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Abstract In this paper we evaluate and extend the PORTRAIT tool. PORTRAIT applies an argumentation based methodology for composing fund portfolios. Argumentation allows for combining different contexts and preferences in a way that can be optimized. It allows for defining a set of different investment policy scenarios and supports the investor/portfolio manager in composing efficient portfolios that meet her/his profile. The performance and risk of the constructed portfolios is compared with portfolios based on a traditional performance index under different scenarios. This approach is applied on data of Greek domestic equity mutual funds over the period from January 2006 to December 2011 with positive results. The empirical results of our study showed that argumentation is well suited for this type of applications giving answers to two important questions, i.e. which mutual funds are the most suitable to invest in, and, what portion of the available capital should be invested in each of these funds.

Keywords Decision making · Argumentation · Mutual funds · Portfolio selection

Mathematics Subject Classification 90B50

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1 Introduction

The traditional portfolio theory developed by Markowitz (1952, 1959), is concerned with constructing a portfolio of assets, e.g. stock, bonds, funds, etc., that maximizes the investor's utility. It accommodates the portfolio construction problem on the basis of the existing trade-offs of risk and return in the mean–variance context. Taking into account the considerable amount of the available investment alternatives, the portfolio management problem is often addressed through a two-stage procedure. At a first stage the mean–variance efficient frontier is constructed. At a second stage, on the basis of the investor's preferences, the optimal portfolio is selected from the set of efficient portfolios.

In the international literature, since the pioneering work of Markowitz (1952, 1959), a series of programming approaches have dealt with the problem of mutual fund portfolio selection. For example, in 1967, Sharpe proposed a linear goal programming model for the portfolio selection of open-end mutual funds. Lee Sang and Lerro (1973) and Sharma and Sharma (2006) used lexicographic goal programming for the mutual fund portfolio selection problem. Ballestero and Romero (1996) used a compromise programming model. Arenas-Parra et al. (2001) utilized a fuzzy goal programming model. Pendaraki et al. (2004) applied a weighted goal programming, while Pendaraki et al. (2005) used a combination of discrete and continuous multicriteria decision aid methods for equity mutual funds selection and composition. Joo Oh et al. (2005) used a genetic algorithm to support portfolio optimization for index fund management. Chen and Huang (2009) solved the optimal asset allocation using fuzzy optimization. Davies et al. (2009) applied a multiobjective approach to the hedge funds portfolio selection problem.

For a completed literature review of portfolio management studies you can see the paper of Zopounidis and Doumpos (2013) that present the state of the art of the different multicriteria aggregating procedures for the financial portfolio selection problem. Additionally, bibliographic studies on multiple criteria decision making combined with finance can be found in the seminal studies of Zopounidis (1999), Zopounidis and Doumpos (2002), Steuer and Na (2003), Spronk et al. (2005) and Xidonas et al. (2009). In the paper of Aouni et al. (2014) the state of the art of the financial portfolio management through goal programming models is presented.

Studies on Greek mutual funds performance evaluation based on traditional risk returns approaches have been applied by Milonas (1999), Philippas (1999), Sorros (2003), Artikis (2004), etc. Moreover, Pendaraki et al. (2003) and Babalos et al. (2012b) evaluated the Greek mutual fund's performance through multicriteria analysis, while studies on Greek mutual fund performance using Data Envelopment Analysis are presented by Alexakis and Tsolas (2011), Babalos et al. (2012a) and Pendaraki (2012).

In our recent work (Spanoudakis et al. 2009; Pendaraki and Spanoudakis 2012), the two stage portfolio problem is solved through the PORTRAIT (Portfolio construction based on Argumentation Technology) tool that uses, for the first time, argumentation-based decision making (Kakas and Moraitis 2003) for selecting the proper assets which will compose the portfolios. For the second stage (portfolio composition), this work uses different scenarios in order to define the proportion of the selected fund in the final portfolios.

The present study extends our previous work by incorporating more robust approaches for the second stage of our problem under concideration and evaluating it by comparing argumentation results with a traditional performance index. In the previous study the proposed methodology was only compared to the Athens Stock exchange index. Moreover, we have extended our data base, taking into consideration all domestic equity mutual funds for the period 2006–2011.

Additionally, we compose portfolios taking into account the past performance of the examined funds after having confirmed our findings that there is statistically significant performance persistence for 1-year and 4-years holding periods through the "winner–winner, winner-loser" methodology developed by Brown and Goetzmann (1995), Goetzmann and Ibbotson (1994), and Malkiel (1995). Furthermore, in order to give the opportunity to investors to select optimally among the most promising funds in terms of risk and return characteristics, for the second stage of our problem we develop the Markowitz optimum and minimum variance portfolios (Markowitz 1952, 1959), which are not only more efficient but also less risky.

The proposed approach gives the opportunity to an investor/portfolio manager to define different investment scenarios according to his preferences, attitude (risk tolerant or risk averse) and the financial environment (e.g. bull or bear market), in order to select the best mutual funds which will compose the final portfolios through different portfolio construction scenarios.

The rest of the paper is organized as follows. Sections two and three describe the data set and methodology used respectively. Section four presents the obtained results and finally, section five concludes the paper and points out some future directions.

2 Data set description

We received our data from the Association of Greek Institutional Investors and consist of daily data of all domestic equity mutual funds over the period January 2006 to December 2011. For the present application, further information is derived from the official web pages of the Athens Stock Exchange (www.ase.gr) and the Bank of Greece (www.bankofgreece.gr), regarding the return of the market portfolio and the return of the 2-months Treasury bill respectively. Furthermore, we used the 3-months Treasury bill as a risk-free asset. Based on this information, we compute five variables that measure the performance and risk of the MFs which have been used extensively in the literature. A brief description of these variables follows.

(1) Return of the funds: The return on a mutual fund investment in a given time period is calculated by taking into account the change in a fund's net asset value. The fund's return in period t is defined as follows:

$$R_{it} = \frac{NAV_t + DIST_t - NAV_{t-1}}{NAV_{t-1}},$$

where R_{it} is the return of a mutual fund i in period t, NAV_t is the closing net asset value of the fund on the last trading day of the period t, NAV_{t-1} is the closing net asset value of the fund on the last trading day of the period $t - 1$, and $DIST_t$ is the income and capital distributions (dividend of the fund) taken during period t.

