Emperor's portfolio construction methodology is explained in the following academic paper by members of the Emperor Investments team.

A blended portfolio construction technique using fundamentals and the Markowitz mean-variance methodology

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Abstract:

When constructing a portfolio of stocks, do you turn a blind eye to the firms' future outlook based on careful consideration of companies' fundamentals, or do you ignore the stocks' correlation structures which ensures best diversification? The fundamental indexing (FI) and Markowitz mean-variance optimization (MVO) approaches are complementary but, until now, have been considered separately in the portfolio choice literature. Using data on S&P 500 constituents we evaluate a novel portfolio selection technique that utilizes the benefits of both approaches. Relying on the idea of forecast averaging, we propose to blend portfolios that provide investors with a clear binocular vision. The out-of-sample results of the blended portfolios attest to their superior performance when compared to portfolios constructed solely based on the FI or MVO methods as well as common market benchmarks. In pursuit of the optimal blend between the two distinct portfolio construction techniques, MVO and FI, we find that the ratio of market capitalization to GDP, being a leading indicator for an overpriced market, demonstrates remarkably favourable properties.

1. Introduction

The following analogy will help motivate our argument. Metallurgy teaches us that blending different metals produces alloys with better properties than their pure constituents. Even if new additions represent a very small percentage of the new alloy, its properties can change dramatically. For instance, duralumin, contains less than 6% of additives to 94% aluminium, but these additives dramatically change the properties of otherwise soft aluminium to an aircraft-grade strong alloy. We show that in composing stock portfolios the same phenomenon exists: blending portfolio construction methods results in "blended" portfolios that outperform the benchmarks that single method portfolios do not beat. In this paper, we propose an innovative portfolio blending technique, combining the efficient portfolio selection method of Markowitz

[1952] that takes into account the covariance structure of portfolio holdings and the fundamental indexing (FI) approach that favours investments with sound economic, financial, and managerial features. Markowitz [1952] identifies two stages in the portfolio selection process. The first stage is about forming beliefs about future performance. In practice, this often translates into reliance on historical data in estimating future rates of returns and their correlations. The second stage relies on the beliefs formed in the first stage and involves selecting a portfolio. Focusing only on the second stage, Markowitz [1952] introduces the mean-variance optimization (MVO) method for portfolio selection recommending that the choice of appropriate expected return and variance-covariance matrix "...should combine statistical techniques and the judgment of practical men..." [Markowitz, 1952, p.91]. The conventional approach often ignores the need to develop appropriate beliefs. As Markowitz emphasizes, it is our responsibility to use "observation and experience" to develop "beliefs about the future performances" [Markowitz, 1952, p.77]. While predicting future performance of stocks may be a daunting task, there is strong evidence that fundamental analysis may have some merit (Arnott et al. [2005], Walkshäusl and Lobe [2010], Basu and Forbes [2014]). Combined with evidence from the forecast combination literature [Eklund and Karlsson, 2007, Smith and Wallis, 2009, etc.], we believe that fundamental security analysis may improve the out-of-sample performance of MVO portfolios.

In practice, the MVO method relies on past returns to predict expected returns and estimate correlations. Past correlations predict future correlations much better that past returns predict future returns [Cuthbertson and Nitzsche, 2005, p.158]. Moreover, past returns fail to predict future returns in the long-run [Jorion, 1986, Poterba and Summers, 1988]. Given the volatile nature of these underlying processes, the MVO method likely produces superior out-of-sample results only for short-term investments. To mitigate this, frequent portfolio rebalancing based on the latest historical data is recommended for consistent superior results, but leads to high portfolio turnover and increased transaction costs. Transaction costs are of particular concern for funds with long-term performance objectives. Thus, in the industry, long-term investments are often based on "the judgment of practical men", rooted in fundamental security analysis. In turn, fundamental analysis focuses on financial statements and the well-being of a company in an attempt to evaluate its long-term economic prospects, assessing its future growth, and investment potential. Taken separately, both the classical MVO and the FI methods have their own limitations: the FI approach ignores the correlation structure of stocks' returns, while the classic MVO method is silent about the firms' fundamentals, which may well be the driving factors of the stocks' future performance.

