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Two-layer Investment Decision-making Using Knowledge about Investor's Risk-preference: Model and Empirical Testing*

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ABSTRACT

There have been many studies to build a model that can help investors construct optimal portfolio. Most of the previous models, however, are based upon the path-breaking Markowitz model (1959) which is a quantitative model. One of the most important problems with that kind of quantitative model is that, in reality, most of the investors use not only quantitative, but also qualitative information when they select their optimal portfolio. Since collecting both types of information from the markets are time consuming and expensive, making a set of target assets smaller, without suffering heavy loss in the rate of return, would attract investors. To extract only desired assets among all available assets, we need knowledge that identifies investors' preference for the risk of the assets.
This study suggests two-layer decision-making rules capable of identifying an investor's risk preference and an architecture applying them to a quantitative portfolio model based on risk and expected return. Our knowledge-based portfolio system is to build an investor's preference-oriented portfolio. The empirical tests using the data from Korean capital markets show the results that our model contributes significantly to the construction of a better portfolio in the perspective of an investor's benefit/cost ratio than that produced by the existing portfolio models.

Keywords: Optimal portfolio, Utility function, Benebit-cost analysis

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1. INTRODUCTION

As the types and the number of investment assets in the markets increase significantly, it becomes more difficult for investors to select their best portfolio efficiently. Since Markowitz (1959) developed path-breaking portfolio theory, a large number of studies have proposed useful models that can help investors construct their optimal portfolio. Some models [Sharpe (1964), Shane et al. (1987), Nam and Lee (1997), Cai et al. (2000), and others] utilized mathematical programming, while some others [Heuer (1988), Stanfield et al. (1987), Skalak (1993), Nikolopoulos (1994), and others][1] made use of brand-new methods, such as neural network, case-base reasoning, forward chaining, and others, in order to develop portfolio-selection models. The common problem of those models that use mainly quantitative information in selecting the best portfolio, however, is that, in reality, most of the investors use not only quantitative, but also qualitative information. Therefore, one of the most important goals of this study is to build a knowledge-based model that incorporates qualitative information, such as risk preference of investors, into the model.

Since collecting both types of quantitative and qualitative information from the markets are time consuming and expensive, making a set of target assets for investment smaller, without suffering heavy loss in the rate of return, would attract investors. To extract only desired assets among all available assets, we need knowledge that identifies investors' preference for the risk of the assets. The qualitative knowledge like an investor's preference could be used and, through repeated investment, many cases will be stored to be used continuously.

This study suggests two-layer decision-making rules capable of identifying an investor's risk preference and an architecture applying the rules to a quantitative portfolio model based on risk and expected return. Our knowledge-based portfolio system is to build an investor's preference-oriented portfolio. From applying the system to Korean capital markets, we obtain the results that the framework contributes significantly to the construction of a better portfolio in the perspective of an investor's benefit/cost ratio than that produced by the existing portfolio models. In other words, to be sure that our model is effective even in practice, we perform empirical tests using the real data obtained from Korean capital markets. This is probably the first attempt to use both qualitative and quantitative data in the composition of the optimal portfolio.

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[1] For the full description of related literature, please refer to Table 1.

The remainder of this paper is organized as follows: In the next section, we review the literature about portfolio decision-making problem, and then two-layer decision-making system is described in Section 3. Section 4 explains an investment system using knowledge layers. In the following section, we empirically test our model using real market data after narrowing the investment asset pool using our system for an arbitrarily selected representative investor. In the final section we conclude the paper with some remarks and discussion.

2. INVESTOR'S RISK PREFERENCE IN PORTFOLIO DECISION-MAKING

2.1 Portfolio Decision-making using expected return and risk

In general, the modern investment science shows that people invest their own wealth in lucrative assets (such as, financial and real assets) to maximize their utilities. Since it is very difficult to quantify 'utility', risk and expected return that are quantifiable variables are generally used for portfolio decision-making. By rationally constructing the best portfolio that maximizes his portfolio return under an allowable risk level, or conversely, minimizes his portfolio risk on a given return level, an investor can achieve the investment goal of maximizing his utility (Sharpe, 1964). This study considers investment in that an investor dispersedly assigns his wealth to several assets. The assignment should be considered multiple assets, interrelations between assets, and multiple factors, especially expected return and risk as vital factors, influencing the performance of investment (Elton et al., 1995; Markowitz, 1959).

