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Managing cryptocurrency risk exposures in equity portfolios: Evidence from high-frequency data

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ABSTRACT

We investigate the evolving relationships between cryptocurrencies and equity portfolios and find that Bitcoin's contributions to the active risks of equity portfolios have grown over time, exceeding 10% in defensive strategies. This underscores the increasing importance of investment professionals quantifying and managing crypto-related risk exposures in their portfolios, a task for which we provide guidance. For risk measurement, we use intraday returns to significantly improve the forecast accuracy of equity portfolio sensitivities to cryptocurrency risks. For risk management, we advocate direct hedging for optimal risk reduction and suggest using stock selection constraints as an alternative approach to limit the influence of cryptocurrencies on portfolio risk exposures.

1. Introduction

The financial landscape is transforming profoundly, fuelled by the advent of cryptocurrencies and blockchain technologies. These digital innovations have begun to disrupt traditional economic sectors, from asset management and trading platforms to financial derivatives and market infrastructure. Concurrently, financial markets have witnessed an infusion of risk and volatility, both stemming from the erratic behaviour of cryptocurrencies and being shaped by this wave of digital transformation. As the adoption of cryptocurrencies continues to rise, a practical question emerges: What is the impact on the broader financial markets, specifically on equity portfolio management? This paper addresses this question, focusing on the intersection of cryptocurrencies and equity markets from the lens of portfolio risk management.

The sharp correction in cryptocurrency prices from 2022 to 2023 led to the underperformance of companies with heavy exposure to these digital assets.[2] These developments highlight the inherent risks and interconnectedness of companies involved in or influenced by the dynamics of cryptocurrency markets (Aloosh et al., 2022; Xu et al., 2022; Doan et al., 2024; Leong and Kwok, 2024). The risk spillover from unregulated assets like Bitcoin and Ethereum to regulated securities like equities underscores the systemic implications of this emergent risk and continues to heighten apprehension among equity investors regarding unintended cryptocurrency-related

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1 All authors have nothing to disclose.

2 The cryptocurrency industry witnessed a series of high-profile failures, including the collapse of FTX, Celsius Network, and BlockFi, while large investors like Three Arrows Capital and Genesis Global declared bankruptcy. The fallout was not confined to unlisted companies, as listed companies such as Silvergate, Signature Bank, MicroStrategy and Tesla were also affected by the sell-off in the cryptocurrency market.

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risks in their portfolios. As cryptocurrencies transition from a market curiosity to a subject of financial strategy, their risk implications on traditional capital markets become a concern that warrants investigation. This paper explores three research questions:

1. Which styles of equity investing are most exposed to cryptocurrency-related risks?
2. How can equity portfolio managers accurately quantify cryptocurrency-related risks in their portfolios?
3. How can these risks be managed effectively?

Bitcoin, as a global, decentralised asset class, represents a significant departure from traditional financial assets. Its volatility, lack of regulation, and unique market dynamics necessitate a re-evaluation of existing risk frameworks. By exploring Bitcoin's impact on equity factor portfolios, our study provides insights into how emerging digital assets integrate into traditional capital markets, contributing to the broader discourse on international financial stability and systemic risk.

We focus on Bitcoin within the context of the U.S. equity market for both specificity and relevance. As the pioneering and most well-capitalised cryptocurrency, Bitcoin is the de facto benchmark for the digital asset class. It provides the longest history of a liquidly traded cryptocurrency, making it an essential subject for our high-frequency analysis.[3] Furthermore, we bolster our research by employing Ethereum as an alternate proxy for cryptocurrency risk in our robustness analysis. Similarly, the U.S. equity market is one of the world's most liquid, diversified, and rigorously regulated financial ecosystems. As a result, our insights are likely to be robust and broadly applicable.

Our study explores equity portfolio sensitivity to cryptocurrencies, focusing on the first-order risk exposure of several stylistic equity portfolios commonly held by investment managers.[4] Our analysis is motivated by the growing interest among practitioners in understanding the underlying exposures in their portfolios, especially in the context of emerging assets like Bitcoin. The exposure of equity portfolios to cryptocurrencies can significantly affect portfolio risk management and financial market stability in extreme and normal market conditions (Yousaf et al., 2023). Therefore, our paper provides a framework for quantifying and managing the linear exposure of equity portfolios to cryptocurrencies. We intentionally focus on the more immediate and tangible aspect of portfolio exposure, offering practical insights that portfolio managers can directly apply.

Our contributions are threefold. First, this research pioneers the investigation of cryptocurrency-related risks in equity portfolio management. Previous studies explore the utility of cryptocurrencies in multi-asset portfolio diversification (Guesmi et al., 2019; Goodell et al., 2021), safe haven hedging during periods of economic stress (Urquhart and Zhang, 2019; Conlon et al., 2020; Yousaf et al., 2023) and asset pricing within the cross-section of cryptocurrencies (Liu et al., 2022; Leong and Kwok, 2023). None of these previous studies have evaluated how Bitcoin and Ethereum's price dynamics can affect equity factors. Second, we employ robust econometric methods and high-frequency data to study the relationship between cryptocurrencies and U.S. equities and offer precise risk measurements. This approach fills a gap in the existing literature that relies on less granular, daily or monthly data.[5] Finally, we do not merely identify the problems; we propose actionable solutions to guide portfolio managers in mitigating unintended cryptocurrency risk exposures.

Our study is motivated by recent discussions within the literature focusing on linkages between cryptocurrencies and stocks (Aloosh et al., 2022; Xu et al., 2022; Doan et al., 2024; Leong and Kwok, 2024). There are two distinct approaches to exploring these linkages – examining the spillover of cryptocurrency risks to equities versus studying the contemporaneous relations between cryptocurrency and stocks. These approaches serve distinct analytical purposes and yield complementary and divergent insights. The spillover approach seeks to understand how cryptocurrency price and volatility fluctuations can dynamically impact, or 'spillover', into the broader equity market. Focusing on the directional influence of cryptocurrencies over the equity markets, this approach provides a nuanced view of the systemic risks and market dynamics that cryptocurrencies introduce. On the other hand, the contemporaneous approach assesses the simultaneous interactions between cryptocurrencies and individual stocks or equity portfolios. This method offers a snapshot of how cryptocurrencies and equities co-move with each other at a given point in time, allowing for more direct comparisons and immediate investment implications.

Aloosh et al. (2022) explore the relations between cryptocurrencies and meme stocks, attributing observed spillovers to behavioural factors amplified by social media echo chambers. Given the pro-tech orientation and social media activity of meme stock investors, who often overlap with cryptocurrency traders, shared sentiments can fuel price movements in both asset classes (Shen et al., 2019; Hasso et al., 2022). In contrast, Xu et al. (2022) examine the spillovers of cryptocurrency shocks to Blockchain and Cryptocurrency-Exposed stocks (BCEs). Their research demonstrates that cryptocurrency price jumps can trigger analogous jumps in BCEs, offering another lens through which cryptocurrency volatility affects equities.

[3] Our study focuses on the high-frequency analysis of cryptocurrencies and equity portfolios We determined that employing a composite cryptocurrency index to gauge cryptocurrency risk is impractical, primarily because many cryptocurrencies do not possess the necessary liquidity, historical data, or trading frequency required for such an in-depth, high-frequency analysis. This narrows down the cryptocurrencies available in our analysis to Bitcoin and Ethereum.

[4] While we appreciate the implications of extreme movements in the unregulated Bitcoin market and its spillover effects to equity markets (Aloosh et al., 2022; Xu et al., 2022), our primary objective is to address a specific aspect of portfolio risk management, which is the first-order risk exposure of equity portfolios to cryptocurrencies.

[5] There are significantly fewer studies exploring the risk characteristics of cryptocurrencies at high frequency, with many of these studies limited to Bitcoin's univariate jumps and volatility (Scaillet et al., 2020; Conlon et al., 2024), intraday dynamics across different cryptocurrencies (Naeem et al., 2022), or multi-asset correlations and spillovers at the aggregate asset class levels (Urquhart and Zhang, 2019, Corbet et al., 2020). Notably, the only other studies to investigate the intraday relations between cryptocurrencies and U.S. securities is that of Leong and Kwok (2024) and Doan et al. (2024).

While the previous studies by Aloosh et al. (2022) and Xu et al. (2022) have established a link between cryptocurrencies and a narrow subset of U.S. stocks, specifically meme stocks and BCEs, the studies by Doan et al. (2024) and Leong and Kwok (2024) offer a broader examination. Leong and Kwok (2024) study the spillover effects from Bitcoin across a range of S&P indices, covering large-cap, mid-cap, and small-cap stocks. Their findings highlight an amplified spillover of both jump and diffusion risks from Bitcoin to these equities in the post-COVID-19 landscape, with BCEs being the most vulnerable. Additionally, they uncover that the technology, consumer discretionary, and communication services sectors are susceptible to extreme Bitcoin fluctuations. Such observations underscore the increasing integration of cryptocurrency risks into traditional capital markets, which motivates our research questions.

The study by Doan et al. (2024) is similar to ours in that both papers investigate the sensitivity of equities to high-frequency price movements in cryptocurrencies such as Bitcoin and Ethereum. However, for two reasons, our focus is distinctly different from that of Doan et al. (2024). First, Doan et al. (2024) estimate Bitcoin and Ethereum betas of U.S. equities within the S&P 500 and Nasdaq 100 indices and do not form equity portfolios in their study. Their findings are confined to interpreting cryptocurrency betas in single-name U.S. securities. In comparison, our study evaluates Bitcoin and Ethereum betas in equity factor portfolios, where our discussion focuses on equity factor risks. This allows us to relate our findings to the asset pricing literature, which has traditionally been heavily rooted in equities (Fama and French, 1993; Baker and Wurgler, 2007; Bali et al., 2011; Frazzini and Pedersen, 2014; Fama and French, 2015; Asness et al., 2019). Second, the motivation for our study stems from practical considerations in managing equity factor portfolios and our analysis is geared towards managing constrained portfolios, following the discussions in Grinold and Kahn (2000), Clarke et al. (2002) and Bajeux-Besnainou et al. (2011). As such, we provide practical solutions to guide portfolio managers in mitigating unintended cryptocurrency risk exposures.

Our results reveal a heightened impact of Bitcoin on the active risk within equity portfolios, with the marginal contribution to active risk (MCAR) surpassing 10 % in defensive investing styles, including low volatility and investment factor portfolios. The pronounced active bet against Bitcoin in these styles is due to the defensive factors' tilt towards firms with lower volatility, higher profitability and more conservative investment policies. As a result, these portfolios are likely to tilt away from risky, unprofitable growth companies that were correlated with Bitcoin during periods marked by excess liquidity and speculative bubbles (Baker and Wurgler, 2007; Anderson and Brooks, 2014). Conversely, we observe that portfolios focusing on the 'size' factor have consistently shown positive exposure to Bitcoin risk, echoing trends witnessed during the dot-com bubble of the 1990 s. Notably, our findings are robust to our choice of cryptocurrency, as the Ethereum betas in equity factors are shown to be consistent with Bitcoin's betas in these portfolios.

To quantify these Bitcoin risks, we adopt intraday returns as per Lee et al. (2019) and Hollstein et al. (2020), demonstrating a considerable enhancement in the out-of-sample accuracy of Bitcoin beta estimates for U.S. equity portfolios. Similarly, we also show that using intraday returns considerably improves the out-of-sample accuracy of Ethereum's beta estimates for these portfolios.

To mitigate Bitcoin-related risks in equity portfolios, we explore two distinct strategies. First, we examine the efficacy of establishing direct offsetting positions in Bitcoin or its associated futures, concluding that this direct hedging approach is more effective in managing Bitcoin-related risks. However, recognising the operational challenges tied to direct positions in Bitcoin or its futures, we also consider an alternative, indirect approach, entailing setting stock constraints to limit the portfolio's active exposure to Bitcoin. Our analysis confirms that imposing such constraints serves as a partial hedge against Bitcoin, offering a pragmatic risk management solution for portfolio managers. Thus, our study presents a comprehensive, actionable assessment of the risks posed by Bitcoin to equity portfolios, thereby addressing a notable void in the existing literature.

