“Investor’s behaviour and the relevance of asymmetric risk measures”

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Investor's behavior and the relevance of asymmetric risk measures

Abstract

Numerous articles use the Markowitz mean-variance approach for computing the capital asset pricing model (CAPM) and to determine the best set of assets an investor should hold. But using a symmetric risk measure is not necessarily straightforward in the mind of many investors. Many other approaches to determine a portfolio composition, e.g. faith or other behavioral determinants, appear more natural. Especially an asymmetric downside risk approach is more appealing to many investors. This work investigates the differences between portfolios based on a symmetric and on an asymmetric risk measure. Based on the Behavioral Portfolio Theory (BTP) model by Shefrin and Statman and the Markowitz classical portfolio approach the authors compare portfolios composed by stocks of the French SBR 120 market over a period of 6 years. Simulation of 100,000 virtual portfolios over the study period shows that there are only minor differences between portfolios obtained by downside or symmetric risk. Therefore, the results leave room for taking into consideration other choice criteria to complete the approach, such as the computing power if an investor wants to use much more demanding downside risk methodology or faith bases selection criteria to pick the assets.

Keywords: portfolio selection, behavioral finance, symmetric risk, downside risk.
JEL Classification: G02, G11, G17.

Introduction

The definition of risk, its measure and the implication it has on the investor's behavior have been at the core of managerial finance from the very beginning. Early research efforts on how investors facing risk allocated their capital across different assets culminated in two groundbreaking papers on the definition and measure of risk in portfolio analysis, Markowitz (1952) and Roy (1952), which marked the emergence of finance as a separate discipline. The former suggested that variance is used as a proxy for risk while the latter recognized the importance of downside risk in the investor's decision making. Mainly because of its computational convenience, variance, along with standard deviation, quickly became widely accepted as a measure of risk in the mainstream of finance literature. More recently the behavioral finance approach pinpointed the fact that the use of such a measure is not straightforward for all investors. As defined by De Bondt et al. (2008) behavioral finance is about the study of how the psychology of investors influences their financial decisions whether this specific psychology is influenced by the environment, personal factors, culture, faith or any other factors. Thereby the psychology of the investor can influence the selection of the risk measure (asymmetric of symmetric) leading to the building of a portfolio. This point can be problematic when the use of one risk measure leads to a different portfolio selection than the other.

As a matter of fact variance minimization is counter-intuitive as it entails punishment both for low and high returns equally. The more intuitive downside risk measure did not take off for a few decades due to its computational complexity. With the advancement of computing technology and the extensive growth of the financial derivatives industry the appeal of using downside risk measures has gained ground. The increase in computation power makes the question of the selection of assets for a portfolio depending on the two risk definition relevant and answerable. If the two approaches deliver the same result there is, on the one hand, no reason to employ the more costly method (from a computational point of view) nor, on the other hand, any reason to force investors to make their choices based on counterintuitive risk modelling which can lead to a non rational behavior. Surprisingly, empirical investigation of this issue has so far received very little attention in the literature. This paper aims to contribute to the literature by offering a comparative analysis of portfolio choices under the two risk concepts. Since efficient frontier plays a critical role in the selection of optimal portfolios in this study we specifically focus on the implications of two risk measures on the efficient market frontier.

Using the data from the French stock market, we compare optimal portfolios of two different investors that use the downside and symmetric risk measures. While for a symmetric risk investor we employ the seminal mean-variance model of Markowitz (1952), for a downside risk investor we rely on the model of Shefrin and Statman (2000). Those authors developed a Behavioral Portfolio Theory (BPT) where an investor seeks to maximize his expected return subject to the probability of ruin being no greater than a given critical level. Shefrin and Statman (2000) claim that in contrast to the capital asset pricing model (CAPM), that uses symmetric variance to account for risk, in equilibrium investors hold a portfolio that resembles a combination of bonds and a lottery ticket. Thus, according to BPT, investors deviate from the optimal portfolio diversification of Markowitz, and consider their portfolios as a pyramid of assets with riskless instruments in

the bottom layer and risky equity in the top layer (this idea was earlier articulated by Fisher and Statman (1997) among others).