Our blending technique combines the classical method and the FI approach, by bridging the two stages of portfolio construction mentioned in Markowitz [1952]. Relying on 29 years of historical data we backtest and analyze the out-of-sample performance of our proposed method and show that our blended portfolios are superior to conventional benchmarks as well as portfolios based on each method alone. Heteroskedasticity and autocorrelation (HAC) robust inference tests developed by Ledoit and Wolf [2008] show that our technique delivers statistically significantly higher Sharpe ratios than the value weighted S&P 500 and the equally-weighted S&P 500. Currently the MVO and the FI literatures are isolated from each other.1 Each of these literature streams considers stocks through a specific "oculus" described in the next two paragraphs. Up until now stocks have been considered separately through either one of these oculi.

In the first "oculus" considered, the MVO method, the expected returns and the variance matrix are calculated based on in-sample information. Securities are picked according to the MVO procedure, by maximizing the expected portfolio return while attaining the specified level of standard deviation. Since the introduction of the MVO by Markowitz [1952], a myriad of methods have been proposed in an attempt to refine this approach and offer superior out-of-sample performance. Among the most noticeable and practical extensions of the MVO method are those that control for outliers. Outliers often result in biased estimates of sample statistics translating in disproportionate portfolio holding weights. Several prominent robust techniques have been proposed to take this into account. For example, Ledoit and Wolf [2004] introduce a method that shrinks the sample covariance matrix to a well-conditioned parsimonious structure to reduce estimation errors that were shown to bias the classic MVO method. As an alternative to shrinkage methods, limiting portfolio holdings to long positions only can produce similar results [Jagannathan and Ma, 2003]. However, Jagannathan and Ma [2003] note that such methods might lead to poor diversification, with only 20-25 stocks in the portfolio; thus, to increase diversification and reduce the effect of measurement errors, it is possible to set up an upper bound on weights (e.g., 5-10%). Since the MVO method suffers from the negative effects caused by measurement errors, outliers and blindness to firms' fundamentals (which is our second "oculus"), the performance of the classic MVO method, even with adjustments for outlier effects, often does not exceed market benchmarks such as equally- or capitalization-weighted portfolios in out-of-sample tests. Therefore, if the blended approach shows statistically significant results, they cannot be attributed to the MVO part of the technique alone.

We now shift our focus to the other "oculus", the FI approach, pioneered by Arnott et al. [2005]. In this approach, firms are ranked based on their fundamentals and securities are allocated proportionally to their overall fundamental scores. The fundamentals might include book value, free cash flow, revenue, sales, dividends, total employment, etc. In a recent paper, Asness et al. [2015] argue that FI indexing is, basically, systematic value investing. The FI approach significantly outperforms major benchmarks based on US market data [Arnott et al., 2005]. Walkshäusl and Lobe [2010] apply the FI approach to stocks from 50 countries and find that the FI approach outperforms capitalization-weighted portfolios in most countries. However, after applying the robust-to-fat-tails performance test proposed by Ledoit and Wolf [2008], the FI portfolios in only 6 countries and the global FI portfolio have statistically significant positive differences in Sharpe ratios. Our empirical results confirm that in the US, the FI portfolio outperforms the cap-weighted portfolio, but the result is not statistically significant. Hence, if the blended approach shows statistically significant results in our US-based study, they cannot be attributed to the FI part of the technique alone.

Before we discuss the "how" in our next section, one question remains: In what proportion do we combine MVO and FI portfolios? Given that the FI approach is relatively new, and is profoundly different from the MVO method, these two approaches have not yet been combined, even though each method offers distinctive benefits for portfolio choice problems. In fact, Hong and Wu [2016] show empirically that information on past returns and on the firms' fundamentals are complementary. They also show that in "good times", when volatility is low, past returns provide better information about future returns. However, fundamentals perform better in "bad times", when volatility in the market is high. In such periods, past returns are not that informative and investors are forced to rely on firms' fundamentals. Thus, a portfolio allocation strategy should rely more on past returns in times of low volatility and rely more on the firms' fundamentals in times of high volatility. It is a daunting task to predict "good" and "bad" times. We, however, use a metric often mentioned by Warren Buffett as a lead indicator of a stock market "bubble" - market capitalization to the nominal GDP ratio. This approach is in the same spirit as Shiller's cyclically adjusted price-to-earnings (CAPE) ratio [Campbell and Shiller, 1988], where earnings per share

