt market and increase leverage. (Reilly and Brown 2009) point out that high levels of debt increase bankruptcy costs, and accordingly extremely high amounts of debt in the capital structure would be detrimental to the interest of increasing returns to shareholders. Accordingly, financial leverage is a minimizing variable in this study. As higher overall solvency ratio indicates more equity in the capital structure, and like the self-financing ratio, it is considered to be a maximizing variable. The capital employed ratio is considered to be a maximizing variable, as it shows the fraction of the total capital deployed in productive assets.

Price earnings, and price to sales ratios are considered to be minimizing variables. As (Bodie *et al*. 2018) point out risker firms have lower P/E ratio, a low value for this ratio is indication for higher returns in the future for such stocks. Higher P/E ratios, on the other hand are indication for lower future returns. A similar logic is used to consider price to sales ratio as a minimizing variable, and this variable is especially relevant if a firm has a negative net income. The book to price ratio is considered as a maximizing variables as it is found to be positively correlated with subsequent stock returns (Fama and French 1992; Penman, Richardson, and Tuna 2007).

We consider volume to be a maximizing variables primarily from the findings of (Chordia and Swaminathan 2000), who find that returns of higher trading volume stocks lead those with lower trading volume. The rationale for using lagged returns as maximizing variables comes from findings of (Jegadeesh and Titman 1993, 2001) who show

that buying stocks with past positive returns lead to higher returns in the future.

Our motivation for considering size as a minimizing variable arises from the findings of (Fama and French 1992) who find that the coefficient of size to have a negative coefficient, thereby implying large size to provide lower returns. We consider the growth rate in sales to be a maximizing variable, because everything else the same, an increase in sales would improve a firm's bottom line, optimism about the future, higher profits, cash flows and returns to shareholders. As an increase in dividends exhibit managerial confidence about future prospects about of the firm, the dividend growth rate is considered a maximizing variable.

This methodology of portfolio formation would nevertheless be implementable. Raw variables are converted into fuzzy values using a membership function shown below. This function is similar to one shown in Equation 1.

$$f(var_i) = \begin{cases} \frac{1-0}{max(var_i)-min(var_i)}(var_i) + b, & if\ maximizing\ factor \\ \frac{1-0}{min(var_i)-max(var_i)}(var_i) + b, & if\ minimizing\ factor \end{cases} \quad (6)$$

where b is estimated as

$$b = \begin{cases} 1 - \frac{1}{max(var_i) - min(var_i)}(var_i), & if\ maximizing\ factor \\ 1 - \frac{1}{min(var_i) - max(var_i)}(var_i), & if\ minimizing\ factor \end{cases}$$

The standardized beta coefficients are estimated by running the following multiple regression.

$$ret_{i,t,f} = a_{i,t} + beta_{i,t,f} + qr_{i,t,f} + opm_{i,t,f} + sfr_{i,t,f} + cer_{i,t,f} + os_{i,t,f} + ps_{i,t,f} + tatr_{i,t,f} + tq_{i,t,f} + pe_{i,t,f} + pm_{i,t,f} + pdps_{i,t,f} + lag\_ret_{i,t,f} + vol_{i,t,f} + s\_g_{i,t,f} + dps\_g_{i,t,f} + bp_{i,t,f} + pout_{i,t,f} + fl_{i,t,f} + mv_{i,t,f} + \epsilon_{i,t} \quad (7)$$

The letter f in the subscript is indicate that the multiple regression was carried out using fuzzy values. These regressions are run every year and the standardized beta coefficients discussed in (Bring 1994) are extracted. Using the standardized coefficients, the relative weights of each variable is estimated by using the following equation which is similar to Eq. (4).

$$w_i = \frac{abs(std\_coeff\_var_i)}{\sum_{i=1}^{i=20} abs(std\_coeff\_var_i)} \quad (8)$$

Using the fuzzy values from the membership functions in Eq. (6) and the weights of the standardized coefficients in Eq. (8), the composited fuzzy scores are obtained by using the equation below. This equation is similar to Eq. 5.

$$fuzz\_score_i = \sum (w_i)(f(var_i)) \quad (9)$$

Eq. (9) results in each stock having a unique fuzzy score. These scores are then sorted quintiles. The quintiles numbers are then used to group the stocks into five different portfolios: P1, P2, P3, P4 and P5, which are held for one year. At the end of the year the return on the five portfolios are calculated. A portfolio strategy, hereby referred to as the net portfolio, which involved shorting Portfolio P1 and taking a long position in portfolio P5 was also implemented. The entire methodology is repeated and portfolios rebalanced each year for the years between 1994 and 2014.