Our paper is related to a small set of empirical papers that compare portfolio choices under downside and symmetric risk frameworks. Harlow (1991) and Alexander and Baptista (2002) demonstrate that if return distributions are normal, the difference between the optimal portfolio choices of a symmetric-risk and downside-risk investors will be small. Jarrow and Zhao (2006) show that when asset returns are almost normally distributed investors using variance and lower partial moment to measure risk choose similar portfolios (Galagedera, 2007) for an extensive review of portfolio selection models and CAPM). When asset returns are non-normal with large left tails they obtain the opposite result. However, numerous empirical studies carried out for different markets and for different periods confirm that the real returns are not normal (Mandelbrot, 1963; Brenner, 1974; Jorion, 1988). In line with these empirical studies, our simulations are insensitive to return distributions.

By simulating portfolio choices under two risk concepts we find that the optimal portfolio constructed by a downside risk-averse investor belongs to the mean-variance efficient frontier. This specific portfolio has been constructed under constraints that can be seen as the willingness for an investor under limited rationality to choose a limited number of assets or to pick up the assets following different criteria (including the downside risk, but not limited to this aspect).

The rest of the paper is structured as follows. The next section discusses the portfolio theory of the downside risk investor in the context of the BPT in contrast to the symmetric risk investor in mean-variance framework. Then the dataset used, the methodology and the results are exposed. The final section concludes the paper.

1. The model

To model the portfolio choice of a downside risk investor we rely on Shefrin and Statman (2000). To define risk Shefrin and Statman (2000) draw on Roy's (1952) concept of safety first approach. According to this concept an investor is characterized by a subsistence level of wealth. The investor is considered "ruined" if his terminal wealth falls below this exogenously given level. Thus, the investor seeks to minimize the probability of failure. Telser (1955) goes one step further and introduces an acceptable level for the ruin probability such that the portfolio is considered "safe" if the probability of failure does not exceed this specified level. Arzac and Bawa (1977) extend Telser's model by considering an investor whose objective function depends on the expected terminal wealth under this ruin probability. These older results serve as the basis for Shefrin and Statman's (2000) Behavioral Portfolio Theory a simplified exposition of which we present in the following section.

In this model there are n states of nature, w represents the wealth of the investor, w_1,... w_n each occurring with the probability p_i, $i = 1,...,n$ respectively. The payoff from an asset is 1 if w_i occurs and 0 otherwise. The price of each asset is known and denoted by π_i. We suppose that states are ordered so that state prices per unit probability $\pi_i./p_i$ are monotonically decreasing in i. At date zero, the investor chooses a portfolio composed of the contingent claims that maximize his expected terminal wealth subject to his budget constraint. A mean-variance investor with a quadratic utility function thus solves the following program where b is a constant:

$$\max \sum p_i \left(W_i - \tfrac{b}{2} W_i^2\right) \quad s.t. \sum \pi_i W_i \le W_0. \tag{1}$$

The solution to this portfolio problem has the following form:

$$W_i = \frac{1}{b}\left[1 - \frac{\sum \pi_j - bW_0}{\sum \pi_j^2 / p_j} \frac{1}{\pi_j / p_j}\right], \tag{2}$$

A behavioral investor at date 1 maximizes is expected terminal wealth subject to the safety-first constraint in addition to the budget constraint, so the optimization program of a BPT investor is defined as:

$$\max E\left(\tilde{W}\right) \ \ s.t.\ P\left(\tilde{W} < A\right) \le \alpha \text{ and } \sum \pi_i W_i \le W_0, \tag{3}$$

where A is the aspiration level and α is the maximum probability of failure. Both A and α are private characteristics of the investor, also called security parameters. Thus, the agent seeks to maximize the expected wealth in a particular set of portfolios that meet the security constraint. $\tilde{W}$ denotes the future wealth distribution and takes the value W_i, $i = 1,...,n$, if w_i occurs. An analytical solution to the maximization program of the BPT investor may not exist. However, we can show the portfolio choice of a BPT investor with a simple numerical example following Shefrin and Statman (2000). To do so, let us consider an economy with 8 states of nature, the arbitrary prices of which are given in Table 1.

Table 1. An example of state price

	1	2	3	4	5	6	7	8
π_i/p_i	0.37	0.19	0.12	0.09	0.07	0.06	0.05	0.04

For the sake of simplicity let us suppose that the probability is uniformly distributed: $p_1 = p_2 = ... = p_8$. The distribution for the optimal portfolio as a function of the realized state at date 1 given $W_0 = 1$ (the agent invests 1 at date 0) is shown in Figure 1

both for Markowitz and Shefrin-Statman investors. In this example, both have the same expected return on their portfolios, but the latter is also characterized with α = 0,25 and A = 2. We observe that a Markowitz investor invests in each individual asset to lower its risk while the Shefrin-Statman does not. In the Shefrin-Statman case, this payoff pattern can be described as the combination of payoffs from a portfolio consisting of a bond and a lottery ticket that payoff only in state 8.