Expected return (ER) is that an individual expects an asset to earn over a certain period of time. This is only an expectation, so the actual return may be higher or lower. An individual's expectation may simply be the average return earned per period in the past. Alternatively, it may be based upon detailed analysis for the firm's prospects, upon some computer-based model, or upon special (or inside) information. Regardless of the source of expectation, it is true that an investor relies his portfolio decision-making on the expected return for each asset. So he tries to invest in effective assets that earn a higher expected return.

In the investment area, risk or volatility (σ) is defined as the variability of price or return for an asset. That is, the higher the variability of an asset, the higher the risk. Since standard deviation (or variance) for an asset represents 'variability' in statistics, it is considered a measure for the risk. This measure is also very important in selecting a portfolio in that an investor tries to minimize the risks of their portfolios under equivalent condition else (Elton et al., 1995; Merton, 1972; Sharpe, 1964).

The way of constructing a portfolio is to maximize expected return on a desired risk level or to minimize the total risk for an investment under a desired return level. Interestingly, one problem above is dual for the other in a mathematical programming sense. According to an optimality theory in operations research, the optimal solution of a primary problem should be equivalent to the one of its dual problem if the feasible set is convex. Thus, an optimal portfolio can be found by solving only one of both problems.

2.2 Major factors affecting portfolio decision-making

According to the literature and experiences of many investors, economic factors (such as interest rate, exchange rate and inflation) and personal factors (such as investor's age and his available fund amount) are well known as the most important things in portfolio decision-making. To consider the above factors in finding an optimal portfolio, we need knowledge about the relations between the level of a threshold for each factor and an investment behavior. The 'threshold' value can be determined from his past investment behavior (Chen, 1977; Elton et al., 1995). Through the extraction of the knowledge, we are able to build a new model that incorporates the preference into the existing quantitative model.

2.3 Personal risk preference

By considering major factors and their thresholds for an investor, we can easily identify a personal risk preference suitable for him. The relationship between the condition of each factor and an investment behavior can be expressed by rules, which is used to determine the most appropriate asset set to an investor. All assets in the set are used as decision variables of a quantitative decision-making problem (i.e., a quadratic programming problem in this paper). The details about them will be explained in Section 3.

Let us see the effect obtained from the consideration of an investor's risk preference in portfolio decision-making. To do that, we first introduce an indifference curve as shown in Figure 1. An investor, by using his utility function, can choose an optimal portfolio at the point that the indifference curve of utility function is tangent to the expanded efficient frontier (i.e., point P* in Figure 1). In the figure, the efficient frontier (E.F.) by our new model looks inferior to the one by the existing quantitative model, Markowitz's model here. But, the EF for the existing model is not better than EF for our model in the perspective of total utility or benefit/cost ratio. In reality, composing assets suitable to an investor's risk preference can significantly reduce the information search costs and time for target assets. In Figure 1, we introduce two utility functions, U_T (ER, σ) (utility function in traditional framework) and U_N(ER, σ, Others) (utility function in our new framework), where 'Others' denote any other factors except ER and σ, such as preference (P) and search costs and time (E). The point that the total utility or benefit/cost ratio from our new model (i.e., U_N(ER, σ, Others) at the point P** in Figure 1) can be higher than the one (i.e., U_T at the point P*) from the quantitative models is well exhibited in the figure.

