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Hedge fund allocation: Evaluating parametric and nonparametric forecasts using alternative portfolio construction techniques

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ABSTRACT

We propose a model for constructing Asian funds of hedge funds. We compare the accuracy of forecasts of hedge fund returns using an ordinary least squares (OLS) regression model, a nonparametric regression model, and a nonlinear nonparametric model. We backtest to assess these forecasts using three different portfolio construction processes: an "optimized" portfolio, an equally-weighted portfolio, and the Kelly criterion-based portfolio. We find that the Kelly criterion is a reasonable method for constructing a fund of hedge funds, producing better results than a basic optimization or an equally-weighted portfolio construction method. Our backtests also indicate that the nonparametric forecasts and the OLS forecasts produce similar performance at the hedge fund index level. At the individual fund level, our analysis indicates that the OLS forecasts produce higher directional accuracy than the nonparametric methods but the nonparametric methods produce more accurate forecasts than OLS. In backtests, the highest information ratio to predict hedge fund returns is obtained from a combination of the OLS regression with the Fung–Hsieh eight-factor variables as predictors using the Kelly criterion portfolio construction method. Similarly, the highest information ratio using forecasts generated from a combination of the nonparametric regression using the Fung–Hsieh eight-factor model variables is achieved using the Kelly criterion portfolio construction method. Simulations using risk-adjusted total returns indicate that the nonparametric regression model generates superior information ratios than the analogous backtest results using the OLS. However, the benefits of diversification plateau with portfolios of more than 20 hedge funds. These results generally hold with portfolio implementation lags up to 12 months.

1. Introduction

As of September 1, 2014, the hedge fund industry had roughly $2.6 trillion asset under management managed by 11,000 funds by more than 4500 separate companies (Delevingne, 2014). The fund of hedge funds industry includes more than 2000 fund of hedge funds seeking to invest client capital in underlying hedge funds. Their objective is to construct a diverse portfolio of individual hedge funds to provide broad exposure to the hedge fund industry while diversifying the risks associated with individual hedge funds.

Lack (2012) suggests hedge fund investments have been poor, controversially quoting "Shocking but true: if all the money that's ever been invested in hedge funds had been in treasury bills, the results would have been twice as good". Lack also points out "Hedge funds could still have a place in portfolios but investors need to be thoughtful about hedge fund … allocations". In 2012, HFR quotes "Funds of hedge funds have underperformed single manager hedge funds in eight of the past ten years."[1] Despite such performance, in 2012, fund of hedge funds managed over $640 billion after experiencing a $184 billion outflow following the 2008 financial crisis.

This performance suggests that there is room for improvement in allocating assets among hedge funds. In this paper we propose a model to assist in constructing an Asian funds of hedge funds by using three statistical methodologies – the ordinary least squares (OLS) regression, a nonparametric regression, and a nonlinear nonparametric approach (the simplex projection) – to forecast hedge fund returns. After comparing the accuracy of these forecasts, we backtest to evaluate each model's relative performance using three different portfolio construction processes: an "optimized" portfolio, an equally-weighted portfolio, and a Kelly criterion-based portfolio.

The paper is organized as follows. Section 2 provides a review of hedge fund return models and how our methodology and data tie into that used in prior studies. Since there are various methods that can be used to construct a portfolio, in Section 3 we review the three portfolio

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[1] "Going, Going, Gone?" *The Economist* June 2, 2012.

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construction methods that we evaluated in this paper. Section 4 describes the data, the procedures for removing any data biases. Section 5 describes how the model's exogenous data are used as predictor variables in the analysis. Section 6 describes (1) the methodologies for return forecasts using regression methods and simplex projection, and (2) portfolio construction using three portfolio construction methods (an equally-weighted portfolio, an "optimized" portfolio, and the Kelly criterion-based portfolio). In Section 7, we report the (1) return forecast results from all three methods relative to the observed returns in individual funds and hedge fund indices, (2) results of the backtests using the three portfolio construction methods and each of the return forecasts, (3) robustness checks which include lagged implementation of the return forecasts, a range of portfolio holding settings in the portfolio construction process, and different portfolio horizons/portfolio rebalancing frequencies. Our conclusions are summarized in Section 8.

2. Hedge fund literature

Sharpe's "style regression" (see Sharpe, 1992) given by

$$R_t = \alpha + \sum_k b_k F_{kt} + u_t$$

works well in capturing the styles of open-end mutual funds, whose returns are highly correlated to those of standard asset classes. Fung and Hsieh (1997) introduce five dominant investment styles in hedge funds which when added to Sharpe's asset class factor model can provide an integrated framework for style analysis for both buy-and-hold and dynamic trading strategies. Fung, Hsieh, Naik, and Ramadorai (2008) report that a large proportion of the variation in hedge fund returns can be explained by market-related factors.[2] Fung and Hsieh (2004a) propose a seven[3] factor "APT-like" model of hedge fund returns with dynamic risk factor coefficients. They find that their model can explain up to 80% of the variation in global hedge fund returns. Fung and Hsieh (2007) extend their model, presenting an eight factor model by adding an emerging market factor. As explained in Section 5, we use these eight factors as our set of explanatory variables in our regressions.

