LOW-RISK STRATEGIES IN THE CRYPTOCURRENCY MARKET

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Abstract

Empirical evidence shows that low-volatility securities deliver higher returns compared to high-volatility ones in international financial markets and across asset classes. This study investigates the performance of low-volatility investment strategies within the cryptocurrency market using a sample of highly liquid digital coins from 2016 to 2025. We find that some strategies have a positive and statistically significant payoff, but this does not survive to conservative transaction costs and benchmark risk-adjustment. Subsample splits and alternative estimation windows corroborate our findings. These results are relevant for the asset management industry, which may seek to replicate popular style investing in the cryptocurrency space.

Keywords: Cryptocurrency, low-volatility, Betting against beta.

Extended abstract

Over the past several decades, the low-volatility anomaly has emerged as a central puzzle in empirical asset pricing, challenging the foundational assumption of a positive risk–return trade-off (Black et al., 1972). A substantial body of literature has investigated this phenomenon across a wide range of equity markets, consistently finding that portfolios composed of low-risk stocks tend to deliver superior risk-adjusted returns relative to their high-risk counterparts. This empirical regularity has been analyzed using diverse risk metrics, asset classes, and methodological approaches, laying its prominence in both academic research and practical asset management (e.g., Frazzini & Pedersen, 2014; Asness et al., 2015; Asness et al., 2020). Despite the breadth of evidence in traditional financial markets, the application of low-volatility strategies to the rapidly evolving market for cryptocurrencies remains relatively underexplored. Existing contributions offer inconclusive findings, with some studies reporting no consistent return premia for low-risk digital assets, and others emphasizing liquidity frictions and estimation risk as impediments to realizing these strategies in practice (e.g., Platanakis and Urquhart, 2019; Burggraf and Rudolf, 2021; Culjak, 2022).

What is lacking in this literature is a comprehensive evaluation that systematically compares various low-volatility strategies within the cryptocurrency market. This omission represents a relevant gap, particularly in light of works such as Grobys et al. (2025), Soe (2012), Traut (2023) and Walkshäusl (2014), which provide a comparative analysis of alternative low-risk strategies in different equity markets. Adopting a similar perspective, the present study examines a broad set of low-volatility approaches in the context of cryptocurrencies, assessing whether the low-volatility effect might extend to this emerging and volatile asset class.

We do so by analyzing the performance of different minimum variance portfolios, including the standard minimum variance portfolio (MVP) (Markowitz, 1952), the minimum semi-variance portfolio (MSemiVP) (Estrada, 2007) and the minimum Conditional Value at Risk portfolio (MCvarP) (Petukhina et al., 2021). Moreover, we construct the low-volatility factor as proposed in Blitz & Vliet (2007) and implement the Betting against Beta (BAB) strategy following the corrected methodological approach of Novy-Marx & Velikov (2022). To address implementation and liquidity constraints in the digital asset market, we adopt the sampling methodology of Grobys et al. (2025), constructing strategies based on a dynamic investment universe consisting of the top 30 cryptocurrencies by market capitalization, reassessed at the end of each year. Weekly financial data on digital coins is mainly sourced from coinmarketcap.com, a leading crypto database (Liu et al., 2022), covering nearly a decade from the first week of January 2016 to the end of April 2025.

Our portfolios rely on a formation/estimation period of 52 weeks (1 year) and are rebalanced every week. Moreover, we assess the risk-adjusted returns of the strategies by means of an OLS regression against two benchmarks, represented by the naïve 1/n asset allocation (DeMiguel et al., 2009) and the market portfolio. Finally, performance is reassessed in light of conservative transaction costs, subsamples analysis and different estimation/formation windows.

Our study advances the literature on low-volatility strategies in cryptocurrency markets by applying a multi-faceted approach to synthesize and evaluate commonalities across different volatility-based portfolio construction techniques. Prior work presents a more skeptical view of the low-volatility anomaly in this domain. Burggraf and Rudolf (2021), Liu (2019), and Ma et al. (2020) consistently show that low-volatility cryptocurrencies do not yield superior returns, implying that diversification benefits are primarily attributable to low correlations rather than volatility premia. Similarly, Culjak (2022) documents that volatility contributes little predictive power in return forecasting using machine learning models, while Petukhina et al. (2021) argue that liquidity constraints materially limit the viability of such strategies, particularly for institutional investors. Additionally, Platanakis et al. (2018) and Platanakis and Urquhart (2019) reveal that estimation error and market instability pose significant challenges to optimized portfolio construction in the crypto space. Although these studies already provide a general perspective on optimized and minimum variance portfolio applications in the cyrpto market, they do not offer an overall and comparative assessment of multiple low-volatility frameworks. Our study deals with this shortcoming by evaluating a wider comprehensive set of low-volatility strategies, including different minimum variance portfolios and, notably, the Betting Against Beta (BAB) strategy, which we implement for the first time in the cryptocurrency context using a representative sample of large-cap digital assets spanning roughly one decade of data.