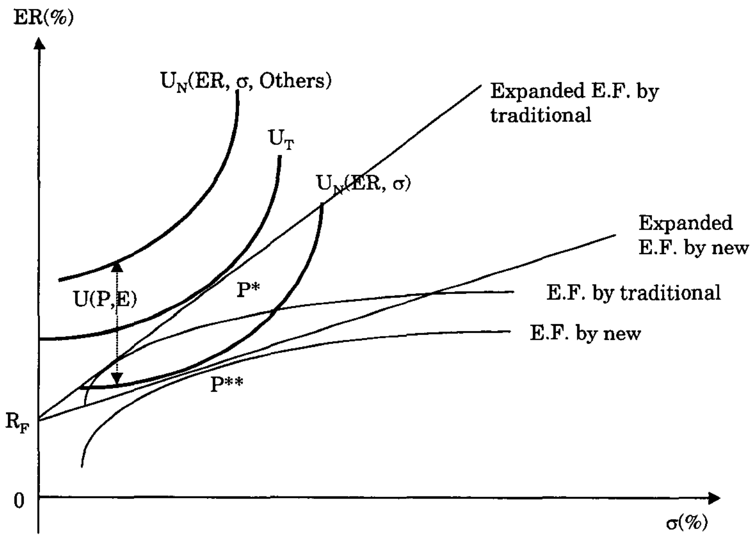

Figure 1. Comparison of total utility: New (N) vs. Traditional (T) model

Common sense tells us that in real situation, most investors consider only handful number of assets in portfolio decision-making because of the limited time and cost which can be spent to search for quality assets. It is, in reality, impossible for an investor to consider thousands of assets to construct his optimal portfolio. Instead, he can choose the quality assets from his own preference mechanism. This fact implies that an investor's real utility function should be U_N rather than U_T in Figure 1. In this sense, the incorporation of the preference into the existing simple quantitative model definitely increases the investor's utility or benefit/cost ratio. Accordingly, by reflecting the preference on the process of finding an optimal portfolio, an investors can increase their utility through the new model by the amount of U(P, E). The increase in utility through the application of risk preferences exceeds the decrease in utility due to the contraction of the efficient frontier by focusing on a smaller asset pool. Figure 1 shows this point very well.

3. TWO-LAYER INVESTMENT DECISION-MAKING

An investment decision-making problem is to minimize the total risk on a desired return level, where a risk in investment is defined as the variability of price or return of an asset and a desired return is just expected level for a return that an investor expects an asset to earn over a certain period of time.

Traditional models for financial investment, such as Markowitz's model, CAPM (Capital Asset Pricing Model) and APM (Arbitrage Pricing Model), have focused on the portfolio decision-making [Markowitz (1959), Black (1972)]. Lately, many studies have concentrated on portfolio decision making with techniques related to Artificial Intelligence (AI) and Management Science (MS) such as knowledge-based system, case-based reasoning, genetic algorithms, and neural networks (Nikolopoulos 1994, Madhavan, 1994; Nissen, 2000). Table 1 summarizes representative investment systems by the methods of AI and MS.

None of these, however, deals with a portfolio decision-making that considers personal risk preferences for an investor as yet. So this paper concentrates on such related issues.

In general, a portfolio decision-making problem is composed of a knowledge component and an optimization problem component. First, a knowledge component makes an asset set so that it could select an investor's preferred assets. Second, an optimization problem incorporating the set is modeled a quadratic programming model that generates an optimal weight for each asset considering expected total return level and risk.

To select investor-preferred assets, it receives the thresholds for five factors from investor directly through an iterative interface or doing a case base reasoning with the past investment records for the investor. Most investors would not know their own preference correctly. By considering an investor's threshold for each factor, we can determine his investment behavior, and rules involved are used to do that. Through the inference of rules with the thresholds, we can identify the investor risk preference and obtain the investor-preferred asset set. For the identification of risk preference for an investor, asset related data is required. The data can indicate real and financial assets (classified as capital market assets and money market assets) by the type of domestic and foreign assets, respectively.

Table 1. Major investment systems appeared in artificial intelligence and management science

Methods	System and Studies	Characteristics	Preference
Neural network	Investor [Nikolopoulos (1994)]	Multiple assets, ES methodology	Not considered
Case-base reasoning	CABARET [Skalak, (1993)]	Stock asset	Not considered
Forward chaining	PlanPower [Stanfield et al. (1987)]	Multiple assets, Backward chaining method	Not considered
Backward chaining	INVEST [Heuer (1988)]	Stock asset	Not considered
Natural language	Investor Assistant [Buta et al. (1989)]	Stock, Cash, Real assets	Not considered
Qualitative reasoning	Portfolio Management Advisor [The Athena Group (1987)]	Investment knowledge used	Partly considered
Tree search	Port-Man [Chan, et al. (1989))		Not considered
Pattern recognition	FIA [Financial Investment Assistant; Kandt, et al. (1988)]	Stock, Option	Not considered
Machine learning	K-FOLIO [Lee et al. (1991)]	Markowitz model	Partly considered
GDSS	Innovator [Ram (1990)]	Multiple assets, Inference function	Partly considered
Goal based reasoning	SAP [Madhavan (1994)]	Stock asset	Not considered
Semantic representation	FAME [Mays et al. (1987)]	Knowledge about organization used	Partly considered
Gaming theory	PFIDSS [Shane et al. (1987)]	Multiple assets	Not considered
Quadratic programming	CAPM [Sharpe (1964)]		Not considered
Linear programming (MiniMax)	[Cai et al. (2000)]	Multiple assets	Not considered
Integer programming	HYPER-SAVINGS [Nam and Lee (1997)]	Object-oriented, optimal savings system	Partly considered