(2) The *standard deviation* is the most commonly used measure of variability. For a fund the standard deviation σ is used to measure the variability of its daily returns and is defined as follows:

$$\sigma = \sqrt{(1/T)\sum (R_{it} - \bar{R}_{it})^2},$$

where σ is the standard deviation of the fund in period t, $\bar{R}_{it}$is the average return in period t, and T is the number of observation (days) in the period for which the standard deviation is being calculated.

(3) The *beta coefficient* (β) is a measure of a fund's risk in relation to the capital risk. The β coefficient shows the sensitivity of mutual funds' value on the increasing and decreasing ratings of financial market and is defined as follows: $\beta = cov\,(R_{it}, R_{Mt})/var\,(R_{Mt})$, where $cov\,(R_{it}, R_{Mt})$ is the covariance of the daily return of a fund with the daily return of the market portfolio (Athens Stock Exchange), and $var\,(R_{Mt})$ is the variance of the daily return of the market portfolio.

(4) The *Sharpe index* (Sharpe 1966) is used to measure the fund's excess return with regard to the risk-free rate divided by its standard deviation. This measure is defined as the ratio $(R_{it} - R_{ft})/\sigma$ where R_{ft} is the return of the risk free portfolio in period t.

(5) The *Treynor index* (Treynor 1965) is obtained by simply substituting volatility for variability in the Sharpe index. This measure is defined as the ratio $(R_{it} - R_{ft})/\beta$. The evaluation of funds with these two indices shows that a fund with higher performance per unit of risk is the best-managed fund, while a fund with lower performance per unit of risk is the worst managed fund.

Table 1 reports some useful descriptive statistics of the variables used in the analysis. For comparison purposes we present the annual return of the Athens Stock Exchange Index (R_{ASE}). The examined period contains both bull and bear market sub-periods due to major fluctuations, a considerable decline in all stock prices and high liquidity conditions that characterize the Greek market in the last decade.

3 Methodology

3.1 Argumentation based decision-making for selecting funds

Argumentation can be abstractly defined as the principled interaction of different, potentially conflicting arguments, aiming to arrive to a consistent conclusion (Rahwan et al. 2005). This approach was selected among a number of different approaches as it: (a) allows for decision making using conflicting knowledge, (b) allows defining non-static priorities between arguments, and (c) the modularity of its representation allows for the easy incorporation of views of different experts. Traditional approaches such as statistical methods need to make strict statistical hypothesis (Sharpe 1966), multi-criteria analysis methods need significantly more effort from experts (e.g. Electre-tri, Gladish et al. 2007), and neural networks

Table 1 Descriptive statistics for the five variables

Year	R	σ	β	Sharpe	Treynor
2006					
Mean	25.48	17.37	0.64	0.90	0.90
SD	1.11	0.27	0.04	0.01	0.01
Min	−1.14	6.34	−0.17	0.63	0.63
Max	50.09	21.22	1.62	1.02	1.02
R_{ASE}	*19.95*				
2007					
Mean	14.27	14.77	0.89	−0.20	−3.38
SD	4.62	1.82	0.07	0.32	4.99
Min	4.07	6.88	0.69	−0.98	−13.98
Max	24.76	20.31	1.06	0.88	10.29
R_{ASE}	*15.95*				
2008					
Mean	−58.00	31.28	0.75	−0.21	−0.80
SD	5.11	4.41	0.20	0.02	1.25
Min	−66.05	21.69	0.06	−0.25	−6.39
Max	−43.30	42.79	1.10	−0.17	−0.42
R_{ASE}	*−65.69*				
2009					
Mean	22.30	26.93	0.74	0.05	0.15
SD	5.96	3.68	0.20	0.01	0.25
Min	8.84	19.52	0.06	0.02	0.04
Max	36.58	37.54	1.12	0.07	1.25
R_{ASE}	*21.21*				
2010					
Mean	−30.41	28.75	0.78	−0.10	−0.31
SD	3.36	3.67	0.20	0.01	0.39
Min	−38.86	22.85	0.09	−0.12	−2.02
Max	−22.91	39.71	1.16	−0.08	−0.18
R_{ASE}	*−35.42*				
2011					
Mean	−45.47	31.45	0.75	−0.15	−0.14
SD	7.46	5.47	0.25	0.01	1.21
Min	−58.04	15.51	−0.06	−0.18	−0.97
Max	−19.24	44.89	1.19	−0.13	5.57
R_{ASE}	*−52.07*				

require increased computational effort and are characterized by inability to provide explanations for the results (Subramanian et al. 1993).

In our work we adopt the argumentation framework proposed by Kakas and Moraitis (2003), where the deliberation of a decision making process is captured through an argumentative evaluation of arguments and counter-arguments. A theory expressing the knowledge under which decisions are taken compares alternatives and arrives at a conclusion that reflects a certain policy. It is a rule-based approach, where rules also define context-based priorities between rules. Briefly, an argument attacks (or is a counter argument to) another when they derive a contrary conclusion. These are conflicting arguments. A conflicting argument is admissible if it counter-attacks all the arguments that attack it. It counter-attacks an argument if it takes along priority arguments and makes itself at least as strong as the counter-argument.

In defining the decision maker's theory we specify three rule levels. The first level defines the (background theory) rules that refer directly to the subject domain, called the *Object-level Decision Rules*. In the second level we have the rules that define priorities over the first level rules for each *role* that the decision maker can assume or *context* that he can be in (including a *default context*). Finally, the third level rules define priorities over the rules of the previous level (which context is more important) but also over the rules of this level in order to define *specific contexts*, where priorities change again.

In our application we needed on one hand to transform the criteria for fund's performance to background theory (facts) and rules of the first and second level of the argumentation methodology and on the other hand to define the strategies (or specific contexts) that we would define in the third level rules.