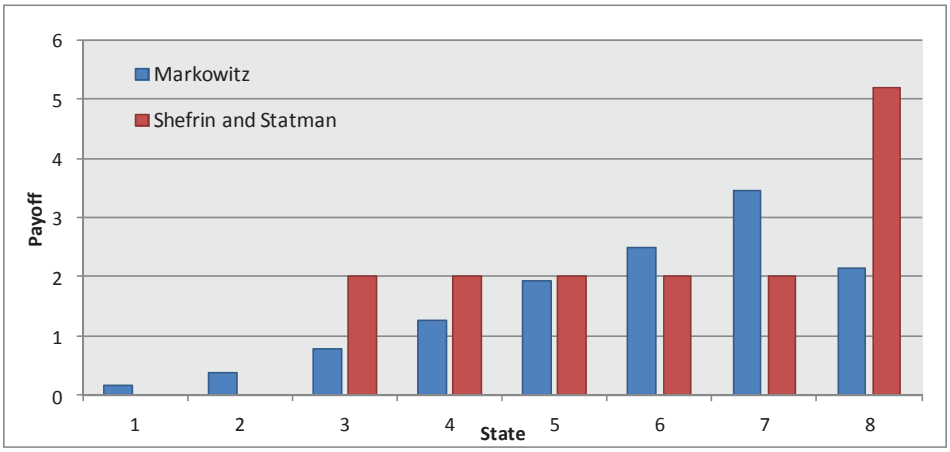

Fig. 1. Optimal portfolios payoff

Shefrin and Statman (2000) show that efficient solutions of the behavioral portfolio problem are typically non mean-variance efficient. The idea is that an investor who perceives risk as the downside deviation from the expectation makes two distinct investment decisions. First, the investor seeks to create a portfolio satisfying the safety-first criteria for his level of capital at the lowest possible level of required investment, i.e. at the cheapest price. Second, if the budget constraint is not satiated he allocates the remaining investment capital to the asset with the highest expected payoff. In the example above, for his initial wealth W_0 = 1 the investor proceeds in two simultaneous steps. He starts out by investing in the assets with the lowest ratio ($\pi_i./p_i$) in order to ensure terminal value of the portfolio at date 1 at the level A = 2 in 75% of states of nature. In our example, he invests in the 6 cheapest assets. This strategy enables him to meet the security constraint with the lowest cost. This is why the payoffs in states 1 and 2 are zero. Then, he invests all the rest of the initial wealth in the cheapest available asset.

Thus, the composition of the resulting optimal portfolio of a downside risk investor differs from that of a mean-variance investor who simply allocates all the capital to the portfolio with a minimum level of variance for a given level of expected return. This hypothesis is the object of our tests in the following section.

2. Data

To collect the data, we consider stocks that composed the SBF120 French Index over the period from June 2001 to June 2007. Stock price observations were obtained from the database maintained by Fininfo, a French financial market data provider. At the beginning of that period the index included 119 assets (as of June 1, 2001). To preserve continuity, of these 119 assets we eliminated the ones with incomplete data. Incompleteness of the data resulted from the exclusion of some individual stocks from the index over the period under consideration. Incomplete data were also observed for assets with missing observations and such assets were also eliminated. As a result we were left with 71 assets in the final sample, as opposed to the initial 119, with daily observations over 1535 days.

Using these 71 stocks we computed 1534 daily stock returns. The main descriptive statistics are given in Table 2. To test for normality we resorted to the Jarque-Bera test which reveals departure from normality. The Markowitz model was initially built for normality satisfying distribution of returns. However several works underlined the practical and empirical relevance of employing non normal distribution. Galagedera (2007) reviews these situations when researchers pay more attention to third and fourth moments (skewness and kurtosis). This author reports that investors often compensate the higher risk of such a distribution by expecting higher returns and that skewness and kurtosis cannot be satisfyingly diversified by increasing the size of the portfolio. Therefore part of our later results could be explained by the type of distribution, but do not make the use of the CAPM model unfounded.

