A Downside-Risk Augmentation of the BAB Factor

Anika Handa, Deep Marwadi, Dhruv Jain MK, Saakshi Dedhia

Professor Shane Shepherd – FBE 551

November 30, 2025

1. Introduction

The relationship between market beta and expected returns has been a central topic in asset pricing since the development of the Capital Asset Pricing Model (CAPM). However, a growing body of empirical evidence shows that low-beta stocks systematically outperform high-beta stocks on a risk-adjusted basis, contradicting CAPM's linear risk–return tradeoff. This phenomenon, formalized in the Betting Against Beta (BAB) factor of Frazzini and Pedersen (2014), has become one of the most robust anomalies in cross-sectional equity returns. While the BAB strategy captures mispricing caused by leverage constraints and delegated portfolio management, its implementation remains sensitive to periods of market stress, volatility clustering, and large drawdowns, conditions under which beta estimates become unstable and traditional BAB portfolios can experience sharp reversals.

This paper investigates whether incorporating downside risk, specifically maximum drawdown, can improve the stability and performance of the traditional BAB strategy. Maximum drawdown captures persistent loss potential and path-dependent risk that is not reflected in beta alone, making it a natural conditioning variable for defensive investing. We construct a drawdown-filtered BAB portfolio (BAB-DD) by integrating recent drawdown behavior into the security-selection stage of the BAB framework, separating stocks not only on beta but also on their susceptibility to severe price declines. Using U.S. equities from 2014 to 2024, we evaluate whether a drawdown-conditioned BAB factor delivers superior risk-adjusted returns, reduced crash risk, and improved resilience during market stress. This study contributes to the literature by showing how downside-risk conditioning interacts with the beta anomaly and whether drawdown filters can strengthen or weaken the defensive premium documented in prior research.

2. Literature Review

The study of beta anomalies originates with early challenges to the Capital Asset Pricing Model (CAPM). Black, Jensen, and Scholes (1972) first documented that the empirical security market line is substantially flatter than predicted, implying that high-beta assets underperform and low-beta assets outperform relative to CAPM expectations. This line of research culminates Frazzini and Pedersen (2014), who formalize the Betting Against Beta (BAB) factor by showing that leverage constraints among institutional investors prevent them from scaling low-beta assets, forcing them toward high-beta securities instead. Their model demonstrates that these constraints distort equilibrium pricing, leading low-beta portfolios to earn persistent abnormal returns across asset classes including equities, credit, bonds, and futures.

Subsequent empirical work extends the BAB framework by exploring beta instability and sensitivity to market stress. Frazzini and Pedersen show that BAB returns vary with funding liquidity: when margin conditions tighten, betas compress toward one and the performance of the BAB factor declines. More recent research examines whether conditioning beta strategies on downside-risk measures can mitigate these weaknesses. Drawdown-based metrics such as maximum drawdown capture path-dependent risk that beta alone cannot, especially during periods of market turbulence. Studies on crash risk, downside semi variance, and tail-sensitive volatility measures suggest that integrating downside filters can improve the robustness of traditional factor strategies by excluding financially fragile or crash-prone securities. Motivated by these extensions, our work incorporates a drawdown filter into the BAB framework to investigate whether conditioning on recent downside risk enhances the stability, resilience, and predictive power of beta anomaly.

3. Data and Methodology

3a. Data Description

Our dataset is constructed from the CRSP daily files and includes all common equities listed on the NYSE, NASDAQ, and AMEX exchanges. For each month from 1990 to 2024, we sort stocks by market capitalization and retain the largest 1,000 securities, ensuring a liquid and representative universe while excluding microcaps and thinly traded firms. The variables used include daily prices (PRC), returns (RET), shares outstanding (SHROUT), and delisting returns, from which we construct adjusted prices and cleaned daily returns to correct for stock splits and missing values.

Although the full sample spans 1990–2024, our empirical analysis focuses on 2014–2019 (in-sample) and 2020-2024 (out-of-sample), a period selected for its data completeness and relevance to modern equity market conditions. To avoid survivorship and re-listing bias, we require each firm to have continuous monthly CRSP coverage during this decade. From this filtered panel, we compute rolling betas using 252-day windows and maximum drawdowns using 66-day windows, forming the basis for the drawdown-conditioned BAB portfolios evaluated in the study.

3b. Data Methodology

Our methodology begins with a rigorous data-cleaning process to address limitations in the raw CRSP dataset. Because CRSP's price (PRC) variable is not split-adjusted, we construct pseudo–adjusted prices by taking the cumulative product of daily returns, ensuring that all split events and corporate actions are incorporated without relying on external adjustment factors. Cleaned daily returns are then derived from these adjusted prices, and extreme or erroneous values are removed to ensure a consistent return series across firms. After filtering the universe to include only stocks with continuous monthly observations, we compute each firm's rolling 252-day market beta and 66-day maximum drawdown, yielding measures of systematic risk and downside behavior that serve as inputs to our factor-sorting strategy.