are averaged over a long period. Likewise, we average nominal GDP over five years. When this ratio indicates overpricing, and the likelihood of "bad times" is higher, we tilt the blend of our portfolio closer to the FI and away from the Global Minimum Variance (GMV) portfolio. We discuss this in more detail in the methodology section. Out of all portfolios constructed with the MVO method, the richest information about the correlation structure is contained in the GMV portfolio, which is based solely on the variance-covariance matrix and achieves the highest level of diversification. More importantly, construction of the GMV portfolio does not rely on often noisy estimates of individual expected returns, which makes it the portfolio of choice in blending with the FI portfolio. Firms' fundamentals help us detect and concentrate on "healthy" stocks that are likely to grow in the long-run, while the assessment of the correlation structure allows us to construct well-diversified portfolios.

The rest of the paper is organized as follows. We introduce the methodology in Section 2. We summarize the data and discuss the data preparation procedures in Section 3. We discuss our empirical findings in Section 4. Finally, Section 5 concludes.

2. Methodology

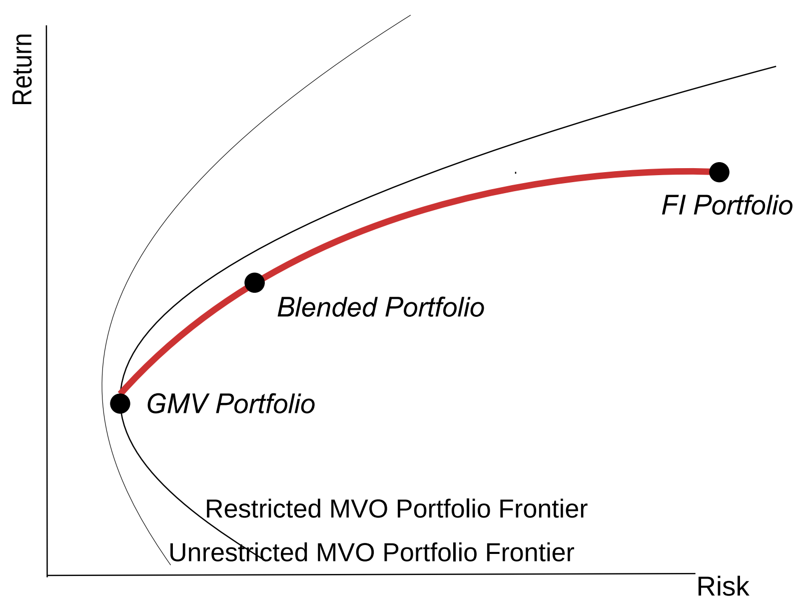

Figure 1. Blended Portfolio Construction

The FI and the GMV portfolios are depicted in Figure 1. The technique that we propose blends these two portfolios into one. First, the FI portfolio is constructed based on firms' fundamentals using the FI approach. Second, the Global Mean Variance (GMV) portfolio is identified on the mean-variance portfolio frontier. We construct 101 blended combinations (in one percent increments) of these two portfolios, which generate the new, blended GMV/FI mean-variance frontier (in red). On the blended GMV/FI portfolio frontier, we select a portfolio depending on the prediction of a stock market correction (captured by the Buffett Indicator Index, which is discussed in more detail in subsection 2.3). This Predictive Blended Portfolio (PBP) is the final outcome of our blended GMV/FI technique. In what follows we describe several desirable features of our proposed technique.

First, the two initial portfolios are formed using profoundly different methods that should result in better performance of the combined model. Since we are concerned with out-of sample performance of our portfolios in mean-variance space, our proposed blended approach is inspired by methods proposed in the forecast combination literature. Models with combined forecasts have been shown to outperform individual forecasts [Bates and Granger, 1969, Ericsson, 2017].

Second, since portfolios constructed based on the classic MVO (e.g. GMV) and FI approaches (e.g., Arnott FI), are most likely not perfectly correlated, the mean-variance optimal frontier (red curve in Figure 1) will not result in a straight line. This "second-stage" (blended GMV/FI) mean-variance frontier offers further refinement combining the weights of the GMV and the FI portfolios proportionally (see Figure 1). Since the FI portfolio brings additional relevant information which was not included in the estimated mean-variance frontier, the new blended portfolio may generate a frontier that outperforms the MVO efficient frontier in out-of-sample tests.

