Investment Proposal

US Beta-Neutral Arbitrage Fund

ASSET ALLOCATION AND INVESTMENT STRATEGY
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Introduction

As an institutional investor, common goals in searching for the right strategy include achieving a high Sharpe Ratio, low risk exposure to the market, and something that's applicable across different asset classes. The strategy we'd like to introduce aims to accomplish exactly that. Let us present the US Beta-Neutral Arbitrage Fund.

Our preposition relies on the Betting Against Beta (BAB) strategy presented in the work by Andrea Frazzini and Lasse Heje Pedersen[1]. The strategy is based on a modification of the Capital Asset Pricing Model (CAPM), which assumes that all investors can lever or de-lever the market portfolio to match their risk preferences. However, many investors such as mutual funds and retail investors face leverage constraints. Because they can't borrow easily, they instead tilt their portfolios toward high-beta assets to achieve higher expected returns, even though this results in overpaying for risk.

The BAB strategy exploits this mispricing. The theory posits that high-beta assets are overpriced relative to their systematic risk, while low-beta assets are underpriced and offer better risk-adjusted returns. Hence, an unconstrained investor can go long low-beta assets using leverage and short high-beta assets. Empirically, this strategy earns a significant alpha and flattens the security market line which contradicts the standard CAPM assumptions by showing that beta does not linearly predict returns.

Portfolio Construction and Results

Our basic US Beta Neutral Arbitrage Fund strategy focuses on big cap stocks traded on the US stock exchange. In particular, we focus on the stocks in the SP500 index at each rebalancing date. We also demand the stock to be present in the index for the past 12 calendar months. This gives us, at each rebalancing date, around 450 stocks from which to choose, but the number changes each time. The Betas are calculated at each last day of trading of the month using daily returns from a 12 month rolling window at each calendar month's last trading day. The proxy for the Markets excess return we use is the "Mkt – rf" index in the Fama & French website. Our strategy consists in splitting the universe of our available stocks in half based on their beta rankings. We are going long on the top-half of stocks (the ones with lowest estimated beta) and short on the bottom half (the ones with the largest beta). If there is an odd number of stocks available at a given rebalancing date we don't invest in the median-beta stock. We tried applying other methods for selection of the stocks, instead of simply dividing our available universe in half. We tried for exemple using a wild bootstrap method on our estimated betas to have better confidence intervals, then we took out the stocks whose estimated beta had 1 inside its confidence interval and we went long/short in the rest of the stocks. Our finding has been of inferior performance and more volatility for this strategy compared to a strategy that does not exclude stocks with "uncertain" betas. Our explanation is that by including as many stocks as possible, the fund is able to better capture the hedge that is present in low beta stocks, whereas by arbitrarily picking an arbitrary lower number of low beta and high beta stocks to go long/short on, our fund would carry more idiosyncratic risk. After having separated in two our available stocks, we apply equal weights to all the stocks. We prefer this strategy, compared to the one used in the original BAB paper, for the same reason as why we prefer including as many stocks as possible in our fund. By not over weighting our long (short) positions in stocks with relatively low (high) betas we limit the impact of estimation errors

and change of betas across time that are inevitable. This is especially important for a small universe of stocks like ours compared to the bigger one used by Frazzini and Pedersen.
Then, we calculate the portfolio's beta by simply taking the average of the Betas of the two portfolios. This is possible because the beta is linear across portfolios, which means that:

$$\beta_{ptf} = w_1\beta_1 + \cdots + w_n\beta_n$$

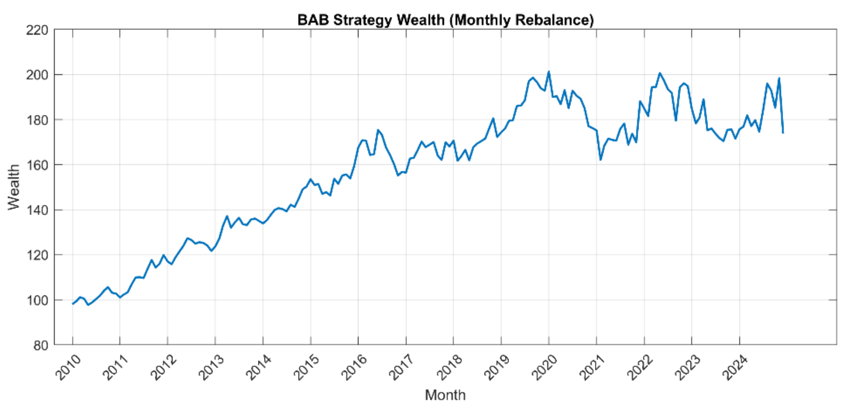
where w_i is the weight of the stock in the portfolio. By setting: $w_i = \frac{1}{\# \, of \, stocks}$ we simply get:

$$\beta_{ptf} = \frac{\sum_{i=0}^{\# \, stocks} \beta_i}{\# \, of \, stocks}$$

As final step for our strategy, we use leverage on the long leg and de-lever the short leg. This allows us to achieve (on average) Beta neutrality. To do so, we multiply all our long leg portfolio wights by $\frac{1}{\beta_{long}}$ (which will be bigger than 1 because $\beta_{long} < 1$) and the short leg portfolio weights by $\frac{1}{\beta_{short}}$ (which will be smaller than 1 because $\beta_{short} > 1$). The resulting portfolio's beta should be: $\beta_{BAB} = \beta_{long} * \frac{1}{\beta_{long}} - \beta_{short} * \frac{1}{\beta_{short}} = 1 - 1 = 0.$
We have therefore constructed a Mkt-neutral long/short equity portfolio. The portfolio is not self-financing (yet) because we buy more stocks than we sell (say for exemple $\beta_{long} = 0.5$ while $\beta_{short} = 2$, the position would use $\frac{1}{0.5} - \frac{1}{2} = 1.5$ units of leverage. We assume we can get this leverage at the risk free rate. The total return for each period of our long/short market neutral self-financing portfolio is then :

$$r_{BAB} = r_{long} * \frac{1}{\beta_{long}} - r_{short} * \frac{1}{\beta_{short}} - rf * \left(\frac{1}{\beta_{long}} - \frac{1}{\beta_{short}}\right)$$

This is our initial framework for the strategy. The graph of wealth (starting from 100 units of investment is this:



And the following main return characteristics:

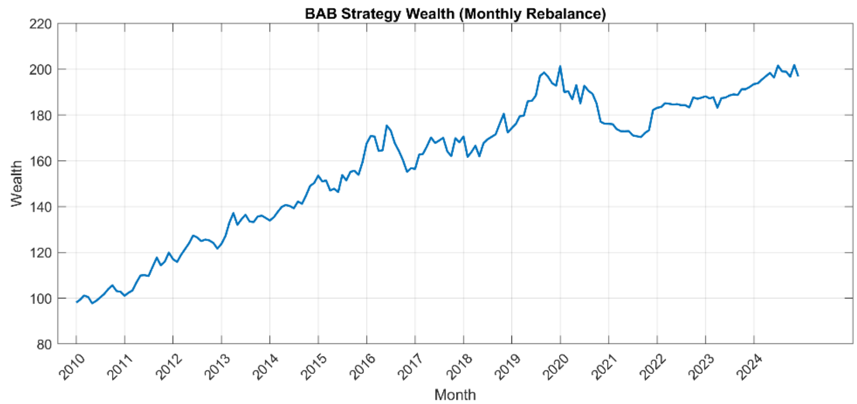
Average return (annualized)	3.7%
Standard deviation (annualized)	10.4%
Sharpe Ratio	0.35
Jensen's Alpha (annualized)	3.2%
Mkt Beta	0.09
Maximum Drawdown	-19.5%