The investor preferred assets and the related asset DB are employed as variables and coefficients for a quadratic programming (QP) problem that solves a quantitative portfolio decision-making problem based on risk and expected return as follows(Chen, 1977).

$$\text{Minimize } \sigma_P^2 = \sum_{i=1}^{n} X_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} X_i X_j \sigma_{ij}$$

$$\text{Subject to } \sum_{i=1}^{n} X_i = 1$$

$$\sum_{i=1}^{n} X_i ER_i = \overline{ER}_P$$

where X_i = portfolio weight invested in asset i (i = 1, 2, 3, ⋯, n).

To operate two components, it uses a knowledge-based optimization-model formulator, UNIK-OPT in an optimization problem component. A QP problem generated by UNIK-OPT is represented with the format of frames, and any frame in a problem should belong to only one object among four kinds of objects: Model object, Constraint object, BOT (Blocks Of Term) object, and Attribute object.

4. INVESTMENT SYSTEM USING TWO KNOWLEDGE LAYERS

An investor-oriented portfolio decision-making problem has two kinds of knowledge; risk preference-based qualitative knowledge and quantitative knowledge of allocating optimal weights into assets. The two layers decision-making is shown in Figure 2.

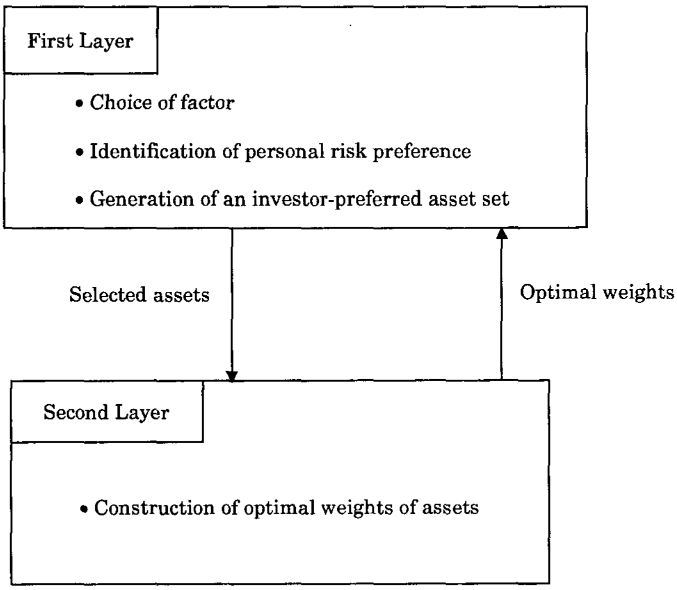

Figure 2. Two layers investment decision-making

The risk preference-based qualitative problem has three steps to construct the best investor-preferred assets: choice of factors, identification of personal risk preference for an investor, generation of an investor-preferred asset set. And by using quadratic programming, a quantitative problem finding the optimal weights given selected assets is processed.

A system UNIK-PRP is developed to implement above four steps. In first step, it considers all the factors that affect planning a portfolio, and experts' helps make an important factor set from all assets. Construction of the important set depends on an investor's risk preference. In second, to make an asset set appropriate to an investor, we have to identify his personal risk preference. For the identification, the investor's accurate thresholds for factors should be determined. There are two ways to do that. One is to get them from the investor directly and the other is from his past investment records with cases. The former would certainly be simpler than the latter. However, the latter way can produce the thresholds without giving much difficulty to an investor whereas the former one may generate poor results due to incorrect data. After the identification of an investor's preference, UNIK-PRP performs inference with rules and the five thresholds to generate an investor-preferred asset set in a third step. It needs rules to determine an investor's attitude, passive or active for an investment. In Figure 3, the rules represented by syntax of the UNIK-FWD are exhibited (Lee, 1995). For explanation, the first rule is to determine an investor's attitude, passive or active for an investment. Through comparison of his current age CURRENT_AGE with his threshold TH_AGE, it could find out the value for the attitude easily.