We construct a modified beta–drawdown framework by jointly sorting stocks into quintiles based on their historical market beta and recent maximum drawdown. Portfolio formation occurs monthly: firms are sorted into five beta quintiles using lagged beta estimates to avoid look-ahead bias, and within each beta quintile they are further sorted into five drawdown quintiles based on their 66-day maximum drawdown. This produces a 5×5 matrix of long-only portfolios, each representing a distinct combination of beta and downside-risk characteristics. For each bucket, we compute equal-weighted daily returns, which are then aggregated into monthly and cumulative performance series. We evaluate each portfolio using annualized returns, cumulative returns, volatility, Sharpe and Sortino ratios, downside deviation, and maximum drawdown. This approach allows us to examine how conditioning beta exposures on recent downside behavior alters the performance hierarchy across the cross-section, and whether drawdown filters strengthen, weaken, or reshape the traditional patterns associated with beta-sorted portfolios.

4. Analysis and Results

To evaluate the performance of the drawdown-conditioned Betting Against Beta strategy, we compute portfolio returns across beta-sorted quintiles, where Quintile 1 contains the lowest-beta stocks, and Quintile 5 contains the highest-beta stocks. We analyze multiple key metrics: annualized mean returns, annualized volatility, Sharpe ratio, Sortino ratio, Calmar ratio and cumulative returns, over two periods: an in-sample window (2014–2019) used for model development and an out-of-sample window (2020–2024) used to assess robustness.

4.1. Overview of In-Sample Findings (2014–2019)

Our in-sample results reveal that drawdown (DD) plays a significant role in explaining cross-sectional return differences. When the full 1000-stock universe is double-sorted into quintiles by beta and maximum drawdown, the low-DD buckets outperform consistently across all beta levels. This pattern is extremely robust, appearing even when controlling for survivorship adjustments, pseudo-split-adjusted prices, and the cleaning procedures implemented in the preprocessing stage.

For example, the high-beta × low-DD portfolio delivers an annual return of approximately 7.78% and a Sharpe of 0.36 over the 2014–2019 period. This example reflects the broader pattern we find across most beta quintiles: portfolios with lower drawdowns consistently outperform their higher-drawdown counterparts.

This dominance of the low-DD portfolios suggests that investors systematically reward recent resilience, potentially interpreting shallow drawdowns as signals of stability, improving fundamentals, or lower tail-risk. In effect, low-drawdown stocks embody a momentum-plus-quality hybrid, consistent with Frazzini & Pedersen (2014), Asness et al. (2013), and the literature linking downside protection with future outperformance.

4.2 Interesting Findings:

Both the theoretical and empirical patterns converge to highlight two dominant portfolios:

(1) High Beta × Low DD (Sharpe ~ 0.57)

The strongest-performing portfolio in our results is the High Beta × Low DD bucket. Despite its high sensitivity to market movements, this portfolio delivers some of the highest cumulative returns in the sample, driven by the fact that it exclusively selects high-beta stocks that have recently shown stability and avoided major drawdowns. This creates a powerful combination: the portfolio participates aggressively in market recoveries while filtering out the fragile names that typically drag down high-beta strategies. In effect, this bucket behaves like a momentum-filtered version of high beta, capturing upside volatility without inheriting the typical tail-risk penalties.

(2) Low Beta × Low DD (Sharpe ~ 0.92)

The second consistently strong performer is the Low Beta × Low DD portfolio. It offers a much smoother equity curve, lower volatility, and some of the highest risk-adjusted returns, including superior Sharpe, Sortino, and Calmar ratios. This bucket resembles an enhanced version of the classic low-risk anomaly, where stable, low-beta stocks outperform despite their lower market exposure. The addition of the drawdown filter strengthens this effect even further, ensuring that the portfolio is tilted toward companies exhibiting both structural stability and recent resilience. The result is a defensive but highly efficient return profile that compounds steadily across market regimes.

(3) Low Beta × High DD (Sharpe ~ 0.35)

A third notable performer is the Low Beta × High DD portfolio, which, though more volatile than the low-DD buckets, still generates meaningful returns and a moderate Sharpe ratio. Interestingly, this bucket constitutes an exception to the broader pattern in which high-drawdown portfolios generally produce negative or negligible Sharpe ratios. Its comparatively strong risk-adjusted performance indicates that low-beta exposure may confer a stabilizing influence, enabling a more efficient recovery from drawdowns relative to higher-beta counterparts in the same drawdown category. This behavior reflects a mild reversal dynamic: low-beta stocks that have recently experienced deep drawdowns tend to be fundamentally stable but temporarily oversold, leading to partial recoveries in subsequent periods. While not as strong as the low-DD portfolios, this bucket's performance highlights how combining defensive beta characteristics with short-term mean-reversion effects can still produce attractive outcomes. Together, these three buckets reinforce the central conclusion that drawdown is the dominant dimension of performance, with beta shaping the overall return patterns.