Table 2. Descriptive statistics

	Mean	St. dev.	Skewness	Kurtosis
Max	1.9735	26.5	10.78	298.24
Min	-1.4493	13.3	-2.56	5.55
Average	0.1896	21.8	0.05	16.22

Several works in the behavioral finance literature question the practical relevance of an efficient portfolio composed of a huge number of assets. Asking

the question of the number of different assets an investor could add to a portfolio is especially relevant for a comparison of a mean variance portfolio and a behavioral built portfolio. The philosophy of the latter implies that the portfolio should be composed of assets selected by the investor on the basis of several criteria making the mean variance not the sole indicator of choice. As recalled by De Bondt et al. (2008, p. 9) "Behavioral finance is based on three main building blocks, namely sentiment, behavioral preferences, and limits to arbitrage". Consequently such additional criteria could include naturally downside risk, but also other principles like the ethical nature of the firms, sin portfolios and faith-based stocks selection and so on. Liston and Soydemir (2010), Lin and Vanderlinden (2006) highlight the influence that religious and ethical principles can have on the behavior of investors. Porter and Steen (2006) show different ways of integrating faith in stock investing. Vieira (2011) and Beaumont et al. (2008) show that the sentiment of the investor can lead to strong variations in the investment behavior.

Therefore, we choose to compare portfolios with a limited number of assets and not all the available assets. This would partially constrain the mean variance approach and in contrast give more relevance to a behavioral approach. Nevertheless the number of assets in the portfolio must be sufficient to make diversification suitable and the portfolio approach still relevant. For this we try to construct well diversified portfolios with a sufficient small size to allow a theoretical stock picking behavior from a small investor. We define a well-diversified portfolio as one which generates at least 90% reduction of the variance relative to that of the least-diversified portfolio, i.e. the 2-asset case. This definition is consistent with the one used in the research literature (Statman, 2004). Thus, for robustness reasons, following the methodology of Campbell et al. (2001) we determine whether a reasonably good diversification can be achieved with a small number of stocks. We denote the number of assets in a portfolio by n = 2, 3,..., 71. The assets are chosen randomly and enter the portfolio with equal weights. For each value of n we compute the average variance of 10,000 randomly constructed portfolios composed of n assets. We obtain that in the market under consideration (71 assets) a portfolio composed of 15 assets can reach a sufficiently high diversification level. Figure 2 depicts the decrease in variance when the number of assets in the portfolio increases. In practice the number of assets in the composition of a well-diversified portfolio varies depending on the market and the time period under consideration. It is 20 for Bloomfield et al. (1977), 30 for Statman (1987), 120 for Statman (2003).

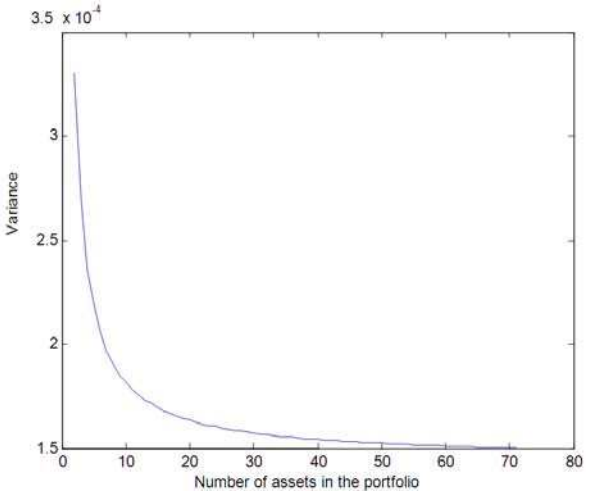

Fig. 2. Diversification effect

Naturally the difference in variance of the portfolio falls when the number of assets in the portfolio increases. Table 3 reveals the numerical expression of this effect: 52% of variance is reduced when the number of assets in the portfolio goes from 2 to 4. If the portfolio contains 15 assets the variance is reduced by over 90% in comparison with the least-diversification scenario.

Table 3. Diversification effects

Number of assets	2	4	6	8	10	12	15	20	30	50	71
Reduction of variance*	0	0.52	0.69	0.78	0.83	0.86	0.91	0.94	0.96	0.98	0.99

Note: *Proportion by which the variance is reduced.

3. Methodology

To run portfolio simulations we construct optimal portfolios of Markowitz and of Shefrin-Statman. We proceed in the following two steps. First, we estimate expected annual returns using the bootstrap method. Second, we construct the portfolios using the state space from the first step.

