Risk-Mitigated Momentum - Literature Review

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Introduction

Ever since Jegadeesh and Titman (1993) first introduced the strategy of buying historical winners and selling losers, momentum has become one of the most studied factors within finance. This financial anomaly has been demonstrated to occur consistently throughout different asset classes, and financial markets, providing excess returns even after controlling for other common risk factors (Asness et al., 2013). Despite consistent returns with a high Sharpe Ratio, deeper analysis of momentum-based portfolios has found that they often experience extreme crashes during turbulent markets. Numerous potential explanations have been proposed for this behavior, demonstrating that the momentum factor can be improved by accounting for this risk. Three such articles will be examined, explaining these momentum crashes through momentum-specific risk, the short leg of the portfolio in bear markets, or the cross-sectional stock volatility. Then, a plan to further the existing research will be provided.

Momentum Has Its Moments

The article "Momentum Has Its Moments" by Barroso and Santa-Clara (2015) analyzes the momentum factor of winners minus losers (WML) and how it can be optimized within a portfolio setting. They find that although the base WML portfolio does provide an impressive Sharpe Ratio when compared to traditional Fama and French (1992) risk factors, it comes with a hidden cost. In comparison to excess market returns (RMRF), size (SMB), and value (HML), momentum exhibits a high kurtosis and large negative skew, meaning it is susceptible to immense crashes. Within their tested sample, momentum had a return of −91.59% over just two months in 1932, with a similar crash of −73.42% within three months in 2009. This is an immense risk for any investor to take on, with decades of earnings wiped out in an instant. They then look to explain this excess kurtosis by examining the factor's properties, finding that the factor has an immense time-varying volatility that is not traditionally captured. The monthly deviation of the portfolio changes dramatically from period to period as measured with a rolling Sharpe Ratio, meaning that a single summary statistic hides the underlying details. The authors propose that this is a momentum-specific risk that needs to be accounted for when building a portfolio. They look to address this issue through using a risk-adjusted momentum strategy where the portfolio's weighting is based on the realized daily volatility of the portfolio itself over the past 6-month period. They demonstrate that this has a profound impact on the overall risk-to-reward trade-off, almost doubling the Sharpe Ratio from the base momentum factor. This risk mitigation also standardized the kurtosis and skew of the portfolio returns to far less extreme values, more consistent with a normal distribution (kurtosis to 2.68 from 18.24 and skew to -0.42 from -2.47). The overall findings of this article suggest that momentum risk is predictable and that managing it greatly reduces exposure to crashes.

Overall, this is a good article that clearly illustrates the background of the topic. The authors take the time to analyze the distribution of the factor and decompose the portfolio risk, providing a solid economic and statistical basis for their strategy. The dramatic change in distributional properties (skew and kurtosis in particular) clearly demonstrates that time-varying portfolio deviation is a key component of momentum crash risk. The biggest problem with the article, however, is that all the portfolios analyzed and compared are only based on single factors (just SMB, or just WML for example). In a practical investment setting, even a momentum-based portfolio will generally consider other factors for a more robust model. This risk-adjustment method misses one alternative explanation that a combination of other factors traditionally used in multi-factor models might already be capturing this risk, explaining away this additional predictive power. Practical implementations of zero-cost strategies like HML often face extreme transaction costs due to their high turnover which greatly reduces their effectiveness. As will be shown in later articles, alternative explanations for this risk are found.

Momentum Crashes

Daniel and Moskowitz (2016) explore the nature of these large crashes in momentum in their paper “Momentum Crashes”. Based on their findings, they test a dynamic momentum strategy with significant improvements across asset classes and economic markets. The article begins with a case study of the WML portfolio over the past century, largely focusing on the historical predictability of these momentum crashes using bear market indicator variables. The authors suggest that the momentum factor performs similarly to the short side of call option within bear markets, exposing the portfolio to immense risk as the stocks recover from their downward trend. Through examining portfolio composition, Daniel and Moskowitz suggest that the fault of these momentum crashes is mainly on the short side of the portfolio overperforming. Several separate regression analyses are conducted, trying to explain this property of momentum through features like market variance or the three Fama French (1993) factors. However, none of the tested factors could sufficiently explain the momentum crashes. To capture this feature, they create a dynamically weighted momentum portfolio where the weight is based on past market volatility in addition to a forecast of future market volatility using a bear-market indicator. In their testing, this portfolio performs far better than the base momentum strategy, greatly increasing the Sharpe Ration and reducing the large negative kurtosis from crashes. They replicate these results across various asset classes, and financial markets, consistently demonstrating the same strong performance. Daniel and Moskowitz conclude that although the momentum effect does seem to reverse in the aftermath of market crashes, accounting for this feature can dramatically improve the performance of momentum-based portfolios.