The remainder of this paper is organised as follows. Section 2 describes the data and methodology employed in this study. Section 3 discusses the relationship between Bitcoin and equity factors, illustrating Bitcoin's increasing contribution to the active risk of equity portfolios. Section 4 considers the practical steps towards managing the Bitcoin risks. Finally, Section 5 concludes. Robustness and additional analyses are provided in the appendices. Furthermore, Section G of Supplementary Appendix provides our robustness analyses related to the alternate choice of Ethereum as our proxy for cryptocurrency risk.

2. Data and methodology

2.1. Data

Our analysis spans from June 2015 to March 2023. We use the NYSE Trade and Quote (TAQ) database for U.S. equities, the Thomson Reuters Tick History (TRTH) for high-frequency Bitcoin and Ethereum return data, and Compustat for firm-level fundamentals. Our subset is confined to the largest 1,500 companies (assessed each month) with ordinary common shares listed on the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ). We adopt the data-cleaning procedures outlined in Barndorff-Nielsen et al. (2009), using only data within the exchange trading hours of 9:30 a.m. and 4:00p.m. Eastern Standard Time and eliminating observations with zero bid, ask, or transaction price. To mitigate the potential distortion caused by overnight corporate actions like stock splits and spin-offs, we adhere to the approach of Lee et al. (2019) and exclude overnight returns from our analysis. Our core analyses are performed based on a 30-minute sampling frequency, mitigating the infrequent trading issue for smaller stocks, as Hollstein et al. (2020) noted. We conduct robustness checks using alternative sampling frequencies ranging from 15-minute to hourly intervals. Furthermore, we use Bitcoin as our proxy of cryptocurrency risk and returns in our core analyses and provide Ethereum as an alternative for our robustness analysis in Section G of Supplementary Appendix.

We consider the most prevalent equity investment styles: size, value, profitability, investment, Quality-minus-Junk (QMJ), momentum, Betting-against-Beta (BAB), and low volatility. To define the size and value factors, we follow Fama and French's (1993) three-factor model, where size is represented by market capitalisation and value by the book-to-market ratio. Following Fama and

French's (2015) extension, we also include profitability, assessed through return on equity, and investment, determined by the rate of total asset growth.[6] Additionally, we construct the QMJ factor as per Asness et al. (2019), which extends the profitability factor to include additional dimensions of quality beyond simple profitability.[7] For momentum, we follow Carhart (1997), employing a 12-month return as the chosen momentum factor. Lastly, we include low-risk factors through the BAB factor defined by Frazzini and Pedersen (2014) and the low volatility factor, following Baker et al. (2011). We provide detailed definitions of these equity factors in Table A1 in the appendix.

2.2. Equity portfolio construction

Given our aim to underscore the practical implications of Bitcoin risks, our portfolio construction approach follows the studies by Grinold and Kahn (2000), Clarke et al. (2002) and Jacobs and Levy (2007). We focus on maximising factor exposures through constrained optimisation and categorise portfolios into three types: long-only factor tilt strategies, 130/30, and self-financing long-short.[8] Within the category of self-financing strategies, we consider both equal and cap-weighted quintile factor-mimicking portfolios, as well as optimised long-short portfolios. We rely on constrained optimisation for the long-only and 130/30 strategies.[9]

Table 1 summarises key portfolio settings. Long-only and 130/30 portfolios maintain 100 % net market exposure, contrasting with the net-neutral self-financing portfolios. Sector and industry constraints on the self-financing optimised portfolio are set at +/- 20 % and +/- 15 % against a cap-weighted market benchmark, respectively; this limits the maximum sector and industry tilts for the portfolio as a practical risk control. Our long-only portfolio is intentionally designed with a low annualised tracking error of 1.5 % to 2.5 %, following the discussion in Grinold and Kahn (2000, pp. 419-444). Finally, the 130/30 strategy adopts similar sector, industry and stock constraints as its long-only counterpart to illustrate the relaxation of the no-shorting constraint. For completeness, we provide further details, including methodology, constraints, and optimisation diagnostics, in Supplementary Appendix, Section B.

2.3. Estimating Bitcoin betas

We investigate the risk implications for portfolio managers stemming from the co-movements between Bitcoin and equity portfolios. Precisely, we assess the Bitcoin betas of equity portfolios as managing exposure to speculative assets like Bitcoin is becoming increasingly pertinent for investment professionals. Following the literature on high-frequency risk estimation (Lee et al., 2019; Hollstein et al., 2020), we construct three distinct measures of Bitcoin betas: daily estimates, daily Dimson (1979)-adjusted estimates, and intraday betas based on Andersen et al. (2006). Once these risk measures are constructed, we focus on the out-of-sample accuracy of these different beta estimates. We partial out known risk factors, such as equity and bond market returns, to evaluate the marginal contribution of Bitcoin's exposure to portfolio risks.

Consider the time series regression of returns of an equity, R_p, on Bitcoin returns, R_{BTC}, and known controls:

$$R_{p,t} = \beta_0 + \beta_{BTC}R_{BTC,t} + \beta_{Mkt}R_{Mkt,t} + \beta_{ShortT}R_{ShortT,t} + \beta_{MidT}R_{MidT,t} + \beta_{LongT}R_{LongT,t} + \epsilon_t, \tag{1}$$

where the time index, t, denotes the time index. The coefficients are estimated on a quarterly rolling window basis to capture the dynamic of risk exposures. We control for known risk factors, such as the returns on the U.S. equity market, using the S&P 500 index as a proxy (Sharpe, 1964), and returns on the U.S. bond market (Sweeney and Warga, 1986). The return of the U.S. equity market is represented by $R_{Mkt,t}$, and the returns on the short-term, mid-term and long-term U.S. treasuries are $R_{ShortT,t}$, $R_{MidT,t}$, and $R_{LongT,t}$, respectively.

The key parameter that is of interest to us in this study is Bitcoin's beta, β_{BTC}, which measures the portfolio's sensitivity to Bitcoin risk after controlling for equity and bond market returns. The regression framework in eq. (1) is then applied to both continuously compounding intraday and daily returns to estimate high-frequency ($\widehat{\beta}_{BTC}^{HF}$) and daily ($\widehat{\beta}_{BTC}^{Daily}$) betas, following the discussions in Lee et al. (2019) and Hollstein et al. (2020). The motivation for using high-frequency returns to estimate Bitcoin betas is primarily driven by the realised beta estimator converging to the true underlying integrated beta when the sampling frequency increases (Lee et al., 2019). Furthermore, as in Hollstein et al. (2020), we employ Dimson's (1979) adjustment by controlling for the serial correlation in returns to mitigate bias in the beta estimate due to infrequent trading. We include four lagged daily returns, effectively spanning a week when including the contemporaneous return. Specifically, we run the time series regression:

$$R_{p,\tau} = \beta_0 + \beta_{BTC}^{(0)}R_{BTC,\tau} + \sum_{i=1}^{4}\beta_{BTC}^{(i)}R_{BTC,\tau-i} + \beta_{Mkt}R_{Mkt,\tau} + \beta_{ShortT}R_{ShortT,\tau} + \beta_{MidT}R_{MidT,\tau} + \beta_{LongT}R_{LongT,\tau} + \epsilon_t. \tag{2}$$

The Dimson-adjusted beta estimator is given by:

[6] Note that Fama and French's (2015) investment equity factor portfolio is constructed by taking a long (short) position in firms with conservative (aggressive) investment profiles.

[7] The QMJ factor in Asness et al. (2019) consists of profitability, growth and safety measures, which we provide in the Table A1 in the appendix.

[8] Refer to Supplementary Appendix, eq. B1, B2, and B3.

[9] The choice of a 130/30 long-short strategy was motivated by discussions within the literature, as in Grinold and Kahn (2000), Jacobs and Levy (2007), Clarke et al. (2008), among others.

Table 1
Portfolio Overview.

Portfolio	Net Weight	Gross Long Weight	Gross Short Weight	Sector Limits	Industry Limits	Stock Limits
Long-Only	100.0 %	100.0 %	0.0 %	BM +/- 25bps	BM +/- 25bps	BM +/- 2.5 %
Long-Short 130/30	100.0 %	130.0 %	−30.0 %	BM +/- 25bps	BM +/- 25bps	BM +/- 2.5 %
Long-Short Optimised Self-Financing	0.0 %	100.0 %	−100.0 %	BM +/- 20 %	BM +/- 15 %	BM +/- 5 %
Long-Short Quintile (Cap-Weighted)	0.0 %	100.0 %	−100.0 %	No Limit	No Limit	No Limit
Long-Short Quintile (Equal-Weighted)	0.0 %	100.0 %	−100.0 %	No Limit	No Limit	No Limit

The table presents an overview of the equity portfolios constructed from June 2015 to March 2023. Net weight is the sum of gross long and short positions within each portfolio. Sector, industry, and stock constraints are applied to limit risks. BM refers to the broad equity market benchmark. For completeness, we detail the portfolio construction process in Supplementary Appendix, Section B.

$$\widehat{\beta}_{BTC}^{Daily^{(4)}} = \sum_{i=0}^{4} \widehat{\beta}_{BTC}^{(i)}.$$

2.4. Measuring Bitcoin's marginal contribution to the active risk of equity portfolios

To estimate Bitcoin's marginal contribution to the active risk of an equity portfolio, we employ the methodology outlined in Grinold and Kahn (2000, Chapter 3). We define the active returns of an equity portfolio by subtracting a cap-weighted equity market return from the portfolio's return (for long-only and 130/30 strategies) or subtracting the U.S. 30-day T-Bill from the portfolio's return (for self-financing and quintile long-short strategies).[10]

By imposing a factor structure, we decompose an equity portfolio's active variance into the factor loadings, factor variances and covariances (see Supplementary Appendix, Section C for details). Since the purpose of our study is to demonstrate the impact of Bitcoin's risk on equity portfolios, we consider a simple factor structure involving five economic factors: the equity market factor (R_{Mkt}), three bond market factors corresponding to the short, medium and long ends of the yield curve $\left(R_{ShortT}, R_{MidT}, R_{LongT}\right)$ and the Bitcoin factor (R_{BTC}).[11] Bitcoin's marginal contribution to a portfolio's active variance ($MCAR_{BTC}$) is defined as:

$$MCAR_{BTC} = \frac{\beta_{BTC}^{Active} \sum_{i=1}^{5} \beta_{i}^{Active} Cov(R_{BTC}, R_i)}{\sigma_{Active}^{2}}, \quad (3)$$

where β_{BTC}^{Active} is the portfolio's active Bitcoin beta and β_{i}^{Active} is the portfolio's active beta to each of the five factors denoted by i and representing Bitcoin, the U.S. equity market and the short-term, mid-term, and long-term U.S. treasuries. $Cov(R_{BTC}, R_i)$, captures the covariance between returns on Bitcoin and factor i and σ_{Active}^{2} denotes the portfolio's active variance. Notably, $MCAR_{BTC}$ is highly relevant since it captures the amount of risk contribution stemming from Bitcoin's variance and covariances. In contrast, an equity portfolio's Bitcoin beta $\left(\beta_{BTC}^{Active}\right)$ does not quantify the impact of the large factor variance and covariances.

2.5. Summary statistics

Table 2 presents summary statistics for the intraday return series, covering June 2015 to March 2023. Using 30-minute returns, we report the statistical moments and percentile metrics for broad-based asset class returns in Panel A and equity portfolio returns in Panel B. Bitcoin exhibits significant volatility, evidenced by a standard deviation of 0.505 %, outpacing U.S. equities and bonds. As a result, Bitcoin's price fluctuations at the 1st and 99th percentiles exceed 1.50 % over these 30-minute intervals. In contrast, U.S. treasuries display lower levels of volatility with far less extreme tails. Short-term and mid-term U.S. treasuries are less exposed to interest rate risks and, thus, are less volatile than long-term U.S. treasuries.

