Integrating Crypto Assets into Portfolio Management:

A Comprehensive Analysis across Asset Allocation Techniques

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ABSTRACT

Title: Integrating Crypto Assets into Portfolio Management: A Comprehensive Analysis across Asset Allocation Techniques

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The increased relevance of crypto assets raises questions regarding their role in traditional portfolio optimization. This thesis investigates whether incorporating the Crypto Currency Index 30 (CCI30) or Bitcoin (BTC) enhances portfolio performance across several asset spaces and portfolio optimization techniques. The applied techniques include risk-based, return-based, and utility-based approaches. Furthermore, this thesis investigates whether crypto-inclusion effects are time-varying or constant and whether there is a superior optimization technique or superior design choices (e.g. different windowing-approaches) for crypto-inclusion.

The portfolios are constructed purely out-of-sample based on daily return data from 2015 to 2024. The final assessment uses statistical comparisons based on block-bootstrapping and fixed-effects panel regression analyses.

The results show that crypto assets generally improve performance. Their inclusion increases risk-adjusted returns and utility measures, but also increases risk measures substantially, with benefits differing across strategies. The simple 1/N, maximum diversification and utility-based approaches display the strongest gains. Furthermore, crypto-inclusion benefits exhibit substantial time variation. In both applied subperiods - pre- and post-COVID - adding crypto leads to alternating periods of over- and underperformance compared to traditional portfolios. This pattern suggests that crypto assets act as performance amplifiers, magnifying both positive and negative performances. Overall, crypto inclusion improves performance, as the positive amplification outweighs its negative counterpart.

This thesis contributes to existing literature by comprehensively evaluating crypto-inclusion effects over an extended period and by systematically comparing various strategies and design choices. Future research could explore dynamic optimization approaches or focus on explaining the time-varying nature of crypto-inclusion benefits.

Key words: Crypto Assets, CCI30, Bitcoin, Portfolio Optimization, Portfolio Optimization Techniques, Portfolio Performance Measures, Block-Bootstrapping, Risk-based Approaches, Utility-based Approaches, Risk-adjusted Return-based Approaches, Fixed-effect Panel Regression

RESUMO

Título: Integração de Criptoativos na Gestão de Portfólios: Uma Análise Abrangente das Técnicas de Alocação de Ativos

Autor: Thomas Pramel

O aumento da relevância dos criptoativos levanta questões sobre o seu papel na otimização de portfólios tradicionais. Esta tese investiga se a incorporação do Crypto Currency Index 30 ou do Bitcoin melhora o desempenho dos portfólios. Foram aplicadas técnicas com abordagens baseadas no risco, no retorno e na utilidade. Além disso, examina a possibilidade dos efeitos serem constantes ou variáveis no tempo e se existe uma técnica de otimização superior para a integração dos criptoativos.

Os portfólios são construídos fora da amostra, com base em dados de retornos diários entre 2015 e 2024. A avaliação final utiliza comparações estatísticas através de bootstrapping em blocos e regressões de painel com efeitos fixos.

Os resultados demonstram que os criptoativos melhoram o desempenho. A sua inclusão aumenta os retornos ajustados ao risco e a utilidade, mas também eleva substancialmente o risco. Ademais, os benefícios da inclusão de criptoativos apresentam forte variação temporal. Nos dois períodos aplicados, antes e depois do COVID, adicionar cripto leva a períodos alternados de melhor ou pior desempenho em comparação aos portfólios tradicionais. Esta conclusão sugere que criptoativos atuam como potenciadores de desempenho. Em geral, a integração de criptoativos melhora o desempenho, porque a amplificação positiva supera a negativa.

Esta tese contribui para a literatura ao avaliar os efeitos da inclusão de criptoativos num período alargado e ao comparar sistematicamente diversas estratégias e escolhas de conceção. Investigações futuras poderão explorar abordagens de otimização dinâmicas ou concentrar-se em explicar a natureza variável no tempo dos benefícios da inclusão de criptoativos.

Palavras-chave: Criptoativos, CCI30, Bitcoin, Otimização de carteiras, Técnicas de otimização de portfólios, Medidas de desempenho dos portfólios, Bootstrapping em blocos, Abordagens baseadas no risco, Abordagens baseadas na utilidade, Abordagens baseadas em retornos ajustados ao risco, Regressão em painel com efeitos fixos

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IV. LIST OF ABBREVIATIONS

ADF .... *Augmented Dickey-Fuller*
AIC .... *Akaike Information Criterion*
ARCH .... *Autoregressive Conditional Heteroskedasticity*
ARMA .... *Autoregressive Moving Average*
BIC .... *Bayesian Information Criterion*
bps .... *Basis Points*
bs-mv .... *Bayes-Stein Mean-Variance*
BTC .... *Bitcoin*
CAPM .... *Capital Asset Pricing Model*
CC .... *Cryptocurrency*
CCI30 .... *Crypto Currency Index 30*
CEQ .... *Certainty Equivalent*
Corp .... *Corporate*
COVID .... *Corona Virus Disease*
crra .... *Constant Relative Risk Aversion*
CVaR .... *Conditional Value at Risk*
DCC-GARCH .... *Dynamic Conditional Correlation GARCH*
Dev .... *Developed*
eGARCH .... *Exponential GARCH*
EM .... *Emerging Markets*
EPRA .... *European Public Real Estate Association*
ERC .... *Equal Risk Contribution*
ETF .... *Exchange-Traded Fund*
ETH .... *Ethereum*
ew .... *Equally-Weighted*
ew_bh .... *Equally-Weighted Buy and Hold*
FE .... *Fixed-Effects*
FF .... *Fama French*
FTSE .... *Financial Times Stock Exchange*
GARCH .... *Generalized Autoregressive Conditional Heteroskedasticity*
GJR-GARCH .... *Glosten-Jagannathan-Runkle GARCH*
gmv .... *Global Minimum Variance*

GSCI .... *Goldman Sachs Commodity Index*
HAC .... *Heteroskedasticity and Autocorrelation Consistent*
HMM .... *Hidden Markov Model*
i.e. .... *id est (that is)*
i.i.d. .... *Independent and Idendically Distributed*
iGARCH .... *Integrated GARCH*
JB .... *Jarque-Bera*
LB .... *Ljung-Box*
Max. .... *Maximum*
maxDiv .... *Maximum Diversification*
maxR .... *Maximum Return*, *Maximum Return*
maxSR .... *Maximum Sharpe Ratio*
maxSTARR .... *Maximum STARR*
Min. .... *Minimum*
minCVaR .... *Minimum Conditional Value at Risk*
MSCI .... *Morgan Stanley Capital International*
mv .... *Mean-Variance*
OLS .... *Ordinary Least Squares*
OOS .... *Out of Sample*
pp .... *Percentage Points*
REIT .... *Real Estate Investment Trust*
RQ .... *Research Question*
SR .... *Sharpe Ratio*
STARR .... *Stable Tail Adjusted Return Ratio*
Std.Dev. .... *Standard Deviation*
TGARCH .... *Threshold GARCH*
USD .... *United States Dollar*

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1 INTRODUCTION

1.1 The Rise of Cryptocurrencies

Since Satoshi Nakamoto (2008) first introduced the concept of cryptocurrencies (CCs), their relevance has been on the rise, peaking at a market capitalization of about 3.7 trillion USD in December 2024, distributed amongst over 11.5 million CCs, with Bitcoin (BTC) accounting for about 50-60% of the total market capitalization throughout the last calendar year (CoinMarketCap, 2025). Although the market capitalization is still low compared to traditional asset classes such as equities or bonds, CCs are gaining interest among institutional investors (Huang, Lin, & Wang, 2022). A 2022 Bridgewater article states that CC exposures from institutional investors are likely to grow due to the rapid development of investment products and major banks building trading desks and infrastructure specifically for CCs. Eight out of ten institutions view crypto and digital assets as a potential fit for portfolios (Karniol-Tambour, Tan, Tsarapkina, Sondheimer, & Barnes, 2022). As of 2023, over 40% of a sample of over 250 institutions were already invested in spot CC, i.e. direct holdings of CC without using derivative products. Including the institutions planning to invest within the next three years, this number grows to more than 50%. The most common allocation is typically within the 1% to 5% range, with most of the allocation flowing into BTC and Ethereum (ETH). However, 60% of investors also invest in a variety of other CCs (Elinson & Kher, 2023). A more recent study finds that two-thirds of institutional investors are planning to invest in crypto assets and that CCs are especially appealing due to their high upside potential, innovative technology and low correlation to other assets (Fidelity Digital Assets, 2024). However, the studies also emphasize obstacles regarding crypto exposure, such as high volatility, concerns around market manipulation, lack of regulatory clarity and general security concerns (Elinson & Kher, 2023; Fidelity Digital Assets, 2024; Karniol-Tambour et al., 2022). The regulatory issues have been partly addressed by the approval of Spot BTC Exchange-Traded Products by the United States Securities and Exchange Commission in January 2024 (Gensler, 2024) and of similar Ether-based products in July 2024 (Schmitt, 2024), which make it easier for institutional investors to invest into CC.

1.2 Relevance, Motivation and Research Objectives

The increasing adoption and relevance of CCs highlight the demand for data-driven insights and analyses regarding their impact on asset allocation strategies. Both private and institutional investors seek viable guidance from academia in questions such as ‘Should crypto assets be included in well-diversified portfolios?' and 'If so, how should they be incorporated?'. This demand for clarity is reinforced by publications from some of the world's leading financial institutions, such as JP Morgan, State Street or Morningstar, which are trying to answer these questions and come to different conclusions on how or whether CCs and their unique risk-return profiles should be combined with traditional asset classes (Arnott, 2024; Czasonis, Kritzman, Pamir, & Turkington, 2022; Manley & Gauba, 2024; Sigel, Bush, & Zinoviev, 2024).

The academic and practical relevance, paired with a deep personal interest in being on the edge of time regarding the exploration of innovative and forward-looking investment opportunities, are thus the key drivers behind the motivation for this thesis. The main objective of this thesis is twofold. First, this thesis aims to assess whether CCs can enhance portfolio performance using various traditional asset allocation techniques. The focus hereby lies on the creation of implementable strategies that will be tested out of sample (OOS) to assess their real-world effectiveness. Second, this thesis aims to provide guidance regarding the selection of the most appropriate asset allocation technique when including CCs in a portfolio.

1.3 Structure of the Thesis

First, a comprehensive literature review will be conducted. This literature review aims to define CCs and examine their return behavior and usage in portfolio optimization. Subsequently, the methodology chapter will guide through the derivation of the research questions (RQ), and explain the applied portfolio optimization techniques, the performance measures, and the overall approach used to answer the RQs. Chapter four, 'Empirical Analysis', presents the derived results per RQ in detail and provides additional information from robustness tests. In chapter five, 'Discussion', the results will be interpreted in further detail, compared to previous literature, and specific recommendations for investors in practice will be derived. This chapter also discusses the limitations of this thesis and introduces potential future research areas. The last chapter, 'Conclusion', briefly summarizes all previous parts, focusing on the derived findings and their implications.

2 LITERATURE REVIEW

2.1 Cryptocurrencies - A Definition of the Term

Before diving into detail, a definition of the term 'cryptocurrencies' is introduced to create a uniform understanding. In this context, it is necessary to distinguish between two fundamental concepts: electronic money and virtual currencies. Electronic money can be seen as digital cash.

It describes the digital storage of monetary value issued and governed by a central authority, which can be used for payment transactions and easily converted into traditional money (European Union, 2009; Lansky, 2018). Instead, virtual currencies are digital representations of value that are not issued by public authorities or central banks, are not necessarily pegged (i.e., fixed or closely tied) to a fiat currency and typically do not have legal tender status. They can be issued centralized or decentralized (European Banking Authority, 2014).

CCs belong to the decentralized form. Nakamoto (2008), who introduced the first CC and the underlying mechanisms, describes a system that allows transactions between parties without needing a trusted third party. This is achieved by reliance on cryptography and a decentralized network, commonly referred to as blockchain. These networks are designed to keep the overview of units and ownership, control the creation of additional units, allow transactions, and eliminate errors such as double spends on their own. Common principles include decentralization, pseudo-anonymity, and transparency, as all transactions are stored within the network using codes rather than names or other personal information (Chu, Chan, Nadarajah, & Osterrieder, 2017; Lansky, 2018; Trozze et al., 2022).

Academic research is still divided on whether CCs should be considered currencies or an alternative asset class. The European Central Bank names three essential functions of a currency. (1) Medium of Exchange: It is usable for payments as it is a legal tender and has a value that people trust. (2) Unit of account: It allows goods and services to be priced and those prices to be compared. (3) Store of value: It can be stored to preserve value over time (European Central Bank, 2015). CCs' high volatility (compare section 2.2.1) and the fact that exchange-traded volume makes up a large portion of the total transaction volume suggest that CCs are more commonly used as an asset (Glasner, Zimmermann, Haferkorn, Weber, & Siering, 2014). This is further supported by several studies which show that they are investible and their prices fluctuate according to supply and demand. This is not necessarily the case for currencies (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Urquhart, 2017; Wei, 2018). Holovatiuk (2020) and Pele et al. (2023) characterize them as an asset class and check several requirements, such as stable aggregation, investment accessibility, internal homogeneity, and external heterogeneity. Additionally, they apply dimensionality reduction techniques. This thesis classifies CCs as an asset class and subsequently refers to them as crypto assets.

2.2 Statistical Properties and Correlation Dynamics of Crypto Assets

2.2.1 The Return Behavior of Crypto Assets

While earlier papers mainly focus on the return behavior of BTC, later papers expand the subsequently mentioned findings to a broader sample of crypto assets. Generally, crypto assets offer high returns but also exhibit high volatility, heavy tails, and skewness (Blau, 2018; Cheah & Fry, 2015; Chu, Nadarajah, & Chan, 2015; Osterrieder, 2017). Other common features are long memory, conditional heteroskedasticity, and negative leverage effects (Fung, Jeong, & Pereira, 2022). Speculative bubbles are observable within the crypto asset space and prices tend to cluster around even numbers (Cheah & Fry, 2015; Urquhart, 2017). Gandal et al. (2018) even find evidence for price manipulations through large individual investors or investor groups. Crypto assets furthermore exhibit stylized facts that are also often found in return series of other financial assets (Cont, 2001). When analyzing crypto returns, it is common to find an absence of significant linear autocorrelations, a slow decay of autocorrelation in absolute returns, volatility clustering, a leverage effect, and a significant volume/volatility correlation (Ghosh, Bouri, Wee, & Zulfiqar, 2023; Hu, Parlour, & Rajan, 2019; Zhang, Wang, Li, & Shen, 2018).

While academic research does not fully agree on the most suitable distribution for crypto asset return series, it does share the opinion that it is important to choose a distribution that accounts for heavy tails. It concludes that a t-student distribution regularly is amongst the best fitting distributions across several Goodness-of-Fit tests and information criteria (Osterrieder, 2017; Phillip, Chan, & Peiris, 2018).

Dunbar and Owusu-Amoako (2022) find that crypto asset returns are predictable based on a crypto market risk premium, consistent with the classical CAPM for equity returns. Other papers extend this and introduce more sophisticated factor models for crypto assets, similar to well-established factor models for the pricing of traditional assets, such as 3FF or 5FF. They find that expected crypto asset returns are at least partially captured by a market, a size and a momentum factor (Liu & Tsyvinski, 2021; Liu, Tsyvinski, & WU, 2022).

2.2.2 Crypto-Correlations: Internal and Cross-Market Relationships

Even though crypto assets tend to exhibit similar characteristics regarding their return series, the literature on the correlation structure within the crypto space is divided. Holovatiuk (2020) and Borri (2019) find relatively high correlations of up to 0.8 and show that this co-movement is especially pronounced between major coins, such as BTC and ETH (Katsiampa, 2019; Liu & Serletis, 2019). However, those studies also argue that constructing pure crypto-portfolios can significantly reduce idiosyncratic risk (Borri, 2019; Katsiampa, 2019). In contrast, other studies find that over 90% of pairwise correlations can be considered relatively low and fall within a range of -0.1 to 0.2 (Borri, 2019; Brauneis & Mestel, 2019; Holovatiuk, 2020; Liu, 2019).

However, a broad majority of previous researchers find that crypto assets show low correlations with other asset classes. They find pairwise correlations to mainly be below 0.2. Their analyses use a broad sample of up to 52 crypto assets and several traditional asset classes such as stocks, fixed income, currencies, commodities, real estate, and hedge funds. (Baur, Hong, & Lee, 2018b; Borri, 2019; Brière, Oosterlinck, & Szafarz, 2015; Gil-Alana, Abakah, & Rojo, 2020; Gorman & Hughen, 2024; Holovatiuk, 2020; Liu & Tsyvinski, 2021; Petukhina, Trimborn, Härdle, & Elendner, 2021). Other studies prove BTC's diversification or hedging potential using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approaches (Baur, Dimpfl, & Kuck, 2018a; Dyhrberg, 2016a; Dyhrberg, 2016b). Nevertheless, academic literature does not fully agree on crypto assets' ability to serve as diversifiers in times of high volatility. While some studies argue that low correlation and, thus, diversification benefits persist in times of financial turmoil (Bouri, Hussain Shahzad, & Roubaud, 2020; Dwita Mariana, Ekaputra, & Husodo, 2021), other studies find certain spillover effects and increased correlation in times of financial turmoil, e.g., throughout and following the Corona Virus Disease (COVID19) crisis (Gorman & Hughen, 2024; Nguyen, 2022). Li and Miu (2023) find that the correlation between stocks and crypto assets is significant and high when both markets are in high-volatility states, while insignificant or even negative when at least one is in a low- or medium-volatility state.

