UNIVERSIDADE CATÓLICA PORTUGUESA

Betting Against Beta strategies using option-implied correlations

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Resumo

A estratégia *Betting Against Beta* (*BAB*) oferece retornos ajustados ao risco muito altos, superando outras estratégias baseadas em fatores como o mercado, tamanho, valor, *momentum*, entre outros. A recente literatura (Barroso & Maio, 2018) constata que a gestão de risco da estratégia *BAB* (*Risk-managed BAB)* possibilita um ganho substancial em *Sharpe ratio*. No entanto, ao contrário da gestão de risco da estratégia *momentum*, a gestão de risco da estratégia *BAB* apresenta um elevado potencial de perda. Nesta dissertação, o objetivo é melhorar o perfil risco-retorno da estratégia BAB, reduzindo, principalmente, o seu potencial de perda. Com isto em mente, concentramo-nos na construção de uma estratégia *BAB* otimizada. Pela primeira vez na literatura de estratégias BAB, usamos informação implícita nos preços de opções sobre um índice acionista de referência (S&P500) acerca da correlação esperada dos retornos dos seus constituintes. Na linha do recente trabalho (Nogueira & Faria, 2017) acerca de estratégias *momentum*, usamos uma média móvel a 2 meses como um proxy da estrutura temporal dessas expectativas. Propomos uma nova estratégia, a estratégia *Dynamic BAB*, que tem um desempenho substancialmente melhor que a versão original. Em particular, otimiza a exposição ao potencial de ganho do *BAB*, minimizando a exposição ao potencial de perda. Além disso, para aumentar ainda mais a exposição ao potencial de ganho, combinamos a *Dynamic BAB* com a estratégia de gestão de risco de (Barroso & Maio, 2018) (*Risk-managed BAB)*. Denominamos a estratégia resultante de *Hybrid BAB.* Ao testar a sua robustez, é de notar que a *Hybrid BAB* pode ser implementada em tempo real, usando apenas informação disponível no momento do *trading*. Além disso, a estratégia mostra-se robusta a mudanças nos pesos do fator. A estratégia *Hybrid BAB* oferece retornos com o dobro do *Sharpe ratio* da estratégia *BAB* original, permitindo concluir que, à semelhança do reportado em (Nogueira & Faria, 2017) para estratégias de *momentum*, também existe informação relevante a ser explorada nos preços de opções sobre índices acionistas de referência que contribuem para o desenho e implementação de estratégias BAB.

Palavras-chave: *Betting Against Beta;* Expectativas de Correlação Ímplícita em preços de opções; Risco de perdas

Abstract

The Betting Against Beta (BAB) strategy offers very high risk-adjusted returns, outperforming other strategies based on factors as the market, size, value, momentum, and others. Recent literature of (Barroso & Maio, 2018) finds that managing the risk of the BAB strategy (Risk-managed BAB) allows a substantial gain in Sharpe ratio. However, unlike Risk-managed momentum, Risk-managed BAB has a large downside risk. In this dissertation, the objective is to improve the BAB strategy risk-return profile, particularly by reducing its downside risk. With that in mind, we focus on the construction of an optimized BAB strategy. For the first time in the BAB related strategies literature, we use implied information on the S&P500 index option-implied correlation of its constituents returns. In line with the recent work (Nogueira & Faria, 2017) about momentum strategies, we use a 2-month moving average as a proxy for the term structure of expected correlations in the S&P500 index. We propose a new strategy, Dynamic BAB strategy, that has a substantially better performance than the original version. Particularly, it optimizes the exposure to the BAB upside risk, reducing the exposure to its downside risk. Additionally, to increase even more the upside potential, we combine the Dynamic BAB strategy with the Risk-managed BAB strategy of (Barroso & Maio, 2018). We denominate the resulting strategy Hybrid BAB strategy. Testing for its robustness, the Hybrid strategy can be implemented in real-time, only using available information in the moment of the trading. Moreover, the strategy is robust to changes in the weights. The Hybrid BAB strategy provides returns with a Sharpe ratio that almost doubles one of the original BAB, allowing to conclude that, similarly with the reports in (Nogueira & Faria, 2017) for the momentum strategies, there is also relevant information to be explored in the option prices of equity indexes that contribute to build and implement BAB strategies.

Keywords: Betting Against Beta; Option-Implied Correlation; Downside Risk

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Introduction

"Buffet bets against beta as Fisher Black believed one should"

(Frazzini & Pedersen, 2014)

The capital asset pricing model (CAPM) of (Sharpe, 1964) and (Lintner, 1965) is the most used asset pricing model in finance, used to evaluate investments and measure portfolio performance (Damodaran, 2012; Fama & French, 2004). It relies on the premise that the beta of an asset can be a measure of its risk. As a result, there is a positive relationship between the beta of an asset and its expected returns. This relationship is often represented as the security market line (SML) and implies that the higher the beta of an asset, the higher its expected returns. However, empirical evidence from (Black, Jensen, & Scholes, 1972) finds that the SML is flatter than initially thought, leading the finding of the beta anomaly.

BAB is a strategy that exploits the beta anomaly (Black et al., 1972). The beta anomaly is known as one of the most puzzling anomalies in finance because it questions the risk-return parity. The strategy consists of buying low-beta stocks and shorting high-beta ones (Frazzini & Pedersen, 2014). While investing in this strategy, investors expect low-beta stocks to have positive risk-adjusted returns and high-beta stocks to have negative risk-adjusted returns, allowing them to obtain profitable payoffs. Tested in, at least, 20 countries and in diverse asset classes (Frazzini & Pedersen, 2014), the strategy generates robust positive returns in the long-run, competing and outperforming the strategies based on the market, value, size, and even momentum factors. However, there is empirical evidence in (Barroso & Maio, 2018) that non-market risk-factors explain a substantial part of the strategy mystery, almost causing the death of the anomaly. Nevertheless, (Barroso & Maio, 2018) find a "hidden puzzle" in BAB, resurrecting, in some way, the idea of the existence of an anomaly. Nevertheless, the new strategy proposed by (Barroso & Maio, 2018) has substantial downside risk.

This dissertation adds novelty to the latest BAB related literature by focusing on the construction of an optimized BAB strategy. We propose to answer the following question: Is it possible to obtain an optimized strategy that combines the strategy proposed by (Barroso & Maio, 2018) and a strategy that efficiently manages the downside risk of the BAB strategy?

Firstly, we aim to build a strategy that dynamically exposes our portfolio to the BAB factor. We want to overexpose our portfolio to the BAB factor in "good" periods, i.e. periods during which the BAB factor is delivering positive returns, and underexpose our portfolio to the BAB factor in "bad" periods, i.e. periods during which the BAB factor is delivering negative returns.

Recent work about momentum strategies using option-implied correlations (Nogueira & Faria, 2017) find that using information related to the term structure in the equity market provides useful information to adjust a portfolio exposure to the momentum factor dynamically. We extend this analysis for a hypothetical portfolio exposed to the BAB factor, assessing if and how the S&P500 index option-implied correlation information can be useful to drive its exposure to the BAB factor.

The first outcome of our analysis is a strategy we denominate by Dynamic BAB. The strategy uses the 2-month moving average of the spread between the S&P500 option-implied correlation for 365 days and the S&P500 option-implied correlation for 30 days, which we use as a proxy of the implied correlation term structure. This strategy is found to outperform the plain-vanilla BAB strategy.

Then, we combine the Dynamic BAB strategy with the Risk-managed strategy from (Barroso & Maio, 2018). We denominate this strategy as Hybrid strategy. The Hybrid strategy will increase the upside potential of the Dynamic strategy by taking leverage positions in “good” moments, while, at the same time, decreasing the downside risk, by short selling, in “bad” moments. All information used is publicly available, allowing any investor to replicate it.

In summary, the Hybrid strategy substantially outperforms the plain-vanilla BAB, with a Sharpe ratio that almost doubles the original strategy (1.04 vs. 0.55, respectively), providing lower downside risk for higher upside. Moreover, the strategy is robust in different weighting settings and real-time trading, reasons why we consider the strategy to be an effective improvement versus the original BAB.

Chapter 2

Literature Review

In their seminal empirical contribution, (Black et al., 1972) show that low-beta stocks tend to have positive risk-adjusted returns, and high-beta stocks tend to have negative risk-adjusted returns. The authors call it the beta anomaly, which resolutely defies the Capital Asset Pricing Model (CAPM). Other authors also investigate the anomaly, such as (Blume & Friend, 1973; Fama & French, 1993; Fama & MacBeth, 1973) and, more recently, (Fama & French, 2006) show that controlling by size and book-to-market, the anomaly increased. Also, (Ang, Bekaert, & Wei, 2008; Blitz & Van Vliet, 2007) show that low-volatility stocks generate higher returns than high-volatility stocks.

(Frazzini & Pedersen, 2014) propose a strategy that exploits the beta anomaly. The authors are the pioneers behind the construction and dissemination of the betting-against-beta strategy. They take advantage of the fact that low-beta stocks have higher alphas and Sharpe ratios than high-beta stocks, as documented in (Black et al., 1972). To do so, they build a strategy that buys low-beta stocks and shorts high-beta stocks. The returns provided by the strategy are robustly positive and economically and statistically significant, competing with the value, size, and momentum factors, reasons that justify its current popularity in the asset management world.

Furthermore, (Novy-Marx & Velikov, 2014) study beta and total volatility sorted portfolios, finding that returns are flat across volatility and beta quintiles, revealing almost the same findings as (Frazzini & Pedersen, 2014). (Auer & Schuhmacher, 2015; Buchner & Wagner, 2016) in similar studies obtain similar results.

(Frazzini & Pedersen, 2014) also addresses behavioral explanations of the beta anomaly and, consequently, the reason for the viability of the betting-against-beta strategy. As in (Black et al., 1972), (Frazzini & Pedersen, 2014) empirically shows that the security market line (SML) is flatter than what CAPM shows. In fact, unlike CAPM, (Frazzini & Pedersen, 2014) assumes that investors have a leverage limit. As a result, the slope of the SML, which is the difference in returns of high-beta stocks and low-beta stocks, depends on the investor's leverage constraints tightness. The tighter the leverage constraints, the tighter the SML.

Furthermore, they also show that it does not only happen for U.S. equities, but also in other international markets, in Treasury markets, in corporate bonds sorted by maturity and rating, and in future markets. They associate the sentiment of this strategy with leverage-constrained investors that bid up the price of high-beta stocks for their embedded leverage, leading to negative risk-adjusted returns. As a result, being long on low-beta assets and short on high-beta assets generates positive risk-adjusted returns. They give the example of leveraged buyout funds and Berkshire Hathaway, that consistently invest in low-beta stocks. Since Berkshire Hathaway has full access to leverage, it invests the leverage in safe stocks. As a result, they beneficiate with the BAB effect, caused by leverage constrained investors taking the opposite position. In the end, the leverage constrained investors are the ones that hold riskier assets in their portfolios.

There is very diverse literature with different approaches to the BAB strategy. We start by analyzing the literature that tries to explain the outstanding performance of the strategy economically. The leading theory for the anomaly in the literature also defended in the original paper of (Frazzini & Pedersen, 2014), is the leverage constraints theory, a borrowing restriction explanation. This theory tries to explain the betting-against-beta performance, reporting that investors with leverage constraints bid up the price of the high-beta stocks because of the embedded leverage. As a result, high-beta stocks start to generate negative risk-adjusted returns. There are empirical studies that support the leverage constraints theory by providing empirical results from factors that shape the SML. Some empirical studies are (Antoniou, Doukas, & Subrahmanyam, 2016; Black et al., 1972; Blitz et al., 2007; Boguth & Simutin, 2018; Cohen, Polk, & Vuolteenaho, 2005; Frazzini & Pedersen, 2014; Hedegaard, 2018; Hong & Sraer, 2016; Huang, Lou, & Polk, 2015; JylhÄ, 2018; Modigliani & Cohn, 1979; Savor & Wilson, 2014). There are also empirical studies that support a constrained version of CAPM, giving strength to the (Frazzini & Pedersen, 2014) model, such as (Barber, Huang, & Odean, 2016; Berk & van Binsbergen, 2015). (Chen & Lu, 2019) even refined the BAB factor by picking stocks that are more exposed to funding conditions, thus increasing the anomaly and, consequently, the strategy returns.

An essential contribution to the leverage constraints theory is from (Boguth & Simutin, 2018), that find that the exposure to leverage constraints has essential consequences for asset prices. It builds on (Brunnermeier & Pedersen, 2009) that suggests that there is a relationship between the time-varying tightness of leverage constraints and the pricing kernel. It empirically shows, using a proposed measure for the "tightness" of leverage constraints, that when mutual funds want to take more leverage, but face leverage restrictions, they invest in high-beta stocks to take advantage of its embedded leverage.

Another significant contribution to the leverage constraints theory is from (Hedegaard, 2018) that empirically confirms the possibility to predict BAB returns using past market returns. When there is an outward shift in investor's demand functions, the prices increase, and the investors are more constrained, meaning that future BAB returns are going to increase. In summary, it reports that the BAB strategy has a better performance in periods when past market returns have been high.