Given the efficient set of portfolios, investors will choose the one that is in accordance to their risk preferences. A risk averse investor will want a portfolio that has low volatility (risk) and will select a portfolio very close to the global minimum variance portfolio, while a risk tolerant investor will ignore volatility and select portfolios with high expected returns. In addition simple performance per unit of risk indicators are often used to rank funds and investors choose the ones with the higher values. Thus, we identified several contexts, i.e. two types of investors (risk averse and risk tolerant), a performance option (selection of funds with high Sharpe and Treynor indices), and two market contexts (bull and bear).

To give the reader an idea of how we modeled the facts and rules, for each factor we classified the available mutual funds to three classes:

- High (the 30 % of the population with highest scores)
- Medium (the 40 % of the population)
- Low (the 30 % of the population with lowest scores)

Except for the return on funds (R) which was classified to two classes

- High (the median and better)
- Low (the rest)

We created (automatically using a visual basic script) the facts. These facts contained the raw data in logic form, e.g. the value of a factor for a specific year for a specific fund. Then using a number of rules we derived new facts (or metadata).

For example, we used these rules to compute the fact that a mutual fund has a high return on funds, using the *highR/1* predicate. We represented the fact that a mutual fund has a high systematic risk, using the *highB/1* predicate.

Then we developed the first (object) level decision rules. These rules are meant to answer the following questions:

- When does a fund qualify for participation in our portfolio?
- When is it rejected?

The following rules define that a mutual fund should be selected for the portfolio if it has a high return (rule with signature r_1) and that a mutual fund should not be selected if it has high systematic risk (rule with signature r_2). For representing the rules we adopt a prolog-like style, where variables start with a capital letter, while literals start with a lowercase letter. The predicate *selectFund/1* is used as head of these rules (or its negation, as in rule r_2):

$$r_1(Fund) : selectFund(Fund) \leftarrow highR(Fund)$$
$$r_2(Fund) : \neg selectFund(Fund) \leftarrow highB(Fund)$$

Such rules often lead to inconsistencies as they are out of context. This is why we need to define contexts. The contexts define priorities over the object level rules. To do that we use rules having as head the *h_p/2* predicate whose first argument is the signature of a rule which will have higher priority over the rule whose signature is its second argument, when the rule premises are *true*. These arecontexts (with signatures the second (default context) level rules and they are meant to answer the questions:

- Does a context or role influence the object level rules?
- Which is more important each time?

With relation to the two previously defined object level rules we can identify two contexts, (a) the general case (general context), where a mutual fund should be selected if it has a high return, and (b) the bear market context, where a mutual fund should not be selected if it has high risk, regardless of its performance on other variables (such as its return). We write the following context rules to define these two contexts (with signatures R_1 and R_2):

$$R_1 : h\_p(r_1(Fund), r_2(Fund)) \leftarrow true$$
$$R_2 : h\_p(r_2(Fund), r_1(Fund)) \leftarrow market(bear)$$

Note that we use the *market/1* predicate with the instances *market(bull)* and *market(bear)* for representing the bull and bear market respectively. The specific contexts are formed by combining the above roles and contexts by defining priorities over possibly conflicting rules. Thus, we develop the third level (specific context) rules that define which context and under what circumstances should have greater priority to another.

Continuing our small example we can define two specific contexts, (a) the combination of the general and bear market context, where the bear market context has priority over the general context, and (b) the risk tolerant investor and bear market context, where the general context has priority over the bear market. For modeling the roles we defined the *investor/1* predicate. A risk tolerant investor is expressed with the predicate *investor(risk_tolerant)*, while a risk averse investor with the predicate *investor(risk_averse)*. These specific contexts are programmed using the following rules (with signatures C_1, C_2):

$$C_1 : h\_p(R_2, R_1) \leftarrow true$$
$$C_2 : h\_p(R_1, R_2) \leftarrow investor(risk\_tolerant)$$
$$C_3 : h\_p(C_2, C_1) \leftarrow true$$

When nothing is known about the market or the investor preference, while there is a fund *f* with *highR(f)* and *highB(f)* then rules r_1 with R_1 form an admissible argument with the conclusion *selectFund(f)*. However, if the predicate *market(bear)* is asserted into the knowledge base the previous argument is attacked by the argument formed with the rules r_2 with R_2 and C_1 with the contrary conclusion *¬selectFund(Fund)* and is no longer admissible. Only the new argument is admissible. The situation changes again if *investor(risk_tolerant)* is asserted as the new argument with rules r_1 with R_1, C_2 and C_3 attacks the previous one and is the only admissible with the conclusion *selectFund(f)*.

We provide a brief summary of the strategies that we defined in order to validate the use of the argumentation framework. In the specific context of:

- Bull market context and risk tolerant investor role, the final portfolio is the union of the individual context and role selections
- Bear market context and risk tolerant investor role, the final portfolio is their union except that the risk tolerant investor now would accept to select high and medium risk funds (instead of only high)
- Bull market context and risk averse investor role, the moderate investor limits the selections of the bull market context to those of medium or low risk (higher priority to the moderate role)
- Bear market context and risk averse investor role, the final portfolio is their union except that the risk averse investor no longer selects a medium risk fund (only low is acceptable)
- Bull market context and high performance per unit of risk context, the final portfolio is the union of the individual context and role selections
- Bear market context and high performance per unit of risk context, the final portfolio is their union except that the bear market context no longer selects funds with low or medium reward-to-variability ratio (Sharpe ratio) or with low or medium reward-to-volatility ratio (Treynor ratio)
- Risk tolerant investor role and high performance per unit of risk context, the final portfolio is their union except that the risk tolerant investor no longer selects funds with low reward-to-variability ratio or with low reward-to-volatility ratio

- Risk averse investor role and high performance per unit of risk context, the final portfolio is their union except that the risk averse investor no longer selects MFs with low reward-to-variability ratio or with low reward-to-volatility ratio
- Every role and context has higher priority when combined with the general context.