This strategy has a positive Average Return (it's already in excess, since the strategy is self-financing and with zero initial investment (apart from the collateral we have to keep to obtain debt)) and low volatility. It's not right to compare the strategy with the market index (which has an average 11.8% excess return over the same time period) because our goal is to obtain excess returns indipendent from the market, not to beat it. When we regress our monthly returns against the 3 FF Facctors + Momentum, our alpha becomes basically negligible and the coefficients over the whole time period (2010-2024, 15 years) are the following:

Alpha (annualized)	0.36%
MKT	0.22
SMB	-0.33
HML	0.08
Momentum	0.30

All significantly different than zero apart from the HML. It's easy to see why we are short the SMB factor (we leverage up on big stocks), while the other exposures are due to market fluctuations in our positions and are unintentional.

This performance is still good on our opinion because it's a low volatility strategy that's self-financing, but we wanted to try something else to improve it. We wanted to try to "time" the BAB factor. We tried a few lagged variables which we will dive deeper in the next section, but they didn't work on our dataset (SP500 instead if all traded US stocks). So we had to get creative. And in our opinion we got creative quite well and found a way to "time the factor" without having look-ahead bias. This method has never been tried in the previous BAB literature, as far as we know.
The section regarding the theory on the construction of the trading signal has been omitted. This signal aims at "timing" the BAB strategy using a "scaled historical percentile rank" to change the weights of our positions. Basically, very simply, we took all historical observations of our signal until that time, we ranked our forecasted signal for next period in the historical observations, then we took the percentile rank, multiplied in by 2 and subtracted 1. For exemple, a forecasted signal that would rank in the 60th percentile of historical observations would multiply our weights by: 0.6 * 2 – 1 = 0.2. This way we created an estimator to "weight our weights" by how much we forecast the signal (and therefore the profitability of the strategy) will be. This estimator takes the values between -1 and 1, so our new rescaled strategy is actually different from the original BAB, as we go long the BAB only half the time (when the estimator is negative we flip the weights and actually short the low beta stocks) and use way less leverage (we would use same leverage of the base strategy only if we forecasted a signal strength in the 100^{th} percentile).
Our new results are improved by quite a bit compared to the simple BAB strategy we used in the first part. The graphic of wealth is the following (until 2021 it will be the same)



While it's graphically difficult to see, the results improve substantially, especially considering the limited timeframe we modified the strategy compared to before. The overall results are the following:

Average return (annualized)	4.5%
Standard deviation (annualized)	7.4%
Sharpe Ratio	0.62
Jensen's Alpha (annualized)	4.78%
Mkt Beta	0.0
Maximum Drawdown	-15.4%

What is surprising (but really shouldn't) is that now our alpha not only survives the 3 FF Factors + Momentum test (we omit for brevity), but it also survives the regression against the BAB factor itself. The results of the regression for only the last 4 years are the following:

Alpha (annualized)	2.6%
BAB coefficient	0.08

This is because we are de-facto not doing BAB in the last period, but we are timing it, and as we said half the time we will actually be short the BAB factor, this drives the Beta of our strategy wrt the BAB factor lower. In the last 4 years, our strategy yields a Sharpe Ratio of 0.63. Overall, we feel like our new strategy can be of extreme interest for future study and deserves a longer time period of backtest (which was not possible given the short timeframe of SP500 stocks returns in our sample).

Macroeconomic Impact and "Failed Signals"

Macroeconomic conditions significantly affect the performance of the BAB strategy. This is due to the fact that a key factor is funding liquidity. During periods of tight funding, when interest rates rise or the TED spread widens, leverage becomes more expensive or unavailable. This forces even unconstrained investors to de-leverage their positions, which negatively impacts the BAB strategy's returns. The TED spread, which measures the difference between LIBOR and Treasury yields, is used in the paper as a proxy for such funding constraints. As for the strategy, a higher TED spread contemporaneously correlates with lower BAB returns. The lagged TED spread instead negatively predicts the next period's BAB return, according to FP's paper. This result is inconsistent with the author's theory. Therefore we don't consider the TED spread as a predictor for our strategy.