2.3 Crypto Assets in Portfolio Optimization

A broad stream of literature has used several alternative asset classes in portfolio optimization approaches to achieve diversification benefits and thereby improve the risk-return profile of portfolios. Common extensions to a portfolio consisting of equities, fixed income, and a potential risk-free asset that are widely proven to offer diversification benefits include foreign exchange, commodities, and real estate (Ackermann, Pohl, & Schmedders, 2017; Barroso & Santa-Clara, 2015; Belousova & Dorfleitner, 2012; Benjamin, Sirmans, & Zietz, 2001; Hoang, Lean, & Wong, 2015; Kroencke, Schindler, & Schrimpf, 2014). As this thesis focuses on crypto assets, a more detailed overview of their use in portfolio optimization is provided in the subsequent sections.

2.3.1 Pure Crypto-Portfolios

Several papers have constructed pure crypto portfolios without using other asset classes. Approaches applying traditional mean-variance optimization to portfolios composed entirely of different and up to 500 crypto assets show that performance improvements are achievable compared to investing in single crypto assets (Brauneis & Mestel, 2019; Platanakis, Sutcliffe, & Urquhart, 2018; Platanakis & Urquhart, 2019). Liu (2019) and Burggraf (2019) extend this research by using broader sets of portfolio optimization techniques and find that optimal asset allocation amongst crypto assets enhances Sharpe Ratios (SR) and utility across all the used techniques.

2.3.2 Adding Bitcoin to Optimal Portfolios

In an early study, Brière et al. (2015) found that adding BTC to portfolios consisting of (1) traditional assets (2) alternative assets, and (3) a mix of all assets, allows them to achieve higher risk-adjusted returns in spanning tests. Diversification benefits can also be achieved using Mean-Conditional Value at Risk (CVaR) approaches, as higher returns overcompensate the increased CVaR from adding BTC to portfolios. This also holds when introducing short sale constraints or maximum weights (Eisl, Gasser, & Weinmayer, 2014; Kajtazi & Moro, 2019). Platanakis and Urquhart (2020) offer a comprehensive study that examines the impact of the addition of BTC using (1) eight asset allocation techniques, (2) quadratic and constant relative risk aversion (CRRA) utility functions, (3) three different levels of risk aversion and (4) several portfolio performance metrics. They find that adding BTC improves SRs, Sortino Ratios and Omega Ratios in almost all considered scenarios, leading to the conclusion that BTC should be a part of today's portfolios. This conclusion even stands after several robustness tests, which include using price data from different exchanges, short sale constraints, and a proxy for transaction cost. While their results are confirmed by Guesmi et al. (2019), Gorman and Hughen (2024) challenge this view in a more recent study. By applying a Dynamic Conditional Correlation (DCC)-GARCH model, they find a structural break in the covariance of BTC and traditional asset classes around the COVID-19 outbreak. Furthermore, they perform mean-variance spanning tests and construct in-sample optimal portfolios and find reduced performance improvements in latter periods under a mean-variance setting. Symitsi and Chalvatzis (2019) perform another comprehensive study in which they add BTC to portfolios consisting of currencies, commodity indices, stocks and a mixed portfolio of all the aforementioned. They use four asset allocation techniques, namely (1) equally-weighted (ew), (2) global minimum variance (gmv), (3) short sale constrained gmv, and (4) short sale constrained gmv with covariance forecasts retrieved from a DCC-GARCH model. They find that adding BTC significantly improves SRs in almost all scenarios but at the cost of significantly increased portfolio turnover. Removing so-called ‘bubble-periods’, periods in which BTC earned extraordinary returns, which are followed by strong downturns, they found that the increases in SRs became insignificant or even turned negative. Furthermore, they document that the mean weight attributed to BTC, when added to a long-only and mixed portfolio, is between 0.08% and 3.36% depending on the applied rebalancing frequency and asset allocation technique.

2.3.3 Adding Several Crypto Assets to Optimal Portfolios

Trimborn et al. (2020) find that the addition of 42 crypto assets to stocks, or a mix of stocks, bonds, and commodities, generally improves OOS SRs when using a gmv or a minimum CVaR (minCVaR) approach. Additionally, those portfolios exhibit reduced negative skewness and kurtosis, and the results remain robust but less pronounced when introducing liquidity constraints and when using monthly instead of weekly rebalancing. However, they find that the maximum drawdown increases in some scenarios. These results are supported by Holovatiuk (2020), who forms tangency portfolios based on a mean-variance and a mean-CVaR approach and includes the CRIX as the crypto asset. The CRIX is an index created by Trimborn and Härdle (2018) that captures the movement of the crypto market. Holovatiuk (2020) furthermore concludes that SRs improve across all asset allocation methods, while Sortino Ratios typically worsen. Hence, investors concerned about limiting their downside risk should not necessarily include crypto assets in their portfolios. Ma et al. (2020) also find increased SRs when constructing tangency portfolios that include five crypto assets, especially when allowing short sales. Constructing portfolios with BTC, ETH, four industry portfolios and cash and using an asset allocation approach based on risk parity with an EWMA risk estimation and a 10% maximum weight constraint on crypto assets increases returns without significantly increasing volatility or drawdown. This also holds for a simple approach that invests 90% equally in the four industry portfolios and 10% equally in BTC and ETH (Johansson & Boyd, 2024). Petukhina et al. (2021) performed an extensive study using a broad set of assets and nine asset allocation techniques and found mixed results. First, they find that cumulative wealth over the entire period tends to be higher when including crypto assets, but with substantial differences between asset allocation techniques. At the same time, SRs of portfolios which include crypto assets tend to be higher than those of the benchmark portfolios. Besides the Equal Risk Contribution (ERC) approach, none of these increases show statistical significance. They also assess the weights and different diversification measures and find that diversification benefits depend strongly on the applied asset allocation technique. Additionally, they conclude that adding crypto assets extends the efficient frontier, especially in the high-risk, high-return area. These results hold for daily, weekly, and monthly rebalancing. However, they do not find increases in risk-adjusted returns when using gmv or Minimum CVaR, which opposes the previously mentioned literature.

2.4.4 Limitations and Research Gaps of Current Literature

One common limitation in the existing literature is the relatively short time horizon considered, which is mainly rooted in the fact that crypto assets have only existed for a limited period that does not allow excessive OOS testing. Moreover, several papers restrict their analysis to crypto-inclusive portfolios compared against a single previously defined benchmark instead of systematically applying each optimization technique in both a crypto-inclusive and a traditional setting. Others conduct purely in-sample analyses, which may not adequately reflect real-world OOS circumstances. In addition, many papers examine a limited set of performance metrics and often do not account for estimation errors in the input parameters. This is a severe shortcoming, as asset allocation models are known to be highly sensitive to such errors, potentially resulting in extreme weights, poor OOS performance, and a neglection of higher order moments (Best & Grauer, 1991; Chopra, Hensel, & Turner, 1993; Jobson & Korkie, 1980; Lai, Xing, & Chen, 2011; Michaud, 1989). In many cases, portfolios formed without consideration of estimation errors can even be outperformed by simple equally-weighted portfolios despite their theoretical inefficiency (DeMiguel, Garlappi, & Uppal, 2009; Jobson & Korkie, 1980).

Beyond those methodological limitations, several research gaps remain. Previous research did not conduct an OOS analysis of whether crypto-inclusion effects are of a constant or time-varying nature. This aspect appears increasingly relevant as several indications for time-varying effects are already provided (reduced correlations and in-sample performance after COVID-19, etc.). Furthermore, while previous research has focused on examining whether benefits are achievable across different optimization strategies, no prevalent study has analyzed whether crypto-inclusion effects significantly vary across strategies or assessed whether there is a clearly superior optimization strategy for capturing the theoretical crypto-inclusion benefits.

3 METHODOLOGY

3.1 Derivation of the Research Questions

The historically high average returns and the low – or even negative – correlations (see section 2.2) suggest that including crypto assets in portfolios enhances risk-adjusted returns and utility. This is supported by several studies that successfully used BTC or several crypto assets in different portfolio optimization settings (see section 2.3). However, most existing evidence is based on data ending in 2020. More recent literature finds a noteworthy shift: Correlations between crypto assets and other asset classes have substantially increased in recent years, especially after the COVID-19 crisis. These developments might represent a structural change, influence the potential outperformance from crypto-enhanced portfolios and raise the following questions:

RQ1: Does adding crypto assets improve the performance of portfolios constructed using traditional portfolio optimization techniques over an extended OOS period up to the end of 2024?

RQ2: Does the performance contribution of crypto assets to portfolios constructed using traditional portfolio optimization techniques significantly vary over time?

In addition, the literature review reveals lacking consensus on a superior portfolio optimization technique when integrating crypto assets into diversified portfolios. This leads to an additional research question:

RQ3: Is there a consistently superior portfolio optimization technique to integrate crypto assets into diversified portfolios and how do specific design choices (e.g., rebalancing frequency, estimation procedure, etc.) influence the potential enhancement of portfolio performance?

A comprehensive comparison across different portfolio optimization techniques will be conducted to address these questions (see section 3.3). Each technique will be applied in two scenarios (1) a case without, and (2) another case including crypto assets. These scenarios will then be evaluated using a broad set of portfolio performance measures (see section 3.5). Subsequently, extensive robustness tests will be conducted to validate the observed findings. The following chapters describe the dataset, the portfolio optimization techniques, and the portfolio performance measures. They furthermore introduce the overall methodology employed in this thesis in further detail. A visual summary of the whole empirical process can be found in Appendix A.6.

3.2 Description of the Used Data

Table 1 provides an overview of the assets used in the portfolio optimization procedures and their respective asset classes. Subsequently, equities, fixed income, commodities and real estate will be referred to as traditional assets. In contrast, BTC and the Crypto Currency Index 30 (CCI30), an index that captures the broad movement of the crypto market (Rivin & Scevola, 2017), will be referred to as crypto assets. CCI30 was selected due to its transparent and strictly mathematical derivation and because it is the longest existing broad crypto index. This enables a longer OOS period, which is of high relevance, considering the youth of crypto assets. The indices for the traditional assets have been selected as they represent broad portfolios within their respective asset class. The FTSE EPRA Nareit Developed Index is used as a proxy for real estate, as it globally tracks the performance of listed real estate companies and real estate investment trusts (REITs) across different types of properties (residential, office, etc.) while offering liquidity, investment accessibility and data availability. The main asset classes in classical portfolio optimization procedures – equities and fixed income – are represented by two indices to capture specific subgroups: industrial and emerging economies for equities and government and corporate bonds for fixed income.

Asset	Abbreviation	Asset Class
Traditional Assets		
MSCI World USD Total Return Index	MSCI.World	Equities
MSCI EM USD Total Return Index	MSCI.EM	Equities
FTSE World Government Bond Index - Total Return USD	FTSE.World.Gov.	Fixed Income
FTSE US Broad Investment Grade Corporate Bond Index - Total Return USD	FTSE.US.Corp	Fixed Income
S&P GSCI Commodity Total Return USD	S.P.GSCI	Commodities
FTSE EPRA Nareit Developed Total Return USD	FTSE.EPRA.Dev.	Real Estate
Crypto Assets		
CCI30 Crypto Currencies Index USD	CCI30	Crypto
Bitcoin Price USD	BTC	Crypto

Table 1: List and Classification of Assets Used for Portfolio Optimization including Abbreviations

For each traditional asset, the daily total return index was downloaded from Refinitiv Workspace. The BTC price history was downloaded from CoinMarketCap, a leading crypto data provider, using the R-package *crypto2* (Stoeckl & Vent, 2024), while the CCI30 data was extracted directly from its website (Rivin, Scevola, Davis, & Yaron, 2025). All downloaded time series are denominated in USD for consistency. The risk-free rate was downloaded from the Kenneth R. French - Data Library (French & Fama). Each time series starts at the first available data point after or equal to January 1, 2015 and ends with the last available data point before or on December 31, 2024. This results in 2,608 daily return observations. The starting date was set from 2015 onwards, as the CCI30 index is only available thereafter. Additionally, 2015 marks the first year in which crypto assets continuously exhibited trading volumes above ten million USD. Thus, market liquidity can be assumed sufficient to support regular rebalancing.

Name	Base constituents
simple	MSCI.World, FTSE.World.Gov.
eq_fi	MSCI.World, MSCI.EM, FTSE.World.Gov., FTSE.US.Corp.
gsci	MSCI.World, MSCI.EM, FTSE.World.Gov., FTSE.US.Corp., S.P.GSCI
epra	MSCI.World, MSCI.EM, FTSE.World.Gov., FTSE.US.Corp., FTSE.EPRA.Dev.
all	MSCI.World, MSCI.EM, FTSE.World.Gov., FTSE.US.Corp., S.P.GSCI, FTSE.EPRA.Dev.

Table 2: List of Created Asset Spaces

Table 2 provides an overview of the created asset spaces. Each asset space is subsequently created in a version including CCI30 and a version including BTC. This is conducted to evaluate whether crypto assets contribute additional value in all asset spaces or if their potential benefits are limited to specific settings, as the benefits might also be attainable through diversification across a broader set of traditional assets themselves. The main comparison will be performed between purely traditional portfolios and versions that include the CCI30. In contrast, the BTC versions will mainly be used in robustness tests to verify whether potential crypto effects depend on the selection of the crypto asset.

3.3 Portfolio Optimization Techniques

Table 3 provides an overview of the portfolio optimization techniques used. The techniques can be subdivided into approaches that (1) attribute equal weights to each asset according to a naïve 1/N rule, (2) focus on minimizing risk measures, (3) focus on maximizing returns, (4) focus on optimizing the risk-reward trade-off, (5) maximize the expected utility of investors.

Portfolio Optimization Technique	Abbreviation
Naïve approaches	
Equally Weighted Portfolios with Rebalancing	ew
Equally Weighted Portfolios Buy and Hold	ew_bh
Risk-based approaches	
Global Minimum Variance Portfolios	gmv
Minimum Conditional Value at Risk Portfolios	minCVaR
Risk Parity Portfolio with Equal Risk Contribution	ERC
Maximum Diversification Portfolio	maxDiv
Return-based approach	
Maximum Return Portfolios	maxR
Risk-Adjusted Return-based approaches	
Maximum Sharpe Ratio / Tangency Portfolios	maxSR
Maximum STARR Portfolios	maxSTARR
Utility-based approaches	
Mean-Variance Utility Maximizing Portfolios	mv
Bayes-Stein Shrinkage Mean-Variance Portfolios	bs-mv
CRRA Utility Maximizing Portfolios	crra

Table 3: List and Classification of Portfolio Optimization Techniques including Abbreviations

3.3.1 Constraints Applied to all Portfolios

All portfolios are implemented including a 'full investment' constraint, meaning that the sum of the weights $\boldsymbol{\omega}_t$ of all risky assets must be equal to 100%. A rolling investigation of the condition number of the covariance matrices for each created asset space shows that they become numerically unstable/ill-conditioned once either BTC or CCI30 is added. A more detailed overview can be seen in Appendix A.2. Jagannathan and Ma (2003) show that imposing a short sale constraint on portfolio weights, even though seemingly wrong, is effectively similar to using a shrinkage estimator for the covariance matrix. The constraint thus helps to stabilize the covariance matrix and reduce the effect of sampling error. Therefore, approaches based on shrinking the covariance matrix (e.g. Best and Grauer; Ledoit and Wolf; Ledoit and Wolf (1992; 2004b; 2004a)) will not be applied. Instead, this thesis will perform all subsequently listed portfolio optimization techniques including a short sale constraint: $\boldsymbol{\omega}_t \geq 0$ for all $t = 1, \ldots, N$. This constraint reflects a realistic, practical case, as many investors are short sale restricted. Furthermore, it typically positively impacts a portfolio's risk-adjusted OOS performance. Another argument supporting the introduction of this constraint is that it was not easily feasible to short crypto assets before the CME Group introduced BTC futures in December 2017 (CME Group, 2017). Additionally, all subsequently described optimization techniques will solely invest in the risky assets.

3.3.2 Notation for Portfolio Optimization Techniques

In the following introduction of the optimization techniques, $\boldsymbol{\omega} \in \mathbb{R}^n$ is a vector of length n of the portfolio weights, $\mathbf{1} \in \mathbb{R}^n$ is a vector of ones, $\boldsymbol{\mu}_r \in \mathbb{R}^n$ is a vector of the expected asset returns, $\boldsymbol{\Sigma}_r \in \mathbb{R}^{n \times n}$ is the expected covariance matrix of asset returns, $\boldsymbol{\sigma}_r \in \mathbb{R}^n$ is a vector of individual asset volatilities, $\boldsymbol{\mu}_R \in \mathbb{R}^n$ is a vector of the expected asset excess returns, $\boldsymbol{\Sigma}_R \in \mathbb{R}^{n \times n}$ is the expected covariance matrix of asset excess returns, $rf \in \mathbb{R}$ is the risk-free rate, $\boldsymbol{r}_t \in \mathbb{R}^n$ is the return vector at time t, $\boldsymbol{R}_t \in \mathbb{R}^n$ is the excess return vector at time t, $T \in \mathbb{R}$ is the number of time-periods, $\boldsymbol{\gamma}$ is the risk aversion of an investor, $\alpha \in (0,1)$ is the confidence level for the Conditional Value at Risk (in this thesis 0.95) and $CVaR_\alpha$ denotes the Conditional Value at Risk at the previously specified confidence level computed using the historical distribution of (excess) portfolio returns.

