OptionMetrics

THE IMPLIED BET AGAINST BETA (IBAB) FACTOR:

A New Frontier for Low-Volatility Investing

Garrett DeSimone, PhD, Head of Quantitative Research
Abhi Gupta, Quant Research Associate
Anton Rotach, Quant Research Associate
Oscar Shih, Junior Quant Researcher

Abstract

In this research, we introduce a new factor, IBAB, which utilizes implied betas to construct a long-short portfolio of leveraged low-beta and short high-beta securities. Our results show that in the universe of S&P 500 constituents, IBAB outperforms the traditional BAB factor, with an annualized return of 5.3% compared to BAB's -3.0%. Moreover, IBAB delivers a positive FF5 alpha of 2.5% while BAB exhibits a negative alpha of -6.0%. We further investigate the economic drivers behind the performance difference between IBAB and BAB and find that the implied correlation component of IBAB is the main driver of its superior performance. Additionally, we demonstrate that IBAB's returns fluctuate considerably across correlation regimes, and that the spans of weak factor performance can be attributed to beta compression that occurs during periods of high correlation. Overall, our findings suggest that IBAB is a superior low-volatility strategy to the traditional BAB.

Introduction

The low-beta anomaly dates its origin back to Black (1972), who identified a failure of the CAPM such that high (low) beta stocks generated lower (higher) returns than predicted by the model.

Over the past decade, Frazini and Pedersen (2014) (FP) have introduced the Betting Against Beta (BAB) factor. This strategy involves taking long positions in leveraged low-beta assets and short positions in high-beta assets, resulting in noteworthy risk-adjusted returns. The rationale behind this strategy's success is attributed to the leverage aversion theory, which suggests that investors avoid using leverage and instead overweight high-beta securities. This research has been so influential amongst practitioners and academics that it has spawned an entire cottage industry of defensive low vol strategies.

Despite its success, Betting Against Beta has had its share of recent criticisms. Novy-Marx and Velikov (2022) argue that the unconventional weighting of the BAB factor results in large portfolio concentration on small and micro-cap stocks with high transaction costs. Cederberg and O'Doherty (2016) demonstrate that the unconditional alpha of the BAB strategy is a biased estimate of the true alpha. This bias can be corrected by utilizing a conditional CAPM, which resolves the anomaly.

Given these shortfalls, this research seeks to reimagine the future of BAB. Traditionally, the beta calculation relies on the historical covariance between the individual stock and the market. The expansion of liquid options markets has facilitated the derivation of forward-looking or "implied betas." By harnessing the information of implied betas, we construct a superior factor (IBAB) that outshines the conventional BAB approach. Within our universe of 500 SPY securities, IBAB boasts an annualized return of 5.3%, a stark contrast to the -3.0% return of BAB, while also delivering a positive FF5 alpha of 2.5% compared to BAB's negative alpha of -6.0%.[1]

In this research, we apply the methodology from Buss and Vilkov (2012) to extract option implied market betas. Their results demonstrate the implied beta approach is superior to historical approaches since they serve as a more accurate predictor of future realized betas. Recently, Clara (2018) demonstrates the existence of a significant term structure in implied betas for single stocks and portfolios. This term structure exhibits meaningful time-variation, spiking prior to macroeconomic news and earnings. This finding is relevant to our paper because it solidifies the notion that risk-neutral betas can display large deviations from their physical counterparts.

As a next step in this research, we aim to investigate the economic drivers behind the significant performance differential observed between portfolios constructed using implied beta and historical beta, by asking the question: what factors contribute to this difference? High implied beta can stem from two components in the formula: high risk-neutral volatility or high risk-neutral cross-stock correlations with the portfolio constituents.

Our study follows the approach of Asness et al. (2020) by constructing conditionally sorted portfolios that break down implied beta into its implied volatility and implied correlation components. We then neutralize one component while examining the other. Our results suggest that the performance of IBAB is mainly due to the implied correlation component. Specifically, we find that stocks with low aggregate implied cross-stock correlations outperform those with high correlation by an average of 50 basis points per month.