A related strand of the literature focuses specifically on the minimum variance portfolio (MVP). Clarke, De Silva, and Thorley (2006, p.10f) note that “[t]he minimum-variance portfolio at the left-most tip of the mean-variance efficient frontier has the unique property that security weights are independent of the forecasted or expected returns on the individual securities.” Their early work, along with Clarke et al. (2011), provides empirical support for the MVP’s favorable performance relative to traditional benchmarks, attributing much of this to implicit exposure to known risk factors such as size and value. Furthermore, Walkshäusl (2014) documents that minimum volatility strategies do not differ significantly in performance from low-volatility and low-beta ones, sharing a general large and significant co-movements across and within markets. More recently, Han et al. (2024) propose a global MVP construction framework rooted in asset pricing models that use residuals to mitigate estimation risk associated with unstable covariance matrices. In this study, we extend this line of inquiry by analyzing MVP implementations in the cryptocurrency market, using multiple specification approaches to identify recurring strengths and weaknesses of the strategy in a non-traditional, high-volatility setting.

Overall, the results of our analysis show that only the MVP, MSemiVP and BAB strategies generate a positive and significant raw payoff. However, when accounting for transaction costs and risk-adjusting returns, their associated better performance are not statistically significant anymore. These findings are confirmed across different estimation windows and subsamples.

This study holds important implications for the asset management industry, as traditionally appealing strategies that exploit the low-volatility anomaly cannot be effectively pursued when implemented in the cryptocurrency market.

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Tables

Table 1. Strategy returns with transaction costs

This table reports the descriptive statistics of the optimized variance strategies and zero-costs factors, accounting for transaction costs. The Naïve portfolio is a simple 1/n allocation strategy whereas the market portfolio is a value-weighted portfolio consisting of cryptocurrencies available in the investable opportunity set. The optimal variance strategies buy coins based on an optimized underlying risk parameter estimated in a prior rolling window of j=52 weeks. The low-volatility factor is a strategy that buys cryptocurrencies with the lowest volatility in the 52-weeks formation period and shorts those with the highest volatility in the 52-weeks formation period. BAB assumes a long position in cryptocurrencies with the below median market beta in the 52-weeks formation period and a short position in those with the above median market beta. Each strategy is held one week and then rebalanced until the end of the sample. The weekly data sample is from the first week of January 2016 to the fourth week of April 2025. All the reported returns are in excess of the one-month Treasury-bill rate and account for a proportionate conservative transaction cost equal to 30 bps. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, ** and, *** respectively.

Portfolio	**MVP**	**MSemiVP**	**MCvarP**	**Low Volatility**	**BAB**	**Naïve P**	**Market P**
Mean	0.0197***	0.0219**	-0.0011	0.0015	0.0182***	0.0196***	0.0212***
t-stat	(3.00)	(2.01)	(-0.07)	(0.25)	(3.28)	(3.03)	(4.11)
Median	0.01	0.00	0.01	0.00	0.01	0.01	0.01
Maximum	1.43	2.64	2.38	1.66	0.96	1.08	0.58
Minimum	-0.84	-1.50	-2.80	-1.30	-0.88	-0.45	-0.41
Std. Dev.	0.14	0.24	0.33	0.13	0.12	0.14	0.11
Skewness	3.23	4.59	-0.86	2.15	0.82	2.01	0.68
Kurtosis	35.15	55.87	22.87	83.42	21.28	15.72	6.40
Jarque-Bera	21727.86	58190.97	8039.16	131077.90	6809.42	3598.33	271.62
Probability	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	485	485	485	485	485	485	485

Table 2. Strategy alphas with transaction costs
This table reports point estimates for the following regression model:

$$S_{i,t} = a + \beta_1 Benchmark_{k,t} + \varepsilon_{i,t}$$

where S denotes the strategy $i \in \{MVP, MSemiVP, MCvarP, LowVol, BAB\}$ at time t, $Benchmark$ is a vector containing the $k \in \{NaiveP, MarketP\}$ comparative portfolios and $\varepsilon_{i,t}$ denotes a white noise error. Panel A reports the results for the regression on the naïve portfolio (NP) while Panel B reports the results for the regression on the market portfolio (MP). The weekly data sample is from the first week of January 2016 to the fourth week of April 2025. Newey and West (1987) adjusted standard errors are used to calculate the t-statistics reported in parentheses. Strategy returns are in excess of the one-month Treasury-bill rate and account for a proportionate conservative transaction cost equal to 30 bps. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, ** and, *** respectively.