3.3.3 Naïve Equally-Weighted Portfolios

DeMiguel et al. (2009) find that none of a broad set of 14 models across seven asset spaces can consistently outperform the 1/N portfolio in terms of SR or certainty equivalent (CEQ) returns.

Hence, this model will be applied and partly be used as a benchmark for other strategies. The vector of portfolio weights $\boldsymbol{\omega}$ is retrieved according to the formula: $\boldsymbol{\omega}_t^{ew} = 1/n$, where n is the number of risky assets. This naïve approach neither performs any optimization nor does it rely on historical data. In this thesis, the 1/N portfolios will be constructed in two ways, namely (1) with rebalancing (ew) and (2) with an even simpler buy-and-hold approach (ew_bh).

3.3.4 Risk-Based Approaches

Global Minimum Variance Portfolios

The Global Minimum Variance Portfolio (gmv) aims to minimize the expected portfolio variance and does not consider returns. It is the leftmost point on the mean-variance efficient frontier with only risky assets. The only input parameter required to derive the gmv is the covariance matrix estimate. As this thesis operates under a long-only constraint, where the closed-form solution is no longer applicable, the weights are estimated using a numerical solver for the following optimization problem:

$$\min_{\boldsymbol{\omega}} \boldsymbol{\omega}^\top \boldsymbol{\Sigma}_r \boldsymbol{\omega} \tag{1}$$

Minimum Conditional Value at Risk Portfolios

Asset returns often exhibit heavy tails and do not follow normal distributions (Cont, 2001). This is especially true for crypto assets (compare section 2.2.1). Therefore, approaches that use alternative risk measures will be applied. The CVaR approach, first introduced by Rockafellar and Uryasev (2000; 2002), is an optimization framework which considers higher moments and their respective risks. Using the CVaR as the risk estimate is especially beneficial for investors who care about minimizing the risk of significant losses. The first portfolio based on this risk metric is the minCVaR portfolio, which aims to minimize CVaR without considering expected returns. It is comparable to the gmv but solves a different optimization problem of the form:

$$\min_{\boldsymbol{\omega}} CVaR_\alpha(\boldsymbol{\omega}^\top \boldsymbol{r}_t) \tag{2}$$

Risk Parity Portfolios with Equal Risk Contribution

Another common, purely risk-based allocation strategy is the risk parity portfolio with equal risk contribution, subsequently referred to as ERC. According to Petukhina et al. (2021), this strategy is amongst the best-performing strategies when combining crypto assets with traditional ones. The concept of the ERC approach is to assign weights to each asset so that they contribute equally to the total portfolio's volatility. It thus diversifies risk rather than capital and can increase robustness when working with uncertain return estimates (Maillard, Roncalli, & Teïletche, 2010).

Using the Euler decomposition allows the volatility of a portfolio $\sigma_P(\boldsymbol{\omega}) = \sqrt{\boldsymbol{\omega}^\top \boldsymbol{\Sigma}_r \boldsymbol{\omega}}$ to be presented in the following form:

$$\sigma_P(\boldsymbol{\omega}) = \sum_{i=1}^{n} \omega_i \frac{\partial \sigma_P(\boldsymbol{\omega})}{\partial \omega_i} \tag{3}$$

Where the term following the summation defines the risk contribution of asset i to the portfolio in absolute terms. The ERC portfolio is derived by solving for ω such that:

$$\sigma_i(\omega) = \frac{1}{n} \sigma_P(\boldsymbol{\omega}) \tag{4}$$

$$\forall i \in \{1, \dots, n\}$$

In the setting of this thesis, a numerical optimization approach to minimize the squared deviations of the relative risk contributions from their target level (1/N) is used:

$$\min_{\boldsymbol{\omega}} \sum_{i=1}^{n} \left(\frac{\omega_i [\boldsymbol{\Sigma}_r \boldsymbol{\omega}]_i}{\boldsymbol{\omega}^\top \boldsymbol{\Sigma}_r \boldsymbol{\omega}} - \frac{1}{n} \right)^2 \tag{5}$$

Maximum Diversification Portfolios

Instead of minimizing risk measures, the Maximum Diversification Portfolio (maxDiv) is an asset allocation technique that maximizes the diversification ratio, thus aiming to achieve the largest possible risk reduction through diversification. This technique is proven to outperform traditional portfolios in certain settings, especially when asset correlation structures tend to be unstable (Choueifaty & Coignard, 2008; Choueifaty, Froidure, & Reynier, 2013). The diversification ratio to be maximized is defined as:

$$DR(\boldsymbol{\omega}) = \frac{\boldsymbol{\omega}^\top \boldsymbol{\sigma}}{\sqrt{\boldsymbol{\omega}^\top \boldsymbol{\Sigma}_r \boldsymbol{\omega}}} \geq 1 \tag{6}$$

The portfolio is obtained by numerically solving the following optimization problem:

$$\max_{\boldsymbol{\omega}} DR(\boldsymbol{\omega}) \tag{7}$$

3.3.5 Return-Based Approach

Maximum Return Portfolios

The Maximum Return Portfolio (maxR) can be interpreted as the opposite of the gmv. It is obtained by purely maximizing expected returns, regardless of risk estimates, and can be created purely based on the return estimates. In a long-only framework, this strategy typically attributes 100% of the weight to the asset with the highest expected return at each time t. As it does not consider risk, it is generally not part of the mean-variance efficient frontier. The optimization problem to be solved is:

$$\max_{\boldsymbol{\omega}} \boldsymbol{\omega}^\top \boldsymbol{\mu}_r \tag{8}$$

3.3.6 Risk-Adjusted Return-Based Approaches

Maximum Sharpe Ratio Portfolios

The maximum SR portfolio (maxSR) is based on the mean-variance approach and is also commonly referred to as the tangency portfolio. This portfolio maximizes the expected excess return per unit of its standard deviation. In an unconstrained setting, it can be obtained using a closed-form solution and would be equal to the mean-variance utility maximizing portfolio for an investor with a risk aversion γ of 1. In the constrained setting of this thesis, the optimal solutions of the mean-variance utility maximizing portfolio and the tangency portfolio might differ, as the constraints change the efficient frontier. Therefore, the maxSR portfolio is implemented using a numerical solver for the following optimization problem:

$$\max_{\boldsymbol{\omega}} \frac{\boldsymbol{\omega}^\top \boldsymbol{\mu}_R}{\sqrt{\boldsymbol{\omega}^\top \boldsymbol{\Sigma}_R \boldsymbol{\omega}}} \tag{9}$$

Maximum STARR Ratio Portfolios

This portfolio maximizes the ratio between the expected excess returns and the CVaR, which is known as the Stable Tail Adjusted Return Ratio (STARR). It is part of the previously mentioned portfolio construction techniques that replace variance with a different risk estimate (see minCVaR) and closely related to the SR maximizing portfolio. The numerical optimization problem to be solved is defined as:

$$\max_{\boldsymbol{\omega}} \frac{\boldsymbol{\omega}^\top \boldsymbol{\mu}_R}{CVaR_\alpha(\boldsymbol{\omega}^\top \boldsymbol{R}_t)} \tag{10}$$

3.3.7 Utility-Based Approaches

Mean-Variance Utility Maximizing Portfolios

Markowitz's groundbreaking approach of mean-variance optimization is typically seen as the cornerstone of modern portfolio theory. The key assumption is that investors construct their portfolios solely based on expected returns and risk, which is measured by variance. He proposes a framework that enables the investor to construct portfolios that maximize expected utility based on an investor's risk aversion by finding the sweet spot of the trade-off between expected risk and return (Markowitz, 1952). The optimization problem in this setting is:

$$\max_{\boldsymbol{\omega}} \boldsymbol{\mu}_R^\top \boldsymbol{\omega} - \frac{\gamma}{2}\, \boldsymbol{\omega}^\top \boldsymbol{\Sigma}_R \boldsymbol{\omega} \tag{11}$$

Bayes-Stein Shrinkage Mean-Variance Portfolio

Based on the ideas of Stein (1955) and James and Stein (1961), who pioneered shrinkage estimation, Jorion (1986) proposed shrinking the means of assets towards the mean of the gmv portfolio. The vector of the expected Bayes-Stein mean excess returns $\boldsymbol{\mu}_R^{BS}$ is derived using:

$$\boldsymbol{\mu}_R^{BS} = (1 - \Phi)\boldsymbol{\mu}_R + \Phi Y_0 \mathbf{1} \tag{12}$$

Where the parameters Φ and Y_0 are derived using a Bayesian approach:

$$\Phi = \frac{n + 2}{(n + 2) + (\boldsymbol{\mu}_R - Y_0 \mathbf{1})^\top \boldsymbol{\Sigma}_R^{-1} (\boldsymbol{\mu}_R - Y_0 \mathbf{1})} \tag{13}$$

$$Y_0 = \frac{\mathbf{1}^\top \boldsymbol{\Sigma}^{-1}}{\mathbf{1}^\top \boldsymbol{\Sigma}^{-1} \mathbf{1}} \boldsymbol{\mu}_R \tag{14}$$

The new estimates are then plugged into the optimization problem in Equation 11, to retrieve the mean-variance portfolio based on shrunk mean return estimates.

CRRA Utility Maximizing Portfolios

To find the optimal weights for investors with CRRA, utility is no longer modelled via the quadratic utility function. Instead, a power utility function according to Equation 15, where W denotes the final wealth, is applied:

$$U(W) = \frac{W^{1-\gamma}}{1 - \gamma} \tag{15}$$

This utility function assumes that the investor seeks to maximize the utility of final wealth and thus indirectly incorporates volatility and higher moments such as skewness and kurtosis. Assuming an initial wealth of 1, the optimization problem becomes:

$$\max_{\boldsymbol{\omega}} \frac{(1+\boldsymbol{\omega}^{\top}\boldsymbol{\mu}_R)^{1-\gamma}}{1-\gamma} \tag{16}$$

All utility-based approaches are implemented using a risk aversion γ of 3 in the base scenario, which is common in empirical studies and is used e.g. by Tu and Zhou (2011) and Campbell and Sigalov (2022).

The portfolio optimization techniques have been selected to balance broad coverage of portfolio philosophies (Risk-based, Return-based, Utility-based) and the underlying investor preferences with feasibility and interpretability, as well as real-world applicability and theoretical insight. Approaches that consider higher order moments have been explicitly included due to crypto assets' heavy tails. The selected techniques allow the assessment of potential performance enhancements from different perspectives and enable benchmarking between strategies to investigate whether complex techniques add more value.

The portfolio weights are generally obtained using the R-package *PortfolioAnalytics* (Peterson et al., 2024a). For the maxDiv and ERC portfolios, the R-package *RiskPortfolios* (Ardia, Boudt, & Gagnon-Fleury, 2021) is used. The derivation of the shrunk return estimates in the Bayes-Stein approach is performed using the R-package *HDShOP* (Bodnar, Dmytriv, Okhrin, Otryakhin, & Parolya, 2024).

3.4 Rolling Window Approach

The portfolio weights for each strategy/asset space combination are derived using a rolling window approach. The model's input parameters are estimated over a window with a fixed range that moves one step (day, week or month) ahead at each application. The input parameters are estimated over $t - T + 1$ to retrieve the weights applicable until the next rebalancing. The rolling window allows a dynamic evolution of the model's input parameters, which captures changes within them. The length of the rolling window T is set to 252 days following Petukhina et al. (2021) and Platanakis and Urquhart's (2020) choice of one year as the window size. This window size is assumed to be sufficient to retrieve solid estimates yet flexible to accommodate changes such as structural breaks or regime shifts.

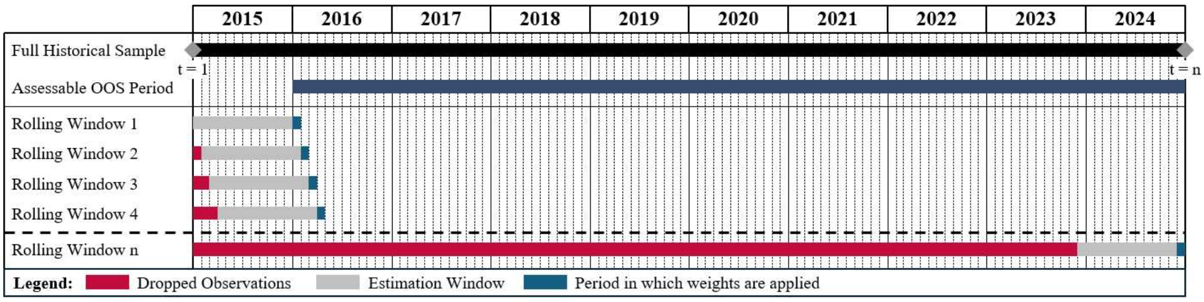

Figure 1: Visualization of Rolling Window Logic - Example with Monthly Rebalancing

Subsequently, a buy-and-hold approach between rebalancing dates is applied for the return calculation. The retrieved weights from the optimization are applied at time $t + 1$ and are allowed to drift according to the assets' cumulative performance up until the next rebalancing date. The resulting daily drifted weights are then multiplied with the actual OOS returns of the used assets at each time t to calculate the daily OOS returns of the respective strategy. This method allows the calculation of accurate daily return series, adequately captures the behavior between rebalancing dates, and enables a proper assessment of the OOS performance regarding wealth paths and risk measures.

3.5 Portfolio Performance Measures

To provide a comprehensive comparison between the constructed portfolios, a broad set of portfolio performance measures, which are subdivided into (1) descriptive statistics, (2) downside and tail risk measures, (3) risk-adjusted return measures, (4) utility-based performance measures, and (5) others, will be calculated and compared across different scenarios (e.g., traditional versus (vs.) crypto-enhanced portfolios). An overview of all performance metrics, including a formal definition, is provided in Appendix A.3.

3.5.1 Main Performance Metrics

The main measures to answer the RQs are (1) risk-adjusted return and (2) utility-based performance measures, as well as (3) cumulative returns. They are selected with a specific purpose as they assess portfolio performance from different perspectives. The SR, introduced by Sharpe (1966), measures the excess returns R per unit of risk, which is measured as the standard deviation σ_R of the excess returns and can still be considered the gold standard in assessing a portfolio's performance. As the SR can be misleading if the return distribution is not normal, several modifications are introduced. (1) The adjusted SR, following Pezier and White (2006), which penalizes negative skewness and high (excess) kurtosis. (2) The Sortino Ratio, which uses downside deviation, i.e. the standard deviation of excess returns below a certain threshold (zero in this thesis), as the risk measure and thereby ensures that only negative volatility is punished (Sortino & Price, 1994). (3) The STARR, which uses CVaR as the denominator and thereby puts strong emphasis on the downside tail risk.

The second key section of the metrics contains the utility-based CEQ return measures, which are calculated for both the quadratic and the CRRA utility functions. They represent the guaranteed return an investor would require to be indifferent between the risk-free return and investing in a risky portfolio.

As none of the previously mentioned metrics adequately addresses the wealth path, cumulative returns will be calculated and assessed. The remaining measures serve mainly simple comparison purposes, whereas the portfolio turnover gives an intuition about the amount of trading needed to implement the strategies and is used to introduce a proxy for transaction costs in a robustness test.

3.6 Procedures for Paired Portfolio Comparisons

The statistical significance of differences between traditional and crypto-enhanced portfolios is assessed via a bootstrapping procedure. This non-parametric method is applied, as it relies on fewer assumptions regarding distribution and dependence structure. These assumptions are often violated by financial return data, which is also the case in this thesis (see Appendix A.4). To account for the presence of autocorrelation, a block-bootstrapping approach that preserves the time-series dependence by resampling blocks of sequential returns is used. The procedure is performed with a fixed block length of 21 (approximately one trading month) and 1,000 replications[1]. Every replication gives a new bootstrapped pair of return series from which the difference of the performance measure of interest is calculated. Subsequently, the two-sided p-value is derived by:

$$p = \frac{1}{R}\sum_{b=1}^{R} I(|\vartheta_b - \vartheta_m| > |\vartheta_{obs}|) \tag{17}$$

Where ϑ_{obs} denotes the observed difference of the metric from the original portfolios, while ϑ_b denotes the bootstrapped differences with mean ϑ_m and R replications. This procedure is used for all metric comparisons besides SRs.

[1] The parameters have been determined as a trade-off between reliability of results, simplicity and feasibility regarding computational capacity. Tests with other parameters (up to block length 30 and 5,000 replications) displayed very similar results and can be downloaded under the link provided in Appendix A.35.

Differences in the SRs are evaluated using the testing procedure suggested by Ledoit and Wolf (2008), which accounts for non-normality and heteroskedasticity in returns.