Overall, this is a very compelling article that does thorough research into the nature of the momentum factor, and potential explanations for its behaviour. The authors do numerous robustness checks, testing their strategy with different periods, assets, and even across international markets. This goes well beyond the testing done in “Momentum Has Its Moments”, demonstrating the persistent nature of their findings. Daniel and Moskowitz also fix another problem in that article by using regression to attempt to explain these excess returns through other factors like volatility risk, or Fama French (1993) factors. One potential criticism of their analysis, however, is that the dynamic strategy utilized an immense amount of leverage. This likely inflated the ultimate returns of the portfolio, since the overall market trend of the past century has been predominately positive. Additionally, if the momentum crashes are truly caused by the short side of the portfolio, this raises the question of if this risk can be mitigated in another manner to capture the reversing market trend, rather than simply investing less money. Although the article demonstrates a strong case for utilizing their risk-adjusted momentum factor, it still leaves room for further analysis to find the most effective one.

Momentum and the Cross-section of Stock Volatility

Fan et al. (2022) provide a third explanation for these crashes through their article "Momentum and the Cross-section of Stock Volatility". They suggest that the crash-related risk is based on the individual stocks' volatility, as opposed to momentum-specific volatility. They demonstrate that within the stock-selection process, momentum portfolios tend to choose high-volatility (often high Beta) stocks since these tend to have the highest absolute returns. Then, these same high-volatility stocks tend to have immense losses in times of market uncertainty (crashes). Interestingly, they find that when controlling for these high-volatility stocks, low-to-medium volatility stocks with high momentum are far more likely to carry forward this momentum. In a similar manner to Barros and Santa-Clara, the authors establish that simple risk-adjustment methods such as a Sharpe Ratio are not sufficient to mitigate these risks. They suggest that the Sharpe Ratio often does not penalize deviation enough and propose a modified Sharpe Ratio that uses higher powers of the realized volatility (which they denote N). To try and adjust for the time-varying volatility of the market, N shifts over time based on investor preference and the market conditions. In the end, Fan et al. demonstrate that this methodology can be used to create a superior momentum portfolio by reducing their reliance on these high-volatility stocks. They regress their model with a four-factor extended Fama-French model (Cahart, 1997) in addition to various risk factors and show that it exhibits statistically significant unexplained alpha.

This is another strong article that further examines the momentum factor and potential underlying causes for its sudden crashes. It also does an effective job of not just presenting a portfolio strategy, but in building a strong economic case. It studies the relationship behind the factor and demonstrates the clear clustering of high volatility stocks within momentum portfolio selection. This article provides an alternative perspective to the portfolio volatility perspective suggested in “Momentum Has Its Moments”, with the authors running a direct performance comparison between the two strategies to show that their model performed better (at least in their testing). The robustness checks at the end show that their factor provides new information that is not just captured by traditional risk factors. However, these checks are nowhere near as in-depth as “Momentum Crashes” with its numerous different markets and asset classes. These conflicting explanations raise the question of the true cause of momentum crashes, and the best way to mitigate these risks.

Research Summary

Overall, even though momentum-based strategies are exposed to extreme crash risks, risk-mitigation techniques can capture at least part of this risk, producing more robust portfolios. Barrosa and Santa Clara (2015) suggest that this crash risk is momentum-specific and is caused by time-varying volatility. An alternative decomposition of this risk shows instead that these crashes are caused by the short leg of the portfolio during bear markets, which can be addressed through bear market indicators (Daniel & Moskowitz, 2016). Finally, an entirely different rationale is suggested by Fan et al. (2022); the risk comes from the cross-sectional stock volatility rather than any risk inherent to the momentum strategy. Although accounting for this crash risk provides clear benefits to a momentum strategy, it remains to be seen what factor best captures this risk.

Next Steps

To further this research, I am looking to test these different explanations within a factor investing framework. The core idea will be to create several different portfolios based on different risk-adjusted momentum factors to see which has the strongest predictive power.

Most of the literature in question used the Fama and French (1993) 3-factor model as a basis for comparison, capturing traditional and economically sound risk factors. So, each portfolio tested will contain 4 factors: the excess market return (RMRF), size (SMB), and value (HML), along with a momentum factor. Our benchmark will use the base momentum factor (WML), while the other portfolios will use different risk-adjusted versions based on the articles in question, with potentially more added, time permitting. For a more robust analysis that captures non-linear trends, an ensemble of uncorrelated machine learning algorithms will be used on these 4-factor models using historical stock data. The performance of these portfolios can then be tested over the past decade, determining which method performs best overall, with particular emphasis on capturing the risk throughout the Covid market crash. Further analysis could also test portfolios with multiple risk-adjusted momentum factors, though care needs to be taken to avoid potential multicollinearity. This research will supplement the existing literature, serving as an investigation into the nature of momentum risk, while supporting its use within a broader quantitative investing framework.

Works Cited

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