Table 3 presents the average return for each of these five portfolios, the risk-free return and the return on the market as measured by the return on the S&P 500 for the period between 1994 and 2014. The performance of the portfolios are measured by the Sharpe ratio and the Treynor ratio, which are also presented in Table 3. These ratios are estimated using the formulae in Eq. 10a and 10b respectively.

$$Share\ Ratio_{p,t} = \left(\frac{R_{p,t} - Rf_t}{\sigma_p}\right) * 100 \quad (10a)$$

$$Treynor\ Ratio_{p,t} = \left(\frac{R_{p,t} - Rf_t}{\beta_{p,t}}\right) * 100 \quad (10b)$$

The beta of the market is taken to 1, while the beta of the portfolios is the average of the betas of the stocks in a portfolio. The annual betas of the portfolios are then averaged to obtain the portfolio betas for each portfolio between 1994 and 2014. The beta for the net portfolio is the difference between the betas of portfolios P1 and P5. The standard deviation of the portfolio is estimated using the returns of the portfolios. **Table 3** also contains the performance of a portfolio strategy that involves shorting portfolio 1 and taking a long position in portfolio 5.

The average returns of the portfolios range from -0.28% for portfolio 1 to 10.46% for portfolio 5. During this

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period the average risk-free return was 2.69% and the average annual return on the market was 7.07%, while the net portfolio had an average return of 10.75% over the 21 years, between 1994 and 2014. While the average return on the market is higher than portfolios 1, 2, 3, and 4, it is 3.39% lower than that of portfolio 5, and 3.68% lower than the net portfolio. While the Sharpe ratios for P5 and net portfolio is higher than that of the market, the Sharpe ratio of the market is higher than those of P1, P2, P 3, and P4. For the Treynor ratio, except for P1, all the other portfolios outperform the market on a risk-adjusted basis.

Table 4 provides the annual portfolio returns for each of the years in consideration. We can observe that the highest return on the market was 29.35% in 1995 while the worst at -48.59% was in 2008. While the worst performances of all five portfolios are lower than negative sixty-five percent, the worst performance for the net portfolio is -48.91%. The best performances for all five portfolios were above 35%, with the highest being 76.40% for portfolio 5 in year 2000, and 84.30% for the net portfolio also in year 2000. During this period the risk-free rate ranged from a minimum of 0.03% in 2014 to a high of 5.82% in 2000. While a clear dominance of any of the portfolio over the market is not observed, the market also does not dominate all five portfolios between 1994 and 2014.

Portfolio	Average Return	Sharpe Ratio	Treynor Ratio
P1	-0.28%	-11.78	-27.77
P2	3.91%	4.55	5.39
P3	4.59%	5.93	7.98
P4	4.07%	4.39	4.75
P5	10.46%	23.71	15.76
(P5 – P1)	10.75%	27.47	20.86
Market	7.07%	22.64	4.38
Risk-Free	2.69%		