Portfolio	**MVP**	**MSemiVP**	**MCvarP**	**Low Volatility**	**BAB**
Panel A. Regression on Naïve Portfolio					
α	0.0091*	0.0077	-0.0044	0.0065*	0.0129***
	(1.93)	(1.07)	(-0.31)	(1.93)	(2.97)
β_{NP}	0.5408***	0.7253***	0.1673	-0.2556	0.2752*
	(4.63)	(2.74)	(1.06)	(-1.43)	(1.74)
R^2	0.2837	0.1861	0.0051	0.0817	0.1027
Panel B. Regression on Market Portfolio					
α	0.0056	0.0027	-0.0137	0.0051	0.0076*
	(1.21)	(0.39)	(-0.98)	(1.48)	(1.92)
β_{MP}	0.6659***	0.9033***	0.5904***	-0.1698	0.5036***
	(5.28)	(3.49)	(3.29)	(-0.91)	(3.91)
R^2	0.2745	0.1841	0.0403	0.023	0.2194

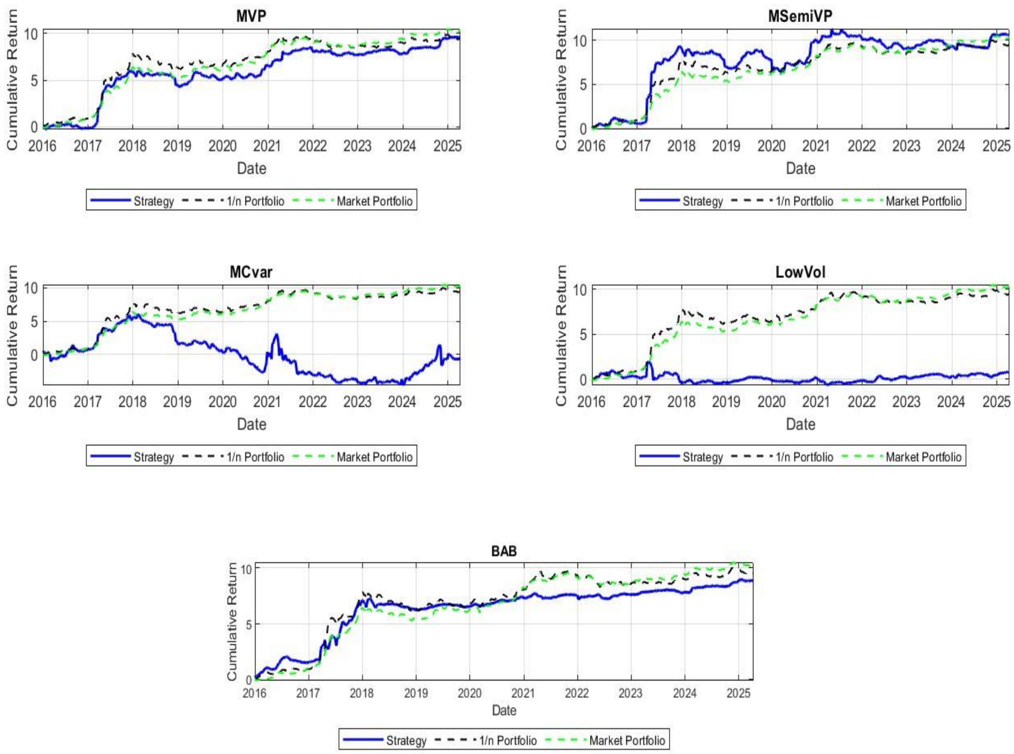

Figure 1. Cumulative return comparison with transaction costs: Strategies vs Naïve and Market Portfolios
This figure plots the evolution of the cumulative returns after costs for each considered strategy and two benchmark indices, the naïve and the market portfolio. The weekly data sample is from the first week of January 2016 to the last week of April 2025 period comprised of 485 observations. Returns are net of a proportionate conservative transaction cost equal to 30 bps.