We attribute the market variance risk premium as a key driver of the difference between BAB and IBAB. Stocks with lower betas are more sensitive to changes in market variance due to lower leverage (balance sheet debt-to-equity), and the market variance risk premium encompasses market-wide risk-neutral correlations. When risk neutral correlations increase, IBAB tends to exhibit lower returns.

[1] Our backtest ranges from Jan 2007 to December 2022. Our universe consists of S&P 500 stocks with valid implied volatilities.

Lastly, we investigate whether the IBAB factor displays time-varying performance. According to FP (2014), deteriorating funding liquidity results in losses to the BAB factor. This is due to investors' inability to access leverage, leading to a shift towards riskier (high beta) assets. Our methodology examines IBAB's performance conditional upon implied correlation regime. Our results suggest that IBAB's returns fluctuate considerably in low, medium, and high regimes. Specifically, IBAB delivers significantly higher risk-adjusted returns in low correlation environments.

The spans of weak factor performance can be attributed to beta compression that occurs during periods of high correlation. As correlations rise, the variation in betas across assets reduces. This is reflected in the average implied correlation, which directly reflects funding constraints. As a result, investors are compelled to divest from low beta assets to reduce their leverage.

The structure of this research paper is as follows: In the next section, we will provide an overview of the methodology used in this study. Subsequently, we will present and discuss the empirical results. Finally, we will draw our conclusions in the last section.

Methodology

Our analysis is based on the top 500 SPY constituents and market capitalization single name securities listed in the US from January 2007 to December 2022 contained in IvyDB Beta.

The implied beta calculation follows Buss and Vilkov (2012) methodology. This is separated into two steps: derivation of an implied correlation $\rho_{ij,t}^{Q}$ matrix and an implied beta $\beta_{iM,t}^{Q}$ calculation. Buss and Vilkov (2012) utilize a semi-parametric formula to extract an implied correlation matrix from the physical (realized) correlation matrix. The implied correlation matrix is calculated as:

$$\rho_{ij,t}^{Q} = \rho_{ij,t}^{P} - \alpha_t(1 - \rho_{ij,t}^{P}),$$

where $\rho_{ij,t}^{P}$ is the physical correlation under the objective measure, and α_t denotes the parameter calculated as follows:

$$\alpha_t = -\frac{(\sigma_{M,t}^{Q})^2 - \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{i,t}^{Q}\sigma_{j,t}^{Q}\rho_{ij,t}^{P}}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{i,t}^{Q}\sigma_{j,t}^{Q}(1-\rho_{ij,t}^{P})},$$

where $i = 1 \ldots N$ are all market index constituents, $\sigma_{M,t}^{Q}$ denotes the implied volatility of the market, w_i are the constituent weights, and $\sigma_{i,t}^{Q}$ denotes the implied volatility of individual securities.[2]

To ensure that the correlation matrix $\rho_{ij,t}^{P}$ is noise-free and semi-positive definite, we first normalize an individual's historical return data. This involves subtracting the cross-sectional mean and dividing by the respective implied volatility prior to computation.

Lastly, the option-implied beta $\beta_{iM,t}^{Q}$ of stock i can be computed from the following equation:

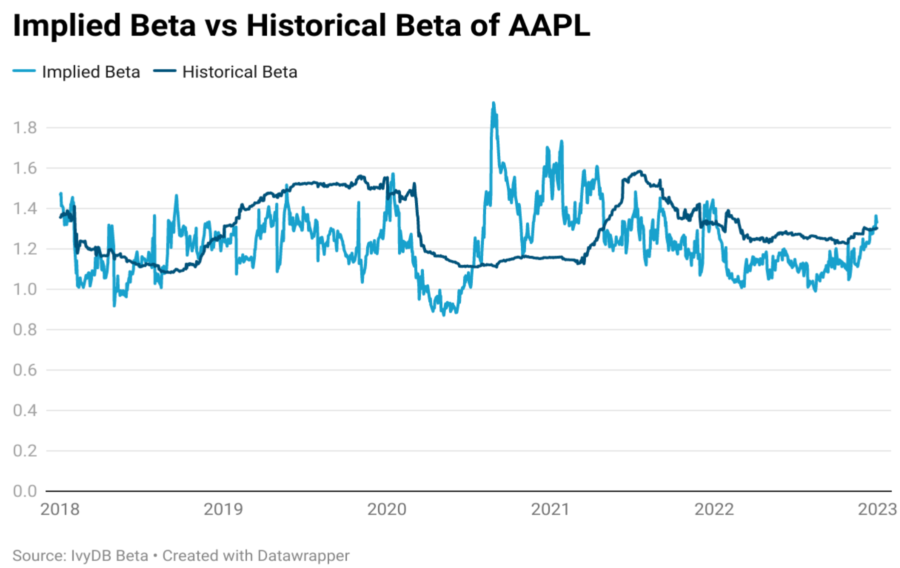
$$\beta_{iM,t}^{Q} = \frac{\sigma_{i,t}^{Q} \sum_{j=1}^{N} w_j \sigma_{j,t}^{Q} \rho_{ij,t}^{Q}}{(\sigma_{M,t}^{Q})^2}$$

Traditionally, betas have been calculated using a historical rolling regression approach. This usually involves using one year of daily returns (Baker, Bradley, and Wurgler 2011) in academic studies. To evaluate the effectiveness of our improved IBAB factor generated from implied beta, we computed historical beta using a one-year rolling regression of market returns on individual stock returns.

Graph 1 showcases the historical beta estimates and the 60-day implied beta for Apple Inc. spanning 2018 to 2022. It's evident that implied beta experiences significantly more variation than traditional beta, with a daily variance of 0.0272 compared to 0.0216. This variation can be attributed to the forward-looking nature of implied beta, which promptly prices in periods of varying systematic risk into options. On the other hand, the drawback of backward-looking historical beta lies in its slow incorporation of information. This is clearly demonstrated by an extremely flat beta during the COVID-19 pandemic in 2020.

[2] Implied betas are restricted to optionable securities with valid 50-delta, 60-day implied volatilities, and a complete one-year return history. Market volatility is also estimated by 50-delta, 60-day volatility on SPY options.

Graph 1



We utilized the IvyDB Beta dataset to create our IBAB portfolio, which comprises long positions in low-implied beta securities and short positions in high-implied beta securities. To construct the IBAB factor, we ranked all securities based on their implied beta, with the bottom and top deciles forming the low-beta and high-beta portfolios, respectively. Within each portfolio, securities were rank-weighted, meaning that lower-beta securities had a larger weight in the low-beta portfolio, while higher-beta securities had a larger weight in the high-beta portfolio. We rebalanced the portfolios on the final trading day of each month.[3]

More formally, let z^L be the $n \times 1$ vector of low-beta (long) portfolio constituents rank and z^H be the $n \times 1$ vector of high-beta(short) portfolio constituents rank. The weights of the low-beta and high-beta portfolio are given by:

$$w^L = z^L / 1'_n z^L$$
$$w^H = z^H / 1'_n z^H$$

where 1_n is an $n \times 1$ vector of ones. By construction, we have $1'_n w^+ = 1$ and $1'_n w^- = 1$. To construct the IBAB factor, both portfolios are rescaled to have an implied beta of zero at portfolio formation. The IBAB portfolio is a self-financing zero-beta portfolio that longs the low-beta portfolio and short sells the high-beta portfolio. The IBAB factor utilizes implied beta estimate to adjust both for leverage component and constituent weights.