Regarding the conditional behavior of the beta anomaly, (Cohen et al., 2005) find that the low-beta anomaly is more present in periods of high inflation caused by the presence of money illusion in the stock market. Also, (Antoniou et al., 2016) find that beta anomaly is more present in periods of optimism. They attribute the increase in the anomaly due to amateur investors who enter the stock market in times of increased optimism. Amateur investors are usually overconfident regarding their experience and tend to cause the mispricing of beta. Other authors also study the psychological overconfidence factor as an explanation for the anomaly, namely (Baker, Bradley, & Wurgler, 2011; Kaustia & Perttula, 2012).

Additionally, (Bali, Brown, Murray, & Tang, 2018) propose that the BAB phenomenon has origin in demand for lottery-like stocks, an empirical explanation documented by (Bali, Cakici, & Whitelaw, 2011). Much like the original paper of (Frazzini & Pedersen, 2014), the explanation is that there is an intense upwards pressure in high-beta stock prices. However, in this case, the cause is lottery demand. They conclude that the abnormal returns generated by a portfolio that buys low-beta stocks and shorts high-beta ones are only caused by the demand for lottery-like stocks, explaining why so many studies fail to find a positive relationship between market beta and stock returns. They report that, if we control for lottery-demand, the BAB phenomenon disappears.

There are other alternative explanations for the betting-against-beta strategy performance, including explanations related with the non-standard choices of (Frazzini & Pedersen, 2014) in the BAB construction (e.g. (Novy-Marx & Velikov, 2019)), with CAPM not capturing risk well (e.g. (Buchner & Wagner, 2016)), with liquidity risk (Malkhozov, Mueller, & Vedolin, 2017), with benchmarking (e.g. (Baker et al., 2011)), decentralized investment approach (e.g.(Blitz & Van Vliet, 2007)), representativeness (e.g. (Kaustia, Laukkanen, & Puttonen, 2009)) and limits to arbitrage (e.g. (Kaplan, Sensoy, & StrÖmberg, 2009)).

Lastly, there is literature that reports the viability of betting-against-beta strategy in several other countries (e.g. (Agarwalla, Jacob, Varma, & Vasudevan, 2014; Frazzini & Pedersen, 2014)) and in different asset classes, for example, the bond markets (e.g. (Durham, 2016)).

There is literature that approaches BAB from a different perspective, namely volatility management. This literature investigates the time-varying volatility of BAB and analyzes the results to understand the anomaly better. This stream of literature builds on the literature that documents the time-varying risk of the stock market (Bollerslev, 1987; Schwert, 1989) and the benefits of timing its volatility (Fleming, Kirby, & Ostdiek, 2001). More recently, (Moreira & Muir, 2017) show that volatility management produces abnormal returns, explaining that it might be due to the slow response of prices to volatility.

Furthermore, (Barroso & Maio, 2018) show that BAB's returns volatility has extraordinary predictive power for strategy performance. It reports a Sharpe ratio of 1,97 after low-volatility months vs. a Sharpe ratio of 0.23 after high-volatility months. Consequently, the authors build a strategy that exploits the predictive volatility predictive power of the strategy performance by investigating the time-varying volatility of BAB. They find support for the leverage constraints theory and multidimensional explanations, reporting that the beta anomaly can be well explained in periods when the volatility is high, but it is more puzzling when volatility is low. These findings follow the leverage constraints theory and meet the findings of (Hedegaard, 2018) that embedded leverage is more valuable when the volatility is low, increasing the anomaly, thus leading to higher risk-adjusted returns for BAB. In summary, (Barroso & Maio, 2018) report that risk-management increases BAB gains and resurrects the beta anomaly. However, the tail risk of portfolios that include the Risk-managed BAB is still very high, showing that Risk-managed BAB has significant downside risk.

In this dissertation, we work on this stream of literature, making use of the Risk-managed BAB strategy of (Barroso & Maio, 2018). Our objective is to optimize the plain-vanilla BAB strategy by managing its downside risk while, at the same time, increasing its upside potential.

More concretely, the main novelty of this dissertation is the application, for the first time in the BAB-related literature, of equity option-implied information to scale the exposure of a portfolio to the plain-vanilla BAB factor. As a result, we propose a strategy that dynamically weights the exposure of a portfolio to the BAB factor regarding the information provided by the dynamics of the S&P500 index option-implied correlation term structure.

Our work relates to the literature that studies the option implied expectations of future correlations in equity markets or, more generally, the correlation risk. There exists diverse and recent literature about correlation risk. (Buraschi, Trojani, & Vedolin, 2014; Driessen, Maenhout, & Vilkov, 2009) find that report that correlation risk premium explains a big part of the variance risk premium. Additionally, some economic models explain why correlation risk should carry a risk premium, such as (Ehling & Heyerdahl-Larsen, 2017; Piatti, 2014). Empirically, some studies show that stochastic correlation can be a good predictor of market returns, studies that use options data (Buraschi et al., 2014; Buss, Schoenleber, & Vilkov, 2017; Driessen et al., 2009) and hedge fund return data (Buraschi et al., 2014). Lastly, (Faria, Kosowski, & Wang, 2018) show that it is possible to obtain a global correlation risk factor priced in international option markets. Concretely, in this dissertation, we build on the dynamics of the option-implied correlation risk and its term structure. The information contained in the term structure for different maturities reflects the market expectations of future correlations, which is very useful to build a strategy that predicts the state of the financial markets. (Nogueira & Faria, 2017) show that the S&P500 index option-implied correlation can be efficiently used to improve the risk-adjusted performance of a portfolio exposed to the momentum factor. In this dissertation, we use data provided by (Faria & Kosowski, 2014) to build a strategy that efficiently manages the downside risk of BAB, resulting in a total novelty in the BAB-related literature.

Chapter 3

Data Description and Methodology

3.1. Data Description

We use daily and monthly data from July 1967 to December 2016, for the returns of long/short equity BAB factor. The portfolios we use are an updated and extended version of the equity portfolios used in (Frazzini & Pedersen, 2014), long in low-beta stocks, and shorting high-beta stocks, for U.S. equities and 23 international equity markets. This set of data is from AQR Capital Management's data library[1]. Additionally, we use daily and monthly data from July 1967 to December 2016 for the excess return on the market (RM-RF), the Small Minus Big (SMB), the High Minus Low (HML), the Robust Minus Weak (RMW), the Conservative Minus Aggressive (CMA) and the momentum factor (MOM). This set of data is from Kenneth R. French's data library[2].

The main innovation of this dissertation is the optimization of the plain-vanilla BAB strategy by dynamically adjusting the exposure of our portfolio to the BAB factor, using S&P500 index option-implied information. Namely, we use the model-free expectations of future correlation of returns of the S&P500 implied in the S&P500 index options for different maturities (30,60,91,182 and 365 days). Therefore, we use daily and monthly time series of the S&P500 index option-implied correlations for different maturities, from January 1996 to January 2013, as in (Faria & Kosowski, 2016)[3]. This set of data is crucial to our dissertation, and it has fundamental properties. The data is publicly available because it is based on tradable options. The options are from a benchmark for global equity markets, the

[1] https://www.aqr.com/Insights/Datasets
[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research
[3] The time series of expected correlations start at January 1996 due to option data availability.

S&P500. Moreover, since it is option-implied, the computation is forward-looking, as well as model-free. Most importantly, when working with option-implied correlations and its term structure, we can obtain information related to market timing and market conditions as stated in (Buraschi et al., 2014; Driessen et al., 2009; Faria & Kosowski, 2016).

3.2. Methodology

We rebalance the BAB strategy every month, after the last trading day of each month. Since, we rebalance the strategy at the end of month t-1, the holding period of the rebalanced portfolio is the following month t.

The underlying data can differ from (Frazzini & Pedersen, 2014), since it is updated and refreshed monthly to utilize the best available data, and data sources can differ to allow for continuous updating. The data AQR Capital Management uses for portfolio construction is from the union of the CRSP tape and the Computstat/XpressFeed Global database. Domestic data include all available common stocks in the merged CRSP/XpressFeed data. International data include all available common stocks on the Computstat/XpressFeed Global database for 23 developed markets. They rank all securities in a country in ascending order based on their estimated beta and assign the ranked securities to one of the two portfolios: low-beta and high-beta. They weight securities by their ranked betas. Lower-beta securities have larger weights in the low-beta portfolio, and higher-beta securities have larger weights in the high-beta portfolio. They rebalance portfolios every month and rescale them to have a beta of one at portfolio formation, i.e. both portfolios have a beta of one. The plain-vanilla BAB is a self-financing zero-beta portfolio that is long in the low-beta portfolio and short in the high beta portfolio. In this dissertation, we propose two BAB strategies (Dynamic and Hybrid) obtained by adjusting the exposure to the BAB strategy by considering the option-implied correlation.

The S&P500 option-implied correlation and its application to dynamically adjust the exposure of our portfolio to the BAB factor is the main novelty of this dissertation. As a result, we find it useful to review (Faria & Kosowski, 2016) methodology to estimate the risk-neutral expectation of average pairwise correlation for the period (t, T), $E_t^Q(RC_{t,T})$, using option prices.

Starting by estimating the index and index constituents synthetic variance swap rates, which are an approximation of the risk-neutral expectations of future variance, $SV_{t,T}^I$ and $SV_{t,T}^i$, respectively, from listed vanilla option prices. (Faria & Kosowski, 2016) use market prices of out-of-the-money (OTM) European calls and puts to obtain the synthetic variance swap rates $SV_{t,T}$ computed as below:

$$SV_{t,T} = \int_{S_t}^{\infty} \left[\frac{2(1 - \ln\left(\frac{K}{S_t}\right)}{K^2} \right] C(t, T - t; K) dK + \int_{0}^{S_t} \left[\frac{2(1 + \ln\left(\frac{S_t}{K_t}\right)}{K^2} \right] P(t, T - t; K)\, dK, (1)$$

Where $C(t, T - t; K)$ and $P(t, T - t; K)$ are the European calls market prices and puts market prices at time t, with time to maturity of (T-t), and strike price K. This method generates an estimation of the option-implied integrated variance until the option's maturity, if the prices are continuous and the volatility stochastic, as referred by (Faria & Kosowski, 2016). Additionally, they use interpolated implied volatility surfaces for different maturities and option deltas from IvyBD (Optionmetrics) to get the option prices.

After these steps, the risk-neutral expectation of average pairwise correlation for the period (t,T), $E_t^Q(RC_{t,T})$ also denominated as the Implied Correlation rate, is computed as follows:

$$IC_{t,T} = \frac{SV_{t,T}^I - \sum_{i=1}^{n} W_i^2 SV_{t,T}^i}{\sum_{i \neq j} w_i w_j \sqrt{SV_{t,T}^i SV_{t,T}^j}}, (2)$$

Where $SV_{t,T}^I$ and $SV_{t,T}^i$ are the index and single stock synthetic swap variance rates over the period (t,T), and w_i is the market capitalization of stock i.

In this dissertation, we use the spread between the expected correlation for the longest maturity (365 days) and the shortest maturity (30 days) each computed as in equation (2) as a proxy for the option-implied correlation term structure.

3.3. Empirical Evidence: S&P500 Term Structure

We use data on option-implied correlation expectations to adjust a portfolio's exposure to the BAB factor dynamically. We expect that the information provided by the data allows overexposing the portfolio in "good" periods and underexposing it in "bad" periods. In this section, we document a piece of empirical evidence about the dynamics of the implied correlation of the S&P500 index constituents returns for different maturities and its term structure (Faria & Kosowski, 2016). We pretend to explain the motivation for using this set of data, particularly, what is the economic pattern that makes the information valuable to predict the market conditions.

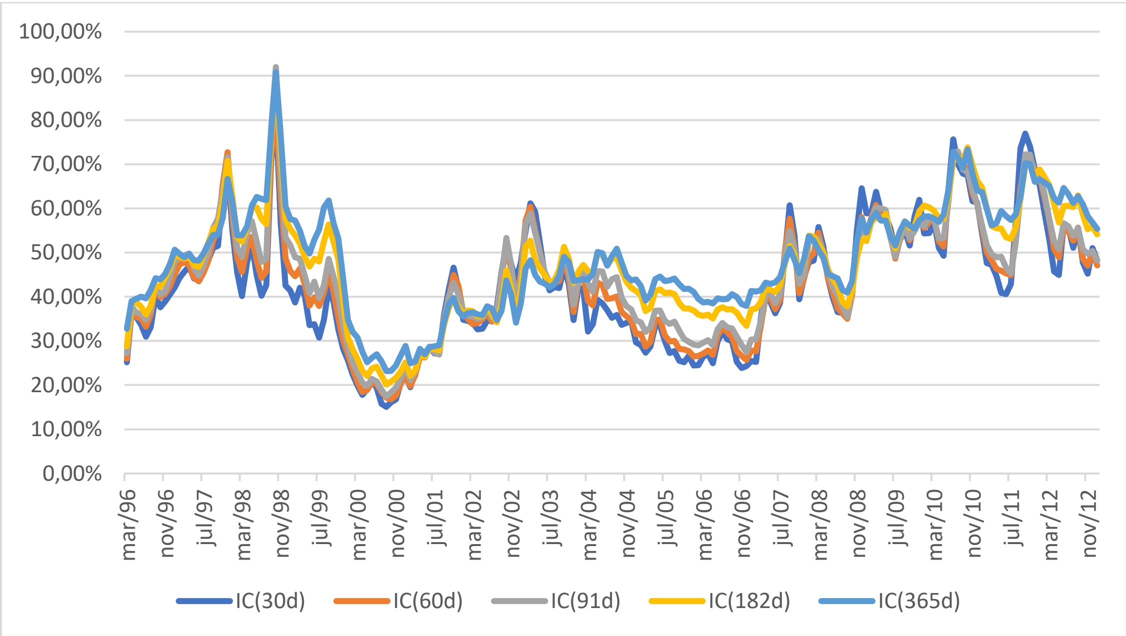

Figure 1: S&P500 Implied Correlation (IC) 2-month moving average for 30, 60, 91, 182, and 365 days. ICs are computed as in equation (2), using daily observations for the period between 1996:01 and 2013:01.