Step 1. From among the 71 stocks in our sample we randomly choose 15 assets. We also select a random interval within the period from June 1, 2001 to June 1, 2007 of 250 consecutive days. Thus, we construct the following matrix of daily returns, where A_i denotes an individual asset, each element $r_{i,j}$ denotes a daily return of the asset i at the date j:

$$R_{daily} = \begin{matrix} A_1 & A_2 & \cdots & A_{15} \\ r_{1,1} & r_{2,1} & \cdots & r_{15,1} \\ r_{1,2} & r_{2,2} & \cdots & r_{15,2} \\ \vdots & \vdots & \ddots & \vdots \\ r_{1,1534} & r_{2,1534} & \cdots & r_{15,1534} \end{matrix}. \quad (4)$$

We resort to the historical simulation method (Hull and White, 1998) to compute the expected annual returns. Namely, to simulate the expected returns at a future date, in a one year period after the date of the stock price observations for 15 random assets, we randomly select a 250-day period in our sample. In France a year is made, on average, of 250 trading days. By selecting a string of 250 days we choose a one year moving windows with random start. For each of these random windows we compute the daily returns for each stock. In line with the general principles of the Hull and White (1998) method we take the future uncertainty to be represented by 1,000 states of nature. For that, we repeat the bootstrap procedure 1,000 times to simulate 1,000 lines of future annual returns for 15 assets.

Step 2. To compute the optimal portfolios of 15 assets we need to solve the following optimization problems: minimization of portfolio's variance given the expected returns for Markowitz portfolio and maximization of the portfolio's expected return given the probability α of earning below a threshold value r^* for Shefrin-Statman portfolio.

In the Markowitz (1952) problem the program is to minimize the variance of the portfolio returns given the expected return $E(r)$ or to maximize the expected return subject to an acceptable level of variance of returns (*Var*). This problem is well known to have a closed form solution. In the Shefrin-Statman problem given the expected return $E(r)$ and probability $P(r < r^*)$ of earning less than r^* the program writes:

$$\max E(\tilde{r}) \quad s.t.\ P(\tilde{r} < r^*) \le \alpha . \tag{5}$$

Due to the absence of analytical solutions, the solution to this problem requires numerical methods. We consider 12 different cases for the Shefrin-Statman problem following their own numerical examples: $r^* \in \{0; 0.05; 0.1\}$ and $\alpha \in \{0; 0.1; 0.2; 0.3\}$. With these 12 scenarios we construct the state-space matrix from the previous step 140 times (the choice of 140 repetitions is somewhat arbitrary, we stopped the trials sufficiently long after the results started showing identical values). Thus, we repeated the matrix simulation 1680 times. For each matrix we construct the Markowitz (1952) portfolio frontier and the portfolio optimal for a downside risk investor who makes her choice within the Shefrin-Statman framework. We presume that the part of the initial wealth invested in a single asset is equal to $k/15$, $k = 0, 1,..., 15$ and we consider a sample of 100,000 portfolios. It can be shown that the total number of different portfolios is about 77 million. For each of the 100,000 portfolios we verify if the security constraint is met. The set of portfolios that meet the security constraint is called the security set. According to the Shefrin-Statman problem the optimal downside risk portfolio is the one that belongs to the security set and that allows us to reach the maximum expected value of returns. Whenever such a portfolio exists, i.e. meets the regularity conditions, we compute its standard deviation and expected return. These two values for each portfolio enable us to locate the portfolio in the traditional risk-return space. In each case we compare the two portfolios to identify if the downside risk portfolio is superior to the symmetric risk portfolio in the weak Pareto sense, that is, provides a higher expected return with the same level of standard deviation or reduces standard deviation without affecting the expected return.

4. Results

Out of 1680 we obtain 651 cases where no optimal downside risk portfolio exists as none of those 100,000 portfolios under consideration meets the security constraint. The results of our calculations are shown in Table 4. We denote N_S the number of the optimal downside risk portfolios constructed for each couple (r^*, α). The more demanding the investor in terms of the individual asset characteristics, the fewer the elements his set of security contains. For example, we observe that when the admissible probability of failure α increases (and subsistence level r^* remains the same) the number of portfolios that meet the security constraint increases. Similarly, if r^* increases (and α remains unchanged), the security set becomes smaller. When $\alpha = 0$, the investor seeks insurance in all states of nature and, if $r^* = 0$, he recovers his initial investment in all states of nature. In this case there are only 30 cases in which the investor could reach his goal. When $\alpha = 0$ and $r^* = 0{,}05$ the investor seeks to reach at least a 5% return regardless of the state of nature. This scenario is even more difficult: there are only 20 situations when it is possible. Finally, if $\alpha = 0$ and $r^* = 0{,}1$ the investor will be satisfied only if he earns 10% without any possibility of failure. The number of portfolios meeting this constraint is limited to 14 only.