3.2 Portfolio construction and validation

Having selected the funds that will participate in the investment portfolio, the next stage is to decide on the magnitude of the participation of each fund in the final portfolio. Let a portfolio of n funds be constructed on the basis of a weight vector $w = (w_1, w_2, \ldots, w_n)$, where each w_i defines the proportion of the available capital invested in fund i. In particular, the obtained portfolios are composed using the data available in year t and their performance is calculated in year $t + 1$. The performance of the constructed portfolios is given by the measurement of return and risk. The portfolio return is the weighted average return of the funds included in the portfolio, while its variance is equal to the weighted average covariance of the returns on its individual funds. These variables were estimated from historical data. We compute the expected portfolio returns as follows:

$$E\left(r_p\right) = \sum_{i=1}^{n} w_i E(r_i),$$

where $\sum_{i=1}^{n} w_i = 1$; r_i, r_p is the return on the ith fund and portfolio p, and $E(r_i)$ the expectation of the mean return on ith fund. The formula of portfolio risk is:

$$\mathrm{Var}\left(r_p\right) = \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \mathrm{Cov}\left(r_i, r_j\right),$$

where $\mathrm{Cov}\left(r_i, r_j\right)$ is the covariance of the returns on the ith and jth funds.

For validating our approach, firstly we compare the performance of portfolios constructed from argumentation approach with that constructed from the most promising funds according to the traditional financial index, i.e. the Sharpe index, using three performance persistence fund participation scenarios. These scenarios are developed through the analysis of the persistence of examined equity mutual funds, where a fund is defined to persist, if for consecutive time periods, it has returns above the median of the examined sample, relative to comparable funds. We applied the "winner–winner, winner–loser" methodology, which is complemented with three contingence table tests precisely the Z-test for repeat winners (Malkiel 1995), the Odds Ratio Z-statistic (Brown and Goetzann 1995) and the Chi Square statistic (Kahn and Rudd 1995), already applied in the financial literature (Vicente and Ferruz 2005; Vidal-García 2013). The description of the method and the obtained results are presented in the "Appendix". After we confirmed our findings that there is statistically significant performance persistence for 1-year and 4-years holding we use the following three portfolio construction scenarios:

In the first case (PP1), the short-run performance persistence scenario, the weight of fund i (w_i) is dependent on the performance of the ith fund in the year under consideration:

$$w_i = \frac{I_i^{y_0}}{\sum_{j=1}^{N} I_j^{y_0}},$$

where y_0 is the year under consideration and I_i^y is the normalized return using the Min–Max normalization method. According to this method:

$$I_i^y = \frac{r_i^y - \min\{\mathrm{r_i^y}|\mathrm{i} = 1, \ldots, N\}}{\max\{r_i^y|i = 1, \ldots, N\} - \min\{r_i^y|i = 1, \ldots, N\}},$$

where r_i^y is the return of the ith selected fund for year y. Normalization is important as r_i^y can have positive and negative values.

In the second case (PP2), the long-run performance persistence scenario, the w_i is defined as follows:

$$w_i = \frac{\sum_{y=y_k}^{y_0} h_i^y}{\sum_{j=1}^{N} \sum_{y=y_k}^{y_0} h_j^y}$$

where y_k is the year from which we have historical data andh_i^y is defined as:

$$h_i^y = \begin{cases} 1, r_i^y \geq median\{r_i^y|i = 1, \ldots, N\} \\ 0, r_i^y < median\{r_i^y|i = 1, \ldots, N\} \end{cases}.$$

In the third case (PP3), the combination of previous two performance persistence scenarios, w_i is defined as follows:

$$w_i = \frac{\sum_{y=y_k}^{y_0} h_i^y I_i^y}{\sum_{j=1}^{N} \sum_{y=y_k}^{y_0} h_j^y I_j^y}$$

Secondly, we compare the performance of portfolios constructed from augmentation approach with that constructed from the most promising funds according to the Sharpe ranking, using a Naïve (equal weighing) an Optimum (OPT) and a Minimum Variance (MVP) Markowitz portfolio. The Markowitz's optimum portfolio calculated according to Markowitz (1959) quadratic optimization method, which may simply be written as follows:

$$\max \mu \sum_{i=1}^{n} w_i \mathrm{E}(r_i) - \rho \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \mathrm{Cov}(r_i, r_j)$$

$$s.t.$$

$$\sum_{i=1}^{n} w_i = 1$$

$$w_i \geq 0$$

where $\mu \geq 0$ and $\rho \geq 0$. The ratio $\rho/\mu \in [0, +\infty]$ represents the degree of absolute risk aversion. In the case where we set $\mu = 0$ and $\rho = 1$ the return information is eliminated and this quadratic mathematical program gives the efficient portfolio with minimum risk.

4 Empirical results

For evaluating our results, we defined scenarios for all years and for all combinations of contexts. That resulted to two investor roles (risk tolerant and risk averse) combined with the market status (bull or bear), plus these two investor roles combined with the fund's performance per unit of risk (high performance option), plus the market status combined with the high performance option, plus the simple contexts, roles and preference, all together fourteen different scenarios run for all the examined years. Each one of the examined scenarios refers to different investment choices.

The average performance of the portfolios constructed through the funds selected according to the argumentation approach for all different contexts and all periods under consideration are presented on Tables 2 and 3. On these tables, for comparison purposes, we also present the performance of portfolios constructed according to the Sharpe ranking with a number of funds equal to the number of funds selected by the argumentation framework, using firstly the performance persistence approach (Table 2), and secondly, the Markowitz's optimum portfolios (Table 3).

Table 2 presents the three performance persistence construction scenarios, i.e. the short-run (PP1), the long-run (PP2) and their combination (PP3). In all three cases, argumentation outperforms the Sharpe index in portfolio performance except for two cases in the risk averse bull context, where the portfolios constructed through the Sharpe rankings have higher returns than the portfolios of the proposed approach. Furthermore, the short-run combined with long-run based participation scenario (PP3) has higher returns, while the short-run based participation scenario (PP1) has lower risk compared to other two scenarios, for the portfolios constructed through argumentation. The same stands for the portfolio risk regarding the portfolios constructed through the Sharpe index, while we have mixed results concerning the higher returns.

According to the results of Table 3, the optimum portfolios of argumentation outperforms those based on Sharpe index except for one case in the risk tolerant context, where the portfolios constructed through the Sharpe rankings have higher returns than the portfolios of the proposed approach. The same stands for the minimum variance portfolios, except for three cases in the bull market context, the risk averse bull context and the risk tolerant context. In both the optimum portfolios and minimum variance portfolios, argumentation presents lower portfolio risk compared to Sharpe index.