Financial literature has found other variables to be impacting of the returns of the BAB strategy. The main work we looked into for this exercise is Esben Hedegaard's paper "Time-Varying Leverage Demand and Predictability of Betting-Against-Beta" [2] (2018). He sums up previous literature and tries new predicting variables for the forecast of next period's BAB return. The main finding of the paper is the predictive power of three lagged variables on the strategy return. These are the 1-month and 6-month average previous market returns and the LCT factor from Boguth, O. and M. Simutin (2018) [3]. This factor is another proxy for leverage constraints and represents the average Beta exposure of US mutual fund holdings. When mutual funds hold more market exposure than "normal times", we interpret it as the tightening of leverage constraints with fund managers that are constrained to use high-beta assets to gain exposure to the market instead of using leverage. For the exact construction of the LCT factor, we refer to their paper. While promising for our exercise, unfortunately the public data for the factor only goes back to 2014, and since our fund performance is back tested from 2010 to 2024, we don't include this factor in our model. We try instead the predictive power of the average past 1-month and 6-month market returns on our strategy. As a proxy for the market return we take Fama & French's "Rm-rf" market factor. We find no significant predictive power of these variables on our fund's returns. We conclude this derives from the different "pool" our fund draws stocks from (SP500 instead of the whole US stock universe) and we omit these variables from our alpha research.

Scalability

Some of the good things about the BAB strategy is that it has shown strong historical returns across equities, bonds, and other asset classes, but there are also some limitations in terms of scalability.

First, executing the BAB strategy at scale requires a lot of leverage on the long side, which can raise margin requirements and regulatory scrutiny. Secondly, if many large institutions attempt to implement the strategy simultaneously, returns may be arbitraged away, or the strategy could result in large moves in the markets.

Lastly, the need to short high-beta assets introduce potential constraints, especially in illiquid markets or during downturns when shorting becomes more expensive. In general, there are also some limitations in terms of transaction costs, financing costs, and risk management practices also limit how large the strategy can grow while remaining profitable.

In our model, we try to take into account these limitations in two main ways, thus making our fund results very realistic compared to the BAB portfolio. First of all, we limit our stock universe to the SP500 stocks. At every rebalancing period (final trading day of each calendar month from 2010 to 2024) we only take as tradable stocks the ones that satisfy these two conditions: stocks that are included in the index at that point in time and stocks that have been in the index for at least 12 calendar months. We think the stock's Beta exposure might change significantly from the period the stock is not included to the period the stock is in the index, and including previous observations would only distort our estimations. Limiting our fund's exposure to only these stocks makes both going long and short on these stocks very easy and a plausible hypothesis, since these are the most

liquid and easily tradable stocks in the world, with tight bid and ask spreads. Secondly, we introduce transaction costs that the original BAB paper ignores (as it's meant to be, the paper aims to construct a "risk factor" and not a trading strategy). The transaction costs are set to be 2 bp for long positions and 3 bp for short positions. These are reasonable estimates given the large liquidity of the stocks considered and the fact that we trade for them in the last minutes of the last trading day of each month, which is a period of high liquidity in the market.
The only "non-realistic" parameter in our model is the cost of funding. We set it equal to the daily risk-free rate obtained from Fama & French's website. Since the spread of spreads applied by institutions to mutual funds, hedge funds and asset managers varies significantly based on credit worthiness, collateral, etc. we set the spread to 0 for simplicity.

Reference List

1 Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics, 111*(1), 1–25.

2 Hedegaard, E. (2018). *Time-varying leverage demand and predictability of betting-against-beta*. SSRN.

3 Boguth, O., & Simutin, M. (2016). *Leverage constraints and asset prices: Insights from mutual fund risk taking* (Rotman School of Management Working Paper No. 2517704). SSRN.