Teo (2009) investigates the performance of Asian hedge funds using the Asiahedge and Eurekahedge databases, the same databases we use in this paper, and the Hedge Fund Research Inc. (HFR) global hedge fund database. One of the few studies that focuses on Asian-based hedge fund returns, they find that hedge funds with a physical presence in their investment region outperform other hedge funds by 3.72% per year. Consistent with Bali, Brown, and Caglayan (2012), Fung and Hsieh (2004a) investigate the extent to which market risk, residual risk, and tail risk explain the cross sectional dispersion in hedge fund returns. They find that systematic risk is a highly significant factor in explaining the dispersion of cross-sectional returns while residual risk and tail risk have little explanatory power. Sadka (2010) provides evidence of liquidity risk as a contributing factor for hedge fund returns.

After controlling for common risk factors to explain hedge fund returns, Agarwal, Bakshi, and Huij (2009) find risk premiums for volatility, skewness, and kurtosis of about 6%, 3%, and −3% per annum, respectively. Kelly and Jiang (2012) find that a conditional tail risk factor is an important determinant of hedge fund returns, even after controlling for the Fung–Hsieh factors, option-based risk measures in Agarwal et al. (2009) and a liquidity risk factor by Sadka (2010).

Anand, Kutsarov, Maier, and Storr (2011) show the importance of tactical asset allocation in fund of hedge funds allocation, and present statistics on the distribution of returns prior to, during, and after the 2008 global financial crisis. They report the presence of large right tail distributions pre- and post-crisis. Using a nonparametric regression model, Anand, Kutsarov, Maier, and Storr (2013) extend their earlier work by presenting sensitivities of hedge fund indices to a four-factor model which includes macroeconomic and behavioral factors.

3. Portfolio construction techniques

A number of methods are available for constructing a portfolio of hedge funds. In this study we consider three portfolio construction techniques: an equally-weighted portfolio, an "optimized" portfolio, and the Kelly criterion-based portfolio.

DeMiguel, Garlappi, and Uppal (2009) consider 15 asset allocation models and conclude that a simple equally-weighted ($1/N$) approach is difficult to improve upon. There are many papers on optimization techniques for portfolio construction, the most popular being the mean–variance framework formulated by Markowitz (1952) based on means, variances, and covariances of asset returns for generating efficient portfolios. We implement a mean–variance optimizer as one of our portfolio construction methods and provide further details later (see Section 6.3).

Kelly (1956) introduced the criterion for portfolio construction (now referred to as the "Kelly criterion"). Applying Kelly's criterion, we can allocate a fraction of capital, f, such that $f = p/L - q/W$, where p is the probability of "winning", q the probability of "losing" $(1 - p)$ and W is the amount "won" for each $1 bet, and conversely L the amount "lost" for each $1 bet. There is support for this approach to portfolio construction in the literature. Breiman (1961) proved "that Kelly's approach beats any other money management approach" and Ethier (2004) showed that "the Kelly criterion maximizes the median of terminal wealth". The theory has been extended to multivariate portfolios by Maslov and Zhang (1998) and Laureti, Medo, and Zhang (2010), among others.

4. The hedge fund sample

All hedge fund databases have some problems. Fung and Hsieh (2004a) and Titman and Tiu (2011) provide a detailed explanation of some of these problems as they pertain to hedge fund databases. Following Agarwal and Naik (2004) and Titman and Tiu (2011) we aggregate multiple databases to provide a more comprehensive dataset. The three databases that we consolidate are Morningstar CISDM,[4] Asiahedge, and Eurekahedge. Our access to CISDM data was restricted[5] to a fund-level dataset ending in 2009, while Asiahedge fund database and Eurekahedge fund database cover through 2012.

Fig. 1 shows the funds coverage.

We first filter the global CISDM database of hedge funds from 11,402 funds down to 250 funds, including only funds listed as either Asia/Pacific, Asia/Pacific (excluding Japan), and Australia/New Zealand. Similar filters were applied to the Eurekahedge and Asiahedge fund databases, and then overlapping funds were filtered leaving only the data source with the longest history of a fund.

[2] See, for example, Agarwal and Naik (2004) and Fung and Hsieh (1997, 2001, 2002, 2004).

[3] S&P: Standard & Poors 500 stock return; SC-LC: Wilshire 1750 Small Cap − Wilshire 750 Large Cap return; 10Y: month end-to-month end change in the Federal Reserve's ten year constant maturity yield; Cred spr: month end-to-month end change in the difference between Moody's Baa yield and the Federal Reserve's ten year constant maturity yield; Bd Opt: return of a portfolio of lookback straddles on bond futures; FX Opt: return of a portfolio of lookback straddles on currency futures; Com Opt: return of a portfolio of lookback straddles on commodity futures.

[4] The Morningstar CISDM Database (formerly the MAR Database) is the oldest hedge fund database. Information about the database is available from the Center for International Securities and Derivatives Markets (CISDM) at https://www.isenberg.umass.edu/CISDM/Hedge_FundCTA_Database/

[5] CISDM data up to 2009, was provided to EDHEC as a one offset of historic data, rather than a "current" ongoing subscription.