[3] We apply the same rank-weighting methodology utilized by FP (2014). Our results are similar for an equal weighted portfolio scheme.

$$r_{t+1}^{IBAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f)$$
where $r_{t+1}^L = r'_{t+1}w_L$, $r_{t+1}^H = r'_{t+1}w_H$, $\beta_t^L = \beta'_t w_L$, and $\beta_t^H = \beta'_t w_H$.

In the subsequent section, we provide empirical evidence regarding the performance and risk characteristics of the IBAB factor.

Empirical Results

Graph 2 below presents a comparison of the performance of the IBAB and traditional BAB factors from 2007 to 2022. The traditional BAB factor is created using historical betas for portfolio sorts, rank weighting, and beta neutralization. To conduct a like-for-like comparison, we utilized the same universe of SPY constituent securities as IBAB. Throughout the entire time frame, IBAB outperformed the traditional BAB factor, with the gap between the two widening after 2012. Despite both factors performing poorly during the Global Financial Crisis in 2008, IBAB recovered its losses more quickly than BAB over the next several years, up to 2018. After the 2020 crash, the IBAB factor experienced a V-shaped recovery, while the BAB factor is yet to recover. When starting with $1 invested in each portfolio, the IBAB factor yielded a return of $2.19, whereas the BAB factor only returned $0.58.

Graph 2

Performance of $1 in Implied BAB and Traditional BAB Factor

Factors are constructed by long low beta stocks and short high beta stocks. Stocks are rank-weighted by beta in each portfolio and leveraged to beta-neutral.

Source: IvyDB Beta • Created with Datawrapper

Table 1 presents an analysis of the beta factors. The annualized returns of the IBAB portfolio were significantly higher at 5.28% compared to the BAB portfolio's negative return of -3.04%, while maintaining a lower volatility profile (0.18 vs. 0.22, respectively). As a result, the Sharpe ratio of the IBAB portfolio was substantially higher at 0.30. Both portfolios had a beta near 0 due to beta neutralization, with the beta of IBAB being closer to 0 (-0.11) because the IBAB returns were more accurately scaled, using implied beta as a better predictor of realized betas. Finally, the 5-factor alpha of the IBAB portfolio was positive at 2.5%, while the BAB portfolio had an exceptionally negative alpha of -6.2%.

Table 1

Portfolio Analytics

Monthly Performance of BAB Factors. Factor is constructed by long low beta stocks, short high beta and leveraged to be beta neutral.

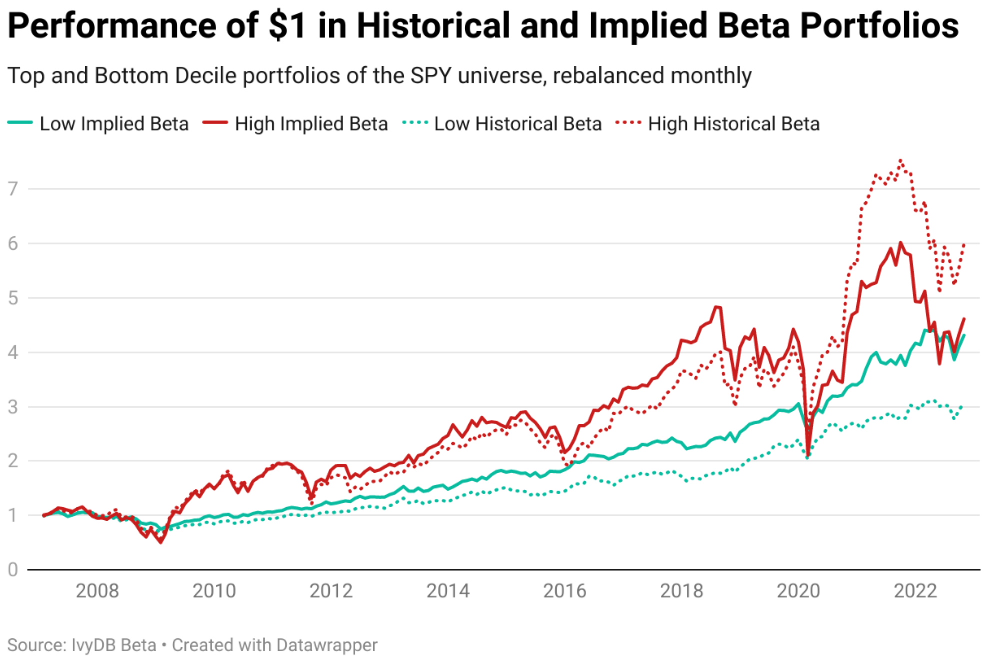
Portfolio	Average Returns	Annualized Returns	Annualized Volatility	Sharpe Ratio	Beta	Annualized 5F Alpha
Traditional BAB	−0.0003	−0.0304	0.2285	−0.0717	−0.2797	−0.0622
Implied BAB	0.0057	0.0528	0.1835	0.3067	−0.1145	0.0250