First, let us look at the S&P500 Implied Correlation (IC) 2-month moving average dynamics for different maturities. From Figure 1, we can conclude that expected correlations increase with maturity, but also change substantially around periods of increased uncertainty, e.g., the 2007/2008 financial crisis. Moreover, around the periods of increased uncertainty, the expected correlation for shorter maturities tend to increase more than the expected correlation for longer maturities. As a result, the 2-month moving average of the spread between the S&P500 Implied

Correlation with the more extended maturity (365 days), and the S&P500 Implied Correlation with the shortest maturity (30 days) will not also change with time, but also become close to zero or even negative in periods of increased uncertainty, as it is clear in Figure 2.

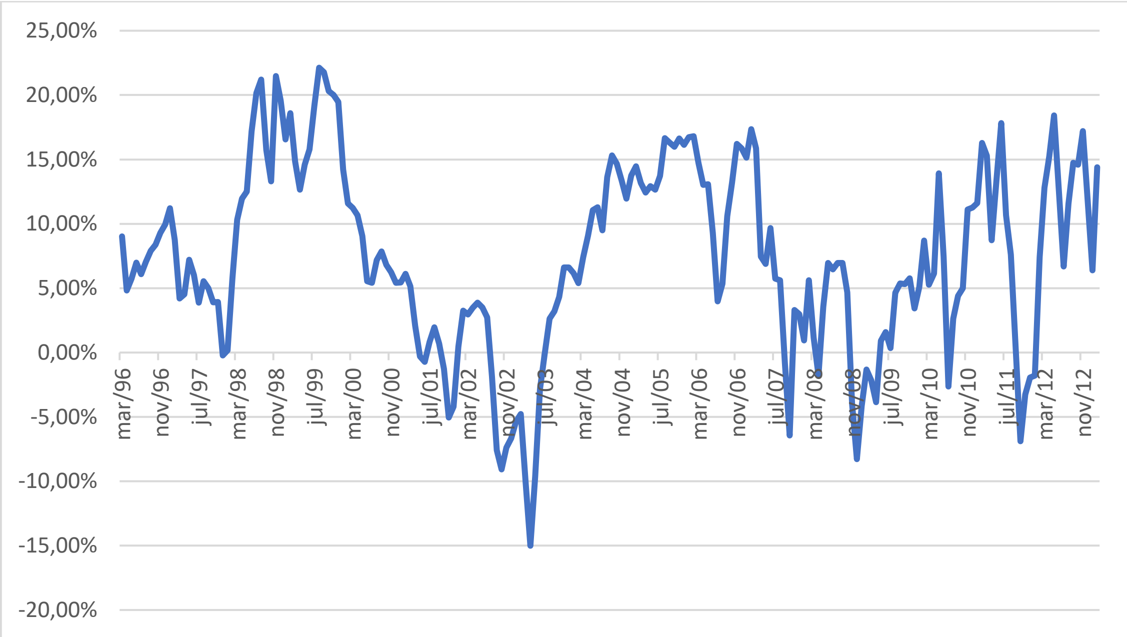

Figure 2: 2-month moving average of the spread between the S&P500 Implied Correlation (IC) for 365 days and the IC for 30 days. ICs are computed as in equation (2), using daily observations for the period between 1996:01 and 2013:01.

Since the 2-month moving average of the spread between the I.C. (365d) and the I.C. (30d) represents our S&P500 IC term structure, we can infer from Figure 2 that most of the time the term structure is positive and, in periods of increased uncertainty, the I.C. term structure becomes close to zero or even negative. We can give as examples the instability in the U.S. equity market between 2002 and 2003, the subprime crisis that started in 2007, worsening in 2008 with the collapse of the Lehman Brothers. (Faria & Kosowski, 2016) study a structural explanation for the empirical evidence about the flattening of the I.C. term structure, using a general equilibrium Lucas tree model.

Based on this empirical evidence of the dynamic of the I.C. term structure, we are motivated by a pattern that may be crucial in our objective of reducing the downside risk of the BAB strategy: that in periods on enhanced uncertainty in financial markets, expected correlations for longer maturities increase less than expected correlations for shorter maturities, causing a flattening of the I.C. term structure. In summary, we see an opportunity to use this pattern and overexpose our portfolio to the BAB strategy in "good" periods, when the I.C. term structure is positive, and underexpose our portfolio to the BAB strategy in "bad" periods, when the I.C. term structure is negative. As a result, we propose the Dynamic BAB strategy, as we explore in Chapter 5.

Chapter 4
Profiling BAB

In this chapter, we present the summary statistics of BAB, Fama and French 5 (RMRF; SMB; HML; RMW; CMA) and momentum (MOM) portfolios for the period of July 1967 to December 2016, computed using monthly data.

Portf.	Mean (%)	Standard Deviation (%)	Max. (%)	Min. (%)	Kurt.	Skew.	Sharpe Ratio
RMRF	6.01	15.69	16.10	-23.24	1.83	-0.52	0.38
SMB	2.13	10.76	21.70	-16.86	5.71	0.53	0.20
HML	4.47	10.02	12.87	-11.18	1.98	0.06	0.45
RMW	3.32	7.80	13.33	-18.33	11.86	-0.33	0.43
CMA	4.19	7.00	9.56	-6.86	1.58	0.33	0.60
MOM	7.72	14.97	18.36	-34.39	10.37	-1.34	0.52
BAB	10.92	11.81	15.39	-15.68	4.07	-0.53	0.92

Table 1: Summary statistics of RMRF (excess return of the market portfolio), SMB (Small Minus Big portfolio), HML (High Minus Low portfolio), RMW (Robust Minus Weak portfolio), CMA (Conservative Minus Aggressive portfolio), MOM (momentum or winners minus losers portfolio), BAB (Betting Against Beta portfolio). We compute the statistics using monthly observations from 1967:07 to 2016:12. The mean, standard deviation, and Sharpe ratio are annualized.

We can observe that BAB offers an average yearly return of 10.92%, which is considerably higher than the second-highest average yearly return (the momentum portfolio factor (MOM), with an average yearly return of 7.72%) and almost double the third-highest (the market portfolio factor (RMRF), with an average yearly return of 6.01%). Furthermore, BAB has an 11.81% yearly standard deviation, meaning that its average yearly return does not depend on a high yearly standard deviation. Factors with the same or close standard deviations (the small minus big portfolio factor (SMB), with a yearly standard deviation of 10.76% and the high minus low portfolio factor (HML), with a yearly standard deviation of 10.02%) have a way lower average yearly return (2.13% and 4.47%, respectively). Even portfolios with higher yearly standard deviations have a lower average yearly return (the momentum portfolio with a yearly standard deviation of 14.97% and an average yearly return of 7.72%), leading us to the inevitable conclusion that BAB has the highest Sharpe ratio(0.92), much higher than the second-highest (the conservative minus aggressive portfolio factor (CMA) with a Sharpe ratio of 0.60).

Furthermore, it is possible to observe that BAB has a kurtosis of 4.07, which predicts fatter tails than a normal distribution, and negative skewness of -0.53, which suggests that the left tail is more substantial than the right tail. Although these numbers are not very worrisome, the BAB strategy still has considerable downside risk.

Recently, Antoniou, Doukas, and Subrahmanyam (2015) showed that optimism attracts unsophisticated and overconfident investors causing the mispricing of beta and increasing the beta anomaly. So, what should we expect of the beta anomaly in pessimistic periods? For a better perception, we selected two turbulent periods and tested the cumulative returns performance of the BAB strategy using the market as a benchmark.

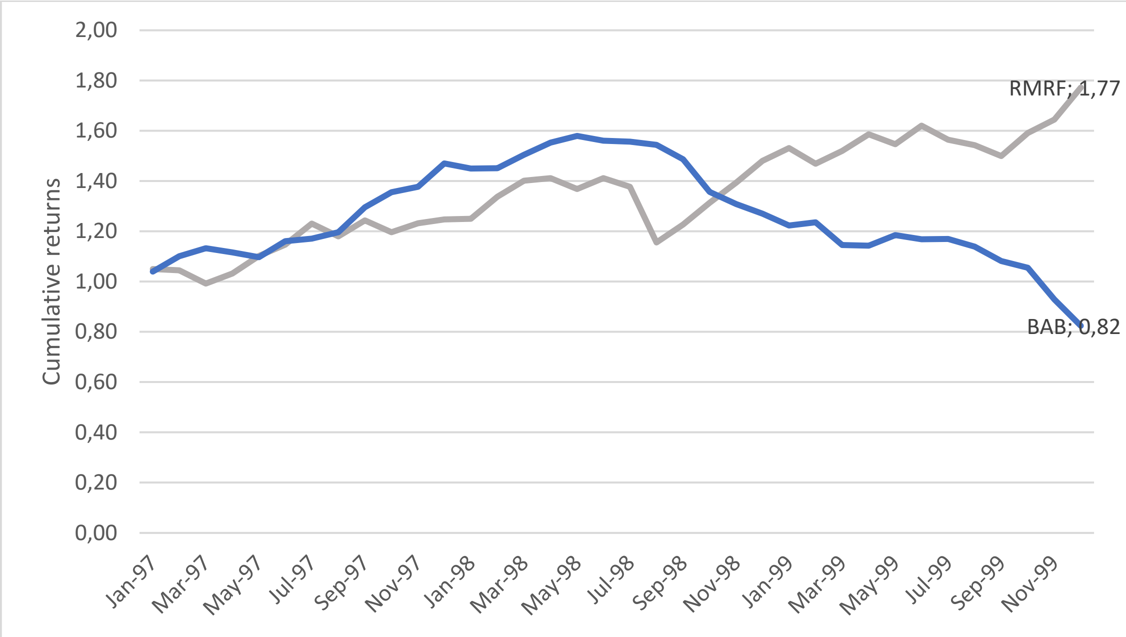

Figure 3: Betting Against Beta (BAB) and Market (RMRF) factors performance between 1997:01 and 1999:12.

Figure 3 shows the cumulative returns performance of the strategies based on the BAB and the RMRF (market) portfolios around the burst of the Asian Financial Crisis (1997/1998). A practical exercise shows that an investor that invested 1 monetary unit in a BAB strategy on the first trading day of January 1997 would end up with only get 0.82 monetary units on the last trading day of 1999, suffering a loss of 18%. To receive his initial investment, the investor would have to wait until March 2001, that means, 1 year and 3 months later.

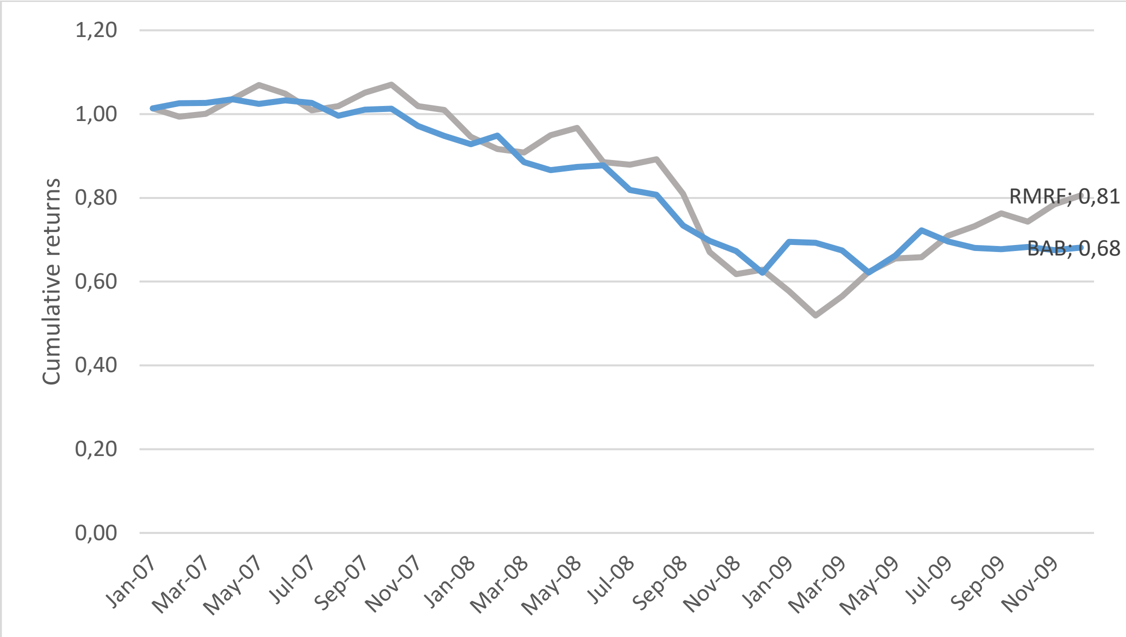

Figure 4: Betting Against Beta (BAB) and Market (RMRF) factors performance between 2007:01 and 2009:12.