Table 4. Results

3	0	0	0	0	0.05	0.05	0.05	0.05	0.1	0.1	0.1	0.1
α	0	0.1	0.2	0.3	0	0.1	0.2	0.3	0	0.1	0.2	0.3
N_s	30	102	114	117	20	102	113	120	14	82	99	116
N_s/140	0.21	0.73	0.81	0.84	0.14	0.73	0.81	0.86	0.1	0.59	0.71	0.83
N_M	6	0	0	0	0	0	0	0	1	0	0	7

We denote N_M the number of cases, where a Markowitz investor selects an optimal portfolio different from the optimal downside risk portfolio. We realize that there are only 7 cases out of the 1029 (only 0,68 %) in which the choice of a Markowitz investor does not coincide with that of a downside investor. Let us take a closer look at such a case. We illustrate a common case where $N_M = 0$, which implies that the downside investor chooses a portfolio on the Markowitz frontier. Figure 3 depicts all 100 000 portfolios that are characterized by their standard deviation (on the horizontal axis) and their expected return (on the vertical axis). Each grey point represents one portfolio of 15 individual assets.

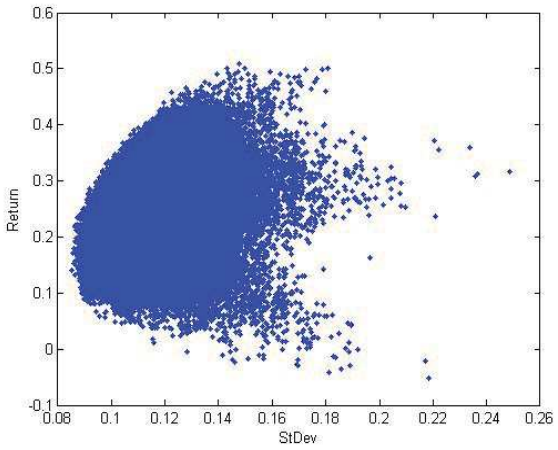

Fig. 3. Set of all 100,000 portfolios

In Figure 4, we depict the previously obtained traditional umbrella shape of the portfolio and take a deeper look at how the assets in this portfolio are influenced when the r^* and α parameters are modified.

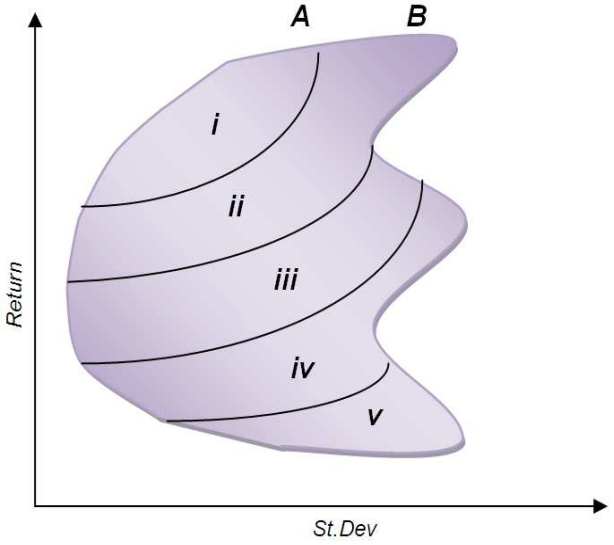

Fig. 4. Evolution of the portfolio under different assumptions

Thereby we can depict on the same drawing the result obtained for various levels of aspiration and admissible failure. Let us imagine an investor, who is more risk-averse. Naturally, his security set will contain fewer portfolios. Let us consider the following values of α = 20, 10 and 0 percent. These cases are represented in Figure 4. Zone *i* identifies portfolios that allow the investor to recover his initial investment in any state of nature, i.e. that create a perfect insurance against any loss. The set of portfolios (zone *ii*), which includes the previous set (zone *i*) allows the investor to recover his initial investment in 90% of cases; the lower set (zone *iii*) is for an investor whose α equals 80% and so on. We find the same result when r^* increases and α remains at the same level. Each zone encompasses the previous one for the same level of confidence.