Sample covers from Jan 2007 to November 2022. SPY annualized returns over this was 6.7% with a Sharpe ratio of 0.39

Source: OptionMetrics • Created with Datawrapper

Next, in order to gain an understanding of the differential performance of the beta factors, we analyze the legs of each portfolio. For Graph 3, we focus on equal weighted portfolios without enforcing beta neutralization. Our analysis shows that low implied beta consistently outperformed low historical beta over the entire time frame with similar variation, while high implied beta only began demonstrating underperformance to high historical beta after 2020. These results suggest that the outperformance of the IBAB Long/Short portfolio primarily comes from the long portfolio.

Graph 3



Conditional Double Sorts

In this section, we aim to determine the economic factors that drive the returns of IBAB. To achieve this, we adopt the methodology proposed by Asness et al. (2020), which involves creating sorted portfolios to break down implied beta into its implied cross-correlation and implied volatility components. Our double sorting procedure consists of first segregating our universe based on the 60-day implied correlation of each security into five equal buckets. Then, each bucket is further sorted based on their 60-day ATM volatility into five additional buckets. This approach allows us to hold implied volatility constant while analyzing the differences in returns between low and high correlation portfolios.

The table below depicts the average monthly returns of the 25 equally weighted portfolios created from this double sorting method. On average, the spread between low and high correlation portfolios is 50 basis points (equivalent to 6% annualized). Notably, the portfolio of the most volatile securities achieves the highest return at 73 basis points, while the portfolio of middle-of-the-pack securities displays the lowest return at 28 basis points.

Based on our findings, it appears that the implied correlation component is an economically significant driver of IBAB's performance. More precisely, we observe that stocks having low overall implied cross-stock correlations yield superior returns compared to those with high overall implied cross-stock correlations.[4]

Table 2

Average Returns of 5X5 Portfolios Sorted on Implied Correlation and ATM IV

Average Return	High IV	High Mid IV	Mid IV	Mid Low IV	Low IV
High Corr	0.0083	0.0073	0.0078	0.0074	0.0068
Mid High Corr	0.0101	0.0077	0.0082	0.0086	0.0080
Mid Corr	0.0053	0.0059	0.0070	0.0085	0.0093
Mid Low Corr	0.0106	0.0090	0.0081	0.0095	0.0098
Low Corr	0.0156	0.0135	0.0106	0.0129	0.0118
Low - High Spread	0.0073	0.0062	0.0028	0.0055	0.0050

Universe is comprised of S&P 500 optionable constituents. Stocks are sorted on 60-Day Implied Correlation, then on ATM volatility.Spread is the difference between low corr and high corr portfolio.

Source: IvyDB Beta • Created with Datawrapper

Next, if we sort first by implied volatility, we can keep implied correlation constant and gain insights into the returns of volatility-isolated portfolios. This approach examines whether risk-neutral volatility alone has a significant impact on IBAB returns. We calculate the return spread by comparing the low implied volatility portfolio with the high implied volatility portfolio.