Figure 4 shows the cumulative returns performance of the strategies based on the BAB and RMRF portfolios around the Subprime crisis and the Lehman Brothers collapse (2007/2008). In this case, an investor that invested 1 monetary unit in a BAB strategy on the first trading day of January would end up with 0.68 monetary units on the last trading day of 2009, suffering a loss of 32% of portfolio value. Overall, in both sub-samples considered, the BAB strategy clearly underperforms a strategy exposed to the market risk factor.

	CAPM	FF3	FF5 + MOM
α (%)	9.48 **(6.76)**	7.56 **(5.64)**	3.12 **(2.50)**
β_{RM}	-0.07 **(-2.42)**	0.00 **(-0.15)**	0.10 **(3.51)**
B_{SMB}		0.01 **(0.22)**	0.16 **(3.71)**
β_{HML}		0.41 **(8.69)**	0.34 **(5.65)**
β_{MOM}			0.18 **(6.33)**
β_{RMW}			0.56 **(9.48)**
β_{CMA}			0.34 **(3.89)**
R^2	0.98	12.35	30.84

Table 2: Ordinary Least Squares (OLS) regression of the BAB (Betting Against Beta portfolio) on the CAPM (RMRF, which represents the market portfolio), the Fama and French 3 factors (RMRF, which represents the market portfolio, SMB, which represents the Small Minus Big portfolio and the HML, which represents the High Minus Low portfolio) and the FF5+MOM (FF3 factors plus the RMW, which represents the Robust Minus Weak portfolio, and the CMA, which represents the Conservative Minus Aggressive portfolio + the MOM, which represents momentum portfolio).

In table 2, we examine the ability of other risk factors to explain the returns of BAB, so we regress the BAB factor on other risk factors through the OLS method, using monthly data between July 1967 and December 2016. In our first regression, we conclude that the market factor does not explain the returns of BAB and that the strategy has an annualized CAPM alpha of 9.48%, which is quite high, with a t-statistic of 6.76. The fact that the beta of the market factor is close to zero shows that the objective of having an ex-ante beta of zero, on average, is achieved ex-post, as already seen in (Barroso & Maio, 2018). If we move to the second regression, we can conclude that the size and value factors explain more than 20% (1-(7.56/9.48)) of the CAPM-alpha of the strategy, which means that BAB is very exposed to those sources of risk, more concretely, the value factor, which has a beta of 0.41. Moving to the last regression, we have an annualized alpha of 3.12% with a t-statistic of 2.50, which means it is statistically significant (at the 5% level). We conclude that, with the factors under analysis, we can explain two-thirds of the BAB strategy returns and there is a positive relationship between the BAB and the other risk factors, even if some of them are not statistically significant at the 5% level.

In conclusion, if we analyze the empirical evidence for the extended period in question, BAB outperforms by far the other portfolios. It has a higher Sharpe ratio, a smaller kurtosis, and a smaller negative skewness. However, one third of BAB returns is not captured by the risk factors analyzed.

In summary, BAB is a high-performance portfolio that significantly outperforms the market and the other well-known factors portfolios. However, the considerable downside risk has motivated the work of (Barroso, & Maio, 2018), who try to manage the downside risk of the BAB strategy by using its volatility, which has extraordinary predictive power of the strategy performance. The work consists of creating a Risk-managed version of BAB. The Risk-managed BAB outperforms the original BAB in every aspect, and it shows to be more profitable than the original. However, unlike Risk-managed momentum (Barroso & Santa Clara, 2015), Risk-managed BAB still has considerable downside risk.

In this dissertation, we build on the recent literature that use the S&P500 index Implied Correlation information to optimize the exposure to the momentum strategy (Nogueira & Faria, 2017). Concretely, we use, for the first time, the information contained in the S&P500 index Implied Correlation to manage the downside risk exposure of the BAB strategy.

Furthermore, we build on the recent literature of (Barroso & Maio, 2018) and use the Risk-managed strategy to increase the upside potential of the strategy. In Chapter 5 the proposed strategies and corresponding performance are reported.

Chapter 5

Dynamic and Hybrid BAB Strategies

5.1. Dynamic BAB strategy

Building on (Nogueira & Faria, 2017) Dynamic strategy, we construct a strategy that also uses the S&P500 Implied Correlation to manage the portfolio exposure to the BAB factor. However, our strategy has different objectives and different mechanisms.

We represent BAB's monthly returns as $\{r_{BAB,t}\}_{t=1}^{T}$, where $\{d\}$ corresponds to the last trading day of month t-1, and $\{d_t\}_{t=1}^{T}$ represents the time series of the last trading days of all months in the data.

We use daily data about the S&P500 Implied Correlation (I.C.) with different maturities, from January 1996 to January 2013, to compute the 2-month moving average (M.A.) of the spread between the S&P500 IC for 365 days (I.C. (365d)) and the S&P500 IC for 30 days (I.C. (30d)), for each trading day. We use the 2-month M.A. as a proxy of the S&P500 index I.C. term structure, which is computed in the last trading day of each month t-1, as follows:

$$2MA(Spread)_d = \sum_{j=0}^{41}[IC(365d) - IC(30d)]_{d\text{-}j}/42, \quad (3)$$

We assume each month to have 21 trading days. Consequently, we assume 2 months to have 42 trading days.

For further analyzis, we obtain the Spread Percentile 15 from the 2 M.A. of the ICs spread, denoted in the rest of the chapters as "Spread Percentile 15".

Indicator	Percentile 15
S&P500 IC Spread	-1.16

Table 3: Percentile 15 of the spread between the S&P500 Implied Correlation (IC) for 365 days and the S&P500 Implied Correlation (IC) for 30 days. IC is computed as in equation (2). The values are based on daily data from 1996:01 to 2013:01.

The Dynamic BAB strategy, BAB', adjusts the portfolio exposure to the BAB strategy, using information contained in the S&P500 IC term structure, as follows.

The return of the BAB' strategy in month t is given by:

$$r_{BAB',t} = w'_t \times r_{BAB,t}, \text{ (4)}$$

Where $r_{BAB,t}$ is the return of the BAB strategy in month t, and w'_t is the weight computed in the BAB' strategy in month t, which determines the portfolio exposure to the BAB strategy. We compute the Dynamic strategy weight as follows:

$$w'_t = \begin{cases} 100\%; if\ 2MA(Spread)_d > \ Spread\ Percentile\ 15 \\ -50\%\ ; if\ 2MA(Spread)_d \leq Spread\ Percentile\ 15 \end{cases}, \text{ (5)}$$

When the 2-month moving average of the spread between the S&P500 IC for 365 days and the S&P500 option I.C. for 30 days, in the last trading day of month t-1, is higher than the Spread Percentile 15, the BAB' strategy replicates the original BAB strategy. On the other hand, when the 2-month moving average of the spread between the S&P500 IC for 365 days and the S&P500 option I.C. for 30 days, in the last trading day of month t-1, is equal or lower than the Spread Percentile 15, the BAB' strategy shorts the original BAB strategy by 50%. In this scenario, we leverage the underexposure of the portfolio towards the BAB strategy.

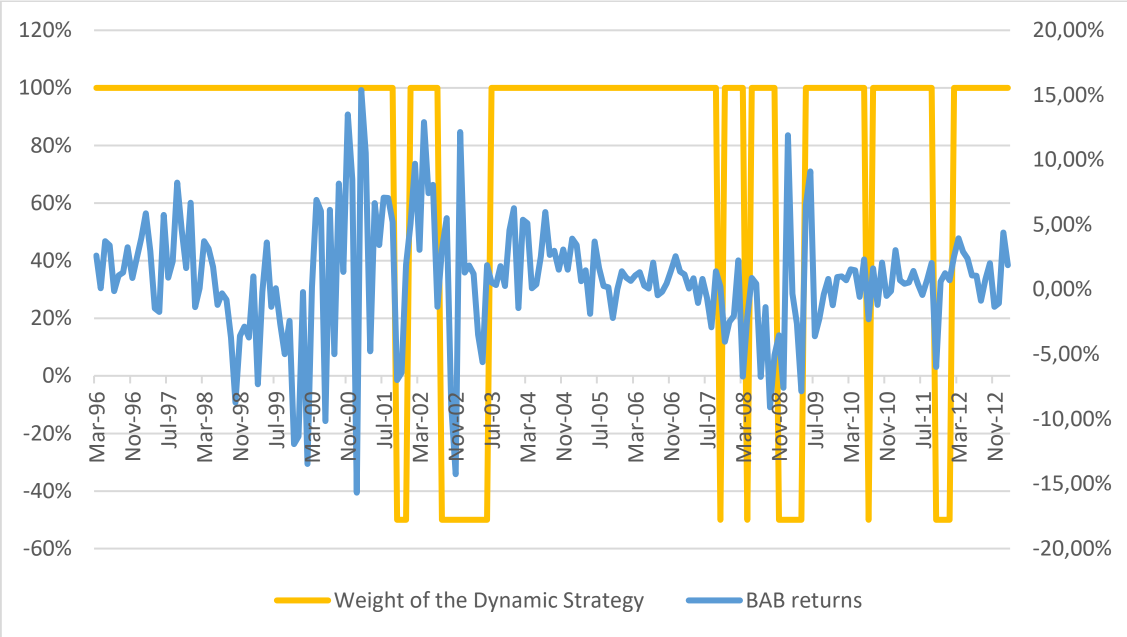

Figure 5: Weight of the Dynamic Strategy (BAB') on the BAB factor, as computed in equation (5), and plain-vanilla BAB returns, between 1996:03 and 2013:02.

In Figure 5, we can compare the weight of the dynamic strategy with the BAB returns. We can infer that most of the time, when BAB returns are positive, the weight of the BAB' strategy is 100%, fully exposing the portfolio to the BAB strategy. Moreover, in periods when BAB returns are negative, the weight of the BAB' strategy tends to be negative, -50%, leveraging the underexposure of the portfolio to the BAB strategy. However, the strategy does not always behave as it should. It is the case of the period between 1997 and 1998 when BAB returns are negative.

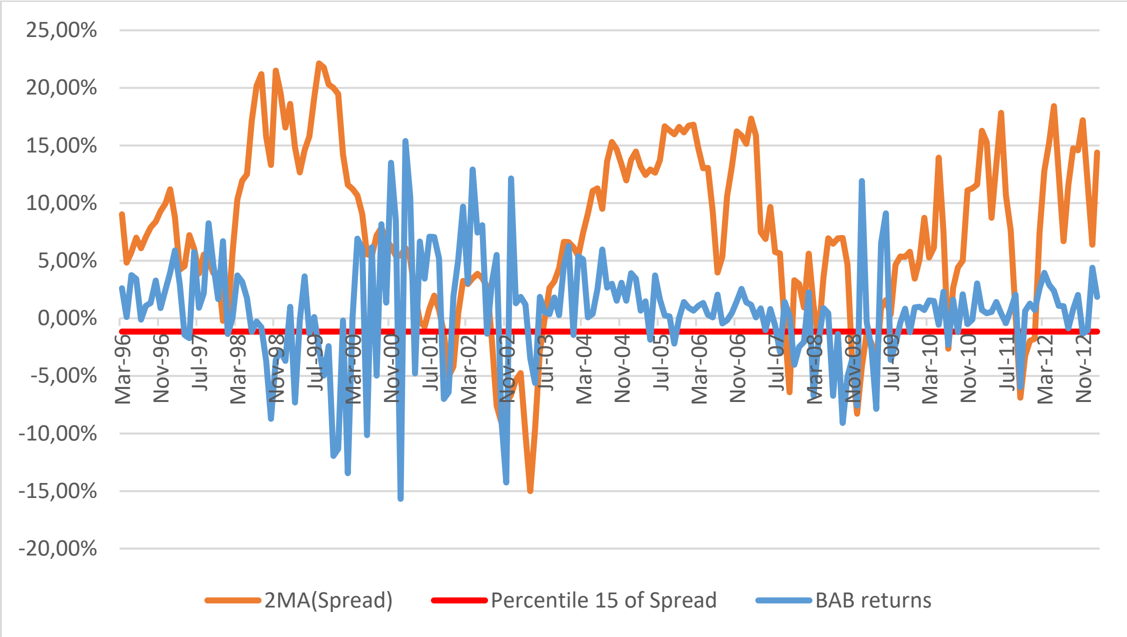

Figure 6: 2-month moving average of the Spread between the S&P500 IC(365d) and IC(30d), its Spread Percentile 15, and plain-vanilla BAB returns between 1996:03 and 2013:02.