Across the equity factor portfolios, both long-only and 130/30 strategies are generally more volatile than self-financing strategies. These portfolios closely mirror the broad U.S. equity market in terms of statistical characteristics due to their 100 % net long exposures and tight sectoral, industrial, and stock constraints (refer to Table 1). By contrast, self-financing portfolios diverge from the broad market profile, with gross long positions offset by short positions. As such, the statistical characteristics of these portfolios represent a pure play on the underlying investment factors; our factor portfolio diagnostic shows that the factor exposures in self-financing portfolios are higher than those in long-only and 130/30 strategies.[12] Lastly, we confirm leptokurtic distributions for intraday returns across all asset classes in Table 2, consistent with stylised facts in the literature (Urquhart and Zhang, 2019; Bekierman and

[10] The active returns of long-only and 130/30 strategies are benchmarked against the cap-weighted equity market return as they contain net equity market exposures of 100%. By contrast, the active returns of self-financing long-short strategies are benchmarked to cash (U.S. 30-day T-Bill) due to having no net equity market exposures.

[11] We note that there are more sophisticated equity factor risk models available commercially, as in Markowitz et al. (2021), although this is beyond the scope of our study; we aim to provide an example of how Bitcoin's risk can impact equity portfolios.

[12] Refer to Supplementary Appendix, Table B4.1.

Table 2
Summary Statistics of Intraday Returns.

Panel A: Summary Statistics of Asset Class Returns

Asset Class	ETF Proxy	Count	Mean (x1,000)	Std. Dev.	Skew	Kurtosis	1st Pctl	20th Pctl	50th Pctl	80th Pctl	99th Pctl
Bitcoin	BTC	25,217	1.959 %	0.505 %	−0.109	10.221	−1.572 %	−0.247 %	0.008 %	0.261 %	1.509 %
U.S. Equities (S&P 500)	SPY	26,179	1.029 %	0.180 %	−0.040	12.199	−0.535 %	−0.095 %	0.007 %	0.099 %	0.497 %
U.S. Treasuries (Long-Term)	TLT	26,179	0.288 %	0.137 %	−0.421	16.546	−0.369 %	−0.083 %	0.002 %	0.085 %	0.365 %
U.S. Treasuries (Mid-Term)	IEF	26,179	−0.075 %	0.055 %	−0.102	9.489	−0.158 %	−0.033 %	0.000 %	0.033 %	0.152 %
U.S. Treasuries (Short-Term)	SHY	25,950	0.045 %	0.012 %	0.159	15.823	−0.034 %	−0.006 %	0.000 %	0.006 %	0.035 %

Panel B: Summary Statistics of Factor Portfolio Returns

Strategy	Factor	Count	Mean (x1,000)	Std. Dev.	Skew	Kurtosis	1st Pctl	20th Pctl	50th Pctl	80th Pctl	99th Pctl
Long-Only	BAB	26,105	1.041%	0.164%	-0.005	14.416	-0.484%	-0.252%	-0.084%	0.005%	0.089%
Long-Short 130/30	BAB	26,105	1.373%	0.158%	-0.003	14.895	-0.469%	-0.242%	-0.081%	0.005%	0.086%
Long-Short Optimised Self-Financing	BAB	26,105	2.112%	0.165%	0.029	8.417	-0.456%	-0.249%	-0.101%	-0.001%	0.100%
Long-Short Quintile (Cap-Weighted)	BAB	26,105	2.202%	0.202%	0.074	8.125	-0.548%	-0.306%	-0.122%	-0.001%	0.123%
Long-Short Quintile (Equal-Weighted)	BAB	26,105	2.153%	0.194%	-0.051	9.258	-0.544%	-0.295%	-0.116%	0.000%	0.120%
Long-Only	Investment	26,105	0.563%	0.175%	0.021	13.654	-0.522%	-0.092%	0.006%	0.095%	0.495%
Long-Short 130/30	Investment	26,105	0.570%	0.173%	0.013	14.038	-0.514%	-0.092%	0.006%	0.094%	0.485%
Long-Short Optimised Self-Financing	Investment	26,105	-0.089%	0.083%	0.058	8.444	-0.237%	-0.050%	-0.001%	0.050%	0.242%
Long-Short Quintile (Cap-Weighted)	Investment	26,105	-0.048%	0.103%	0.071	8.360	-0.288%	-0.063%	-0.001%	0.062%	0.302%
Long-Short Quintile (Equal-Weighted)	Investment	26,105	-0.965%	0.064%	-0.071	9.372	-0.180%	-0.041%	-0.001%	0.039%	0.178%
Long-Only	Low Volatility	26,105	1.061%	0.167%	0.005	14.151	-0.496%	-0.086%	0.006%	0.091%	0.470%
Long-Short 130/30	Low Volatility	26,105	1.431%	0.162%	0.017	14.414	-0.479%	-0.085%	0.005%	0.090%	0.456%
Long-Short Optimised Self-Financing	Low Volatility	26,105	2.046%	0.147%	0.099	11.525	-0.417%	-0.083%	0.000%	0.085%	0.441%
Long-Short Quintile (Cap-Weighted)	Low Volatility	26,105	2.279%	0.224%	0.087	11.570	−0.634%	−0.125%	0.000%	0.127%	0.691%
Long-Short Quintile (Equal-Weighted)	Low Volatility	26,105	1.542%	0.200%	0.003	12.015	−0.571%	−0.115%	0.000%	0.116%	0.584%
Long-Only	Momentum	26,105	0.750%	0.181%	−0.040	12.562	−0.540%	−0.097%	0.008%	0.101%	0.498%
Long-Short 130/30	Momentum	26,105	0.886%	0.180%	−0.056	12.417	−0.537%	−0.097%	0.007%	0.102%	0.500%
Long-Short Optimised Self-Financing	Momentum	26,105	−0.896%	0.167%	−0.346	11.745	−0.506%	−0.093%	0.004%	0.096%	0.463%
Long-Short Quintile (Cap-Weighted)	Momentum	26,105	−0.482%	0.210%	−0.242	13.937	−0.625%	−0.114%	0.003%	0.117%	0.590%
Long-Short Quintile	Momentum	26,105	−0.723%	0.175%	−0.261	13.416	−0.546%	−0.095%	0.003%	0.098%	0.495%

(continued on next page)

Table 2 (*continued*)

Strategy	Factor	Count	Mean (x1,000)	Std. Dev.	Skew	Kurtosis	1st Pctl	20th Pctl	50th Pctl	80th Pctl	99th Pctl
(Equal-Weighted)											
Long-Only	Profitability	26,105	1.023%	0.177%	0.003	13.306	−0.525%	−0.091%	0.006%	0.096%	0.498%
Long-Short 130/30	Profitability	26,105	1.310%	0.176%	0.007	13.437	−0.530%	−0.090%	0.007%	0.096%	0.492%
Long-Short Optimised Self-Financing	Profitability	26,105	1.182%	0.101%	−0.096	10.219	−0.293%	−0.058%	0.001%	0.061%	0.300%
Long-Short Quintile (Cap-Weighted)	Profitability	26,105	1.973%	0.114%	−0.056	9.854	−0.326%	−0.065%	0.002%	0.070%	0.331%
Long-Short Quintile (Equal-Weighted)	Profitability	26,105	1.429%	0.106%	0.088	9.011	−0.305%	−0.062%	0.001%	0.064%	0.318%
Long-Only	QMJ	26,105	1.017%	0.178%	0.012	13.146	−0.525%	−0.278%	−0.091%	0.006%	0.097%
Long-Short 130/30	QMJ	26,105	1.251%	0.175%	0.018	13.147	−0.524%	−0.273%	−0.091%	0.007%	0.096%
Long-Short Optimised Self-Financing	QMJ	26,105	1.678%	0.122%	−0.071	10.171	−0.362%	−0.183%	−0.066%	0.001%	0.071%
Long-Short Quintile (Cap-Weighted)	QMJ	26,105	2.326%	0.118%	−0.046	10.192	−0.334%	−0.177%	−0.069%	0.003%	0.074%
Long-Short Quintile (Equal-Weighted)	QMJ	26,105	1.942%	0.099%	−0.029	9.338	−0.274%	−0.148%	−0.058%	0.001%	0.061%
Long-Only	Size	26,105	0.467%	0.186%	−0.012	12.536	−0.552%	−0.099%	0.007%	0.102%	0.531%
Long-Short 130/30	Size	26,105	0.291%	0.189%	−0.015	12.251	−0.559%	−0.101%	0.007%	0.104%	0.533%
Long-Short Optimised Self-Financing	Size	26,105	−0.461%	0.112%	−0.055	9.765	−0.320%	−0.070%	0.001%	0.069%	0.314%
Long-Short Quintile (Cap-Weighted)	Size	26,105	−0.704%	0.160%	−0.137	10.681	−0.449%	−0.100%	0.000%	0.100%	0.443%
Long-Short Quintile (Equal-Weighted)	Size	26,105	−0.748%	0.153%	−0.060	10.498	−0.423%	−0.097%	−0.002%	0.097%	0.419%
Long-Only	Value	26,105	0.382%	0.181%	0.008	13.537	−0.534%	−0.096%	0.006%	0.099%	0.510%
Long-Short 130/30	Value	26,105	0.154%	0.179%	0.020	13.962	−0.525%	−0.096%	0.006%	0.100%	0.501%
Long-Short Optimised Self-Financing	Value	26,105	−1.713%	0.115%	0.085	11.137	−0.322%	−0.073%	−0.002%	0.069%	0.323%
Long-Short Quintile (Cap-Weighted)	Value	26,105	−1.890%	0.168%	0.338	15.430	−0.481%	−0.099%	−0.003%	0.093%	0.508%
Long-Short Quintile (Equal-Weighted)	Value	26,105	−1.930%	0.141%	0.152	13.385	−0.416%	−0.083%	−0.002%	0.079%	0.414%

The table presents the summary statistics for intraday returns from June 2015 to March 2023. We use (1) the NYSE Trade and Quote (TAQ) database to extract individual stock and ETF intraday returns and (2) the Thomson Reuters Tick History (TRTH) database to obtain Bitcoin's intraday returns. Our main results are presented based on 30-minute intraday returns, for which we present statistical moments and percentile values.
Panel A presents the summary statistics of intraday returns for Bitcoin and four other asset classes, covering U.S. equities and. bonds. *Panel B* presents the summary statistics of intraday returns for the factor portfolios used in this study. In our study, we construct factor portfolios for the BAB, investment, low volatility, momentum, profitability, QMJ, size and value factors. These portfolios are constructed and rebalanced at the end of every

month, following which the intraday returns are constructed by assuming a fixed portfolio composition for the next month. Our portfolio construction methodology closely follows Grinold and Kahn (2000), with further details in Section 2.2 and Supplementary Appendix, Section B.

Gribisch, 2021; Kolokolov, 2022; Conlon et al., 2024; Leong and Kwok, 2024).

3. Equity portfolio exposure to Bitcoin

Drawing on the cross-asset literature on cryptocurrencies, we find that risks associated with Bitcoin's price dynamic have permeated equities over time (Aloosh et al., 2022; Xu et al., 2022; Doan et al., 2024; Leong and Kwok, 2024). This growing synchronicity with U.S. stocks immediately impacts asset allocation and risk management for an equity portfolio manager. For example, if an equity portfolio is exposed to Bitcoin's risks, its performance trajectory becomes more intertwined with Bitcoin's, necessitating mitigation strategies for these unintended exposures. Consequently, there is a practical need for investment managers to understand the source of Bitcoin's exposures in their equity portfolios.

Table 3 presents the active betas associated with our equity factor portfolios across our full sample, covering June 2015 to March 2023. To support our full sample analysis, Figs. 1 and 2 present Bitcoin's time-varying betas and MCARs of different equity portfolios, illustrating the temporal variability of Bitcoin's influence on equity factors.[13] While the initial years of our analysis saw minimal exposure to Bitcoin, there has been a marked increase in subsequent years. Furthermore, the impact of Bitcoin on a portfolio's active variance can be quite material, even if the portfolio had low active Bitcoin betas. For instance, while the Bitcoin betas of the long-only and 130/30 portfolios are relatively low, these do not directly translate to lower MCARs. Since the calculation of MCAR scales the contribution of Bitcoin risks by the factor portfolio variance, the lower active risks in the long-only and 130/30 strategies are proportional to the reduction in portfolio Bitcoin betas.[14]Consequently, this implies that portfolio managers running the more conservative long-only or 130/30 strategies would have been as vulnerable to Bitcoin exposures as their more aggressive self-financing counterparts.

