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Absolute return portfolios

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ABSTRACT

In this paper we consider the problem of selecting an absolute return portfolio. This is a portfolio of assets that is designed to deliver a good return irrespective of how the underlying market (typically as represented by a market index) performs. We present a three-stage mixed-integer zero-one program for the problem that explicitly considers transaction costs associated with trading. The first two stages relate to a regression of portfolio return against time, whilst the third stage relates to minimising transaction cost.

We extend our approach to the problem of designing portfolios with differing characteristics. In particular we present models for enhanced indexation (relative return) portfolios and for portfolios that are a mix of absolute and relative return. Computational results are given for portfolios derived from universes defined by S&P international equity indices.

1. Introduction

Absolute return portfolios (henceforth ARPs) are financial portfolios that aim to produce a good return regardless of how the underlying market performs. This (clearly) is a relatively easy task when the market is performing well, a much less easy task when the market is performing poorly. Essentially investors are interested in ARPs either because

- they believe that the market will perform poorly, and so wish to focus on portfolios that will not perform as poorly or
- they are unsure of how the market will perform and wish to hold an ARP as insurance against market deterioration.

ARPs are a relatively popular strategy amongst managers of some hedge funds, which, as their name suggests, often seek to hedge some of the risks inherent in their investments using a variety of methods. Their objective is to achieve absolute returns by balancing investment opportunities and risk of financial loss. Al-Sharkas [1], Connor and Lasarte [14], Jawadi and Khanniche [24] and Till and Eagleeye [39], discuss the various strategies that hedge funds can adopt.

ARPs are sometimes called market neutral portfolios as they are designed to have a low correlation with overall market return. Whilst, due to this strategy, ARPs may be able to achieve positive returns in falling markets, on the other hand they may not perform as well as market indices or other types of investments in rising markets. However, the fear of significant financial events (we have seen the 2008 subprime financial crisis; in the near future will we see a Eurozone default?) makes ARPs popular amongst investors, who see them as a reasonable strategy to adopt given market uncertainty and volatility.

In this paper, we present a three-stage mixed-integer zero-one program for the problem of designing an ARP. Our formulation includes transaction costs associated with trading, a constraint limiting the number of assets that can be held and a limit on the total transaction cost that can be incurred. The first two stages relate to a regression of portfolio return against time, whilst the third stage relates to minimising transaction cost. *One feature of note in our ARP approach is that we do not specify the return that the ARP should achieve; rather that emerges as a result of an optimisation.*

The original contribution of our model/formulation relates not to the constraints adopted (which are in fact standard and have been seen before in the literature, e.g. in Canakgoz and Beasley [10]). Rather the original contribution of our model relates to a clear definition of an ARP via the three-stage objective function.

Because our approach is flexible we are able to extend it to the problem of designing portfolios with differing characteristics. In particular we present models for enhanced indexation (relative return) portfolios and for portfolios that are a mix of absolute and relative return.

In general terms this paper addresses a financial problem via mathematical modelling and optimisation. This is a common

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theme in the literature, e.g. see [4,6,21,25,28,30–32,38,41] for recent work as to this.

This paper is organised as follows. In Section 2 we present an overview of what has been presented previously in the literature in terms of ARPs. In Section 3 we present our regression based three-stage mixed-integer zero-one program used to decide an ARP. In Section 4 we go on to show how this formulation can be extended to design portfolios with differing characteristics. In Section 5 we present computational results for portfolios derived from universes defined by S&P international equity indices. In Section 6 we present our conclusions.

2. Literature review

The reader should be aware that the term 'absolute return portfolio' is not clearly defined, as noted previously for example by Waring and Siegel [40]. Differing authors interpret the phrase 'absolute return' differently, as will be seen in our discussion of the literature below.

One strand relevant to ARPs that can be found in the literature relates to guaranteed return funds. They fall within the ARP category as they aim to achieve a minimum absolute return. Work that deals with guaranteed return funds is often based on stochastic programming or some other form of future scenario prediction. The minimum return will hence be guaranteed provided the future is one of the predicted scenarios.

Dert and Oldenkamp [18] proposed a stochastic programming model for a single-period guaranteed return portfolio that may include European put and call options. In this work a casino effect is shown to exist when one chooses portfolios to maximise expected return subject to achieving a minimum level of return under all circumstances (scenarios). The casino effect arises where there are high probabilities of obtaining low returns and low probabilities of receiving high returns. Since investors may dislike casino solutions the authors enhance their model by adding chance constraints which require that the probabilities of achieving returns less than pre-specified levels should be small. Numeric testing is based on options from the Standard & Poor's 500 index for 1997 with an investment horizon of 23 days.