To calculate the measures and perform the tests for statistically significant differences, the R-packages *PeerPerformance, PerformanceAnalytics, boot* and *e1071* are used (Ardia, Boudt, Bouamara, & Legros, 2024; Canty, Ripley, & Brazzale, 2024; Meyer et al., 2024; Peterson et al., 2024b).

3.7 Fixed-Effect Panel Regression Analysis

In addition to the previously described procedures for paired portfolio comparisons, a panel regression analysis is applied to examine the impact of adding crypto assets on portfolio performance in more detail.

Base Model Specification: The base model follows the regression equation:

$$Y_{i,t} = \beta_0 + \beta_1 Crypto_{i,t} + \beta_2 StrategyFE_i + \beta_3 YearFE_t + \beta_4 AssetSpaceFE_i + \epsilon_{i,t} \quad (18)$$

Where $Y_{i,t}$ denotes the 21-day rolling portfolio performance metric for portfolio i at time t, and $Y_{i,t} \in \{SR, Sortino, STARR, MV\ CEQ, CRRA\ CEQ\}$. $Crypto_{i,t}$ is a binary variable that indicates whether the portfolio includes crypto exposure, $StrategyFE_i$ denotes strategy fixed-effects (FE), $YearFE_t$ denotes year FE, $AssetSpaceFE_i$ denotes asset space FE, and $\epsilon_{i,t}$ denotes the error term.

The regression analysis is only performed for the key performance metrics (SR, Sortino Ratio, STARR, MV CEQ and CRRA CEQ returns), in line with the definition of risk-adjusted return and utility-based metrics being the main performance metric categories. Further control variables that capture asset-specific or market-wide effects are explicitly not used, as all portfolios are constructed with the same assets and across the same time frame. Asset-specific and market-wide variables would thus affect all portfolios equally at any given time. The use of a fixed-effects model enables to control for systematic differences across strategies, asset spaces, and time periods and thus isolates the average effect of crypto asset inclusion.

Extensions via Interaction Terms: To specifically investigate if the value added through crypto inclusion varies over time or across strategies and asset spaces, the following interaction terms are added individually: $Crypto_{i,t} \times YearFE_t$, $Crypto_{i,t} \times StrategyFE_t$, $Crypto_{i,t} \times AssetSpaceFE_i$. This results in three sub-models, which allow the assessment of specific aspects of the main RQs.

OLS Assumption Diagnostics and Estimation Method: The regressions are estimated using ordinary least squares (OLS). Thus, the core assumptions of OLS estimation are tested. The linearity of relationships is assessed by plotting the residuals against the fitted values. The normality of the residuals is tested using a Jarque-Bera (JB) test, homoskedasticity is tested using an autoregressive conditional heteroskedasticity (ARCH) test, and independence is tested using a Ljung-Box (LB) test. The ARCH and LB tests are performed up to lag 21. The respective results can be found in Appendix A.5. As all assumptions are violated across all model specifications, heteroskedasticity and autocorrelation consistent (HAC) standard errors are used to calculate the p-values. Specifically, this thesis uses the *NeweyWest* function from the R-package *sandwich*, which provides HAC variance-covariance matrices (Newey & West, 1987; Zeileis, Lumley, Graham, & Koell, 2024). *NeweyWest* is optimized for linear models and directly implements a Bartlett kernel with user-specified lag length, ensuring computational efficiency for large datasets. A maximum lag of 21 is set manually (corresponding to approximately one trading month), consistent with the block-bootstrapping approach. This HAC variance-covariance matrix is then passed into the *coeftest* function from the R-package *lmtest* to calculate the p-values while accounting for heteroskedasticity and autocorrelation (Hothorn et al., 2022). Through the consistent introduction of HAC standard errors in the p-value calculation across all regressions, the reliability of reported p-values is assured.

4 EMPIRICAL ANALYSIS

4.1 Statistical Properties of Asset Returns

Before applying the previously described optimization techniques, a thorough analysis of the return series of the eight assets will be conducted. This section aims to familiarize with and gain the first insights from the data set. These insights were not used in the optimizations due to the rolling window approach.

4.1.1 Performance Measures

The summary statistics of the dataset are mainly in line with what the literature suggested (compare section 2.1.1). Table 4 shows the annualized mean returns, standard deviations, and other metrics. It is observable that the two crypto assets offered the highest returns over the considered sample period but also displayed excessively high volatility, larger maximum drawdowns and a lower CVaR (a larger expected loss in the 5% worst-case scenarios).

Nevertheless, crypto assets offer high SRs (0.69 to 0.89), which only MSCI World can match amongst traditional assets.

Asset Returns - Key Metrics (2015 - 2024)

	MSCI World	MSCI EM	FTSE World Gov	FTSE US Corp	S&P GSCI	FTSE EPRA Dev	BTC	CCI30
Mean	0.108	0.051	0.006	0.026	0.037	0.044	0.782	0.795
Std.Dev.	0.150	0.158	0.038	0.072	0.223	0.161	0.677	0.736
Min.	-0.099	-0.067	-0.014	-0.099	-0.118	-0.138	-0.372	-0.384
Max.	0.088	0.058	0.013	0.104	0.079	0.090	0.252	0.217
Skewness	-0.827	-0.383	0.093	0.233	-0.632	-1.401	-0.026	-0.490
Excess Kurtosis	16.054	4.427	2.918	194.633	6.868	25.279	6.663	5.678
Sharpe Ratio	0.744	0.203	-0.208	0.147	0.082	0.199	0.889	0.686
CVaR 95	-0.023	-0.023	-0.005	-0.009	-0.033	-0.024	-0.098	-0.113
MaxDrawdown	0.260	0.360	0.164	0.176	0.818	0.385	0.515	0.500

Note: Mean, Standard Deviation and Sharpe Ratio are displayed in annual terms.

Table 4: Asset Returns – Key Metrics (2015 – 2024)

A negative SR is observable for the FTSE World Government Index, indicating that its excess returns have been below the risk-free rate, which is estimated via one-month US treasury bills.

4.1.2 Time-Series Diagnostics

Normality: The application of JB tests on the time series of asset returns reveals that the hypothesis of normally distributed returns can be rejected for all assets at any reasonable level. The QQ-plots in Appendix A.7 further support this.

Stationarity: The plots of the return series (Appendix A.8) and the conducted ADF tests reject the hypothesis of a unit root (non-stationarity) for each asset.

Autocorrelation: According to LB tests, the hypothesis that there is no autocorrelation up to lag 30 can be rejected at any reasonable level for equities, fixed income, FTSE EPRA Dev, and CCI30, but it cannot be rejected for S&P GSCI and BTC.

Heteroskedasticity: The null hypothesis of the ARCH test, stating that no ARCH effects are present, can be rejected for all assets at a 1% significance level, leading to the conclusion that ARCH effects (heteroskedasticity) are present in the data set.

These properties are typical for financial return series (compare, e.g., Cont (2001)) and provide a rationale for applying portfolio optimization techniques that account for skewness and heavy tails. The following Table 5 summarizes the results and displays the p-values of the respective tests.

Asset Returns - P-Values of Time-Series Diagnostics (2015 - 2024)

	MSCI World	MSCI EM	FTSE World Gov	FTSE US Corp	S&P GSCI	FTSE EPRA Dev	BTC	CCI30
Jarque-Bera	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***
Augmented Dickey-Fuller	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***	0.01 ***
Ljung-Box	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.56	0.00 ***	0.25	0.00 ***
ARCH	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: ADF-tests have been performed with auto-selection of lags and the R-function is not able to plot p-values smaller than 0.01
Ljung-Box and ARCH-tests have been performed up to lag 30

Table 5: Asset Returns - P-Values of Time-Series Diagnostics (2015 - 2024)

4.1.3 Correlation Analysis

Table 6's pairwise correlation matrix over the whole sample period shows that BTC and the CCI30 have low to moderate correlations with traditional assets, with correlation coefficients ranging from 0.02 to 0.25 (Pearson) and 0.00 to 0.20 (Spearman). The highest correlations with traditional assets can be observed with the MSCI World and FTSE EPRA Dev, while all correlations with the fixed-income indices are below 0.05. The correlation between BTC and CCI30 shows coefficients above 0.8, as BTC is one of CCI30's main constituents. Among traditional assets, relatively high correlations (above 0.5) are observable within asset classes (MSCI World and MSCI EM, FTSE World Gov and FTSE US Corp) and between equities and the FTSE EPRA Dev.

Asset Returns - Pairwise Correlations (2015 - 2024)

	MSCI World	MSCI EM	FTSE World Gov	FTSE US Corp	S&P GSCI	FTSE EPRA Dev	BTC	CCI30
MSCI World	1	0.51 ***	0.00 ***	0.00	0.30 ***	0.65 ***	0.18 ***	0.20 ***
MSCI EM	0.56 ***	1	0.00 ***	0.02	0.26 ***	0.37 ***	0.05 *	0.09 ***
FTSE World Gov	-0.05 **	-0.07 ***	1	0.79 ***	-0.15 ***	0.16 ***	0.00	0.02
FTSE US Corp	0.07 ***	0.08 ***	0.63 ***	1	-0.11 ***	0.20 ***	0.01	0.04 *
S&P GSCI	0.35 ***	0.31 ***	-0.14 ***	-0.06 **	1	0.14 ***	0.05 *	0.04 *
FTSE EPRA Dev	0.75 ***	0.48 ***	0.15 ***	0.21 ***	0.24 ***	1	0.11 ***	0.13 ***
BTC	0.22 ***	0.08 ***	0.03	0.03	0.07 ***	0.16 ***	1	0.84 ***
CCI30	0.25 ***	0.12 ***	0.02	0.04 *	0.08 ***	0.18 ***	0.85 ***	1

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: The bottom left half of the table contains Pearson correlation coefficients, whereas the upper right half of the table contains Spearman correlation coefficients

Table 6: Pairwise Correlations for Individual Asset Returns (2015 - 2024)

To capture potential changes in the correlation structures over time, rolling correlations using a 252-day window have been calculated. Appendix A.10 shows these rolling Pearson correlations for BTC and CCI30 compared to all other assets. In line with the results from the literature review, correlations between crypto assets and the MSCI World have risen after COVID-19 and have reached coefficients close to 0.5 between the end of 2022 and the beginning of 2023. However, they seem to have lowered again afterwards. Such temporal increases between 2021 and 2023 can be observed with most traditional assets but with a weaker magnitude and are mostly followed by a phase of decreasing correlations. These findings suggest that adding crypto assets to portfolios potentially still enhances portfolio performance, but they also imply that there might have been a period with weaker benefits from crypto inclusion.

4.2 Analysis of In-Sample Efficient Frontiers

To provide an initial indication of whether the inclusion of crypto assets enhances portfolio performance, the in-sample mean-variance and mean-CVaR efficient frontiers under a long-only constraint are created for each asset space in the following versions: (1) traditional assets only, (2) including CCI30, (3) including BTC. These efficient frontiers represent the set of portfolios offering the best possible return for a given level of risk. They are shown in Appendix A.11.1 (mean-variance) and A.11.2 (mean-CVaR).

In both cases, the efficient frontiers are strongly extended in the upper-right sections once crypto assets are included. This suggests that investors willing to bear high (tail) risk can create a broader set of efficient portfolios. Moreover, the efficient frontiers of portfolios consisting of only traditional assets are consistently dominated by the crypto-enhanced versions in each asset space. The degrees of dominance show no substantial observable differences between asset spaces. These findings strongly suggest that crypto assets add value to portfolios created under a mean-variance or mean-CVaR framework. Since the results are similar across asset spaces, even well-diversified portfolios consisting of equities, fixed income, commodities, and real estate will likely benefit from the addition of crypto assets. This finding is independent of whether CCI30 or BTC is added. However, these benefits are purely theoretical and their practical relevance needs to be confirmed in the OOS analysis.

4.3 Analysis of Assigned Weights

After the application of all previously mentioned optimization techniques, this section analyzes the weights assigned to the portfolios including crypto assets. The assigned weights to crypto assets vary noteworthy across strategies. It is clearly observable that risk-based approaches assign low or even close to zero weights to crypto assets. The gmv and minCVaR consistently allocate below 1%, whereas ERC and maxDiv assign weights up to 7.2% in single periods, with overall averages ranging from 2.4% to 3.6% depending on the asset space considered. The only exception is the ERC strategy in the simple asset space, where weights are considerably higher. The maxR strategy typically assigns 100% to the asset with the highest expected return and, therefore, allocates significant weights to crypto assets except in 2022. The maxSR portfolios assign between 18.2% and 24% to crypto assets, while maxSTARR portfolios assign between 6.6% and 13.1%. Both strategies show substantial variations across the years under investigation. These strong variations are also observable for the utility-based approaches which range from close to 0% in 2022 to almost 100% in 2017 and 2024. On average, the mv portfolios assign roughly 30%, whereas the bs-mv strategy assigns about 16%, likely smaller due to the shrinkage of expected returns. The crra strategy assigns higher weights with overall averages between 44.3% and 56.2%. The assigned weights seem to not strongly depend on the crypto assets used, as portfolios including either CCI30 or BTC show similar crypto allocations. A Table providing an overview and plots per strategy can be found in Appendix A.12.

4.4 Evaluating the Impact of Crypto Assets on Portfolios

The primary analysis to answer RQ1 is a paired portfolio comparison between traditional portfolios and those including CCI30. The analysis spans all strategies, asset spaces and performance measures under monthly rebalancing and is complemented by a panel regression analysis with a crypto dummy and several FEs.

4.4.1 Paired Portfolio Comparisons – Impact of Crypto Assets

Descriptive Statistics: Mean returns significantly increase for most strategies (ew, ew_bh, maxDiv, maxR, and all utility-based approaches) across all asset spaces, once crypto assets are added. Other strategies show varying significance depending on the asset space. Standard deviations significantly and consistently (across strategies and asset spaces) increase at the 1% level, with the exceptions of gmv and minCVaR, where increases are less consistent. Changes in skewness and kurtosis were more heterogeneous. Skewness increased (or negative skewness was reduced) for the equally-weighted and utility-based approaches and maxR, whereas it consistently decreased for gmv. Excess kurtosis consistently increased for gmv, maxSR and all utility-based techniques, while it decreased for the equally-weighted techniques.

Drawdown and Tail Risk Measures: Maximum drawdown increases across almost all strategy/asset space combinations with exceptions including gmv, minCVaR, ERC and maxSTARR in certain asset spaces. These increases are significant for ew_bh, maxR, and the utility-based approaches, at least at the 5% level. For maxSR and ew, the increases are not consistently of statistical significance, whereas they do not show any statistical significance for minCVaR, ERC, maxDiv and maxSTARR. Tail risk, measured by the CVaR at the 95% confidence level, increased statistically significantly, at least at the 5% level, across nearly all strategy/asset space combinations besides gmv and minCVaR. The same pattern can be observed for downside deviation. These results allow to conclude that including crypto assets generally increases risk measures, with exceptions when applying a purely risk-based allocation approach.

Risk-adjusted Return Measures: Including crypto assets typically increases returns and risk measures. In this section the risk-adjusted return measures will be evaluated to investigate whether the return benefits over- or undercompensate the added risk. Surprisingly, consistent increases in the SRs are observable for all portfolios except those constructed with maxSR, which are specifically designed to maximize this measure. The increases show consistent statistical significance for the ew, maxDiv, mv and bs-mv strategies, whereas the significance depends on the asset space for ERC, maxR, maxSR, maxSTARR and crra. The differences in adjusted SRs are not significant in any case. However, they increase in 88.3% of the examined scenarios. The Sortino Ratio increases in 95% of all examined scenarios. However, only ew and maxDiv show constant statistical significance (10% level for ew, 1% level for maxDiv). ERC, maxR, maxSR, maxSTARR and crra only show significant improvements in certain asset spaces, whereas the other strategies do not significantly benefit from including crypto assets. The results for the STARRs mainly mirror those of the Sortino Ratios. The results indicate that the increase in mean returns mostly outweighs the increased risk measures. Significant increases in terms of risk-adjusted return measures, however, vary depending on the strategy/asset space combination under consideration.

Utility-based Measures: MV CEQ and CRRA CEQ returns increase in 86.7% and 78.3% of the scenarios. The increases are consistently statistically significant for ew (at least at the 10% level), and maxDiv (at the 1% level). For ERC and maxSTARR, the statistical significance depends on the asset space under consideration, whereas all other strategies do not exhibit significant improvements once CCI30 is added. The only strategies showing notable deteriorations are ew_bh, maxR and maxSR.

Other Metrics: To assess whether the amount of trading needed to implement the strategies differs between traditional and crypto portfolios, turnover is calculated. For gmv, minCVaR, and maxDiv, the average changes in monthly turnover are relatively small (below 0.5 percentage points (pp) across asset spaces). ERC and crra show average monthly turnover increases of 6.1 and 4.7 pp, with single scenarios increasing by up to 10.3 pp. For the other strategies, increases mainly depend on the asset space considered. It is clearly observable across strategies that adding CCI30 increases the required amount of trading the strongest within the simple asset space, while the differences are smaller (or even negative) in broader asset spaces.