4.3 Out-of-Sample Validation

In 2020–2024, which includes the COVID crash, the patterns remain consistent with the in-sample results. Low-DD portfolios continue to outperform: the high-beta × low-DD portfolio delivers ~11-12% annualized returns, a Sharpe ratio around 0.52 and maintains a max drawdown below –25%. In contrast, the low-beta × high-DD portfolio suffers a drawdown exceeding –26% and a Sharpe ratio below 0.05. The low-beta × low-DD portfolio shows the smoothest path, with volatility around 8.5%, sortino ratio of 0.7, and a Sharpe ratio between 0.52. The low-beta × high-DD reversal effect weakens slightly out-of-sample but still produces positive excess returns in 2021–2022. Overall, low drawdown remains the most reliable predictor of return performance during turbulent and recovery periods.

4.4 Theoretical Interpretation

The performance hierarchy that emerges from the beta–drawdown matrix aligns closely with several established theories in asset pricing. The consistent strength of low-drawdown portfolios reflects characteristics typically associated with both momentum and quality: stocks that avoid deep declines tend to exhibit stable fundamentals, steady earnings, and sustained investor demand.

This stability creates a natural advantage that persists across beta levels, explaining why low-DD portfolios dominate the return matrix.

Within this structure, the strong performance of the low-beta × low-DD bucket maps directly onto the classic low-risk anomaly, where conservative stocks earn outsized risk-adjusted returns. The addition of the drawdown filter strengthens this anomaly by excluding names experiencing recent fragility, yielding an even more defensive and efficient return profile. In contrast, the low-beta × high-DD bucket demonstrates a different mechanism: its positive but moderate performance reflects a short-term reversal effect, where fundamentally stable companies that experience sharp temporary selloffs tend to rebound as prices correct back toward intrinsic value. However, the performance of the low-beta × high-DD deteriorated in the out-of-sample period.

On the opposite end of the spectrum, the consistent underperformance of high-beta × high-DD portfolios aligns with theories of crash sensitivity, leverage constraints, and tail-risk amplification. These stocks combine high market exposure with recent fragility, making them particularly vulnerable during periods of tightening liquidity or risk aversion. Their weaknesses help explain the broader pattern that conditioning on downside stability helps improve risk-adjusted returns.

5. Conclusion

This paper investigates how beta and maximum drawdown interact in shaping the cross-section of equity returns, and our results show that drawdown is the dominant conditioning variable. Across both the 2014–2019 in-sample period and the 2020–2024 out-of-sample window, portfolios with lower recent drawdowns consistently outperform those with higher drawdowns, even when holding beta constant. This pattern persists through major stress episodes, including the COVID-

19 crash, where low-DD portfolios preserve capital more effectively and recover more quickly, underscoring the path-dependent nature of returns and the critical role of downside resilience.

A central implication of our findings is that drawdown, is the effective organizing principle of portfolio performance. Once stocks are sorted by recent drawdown, the return hierarchy becomes immediately clear, and the familiar distinctions across beta levels largely fade.

Overall, the evidence suggests that drawdown acts as a powerful, intuitive filter that sharpens and reorganizes traditional risk premia. Incorporating downside-based metrics into factor construction provides a more realistic characterization of risk, revealing information about investor preference for stability, fundamental durability, and momentum-quality dynamics that beta or volatility alone cannot capture. These findings point toward a broader conclusion: in modern equity markets, downside risk is the primary axis along which return differentials are expressed, and other risk measures function meaningfully only when conditioned on it.

5.1 Future Scope

There are several promising avenues for extending this work. First, future research could explore whether the predictability of drawdowns persists across international equity markets, alternative asset classes, or sector-level portfolios, allowing us to test whether drawdown stability is a universal premium or primarily a U.S. phenomenon. Second, our study could be enhanced by incorporating more advanced forecasting techniques, such as LSTM networks, Transformer-based time-series models, or tree-based machine learning models trained specifically to predict transitions between low- and high-drawdown states. Third, a natural extension would involve investigating the drivers behind drawdown resilience, such as earnings stability, leverage, institutional ownership, or sentiment indicators, to understand whether low-DD stocks systematically exhibit superior fundamentals or whether investor behavior contributes to this premium. Additionally, incorporating transaction costs, turnover analysis, and portfolio capacity constraints would help assess the real-world implementation of the strategy. Finally, future work could examine interactions between drawdown filters and other well-studied anomalies, such as value, profitability, or investment, to determine whether drawdown serves as a unifying conditioner that sharpens multiple factor premiums. Together, these directions offer meaningful opportunities to deepen our understanding of downside-based risk measures and their role in modern portfolio construction.