In Table 3, we find that the defensive equity factors, such as low volatility, BAB, investment, profitability, and QMJ, display negative exposures to Bitcoin.[15] Specifically, the low volatility portfolio, which tilts toward companies with reduced total volatility, registers the most negative active Bitcoin betas among all factors across the respective portfolio construction strategies. This outcome aligns with the 'lottery preference' theory proposed by Bali et al. (2011), where low volatility portfolios tend to eschew speculative, lottery-type payoffs – which Bitcoin epitomises. Similarly, the BAB portfolios show negative exposures to Bitcoin in the same order of magnitude as those of the low volatility portfolios. This is unsurprising since the correlation between the BAB and low volatility factor portfolio returns is relatively high at 86 % (refer to Fig. A1 in the appendix), suggesting that both factors capture similar investor behaviours. While the investment, profitability and QMJ factors do not directly target volatility, they operate under the broader umbrella of 'quality investing' and can be discussed through a similar lens to the low volatility and BAB factors.[16] Dutt and Humphery-Jenner (2013) and French and Gärtner, (2023) provide corroborative evidence, showing that firms with higher profitability exhibit less volatility. In our study, we find that the returns of the investment, profitability and QMJ factor portfolios are positively correlated to those of low volatility and BAB (refer to Fig. A1 in the appendix), suggesting that these investing styles are generally more defensive. Consequently, these defensive styles exhibit negative Bitcoin betas, albeit somewhat less than the low volatility factor. For robustness, we present Ethereum risk exposures for these defensive factor portfolios in Table G1 of Supplementary Appendix. These defensive factors exhibit negative risk exposures to Ethereum, supporting our main findings that the low-risk and quality investing styles actively bet against the speculative cryptocurrency risks.

On the other end of the risk spectrum, size, as a factor, is documented to be negatively correlated with the low-risk (Bali et al., 2011; Frazzini and Pedersen, 2014) and quality (Fama and French, 2015; Asness et al., 2019) factors. Across our entire sample, Table 3 shows that the active Bitcoin betas in size portfolios are highly positive and significant, peaking at 1.39 % for the equal-weighted long-short quintile portfolio. Our robustness check in Table G1 of Supplementary Appendix using Ethereum as our measure of cryptocurrency risk further corroborates our findings, as we find a robust positive association between size portfolios and Ethereum risks, with active Ethereum betas rising to 2.12 %. This is consistent with Baker and Wurgler's (2007) observations about small firms' sensitivity to investor sentiments and further supported by Aloosh et al. (2022), who identified co-movement periods between cryptocurrencies and 'meme' stocks. Small firms, disproportionately swayed by investor sentiments as argued by Baker and Wurgler (2007) and potentially correlated with Bitcoin sentiment as supported by Aloosh et al. (2022), have a consistent positive exposure to Bitcoin risks during the COVID-19 pandemic, evident in Fig. 1.

[13] Grinold and Kahn (2000, Chapter 3) provide the definition of MCAR, which is a function of the portfolio's Bitcoin beta, β_A^{BTC}, Bitcoin variance, $Var(R^{BTC})$, and its covariances with the U.S. equity and bond markets, $Cov(R^{BTC}, R^i)$. For details on the MCAR formula, refer to Section C in Supplementary Appendix, which highlights how portfolio active risks can be decomposed into underlying systematic and idiosyncratic components.

[14] Refer to eq. C4 in Supplementary Appendix.

[15] French and Gärtner, (2023) analyse a range of volatility and quality factor characteristics through both a theoretical and empirical lens and show that low leverage, earnings volatility, and return volatility are the most consistently defensive with profitability being the next most powerful characteristic.

[16] Man Institute (2020, November) discusses the two dimensions to quality investing; (1) earnings quality, as represented by profitability (Fama and French's (2015) Robust-Minus-Weak factor) and (2) investment quality, as represented by asset growth (Fama and French's (2015) Conservative-Minus-Aggressive factor).

Table 3
Intraday Active Betas Across Equity Portfolio Strategies.

Strategy	Factor	$\widehat{\beta}_{BTC}$	$\widehat{\beta}_{Mkt}$	$\widehat{\beta}_{ShortT}$	$\widehat{\beta}_{MidT}$	$\widehat{\beta}_{LongT}$
Long-Only	BAB	−0.0028***	−0.0805***	0.0441	0.0328***	0.0057
		(0.0004)	(0.0021)	(0.0302)	(0.0108)	(0.0038)
Long-Short 130/30	BAB	−0.0046***	−0.1231***	0.0787*	0.0368**	0.0137**
		(0.0006)	(0.0032)	(0.045)	(0.0165)	(0.006)
Long-Short Optimised Self-Financing	BAB	−0.0154***	−0.4494***	0.3646*	0.2561***	0.0506**
		(0.0022)	(0.0136)	(0.1881)	(0.0726)	(0.0245)
Long-Short Quintile (Cap-Weighted)	BAB	−0.026***	−0.5666***	0.1953	0.1992**	0.0612**
		(0.0028)	(0.017)	(0.207)	(0.0786)	(0.0279)
Long-Short Quintile (Equal-Weighted)	BAB	−0.0188***	−0.5042***	0.1922	0.2084***	0.0964***
		(0.0026)	(0.0155)	(0.2115)	(0.0768)	(0.027)
Long-Only	Investment	−0.0014***	−0.0233***	0.0091	0.0005	−0.0047***
		(0.0002)	(0.0013)	(0.0176)	(0.0076)	(0.0037)
Long-Short 130/30	Investment	−0.0032***	−0.0406***	0.0107	−0.0082	−0.0029
		(0.0004)	(0.0022)	(0.0274)	(0.0103)	(0.0046)
Long-Short Optimised Self-Financing	Investment	−0.0066***	−0.1173***	0.0585	−0.0329	−0.0184
		(0.0012)	(0.0064)	(0.0945)	(0.0348)	(0.0147)
Long-Short Quintile (Cap-Weighted)	Investment	−0.0087***	−0.1678***	0.0500	−0.0407	−0.0178
		(0.0015)	(0.0082)	(0.1113)	(0.0422)	(0.0194)
Long-Short Quintile (Equal-Weighted)	Investment	−0.0021**	−0.0469***	0.0254	0.0096	−0.0230*
		(0.0010)	(0.0043)	(0.0698)	(0.0285)	(0.0116)
Long-Only	Low Volatility	−0.0037***	−0.0676***	0.0361	0.0173	0.0073
		(0.0004)	(0.0023)	(0.032)	(0.0146)	(0.0054)
Long-Short 130/30	Low Volatility	−0.0064***	−0.1093***	0.0607	0.0215	0.0128
		(0.0007)	(0.0037)	(0.0526)	(0.0231)	(0.0089)
Long-Short Optimised Self-Financing	Low Volatility	−0.0167***	−0.3393***	0.1575	0.1553**	0.0412*
		(0.0021)	(0.0124)	(0.1545)	(0.0667)	(0.0237)
Long-Short Quintile (Cap-Weighted)	Low Volatility	−0.0332***	−0.5384***	0.0414	0.0991	0.0538
		(0.0034)	(0.0185)	(0.2302)	(0.0989)	(0.0336)
Long-Short Quintile (Equal-Weighted)	Low Volatility	−0.0275***	−0.4418***	0.0915	0.1112	0.0723**
		(0.0029)	(0.0161)	(0.2305)	(0.0864)	(0.0298)
Long-Only	Momentum	0.0007	0.0010	0.0366	−0.0442***	0.0124***
		(0.0004)	(0.0019)	(0.0231)	(0.0090)	(0.0033)
Long-Short 130/30	Momentum	−0.0001	−0.0120***	0.0311	−0.0625***	0.0204***
		(0.0006)	(0.0028)	(0.0356)	(0.0140)	(0.0057)
Long-Short Optimised Self-Financing	Momentum	0.0038	−0.0903***	0.0748	−0.2379***	0.0599**
		(0.0026)	(0.0127)	(0.1449)	(0.0649)	(0.0248)
Long-Short Quintile (Cap-Weighted)	Momentum	−0.0014	−0.0562***	0.1175	−0.2503***	0.0637*
		(0.0031)	(0.0157)	(0.1855)	(0.0842)	(0.0328)
Long-Short Quintile (Equal-Weighted)	Momentum	0.0032	−0.0849***	0.2249	−0.1298*	0.0339
		(0.0026)	(0.0123)	(0.1557)	(0.0663)	(0.0242)
Long-Only	Profitability	−0.0008***	−0.0128***	0.0271	0.0057	0.0053
		(0.0002)	(0.0011)	(0.0178)	(0.0086)	(0.0037)
Long-Short 130/30	Profitability	−0.0011***	−0.0192***	0.0477	0.0167	0.0091
		(0.0004)	(0.0019)	(0.0293)	(0.014)	(0.006)
Long-Short Optimised Self-Financing	Profitability	0.0016	0.0493***	−0.0378	0.0747*	0.0280
		(0.0014)	(0.0075)	(0.1143)	(0.044)	(0.0182)
Long-Short Quintile (Cap-Weighted)	Profitability	−0.0042***	−0.0410***	−0.1203	0.1057**	0.0352*
		(0.0016)	(0.0072)	(0.1237)	(0.0513)	(0.0210)
Long-Short Quintile (Equal-Weighted)	Profitability	−0.0082***	−0.0549***	−0.0932	0.0768*	0.0295*
		(0.0016)	(0.0070)	(0.1248)	(0.0433)	(0.0169)
Long-Only	QMJ	−0.0004*	−0.0085***	0.0402*	0.0174*	0.0036
		(0.0002)	(0.0013)	(0.0204)	(0.0097)	(0.0039)
Long-Short 130/30	QMJ	−0.0002*	−0.0253***	0.0631**	0.0252	0.0055
		(0.0001)	(0.002)	(0.0304)	(0.0156)	(0.0063)
Long-Short Optimised Self-Financing	QMJ	0.0024	0.1112***	−0.0329	0.1246**	0.0415*
		(0.0018)	(0.0099)	(0.1308)	(0.0546)	(0.0215)
Long-Short Quintile (Cap-Weighted)	QMJ	0.0017	0.0167*	0.0371	0.1467**	0.0276
		(0.0018)	(0.0089)	(0.1238)	(0.0627)	(0.0255)
Long-Short Quintile (Equal-Weighted)	QMJ	−0.0027**	−0.0389***	−0.0321	0.0790*	0.0338*
		(0.0012)	(0.0065)	(0.1024)	(0.045)	(0.0178)
Long-Only	Size	0.0014***	0.0201***	−0.0694**	0.0072	−0.0108**
		(0.0004)	(0.002)	(0.0275)	(0.0121)	(0.0048)
Long-Short 130/30	Size	0.0013**	0.0275***	−0.0925**	0.0102	−0.0151**
		(0.0005)	(0.0026)	(0.0374)	(0.0169)	(0.0068)
Long-Short Optimised Self-Financing	Size	0.0002	0.0273***	−0.0855	−0.0045	−0.0387*
		(0.0016)	(0.0083)	(0.1178)	(0.0518)	(0.0199)

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Table 3 (*continued*)