Cumulative wealth increased in 96.7% of the scenarios considered. The amount of outperformance in cumulative wealth differs strongly between strategies, with ew_bh, maxR, mv and crra exhibiting the most substantial increases. The information ratio (IR) is positive and thus indicates an improvement in 96.7% of the scenarios. The highest IRs are observed for ew, maxDiv and all utility-based approaches, which consistently exhibit IRs above 1.0, thus indicating a strong outperformance from crypto-enhanced portfolios compared to the traditional portfolios.

The detailed outcomes of all paired portfolio comparisons, including visualizations, can be found in Appendix A.13.

4.4.2 Regression Analysis – Impact of Crypto Assets

The results from the FE panel regression analysis (see Appendix A.14 and A.15) reinforce those of the paired portfolio comparisons. The coefficients on the crypto dummy are positive and statistically significant across all five performance metrics considered (SR, Sortino, STARR, MV CEQ and CRRA CEQ returns), also after controlling for FEs for strategy, year and asset space. The magnitudes of the crypto dummy coefficients vary depending on the performance measure under consideration and are modest in some cases. On average, however, crypto-enhanced portfolios exhibit superior performance at least on the 5% significance level. Several significant coefficients for StrategyFE and YearFE indicate that the portfolio optimization technique and the prevailing market conditions influence the performance of the constructed portfolios (traditional and crypto-enhanced). This will be assessed in further detail in the subsequent sections 4.5 and 4.6. By contrast, AssetSpaceFE and Crypto x AssetSpaceFE, the interaction term between crypto exposure and asset space FE, are not significant in any model and display mixed signs. This suggests that performance differences between the portfolios overall and crypto-enhancement effectiveness do not systematically depend on the asset space under consideration.

4.4.3 Overall Assessment – Impact of Crypto Assets

Overall, the conducted analyses allow to conclude that adding crypto assets – represented by the CCI30 – significantly increases mean returns, volatility and other risk metrics in most scenarios. Moreover, it mainly offers improved performance in terms of risk-adjusted-return metrics, utility-based metrics, cumulative wealth and IR, as the increased returns typically outweigh the increased risk. However, the significance and magnitude of these increases depend on the strategy under consideration. Furthermore, performance improvements do not significantly differ between the asset spaces considered. This implies that crypto assets add value not only in simple scenarios but also for already well-diversified portfolios, including commodities and real estate. In sum, crypto enhancement tends to offer benefits. Nevertheless, the excessively increased risk and tail risk measures must be considered carefully.

4.4.4 Robustness Tests – Impact of Crypto Assets

Several block-bootstrapping-based robustness tests are conducted to verify the previously derived results. The traditional portfolios are (1) compared to portfolios in which BTC is added instead of CCI30, (2) evaluated under weekly and daily rebalancing, (3) compared using an expanding instead of a rolling window, (4) compared after introducing a gens constraint, and (5) compared while incorporating a proxy for transaction costs.

For most of the performed robustness tests, the results do not change significantly and only show minor deviations for single strategies. The robustness test which introduces a gens constraint even displays a higher number of significant benefits. In contrast, incorporating a proxy for transaction costs lowers the absolute differences between traditional and crypto-enhanced portfolios, but has minor effects on their significance. Given that the block-bootstrapping-based robustness tests reveal no material differences, the FE panel regressions will not be re-estimated for the robustness tests. A detailed discussion of each performed robustness test can be found in Appendix A.16.

4.5 Assessing Time-Varying Performance

This chapter addresses the second RQ and assesses whether a potential performance improvement through including crypto assets is time varying and has diminished or even disappeared after the COVID-19 crisis. First, the OOS period is split into two sub-periods (1) the pre-COVID period lasting until January 31, 2020, and (2) the post-COVID period starting on April 1, 2020. February and March 2020 are excluded to avoid bias from the main COVID market crash. Subsequently, both subperiods are assessed individually to determine whether CCI30 improved performance in each of them. Afterwards, a comparison of those results is performed. COVID-19 is used as a breakpoint, as previous literature (compare sections 2.2.2 and 2.3.2) argues that it might represent a structural shift (e.g., increased correlations between crypto assets and traditional asset classes). To assess potentially time-varying performance on a more granular basis, the rolling differences of main performance metrics are analyzed, and a FE panel regression analysis is performed.

4.5.1 Paired Portfolio Comparisons – Pre- vs. Post-COVID:

Descriptive Statistics: Pre-COVID, mean returns increased across all scenarios, with an average improvement of 39.2 pp. These increases are consistently significant for ew, maxDiv, maxR, and all utility-based strategies, while their significance depends on the asset space for ERC, maxSR, and maxSTARR. Post-COVID, mean returns increased in 96.7% of the scenarios, but with a reduced average increase of 14.4 pp. In this period, significant increases can be observed for ew, ew_bh and maxR across all asset spaces and ERC, maxDiv and maxSTARR, depending on the asset space. Notably, the utility-based techniques no longer exhibit significant improvements at the 10% level post-COVID. Volatility rose in 96.7% (pre-COVID) and 100% (post-COVID) of the scenarios considered. Pre-COVID, these increases show consistent statistical significance for ew, maxDiv, maxR and all utility-based techniques, while significance depends on the asset space for ERC, maxSR and maxSTARR. Post-COVID only ew, ew_bh and maxR show consistently higher volatility with statistical significance, while ERC, maxDiv and maxSTARR only show it across certain asset spaces. Skewness improvements (increased positive or reduced negative skewness) were prevalent in 78.3% of the scenarios pre-COVID but notably diminished to 26.7% post-COVID. Kurtosis increased in 85% of the scenarios pre-COVID and 58.3% post-COVID.

Drawdown and Tail Risk Measures: Maximum drawdowns significantly increased by at least 0.5 pp more often pre-COVID (on average 29.3 pp in 80% of the scenarios) than post-COVID (on average 17.4 pp in 76.7% of the scenarios). In both periods, the increases are consistently significant for ew, ew_bh, maxR and crra and significance depends on the asset space for maxSR. Pre-COVID, the increases additionally are consistently significant for mv and bs-mv (at the 1% level), while they are only significant at the 10% level and in certain asset spaces for mv post-COVID. The CVaR and downside deviations increase rather similarly in both periods, with gmv and minCVaR being the exceptions, which do not displaying increases of statistical significance at any given level.

Risk-adjusted Return Measures: SRs increase in approximately two-thirds of the scenarios pre-COVID, whereas they increase in 85% of the scenarios post-COVID. The main differences are observed for ew and ew_bh, which exhibit significantly lowered SRs at a 10% level pre-COVID. Significant pre-COVID improvements could be achieved with maxDiv across asset spaces and with maxR, maxSR, maxSTARR, mv and crra, depending on the asset space. Post-COVID, the techniques with significant improvements in at least one asset space are ERC, maxDiv and maxSTARR. The average increase in SRs is more pronounced post-COVID, even though less significant improvements are observed in this period. Adjusted SRs do not exhibit any significant increases in both subperiods. Sortino Ratios improved in 86.7% (pre-COVID) and 90% (post-COVID) of the scenarios. These improvements are only statistically significant for maxDiv and, to some extent, maxSR, maxSTARR and crra (pre-COVID), and ERC and maxSTARR (post-COVID). STARRs closely mirror the results of Sortino Ratios. While the average increase in adjusted SRs is relatively similar across periods, Sortino Ratios and STARRs tend to increase slightly more pre-COVID.

Utility-based Measures: MV CEQ returns rise in 90% of the scenarios, by a remarkable average of 22.1 pp pre-COVID, whereas they rise by roughly 1 pp in 73.3% of the considered scenarios post-COVID. Significant pre-COVID improvements can be observed consistently for ew and maxDiv, but they depend on the asset space for ERC, maxSR, and maxSTARR. Post-COVID, significant increases are only observed in some asset spaces for ERC and maxSTARR. The results for the CRRA CEQ returns are very similar, with 88.3% (pre-COVID) and 73.3% (post-COVID) increases and statistical significance for the same strategy/asset space combinations. Similarly, the increases in CRRA CEQ returns are more pronounced pre-COVID.

Other Metrics: Before the COVID-19 crash, substantial turnover increases (> 5 pp per month) are only observable for ERC, maxSTARR, mv and bs-mv and they strongly depend on the considered asset space. Some strategies (maxSTARR, mv, bs-mv and crra) even exhibit substantial turnover reductions (< -5 pp per month). Post-COVID, the analysis shows substantial increases for ERC, maxR, maxSR, maxSTARR, mv, bs-mv and especially crra. At the same time, large reductions are only observable for maxR and maxSR in specific asset spaces. On average, including crypto assets reduced portfolio turnover by 2.6 pp pre-COVID while increasing it by 4.1 pp post-COVID. Cumulative wealth benefits in all considered scenarios pre-COVID and 93.3% of the scenarios post-COVID, however, by a lower extent in the latter subperiod. The strategies benefitting the most pre-COVID are maxR, mv, bs-mv and crra, while maxR and ew_bh benefit most post-COVID. IRs are consistently positive pre-COVID, while they turn negative in some scenarios (minCVaR-simple, maxSR-simple, -eq_fi and -epra) post-COVID. Generally, it is observable that the IRs are lower in the post-COVID period across all strategy/asset space combinations, with ERC and maxSTARR being the exceptions in certain asset spaces.

For complete statistical outcomes and visual summaries, refer to Appendix A.17.

4.5.2 Rolling Comparison of Selected Performance Measures

To assess the previously observed differences in more detail, rolling performance measures over a 126-day window are calculated and plotted per strategy (see Appendix A.18). The rolling mean returns reveal that within pre- and post-COVID and across all strategies besides gmv and minCVaR, periods of out- and underperformance of the crypto-enhanced versions are observable. Gmv and minCVaR are the exceptions, as they hardly allocate weights to crypto assets and thus generally do not exhibit large differences. Furthermore, a tendency for stronger outperformance pre-COVID is observable, especially from 2017 to 2018. Rolling standard deviations show a more heterogeneous picture. The highest peaks per strategy (except for gmv, minCVaR and ERC) are again observed pre-COVID, while the lows typically happen within the post-COVID period. However, some strategies also exhibit sharp increases post-COVID, e.g. following the 2020 stock market crash or towards the end of the sample in 2024. This generally leads to rolling SRs and SR differences being higher pre-COVID. However, also the most considerable negative differences occur pre-COVID with only single exceptions. Sortino Ratio and STARR differences mostly show similar patterns. Rolling MV CEQ and CRRA CEQ returns exhibit comparable patterns to mean returns. However, they are shifted downwards with more negative differences in both subperiods. Overall, it seems like the divergence of the difference lines is reduced post-COVID, but in many cases an outperformance in terms of several of the measures is still observable. Thus, using pre- and post-COVID as a proxy for a structural shift seems insufficient. Even though the magnitude of differences seems to have changed, performance varies strongly also within subperiods. The time-varying performance for all measures investigated is observable across strategies and asset spaces.

To explore potential drivers of the variation in performance, explanatory regressions using variables such as sentiment, liquidity, regime switches, etc. are performed. As these results do not contribute towards the main research goals of this thesis, the methodology, results and summary tables are only briefly presented in Appendix A.34.

4.5.3 Regression Analysis – Time-Varying Performance

To assess whether the observed time variation of the crypto-inclusion effects in the rolling comparison is statistically significant, an FE panel regression analysis with the interaction term between crypto exposure and year (Crypto x YearFE) is conducted (see Appendix A.19). The crypto effect is positive and statistically significant at the 1% significance level in the baseline year 2016. However, the coefficients of the interaction terms show that the effect significantly varies across years. Compared to the baseline year, it increases across metrics in 2017, while it decreases for almost all metrics in the subsequent years. The most substantial decreases are observed in 2018 and 2019. The net crypto effect for a given year t, representing the total estimated impact of crypto asset inclusion in a specific year, is defined as:

$$Net\ Crypto\ Effect = \beta_1 + \beta_{Crypto \times YearFE_t} \tag{19}$$

This effect is positive across metrics in 2016, 2017, 2020 and 2021, negative across metrics in 2018, 2019 and 2022 and mixed in the remaining years. The magnitude of the net crypto effect is highest in the early years and declines over time across all metrics considered. These findings closely align with and reinforce the patterns observed in the paired portfolio comparisons and rolling comparisons.

4.5.4 Overall Assessment – Time-Varying Performance

The previously presented results show that adding crypto assets benefited portfolios substantially before the outbreak of the COVID-19 pandemic. The changes in performance measures, especially utility-based measures, cumulative wealth, and the information ratio, indicate that the effects have decreased and lost statistical significance to some extent in the post-COVID period. The risk-adjusted return measures, in contrast, draw a heterogeneous picture depending on the strategy and metric considered and indicate that some strategies benefitted stronger from adding crypto assets post-COVID, while others do not exhibit significant benefits anymore when crypto assets are added. Across all applied analyses – paired portfolio comparisons, rolling comparisons and FE panel regression analysis – it is clearly visible that the crypto-inclusion effect is time varying not only in magnitude but even in direction.

4.5.5 Robustness Tests – Time-Varying Performance

To verify the results from this section, the paired portfolio comparison between the pre- and the post-COVID periods is performed by adding BTC instead of CCI30 to portfolios. The results mainly remain similar to the base scenario. This could be explained by the high correlation between CCI30 and BTC. As the results remain similar, the rolling metrics are not re-calculated, and regressions are not re-estimated. A detailed discussion of the robustness test can be found in Appendix A.20.

4.6 Evaluation of Strategy Effectiveness and Design Choices

The following section assesses whether a clearly superior strategy for integrating crypto assets into a portfolio exists and examines different design choices. First, it investigates whether any of the applied asset allocation techniques can significantly outperform a naïve, ew approach. For this reason, the previously conducted analyses will be repeated. However, instead of comparing traditional portfolios to crypto-enhanced portfolios, the CCI30-ew strategy is compared to each other crypto-enhanced strategy within its respective asset space. Subsequently, several design choices, e.g. regarding rebalancing frequency, windowing approach, etc., are directly compared. An FE panel regression analysis again complements these analyses.

4.6.1 Paired Portfolio Comparisons – Strategy Effectiveness

Descriptive Statistics: MaxR and crra offer consistent and significant outperformance compared to the naïve ew portfolio regarding mean returns across all asset spaces at least at the 5% significance level. The mv strategy also consistently exhibits higher mean returns but without statistical significance in the simple asset space. All purely risk-based approaches exhibit significantly lower mean returns compared to ew. Volatility is higher in a statistically significant manner at the 1% level across asset spaces when maxR, maxSR, mv, bs-mv and crra are applied, apart from maxSR and bs-mv in the simple asset space. On the other hand, the risk-based approaches show a significantly lower standard deviation compared to the naïve portfolio across all considered asset spaces. Furthermore, maxSTARR tends to exhibit lower volatility, but only in a statistically significant manner within the simple asset space. The differences in skewness and kurtosis show heterogeneous pictures without a clear pattern.

Drawdown and Tail Risk Measures: As expected due to their design, purely risk-based strategies (gmv, minCVaR and maxDiv) show significantly lower drawdown and tail risk measures. ERC displays significantly lower CVaR and downside deviation across all asset spaces but does not consistently exhibit lower maximum drawdown. Significantly higher risk measures compared to ew can be observed when applying maxR, crra, and mv. Additionally, also maxSR and bs-mv mainly exhibit higher risk measures. However, those values do not significantly differ regarding maximum drawdown and in the simple asset space. MaxSTARR displays varying results with a tendency of lower risk measures compared to ew.

Risk-adjusted Return Measures: None of the applied portfolio optimization techniques significantly outperforms the ew portfolio regarding SR. Moreover, only maxSR even exhibits higher absolute SRs in two of the five considered asset spaces. The adjusted SR is higher when applying maxR in the gsci, epra and all asset space and crra in the all asset space. However, all these positive differences do not exhibit significance at any reasonable level. Similarly weak patterns occur for the Sortino Ratios and STARRs. Sortino Ratios are higher with mv and crra across asset spaces, however, at no significant level. STARRs, again without significance, are higher with mv across asset spaces and with bs-mv in two out of the five asset spaces. All purely risk-based approaches significantly underperform compared to the naïve approach, at least at the 10% significance level. The only exceptions are ERC and maxDiv within the simple and maxDiv in the epra asset space.

Utility-based Measures: Utility-based metrics (MV and CRRA CEQ returns) do not display significant outperformance from any strategy compared to the CCI30-enhanced ew portfolios either. Marginal outperformances without significance appear for mv across asset spaces and bs-mv and crra depending on the asset space. All purely risk-based approaches significantly underperform compared to ew, apart from ERC in the simple asset space. A significant underperformance (at least at the 5 % level) can moreover be observed from maxSR in the simple, eq_fi and epra asset spaces and from maxSTARR in the eq_fi asset space.

Other Metrics: As the weight drift between rebalancing periods is not considered for the turnover approximation, all implemented strategies naturally exhibit higher turnover values than the naïve ew portfolio. Regarding cumulative wealth, maxR, mv, and crra consistently yield improvements compared to the ew portfolio. Bs-mv does so for all asset spaces besides simple and maxSR exhibits higher cumulative wealth in the gsci and all asset spaces. These cumulative wealth results align with the IRs, which are positive in the same strategy/asset space combinations. The highest values can be observed for mv and crra across asset spaces.