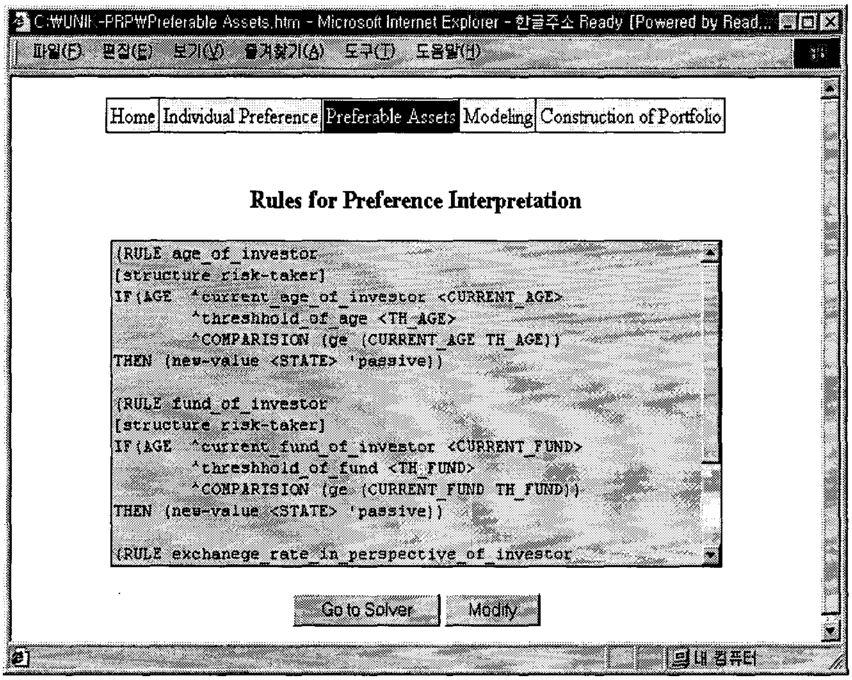

Figure 3. Rules for identifying an investor's preference

Quantitative problem is solved in final step. The step considers assets as the variables of a quadratic programming (QP) problem. To generate the optimal solution for a QP problem, the system transforms the format of frames into the one of a mathematical programming. And simultaneously, all of the input data for the problem are fed into a solver. Through the solver, the obtained result will be stored in the case base to be again used for identification of an investor's risk preference later.

5. EMPIRICAL TEST USING REAL DATA FROM KOREAN CAPITAL MARKETS

This section describes the effect of knowledge-based framework on investor's utility through the empirical testing using real data from Korean capital markets.

5.1 Description of data

To simplify empirical test, we selected a representative investor who is 40 years-old and has sufficient investment funds, and we suppose that interest rate in the market is about 4% which is relatively lower than the average rate of return in stocks recently and expected inflation rate is about 3%. Then, through the system UNIK-PRP which is already explained in the previous section we can reduce the whole asset pool for the investor to the set of financial assets. In other words, according to the system UNIK-PRP, the selected investor has such risk-preference structure that prefers higher return and higher risk assets such as stocks traded in the capital markets. That is the reason that we focus on the stocks for our empirical test.

Then, we randomly selected 30 stocks listed in KSE (Korea Stock Exchange), because it is relatively easy for us to get publicly available data regarding average returns and standard deviation of the returns. The sample stocks and the data of the expected returns for given assets are shown in Table 2. As we can see from the table, most of the data for assets satisfy the basic properties of a capital market that the assets with higher risk levels have higher expected returns. For instance, stocks (such as stock 2 and 14) that have higher risk than other stocks (such as stock 2 and 13, respectively) earn higher expected return as shown in the table.