The results we present in Figure 6, follow the empirical results presented by (Faria & Kosowski, 2014). On the one hand, in more stable periods, implied correlations for longer maturities are higher than implied correlations for shorter maturities, leading to a positive spread. On the other hand, in more turbulent periods, implied correlations for longer maturities increase less than implied correlations for shorter matures, leading to a decrease in the spread, which can even become negative, resulting in the I.C. term structure flattening.

However, this does not always happen. Concretely, in periods of increased turbulence such as the Asian Financial Crisis (1997 to 2000), the 2-month M.A. of the I.C. Spread is very high. As a result, our portfolio continues overexposed to the BAB strategy in a period where it posts a negative performance. So, the BAB' strategy does not allow consistent management of the BAB strategy downside risk. This lag-effect between the BAB and BAB' dynamics can have origin in the fact we compute the weight based on a moving average, or due to the intrinsic properties of option-implied correlation metrics, as explained in (Faria & Kosowski, 2014).

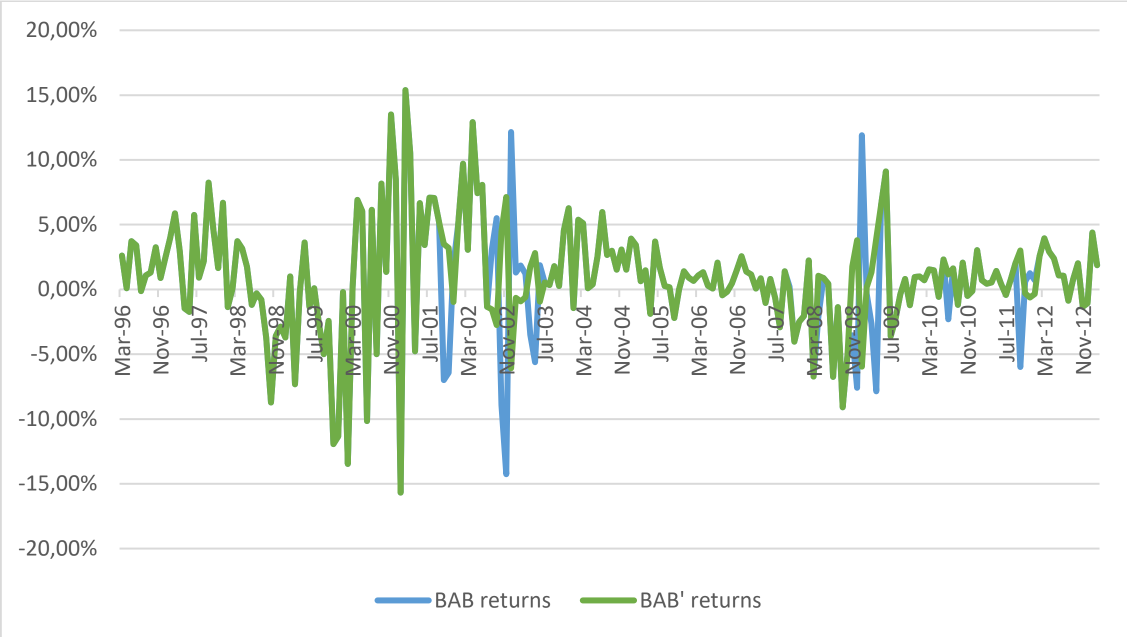

Figure 7: Plain-vanilla Betting Against Beta returns (BAB) and Dynamic Betting Against Beta returns (BAB') as computed in equation (4), between 1996:03 and 2013:02.

In Figure 7, we can compare the returns of both strategies. We notice that BAB', in specific periods, manages the downside risk. There are several periods when BAB' strategy shorts the BAB strategy negative returns, obtaining positive returns. For instance, in the period between June 2001 and March 2002, BAB' converts a BAB negative monthly return of -7.42% in a positive monthly return of 3.21%. Additionally, in the period between March 2002 and December 2002, BAB' converts a BAB negative monthly return of -14.26% in a positive monthly return of 7.13%. However, as pointed before BAB' is far from perfect, as we can see by the way it manages the downside risk between November 2002 and November 2008. The summary statistics of BAB and BAB' strategies are provided in Table 4.

Factor	BAB	BAB'
Maximum	15.39	15.39
Minimum	-15.68	-15.68
Mean	8.89	11.93
Standard Deviation	16.14	14.60
Kurtosis	2.01	2.85
Skewness	-0.34	-0.38
Sharpe ratio	0.55	0.82

Table 4: Dynamic Betting Against Beta strategy (BAB') and plain-vanilla Betting Against Beta strategy (BAB) summary statistics. The statistics are computed using monthly observations between 1996:03 and 2013:02. The mean, standard deviation, and Sharpe ratio are annualized.

The results we present in Table 4 show that BAB' outperforms BAB with the Sharpe ratio increasing from 0.55 to 0.82. In Figures 8, 9, and 10, we identify specific periods where the strategy gained advantage compared with the BAB.

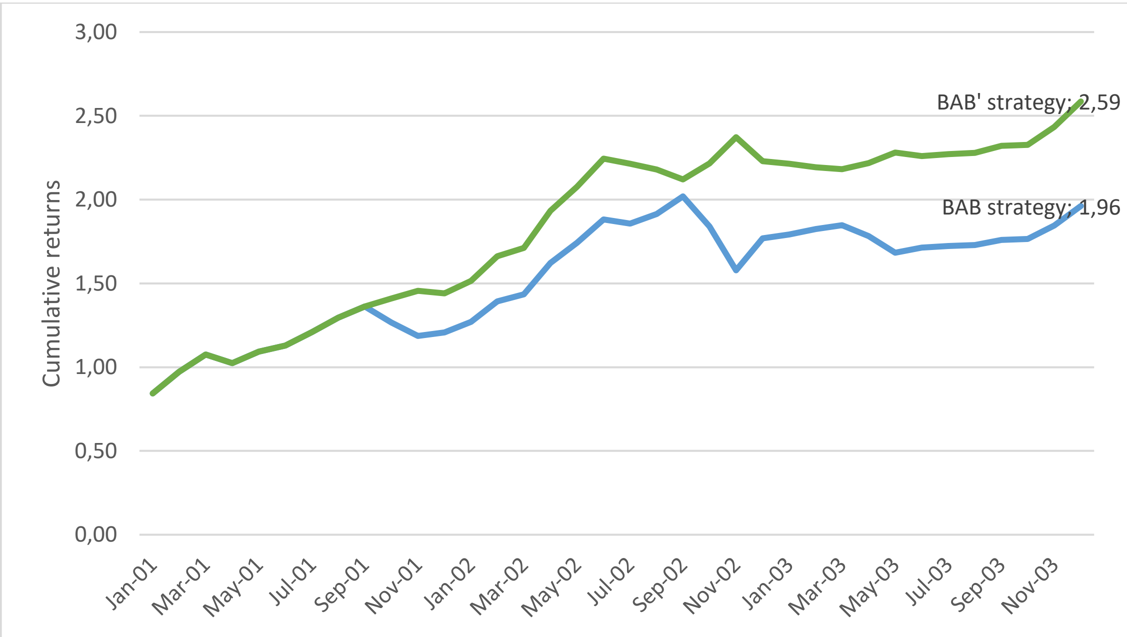

Figure 8: Dynamic Betting Against Beta strategy (BAB') and plain-vanilla BAB strategy (BAB) performance between 2001:01 and 2003:12.

If we look at a three years' time frame around 9/11, a period of increased uncertainty in the U.S. stock market, an investor that invested 1 monetary unit in the BAB strategy on the first trading day of January 2001, and continued invested until

December 2003, would end up with 1.96 monetary units at the end of the holding period. On the contrary, an investor that invested 1 monetary unit in the BAB' strategy, during the same period, would end up with 2.59 monetary units at the end of the holding period.

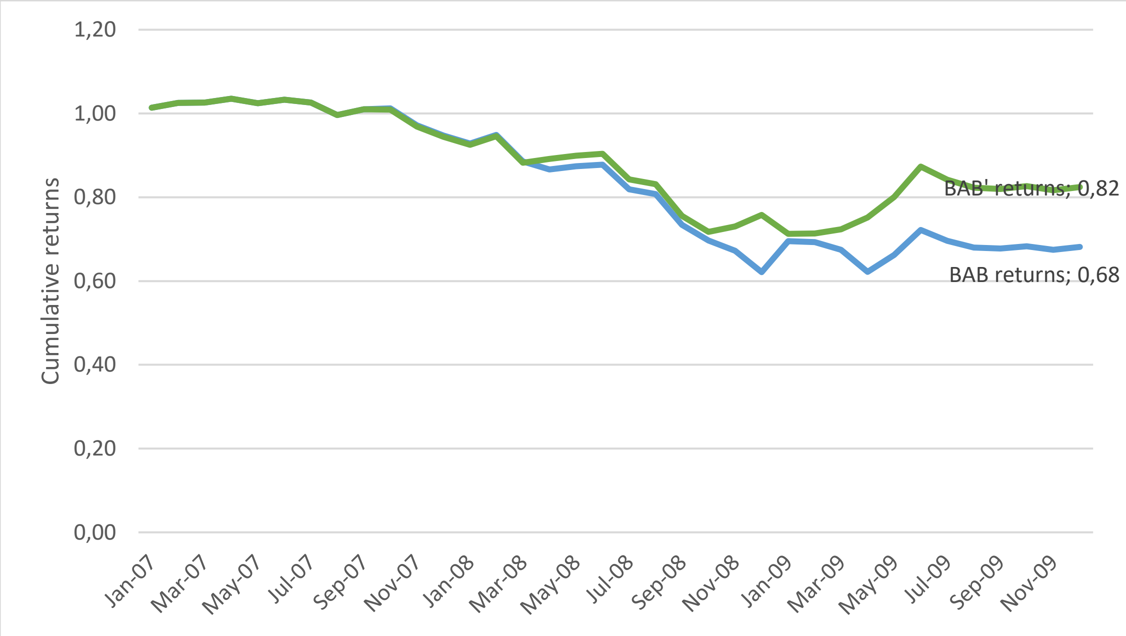

Figure 9: Dynamic Betting Against Beta strategy (BAB') and plain-vanilla BAB strategy (BAB) performance between 2007:01 and 2009:12.

Additionally, looking at a three years' time period around the Subprime Crisis and the Lehman Brothers collapse (2007), an investor that invested 1 monetary unit in the BAB strategy on the first trading day of January 2007, and continued invested until December 2009, would end up with 0.68 monetary units at the end of the holding period, representing a loss of 32% of portfolio value. Alternatively, an investor that invested 1 monetary unit in the BAB' strategy, during the same period, would end up with 0.82 monetary units at the end of the holding period, representing a loss of 18% of portfolio value.

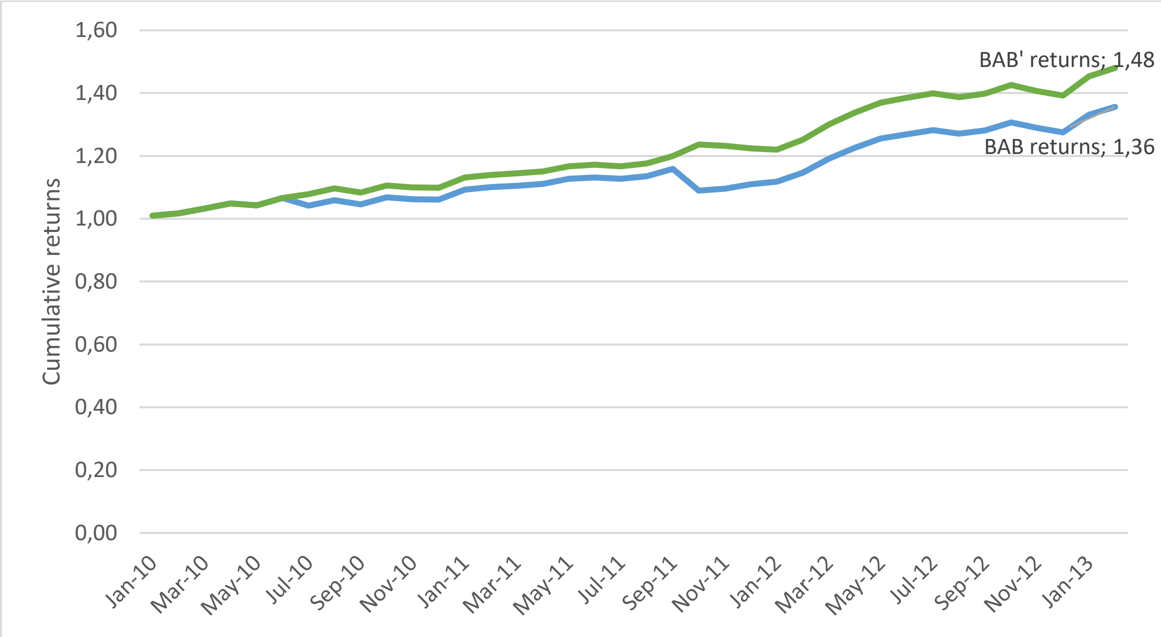

Figure 10: Dynamic Betting Against Beta strategy (BAB') and plain-vanilla BAB strategy (BAB) performance between 2010:01 and 2013:12.