Strategy	Factor	$\widehat{\beta}_{BTC}$	$\widehat{\beta}_{Mkt}$	$\widehat{\beta}_{ShortT}$	$\widehat{\beta}_{MidT}$	$\widehat{\beta}_{LongT}$
Long-Short Quintile (Cap-Weighted)	Size	0.0093***	0.0305**	−0.0955	−0.0494	−0.0592**
		(0.0023)	(0.0125)	(0.1938)	(0.0715)	(0.0259)
Long-Short Quintile (Equal-Weighted)	Size	0.0139***	0.0714***	−0.1289	−0.0397	−0.0475*
		(0.0022)	(0.0122)	(0.1963)	(0.0677)	(0.0240)
Long-Only	Value	−0.0012***	−0.0008	−0.0583**	−0.0117	−0.0108**
		(0.0003)	(0.0017)	(0.0231)	(0.0112)	(0.0047)
Long-Short 130/30	Value	−0.0026***	−0.0182***	−0.0509	−0.0177	−0.0137**
		(0.0004)	(0.0027)	(0.0329)	(0.0152)	(0.0064)
Long-Short Optimised Self-Financing	Value	−0.0032*	0.0431***	−0.0077	−0.2154***	−0.0482**
		(0.0017)	(0.0091)	(0.114)	(0.0528)	(0.0214)
Long-Short Quintile (Cap-Weighted)	Value	−0.0058**	−0.0063	−0.0894	−0.3653***	−0.0590*
		(0.0023)	(0.0134)	(0.1738)	(0.0879)	(0.0352)
Long-Short Quintile (Equal-Weighted)	Value	−0.0031	−0.0001	−0.1546	−0.2375***	−0.0441*
		(0.0019)	(0.0097)	(0.1502)	(0.0599)	(0.0241)

The table reports the active betas of different portfolio strategies. Active returns are computed as the difference between each strategy and its respective benchmark: a market-cap-weighted index for long-only and 130/30 strategies, and the U.S. 30-day T-Bill for self-financing and quintile long-short portfolios. Portfolios are rebalanced monthly (additional details available in Supplementary Appendix Section B). Active betas (β_i) are estimated using a regression model with 30-minute intraday returns over the entire period from June 2015 to March 2023. Specifically, the regression model is given by:$R_p - R_{Benchmark} = \beta_0 + \beta_{BTC}R_{BTC} + \beta_{Mkt}R_{Mkt} + \beta_{ShortT}R_{ShortT} + \beta_{MidT}R_{MidT} + \beta_{LongT}R_{LongT} + \epsilon$,
where the portfolio active returns are represented by $R_p - R_{Benchmark}$; we use ETFs to proxy returns on the equity market (SPY), short-term bonds (SHY), mid-term bonds (IEF), and long-term bonds (TLT). We report Newey and West (1987) standard errors in parentheses. The * , ** , and *** marks indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Fig. 1. Active Bitcoin Betas of Equity Portfolios. The figure contrasts the equity portfolios' active Bitcoin betas. These betas are estimated based on the intraday active portfolio returns, calculated as the difference between equity portfolios and a market-capitalisation weighted benchmark for long-only and 130/30 strategies, and the U.S. 30-day T-Bill for self-financing and quintile long-short strategies. Portfolios are rebalanced monthly (refer to Supplementary Appendix, Section B for further details). Using a quarterly rolling window for each monthly rebalance, we estimate the Bitcoin betas (β_{BTC}) by regressing active portfolio returns $R_{p,t} - R_{Benchmark,t}$ on Bitcoin, U.S. equity, and bond market returns: $R_p - R_{Benchmark} = \beta_0 + \beta_{BTC}R_{BTC} + \beta_{Mkt}R_{Mkt} + \beta_{ShortT}R_{ShortT} + \beta_{MidT}R_{MidT} + \beta_{LongT}R_{LongT} + \epsilon$. We use ETFs to proxy returns on the market (SPY), short-term bonds (SHY), mid-term bonds (IEF), and long-term bonds(TLT).

Moreover, Hasso et al. (2022) suggest that retail traders during the 'meme' stock frenzy heavily influence these small-cap stocks, demonstrating the behavioural channel through which size portfolios become susceptible to Bitcoin's risks. Interestingly, the MCARs of these size portfolios tend to be more muted than the low volatility portfolios. As a caveat, it is crucial to realise that, while our findings are backward-looking, the relationship between the size factor and Bitcoin could transform over time. For instance, the adoption of blockchain and cryptocurrency technologies by large-cap technology and financial companies may increase the exposure of these companies to Bitcoin and alter the historical relationship between the size factor and Bitcoin. Portfolio managers must remain

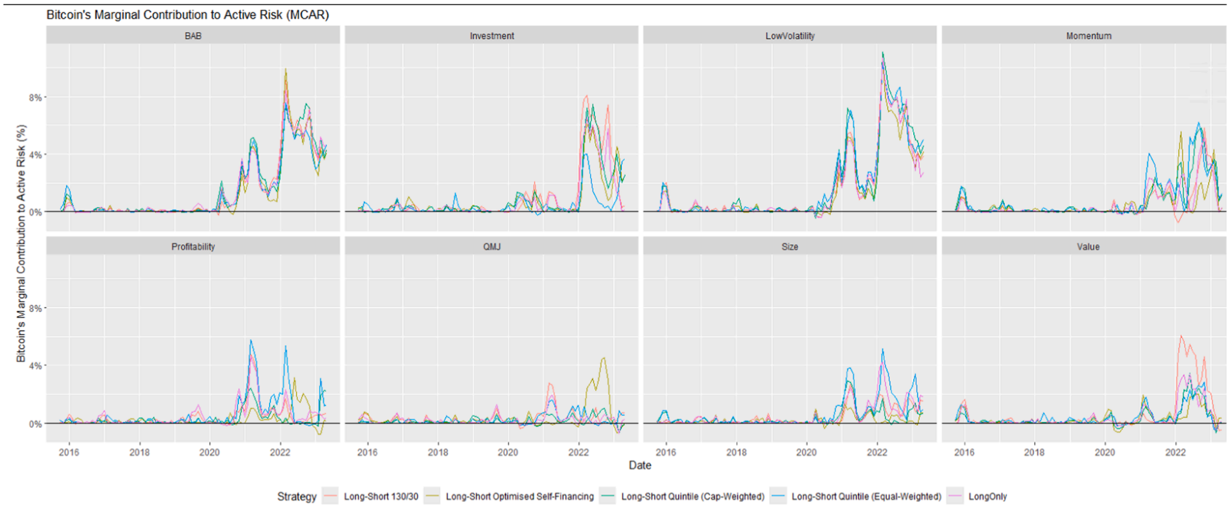

Fig. 2. Bitcoin's Marginal Contribution to Active Risks of Equity Portfolios. The figure illustrates the dynamic of Bitcoin's marginal contribution to the active variance of equity factor portfolios. We define the intraday active portfolio returns as the difference between equity portfolios and a market-capitalisation weighted benchmark for long-only and 130/30 strategies, and the U.S. 30-day T-Bill for self-financing and quintile long-short strategies. Portfolios are rebalanced monthly (the methodology is elaborated in Supplementary Appendix, Section B). Using a quarterly rolling window for each monthly rebalance, we estimate portfolio historical betas by regressing active returns on the factors (Bitcoin, U.S. equity, and bond market returns). Bitcoin's marginal contribution to active risk is calculated as (see Supplementary Appendix, Section C for details): $MCAR_{BTC} = \frac{\beta_{BTC}^{Active}\sum_{i=1}^{5}\beta_i^{Active}Cov(R_{BTC},R_i)}{\sigma_{Active}^2}$, where β_{BTC}^{Active} is the portfolio's active Bitcoin beta and β_i^{Active} is the portfolio's active beta to each of the five factors denoted by i and representing Bitcoin, the U.S. equity market and the short-term, mid-term, and long-term U.S. treasuries. $Cov(R_{BTC}, R_i)$, captures the covariance between returns on Bitcoin and factor i and σ_{Active}^2 denotes the portfolio's active variance. Since the covariance between Bitcoin and factors can be negative, $MCAR_{BTC}$ is not bounded by zero.

cognisant of the evolving Bitcoin exposures and manage risks accordingly.

Like the size factor, value has been shown to have a robust risk premium (Fama and French, 1993; Fama and French, 2015), suggesting that Bitcoin may positively co-move with this factor from a risk appetite angle. On the contrary, our findings in Table 3 indicate that the active Bitcoin betas in value portfolios are negative, consistent with the work by Liu and Tsyvinski (2021). The authors find that cryptocurrency returns are negatively correlated to the value factor and attribute their findings to the tendency of cryptocurrencies to co-move with growth. Given that speculative bubbles usually occur in overvalued growth stocks rather than undervalued firms (Baker and Wurgler, 2007; Anderson and Brooks, 2014), this makes sense as the value factor tilts towards (against) cheap (expensive) stocks. Notably, our findings are consistent with the negative active Ethereum betas of the value portfolios in Table G1 of Supplementary Appendix, supporting the notion that cryptocurrency risks are negatively associated with the value factor.

Finally, we discuss our findings about the equity momentum factor. From Table 3, we do not observe a clear-cut relationship between the momentum portfolios and Bitcoin in our full sample. Mechanically, we can see that the source of these insignificant test statistics is the time-varying nature of the momentum factor to Bitcoin, which fluctuates between extremes. Since, by construction, the momentum factor is positively (negatively) tilted towards winners (losers) over the preceding 12 months, the correlation between Bitcoin and equity momentum can turn negative when Bitcoin undergoes a price correction. In this instance, securities positively exposed to Bitcoin during underperformance are sorted into the 'losers' portfolio and vice-versa. The studies by Jo et al. (2020) and Nepp and Karpeko (2024) show that investor sentiment and hype are significant drivers of Bitcoin returns, an essential consideration in the context of Bitcoin's meteoric rise after the initial COVID-19 shock. Coupled with the surge in retail investors and ease of access to financial markets (Pagano et al., 2021), the pro-tech orientation and social media activity of retail investors often overlap with cryptocurrency traders, fuelling shared sentiments and price movements across both asset classes (Shen et al., 2019; Aloosh et al., 2022; Hasso et al., 2022, Yousaf et al., 2023). Thus, supported by these shared sentiments, Fig. 2 shows the positive Bitcoin exposures in momentum portfolios following the recovery phase of the COVID-19 pandemic. However, sentiment turned during the Russia-Ukraine war in 2022 as investors sold off risk assets in favour of defensive assets like gold and U.S. treasuries (Yousaf et al., 2023). The disproportionate spillover of Bitcoin's risks to equity sectors has been discussed in Leong and Kwok (2024), and it impacts the technology, consumer discretionary, communication services, and financial sectors more severely than others. As such, the momentum portfolios formed during this period will likely reduce exposures to sectors and stocks with positive Bitcoin betas.

4. Estimating and managing Bitcoin exposures

Since we now know that the active Bitcoin exposures in equity factor portfolios are time-varying, we discuss these implications for portfolio management. Measuring an equity portfolio's sensitivity to Bitcoin is a critical first step. In Section 4.1, drawing from the insights of Hollstein et al. (2020) and Lee et al. (2019), we emphasise the enhancement in beta estimation through intraday returns. Once we understand Bitcoin's impact precisely, we develop effective risk management strategies in Section 4.2.

4.1. Estimating Bitcoin betas

To improve the accuracy of our beta forecasts, we adopt intraday returns to refine the precision of these estimates, the method advocated by Hollstein et al. (2020) and Lee et al. (2019). We rebalance the equity portfolios monthly and construct Bitcoin beta estimates based on the preceding quarter's data. We generate three types of 'in-sample' beta estimates: high-frequency Bitcoin betas (β_{BTC}^{HF}), daily Bitcoin betas $\left(\beta_{BTC}^{Daily}\right)$, and Dimson's (1979) adjusted daily Bitcoin betas ($\beta_{BTC}^{Daily^{(4)}}$). These in-sample estimates, fitted to data from the previous quarter, are then contrasted with 'out-of-sample' betas, which are predictive estimates over the next month. Specifically, we define the forward one-month betas as $\beta_{BTC}^{HF,Forward1M}$ and $\beta_{BTC}^{Daily,Forward1M}$.

In Table 4, our primary focus lies in evaluating the quality of the in-sample beta estimates against a one-month forecasting horizon. Consistent with the approach of Hollstein et al. (2020), we employ root-mean-square error (RMSE) as the benchmark for our evaluation. We find that the high-frequency estimates of portfolio Bitcoin beta are generally more accurate than their daily counterparts. When benchmarked against the one-month forward daily beta and the one-month forward high-frequency beta, the high-frequency estimates consistently demonstrate enhanced accuracy. On average, the high-frequency estimates exhibit 9.6 % lower out-of-sample RMSEs than their daily counterparts.