Table 3 depicts an opposite pattern in the portfolio spreads. The average return for the low-high volatility portfolios is -34 bp, which contrasts sharply with Asness et. al's (2020) findings of positive returns to low (historical) volatility portfolios. Our results indicate that single stock risk-neutral volatility carries a zero or slightly positive risk premium, with the implied volatility component acting as a headwind against IBAB return. These results have interesting implications for future research as they represent a possible high volatility anomaly. However, to stay on track, our findings suggest that the implied cross-correlation component of our implied beta formula primarily drives the performance of the IBAB portfolio.

[4]The distinction between implied cross-stock correlation and traditional market correlation (or stock covariance) is subtle yet significant. The implied beta formula accounts for aggregate implied cross-stock correlation, represented as a weighted sum of the implied correlations between the constituent stocks i and j, multiplied by their respective volatilities. Conversely, traditional beta disregards any covariance structure within the underlying constituents and only considers the correlation between stock i and the market basket.

Having isolated the risk underlying IBAB, the objective of this study is to provide a conceptual understanding of the differential performance of IBAB and BAB. Our analysis indicates that the market variance risk premium plays a pivotal role in driving this performance differential. Specifically, stocks with low asset betas exhibit greater sensitivity to changes in market variance owing to their lower leverage (Lotfaliei, 2020). Notably, the market variance risk premium (VRP)[5] embeds the price of market-wide risk-neutral correlations. The empirical findings reveal that assets with the lowest betas display the smallest difference in correlation premiums (i.e., the risk-neutral and physical correlation gap). Therefore, when risk-neutral correlation increases (accompanied by an increase in VIX), IBAB exhibits low returns.

Table 3

Average Returns of 5X5 Portfolios Sorted on ATM IV and Implied Correlation

Average Return	High Corr	Mid High Corr	Mid Corr	Mid Low Corr	Low Corr
High IV	0.0112	0.0097	0.0095	0.0111	0.0159
Mid High IV	0.0084	0.0072	0.0068	0.0099	0.0107
Mid IV	0.0090	0.0084	0.0075	0.0091	0.0102
Mid Low IV	0.0100	0.0082	0.0090	0.0067	0.0095
Low IV	0.0083	0.0058	0.0086	0.0086	0.0088
Low - High Spread	−0.0029	−0.0039	−0.0009	−0.0025	−0.0071

Universe is comprised of S&P 500 optionable constituents. Stocks are sorted on ATM volatility, then on 60-Day Implied Correlation. Spread is the difference between low IV and high IV portfolio.

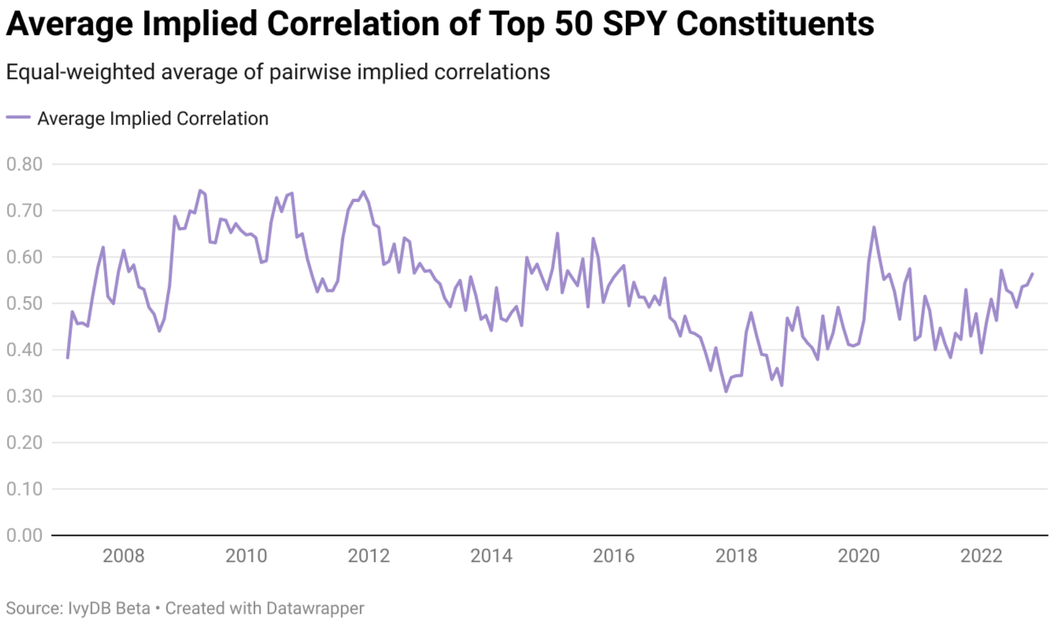
Source: IvyDB Beta • Created with Datawrapper