Table 2. Sample data for the empirical test

Name	No.	μ	σ
Doosan	1	0.125310745	0.390091278
Kia Motors	2	0.256194884	0.856056768
Samsung-Trading Co.	3	0.107785214	0.527346933
Cheil Fabrics	4	0.087422242	0.376469814
Kolon	5	0.092070780	0.472177306
Doosan Contruction	6	0.094708808	0.620796447
Kolon Construction	7	0.153495413	0.777428504
Sansung Precision	8	0.130957118	0.638485937
Samhwa Crown	9	0.042412866	0.314597859
Kohap	10	0.062333847	0.527367716
Hyundai Motors	11	0.162662374	0.535586569
Samsung Electronics	12	0.310237281	0.672691656
Samsung Electricity	13	0.174584710	0.595687461
Hansol CSN	14	0.979020431	4.298803206
Sinwon	15	0.076106149	0.464651517
Kwangdong Ph.	16	0.052609113	0.693456006
Hanol Ph.	17	0.005780314	0.322174755
Hankook Computer	18	0.157093601	0.779491939
Youngwon Tradings	19	0.026027585	0.353382487
Iljin	20	0.013811918	0.333444050
Dongsuh Industry	21	0.036364521	0.427749936
Kolon Chemical	22	9.92773E-05	0.274434462
Ked-Com	23	0.017927343	0.347965459
Hyundai Precision	24	0.060609775	0.199067956
Sambo Computer	25	0.288490969	1.628828731
Iljin Electricity	26	0.053476882	0.434834669
Hanbyul Telecom	27	0.302520480	1.759489144
SK	28	0.084024503	0.408259618
SK Chemical	29	0.097630506	0.428079112
SK Telecom	30	0.444261691	1.174167117

Note: μ = average return of each stock for 20 years (1981– 2000), and
σ = standard deviation of each stock for 20 years (1981 – 2000).

Table 3 shows the correlation coefficient matrix. Given correlation coefficients, all the data for covariance terms can easily be derived from the property that the covariance of two assets is equal to the correlation coefficient multiplied by the standard deviations of two assets (that is, $\sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$). From the table, we can find one interesting fact that stock number 16 (i.e., Kwangdong Pharmaceutical company) has negative coefficient correlations with almost all other sample firms, meaning that the company can play a role of natural hedge for any portfolio that includes the firm. This suggests that any portfolio including the company can achieve lower risk than any portfolio without the company. In addition, from the table, we can see that the correlations among sample stocks are well distributed, indicating that our sample holds good representative power among whole set of stocks in KSE. This is desirable in the sense that it can significantly increase the robustness of our analyses.

Table 3. Correlation coefficients among sample stocks

No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	1.0	.31	.33	.35	.31	.04	.09	.21	.27	.38	-.1	.13	.26	.50	.07	-.3	.08	.52	.08	.60	.28	.29	.47	.41	.43	.45	.38	.25	.27	.28
2		1.0	.67	.27	.06	-.2	-.1	-.1	-.1	.63	.26	.59	.53	.94	-.1	-.3	-.3	.89	-.5	.72	-.1	-.3	.17	.10	.92	.66	.92	.64	.06	.93
3			1.0	.77	.53	.37	.42	.36	.20	.84	.14	.79	.78	.81	.13	-.2	.15	.79	-.1	.89	.32	.03	.53	.37	.90	.90	.85	.97	.59	.93
4				1.0	.72	.65	.66	.57	.48	.65	.07	.61	.68	.42	.47	-.5	.65	.60	.28	.72	.70	.45	.62	.64	.57	.81	.54	.58	.81	.59
5					1.0	.40	.47	.41	.24	.51	.21	.44	.52	.20	.38	-.4	.59	.26	.47	.64	.60	.48	.63	.70	.34	.65	.27	.60	.79	.43
6						1.0	.96	.62	.61	.21	.10	.19	.29	-.2	.32	-.3	.63	.52	.18	.18	.80	.47	.42	.48	-.0	.23	-.1	.12	.61	-.1
7							1.0	.67	.52	.22	.14	.30	.36	-.1	.21	-.3	.58	-.1	.48	.23	.76	.46	.42	.52	.02	.27	-.1	.22	.61	-.1
8								1.0	.48	.48	-.0	.21	.19	.02	.36	-.2	.31	.16	.00	.21	.56	.39	.23	.38	.12	.34	.08	.24	.69	.03
9									1.0	.25	.10	-.1	-.0	-.3	.61	-.1	.48	-.1	.29	.07	.61	.58	.31	.42	-.1	.16	-.1	.02	.39	-.3
10										1.0	.03	.69	.62	.66	.36	-.2	.07	.73	-.3	.71	.20	.12	.45	.28	.74	.77	.74	.71	.67	.63
11											1.0	.14	.05	-.2	.15	-.0	.08	-.2	.02	.03	.16	.07	.04	.25	-.1	.03	-.1	.45	.01	-.1
12												1.0	.89	.65	.11	-.2	.22	.65	-.0	.74	.18	.13	.53	.32	.78	.81	.70	.86	.51	.75
13													1.0	.65	-.0	-.4	.30	.64	.12	.78	.26	.13	.62	.46	.77	.78	.68	.75	.62	.73
14														1.0	-.2	-.2	-.2	.91	-.3	.75	-.2	-.2	.39	.06	.97	.70	.96	.56	.15	.90
15															1.0	-.2	.52	.08	.33	.16	.31	.64	.31	.17	-.0	.33	.07	.20	.46	-.0
16																1.0	-.3	-.3	-.0	-.5	-.4	-.3	.06	-.7	-.2	-.4	-.2	-.1	-.3	-.2
17																	1.0	.01	.75	.26	.52	.79	.55	.61	-.0	.36	-.1	.19	.49	-.1
18																		1.0	-.3	.77	.03	-.0	.44	.21	.92	.77	.93	.57	.29	.81
19																			1.0	..01	.28	.60	.56	.22	-.2	-.0	-.2	-.0	.26	-.3
20																				1.0	.26	.20	.56	.50	.83	.93	.74	.67	.43	.73
21																					1.0	.43	.37	.63	-.1	.29	-.2	.14	.53	-.2
22																						1.0	.48	.61	-.1	.37	-.1	.09	.43	-.1
23																							1.0	.31	.48	.60	.46	.54	.53	.36
24																								1.0	.17	.51	.01	.30	.49	.10
25																									1.0	.83	.97	.66	.30	.92
26																										1.0	.74	.70	.52	.76
27																											1.0	.63	.27	.90
28																												1.0	.51	.59
29																													1.0	.19
30																														1.0