The detailed results and visual summaries can be found in Appendix A.21 and A.22.

4.6.2 Regression Analysis – Strategy Effectiveness

To additionally assess the performance of strategies overall (traditional and crypto-enhanced) and conclude whether the crypto-inclusion effect differs between strategies, an FE-panel regression analysis including the interaction term between crypto exposure and strategy FEs (Crypto x StrategyFE) is conducted (see Appendix A.23). When controlling for several FEs, no strategy offers consistently significant outperformance across metrics compared to the simple ew portfolios. The gmv and minCVaR strategies even significantly underperform across metrics. Furthermore, the crypto-inclusion effects do not differ significantly between strategies for risk-adjusted return metrics, while they are positive and significant at the 1% level for MV and CRRA CEQ returns in the base scenario (ew). The effects on utility-based measures are significantly lower (at least at the 10% level) for several other strategies, namely ew_bh, gmv, minCVaR, ERC, maxDiv and maxSR. At the same time, no differences are exhibited for the remaining strategies.

4.6.3 Overall Assessment – Strategy Effectiveness

No single strategy consistently outperforms the naïve ew portfolio within one asset space, let alone across all asset spaces. This holds true in traditional and crypto-enhanced scenarios. Hence, one can conclude that none of the constructed strategies is clearly superior to a simple 1/N approach. However, some strategies occasionally outperform the naïve portfolio in single measures such as cumulative wealth or mean returns. Thus, investors who aim for high returns and are indifferent regarding risk could prefer different strategies. For a typical investor, acting based on MV or CRRA utility, the sophisticated strategies hardly offer consistent benefits. Some strategies yield higher results in certain measures, but these outperformances are mainly not statistically significant. The results emphasize the robustness of the ew strategy, which represents a competitive yet straightforward way to achieve solid results. Additionally, the results highlight the challenges of portfolio optimization techniques in estimating the input parameters. The differences in crypto-inclusion effects between strategies do not differ in risk-adjusted returns. Regarding utility-based measures, ew shows higher positive or at least similar crypto-enhancement effects compared to other, more complex optimization techniques.

4.6.4 Robustness Tests – Strategy Effectiveness

The results from this section are tested for robustness via the procedure for paired portfolio comparisons through comparing (1) strategies using BTC instead of CCI30, and (2) the other strategies to ew_bh instead of ew. Since no consistent outperformance from any strategy compared to ew is observable in the base scenario, and the other strategies are more sensitive towards transaction costs, a robustness test with transaction costs is not performed in this section. All performed robustness tests do not show essentially different patterns compared to the base scenario. This rationalizes not re-estimating the FE panel regressions. A detailed discussion of the robustness tests can be found in Appendix A.24.

4.6.5 Assessing the Role of Design Choices

The following section goes beyond the comparison of optimized and naïve portfolios and explores whether different design choices can further improve the performance of crypto-inclusive portfolios. Specifically, the following design choices will be assessed: (1) using BTC as the crypto asset instead of CCI30, (2) rebalancing weekly (and daily) instead of monthly, (3) using an expanding window instead of a rolling window, (4) introducing a gens constraint, and (5) using mean and covariance forecasts from a multivariate DCC-GARCH instead of the historical mean and covariance. These comparisons explicitly do not serve as robustness tests but aim to identify practical modifications that either better capture the benefits of crypto exposure or simplify crypto inclusion while not hurting performance. The results for all design choice assessments can be downloaded via the link provided in Appendix A.26.

(1) CCI30 vs. BTC Portfolios

The first design choice to be evaluated is the selection of the crypto asset. For this reason, portfolios using CCI30 will be compared to those using BTC. The analysis of the results from the descriptive statistics shows that mean returns do not significantly differ. However, they tend to be slightly higher for CCI30 portfolios. On the other hand, volatility is significantly higher for the CCI30 portfolios across asset spaces when using either ew, ew_bh, maxR, mv or bs-mv. To some extent, this also applies when using minCVaR or maxSR. Regarding drawdown and tail risk measures, significant differences are only observable when using ew_bh, with risk measures being higher for the CCI30 portfolios. Adjusted SRs, Sortino Ratios and STARRs exhibit no significant differences. This also mainly applies to SRs, besides BTC portfolios significantly outperforming CCI30 portfolios using a minCVaR strategy in the epra asset space and CCI30 portfolios significantly outperforming when applying maxSTARR in either simple, gsci or all. The utility-based measures do not exhibit any significant differences, albeit they tend to be slightly higher when adding CCI30 (+ 1.6 pp for MV CEQ returns and + 0.9 pp for CRRA CEQ returns). The average turnover indicates that the amount of trading needed to implement the strategies mainly does not differ strongly. Single scenarios, however, exhibit differences of up to 16.5 pp. For ERC and crra, more trading is required when using CCI30, whereas for maxR, using BTC requires more trading. Cumulative wealth is higher in two-thirds of the considered scenarios when using CCI30 and lower mainly for the ew_bh, gmv and minCVaR strategies. This is also confirmed by the IRs, which are negative in 66.7% of the scenarios with the CCI30 portfolios as the benchmark.

In summary, the choice of the crypto asset does not significantly impact most performance metrics. Nevertheless, some differences, especially in terms of cumulative wealth, do exist.

Even though many performance metrics are slightly better when CCI30 is added, the simplicity of including BTC makes it a viable option.

(2) Monthly vs. Weekly (and Daily) Rebalancing

The second design choice to be evaluated is the impact of the rebalancing frequency. Specifically, weekly (and daily) rebalancing will be compared to the previously applied monthly frequency. Starting with weekly vs. monthly, mean returns are either not significantly different or tend to be higher when rebalancing is only performed monthly, particularly for ew and maxDiv. In contrast, the monthly rebalanced portfolios exhibit significantly higher volatility for ew, gmv, maxDiv, maxSTARR, mv and bs-mv portfolios across all asset spaces and in most scenarios for maxR. Regarding other risk measures, weekly rebalanced ew portfolios exhibit higher maximum drawdowns, which are significant within the gsci and all asset spaces. At the same time, lower CVaRs are observable. The gmv strategy yields significantly lower CVaR in the gsci and all asset spaces and lower downside deviation across all asset spaces. Other approaches such as ERC, maxDiv, maxR, bs-mv and crra display lower risk metrics when rebalanced weekly as well, but the significance of these differences strongly depends on the metric and asset space under investigation. The only strategy consistently exhibiting decreased risk measures across all asset spaces and metrics at a significant level (at least 5%) when rebalancing is performed weekly is the mv strategy. The risk-adjusted metrics show that gmv, minCVaR, ERC, maxR, maxSTARR, bs-mv and crra do not exhibit significant differences between monthly and weekly rebalancing. The ew, maxDiv, and maxSR strategies perform better in terms of SRs, Sortino Ratios and STARRs when rebalanced monthly, but not consistently across all asset spaces. The only strategy that benefits from more frequent rebalancing is mv, albeit only for certain asset spaces (simple for STARR; all for SR, Sortino Ratio and STARR). Similar patterns can be observed when comparing utility-based metrics. Ew and maxDiv consistently outperform and maxSR outperforms in the gsci and all asset spaces when rebalanced monthly. Again, mv outperforms when being rebalanced weekly. Turnover indicates that weekly rebalancing requires up to 3.4x more trading than monthly rebalancing, while cumulative wealth remains relatively similar. For ew and maxDiv, cumulative wealth is higher with monthly rebalancing, whereas maxR, mv and bs-mv benefit from weekly rebalancing for this performance measure.

Overall, while some strategies, especially mv and maxR, appear to benefit from weekly rebalancing, the sharp increase in turnover likely offsets most of these benefits in non-frictionless scenarios including transaction costs. Given that other strategies (mainly ew and maxDiv) even seem to benefit from monthly rebalancing, a shift to shorter rebalancing periods does not seem advantageous.

When extending the comparison to daily rebalancing, results largely align with the monthly vs. weekly analysis, with a few notable exceptions. With daily rebalancing, volatilities are not higher for ew, and maxSTARR's standard deviations are only higher in certain asset spaces. Regarding risk measures, the differences between monthly and daily are less pronounced than in the previous scenario, but the directions mainly hold. Risk-adjusted return measures exhibit significant underperformance for maxSTARR and significant outperformance for bs-mv in certain asset spaces when daily rebalancing is applied. As in the monthly vs. weekly scenario, mv is the strategy that gains the most (lower risk, better risk-adjusted returns, higher utility) from more frequent rebalancing, while other strategies (e.g., ew, maxDiv) outperform in certain asset spaces when rebalancing is performed monthly. The slight differences in performance, which are not consistent across strategies and asset spaces, come with an even sharper turnover increase (up to 9.2x the amount of trading required). Therefore, also daily rebalancing does not seem to offer a compelling advantage.

(3) Rolling vs. Expanding Windows

The third design choice to be evaluated is using an expanding window instead of a rolling window to estimate the input parameters. The analysis shows that both methods lead to relatively similar mean returns for most strategies. However, utility-based strategies yield significantly lower mean returns with an expanding window. Standard deviations are reduced significantly, except for gmv and maxSTARR, where they remain somewhat similar, and maxR, where they are significantly higher. Maximum drawdown is mostly significantly lower with an expanding window when maxSR is applied, while it is consistently and significantly higher when using crra. Other strategies reveal more varied patterns. CVaR and downside deviation are mostly significantly lower with an expanding window, with maxR being the main exception. In terms of risk-adjusted return measures, differences mainly remain insignificant. The exceptions are maxSR, which yields higher SRs, Sortino Ratios, and STARRs in the simple, eq_fi and epra asset space and ERC, which yields higher results in the gsci asset space. In contrast, crra yields lower results in the gsci asset space. Besides that, a tendency of the expanding window to slightly outperform is observable. However, this outperformance is not statistically significant. Significant outperformance of the expanding window in terms of MV or CRRA CEQ returns can only be observed for ERC in the gsci and maxSR in the eq_fi asset space. Apart from that, mainly modest differences are observed, this time with a slight advantage for the rolling windows. The expanding window reduces portfolio turnover across all strategies and asset spaces and exhibits larger cumulative wealth and positive IRs for gmv, minCVaR, ERC and maxSR, whereas the opposite is true for maxDiv, mv, bs-mv and crra. The two risk-adjusted return optimizing techniques show heterogeneous results.

Overall, neither the expanding nor the rolling window significantly and consistently outperforms. Nevertheless, certain strategies seem to work better with certain estimation methods. The expanding window, while not strongly hurting risk-adjusted and utility-based measures in many cases, generally tends to reduce risk and thus is a viable alternative for investors aiming for more stable performance.

(4) Regular vs. Gens Constrained Portfolios

The next design choice to be evaluated is the introduction of a gens constraint in the form of $\boldsymbol{\omega} \geq a\mathbf{1}$, where $\mathbf{1}$ is a vector of ones and $a \in [0, {}^{1}/_{N}]$. When applying $a = 0.5\ {}^{1}/_{N}$, which sets a minimum weight equal to half of that in the ew portfolio, such a constraint leads to significant increases in mean returns and standard deviations for all purely risk-based approaches. For maxSR and maxSTARR mean returns increase, but not significantly across asset spaces. In contrast, maxR and utility-based approaches show lower mean returns and volatilities. These differences are not consistently statistically significant across asset spaces. The drawdown and tail risk measures show similar behavior – besides maximum drawdown, they are significantly increased for risk-based approaches, whereas they are lowered for maxR and utility-based approaches. In terms of risk-adjusted return and utility-based measures, nearly all performance measures across all strategies and asset spaces are increased over the observed OOS period, with the most substantial and most significant improvements for risk-based approaches, maxSR and maxSTARR. Furthermore, turnover is consistently decreased, besides within single asset spaces when applying maxDiv. Cumulative wealth increases for all strategies besides maxR, mv and crra, which are also the only strategies where negative IRs are observable.

Hence, one can conclude that besides cumulative wealth for three strategies, a gens constraint enhances portfolio performance in most scenarios and should thus be applied when including crypto assets in portfolios.

(5) Historical vs. DCC-GARCH Mean and Covariance Estimates

Literature suggests that portfolio optimization outcomes can significantly improve when employing DCC-GARCH models for mean and covariance estimation (Abdul Aziz, Vrontos, & M. Hasim, 2019). Additionally, the return and volatility dynamics are frequently found to be well-suited to Autoregressive Moving Average (ARMA) and GARCH modelling (see section A.25.1). Consequently, this section evaluates whether portfolio performance benefits from DCC-GARCH estimates. The detailed methodology can be found in Appendix A.25. This comparison is not performed for the CvaR-based minCVaR and maxSTARR[2] approaches as well as for bs-mv[3].

Portfolios based on DCC-GARCH estimates consistently yield significantly lower mean returns for maxR and mv, whereas gmv experiences slightly higher returns, however, not at a significant level. At the same time, standard deviations are significantly lower for maxR and mv, while they are significantly higher for gmv and maxDiv. Maximum drawdowns are lower for utility-based strategies and higher for gmv and maxDiv, but again, rarely at a significant level. CVaRs and downside deviations tend to be significantly higher for risk-based approaches, while they are mainly significantly lower for maxR and mv. SRs are only significantly higher for DCC-GARCH-based optimizations in one case: crra in eq_fi. On the other hand, they are significantly lower in several asset spaces with maxR and mv. Gmv's SRs are notably, but not statistically significantly, higher. The other risk-adjusted return measures mirror this pattern but exhibit even less pronounced and significant differences. Utility-based measures show little evidence of significant variation, but there is a tendency towards improvement for gmv and slight deterioration for ERC, maxR, and mv under DCC-GARCH estimates. Turnover is considerably higher with DCC-GARCH estimates in every setting besides some asset spaces with crra. Cumulative wealth benefits notably from DCC-GARCH estimates, especially when applying gmv and crra (besides in the epra asset space), while strategies like maxR and mv's performances are strongly hindered.

Overall, DCC-GARCH estimates do not consistently improve portfolio performance compared to the simpler historical estimates. Despite observable advantages for some strategies, particularly gmv or maxDiv, it is therefore not recommended to introduce them, as the benefits

[2] The reliance on DCC-GARCH forecasted estimates introduces significant estimation risk for tail-dependent measures.
[3] Combining DCC-GARCH forecasts with Bayes-Stein shrinkage is methodologically inconsistent, as DCC-GARCH aims to model time-varying dynamics while Bayes-Stein assumes mean reversion towards a static covariance structure.

are not sufficiently consistent and significant, and the increased turnover potentially offsets most of the benefits after controlling for transaction costs.

5 DISCUSSION

5.1 Summary of Key Findings

This section summarizes the empirical results from chapter 4 and directly addresses the RQs outlined in section 3.1. The findings are aggregated across performance measures, strategies, asset spaces and periods.

5.1.1 RQ1 – Does the Addition of Crypto Assets Improve Portfolio Performance?

As described in section 4.4, the results provide robust evidence that crypto inclusion – represented by the CCI30 index – enhances performance across various optimization techniques. However, the extent and significance of these improvements depend on the strategy and performance measures considered. The key findings of this section can be summarized as follows:

- **Risk-adjusted returns** (SR, Sortino, STARR) improve in most scenarios and often statistically significantly, particularly for ew, maxDiv, and utility-based approaches (mv, bs-mv, crra).
- **Utility-based metrics** (MV and CRRA CEQ returns) increase in 78% to 87% of the tested scenarios. The significant gains are mainly concentrated in the same strategies as above.
- **Cumulative wealth** typically increases or at least remains similar to non-crypto portfolios, and **IRs** are mainly positive (with traditional being the benchmark), further confirming the outperformance from crypto-enhanced portfolios. Cumulative wealth path plots (raw and volatility adjusted) are provided in Appendix A.27 to assess cumulative returns.

These benefits are driven by significantly increased mean returns in almost all considered scenarios, which mostly outweigh the corresponding and often significant increases in volatility and other risk metrics. Strategies like gmv and minCVaR remained largely unaffected by crypto inclusion due to their close-to-zero allocations to crypto assets. This was expected, as crypto assets exhibit high volatility and CVaR and are hardly ever the asset with the lowest expected (tail) risk. Other strategies that do not consistently and significantly show improvements are ew_bh, ERC, maxR, maxSR and maxSTARR.

The derived results are stable across the considered asset spaces and several robustness tests. RQ1 can thus be answered as follows: Crypto asset inclusion tends to improve performance when the optimization framework allows for diversification and utility-based trade-offs. Strategies based on a single metric (mean return, volatility, CVaR) or pure ratio maximization strategies only show improvements in some scenarios and often fail to realize benefits. A deliberate strategy selection when including crypto assets is therefore important.

5.1.2 RQ2 – Does the Crypto-Inclusion Effect Vary Over Time?

As described in section 4.5, the effect of adding crypto assets to portfolios is not constant over time and substantial time variation could be observed in the considered sample. The key findings can be summarized as follows:

- Crypto inclusion yields benefits in **both the pre- and the post-COVID** period, although the strength and significance of the differences in performance metrics varies across strategies and metrics. Furthermore, all metric categories change stronger pre-COVID apart from risk-adjusted returns.
- **Rolling performance metric differences** (126-day SR, Sortino, STARR, etc.) peaked in 2017, 2020, 2021, and 2024 and often exhibited strong deterioration in 2019 and 2022. The reduction in magnitude is also notable in this analysis.
- **FE panel regression analysis** with year FEs and the interaction term between crypto effects and year FEs (Crypto x YearFE) confirms these patterns by showing significant variation in the crypto-inclusion effect across years.