Berkelaar et al. [8] proposed an interior point approach based on primal–dual decomposition for a two-stage stochastic linear program. Amongst other advantages, the method proposed does not need a feasible starting solution and its computation time seems to grow linearly with the number of scenarios. Their work is more focussed on the presentation of the method itself, but as an illustration their method is applied to a portfolio optimisation problem where an investor can invest in a money market account, a stock index and options on the index. A minimum return has to be guaranteed over a set of future scenarios. In their problem the portfolio (once constructed) can be rebalanced once (on a set date) before the end of the time horizon. Numeric testing is based on high liquidity options for the Standard & Poor's 500 index for 1999. The number of scenarios considered is 50 for the rebalancing date and 100 for the time horizon. No computation time for this portfolio optimisation problem is given. However there is a computational time comparison for some other test problems where their algorithm shows a much better performance than its deterministic equivalent. See Berkelaar et al. [9] for an extension of this work to multistage stochastic convex programs.

Another work that relies on stochastic programming to guarantee a minimum return is that presented by Dempster et al. [17]. They proposed a stochastic formulation to a complex multivariable problem where, after an initial investment in a closed end guarantee fund, the objective is to hedge the risks involved in order to avoid having to buy costly insurance to guarantee the minimum return. This problem requires long-term forecasting in multiple time periods for many investment classes. The authors proposed a dynamic stochastic programming model to solve the problem. Stock prices are modelled using both standard geometric Brownian motion and geometric Brownian motion with Poisson jumps. Backtesting is presented for a 5-year period, from January 1999 to December 2003. The model is compared to the Euro Stoxx 50 index. Given a minimum barrier which the portfolio must exceed over time, the model behaves quite well, the only period where it drops below the barrier is on the 11th of September 2001. The number of scenarios considered is either 7776 or 8192, depending on the tree structure used for different horizon backtests, but no computation times are given. See also Dempster et al. [16].

Herzog et al. [22] applied sequential stochastic programming, maximising multi-period return, albeit where this return is reduced by a penalty function relating to any shortfall below guaranteed return. They presented a case study relating to a Swiss fund with quarterly data over the period 1988–2005 with up to 5000 scenarios.

Barro and Canestrelli [5] used a scenario tree in a multiperiod stochastic programming framework. Their objective tries to balance portfolio deviations from a risky benchmark with portfolio deviations from the minimum guarantee. They presented a formulation of the problem, but no numeric results were given.

There are also papers presented in the literature that (unlike those discussed above) do not use stochastic programming.

Nishiyama [33] considered an absolute return strategy derived from multi-manager investment, a fund of funds approach, in Japan. They focused on the correlation matrix and its decomposition. Simulated results over the period 1995–2000, so including the 1998 Russian crisis and the failure of Long-Term Capital Management, were presented.

Korn [26] proposed a different approach for portfolio selection with a positive lower bound on the final wealth. The solution given consists of transforming the original problem into a portfolio problem without a positive lower bound and a modified utility function. Stock prices are modelled using generalised geometric Brownian motion. Apart from a few examples demonstrating the relationship between stock investment and the growth or decay of total wealth no computational results are given for real world data.

Amenc et al. [2] proposed an approach based on a dynamic core-satellite portfolio. Their approach, drawing on Amenc et al. [3], incorporated a maximum drawdown limit to reflect investor aversion to decreases in the portfolio value. They gave an example where the satellite is an exchange-traded fund relating to the Euro Stoxx 50. They compared their core-satellite approach with an active manager simulation.

Lejeune [27] considered an absolute return strategy derived from a long-only fund of funds approach which was formulated as a mixed-integer nonlinear programming problem. They constrained portfolio variance to be below a given limit and included a probabilistic value at risk constraint for which a deterministic approximation is given by a second-order cone constraint. Computational results were presented for 12 problem instances.

Zymler et al. [42] proposed an approach based on combining robust optimisation with options, an approach they call insured robust portfolio optimisation. Robust optimisation (e.g. see [7]) gives a guarantee provided data variation lies within a specified uncertainty set. They add to this guarantee (since data may vary outside of the uncertainty set) by allowing options to be used. These essentially provide a barrier (insurance) such that the portfolio value cannot drop below a given level. The model they develop is a convex second-order cone program. Numeric results were given based on simulated data as well as historical data.

The papers considered above deal with different models, designed for different purposes, and it is difficult to compare