Overall, the results of the above tables show the added value of our approach. While there are roles and/or contexts that are more successful than others, the results of the proposed approach in all scenarios outperformed the traditional performance index. In all contexts and strategies, portfolios developed through argumentation

Table 2 Argumentation versus sharpe ratio: performance persistence (PP) based portfolios

Context type	Context name	Argum-PP1		Sharpe-PP1		Argum-PP2		Sharpe-PP2		Argum-PP3		Sharpe-PP3	
		Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$
Simple	General	245.83	−9.65	251.61	−9.73	250.49	−9.30	283.93	−9.69	244.96	−9.27	270.36	−9.38
Simple	Bull market	243.66	−9.94	317.68	−10.21	263.76	−9.42	316.71	−9.86	265.97	−9.34	324.60	−9.81
Simple	Bear market	183.04	−9.01	332.68	−11.04	179.73	−8.94	336.33	−10.88	177.90	−8.98	344.34	−10.76
Role	Risk averse	232.74	−10.21	266.13	−9.71	235.93	−9.66	287.54	−9.31	228.76	−9.65	280.20	−9.37
Specific	Risk averse—bull	245.58	−9.55	315.11	−8.76	242.43	−9.22	314.08	−8.06	242.42	−9.19	314.54	−8.25
Specific	Risk averse—bear	199.47	−9.51	342.71	−11.57	194.73	−9.35	346.63	−11.03	192.38	−9.35	352.23	−11.01
Role	Risk tolerant	292.97	−9.58	371.74	−10.29	297.26	−9.21	369.36	−9.65	297.95	−9.17	374.95	−9.79
Specific	Risk tolerant—bull	243.66	−9.94	317.68	−10.21	263.76	−9.42	316.71	−9.86	265.97	−9.34	324.60	−9.81
Specific	Risk tolerant—bear	240.83	−8.95	288.44	−9.88	241.35	−8.88	298.37	−9.51	240.95	−8.82	302.48	−9.47
Preference	High Performance	264.64	−9.68	315.00	−10.00	279.63	−9.32	313.92	−9.71	278.74	−9.30	321.15	−9.60
Specific	High perf.—bear	236.86	−9.08	315.00	−10.00	249.97	−8.79	319.35	−9.40	244.07	−8.73	321.15	−9.60
Specific	High perf.—risk tolerant	272.71	−9.65	319.46	−9.73	288.16	−9.31	303.58	−9.94	288.24	−9.32	322.95	−9.37
Specific	High perf.—bull	264.64	−9.68	303.56	−10.27	279.63	−9.32	313.92	−9.71	265.97	−9.34	312.21	−9.93
Specific	High perf.—risk averse	246.62	−9.70	267.68	−10.04	252.55	−9.30	291.88	−9.74	248.15	−9.29	281.79	−9.74
	Average	243.80	−9.58	308.89	−10.10	251.38	−9.25	315.17	−9.74	248.75	−9.22	317.68	−9.71

Table 3 Argumentation versus Sharpe: Naïve, optimum (OPT) and minimum variance (MVP) portfolios

Context type	Context name	Argum-Naïve		Sharpe-Naïve		Argum-OPT		Sharpe-OPT		Argum-MVP		Sharpe-MVP	
		Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p$)	Var(r_p)	$E(r_p)$	Var(r_p)	$E(r_p)$
Simple	General	246.33	−9.73	262.89	−10.06	135.53	−6.02	136.80	−7.45	135.51	−6.09	136.74	−7.68
Simple	Bull market	241.73	−10.00	327.26	−10.16	193.59	−8.73	251.25	−8.88	193.56	−8.88	251.19	−9.10
Simple	Bear market	185.20	−8.98	341.00	−10.96	158.12	−6.90	289.05	−11.56	158.11	−6.95	241.57	−11.30
Role	Risk averse	234.78	−10.19	271.07	−9.69	137.63	−6.55	159.79	−7.89	137.62	−6.58	159.74	−8.11
Specific	Risk averse—bull	245.64	−9.57	314.93	−8.81	229.46	−8.30	298.15	−7.33	229.43	−8.42	298.15	−7.33
Specific	Risk averse—bear	201.96	−9.53	349.50	−11.48	157.50	−6.77	291.26	−10.27	157.49	−6.82	281.26	−10.35
Role	Risk tolerant	292.81	−9.62	379.66	−10.38	247.31	−9.30	312.15	−8.25	247.30	−9.33	312.09	−8.46
Specific	Risk tolerant—bull	241.73	−10.00	327.25	−10.16	193.59	−8.73	251.25	−8.88	193.56	−8.88	251.19	−9.10
Specific	Risk tolerant—bear	241.58	−9.00	294.34	−9.86	154.45	−6.49	187.14	−8.68	154.42	−6.59	187.08	−8.89
Preference	High performance	264.90	−9.68	323.81	−9.91	195.21	−7.62	247.92	−8.48	195.18	−7.73	247.87	−8.69
Specific	High perf.—bear	243.09	−9.12	326.07	−9.73	156.67	−6.09	247.22	−8.43	156.64	−6.20	247.17	−8.64
Specific	High perf.—risk tolerant	274.34	−9.67	311.07	−10.18	193.16	−7.90	216.03	−8.53	193.14	−7.94	203.97	−8.74
Specific	High perf.—bull	264.96	−9.68	323.81	−9.91	195.21	−7.62	247.92	−8.48	179.38	−6.43	247.87	−8.69
Specific	High perf.—risk averse	250.44	−9.76	272.63	−10.04	154.73	−5.87	163.85	−7.64	154.71	−5.94	163.79	−7.86
	Average	244.96	−9.61	316.09	−10.10	178.73	−7.35	235.70	−8.63	177.58	−7.34	230.69	−8.78

Table 4 Weights of the developed portfolios for the risk tolerant-bear context (2011)