Lastly, if we look at a three years' time period around the European Sovereign debt crisis and U.S. downgrade (2011), a period of enhanced turbulence, an investor that invested 1 monetary unit in the BAB strategy on the first trading day of January 2010, and continued invested until February 2013, would end up with 1.36 monetary units at the end of the holding period. An investor that invested in the BAB' strategy, during the same period, would end up with 1.48 monetary units at the end of the holding period.

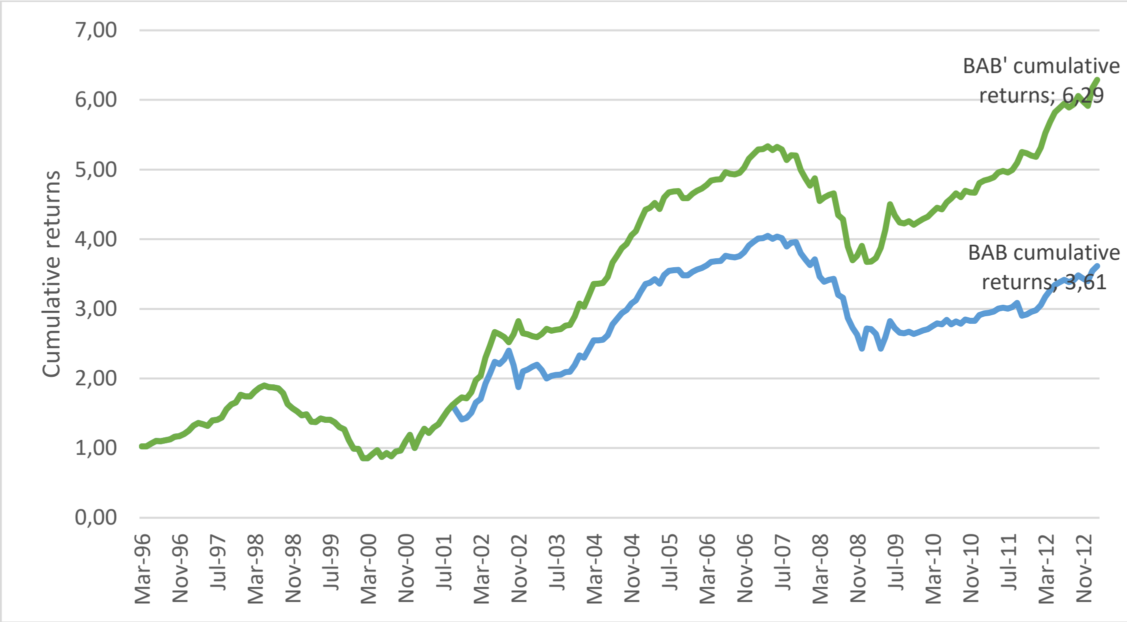

Figure 11: Dynamic Betting Against Beta strategy (BAB') and plain-vanilla BAB strategy (BAB) performance between 1996:03 and 2013:02.

In Figure 11, we have the cumulative returns for the entire period under analysis. An investor that invested 1 monetary unit in the BAB strategy on the first trading day of March 1996, and continued invested until February 2013, would end up with 3.61 monetary units at the end of the holding period. An investor that invested 1 monetary in the BAB' strategy on the first trading day of March 1996 and continued invested until February 2013, would end up with 6.29 monetary units at the end of the holding period.

In conclusion, the BAB' clearly outperforms the BAB strategy during the period under analysis, reflecting an improvement in terms of the strategy risk management by using option-implied correlation information. However, we can find that it is easily possible to improve the efficiency of the BAB strategy downside risk. This is done through the Hybrid BAB strategy presented in the following subchapter 5.2

5.2. Hybrid BAB strategy

The BAB' strategy has a better performance than the original BAB strategy due to its capability of managing the BAB downside risk in turbulent periods. However, there are specific periods when the BAB' strategy cannot manage the downside risk of the BAB strategy. With this in mind, we build on (Barroso & Maio, 2018), and combine their proposed strategy, Risk-managed BAB, denominated BAB*, with the Dynamic Strategy, BAB'. The main objective is to increase the upside potential by overexposing the portfolio to the BAB strategy in "good" times, and, simultaneously improving the management of the downside risk of the BAB' strategy.

(Barroso & Maio, 2018) extend from the Risk-managed version of momentum (with some differences in the computation), constructed by (Barroso & Santa-Clara, 2015), to the BAB factor. The strategy weights are inversely proportional to the realized volatility of BAB past returns. The higher the realized volatility, the less the Risk-managed BAB is exposed to the BAB strategy.

To construct the strategy of (Barroso & Maio, 2018), we start by computing the daily returns realized variance $RV_{F,t}$ of the 21 days of month t-1 (assuming that each month has 21 trading days). We represent the daily returns by $\{r_d\}_{d=1}^{D}$ and the time series of the dates of last trading sessions of each month by $\{d_t\}_{t=1}^{T}$, computing the realized variance of factor F in month t as follows:

$$RV_{F,t} = \sum_{j=0}^{20} r_{F,d_{t-j}}^2, \text{(6)}$$

Then, we square root the realized variance to obtain the realized volatility, $\hat{\sigma}_{F,t}$. The underlying objective is to use the realized volatility as a forecast of the next month's real volatility. Then, as in (Barroso & Maio, 2018), we use the realized volatility to scale the returns, dividing an *ad hoc* given target (12% annualized), represented by $\sigma_{t\arg et}$, by the realized volatility $\hat{\sigma}_{F,t}$. Resulting from this computation is the weight of the BAB* strategy, w_t^*:

$$w_t^* = \sigma_{t\arg et}/\hat{\sigma}_{F,t}, \text{(7)}$$

Lastly, we multiply the obtained weight by the returns of BAB, to obtain the returns of the BAB* strategy, $r_{BAB^*,t}$, as follows:

$$r_{BAB^*,t} = w_t^* \times r_{BAB,t}, \ (8)$$

Where, $r_{BAB,t}$ is the return of BAB strategy in month t, and w_t^* is the weight of the BAB* strategy in month t.

We present the summary statistics of (Barroso & Maio, 2018) Risk-managed BAB returns, BAB*, during our sample period (March 1996 to February 2013). However, unlike (Barroso & Maio, 2018), we assumed that investors are not unconstrained, so we limited the short-selling to -50% and leverage to 150%.

Factor	**BAB**	**BAB'**	**BAB***
Maximum	15.39	15.39	13.41
Minimum	-15.68	-15.68	-15.21
Mean	8.89	11.93	11.83
Standard Deviation	16.14	14.60	15.17
Kurtosis	2.01	2.85	1.24
Skewness	-0.34	-0.38	-0.41
Sharpe ratio	0.55	0.82	0.78

Table 5: Risk-managed Betting Against Beta strategy (BAB*), Dynamic Betting Against Beta strategy (BAB'), and plain-vanilla Betting Against Beta strategy (BAB) summary statistics. The statistics are computed using monthly observations between 1996:03 and 2013:02. The mean, standard deviation, and Sharpe ratio are annualized.

Comparing the summary statistics of BAB with the Risk-managed BAB, we notice that the Sharpe ratio is higher, provided by the higher mean and lower standard deviation. The returns of the Risk-managed strategy have lighter tails, providing returns with fewer outliers. However, it also has a slightly bigger left tail, hurting the strategy performance.

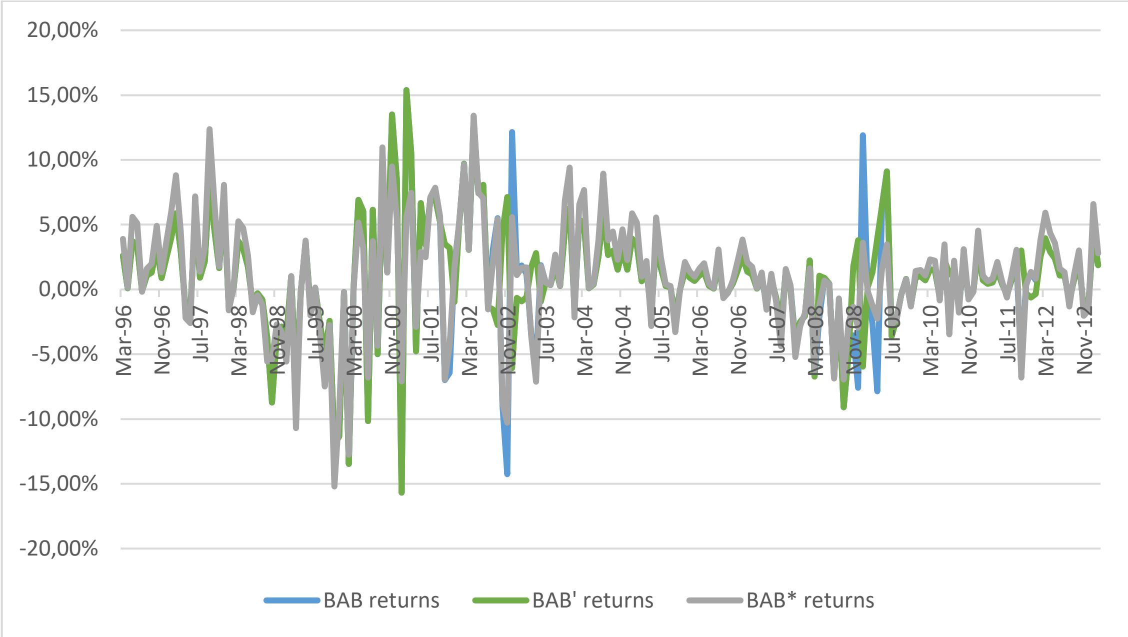

Figure 12: Risk-managed Betting Against Beta returns (BAB*), Dynamic Betting Against Beta returns (BAB'), and plain-vanilla Betting Against Beta returns (BAB), between 1996:03 and 2013:02.

In Figure 12, we notice that BAB* returns are different from BAB returns and BAB' returns. One explanation is that the realized volatility used to scale BAB* returns captures different kinds of information than that captured by the S&P500 IC, for the same periods. If it is the case, there is an opportunity to combine the two sources of information. This motivates merging the two strategies, leading to the proposed Hybrid strategy, henceforth represented by BAB''.

To construct the Hybrid strategy, first, we need to compute the realized volatility Percentile 50, from the daily realized volatility, which we denote by $\hat{\sigma}_t$ *Percentile* 50, calculated using the same method as (Barroso & Maio, 2018).

Indicator	**Percentile 50**
BAB returns forecasted volatility	2.26

Table 6; Percentile 50 of the Betting Against Beta (BAB) returns forecasted volatility. The values are based on daily observations from 1996:01 to 2013:01.

The $\hat{\sigma}_t$ *Percentile* 50 is a threshold. Below this limit, we expect to correspond to favorable moments in the market, when we want to expose our portfolio to the BAB strategy as much as possible. Above this limit, we expect to correspond to turbulent periods in the market, when we want to underexpose the portfolio to the BAB strategy as much as possible.

As a result, the BAB" strategy filters the weights obtained in the Dynamic BAB strategy (w_t'), and the weights obtained in the Risk-managed BAB strategy, (w_t^*). As a result, the weight of the BAB" strategy for month t, w" $_t$, is given by:

$$w_t'' = \begin{cases} Maximum(w_t'; w_t^*) \ ; if \ \hat{\sigma}_t < \ \hat{\sigma}_t \ Percentile \ 50 \\ Minimum(w_t'; w_t^*) \ ; if \ \ \hat{\sigma}_t > \ \hat{\sigma}_t \ Percentile \ 50 \end{cases}, (9)$$

Where w_t' denotes the weight of the Dynamic strategy (BAB'), in month t, w_t^* denotes the weight of the Risk-managed strategy (BAB*), in month t, and $\hat{\sigma}_t$ denotes the BAB return volatility forecast in month t, based on the BAB returns from the previous 21 trading days.

To compute the return granted by the BAB" strategy in month t, $r_{BAB'',t}$, we use the following equation:

$$r_{BAB'',t} = w_t'' \times r_{BAB,t}, (10)$$

Where w_t'' denotes the weight of the Hybrid strategy (BAB") in month t, and $r_{BAB,t}$ is the return of the original BAB strategy in month t.