5.2 Results

Table 4 and Figure 3 show the optimal portfolio weights and the efficient frontier (E.F.) made by connecting each optimal point, respectively, both obtained though our new model using the data set described in the previous section. As we change the level of a target expected return for a specific investor, portfolio weights (Xj) are adjusted together. We use 10% to 40% as the annual target expected return, because many mutual funds traded in developed countries have recently had average annual returns of about 20%.[2] For example, when the target expected return of an investment is 26%, the optimal portfolio is constructed as follows; 11.3%, 24.6%, 55.2%, 1.2%, and 7.8% for asset 1 (Doosan), 11 (Hyundai Motors), 12 (Samsung Electronics), 16 (Kwangdong Pharmaceutics), and 30 (SK Telecom), respectively. If the target return is raised to 40%, asset set in the optimal portfolio only include asset 12 (58.4%, Samsung Electronics), 14 (6.4%, Hansol CSN), and 30 (35.1%, SK Telecom). These results imply that we get narrower set of optimal portfolios as we increase the target returns. Since, in reality, investors only focus on a few target assets for their investment pools, our new model can help them make narrow efficiently their target set of assets using their preference scheme. Otherwise, investors have to collect vast amount of information about all assets in the markets, leading to great amount of costs for the search of information. This means that investors should have had much lower utility if they had used traditional model instead of our new model.

In addition, Table 4 and the shape of Figure 4 are consistent with the standard portfolio theory in the sense that the frontier should be concave to the origin and the relationship between expected returns and risks should be positive. From the figure, we can notice that when the target return is 10%, the risk of the optimal portfolio is about 13% and when the target return is 40%, the risk of the optimal portfolio is 76.2%. By using utility function, an investor can choose his optimal portfolio at the point where the indifference curve of the utility function is tangent to the efficient frontier as P** in Figure 1. If we have a risk-free asset (R_F), then we can get a more favorable expanded efficient frontier as we can see in the figure, because any linear combination of portfolios on the efficient frontier must be efficient (Black, 1972; Chen, 1977; Elton et al., 1995; Markowiz, 1995).

[2] For a simple statistical overview of the average return of mutual funds, refer to *The Economist* (May 26, 2000).