Table 3. Portfolio performance

Year	P1	P2	P3	P4	P5	(P5 – P1)	Market	Rf
1994	-3.66%	-1.76%	-0.51%	-1.96%	-3.12%	0.54%	-1.55%	4.25%
1995	19.46%	25.26%	22.25%	19.04%	27.11%	7.65%	29.35%	5.49%
1996	11.04%	11.67%	17.33%	14.60%	18.83%	7.79%	18.45%	5.01%
1997	20.14%	18.81%	16.87%	17.00%	16.04%	-4.10%	27.01%	5.06%
1998	-11.11%	-2.46%	-10.60%	-12.36%	-19.17%	-8.07%	23.64%	4.78%
1999	1.04%	0.85%	6.71%	6.10%	19.84%	18.80%	17.84%	4.64%
2000	-7.62%	28.79%	56.24%	51.72%	76.40%	84.03%	-10.69%	5.82%
2001	-43.50%	-66.41%	-75.10%	-45.34%	32.44%	75.93%	-13.98%	3.39%
2002	-23.69%	-0.81%	11.05%	18.03%	28.23%	51.92%	-26.61%	1.60%
2003	3.33%	0.35%	-17.04%	-31.84%	-45.58%	-48.91%	23.41%	1.01%
2004	33.81%	43.26%	46.42%	43.59%	38.44%	4.63%	8.61%	1.37%
2005	13.46%	20.28%	14.60%	14.84%	20.88%	7.43%	2.96%	3.15%
2006	7.48%	3.64%	2.75%	1.47%	5.38%	-2.10%	12.77%	4.73%
2007	14.78%	13.12%	12.67%	10.02%	12.17%	-2.61%	3.47%	4.35%
2008	1.44%	-4.59%	-9.22%	-9.58%	-7.86%	-9.30%	-48.59%	1.37%
2009	-74.36%	-61.25%	-65.21%	-76.56%	-68.26%	6.10%	21.07%	0.15%
2010	35.27%	34.89%	53.58%	63.29%	65.76%	30.49%	12.03%	0.14%
2011	-21.59%	-13.83%	-13.80%	-18.17%	-19.87%	1.72%	0.00%	0.05%

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2012	4.82%	12.07%	9.06%	7.49%	5.65%	0.84%	12.58%	0.09%
2013	18.02%	22.47%	23.53%	20.32%	18.56%	0.54%	25.93%	0.06%
2014	-4.51%	-2.23%	-5.08%	-6.10%	-2.11%	2.40%	10.79%	0.03%
Mean	-0.28%	3.91%	4.59%	4.07%	10.46%	10.75%	7.07%	2.69%

Table 4. Annual portfolio returns

This table provides the average annual returns of all the portfolios for each of the years in the study. Portfolios are formed based by grouping stocks into five portfolios (Port 1, 2, 3, 4 and 5) based on their fuzzy scores. The portfolios are rebalanced every year. The market return (Market) and the risk-free returns are also provided. Only those stocks with prices above $5 were considered.

5. Conclusion

Stock picking is a tedious exercise requiring consideration of numerous pieces of information, especially if decisions made are to be objective and rational. Asset pricing models like CAPM and those proposed in (Fama and French 1992, 1993) among others may serve as frameworks to stock selection with only a few variables considered. However, a growing body of work including that by (Welch and Goyal 2008) use an exhaustive list of variables. Our manuscript provides an approach to decision making regarding stock selection and portfolio formation by using fuzzy logic to simplify decision making while considering an exhaustive list, twenty-two financial market and fundamental variables. This approach allows consideration of information contained in different financial ratios and variables, and by appropriately weighting that information, the final decision is based on only one composite fuzzy score. Accordingly, this approach represents the best of both worlds as its imultaneously allows for consideration of numerous variables, and simplify decision making.

In this paper we use fuzzy membership functions to convert raw values into fuzzy values. We weight the fuzzy values using a and standardized regression coefficients to estimated weighted average fuzzy scores. The fuzzy scores are then used to divide stocks into quintile portfolios, P1, P2, P3, P4, and P5. We also have one portfolio strategy where we short stocks We apply this strategy for 21 years between 1994 and 2014. Portfolios are balanced every year and held for one year. We also have one portfolio strategy, the net portfolio, where we short P1 and take a long position in P5.

Our results show the average return of one of the portfolios, P5, is higher than the other four portfolios and that of the market P5 outperforms the market by 3.39% while a portfolio strategy of shorting P1 and taking a long position in P5 would have resulted in a rate of return 3.68% higher than that of the market. The risk-adjusted performance compares favorably for four of the five portfolios and the net portfolio when performance is measure by the Treynor ratio. When the Sharpe ratio is considered, P5 and the net portfolio outperforms the market on a risk-adjusted basis. These results indicated that the process of forming portfolios using a process that considers fuzzy logic could result in portfolios that outperform the market in average returns, as well as on a risk-adjusted basis.

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