	$E(r_i)$	$Var(r_i)$	PP1	PP2	PP3	Naïve	OPT	MVP
Argumentation based fund selection								
Fund 40	−0.19	3.35	0.12	0.11	0.10	0.13		
Fund 11	−0.19	2.35	0.14	0.17	0.19	0.13	0.21	0.23
Fund 12	−0.17	4.19	0.12	0.15	0.14	0.13		
Fund 36	−0.15	2.41	0.13	0.07	0.07	0.13	0.36	0.34
Fund 26	−0.20	2.53	0.13	0.22	0.22	0.13	0.26	0.26
Fund 33	−0.25	3.29	0.13	0.13	0.13	0.13		
Fund 16	−0.26	6.21	0.12	0.04	0.04	0.13	0.17	0.17
Fund 22	−0.24	3.35	0.13	0.11	0.11	0.13		
		$E(r_p)$	−20.78	−20.44	−20.45	−20.80	−19.20	−19.29
		$Var(r_p)$	207.49	218.44	216.20	207.51	156.70	156.68
Sharpe ratio based fund selection								
Fund 41	−0.30	6.08	0.20	0.20	0.18	0.13		
Fund 02	−0.29	8.00	0.09	0.09	0.12	0.13		
Fund 28	−0.27	6.58	0.14	0.14	0.11	0.13	0.26	0.26
Fund 06	−0.25	5.37	0.20	0.20	0.25	0.13		
Fund 01	−0.26	5.40	0.17	0.17	0.22	0.13	0.35	0.35
Fund 34	−0.27	5.53	0.14	0.14	0.06	0.13		
Fund 16	−0.27	6.21	0.06	0.06	0.06	0.13	0.39	0.39
Fund 48	−0.27	5.82				0.13		
		$E(r_p)$	−27.27	−27.12	−26.95	−27.29	−26.68	−26.68
		$Var(r_p)$	377.20	428.98	447.28	389.11	233.84	233.84

present lower risk than those developed based on the Sharpe index. The same stands for the return portfolio performance measure (higher portfolio return), where the portfolios constructed through argumentation rankings have higher returns than the portfolios of the Sharpe rankings. For example, according to the average values of all examined contexts, for all three developed portfolios based on performance persistence (Table 2), portfolio return (portfolio risk) of argumentation rankings is −9.58, −9.25 and −9.22 (243.80, 251.38 and 248.75) versus the portfolio return (portfolio risk) of Sharpe index ranking which is −10.10, −9.74 and −9.71 (308.89, 315.17 and 317.68) for the three performance persistence construction scenarios respectively. Composing an Optimum portfolio based on the argumentation rankings, we obtain a portfolio return of about −7.35, given a portfolio variance of about 178.73, while an optimum portfolio based on the Sharpe index has a portfolio return of about −8.63, given a portfolio variance of about 235.70 (Table 3). The same pattern is followed through the minimum variance portfolio.

Additionally, there are findings that cannot be depicted in such summarizing tables as Tables 2 and 3. We present a representative context for the selected funds and their weights on the developed portfolios in Table 4. According to the results of this table we see that the selection of funds for the developed portfolios does not coincide between the two approaches with the exception of fund 16. The weights of the performance persistence based portfolios for argumentation ranking are ranged between (0.04–0.22) in the PP2 and PP3 construction scenarios we examined, where funds with a good record of performance over the previous years, in this case fund 26, gain a larger share in the final portfolio. The optimum portfolio and the minimum variance portfolio reveal four funds to be positively weighted, with a considerable contribution of funds 36 and 26 with an aggregated weight of about 0.62 and 0.60, respectively. Regarding the weights given by the portfolios developed based in the Sharpe ranking, we see that the performance persistence based portfolios positively weight seven out of eight funds, ranging from 0.09 to 0.25, with the main contributor to be fund 6 in all three cases. The optimum portfolio and the MVP, reveal only three funds to be positively weighted, with a considerable contribution of fund 16 with weight of about 0.39. Finally, according to the results of this table we confirm our findings that argumentation outperforms Sharpe ratio presenting higher returns and lower risk on the developed portfolios, while it gives more diversified portfolios.

5 Conclusion

In this contribution we presented the PORTRAIT tool, which allows a decision maker to construct effective portfolios of funds under different, possibly conflicting contexts. The empirical results of our study showed that argumentation is well suited for this type of applications giving answers to two important questions: (1) which mutual funds are the most suitable to invest in, and (2) what portion of the available capital should be invested in each of these funds. The proposed approach supports the investor in composing a mutual fund portfolio that satisfies his spectrum of investment preferences about return and risk, under different portfolio construction scenarios. The results of our work provide evidence that argumentation-based portfolios perform better than the ones based on traditional approaches.

The proposed tool has been validated using the data set described in this paper and is available for demonstration at the Applied Mathematics and Computers Laboratory (AMCL) of the Technical University of Crete, Greece. It is intended for use by banks, investment institutions and consultants, and individuals.

Our future work is related to the optimization of the strategies so that all combinations add value to the decision maker. We also aim to include operational characteristics such as cost and fund size in our study. Towards this end, we will need to add context specific rules in our knowledge base and to incorporate the relevant information in our database. Moreover, it would be of interest to integrate this methodology with trading approaches, so that one could monitor his portfolio in real time and perform changes to the portfolio composition instantly as new information becomes available. Thus, it would be of a great interest to make our tool web-based incorporating: (a) on-line questionnaire for determining the investor role properties, (b) on-line feed from the capital market, and, (c) capability to determine when to update the portfolio (buy or sell)—possibly with a new knowledge base.

Appendix

A contingency table (Table 5) is used in order to identify the frequency with which funds are defined as winners (W—a fund with returns above the median) and losers (L—a fund with returns below the median) over successive time periods. If a fund is a loser (L) for consecutive periods, it is defined as a loser–loser (LL). Similarly, a winner (W) in the first period that remains a winner (W) in the future period is defined as winner–winner (WW). A fund that shifts from loser (L) to winner (W) is a loser–winner (LW), while a fund that shifts from winner (W) to loser (L) is a winner–loser (WL). A fund that ceases operation and was a winner or loser during the previous year is defined as winner–gone (WG) or loser–gone (LG).

It is obvious that in the case where the number of funds in existence is the same in each period the definition of the funds is simple. However, if funds enter or leave the sample, between period t and t + 1, there is a difficulty in fund classification. Let examine the persistence of returns for N funds in period t, where M new funds are operating (K funds close) in period t + 1, thus M + N (M + N − K) funds are to be ranked. Funds that are new in period t + 1 are classified, but the contingency table includes only funds which operate over consecutive periods.