Table 4. Optimal portfolio weights in case of Korean assets

Sigma	ER	Portfolio weights														
		X1	X2	X6	X7	X8	X9	X11	X12	X14	X15	X16	X17	X19	X24	X30
12.9	10	0.198	0.001	*	*	0.001	0.138	0.129	0.102	*	0.016	0.090	0.002	0.069	0.238	0.017
14.1	12	0.236	*	*	*	0.013	0.095	0.155	0.141	*	0.020	0.089	*	0.055	0.180	0.017
15.7	14	0.277	*	0.011	*	0.021	0.042	0.180	0.177	*	0.025	0.090	*	0.040	0.120	0.017
17.7	16	0.317	*	0.023	*	0.026	*	0.205	0.214	*	0.028	0.091	*	0.023	0.057	0.017
19.9	18	0.341	*	*	0.024	0.022	*	0.225	0.256	*	0.024	0.088	*	*	*	0.019
22.8	20	0.303	*	*	0.021	0.007	*	0.235	0.330	*	*	0.073	*	*	*	0.031
26.2	22	0.246	*	*	0.009	*	*	0.240	0.408	*	*	0.053	*	*	*	0.045
30.1	24	0.181	*	*	*	*	*	0.244	0.482	*	*	0.032	*	*	*	0.060
34.3	26	0.113	*	*	*	*	*	0.246	0.552	*	*	0.012	*	*	*	0.078
38.6	28	0.037	*	*	*	*	*	0.243	0.624	*	*	*	*	*	*	0.096
43.3	30	*	*	*	*	*	*	0.181	0.700	0.001	*	*	*	*	*	0.118
48.5	32	*	*	*	*	*	*	0.081	0.774	0.005	*	*	*	*	*	0.141
54.1	34	*	*	*	*	*	*	*	0.818	0.010	*	*	*	*	*	0.172
60.7	36	*	*	*	*	*	*	*	0.740	0.028	*	*	*	*	*	0.232
68.1	38	*	*	*	*	*	*	*	0.662	0.046	*	*	*	*	*	0.291
76.2	40	*	*	*	*	*	*	*	0.584	0.064	*	*	*	*	*	0.351

Note: Symbol '*' means 'zero' portfolio weight.

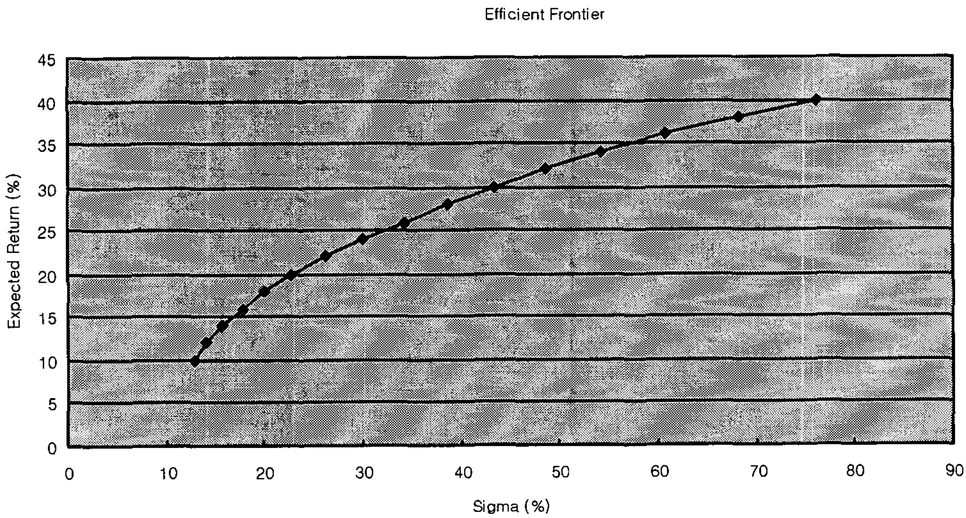

Figure 4. Efficient frontier (E.F.): the case of Korean assets

6. CONCLUDING REMARKS

In this paper we have presented a framework of two-layer decision-making system which is capable of identifying an investor's preference. The framework can form the foundation of a knowledge-based system combining a qualitative problem and a quantitative mathematical programming problem, especially a quadratic programming.

The main contributions in this paper are as follows. First, we have proposed the architecture of a knowledge-based portfolio decision-making system as a way to utilize both quantitative and qualitative information. Second, the proposed procedure for the system is illustrated in detail by each step. Third, in the perspective of feedback of a knowledge system, the framework presented in this paper has an overwhelming advantage over a traditional quantitative system. That is, it includes past investment records and utilizes them in future investment decisions. Finally, through the empirical test using real data from Korean capital markets, we proved that our new model is efficient in the perspective of both the reduced size of target asset pool and the investors' benefit/cost ratio.

In the future research, however, some limitations of this study should be overcome as follows: First, we just introduced a representative agent as an investor who has specific characteristics in investment preferences. To make the model more real, however, empirical test for the real investors with diversified preferences must be conducted. Second, we used handful number of stocks for our empirical tests in this paper, but various asset types, such as commodities, real assets, bonds, and even foreign assets, can be included in order to extend our results further.

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