Third, construction of the GMV and FI portfolios does not depend on individual stocks' expected returns, which, as we mentioned earlier, is a major source of error. We, however, estimate the expected return of the GMV and FI portfolios. In this case, the individual errors are pooled, which, as we show in our empirical section, results in much lower estimation errors of the portfolio's expected returns.

3 Data Description and Preparation

3.1 Data Description

Our investable universe consists of S&P 500 constituent stocks listed on the NYSE, NASDAQ and AMEX from January 1990 to January 2018. To avoid survivorship bias we include delisted stocks in our analysis (see Brown et al., 1992). We obtain daily market values (MV) and return indices (RI), which are price index plus dividend disbursements. We collect annual data on book values (BV), dividends (Div), free cash flows (FCF) and revenues (Rev). We also consider the Wilshire 5000 (daily) and nominal GDP (annual) data from 1971 to 2018 to construct the Buffett Indicator. These data are sourced from Thomson Reuters Datastream. To test our approach we construct 22 trailing sub-samples of six years each: five years are used for estimation (July 1, 1990 - July 1, 1995; July 1, 1991 - July 1, 1996 etc.) with the remaining one year for out-of-sample performance (July 1, 1995 - July 1, 1996; July 1, 1996 - July 1, 1997, etc.). Portfolios are rebalanced on July 1 (or the next available trading day) of every year to ensure availability of fundamental data from previous calendar years. In each in-sample sub-period we select 500 stocks with the highest MV on the date of portfolio construction, which is closely related to our main benchmark, S&P 500 [see Table 1 for descriptive statistics of the data for stocks that are included at least once in our sample of 1095 stocks for the period of 27 years].

3.2 Data Preparation

Since the total return index (RI) reflects both the price of an asset and any dividend disbursements, we obtain daily stock returns as follows: $r_{i,t} = RI_{i,t} - RI_{i,t-1} / RI_{i,t-1}$

Note, that using the simple return formula is essential for accurate aggregation of assets in portfolios, whereas log returns are convenient for time aggregation but result in inaccurate estimates when aggregated across several securities. Our next section discusses the results of out-of-sample tests on the proposed blended portfolios contrasting their performance to common market benchmarks, namely S&P 500 Index, Equally-Weighted portfolio comprised of S&P 500 constituents, GMV and Arnott's FI portfolios.

5 Conclusion

In this paper, we propose a technique of portfolio construction that combines the benefits of Mean-Variance Optimization (MVO) and Fundamental Indexing (FI). Given that the FI approach is relatively new, and is profoundly different from the MVO, these two approaches have not yet been combined, even though each method offers distinctive benefits for portfolio choice problems. Our paper fills this gap in the literature, while our results attest to the superior performance of the proposed Predictive Blended Portfolio (PBP) compared to two hard-to-beat benchmarks - the Equally-Weighted portfolio of S&P 500 constituents and the S&P 500. Applying the MVO method proposed by Markowitz (1952), we find the portfolio that contains the most information about the variance-covariance structure of stock returns - the Global Minimum Variance portfolio (GMV). Applying the FI method proposed by Arnott et al. [2005], we construct a portfolio of stocks that are in sound financial condition. Blending these two portfolios generates a portfolio that has better diversification than the FI portfolio and better risk-adjusted return characteristics than the GMV portfolio. Although, ad-hock fixed-proportion blends provide promising results compared to benchmarks, we find that the dynamic Predictive Blended Portfolio is remarkably superior. We test the out-of-sample performance of the PBP and the fixed blends (for example 25% FI and 75% GMV) using 29 years-worth of data from the S&P 500 companies. The suggested PBP approach is the only portfolio that provides statistically significant superior (over the S&P 500 and the Equally-Weighted benchmarks) Sharpe ratios in out-of-sample tests. The FI, GMV or classic Markowitz Tangency portfolios do not have statistically significant Sharpe ratio (over the Equally-Weighted benchmark). The secondary result of our paper is that almost any fixed blend between the GMV and FI portfolios has a superior performance over the S&P 500 (but not necessarily over the Equally-Weighed benchmark). To keep the focus of the paper on the blending technique, we employ the classic FI introduced by Arnott et al. [2005]. Our future research will concentrate on finding the FI portfolio technique that could improve the PBP performance even further.