Time-Series Variation

In this subsection, we will explore the returns of the IBAB factor, dependent on the implied correlation regime. To define the implied correlation environment, we will compute the simple average of the top 50 SPY constituents. Graph 4 illustrates the end-of-month time-series of implied correlation throughout our sample. The average correlation value over time is 0.53, with a standard deviation of 0.99. As expected, implied correlations increase during periods of crisis such as the GFC in 2008, the EU sovereign debt crisis in 2012, and the 2020 pandemic.

[5] The VRP is often measured as 30-Day VIX minus realized volatility on the S&P 500. Variance risk carries a negative premium, which indicates assets that hedge against increases in market wide volatility perform poorly.

Graph 4



Subsequently, at the conclusion of every month, the correlation values are classified into three distinct regimes, namely, low, medium, and high. For the entire sample period spanning from 2007 to 2022, each regime comprises 64 months of observations. A detailed summary of the average, standard deviation, and Sharpe ratio of the returns for the IBAB factor in the subsequent month (t+1 from observed correlation) is presented in Table 4.

The IBAB's average monthly returns decrease gradually from 1.06% to 0.08% as correlation levels rise from low to high environments. While the standard deviation of monthly returns is similar across categories, the medium regime has the lowest risk. From a risk-adjusted perspective, low correlation periods perform better, with a Sharpe ratio of 0.65.

The considerable variations in returns between regimes can be attributed to the beta compression effect. As implied correlations increase, betas converge towards 1, resulting in a reduction of beta dispersion across assets. Consequently, the risk in IBAB becomes more concentrated in the market factor. During these periods, IBAB tends to exhibit lower returns as it transforms into a "bet against the market” ex-post. In other words, when stocks are highly correlated, IBAB's risk profile becomes similar to a short trade on the broad equity market.

Table 4

IBAB Factor Returns Conditional on Implied Correlation Regime

Correlation Regime	Avg Monthly Returns	Std dev	Annualized Sharpe
Low	0.0106	0.0566	0.6479
Medium	0.0051	0.0479	0.3714
High	0.0008	0.0548	0.0517

Sample is equal sorted into groups based on Implied Correlation level at portfolio formation. Each regime contains an average of 64 months.
Source: IvyDB Beta • Created with Datawrapper

Conclusion

While successful, BAB has been criticized for its unconventional weighting and portfolio concentration on small and micro-cap stocks with high transaction costs. This research seeks to reimagine the future of BAB by using implied betas instead of historical betas to construct a superior factor (IBAB) that outperforms BAB. The study also investigates the economic drivers behind IBAB's performance and finds that the implied correlation component is the main contributor.

Furthermore, the study examines IBAB's performance under various implied correlation regimes and concludes that it delivers significantly higher risk-adjusted returns in low correlation environments. This white paper presents a valuable case study demonstrating the effectiveness of option-implied measures in enhancing defensive and low-volatility strategies.

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