



The effect of downside risk reduction on UK equity portfolios included with Managed Futures Funds

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ABSTRACT

The concept of asymmetric risk estimation has become more widely applied in risk management in recent years with the increased use of Value-at-risk (VaR) methodologies. This paper uses the n -degree lower partial moment (LPM) models, of which VaR is a special case, to empirically analyse the effect of downside risk reduction on UK portfolio diversification and returns. Data on Managed Futures Funds are used to replicate the increasingly popular preference of investors for including hedge funds and fund-of-funds type investments in the UK equity portfolios. The result indicates, however that the potential benefits of fund diversification may deteriorate following reductions in downside risk tolerance levels. These results appear to reinforce the importance of risk (tolerance) perception, particularly downside risk, when making decisions to include Managed Futures Funds in UK equity portfolios as the empirical analysis suggests that this could negatively affect portfolio returns.

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1. Introduction

Academic and practitioner interest in asymmetric risk analysis, in particular relating to the lower partial moment (thereafter, LPM) and the development of practical applications of Value-at-risk¹ (thereafter, VaR) methodologies, has greatly increased in recent years. For example, research by Danielsson, Jorgesen, Sarma, and De Vries (2006) and Hyung and de Vries (2005) have related VaR to the lower partial moments of return distributions. The initial academic interest in LPM can in fact be traced back to Markowitz (1952) seminal paper on portfolio diversification. However, due to the combination of computational costs and the success of his mean-variance framework, Markowitz's insights into the LPM were largely ignored over the subsequent 40 years. With the development of information technology and the limitations of the mean-variance framework becoming more apparent, these constraints no longer apply and hence interest in developing LPM methods has greatly increased. Even so, to date this work has tended not to focus on how the LPM can flexibly capture varying degrees of risk tolerance and their implications in respect of portfolio allocation problems, which is the primary focus of this paper. The purpose of the current paper is to first review and discuss the risk measures related to LPM, its development and the relationship to the currently used VaR model and second to empirically evaluate from a UK investor perspective the practical implications in terms of portfolio

performance. The empirical evaluation of these issues from a UK investor perspective provides the first indication regarding how LPM can be utilised to affect downside risk reduction of portfolio returns and diversification. The paper is structured as follows. In Section 2, the paper reviews the literature dealing with the rationale, structure and development of the LPM model. Section 3 discusses the empirical objective of the study and the data and research method used. Section 4 presents and discusses the main findings, and Section 5 summarises the results and discusses their implications.

2. Literature review

2.1. Variance and below-target-returns variation as risk measures

Since the publication of Markowitz's (1952) seminal paper on portfolio diversification, there have been numerous subsequent studies on portfolio selection and performance, the overwhelming majority of which have focused exclusively upon the first two moments of return distributions: the mean and variance.

The concept of downside risk was first systematically analysed by Markowitz (1959) where he recognises that analyses based on variance assume that investors are equally anxious to eliminate both extremes of the return distribution. Markowitz (1959) suggested however that this does not accurately reflect investor preferences for minimising possible losses and that, therefore, analyses based on the semi-variance, which assumes that investors' primary decision criterion is on reducing losses below-target mean returns, could

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¹ See Jonion (2001) for an overview of Value-at-Risk concepts and applications.

provide a more accurate model of investor decision making. By concentrating on minimising portfolio losses below some target mean returns, this type of analysis produces portfolio allocations that minimise the probability of below-target means returns.²

According to Nawrocki (1999), Markowitz (1959) provides two suggestions for measuring downside risk: a semi-variance computed from the mean return or below-mean semi-variance (SV_m) and a semi-variance computed from a target return or below-target semi-variance (SV_t). The two measures compute variance using the returns below the mean return (SV_m) or below a target return (SV_t). Since only a subset of the return distribution is used, Markowitz called them partial or semi-variances and their computation is as follows:

$$SV_m = \frac{1}{k} \sum_{i=1}^k [\text{Max}(0, (E - R_T))]^2 \quad \text{below - mean semi variance} \quad (1)$$

$$SV_t = \frac{1}{k} \sum_{i=1}^k [\text{Max}(0, (t - R_T))]^2 \quad \text{below - target semi variance} \quad (2)$$

where R_T is the asset return during time period T , k is the number of observations, t is the target rate of return and E is the expected mean return of the asset being considered. *Max* indicates that the formula will square the greater of the two values, 0, or $(t - R_T)$.

Nawrocki (1999) and Harlow (1991) discuss the development and research of both below-target and below-mean semi-variances and emphasize that one of the most enduring and related ideas involves focusing on the tail of the relevant distribution of returns, i.e., the returns below some specific threshold level or target rate. Risk measures of this type are referred to as “lower partial moments” (LPM) because only the left-hand tail (i.e., probability of under-achieving a threshold return) of the return distribution is used in calculating risk. LPM may sometimes reveal the extent³ of skewness, but it cannot be identified as the “third moment” (skewness) since skewness⁴ assumes variance as the primary risk measure while LPM assumes variation of below-target return as the risk measure.