Thus, we can conclude that for any level of α and r^* the security set will always contain a part of the efficient Markowitz frontier. This is what is meant when we suggest that the optimal downside risk portfolios coincide with those of a Markowitz investor. In Figure 4, the letter *B* represents the optimal portfolio for a BPT investor characterized by an aspiration level equal to the initial investment and an α of 90%. At the same time, *B* is optimal in the Markowitz (1952) sense for an investor who requires the level of risk which corresponds to 0,18 of standard deviation. The same reasoning applies to the portfolio represented by the letter A. This portfolio is optimal under BPT (α = 0; r^* = 0) and also in the Markowitz sense.

We notice two interesting points. The first one concerns the measures of risk. In both cases, the Markowitz approach and the BPT, we note that the more risk-averse the investor, the less risky his optimal portfolio. Indeed, under BPT, an investor who requires more security will build up a less risky portfolio (less risky not only in terms of downside risk measure but also in the Markowitz framework). The optimal portfolio of an investor who requires more security is on the left of the Markowitz efficient frontier. Both portfolio *A* and *B* are on the efficient Markowitz frontier.

The second interesting point concerns a specific case when α is equal to 0. Here, loss is not possible: in all cases the investor is able to recover his initial investment. Thus, the risk measured by variance or standard deviation measures uncertainty associated with random but positive returns. Out of these portfolios the BPT investor chooses the one with the highest return. At the same time, an investor following the Markowitz approach chooses the portfolio with the *a priori* fixed standard deviation. By reducing the level of risk this investor denies himself the chance of getting very high returns by ensuring that he cannot lose money. This is the underlying idea behind the criticism of symmetric risk measures such as variance and standard deviation.

Conclusion

Our results show that the Markowitz (1952) portfolio selection model can be a viable and cost effective tool for investors despite the fact that the symmetry of risk with respect to the expectation is non-intuitive. We used historical stock price observations with 71 assets over 1535 days to run portfolio simulations of two different kinds of investors. One investor in our simulations used symmetric risk measure and chose its optimal portfolio by mean-variance analysis. The other one considered downside risk measure following the BPT. We find that the portfolio choices of the two are very similar.

Our research into security constraints and security sets offers empirical evidence that despite the intuitive clumsiness of the symmetric risk measures the mean-variance framework produces outcomes that coincide with the alternative portfolio theories based on safety-first principle and downside risk. The value of this study rests in part with the fact that empirical studies on downside vs. symmetric risk are very limited. We show that mean-variance portfolio optimization and minimum downside risk portfolio choice produce very similar outcomes. The implycation is that computationally complex portfolio choice via downside risk minimization is not a cost-effective avenue to pursue for portfolio managers. Thereby our results do not reject the assertions of a number of papers (Roy, 1952; Fishburn, 1977; Bertsimas et al., 2004) that claim that investors perceive risk to be the downside deviations from the objective levels of returns rather than any deviation by offering the possibility for investors to select a small number of assets to build a portfolio based on their own principles rather that just mean variance analysis.

One limitation is that in this simplified version of the Shefrin-Statman model we use true probabilities and not distorted ones. Therefore it does not incorporate a large variety of extreme behavior of the investors. A possible development of this work would be to allow for more extreme points of view and behavior of the investors. For example Das (2010) transcribed Markowitz's mean-variance portfolio theory and Shefrin and Statman's BPT into a mental accounting (MA) framework. They show that attitudes toward risk vary for each mental account and that this behavioral approach gives mean-variance efficient portfolios under a range of specific conditions. These generalizations of MVT and BPT via a unified MA framework result in a fruitful connection between investor consumption goals and portfolio production. Chiang et al. (2006) show the existing different groups of investors, with such different goals, who perceive the market differently and act differently accordingly to their perceptions.

A promising next step would also be to consider new data in the light of the ongoing financial crisis and credit crunch. CAPM has shown limitations in troubled economic times or with unclear information, as reported on recently in a study on the Greek stock market (Theriou et al., 2005). As investors become more prudent with lack of attractive opportunities perhaps the behavioral portfolio theory becomes more likely to hold.

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