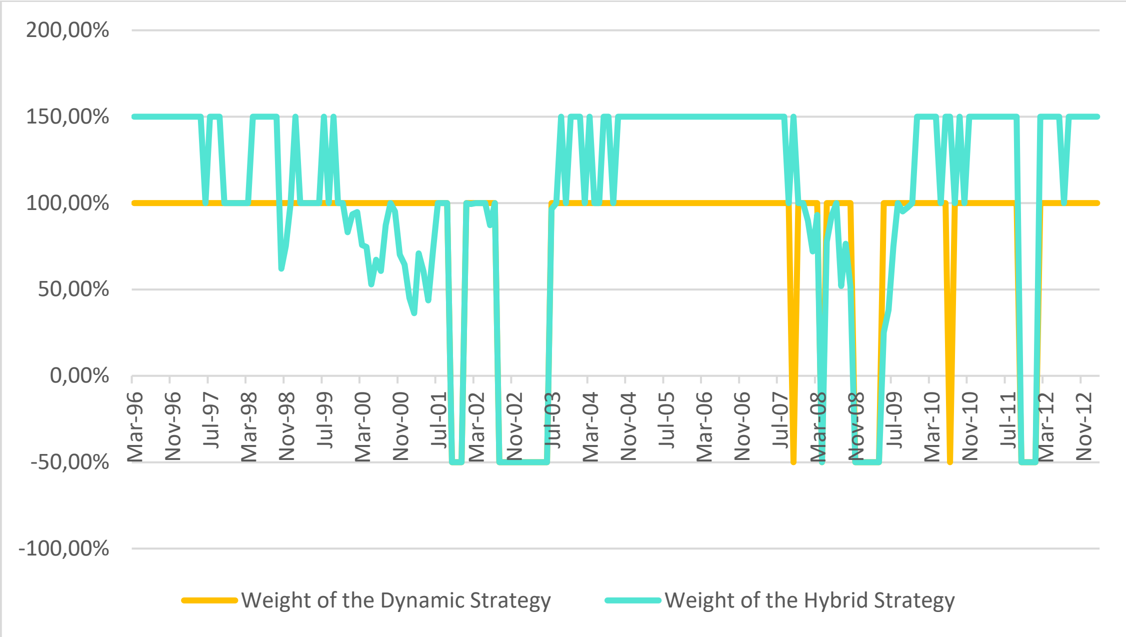

Figure 13: Weights of the Dynamic Strategy (BAB') on the BAB factor and Weights of the Hybrid Strategy (BAB'') on the BAB factor, as computed in equation (5) and (9), respectively, between 1996:03 and 2013:02.

Figure 13 shows that the weights of the Hybrid strategy (BAB") are very different from the weights of the Dynamic Strategy (BAB'). On the one hand, BAB" strategy exposes the portfolio, to the BAB strategy, by 150%, while BAB' only exposed the portfolio at a maximum of 100%, by design. Furthermore, since BAB" strategy has the contribution of the Risk-managed strategy weights, it is not a binary strategy as BAB' (that only takes -50% or 100% positions). It takes very different weights depending on the values provided by the BAB returns forecasted volatility. In summary, BAB" has a more efficient upside exposure and slightly better downside risk management, as we can see in Figure 14.

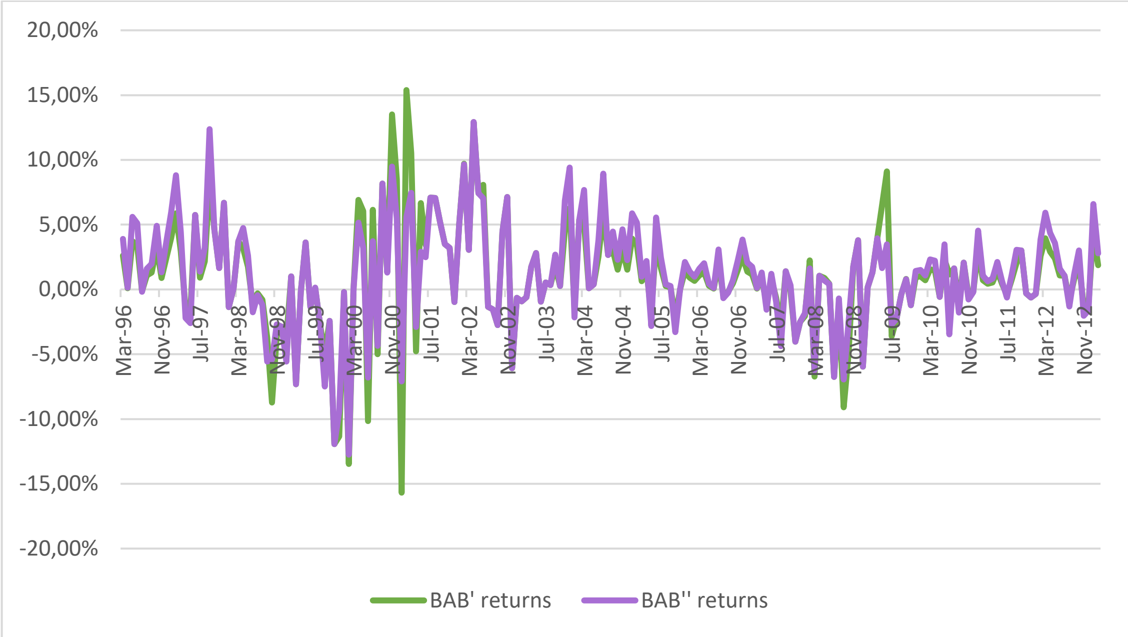

Figure 14: Dynamic Betting Against Beta returns (BAB'), and Hybrid Betting Against Beta returns (BAB''), between 1996:03 and 2013:02.

In table 7, are reported the summary statistics of the BAB strategy (BAB), the Dynamic BAB strategy (BAB'), the Risk-managed BAB strategy (BAB*) (adjusted to the sample period), and the Hybrid BAB strategy (BAB").

Factor	**BAB**	**BAB'**	**BAB***	**BAB"**
Maximum	15.39	15.39	13.41	12.92
Minimum	-15.68	-15.68	-15.21	-12.75
Mean	8.89	11.93	11.83	14.28
Standard Deviation	16.14	14.60	15.17	13.74
Kurtosis	2.01	2.85	1.24	1.21
Skewness	-0.34	-0.38	-0.41	-0.28
Sharpe ratio	0.55	0.82	0.78	1.04

Table 7: Hybrid Betting Against Beta strategy (BAB''), Risk-managed Betting Against Beta strategy (BAB*), Dynamic Betting Against Beta strategy (BAB'), and plain-vanilla Betting Against Beta strategy (BAB) summary statistics. The statistics are computed using monthly observations between 1996:03 and 2013:02. The mean, standard deviation, and Sharpe ratio are annualized.

BAB'' outperforms the rest of the strategies. It has the highest mean and lowest standard deviation. Consequently, it has the highest Sharpe ratio. Even though the strategy has the lowest maximum, it also has the lowest minimum. The kurtosis and the skewness are the lowest, too. Since we aimed to reduce the downside risk, these values are an essential indicator of the strategy performance.

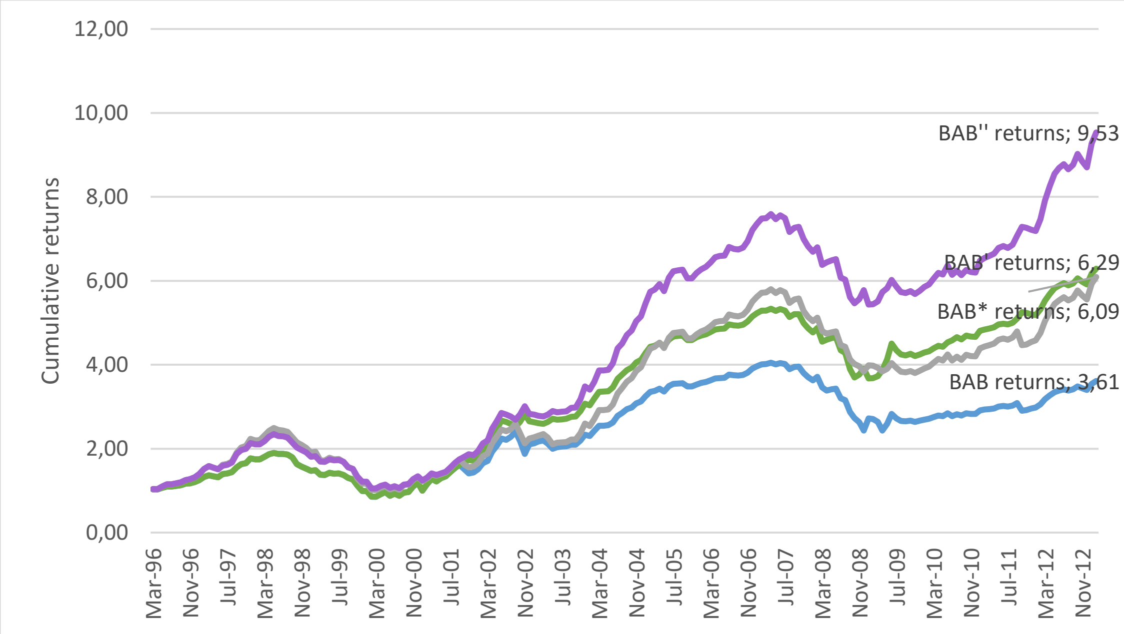

Figure 15: Hybrid Betting Against Beta strategy (BAB''), Risk-managed Betting Against Beta strategy (BAB*), Dynamic Betting Against Beta strategy (BAB'), and plain-vanilla BAB strategy (BAB) performance between 1996:03 and 2013:02.

We compute the cumulative returns of the four strategies for the entire sample period, between March 1996 and February 2013, and the results are plotted in Figure 15.

An investor that invested 1 monetary unit in BAB, BAB', BAB* and BAB'' strategies on the first trading day of March 1996, and continued invested until February 2013, would end up with either 3.61, 6.09, 6.29 and 9.53 monetary units, respectively, at the end of the holding period. In summary, an investor that invested in BAB'', would not only receive a higher payoff for the same investment but also be less exposed to the downside risk.

Chapter 6
Robustness Checks

6.1. Real-Time Information

In this chapter, our objective is to evaluate the performance of the strategy if used in real-time trading. For this purpose, we do not use ex-post information to compute the weights in equation 4. Assume we only have information until December 2002. We make use of the data from January 1996 to December 2002 and apply the BAB'' strategy from January 2003 to February 2013, simulating a real-time trading scenario.

The first step is to compute the Spread Percentile 15 for the sample period of March 1996 to December 2002, as requested by the BAB' strategy. The second step is to compute the $\hat{\sigma}_t$ $Percentile$ 50, as requested by the BAB* strategy, for the same sample period. These two variables are the only ones that differ in a real-time situation. Although we could update these critical values and dynamically adjust the weight computation as time goes by, we decided not to do it, to implement an extreme version of this robustness test.

Indicator	Percentile 15	Percentile 50
S&P500 IC Spread	-0.64	
BAB returns forecasted volatility		3.09

Table 8: Percentile 15 of the spread between the S&P500 Implied Correlation (IC) for 365 days and the S&P500 Implied Correlation (IC) for 30 days. IC is computed as in equation (2). The values are based on daily data from 1996:01 to 2002:12. Percentile 50 of the Betting Against Beta (BAB) returns forecasted volatility. The values are based on daily observations from 1996:01 to 2002:12.

We refer to this real-time strategy by BAB' (I). We present the summary statistics in Table 9, using the sample period between January 2003 and February 2013.

Factor	BAB	BAB'	BAB*	BAB''	BAB'' (I)
Maximum	11.91	9.10	9.41	9.41	9.41
Minimum	-9.10	-9.10	-7.12	-6.95	-6.95
Mean	5.89	8.92	10.42	12.50	11.19
Standard Deviation	10.57	8.91	10.65	9.95	10.38
Kurtosis	2.66	2.89	0.89	1.13	0.96
Skewness	-0.18	-0.53	-0.13	-0.02	-0.15
Sharpe ratio	0.56	1.00	0.98	1.26	1.08

Table 9: Real-Time Hybrid Betting Against Beta strategy (BAB''(I)), Hybrid Betting Against Beta strategy (BAB''), Risk-managed Betting Against Beta strategy (BAB*), Dynamic Betting Against Beta strategy (BAB') and plain-vanilla Betting Against Beta strategy (BAB) summary statistics. The statistics are computed using monthly observations between 2003:01 and 2013:02. The mean, standard deviation, and Sharpe ratio are annualized.

The statistics show that there is no substantial difference between the performance of the Hybrid strategy (BAB'') and the performance of the Hybrid strategy in real-time (BAB' (I)). There is an expected decrease in the Sharpe ratio from 1.26 to 1.08, but it is still much higher than the plain vanilla BAB strategy for this sample period. In conclusion, the results allow us to say that the strategy works in a real-time situation, with a performance similar to the non-real-time strategy. As presented in Figure 16, an investor that invested 1 monetary unit in a strategy based in the BAB'' (I) strategy in the first trading day of January 2002, would end up with 2.94 monetary units in the last trading day of February 2013, almost the double than he would get if he based his strategy in a plain vanilla BAB.