Additionally, when employing the one-month forward high-frequency beta as an alternative metric for out-of-sample accuracy, the superiority of high-frequency estimates becomes more pronounced, with these estimates showing a 27.6 % reduction in out-of-sample RMSEs relative to daily beta estimates. Furthermore, applying Dimson's (1979) adjustment did not yield improvements in forecast quality. The Dimson-adjusted betas resulted in higher average RMSEs than their unadjusted counterparts, suggesting that this adjustment may not be optimal in forecasting Bitcoin beta.

For robustness, we consider four extensions to reconfirm our results: (1) beyond the initial one-month focus, our analysis also covers three and six-month forecast horizons; (2) while initially using 30-minute intervals, we further examine results across 15-minute and hourly intervals; (3) alongside our primary RMSE metric, we use the mean absolute error (MAE) as an additional evaluation criterion; (4) we evaluate the out-of-sample accuracy of Ethereum betas in equity factor portfolios. Our robustness checks in Tables D1 through D5 of Supplementary Appendix affirm our main results, showing a consistent pattern across longer forecast horizons, varied sampling intervals, and alternative evaluation criteria. Furthermore, using Ethereum as an alternative proxy for cryptocurrency risk, we show (in Table G2 of Supplementary Appendix) that intraday returns can be used to forecast betas robustly.

To formally evaluate the out-of-sample goodness-of-fit of our forecasted Bitcoin betas, we regress the one-month forward Bitcoin beta against the in-sample beta estimates as follows:

$$\beta_{BTC,it}^{Forward1M} = a + b\beta_{BTC,it}^{InSample} + \epsilon_t \tag{4}$$

where $\beta_{BTC,it}^{InSample}$ represents the in-sample Bitcoin beta estimates based on either intraday or daily data, and $\beta_{BTC,it}^{Forward1M}$, denoting the out-of-sample one-month Bitcoin beta estimates. Our study encompasses thirty-five investment strategies, comprising different combinations of equity factors (e.g., size, value) and strategic implementations (e.g., long-only, 130/30 long-short). This results in a panel data structure spanning different investment strategies over time. Following Petersen (2008), we employ clustered standard errors for these strategies in our panel regressions. The adjusted R-squared evaluates our beta forecasts' out-of-sample goodness of fit, indicating how much of the variance in forward Bitcoin beta estimates is explained by the in-sample forecasts.[17]

Table 5 presents the results of our panel regressions. We observe that the high-frequency beta, HF_{30}, provides the best fit for forecasting both forward daily and intraday betas. This is evidenced by the higher adjusted R-squared in models (1) and (4), coupled with the lowest AIC and BIC measures in these models. These results suggest high-frequency betas are the most effective predictors of Bitcoin betas in the forthcoming month. The coefficient of the independent variable is crucial for an economic interpretation of the models. While this coefficient does not directly reflect the model's fit, it is essential for understanding the relationship between in-sample beta forecasts and out-of-sample Bitcoin betas. A coefficient close to one implies a strong predictive relationship, whereas a value near zero indicates a weak or negligible influence of in-sample forecasts on out-of-sample betas. In our analysis, the coefficient for the intraday beta forecast, HF_{30}, is statistically significant, is much larger in magnitude, and is closer to one than their daily counterparts, indicating a strong relationship between the intraday beta forecast and the out-of-sample Bitcoin betas. In contrast, the coefficients for the daily beta forecasts in regressions (2) and (3) are insignificant, suggesting their limited predictive power for future Bitcoin betas. These findings corroborate the results presented in Table 4, affirming that intraday measurements of portfolio Bitcoin

[17] We also consider the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), both of which are typically used in the context of model selection.

Table 4
Forecast evaluation of Forward 1-Month Betas.

		RMSE Against 1-Month Forward Beta $\left(\widehat{\beta}_{BTC}^{Daily,Forward1M}\right)$				RMSE Against 1-Month Forward Beta $\left(\widehat{\beta}_{BTC}^{HF,Forward1M}\right)$			
Strategy	**Factor**	HF_{30}**(1)**	**Daily(2)**	$Daily^{(4)}$**(3)**	**Delta %**$(1)/(3)-1$	HF_{30}**(4)**	**Daily(5)**	$Daily^{(4)}$**(6)**	**Delta %**$(4)/(6)-1$
Long-Only	BAB	**0.011291**	0.012507	0.014618	−9.7 %	**0.003967**	0.006048	0.008851	−34.4 %
Long-Short 130/30	BAB	**0.017751**	0.019687	0.021853	−9.8 %	**0.005979**	0.009688	0.013289	−38.3 %
Long-Short Optimised Self-Financing	BAB	**0.069101**	0.077842	0.085028	−11.2 %	**0.025323**	0.041686	0.052419	−39.3 %
Long-Short Quintile (Cap-Weighted)	BAB	**0.079076**	0.092256	0.098319	−14.3 %	**0.026303**	0.049521	0.060789	−46.9 %
Long-Short Quintile (Equal-Weighted)	BAB	**0.083590**	0.094749	0.100358	−11.8 %	**0.027972**	0.043598	0.051280	−35.8 %
Long-Only	Investment	0.006053	**0.006016**	0.007787	0.6 %	**0.003456**	0.004224	0.005154	−18.2 %
Long-Short 130/30	Investment	**0.010214**	0.010782	0.011767	−5.3 %	**0.005620**	0.006842	0.007646	−17.9 %
Long-Short Optimised Self-Financing	Investment	0.033101	**0.032800**	0.040356	0.9 %	**0.020321**	0.025545	0.029771	−20.5 %
Long-Short Quintile (Cap-Weighted)	Investment	**0.038959**	0.041016	0.046475	−5.0 %	**0.023711**	0.028734	0.033497	−17.5 %
Long-Short Quintile (Equal-Weighted)	Investment	**0.027983**	0.030980	0.035575	−9.7 %	**0.014862**	0.018275	0.023658	−18.7 %
Long-Only	Low Volatility	**0.010695**	0.012153	0.013440	−12.0 %	**0.005635**	0.006924	0.009831	−18.6 %
Long-Short 130/30	Low Volatility	**0.019249**	0.022041	0.023708	−12.7 %	**0.009080**	0.012192	0.015972	−25.5 %
Long-Short Optimised Self-Financing	Low Volatility	**0.055746**	0.062046	0.067025	−10.2 %	**0.025972**	0.037227	0.046608	−30.2 %
Long-Short Quintile (Cap-Weighted)	Low Volatility	**0.093132**	0.105228	0.111867	−11.5 %	**0.042778**	0.054716	0.067554	−21.8 %
Long-Short Quintile (Equal-Weighted)	Low Volatility	**0.092775**	0.101189	0.106959	−8.3 %	**0.037420**	0.049078	0.061265	–23.8 %
Long-Only	Momentum	**0.013793**	0.014857	0.016060	−7.2 %	**0.006038**	0.008204	0.010049	−26.4 %
Long-Short 130/30	Momentum	**0.021194**	0.023229	0.024804	−8.8 %	**0.008155**	0.011863	0.014800	−31.3 %
Long-Short Optimised Self-Financing	Momentum	**0.076866**	0.083896	0.086176	−8.4 %	**0.038993**	0.050701	0.053412	–23.1 %
Long-Short Quintile (Cap-Weighted)	Momentum	**0.102906**	0.110482	0.119742	−6.9 %	**0.047565**	0.061934	0.075803	–23.2 %
Long-Short Quintile (Equal-Weighted)	Momentum	**0.094949**	0.101793	0.110246	−6.7 %	**0.044298**	0.057455	0.065706	–22.9 %
Long-Only	Profitability	**0.007565**	0.008736	0.009374	−13.4 %	**0.003184**	0.004552	0.005956	−30.1 %
Long-Short 130/30	Profitability	**0.012794**	0.014298	0.015179	−10.5 %	**0.004988**	0.007781	0.010418	−35.9 %
Long-Short Optimised Self-Financing	Profitability	**0.044053**	0.053759	0.054380	−18.1 %	**0.019222**	0.030484	0.034178	−36.9 %
Long-Short Quintile (Cap-Weighted)	Profitability	**0.047835**	0.055971	0.057706	−14.5 %	**0.019696**	0.029356	0.035910	–32.9 %
Long-Short Quintile (Equal-Weighted)	Profitability	**0.060660**	0.068339	0.071925	−11.2 %	**0.023833**	0.032419	0.039922	−26.5 %
Long-Only	QMJ	**0.006838**	0.008388	0.009133	−18.5 %	**0.003312**	0.005207	0.007158	−36.4 %
Long-Short 130/30	QMJ	**0.011180**	0.012414	0.013843	−9.9 %	**0.004677**	0.006819	0.010514	−31.4 %
Long-Short Optimised Self-Financing	QMJ	**0.049005**	0.055644	0.059425	−11.9 %	**0.021415**	0.028050	0.036366	–23.7 %
Long-Short Quintile (Cap-Weighted)	QMJ	**0.053541**	0.061505	0.062431	−12.9 %	**0.020856**	0.030968	0.036894	–32.7 %
Long-Short Quintile (Equal-Weighted)	QMJ	**0.053543**	0.058933	0.060495	−9.1 %	**0.022159**	0.027879	0.033370	−20.5 %
Long-Only	Size	**0.013412**	0.014271	0.015117	−6.0 %	**0.005178**	0.007676	0.009970	–32.5 %
Long-Short 130/30	Size	0.016465	**0.016416**	0.018785	0.3 %	**0.006722**	0.009654	0.012956	−30.4 %

(*continued on next page*)

Table 4 (*continued*)

Strategy	Factor	RMSE Against 1-Month Forward Beta $\left(\widehat{\beta}_{BTC}^{Daily,Forward1M}\right)$				RMSE Against 1-Month Forward Beta $\left(\widehat{\beta}_{BTC}^{HF,Forward1M}\right)$			
		HF_{30}(1)	*Daily*(2)	$Daily^{(4)}$(3)	Delta %(1)/(3) −1	HF_{30}(4)	*Daily*(5)	$Daily^{(4)}$(6)	Delta %(4)/(6) −1
Long-Short Optimised Self-Financing	Size	**0.052166**	0.059308	0.061555	−12.0 %	**0.021281**	0.035227	0.039434	−39.6 %
Long-Short Quintile (Cap-Weighted)	Size	**0.076440**	0.085043	0.086666	−10.1 %	**0.030608**	0.043110	0.048842	−29.0 %
Long-Short Quintile (Equal-Weighted)	Size	**0.074739**	0.081459	0.083096	−8.2 %	**0.030601**	0.041237	0.046262	−25.8 %
Long-Only	Value	**0.008575**	0.010337	0.010763	−17.1 %	**0.003757**	0.006150	0.008202	−38.9 %
Long-Short 130/30	Value	**0.010861**	0.013566	0.014894	−19.9 %	**0.005692**	0.008047	0.010826	−29.3 %
Long-Short Optimised Self-Financing	Value	**0.052406**	0.061081	0.060446	−14.2 %	**0.017846**	0.029809	0.036975	−40.1 %
Long-Short Quintile (Cap-Weighted)	Value	**0.074542**	0.084802	0.082577	−12.1 %	**0.027380**	0.041524	0.046838	−34.1 %
Long-Short Quintile (Equal-Weighted)	Value	**0.074230**	0.081935	0.083823	−9.4 %	**0.027860**	0.037572	0.042560	−25.8 %
Average		**0.043982**	0.049044	0.051844	−10.2 %	**0.018593**	0.026199	0.031523	−29.2 %