RQ2 can be answered as follows: The effect of crypto inclusion varies significantly over time. Crypto appears to amplify performance, improving already well-performing years while exacerbating weaker ones. Due to an observable asymmetric amplification – larger additional gains in strong years than additional losses in weak years – it is nevertheless beneficial to include crypto assets overall when investing long-term. The generally reduced magnitude of differences (positive and negative) in mean returns and risk metrics in recent years may indicate a maturing crypto market. The lack of this pattern in risk-adjusted returns implies that the ratio of change between risk and return might have been more beneficial in later years (post-COVID period).

5.1.3 RQ3 – Is There a Clearly Superior Strategy/Design Choice for Including Crypto Assets?

No single strategy continuously dominates across asset spaces and performance metrics and with statistical significance when crypto assets are added. However, certain approaches performed more consistently (positive and negative):

- **MaxR** and **utility-based strategies (mv, bs-mv, crra)** typically delivered the most reliable performance across key metrics.
- Despite being a simplistic approach, **ew** portfolios perform competitively and benefit significantly from crypto inclusion, thus providing a reasonable alternative for investors that value simplicity.
- **MaxDiv** can be a potential alternative for very risk-averse investors, as it performs well regarding risk measures while keeping returns, risk-adjusted returns and utility relatively high compared to other risk-based approaches.
- **Gmv** and **minCVaR** yield negative risk-adjusted return metrics, failing to generate a positive excess return within our sample period. This could be caused by turmoil in the bond markets between late 2021 and 2023. Therefore, they can be excluded from the search for the best-performing strategy.

Finally, the impact of certain design choices is not entirely trivial. An additional gens constraint is generally recommended to enhance performance, while other design choices display non-uniform effects and thus do not allow a clear conclusion. Section 5.3.3 will provide a more detailed and practically oriented discussion of potential design choices.

The following heatmap provides an overview of the best and worst performing strategies per performance measure after including crypto assets. A more detailed overview can be found in Appendix A.30.

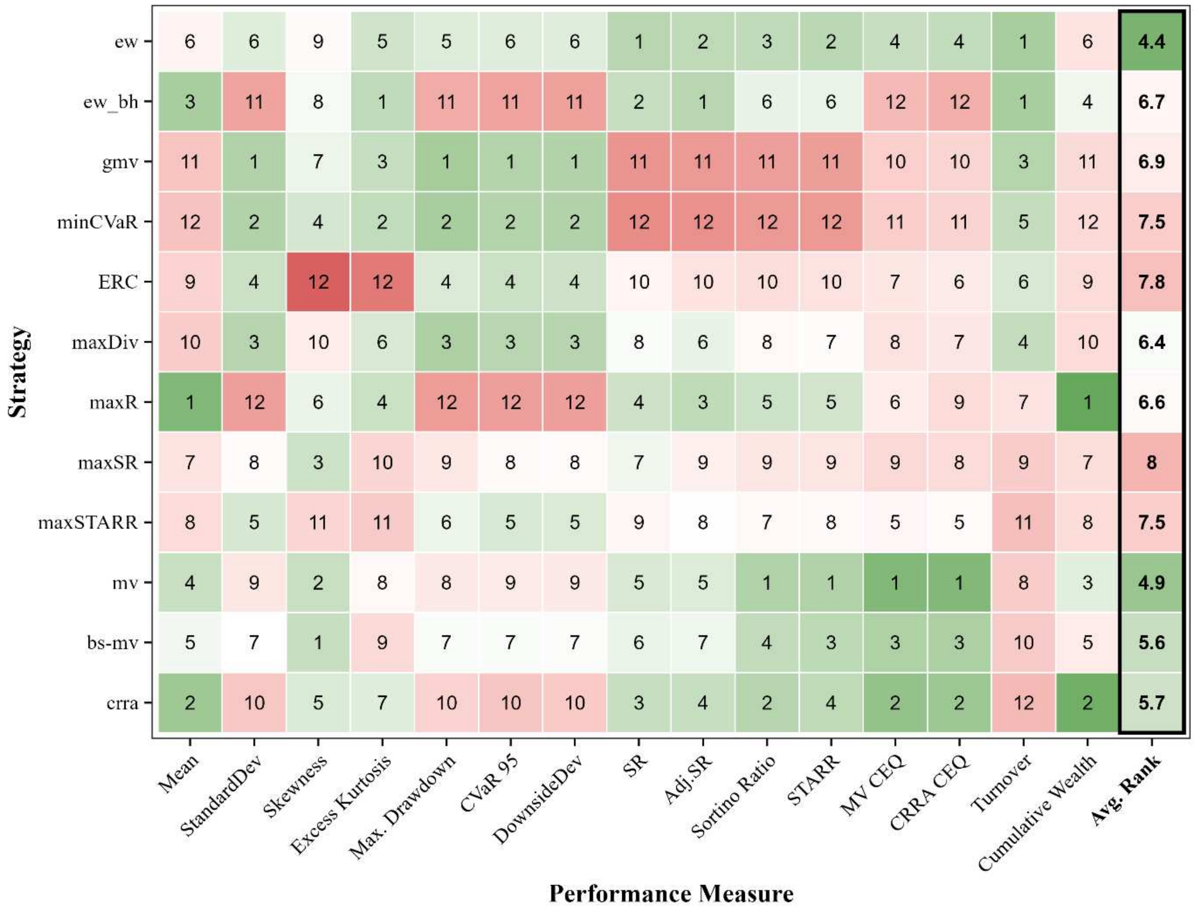

Figure 2: Heatmap – Average Performance Measures per Strategy Within CCI30 Portfolios

Note: Red = Below Average, Green = Above Average, Numbers indicate rank of the respective strategy per performance measure.

5.2 Comparison to Literature

In the following section, this thesis's findings are positioned within the context of previous academic research on crypto asset inclusion in portfolio optimization. In general, the derived findings confirm prior literature while challenging certain aspects and providing a more detailed understanding of the strategy- and time-varying effects of crypto inclusion.

5.2.1 Performance Enhancement Through Crypto Inclusion

The results are generally in line with what previous literature suggests. Crypto assets tend to enhance returns and increase volatility, but since returns are typically increased more strongly, risk-adjusted return measures improve overall.

Specific Comparisons to Selected Papers: Platanakis and Urquhart (2020) found that adding BTC increases risk-adjusted and utility-based metrics across multiple strategies. This thesis mainly confirms this, independent of whether CCI30 or BTC is added. However, the results provide stronger evidence that the magnitude and consistency of gains are strategy-dependent.

Petukhina et al. (2021) also found such increases when adding a broader set of crypto assets, although these increases do not always show statistical significance. They highlight ERC as particularly effective. Here, the results diverge. While this thesis can prove more significant gains for other strategies, ERC shows inconsistent and often insignificant improvements in the considered sample.

Furthermore, the crypto allocations observed in this thesis are higher than in previous studies for all approaches except gmv and minCVaR. This generally leads to more substantial and significant performance differences. Additionally, the improved performance for gmv and minCVaR found by Holovatiuk (2020) and Trimborn et al. (2020) could not be confirmed.

This thesis adds to previous literature by strongly extending the OOS period, which could be a key reason for the previously described differences in the obtained results. Other potential explanations include the universally applied long-only constraint, which is not consistently implemented in other papers, and differences in the asset selection (e.g., CCI30 vs. single crypto assets) and optimization techniques that have been applied. An overview of further related studies can be found in section 2.3.

5.2.2 Time-Varying Effects of Crypto Inclusion

Recent literature acknowledges that crypto's diversification benefits may vary over time. However, no paper has explicitly assessed whether crypto-inclusion effects are time-varying in an OOS setting. Nguyen (2022) and Gorman and Hughen (2024) found increased correlations during or ever since COVID-19, while Li and Miu (2023) found increased correlations when both markets are in high-volatility states. In this thesis, the increases during COVID-19 are observable across assets. Towards later periods, correlations decline again. Furthermore, previous research does not agree on whether crypto assets consistently show diversification or hedging potential during market turmoil (compare section 2.2.2). This thesis clearly shows that crypto-enhanced portfolios both over- and underperform compared to traditional portfolios, depending on the period under investigation. Thus, crypto assets seem to not consistently function as hedging instruments. Instead, they act as performance amplifiers that enhance gains in strong periods and increase losses in weak ones.

Additionally, this thesis adds to existing literature in two main ways: (1) It is the first to explicitly compare the OOS portfolio performance of various optimization techniques over a pre- and post-COVID period and several performance measures. The findings show that the partially increased correlations do not erode the benefits from crypto enhancement, but they tend to lose magnitude in later periods. (2) This thesis is the first to explicitly provide formal statistical evidence for the time-varying nature of crypto-inclusion effects via FE panel regression analysis (see section 4.5).

5.2.3 Strategy and Design Superiorities

Most previous studies examine crypto portfolio performance in specific models but do not systematically compare strategies and design choices. This limits their ability to identify a clearly superior asset allocation technique, often leading to contradictory conclusions and varying recommendations (see section 2.3 and 3.1).

This thesis addresses the gap by conducting a horserace between twelve distinct strategies across five asset spaces. However, also this thesis is unable to identify a clearly dominant strategy and the regression analysis shows that the crypto-inclusion effects themselves do not vary significantly across strategies for most measures besides the utility-based MV and CRRA CEQ returns.

Nevertheless, this thesis provides a comprehensive overview of a broad set of portfolio performance metrics across strategies and asset spaces, which allows to compare the strategies in further detail. It reveals that simple strategies (e.g., ew) can perform well, while some more sophisticated approaches fail to capture potential crypto benefits consistently. Additionally, this thesis explicitly evaluates design choices (e.g., rebalancing frequencies, constraints, etc.), which were not addressed by prior research. Through the systematic, broad and detailed comparison of strategies and design choices across asset spaces and performance metrics, this thesis enables investors to select a strategy for their specific needs and offers a more nuanced understanding of when, how and for whom crypto inclusion may be beneficial.

5.3 Practical Implications for Investors

This section translates the previously derived findings into practical implications and recommendations for investors considering to include crypto assets in their portfolios. Based on the results, several takeaways, structured into general implications, the role of strategy and design choice, and the influence of risk preferences emerge.

5.3.1 Assessment of the Real-World Applicability

Before discussing the implications derived from the performed empirical analysis, the real-world applicability of the employed strategies is briefly evaluated. In principle, all strategies can be implemented in practice, as estimations were based solely on data available at each point (see section 3.4). Furthermore, all assets included in this thesis are investable – either through Exchange-traded funds (ETFs) that track the performance of the selected indices or through direct physical replication of the underlying assets by the investor. Suitable ETFs are available for the MSCI World, MSCI EM, FTSE EPRA Dev, and BTC, while for the S&P GSCI, a commodity pool is available. For the fixed-income assets, no ETFs that directly track the performance of these specific indices are available. However, comparable products do exist (see Appendix A.29 for an overview). For the CCI30 index, the situation is different. As of now, no ETF that directly tracks its performance, nor something closely related, is available. Consequently, investors seeking to invest in the CCI30 must directly invest in the underlying individual constituents. As crypto assets can be traded in fractional amounts, this is feasible starting from small capital outlays. For institutional investors, legislative uncertainties can be a major barrier when investing directly in crypto assets (see section 1.1). Another potential obstacle for institutional and private investors with a substantial allocation is liquidity risk. Limited liquidity can affect ETFs and the smaller constituents from the CCI30 (in terms of market capitalization) and potentially lead to high transaction costs and price slippage during rebalancing. Furthermore, while ETFs aim to track certain indices, they do not necessarily achieve this, e.g. due to less frequent rebalancing or administration fees.

5.3.2 General Implications for Crypto Inclusion

The empirical results show that crypto assets can enhance portfolio performance in a statistically significant manner, but the effect is highly dependent on the considered performance measure, time period and partly also on the considered strategy. For investors, several core implications can be drawn. (1) The inclusion of crypto assets is recommended in the long term as the periods of outperformance outweigh the periods of underperformance. Market timing, which is notoriously difficult for crypto assets and forms a separate stream of literature (e.g., Bergsli et al. (2022); Dong et al. (2020); Dudek et al. (2024); Munim et al. (2019); Phung Duy et al. (2024) and Roy et al. (2018)), is therefore not necessary. However, investors should be aware that inclusion benefits are stronger in certain periods while they can even damage performance in others. (2) These findings are robust across asset spaces. Hence, including crypto assets is beneficial, no matter how broadly diversified the portfolios are previously. (3) Crypto assets should not be viewed as a hedging vehicle. The results clearly show that they do not help in minimizing drawdowns or other risk metrics during crises. Instead, they amplify performance and should be treated as a high-risk, high-upside allocation. (4) Portfolios that promote a certain risk-diversification across several assets (e.g. ew, maxDiv, and utility-based approaches) are generally favorable compared to strategies that only focus on a single objective and thus heavily allocate to one single asset (gmv, minCVaR, maxR). (5) The excessively increased risk metrics across almost all strategies can be seen as a major caveat when including crypto assets. While theoretically being outweighed by increased returns, these increases could be too large for many investors in practice.

5.3.3 Implications Regarding Strategy and Design Choices

As stated in section 5.1.3, some purely risk-based approaches, such as gmv or minCVaR, should not be applied when trying to improve performance by adding crypto assets. Risk-return-based approaches that aim to maximize certain ratios (e.g., SR or STARR) mostly fail in doing so and perform below average overall. ERC, while effectively limiting drawdown and tail risk measures, is only ranked 10th regarding risk-adjusted return metrics. Investors who want to explicitly minimize downside risk while still upholding some return benefits should rather consider maxDiv, which is able to better balance the risk-return trade-off, while keeping risk measures substantially below average. According to the analyses conducted, the simple ew portfolio, especially with rebalancing, is a considerable alternative to more sophisticated asset allocation techniques. It ranks in the upper half for all measures besides skewness and even achieves first place in terms of SR. Another strategy that performs surprisingly well and even ranks best in cumulative wealth is maxR. However, even though risk-adjusted return measures exhibit decent rankings, implementing this strategy seems unrealistic in practice due to the enormous risk measures. This leaves the investors with utility-based approaches, which generally perform well, especially across the defined main performance metrics. The risk measures are also high for these strategies and the strategies must therefore be implemented cautiously.

Once the overall decision regarding the inclusion of crypto assets has been made and a strategy is selected, there are several practical implications regarding design choices that can be drawn from the conducted analyses. (1) To avoid missing out on the initial phases of crypto bull runs and capture more of their generally high SRs, investors willing to bear volatility should consider introducing gens constraints. (2) As the results between CCI30 and BTC do not deviate strongly, investors who prefer a simple and easily implementable approach should consider using BTC instead of CCI30, even though this often results in slightly weaker performance. Until the introduction of an ETF that adequately captures CCI30, this adaptation significantly simplifies adding crypto assets to portfolios. (3) Investors should apply a monthly rebalancing frequency, as shorter frequencies do not increase performance significantly but require considerably more trading to be implemented, which causes higher transaction costs. (4) Investors seeking more stable and less risky portfolios could consider using an expanding window approach. Typically, this does not strongly reduce risk-adjusted and utility-based performance metrics while significantly lowering most risk metrics. (5) DCC-GARCH models seem to not be worth the additional effort, as the resulting portfolios fail to outperform in a consistent and significant manner and sometimes even underperform compared to portfolios constructed with simplistic historical estimates. Furthermore, they cause strongly increased turnover measures and are thus not recommended to investors in practice.

Overall, investors should not only decide whether to add crypto assets but also deliberately choose how to do so. While design choices do not always exhibit significant differences in performance, several other aspects can be improved (e.g., simplification regarding assets used and rebalancing frequency applied).

5.3.4 Implications Based on Risk Aversion

The primary empirical analysis was based on a common risk aversion level of $\gamma = 3$ in the optimization and the calculation of MV and CRRA CEQ returns. However, in practice investors may have different risk tolerances. To better understand whether the choice of strategy and the effectiveness of the utility-based optimization methods depend on the level of risk aversion, the utility-based portfolios are re-optimized with the additional risk aversion levels of $\gamma = 1$ and $\gamma = 5$. Furthermore, the performance measures are recalculated using the portfolios optimized with these risk aversions.

Generally, it can be observed that the optimization process under varying levels of risk aversion performs as intended. As the risk aversion parameter increases, the allocation to crypto assets and mean portfolio returns and portfolio volatility decline, whereas the opposite happens when lowering the risk aversion parameter. Optimizations under high risk aversion levels potentially even exhibit risk measures comparable to purely risk-based optimizations while maintaining substantially higher upward potential. The impact of the level of γ on risk-adjusted return measures is generally low, with a tendency of higher SRs and adjusted SRs for low risk aversions and higher Sortino Ratios and STARRs for higher risk aversion levels. The reduced returns under higher risk aversions also strongly influence cumulative wealth. However, once they are scaled according to their respective volatilities, the results are mainly similar and higher risk aversions even outperform in some scenarios (see Appendix A.33). This implies that adding crypto can be valuable even for highly risk-averse investors if the optimization is performed reflecting their utility-preferences. A plot comparing all performance measures across utility-based approaches with different risk aversion levels as well as a plot summarizing CEQ returns with all risk aversion levels can be found in Appendix A.31 and A.32.