The three statistical tests used to examine the performance persistence of the examined funds for a twelve year period (2000–2011) are described below.

Malkiel's Z-test (1995): $= (\mathrm{Y} - \mathrm{np})/\sqrt{(\mathrm{np}(1 - \mathrm{p}))}$, which shows the proportion of repeat winners (WW) to winner–losers (WL), where Z is the statistic variable that follows a normal distribution (0, 1), Y is the number of winner funds in two consecutive periods, n is the sum of WW + WL, p is the probability of a winner fund in one period to repeat as a winner in the subsequent period. According to this criterion, a percentage of WW to WW + WL above 50 % and a Z-statistic above zero demonstrate performance persistence, while a percentage value below 50 % and Z-statistic above zero shows a reversal in performance. Malkiel's Z-test is concentrated on only one quadrant of both repeat winners and repeat losers.

Brown and Goetzann Odds Ratio (OR) (1995): = (WW * LL)/(WL * LW). Using this ratio, the statistical significance of the OR is determined applying a Z-test to the following Z variable which follows a normal distribution (0, 1), $\mathrm{Z} = \ln(\mathrm{OR})/\sigma_{\ln_{(\mathrm{OR})}}$. An OR of one supports the hypothesis that the performance in one period is unrelated to that in another while an OR greater than one (below one) indicates persistence (reversals in performance dominate the sample). The OR ratio tests the persistence of both repeat winners and repeat losers.

Khan and Rudd Chi-square statistic (1995):

Table 5 Winner/loser contingency table

Period	t + 1	
t	Winner	Loser
Winner	WW	WL
Loser	LW	LL

Table 6 overall performance persistence

Year	Contingency table								Malkiel's test	Brown and Goetsmann's test			Kahn and Rudd's test
	N	WW	LW	WL	LL	LG	WG	RW	Z-test	OR	σ	Z-stat	Chi-square
Consecutive	712	179	141	157	171	40	24	0.53	1.20 (0.23)	1.38	0.16	2.05* (0.04)	10.40** (0.00)
2 year lag	661	148	123	134	140	64	52	0.52	0.83 (0.41)	1.26	0.17	1.33 (0.18)	22.51** (0.00)
3 year lag	604	121	106	118	109	84	66	0.51	0.19 (0.85)	1.05	0.19	0.28 (0.78)	37.36** (0.00)
4 year lag	539	115	77	81	102	88	76	0.59	2.43* (0.02)	1.88	0.21	3.02** (0.00)	63.09** (0.00)

RW percentage of repeat winners, σ the standard error of the logarithmic Odds Ratio, *P* values in parenthesis, * 5 % significant, ** 1 % significant

$$x^2 = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(O_{ij} - E_{ij}\right)^2 / E_{ij}$$

where O_{ij} and E_{ij} are the actual and expected frequency of the ith row and the jth column in the contingency table respectively. The associated p value is used in order to test for performance persistence. The Chi-square test is taking into account the persistence of the contingency table as a whole.

Due to the limited space, we present in Table 6, only the combined results of four tables (available upon request) which shows the contingency table of fund returns along with the results of the statistical tests of the null hypothesis of no performance persistence between consecutive periods. Precisely, Table 6, presents combined results of performance persistence with 1 (t to $t + 1$), 2 (t to $t + 2$), 3 (t to $t + 3$) and 4-year lag (t to $t + 4$).

According to the results of this table, fifty-three percent (RW) of all winners in year 1 are winners in year 2, 179 (WW) of 336 (WW + WL). The percentage of RW for 2, 3 and 4 years are 52, 51 and 59 % respectively. However, the results of the examined tests show strong evidence of statistical significance performance persistence for 1-year and 4-years holding periods. More precisely, according to the first two tests, the percentage of RW is above 50 % while the Z-test is also above zero and statistical significant, thus is indicative of performance persistence. The same stands according to the OR ratio that is greater than one and the Z-stat which is also statistical significant. Thus, the results of the test statistics show that, at the overall level, there is evidence of performance persistence according to all three criteria for 1-year and 4-years holding periods. This evidence is in accordance with the results of other empirical studies which reveal that the relative performance of equity mutual funds persists from period to period (e.g. Hendricks et al. 1993; Gruber 1996; Vidal-García 2013). However, there is a series of empirical studies in support to the efficient markets hypothesis that past performance is no guide to future performance (e.g. Jensen 1969; Kahn and Rudd 1995).

References

Alexakis P, Tsolas I (2011) Appraisal of mutual equity fund performance using Data Envelopment Analysis. Multinatl Financ J 15(3/4):273–296

Aouni B, Colapinto C, La Torre D (2014) Financial portfolio management through the goal programming model: current state-of-the-art. Eur J Oper Res 234:536–545. doi:10.1016/j.ejor.2013.09.040

Arenas-Parra M, Bilbao-Terol A, Rodriguez Uria MV (2001) A fuzzy goal programming approach to portfolio selection. Eur J Oper Res 133:287–297. doi:10.1016/S0377-2217(00)00298-8

Artikis GP (2004) Performance evaluation of the bond mutual funds operating in Greece. Manag Financ 30(10):1–13. doi:10.1108/03074350410769326

Babalos V, Caporale GM, Philippas N (2012a) Efficiency evaluation of Greek equity funds. Res Int Bus Financ 26:317–333. doi:10.1016/j.ribaf.2012.01.003

Babalos V, Philippas N, Doumpos M, Zopounidis C (2012b) Mutual fund performance appraisal using stochastic multicriteria acceptability analysis. Appl Math and Comput 218:5693–5703. doi:10.1016/j.amc.2011.11.066

Ballestero E, Romero C (1996) Portfolio selection: a compromise programming solution. J Oper Res Soc 47:1377–1386. doi:10.1057/jors.1996.173

Brown SJ, Goetzmann WN (1995) Performance persistence. J Financ 50(2):679–698. doi:10.1111/j.1540-6261.1995.tb04800.x