The table presents the root-mean-square error (RMSE) of forward one-month beta forecasts. We construct equity portfolios on a monthly rebalance frequency (see Supplementary Appendix, Section B for details). At every monthly rebalance, we construct (1) high-frequency estimates of portfolio Bitcoin betas, $\widehat{\beta}_{BTC}^{HF}$, using realised returns and (2) daily estimates of portfolio Bitcoin betas, $\widehat{\beta}_{BTC}^{Daily}$, using daily returns. We also include Dimson's (1979) adjustment by controlling for the first four lags for the daily beta, which, alongside the contemporaneous returns, captures a weekly trading window. We follow the beta estimation methodology outlined in Section 2.3 to estimate these in-sample betas. During each rebalance, we also look ahead over the next month and estimate forward (out-of-sample) betas using high frequency and daily returns. RMSEs are then calculated by taking the square root of the average squared errors between the in-sample beta estimates and the out-of-sample beta estimates:.$RMSE_{HF} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\widehat{\beta}_{BTC,t,T}^{InSample} - \widehat{\beta}_{BTC,t}^{HF,Forward1M}\right)^2} RMSE_{Daily} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\widehat{\beta}_{BTC,t,T}^{InSample} - \widehat{\beta}_{BTC,t}^{Daily,Forward1M}\right)^2}$
The high-frequency beta estimates based on 30-minute sampling intervals are denoted by HF_{30}. Similarly, the daily beta estimates are denoted by *Daily*, with the Dimson-adjusted betas denoted as $Daily^{(4)}$. The column 'Delta %' calculates the percentage difference in RMSE between the daily beta estimates (*Daily*) and the high-frequency beta estimates (HF_{30}). For each strategy and factor, we also highlight the model with the lowest RMSE in bold.

betas are markedly more precise than their daily counterparts in predicting future beta values.[18]

4.2. *Managing Bitcoin exposures in equity portfolios*

With more precise estimates of Bitcoin's impact on equity portfolios, we turn to the analysis of risk management strategies. We consider two main approaches for managing Bitcoin's exposures in portfolios: (1) Direct hedging, taking an offsetting position in Bitcoin or its futures and (2) Bitcoin-neutral equity portfolios, employing stock constraints within an optimisation framework to construct portfolios that are neutral to Bitcoin's risks.. We refer to the first approach as the 'direct approach' and the second as the 'indirect approach'. The direct approach, while conceptually straightforward, presents several practical challenges. Notably, Bitcoin futures were not available on regulated exchanges until December 2017, and even afterwards, trading activity was limited. Additionally, taking direct positions in Bitcoin may not align with investment mandates. Given these limitations, the indirect approach emerges as a viable alternative. This strategy allows portfolio managers to apply constraints during portfolio construction to neutralise Bitcoin beta without directly engaging with Bitcoin or its futures, thereby providing a practical solution to managing Bitcoin exposure. The additional constraint to the portfolio construction framework[19] is as follows:

$$\sum_{i=1}^{N} w_i * \widehat{\beta}_{BTC} = 0. \tag{5}$$

[18] To ensure the robustness of the results in Table 5, we consider three alternatives: firstly, we extend our forecast horizon beyond the initial one-month focus to include periods of three and six months. Secondly, we expand our methodology to include different intraday sampling intervals, incorporating 15-minute and hourly intervals. Thirdly, we replicate our methodology on Ethereum, testing the robustness of our base results. Collectively, these robustness checks confirm that our main findings are consistent and resilient over longer forecast periods, alternative sampling intervals, and with Ethereum betas. We present our robustness checks in Tables D6 through D9 and Table G3 of Supplementary Appendix.

[19] Refer to eq. B1, B2, and B3 in Supplementary Appendix for details on portfolio construction.

Table 5
Out-of-Sample Fit of Beta Forecasts using Panel Regressions.

Testing the Out-of-Sample Fit of Beta Forecasts using Panel Regressions

	Dependent variable:					
	1-Month Forward Beta $\left(\widehat{\beta}_{BTC}^{DAILY,Forward1M}\right)$			**1-Month Forward Beta** $\left(\widehat{\beta}_{BTC}^{HF,Forward1M}\right)$		
	(1)	(2)	(3)	(4)	(5)	(6)
***HF*$_{30}$**	0.536*** (0.089)			0.658*** (0.056)		
DAILY		−0.018 (0.080)			0.207* (0.074)	
***DAILY*$^{(4)}$**			0.042 (0.038)			0.159** (0.038)
Observations	13,600	13,600	13,600	13,600	13,600	13,600
R2	0.039	0.007	0.007	0.285	0.112	0.114
Adjusted R2	0.038	0.027	0.043	0.284	0.111	0.113
AIC	−41,569	−41,117	−41,125	−66,195	−63,064	−63,095
BIC	−41,463	−41,012	−41,020	−66,090	−62,959	−62,990

The table presents a formal test of the out-of-sample fit of beta forecasts using panel regressions. At every end-of-month rebalance, we construct (1) high-frequency estimates of portfolio Bitcoin betas, $\widehat{\beta}_{BTC}^{HF}$, using realised returns and (2) daily estimates of portfolio Bitcoin betas, $\widehat{\beta}_{BTC}^{HIST}$, using daily returns. We follow the beta estimation methodology outlined in Section 2.3 to estimate these in-sample betas. We also include Dimson's (1979) adjustment for the first four lags for the daily beta, which, alongside the contemporaneous returns, captures a weekly trading window. During each rebalance, we also look ahead over the next month and estimate forward (out-of-sample) betas using high frequency and daily returns. To test the out-of-sample fit of the beta forecasts, we regress the forward Bitcoin beta against the in-sample beta estimates and cluster standard errors across different factor strategies. Our regression model is of the functional form:.$\beta_{BTC,it}^{Forward1M} = a + b\beta_{BTC,it}^{InSample} + \epsilon_{it}$
Here, $\beta_{BTC,it}^{Forward1M}$ is the forward one-month beta for factor strategy i at time t, and $\beta_{BTC,it}^{InSample}$ is the in-sample beta estimate calculated over the last quarter. The high-frequency beta estimates based on 30-minute sampling intervals are denoted by HF_{30}. Similarly, the daily beta estimates are denoted by *Daily*, with the Dimson-adjusted betas denoted as $Daily^{(4)}$.
The * , ** , and *** marks denote statistical significance at the 10%, 5%, and 1% level, respectively.

It is, however, important to recognise that the indirect approach, while practical, comes with a price. Imposing weight constraints in portfolio selection restricts the opportunity set and often diminishes the information ratio of trading strategies at the optimum when the portfolio manager is free to deviate from the benchmark (Bajeux-Besnainou et al., 2011). Despite this potential limitation, the indirect approach is often favoured due to its operational feasibility. We evaluate these two approaches based on their effectiveness in neutralising the active Bitcoin betas in equity portfolios.

Table 6 contrasts the active Bitcoin betas and Bitcoin's MCAR for various equity portfolios across the entire period. First, although we target in-sample Bitcoin beta neutrality based on a rolling quarterly window, it is essential to note that these in-sample estimates do not inherently ensure out-of-sample neutrality. When examining out-of-sample returns over the whole period, we observe instances where both the direct and indirect approaches overestimate Bitcoin exposures. Second, we note that directly hedged portfolios tend to exhibit the lowest active Bitcoin betas and MCARs. Our analysis does not factor in potential market impact costs or transaction fees, which can vary significantly based on the portfolio's size and the investment manager's operational capabilities. Therefore, the advantages we note here should be considered an upper limit of direct hedging benefits. Finally, we show that portfolio managers can achieve a degree of partial hedging against Bitcoin's exposures using constrained optimisation. The portfolios from this approach display active Bitcoin betas and MCARs that typically range between unhedged and fully hedged portfolios, suggesting a viable middle ground to balance risk management with operational and cost considerations.

We analyse and compare the active Bitcoin betas and Bitcoin's MCAR across several stylised equity portfolios, including hedged, constrained, and unhedged portfolios (refer to Figs. E1 and E2 of Supplementary Appendix). In line with our analysis over the full period, these figures reinforce that directly hedging Bitcoin's risks is the most effective method for reducing active Bitcoin betas in equity portfolios. Nevertheless, for investors unable to pursue direct hedging, the indirect approach emerges as a feasible and practical alternative. For robustness, we extend our analysis to include results based on the 15-minute and 60-minute intraday returns for both hedged and constrained portfolios in Section F of Supplementary Appendix, Tables F1 and F2. The consistency of these results across different intraday sampling intervals highlights the efficacy of constrained optimisation as a viable strategy for mitigating Bitcoin's risk exposures.

Table 6
Active Bitcoin Betas in Unhedged, Hedged and Constrained Equity Portfolios.

		$\widehat{\beta}_{BTC}$			$MCAR_{BTC}$		
Strategy	**Factor**	**Base (Unhedged)**	**Direct (Hedged)**	**Indirect (Constrained)**	**Base (Unhedged)**	**Direct (Hedged)**	**Indirect (Constrained)**
Long-Only	BAB	−0.0028***	**−0.0001**	−0.001***	0.829 %	**0.019 %**	0.260 %
		(0.0004)	(0.0003)	(0.0003)			
Long-Short 130/30	BAB	−0.0046***	**−0.0002**	−0.0014***	0.834 %	**0.026 %**	0.220 %
		(0.0006)	(0.0005)	(0.0005)			
Long-Short Optimised Self-Financing	BAB	−0.0154***	**−0.0004**	−0.002	0.705 %	**0.012 %**	0.067 %
		(0.0022)	(0.0021)	(0.002)			
Long-Only	Investment	−0.0014***	**−0.0005****	−0.0009***	0.450 %	**0.115 %**	0.214 %
		(0.0002)	(0.0002)	(0.0002)			
Long-Short 130/30	Investment	−0.0032***	**−0.0010****	−0.0015***	0.781 %	**0.171 %**	0.264 %
		(0.0003)	(0.0004)	(0.0004)			
Long-Short Optimised Self-Financing	Investment	−0.0066***	−0.0014	**−0.0014**	0.362 %	0.050 %	**0.044 %**
		(0.0010)	(0.0012)	(0.0012)			
Long-Only	Low Volatility	−0.0037***	**−0.0008****	−0.0017***	0.985 %	**0.156 %**	0.413 %
		(0.0003)	(0.0004)	(0.0004)			
Long-Short 130/30	Low Volatility	−0.0064***	**−0.0013***	−0.0028***	1.045 %	**0.146 %**	0.392 %
		(0.0006)	(0.0007)	(0.0006)			
Long-Short Optimised Self-Financing	Low Volatility	−0.0167***	**−0.0022**	−0.0036*	0.826 %	**0.072 %**	0.119 %
		(0.0017)	(0.002)	(0.0019)			
Long-Only	Momentum	0.0007	**0.0003**	0.0009**	0.017 %	**0.003 %**	0.049 %
		(0.0004)	(0.0004)	(0.0004)			
Long-Short 130/30	Momentum	**−0.0001**	0.0003	0.0007	**0.001 %**	−0.003 %	0.007 %
		(0.0005)	(0.0006)	(0.0005)			
Long-Short Optimised Self-Financing	Momentum	0.0038	**0.0001**	0.0045*	0.036 %	**0.001 %**	0.064 %
		(0.0026)	(0.0025)	(0.0024)			
Long-Only	Profitability	−0.0008***	**0.0001**	−0.0001	0.138 %	**−0.005 %**	0.008 %
		(0.0002)	(0.0002)	(0.0002)			
Long-Short 130/30	Profitability	−0.0011***	0.0005	**−0.0001**	0.097 %	−0.017 %	**0.003 %**
		(0.0003)	(0.0004)	(0.0004)			
Long-Short Optimised Self-Financing	Profitability	0.0016	0.0021	**0.0016**	0.020 %	0.029 %	**0.019 %**
		(0.0013)	(0.0014)	(0.0014)			
Long-Only	QMJ	**−0.0004***	0.0006**	0.0007**	−0.009 %	**−0.004 %**	0.032 %
		(0.0002)	(0.0003)	(0.0003)			
Long-Short 130/30	QMJ	**−0.0002***	0.0008**	0.0009**	0.013 %	−0.035 %	**−0.011 %**
		(0.0001)	(0.0004)	(0.0004)			
Long-Short Optimised Self-Financing	QMJ	**0.0024**	0.0065***	0.0056***	0.274 %	0.153 %	**0.121 %**
		(0.0018)	(0.0018)	(0.0017)			
Long-Only	Size	0.0014***	**0.0000**	0.0001	0.151 %	**0.000 %**	0.003 %
		(0.0003)	(0.0004)	(0.0004)			
Long-Short 130/30	Size	0.0013***	**0.0000**	−0.0002	0.096 %	**0.000 %**	−0.005 %
		(0.0004)	(0.0005)	(0.0005)			
Long-Short Optimised Self-Financing	Size	**0.0002**	−0.0013	−0.0031*	**0.001 %**	−0.004 %	0.011 %
		(0.0015)	(0.0016)	(0.0017)			
Long-Only	Value	−0.0012***	−0.0012***	**−0.0010*****	0.094 %	0.078 %	**0.066 %**
		(0.0003)	(0.0003)	(0.0003)			
Long-Short 130/30	Value	−0.0026***	**−0.0016*****	−0.0018***	0.313 %	**0.135 %**	0.186 %
		(0.0004)	(0.0004)	(0.0004)			
Long-Short Optimised Self-Financing	Value	−0.0032*	−0.0043***	**−0.0029***	−0.004 %	−0.001 %	**0.000 %**
		(0.0015)	(0.0016)	(0.0016)			