References

Frazzini, A., & Pedersen, L. H. (2013). Betting against beta. *Journal of Financial Economics*, *111*(1), 1–25. https://doi.org/10.1016/j.jfineco.2013.10.005

Choia, J. (2015). Maximum drawdown, recovery and momentum. *Elsevier*. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.758.1014

Appendix

bucket	alpha	beta	alpha_annual	t_alpha	t_beta	R2
b1_d1	0.00	0.73	0.01	0.19	4.07	0.22
b1_d2	0.00	0.55	-0.02	-0.35	5.35	0.33
b1_d3	0.00	0.55	0.02	0.60	5.77	0.37
b1_d4	0.00	0.43	0.05	1.16	4.36	0.25
b1_d5	0.00	0.30	0.05	1.80	4.13	0.23
b2_d1	-0.01	1.12	-0.14	-2.12	7.39	0.49
b2_d2	0.00	1.04	-0.02	-0.66	12.50	0.73
b2_d3	0.00	0.88	0.01	0.19	12.89	0.74
b2_d4	0.00	0.81	0.03	1.10	14.89	0.80
b2_d5	0.00	0.59	0.02	0.95	10.53	0.66
b3_d1	0.00	1.17	-0.05	-0.79	7.47	0.49
b3_d2	-0.01	1.04	-0.06	-1.56	11.10	0.68
b3_d3	0.00	1.10	0.00	-0.08	15.59	0.81
b3_d4	0.00	0.98	0.04	2.07	19.94	0.87
b3_d5	0.00	0.77	0.05	2.16	14.99	0.80
b4_d1	-0.01	1.12	-0.10	-1.44	6.99	0.46
b4_d2	-0.01	1.22	-0.07	-1.69	12.88	0.74
b4_d3	0.00	1.10	-0.01	-0.29	14.84	0.79
b4_d4	0.00	1.07	0.01	0.46	18.07	0.85
b4_d5	0.00	0.94	-0.02	-0.54	9.80	0.64
b5_d1	-0.01	1.56	-0.16	-1.72	7.07	0.47
b5_d2	-0.01	1.21	-0.07	-1.32	10.03	0.64
b5_d3	0.00	1.14	-0.03	-0.63	9.33	0.60
b5_d4	0.00	1.06	-0.04	-1.19	14.01	0.78
b5_d5	0.00	1.36	0.05	0.65	8.17	0.61

CAPM Results

Explaining CAPM Results: Given the limited time series (~59 monthly points per portfolio), the alpha estimates should be interpreted with caution, as low degrees of freedom suppress statistical power. Even so, several buckets display positive annualized alpha and t-statistics near the 90% confidence level, indicating that the economic signal is non-trivial despite statistical noise. Expanding the horizon, incorporating international data, or extending the sample backwards would materially increase power and may reveal statistically significant alpha where the current sample is simply too short to confirm it.

Beta/DD	High DD	2	3	4	Low DD
Low Beta	6.64	11.43	16.34	20.62	33.1
2	9.94	14.98	18.91	22.14	22.73
3	13.15	17.48	19.02	20.47	18.79
4	18.52	22.77	20.46	16.52	10.2
High Beta	40.27	21.99	13.73	8.79	3.93

(Avg bucket sizes 2014-24)

Beta/DD	High DD	2	3	4	Low DD
Low Beta	0.08	0.04	0.08	0.09	0.09
2	-0.03	0.07	0.09	0.10	0.08
3	0.06	0.03	0.10	0.13	0.12
4	0.01	0.04	0.09	0.11	0.06
High Beta	-0.02	0.04	0.07	0.06	0.14

Mean Return (annualized)

Beta/DD	High DD	2	3	4	Low DD
Low Beta	0.40	0.18	0.44	0.55	0.53
2	-0.22	0.36	0.49	0.61	0.47
3	0.19	0.12	0.55	0.86	0.70
4	-0.06	0.16	0.49	0.64	0.26
High Beta	-0.25	0.14	0.32	0.28	0.57

Cumulative Return

Beta/DD	High DD	2	3	4	Low DD
Low Beta	0.19	0.12	0.11	0.10	0.07
2	0.19	0.15	0.12	0.11	0.09
3	0.20	0.15	0.15	0.13	0.10
4	0.20	0.17	0.15	0.14	0.14
High Beta	0.27	0.18	0.18	0.14	0.21

Volatility

Beta/DD	High DD	2	3	4	Low DD
Low Beta	0.35	0.18	0.55	0.71	0.92
2	-0.27	0.37	0.56	0.76	0.70
3	0.18	0.10	0.54	0.91	0.92
4	-0.07	0.14	0.49	0.65	0.28
High Beta	-0.14	0.13	0.30	0.28	0.57

Sharpe