Chen LH, Huang L (2009) Portfolio optimization of equity mutual funds with fuzzy returns rates and risks. Expert Syst Appl 36:3720–3727. doi:10.1016/j.eswa.2008.02.027
Davies RJ, Kat HM, Lu S (2009) Fund of hedge funds portfolio selection: a multiple-objective approach. J Deriv Hedge Funds 15(2):91–115. doi:10.1057/jdhf.2009.1
Gladish BP, Jones DF, Tamiz M, Terol AB (2007) An interactive three-stage model for mutual funds portfolio selection. OMEGA 35:75–88. doi:10.1016/j.omega.2005.04.003
Goetzmann WN, Ibbotson RG (1994) Do winners repeat? Patterns in mutual fund performance. J Portf Manag 20:9–18. doi:10.3905/jpm.1994.9
Gruber MJ (1996) Another puzzle: the growth in actively managed mutual funds. J Financ 51:783–810. doi:10.1111/j.1540-6261.1996.tb02707.x
Hendricks D, Patel J, Zeckhauser R (1993) Hot hands in mutual funds: short-Run Persistence of Relative Performance, 1974-1988. J Financ 48(1):93–130. doi:10.1111/j.1540-6261.1993.tb04703.x
Jensen CM (1969) Risk, the pricing of capital assets, and evaluations of investment portfolios. J Bus 42:167–247
Joo Oh K, Yoon Kim T, Min S (2005) Using genetic algorithm to support portfolio optimization for index fund management. Expert Syst Appl 8:371–379. doi:10.1016/j.eswa.2004.10.014
Kahn RN, Rudd A (1995) Does historical performance predict future performance. Financ Anal J 51(6):43–53
Kakas A, Moraitis P (2003) Argumentation based decision making for autonomous agents. In: Proceedings of the second international joint conference on autonomous agents and multi-agent systems (AAMAS'03). ACM Press, New York, pp 883–890. doi:10.1145/860575.860717
Lee Sang M, Lerro AJ (1973) Optimizing the portfolio selection for mutual funds. J Financ 28(5):1087–1101. doi:10.1111/j.1540-6261.1973.tb01443.x
Malkiel BG (1995) Returns from investing in equity mutual funds 1971 to 1991. J Financ 50(2):549–572. doi:10.1111/j.1540-6261.1995.tb04795.x
Markowitz HM (1952) Portfolio selection. J Financ 7(1):77–99
Markowitz HM (1959) Portfolio selection: efficient diversification of investments. Wiley, New York
Milonas N (1999) Greek mutual funds. Hellenic Bank Association and Sakoulas Editions, Athens (in Greek)
Pendaraki K (2012) Mutual fund performance evaluation using data envelopment analysis with higher moments. J Appl Financ Bank 2(5):97–112
Pendaraki K, Spanoudakis NI (2012) An interactive tool for mutual funds portfolio composition using argumentation. J Bus Econ Financ 1(3):33–51
Pendaraki K, Doumpos M, Zopounidis C (2003) Assessing equity funds' performance using a multicriteria methodology: a comparative analysis. South East Eur J Econ 1:85–104
Pendaraki K, Doumpos M, Zopounidis C (2004) Towards a goal programming methodology for constructing equity mutual funds portfolios. J Asset Manag 4(6):415–428. doi:10.1057/palgrave.jam.2240120
Pendaraki K, Zopounidis C, Doumpos M (2005) A multicriteria methodology and an application to the Greek market of equity mutual funds. Eur J Oper Res 163:462–481. doi:10.1016/j.ejor.2003.10.022
Philippas ND (1999) Mutual funds and stock exchange environment. Globus Invest, Athens (in Greek)
Rahwan I, Moraïtis P, Reed C (2005) Argumentation in multi-agent systems. Springer, Berlin
Sharma HP, Sharma DK (2006) A multi-objective decision making approach for mutual fund portfolio. J Bus Econ Res 4(6):13–23
Sharpe WF (1966) Mutual fund performance. J Bus 39:119–138
Sharpe WF (1967) A linear programming algorithm for a mutual fund portfolio selection. Manag Sci 13:499–510
Sorros JN (2003) Return and risk analysis: a case study in equity mutual funds operating in the Greek financial market. Manag Financ 29(9):21–28. doi:10.1108/03074350310768454
Spanoudakis N, Pendaraki K, Beligiannis G (2009) Portfolio construction using argumentation and hybrid evolutionary forecasting algorithms. Int J Hybrid Intell Syst 6(4):231–243. doi:10.3233/HIS-2009-0098
Spronk J, Steuer RE, Zopounidis C (2005) Multicriteria decision aid/analysis in finance. In: Figueira J, Greco S, Ehrgott M (eds) Multiple decision analysis: state of the art surveys. Springer, Boston, pp 799–858
Steuer RA, Na P (2003) Multiple criteria decision making combined with finance: a categorized bibliographic study. Eur J Oper Res 250:496–515. doi:10.1016/S0377-2217(02)00774-9

Subramanian V, Hung MS, Hu MY (1993) An experimental evaluation of neural networks for classification. Comput Oper Res 20(7):769–782. doi:10.1016/0305-0548(93)90063-O

Treynor JL (1965) How to rate management of investment funds. Harv Bus Rev 43:63–75

Vicente L, Ferruz L (2005) Performance persistence in Spanish equity funds. Appl Financ Econ 15:1305–1313. doi:10.1080/09603100500389697

Vidal-García J (2013) The persistence of European mutual fund performance. Res Int Bus Financ 28:45–67. doi:10.1016/j.ribaf.2012.09.004

Xidonas P, Mavrotas G, Psarras J (2009) A multicritera methodology for equity selection using finical analysis. Comput Per Res 36(12):3187–3203. doi:10.1016/j.cor.2009.02.009

Zopounidis C (1999) Multicriteria decision aid in financial management. Eur J Oper Res 119:404–415. doi:10.1016/S0377-2217(99)00142-3

Zopounidis C, Doumpos M (2002) Multicriteria classification and sorting methods: a literature review. Eur J Oper Res 138:229–246. doi:10.1016/S0377-2217(01)00243-0

Zopounidis C, Doumpos M (2013) Multicriteria decision systems for financial problems. Sociedad de Estadística e Investigación Operativa 21:241–261. doi:10.1007/s11750-013-0279-7