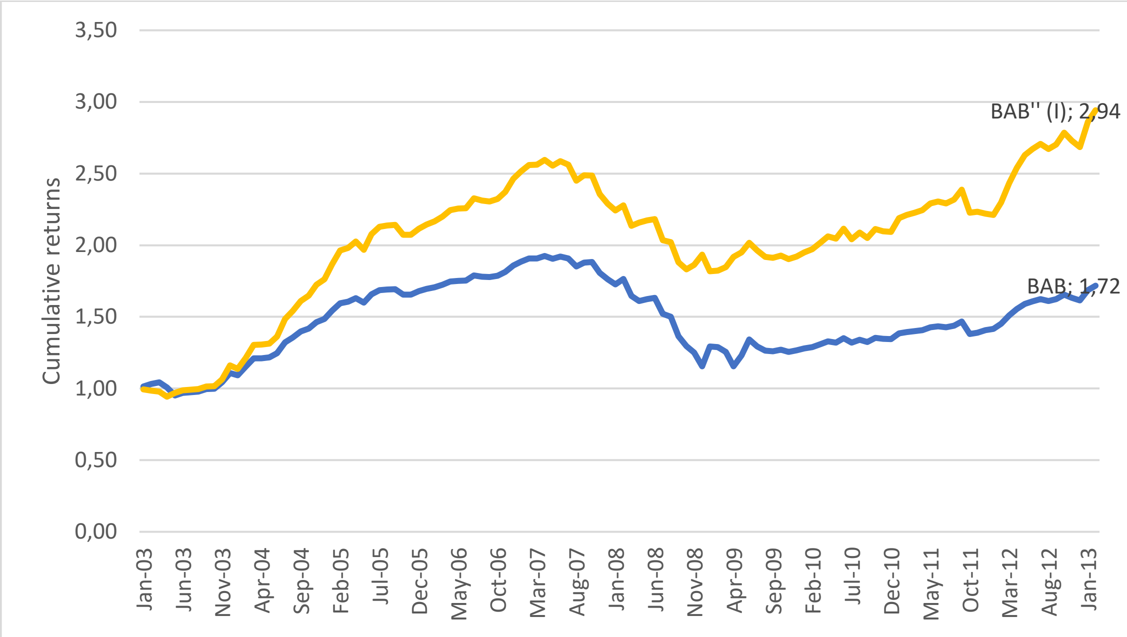

Figure 16: Real-Time Hybrid Betting Against Beta strategy (BAB''(I)), Hybrid Betting Against Beta strategy (BAB''), Risk-managed Betting Against Beta strategy (BAB*), Dynamic Betting Against Beta strategy (BAB') and plain-vanilla BAB strategy (BAB) performance between 2003:01 and 2013:02.

6.2. Limited Weights

In our BAB'' strategy, we decided to limit the weights between -50% and 150%, because not every investor can take a high leverage position or an aggressive short position. We test the robustness of obtained results by analyzing the performance of the proposed strategy BAB'' in four additional scenarios on top of the base case scenario that we designated as (A) -weights between -50% and 150%; (B) – weights between -50% and 100%; (C)- weights between 0% and 150%; (D)- weights between 0% and 100%; (E)- unlimited weights. As a result, we present the summary statistics of each scenario in Table 10.

Factor	BAB''(A)	BAB''(B)	BAB''(C)	BAB''(D)	BAB''(E)
Maximum	12.92	12.92	12.92	12.92	18.78
Minimum	-12.75	-12.75	12.75	-12.75	-12.75
Mean	14.28	10.80	13.32	9.85	19.44
Standard Deviation	13.74	12.29	13.31	11.79	16.24
Kurtosis	1.21	2.17	1.60	2.84	1.14
Skewness	-0.28	-0.41	-0.20	-0.35	0.10
Sharpe ratio	1.04	0.88	1.00	0.84	1.20

Table 10: Four additional scenarios for the implementation of the Hybrid strategy BAB''. Scenario with maximum weight 150% and minimum weight -50% (A), Scenario with maximum weight 100% and minimum weight -50% (B), Scenario with maximum weight 150% and minimum weight 0% (C), Scenario with maximum weight 100% and minimum weight 0% (D), Scenario with maximum weight unlimited and minimum weight -50% (E) summary statistics. The statistics are computed using monthly observations between 1996:03 and 2013:02. The mean, standard deviation, and Sharpe ratio are annualized.

It is possible to infer that the results of the four additional scenarios are substantially different. The scenario (B) and scenario (D) are the scenarios with no leveraging of the portfolio and with the worst performance. On the contrary, scenario (C) and scenario (E) are the ones with the higher amount of leverage and with the best performance. As a result, we notice the importance of leveraging the portfolio for strategy performance.

The strategy that puts no limits to leverage is the one with the best performance, by far. BAB(E) strategy has a Sharpe ratio of 1.20 and, for the first time, a positive skewness. Although these results are hard to obtain by real investors with leverage constraints, the results are still very encouraging.

In summary, the BAB" strategy is very robust towards changes in the weight constraints.

To highlight the robustness of the BAB'' strategy, we compare the cumulative returns of the BAB''(D) strategy, the one with the worst performance, and the BAB strategy cumulative returns. If an investor invested 1 monetary unit in the BAB strategy on the first trading day of March 1996 and continued invested until February 2013, it would end up with monetary 3.61 units at the end of the holding period. On the contrary, an investor that invested 1 monetary unit in the BAB" (D) strategy on the first trading day of March 1996, and continued invested until February 2013, would end up with monetary 4.72 units at the end of the holding period, as plotted in Figure 17. It is clear that BAB"(D), the most weight limited BAB" strategy, performs substantially better than the original BAB, without even short-selling or taking leverage. Moreover, as we can see in Figure 17, it manages the downside risk in periods such as March 2002 to July 2003 and March 2008 to July 2009.

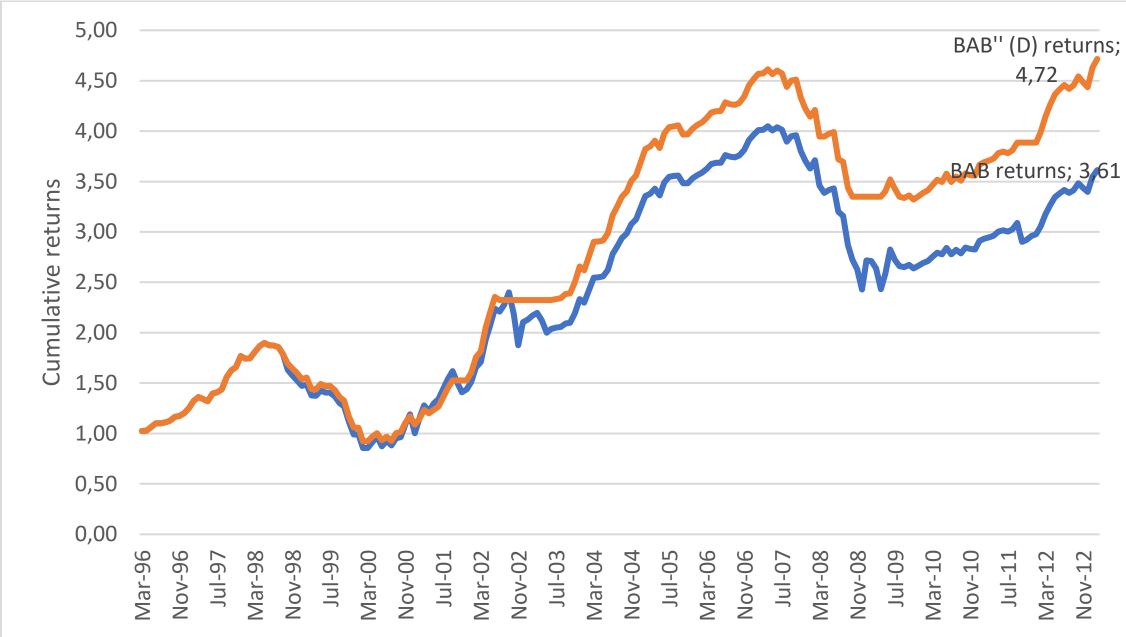

Figure 17: Hybrid strategy BAB'' with a maximum weight of 100% and minimum weight 0% (D), and plain-vanilla Betting Against Beta strategy performance between 1996:03 and 2013:02.

To visualize the payoff of our best strategy, BAB" (E), we can do the same practical exercise. If an investor invested 1 monetary unit in the BAB" (E) strategy on the first trading day of March 1996 and continued invested until February 2013, he would end up with 21.38 monetary units at the end of the holding period, as we can see in Figure 18. This strategy has a payoff 7x higher than the original BAB strategy.

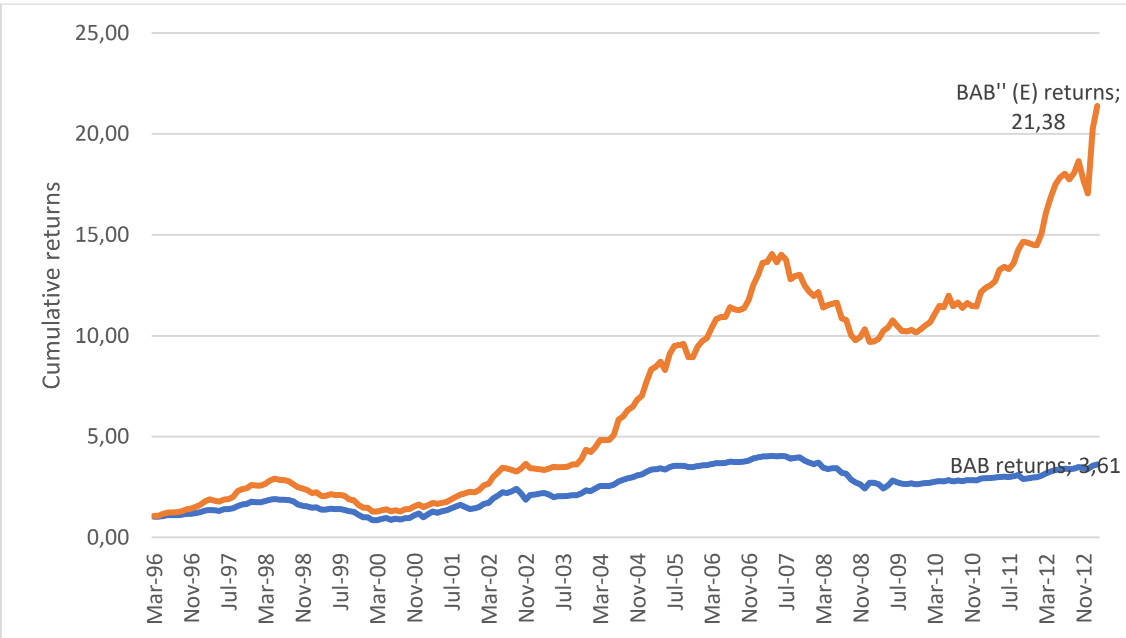

Figure 18: Scenario with maximum weight unlimited and minimum weight -50%, and Betting Against Beta strategy performance between 1996:03 and 2013:02.

Conclusion

The beta anomaly is not only present in the U.S. equity market, but also in ,at least, twenty other countries and diverse asset classes (Frazzini & Pedersen, 2014). The BAB portfolio is a high-performance portfolio, that outperforms other portfolios based on the market, value, size and momentum factors.

In this dissertation, we use, for the first time in the Betting Against Beta (BAB) related literature, information contained in the option-implied correlations, to manage the exposure of a portfolio towards the BAB factor. Namely, we propose two BAB strategies that expose our portfolio to the BAB factor dynamically, depending on the information provided by the dynamics of the S&P500 index option-implied correlation term structure.

In the first strategy, which we denominate by Dynamic BAB strategy, we use the 2-month moving average of the spread between the S&P500 Implied Correlation for 365 days and the S&P500 Implied Correlation for 30 days as a market indicator. The indicator allows increasing the portfolio exposure to the BAB original strategy when we consider that the market is "good" and underexpose our portfolio when we consider that the market is "bad". This strategy provides a better performance by increasing the upside potential while decreasing the downside risk of the strategy.

Furthermore, we combine the Dynamic BAB strategy with the Risk-managed BAB strategy of (Barroso & Maio, 2018), intending to increase the upside potential of the strategy. We denominate this strategy as Hybrid strategy. We expect that the information contained in the forecasted volatility of BAB's returns is useful as a market indicator. The Hybrid BAB strategy generates higher returns, with a lower standard deviation, leading to a Sharpe ratio that almost doubles one of the original strategy. The strategy works in a real-time trading situation and is robust in different weight constraints scenarios, meaning that it does not lose its performance when we place constraints in leverage or short sell.

This dissertation shows that the use of option-implied correlation information helps to improve the performance of a portfolio exposed to the BAB factor. In future research, it might be interesting to analyze whether other option-implied information, such as option-implied skewness and crash-risk, is useful for the construction of BAB related strategies.

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