2.2. Lower partial moment and the relation to Value-at-risk

Nawrocki (1999) observes that the research and subsequent development of downside risk measures and LPM only really progressed following the publication of the Bawa (1975) and Fishburn

² However, due to the complexity and the costs involved in the computation of semi-variance analyses, especially so when such analysis can only be undertaken iteratively, Markowitz (1959) chose not to pursue this line of inquiry. He rejected the semi-variance as the preferred risk measure and concentrated instead on his now famous mean-variance approach to portfolio theory. Even so, Markowitz (1959, p. 194) commented that the superiority of variance with respect to computational and other costs, convenience and familiarity does not, and may not in the future, preclude the use of semi-variance.

³ Skewness measures the concentration of return distributions around the mean values. LPM, however, measures the deviations of return below a certain target rate, which may not necessarily be the mean value. If the target rate is the mean value, then the idea of LPM will be similar to that of positive skewness. In this case, however, computationally both LPM and skewness are entirely different arising from their assumptions about their underlying risk measures.

⁴ To illustrate their differences, consider a portfolio selection problem with skewness that adopts the Polynomial Goal programming (PGP) method for optimisation, see Lai (1991), Chunnachinda, Dandapani, Hamid, and Prakash (1997) and Prakash, Chang, and Pactwa (2003) for more details. In constructing the optimisation, the standard statistical moment of distributions, where investors exhibit a preference for higher values of odd moments (mean return, skewness) and a dislike for higher values of the even moments (variance, kurtosis) (see Scott and Horvath 1980), are incorporated. Here, multiple objectives related to the three moments are defined, i.e., to maximize expected rate of return, minimize variance and maximize skewness and solved by PGF. Unlike the LPM method, the optimisation algorithm of PGP solved the portfolio selection problem (with skewness) assuming variance as a risk measure. In this case, skewness, together with the other two moments, is used to reflect the attitude towards both the upper and the lower parts of the distribution. In the case of LPM, the optimisation algorithm solved the portfolio selection problem by the minimisation of the variation below the assets' return target level, which is the definition of risk measure.

(1977) studies which described the LPM as below-target risk in terms of risk tolerance. Given an investor risk tolerance value n , the general measure, the lower partial moment, was defined as follows.

$$LPM(n, t) = \frac{1}{k} \sum_{i=1}^k [\text{Max}(0, (t - R_T))]^n \quad (3)$$

where k is the number of observations, t is the target return,⁵ R_T is the return for the asset during time period T and n is the degree of the lower partial moment. It is the “ n ” value that differentiates the LPM from the Semi-variance models (in Eqs. (1) and (2)), which only restricts n to 2. The value of n is viewed as the “weights” that are placed on the tolerance for the below-target variation. The higher the “ n ” values, the more the investor is risk averse with respect to below-target variation.

Eq. (3) implies that investors are not likely to be risk averse throughout the entire return distribution and show only risk-averse behaviour based on the target return, since the target return should differentiate and determine the preferred gain and the corresponding risk tolerance of the investors (see, Fishburn, 1977 for additional details). If the target return is the mean value, as in Eq. (1), then the utility measure inherent in the mean-LPM analysis ($n > 1$) exhibits asymmetric pattern, i.e. risk averse on downside risk and risk neutral on upside returns, implying a skewness preference of the investors, and that the higher the degree n , the greater will be the skewness preference.

Bawa (1975) defines LPM as a general family of below-target risk measures, one of which is the below-target mean semi-variance, that was discussed in Markowitz (1959) and described by Eq. (1). Fishburn (1977) regards this as simply a special case and argues that the flexible n -degree LPM allows different values of “ n ” to be approximated, which implies a variety of attitudes towards the risks of falling below a certain target level of returns. According to Fishburn (1977), $n < 1$ is where investors seek additional risk to a portfolio; where $n > 1$ investors are risk averse to below-target returns. Fishburn (1977) and Nawrocki (1992) argue that the LPM algorithm is general enough for it to be tailored to the utility function of individual investors. Conceptually at least, an n -degree LPM algorithm such as Eq. (3) should provide scope for Stochastic Dominance analysis given that the Second degree stochastic dominance (SSD) also includes all LPM utility functions where $n > 1$. Besides, there are also no restrictive assumptions about the probability distribution of security rates of return⁶ underlying the n -degrees LPM model.

Guthoff, Pfungsten, and Wolf (1997) explain how Value-at-risk (VaR) can be transformed into the LPM at $n = 0$.⁷ Comparing the various risk measures, Kaplanski and Kroll (2001) note that VaR can be differentiated from the Fishburn n -degree risk measures. However, like the other below-target-returns risk measures, the VaR measure accounts for risk as being below a fixed reference point. VaR, in this case, is different from Fishburn's n -degree measurement of risk because the latter weighs all the results below a fixed reference point t . However, VaR measures risk or the maximum potential loss assuming this loss has a confidence interval of $1 - P$ (where P is defined as one of the lower quantiles of the distribution of returns that is only exceeded by a certain percentage such as 1%, 5%, or 10%). Hence, VaR considers risk as one potential loss with a cumulative probability of occurrence of $1 - P$, while ignoring both larger and smaller potential losses, involving a target rate.

⁵ The target value is normally assumed to be “zero”. Depending on how target rate is to be defined, alternatively, risk free rate or mean value can also be used as target return.

⁶ This means, despite the distributional characteristics or the probability distribution of the security returns, they are transformed to capture the upside and downside returns by the LPM optimisation algorithm in equation (3).

⁷ Appendix 1 further illustrates this point.

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