The table presents the equity portfolios' active Bitcoin betas across unhedged, hedged and constrained equity portfolios. Active returns are computed as the difference between each strategy and its respective benchmark: a market-cap-weighted index for long-only and 130/30 strategies, and the U.S. 30-day T-Bill for self-financing and quintile long-short portfolios. Portfolios are rebalanced monthly (additional details available in Supplementary Appendix Section B). Active betas ($\widehat{\beta}_i$) are estimated using a regression model with 30-minute intraday returns over the entire period from June 2015 to March 2023. The base (unhedged) equity portfolios assume that the portfolio manager does not take actions to manage the Bitcoin risk exposures in equity portfolios, which are our initial results in Table 3. The direct (hedged) approach is implemented by taking an offsetting position in Bitcoin to neutralise the quarterly 30-minute intraday active portfolio Bitcoin betas, and the indirect (constrained) approach is implemented by constructing

portfolios with a weighted average active Bitcoin beta of zero. Using the hedged and unhedged portfolio returns series, we then estimate the portfolios' active betas $(\widehat{\beta}_i)$ using 30-minute intraday returns. Specifically, the regression model is of the following form:$r_p - r_{Benchmark} = \beta_0 + \beta_{BTC} r_{BTC} + \beta_{Mkt} r_{Mkt} + \beta_{ShortT} r_{ShortT} + \beta_{MidT} r_{MidT} + \beta_{LongT} r_{LongT} + \in,$
where the portfolio active returns are represented by $r_p - r_{Benchmark}$; we use ETFs to proxy returns on the equity market (SPY), short-term bonds (SHY), mid-term bonds (IEF), and long-term bonds (TLT).
From this regression, we also calculate and derive Bitcoin's marginal contribution to active risk (see Section C in the Supplementary Appendix for details) as follows:.$MCAR_{BTC} = \frac{\beta_{BTC}^{Active} \sum_{i=1}^{5} \beta_i^{Active} Cov(r_{BTC}, r_i)}{\sigma_{Active}^2}$
where β_{BTC}^{Active} is the portfolio's active Bitcoin beta and β_i^{Active} is the portfolio's active beta to each of the five factors denoted by i and representing Bitcoin, the U.S. equity market, U.S. short-term, mid-term, and long-term treasuries. $Cov(r_{BTC}, r_i)$, captures the covariance between returns on Bitcoin and factor i and σ_{Active}^2 denotes the portfolio's active variance. Since the covariance between Bitcoin and factors can be negative, $MCAR_{BTC}$ is not bounded by zero.
We highlight the portfolio with the lowest active Bitcoin beta and MCAR for each strategy and factor in bold. In parentheses, we report Newey and West (1987) standard errors with four lags. * , ** , and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5. Conclusion

Our examination of the contemporaneous relationship between Bitcoin and equity factors reveals that Bitcoin's role in shaping the active risk profiles of equity portfolios is undeniable. Bitcoin's marginal contribution to active risk (MCAR) in equity portfolios has grown over time, constituting over 10 % of the active risk in some defensive investing styles. The elevated MCAR in these portfolios can be attributed to the tilt towards firms with lower volatility, higher profitability and conservative investment policies. Furthermore, lower active Bitcoin betas do not always translate to lower MCARs since MCAR scales the contribution of Bitcoin's risk by the portfolio's active variance. In essence, managers of conservative long-only funds should be just as aware of their Bitcoin exposure as those running aggressive long-short strategies. Notably, our main findings are robust to our choice of cryptocurrency. Using Ethereum as an alternative measure of cryptocurrency risk (Section G of Supplementary Appendix), we obtain qualitatively similar findings.

Turning to the best approach to measure Bitcoin's risks in equity portfolios, our findings advocate for using intraday returns in beta estimation, which leads to a notable reduction in the prediction error of daily Bitcoin beta forecasts. Our robustness checks, spanning different intraday sampling intervals, forecast periods, loss functions and using Ethereum as an alternative measure of cryptocurrency risk, further affirm our primary conclusion.

Addressing risk management, we show that directly hedging Bitcoin risks in equity portfolios is more effective. However, we also acknowledge potential practical challenges and operational realities to taking direct positions in Bitcoin or its futures. As an alternative, we suggest employing stock constraints to limit the active Bitcoin exposure, achieving a partial hedge against the unregulated asset, and offering a feasible solution for managers.

Our research demonstrates that cryptocurrency risk implications for equity portfolios are tangible and escalating. Investment professionals cannot overlook this nexus between an unregulated asset and traditional equity factors. Our analysis, backed by empirical data, serves as a guide for practitioners to make informed decisions. Additionally, we challenge the academic community to delve into this intersection, ensuring that research evolves with financial market realities. Finally, our findings have implications for global financial markets, where the interconnectedness of cryptocurrencies and traditional assets could exacerbate systemic risks. As regulators and central banks consider frameworks for cryptocurrency integration, the ability to measure and manage these risks becomes increasingly relevant.

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CRediT authorship contribution statement

Minhao Leong: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vitali Alexeev:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Simon Kwok:** Writing – review & editing, Supervision, Resources, Project administration.

Appendix A

Table A1
Definition of Equity Factors.

Factor	Definition
Market Risk Premium	The market risk premium factor is defined as the excess return of the market portfolio over the risk-free rate, measured as the return on a broad stock market index minus the yield on a risk-free government bond (Fama and French, 1993).
Size	We define the size equity factor following Fama and French (2015, 1993). The size quintile portfolio is constructed by taking a long (short) position in firms with the smallest (largest) market capitalisation.
Value	We define the value equity factor following Fama and French (2015, 1993). The value quintile portfolio is constructed by taking a long (short) position in firms with the highest (lowest) book-to-market ratios.
Profitability	We define the profitability equity factor following Fama and French (2015). The profitability quintile portfolio is constructed by taking a long (short) position in firms with the highest (lowest) operating profitability, as measured through a firm's return on equity.
Investment	We define the investment equity factor following Fama and French (2015). The investment quintile portfolio is constructed by taking a long (short) position in firms with the most (least) conservative investment expenditure, as measured through a firm's change in the rate of total assets.
Momentum	We define the momentum equity factor following Carhart (1997). The momentum quintile portfolio is constructed by taking a long (short) position in stocks that have risen the most (least) over the preceding 12 months.
Low Volatility	We define the low volatility equity factor following Baker et al. (2011). The low volatility quintile portfolio is constructed by taking a long (short) position in stocks with the lowest (highest) return volatility over the preceding three years.
Betting-against-Beta	Following Frazzini and Pedersen (2014), we use a one-year rolling standard deviation for volatilities and a five-year horizon for correlations to compute equity market betas. The BAB factor is constructed by taking a long position in low-beta stocks and a short position in high-beta stocks, designed to exploit the tendency of high-beta assets to underperform low-beta assets on a risk-adjusted basis.
Quality-minus-Junk	We define the QMJ factor following Asness et al. (2019). The QMJ factor is constructed by taking a long position in high-quality firms (measured by profitability, growth, and safety) and a short position in low-quality firms (i.e., "junk" firms with poor profitability, growth, or stability). Following Asness et al. (2019), Quality is defined as: $Quality = z(Profitability + Growth + Safety)$, Where the underlying profitability, growth and safety scores are constructed as: $Profitability = z(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc})$ $Growth = z(z_{\Delta gpoa} + z_{\Delta roe} + z_{\Delta roa} + z_{\Delta cfoa} + z_{\Delta gmar})$ $Safety = z(z_{bab} + z_{lev} + z_{OScore} + z_{ZScore} + z_{evol})$ Within profitability, we follow the steps in Asness et al. (2019) for constructing standardised scores of the variables: gross profits over assets (*gpoa*), return on equity (*roe*), return on asset (*roa*), cashflow over assets (*cfoa*), gross margin (*gmar*) and accruals (*acc*).Next, growth is defined as by averaging the z-scores of various measures (i.e., *gpoa*, *roe*, *roa*, *cfoa*, *gmar*) of five-year growth in residual profits. To elaborate on residual profits, Asness et al. (2019) define residual profits as profits in excess of the capital invested in the risk-free rate. The safety measures in Asness et al. (2019) account for different dimensions of stability and defensiveness. The betting-against-beta (*bab*) measure utilises the BAB factor that we have detailed in this table, following the work of Frazzini and Pedersen (2014). Leverage (*lev*) tilts towards firms with lower level of financial leverage and is computed as minus total debt over total assets. *O-and-Z* scores are proxy measures of bankruptcy risk, as in the work by Ohlson (1980) and Altman (1968). We multiply Ohlson's (1980) *OScore* by -1 to reflect the same direction as Altman's (1968) *ZScore*, which tilts towards firms with low bankruptcy risk. Finally, *evol* is the standard deviation of quarterly *roe* over the past 60 quarters, and is multiplied by -1 to reflect the direction of lower earnings variability.

The table summarises the definitions of the equity factors used in this study. We construct variables by following the methodologies within the asset pricing literature (Fama and French, 1993; Carhart, 1997; Baker et al., 2011; Frazzini and Pedersen, 2014; Fama and French, 2015; Asness et al., 2019).

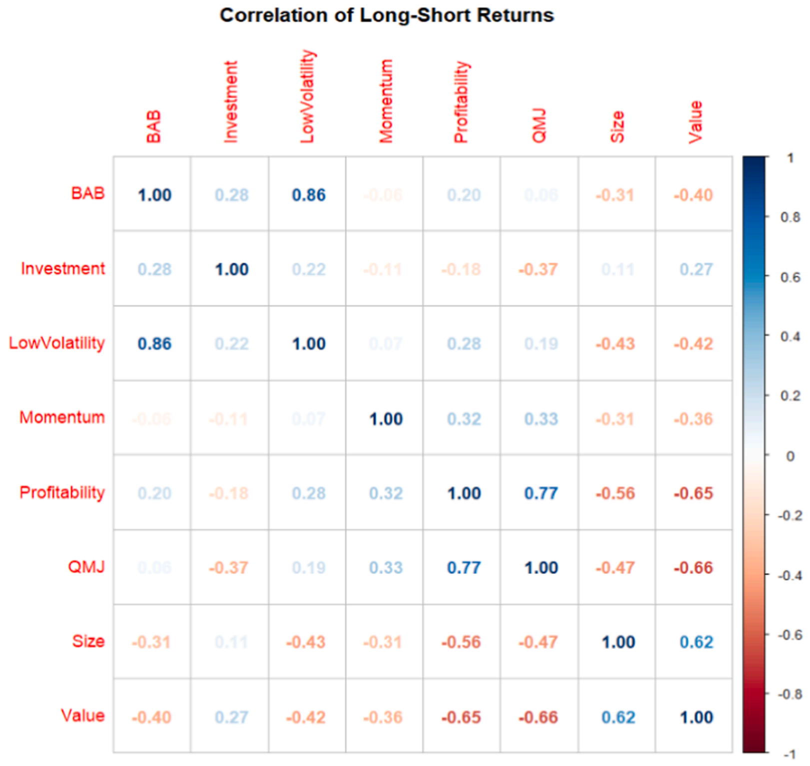

Fig. A1. Correlation Matrix of Equity Factor Long-Short Portfolio Returns

Fig. A1 presents the correlation of long-short portfolio returns for the different equity factor portfolios in our study. The portfolio returns in this figure uses the 30-minute intraday returns, consistent with our base results.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.intfin.2025.102123.

Data availability

Data will be made available on request.

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