5.3.5 Overall Recommendation for Investors

Based on the previously described implications, the general recommendation for investors – regardless of their risk preference – is to include crypto assets using a utility-based strategy. The choice between mv and crra should depend on whether a quadradic or a power utility function better describes the respective investors' preferences. In either case, it is recommended to put a strong emphasis on risk aversion calibration. For investors unwilling to run optimization procedures, a simple ew strategy with monthly rebalancing is a solid and implementable alternative. Further, a strong emphasis should be placed on the specific design choices, as they can strongly influence the results and practical feasibility of the optimization and implementation.

5.4 Limitations

While the conducted research provides a comprehensive assessment of crypto inclusion in portfolio optimization, it is subject to several limitations. The main areas are limitations regarding data and available time horizon, as well as limitations in methodology and modelling.

5.4.1 Data & Time Horizon Limitations

Short OOS Period: While expanding the considered time horizon by several years compared to previous research, the considered OOS period is still short compared to studies which do not include crypto assets. This is because crypto assets are relatively young, and crypto markets were immature before 2015, when the sample started.

Backwards-Looking Data: The whole analysis is based on past data and thus backward-looking to some extent. This was addressed by using a rolling OOS approach that, at each point in time, only considers data that would have been available in real-time at this specific point. Nevertheless, it would be oversimplified to assume that the derived findings will remain unchanged in future, as significant time variance of crypto-inclusion effects can already be observed within the OOS period (see section 4.5). One potential future scenario is that crypto markets become more mature, and the crypto-inclusion effects, which already tended to exhibit lower magnitudes towards the end of our sample, flatten out even further.

Crypto Assets Used: Using CCI30 as the primary and BTC as the secondary crypto assets leaves room for potential winners/survivorship bias, even though CCI30 selects its constituents via a purely rule-based mathematical derivation. Furthermore, CCI30 was created in 2017 and would not have been available from the start of the considered time horizon. Additionally, investing in CCI30 is more difficult compared to investing in traditional asset classes, as it is not simply investable via an ETF and would have to be replicated manually by the investor.

5.4.2 Methodology & Modeling Limitations

Market Frictions: Most analyses are conducted under the assumption of frictionless markets. While one major friction (transaction costs) is considered in robustness tests and does not strongly change results, other frictions like liquidity are not explicitly considered. Additionally, transaction costs are only considered ex-post and not within the optimization procedures themselves, meaning that the constructed portfolios are only theoretically optimal in the frictionless setting.

Selection of Optimization Methods: A broad set of optimization techniques, ranging from purely moment-based optimizations to utility maximization with shrinkage or under a power-utility function, was applied. However, there are still further well-known optimization techniques that could have been used. Possible additions include optimal combinations of portfolios following Kan and Zhou (2007) or Tu and Zhou (2011).

5.5 Further Potential Research Areas

Building on the retrieved findings and acknowledging the limitations, a set of potential future research areas arises, which will be presented subsequently.

Investigating the Root Causes of Positive and Negative Crypto Asset Contribution: As the conducted analyses revealed time periods of positive and negative crypto-inclusion effects, further research could focus on deciphering what causes these differences. Special emphasis in these analyses could be put on the question of why the magnitude of out- and underperformance seems to have lowered and whether this trend is expected to continue. The explanatory regression section in Appendix A.34 presents a purely explorative trial to explain the variation in crypto-inclusion effects and can serve as a starting point.

Extend on Statistical Modelling to enhance estimates: This thesis tried to enhance mean and covariance estimates through a literature-based, but rather simplistic, DCC-GARCH model and could not consistently improve the performance of the resulting portfolios. However, as some strategies displayed benefits, future research could explicitly focus on testing other, more advanced approaches (e.g., GARCH-Copulas, etc.) to predict means and covariances.

Extend on Regime Switching and State Variable Approaches: Depending on the findings from the first suggested research area, future researchers could focus on implementing a dynamic investment strategy that effectively times crypto-inclusion effects and further enhances performance benefits through crypto assets. They could focus on predicting positive crypto-inclusion effects via regimes or state variables and thereby provide valuable guidance for investors wanting to explore adding crypto assets to their portfolios.

Apply a Machine Learning Approach Focused on Long-term Crypto Investing: Papers investigating machine learning approaches in the crypto space already exist (Goutte, Le, Liu, & Mettenheim, 2023; Parente, Rizzuti, & Trerotola, 2024). However, they are mainly focused on short-term or high-frequency trading. An interesting direction to explore could be, whether machine learning approaches can also add value in long-term-oriented approaches and under weekly or monthly rebalancing.

Extend in Terms of Time Horizon, Strategies, Fractions Considered or Assets Used: The conducted research could be repeated in future including additional time periods, optimization strategies (e.g. combinations of portfolios), robustness tests for fractions such as liquidity or slippage and a further extended asset space with industry portfolios or other alternative asset classes such as private equity, etc.

6 CONCLUSION

A primary objective of this thesis was to evaluate whether adding crypto assets enhances portfolio performance for portfolios created with traditional portfolio optimization methods. An important aspect in this regard was to look at portfolio performance from different angles via a broad set of performance measures and put differences through their paces using an approach accounting for the specific structure of the return series. Furthermore, this thesis aimed to investigate whether such crypto-inclusion effects are constant or time-varying, as prior research found increased correlations between crypto assets and traditional assets in more recent years. Lastly, a comprehensive horserace between strategies and direct comparisons of various design choices were conducted to identify superior strategies.

The results of the empirical analysis significantly contribute to the current state of research, as they strongly extend the OOS period and provide a more detailed view on different aspects of performance, e.g., drawdown and tail risk measures. Furthermore, it is the first prevailing study to explicitly investigate the time variance of crypto-inclusion effects by splitting the sample in a pre- and post-COVID period and running FE panel regressions with interaction terms. The following detailed comparison across strategies and design choices is of high practical relevance for investors considering to participate in the rise of crypto assets and the findings entail specific guidance on how one should proceed.

The main findings can be summarized as follows. Crypto assets generally improve portfolio performance significantly across the main performance indicators. This is because the more substantial increases in returns outweigh the increases in risk. These strongly increased risk measures should be considered when adding crypto assets to one's portfolio. The general improvements vary between strategies and over time, with a tendency towards lower gains in later years. Furthermore, crypto assets should be seen as performance amplifiers (in both directions) rather than as hedging vehicles. This statement is derived from the fact that periods of significant over- but also underperformance can be observed within the empirical results. The underlying drivers of the time variation are only briefly investigated and are subject to future research. While the strategy and design choice comparison did not crown a clear winner, it is generally recommended to use utility-based approaches or a simple 1/N approach as they constantly rank amongst the best performing optimization techniques. Furthermore, one can conclude that certain design choices, such as a gens constraint or the use of BTC instead of CCI30, positively influence performance or enhance simplicity. Other design choices, such as shorter rebalancing frequencies (weekly, daily), substantially increase the amount of trading required without compensating adequately through increased returns. Mean and covariance forecasts from a DCC-GARCH did not improve performance significantly, but minor improvements suggest that future research could dive deeper into this topic and try to enhance portfolio optimization settings with more sophisticated mean and covariance forecasts. The results typically do not depend on the asset space, making crypto assets an attractive opportunity also for already diversified investors.

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A. APPENDIX

A.1 Additional used R-packages

The main R-packages used are listed in the Reference List. This section contains additional R-packages mainly used to enhance the performance and structure of the code, improve plotting or enable exporting or importing functionalities.

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A.2 Rolling Condition Numbers of Covariance-Matrices

A.2.1 252-Day Rolling Window

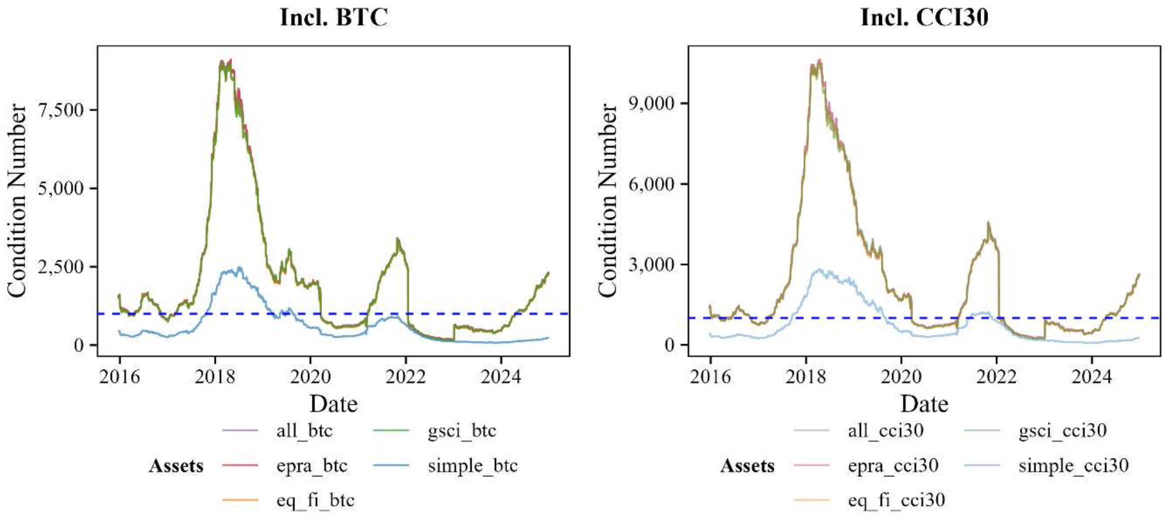

Figure 3: 252-Day Rolling Condition Number of Covariance Matrices

A.2.2 1,008-Day Rolling Window

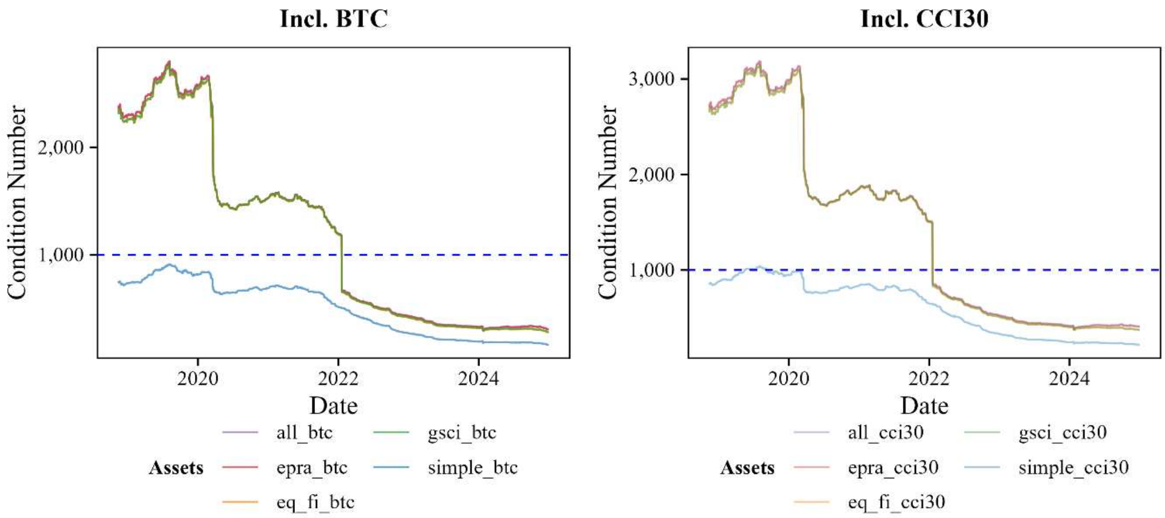

Figure 4: 1,008-Day Rolling Condition Number of Covariance Matrices

In the previous plots, the condition number is defined as:

$$Condition\ Number = \frac{\lambda_{max}}{\lambda_{min}} \tag{A1}$$

Where λ_{max} is the largest eigenvalue of the covariance matrix $\boldsymbol{\Sigma}$ and λ_{min} denotes the smallest eigenvalue of the covariance matrix $\boldsymbol{\Sigma}$.

A.3 Overview Portfolio Performance Measures

Measure	**Equation**	**Annualized**
Descriptive Statistics		
Mean Return	$\mu_r = \frac{1}{N}\sum_{t=1}^{N} r_t$	Yes
Standard Deviation	$\sigma_r = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - \mu_r)^2}$	Yes
Skewness	$S = \frac{N}{(N-1)(N-2)}\sum_{t=1}^{N}\left(\frac{r_t-\mu_r}{\sigma_r}\right)^3$	No
Excess Kurtosis	$K = \frac{N(N+1)}{(N-1)(N-2)(N-3)}\sum_{t=1}^{N}\left(\frac{r_t-\mu_r}{\sigma_r}\right)^4 - \frac{3(n-1)^2}{(N-2)(N-3)}$	No
Drawdown and Tail Risk Measures		
Maximum Drawdown	$MDD = \left(\frac{Peak-Through}{Peak}\right)$	No
Conditional VaR 95%	$CVaR_{95\%} = E(r \mid r \leq VaR_{95\%})$	No
Downside Deviation	$\sigma_D = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N} min(r_t, 0)^2}$	Yes
Risk-adjusted Return Measures		
Sharpe Ratio	$SR = \frac{\mu_R}{\sigma_R}$	Yes
Adjusted Sharpe Ratio	$SR_{adj} = SR(1 + \frac{S}{6}SR - \frac{K}{24}SR^2)$	Yes
Sortino Ratio	$Sortino = \frac{\mu_R}{\sigma_D^R}$	Yes
STARR	$STARR = \frac{\mu_R}{CVaR_{95\%}^R}$	No
Utility-based Performance Measures		
MV CEQ Return	$CEQ_{MV} = \mu_r - \frac{\gamma}{2}\sigma_r^2$	Yes
CRRA CEQ Return	see section A.3.2	Yes
Others		
Portfolio Turnover	$TO = \frac{1}{N}\sum_{t=1}^{N}\sum_{j=1}^{A}\lvert\omega_{j,t+1} - \omega_{j,t}\rvert$	No
Cumulative Return	$CumRet = \prod_{t=1}^{N}(1 + r_t) - 1$	No
Information Ratio	$IR = \frac{E[r_p - r_{benchmark}]}{\sigma_{tracking}}$	No

Note: Performance Measures in bold, are defined as the core set to answer the RQs.

Table 7: List of Portfolio Performance Measures Including Definition

Table 7 summarizes the portfolio performance measures and indicates whether they are reported in annualized form in the paired portfolio comparisons. The rolling performance measures are reported on a daily basis. Returns are denoted as r_t and are calculated as simple holding period returns. Excess returns R_t of the respective portfolios are defined as $R_t = r_t - rf_t$, where rf_t represents the return of a risk-free investment (one-month US treasury bills). The number of observations is denoted by N, and the number of assets is denoted by A, while $\omega_{j,t}$ denotes the weight in a risky asset j at time t, and γ denotes the risk aversion of an investor, which is set to $\gamma = 3$ in the main scenario.

A.3.1 Annualization Procedure

The given return frequency per year is denoted by f and is used to annualize measures. The mean is annualized by simply multiplying by f, while standard deviation and downside deviation are annualized by multiplying by $\sqrt{f}$. Path-dependent measures such as cumulative returns and maximum drawdown or non-parametric risk measures such as CVaR are not annualized to preserve distributional accuracy. Hence, STARR is not annualized as well. Annualizing SR, when autocorrelation is present within the return series, carries the risk of over- or understatement. To account for this issue, the SR is annualized using Lo’s (2002) approach, where ρ_k denotes the autocorrelation at lag k:

$$SR_{annual} = SR_{period} \frac{f}{\sqrt{f + 2\sum_{k=1}^{f-1}(f-k)\rho_k}} \qquad (A2)$$

Due to the lack of a widely accepted approach to correct for autocorrelation when calculating the Sortino Ratio, it will be annualized by multiplying with $\sqrt{f}$. The CEQ return measures (MV and CRRA-based) contain nonlinear transformations and cannot be scaled linearly due to Jensen’s inequality. Thus, they will be annualized by compounding according to:

$$CEQ_{annual} = \left(1 + CEQ_{subperiod}\right)^{f} - 1 \qquad (A3)$$

A.3.2 CRRA CEQ Return

The CRRA CEQ Return is calculated in several steps:

(1) First, each portfolio's retrieved OOS daily return series r is transformed into a gross return series using: $R = 1 + r$.

(2) Second, the utility for each gross return R is computed based on the following utility function:

$$\mathrm{U(R)} = \frac{R^{1-\gamma} - 1}{1 - \gamma} \qquad (A4)$$

(3) Subsequently, the expected utility of the whole vector is computed by taking the mean of all individual utilities calculated in step two.

(4) The expected utility is transformed into the CEQ gross return by applying the inverse of the utility function from Equation A4 onto the previously derived expected utility:

$$R_{CEQ} = e^{\frac{Ln[U(R)(1-\gamma)+1]}{(1-\gamma)}} \qquad (A5)$$

(5) The CEQ net return is derived by subtracting one: $r_{CEQ} = R_{CEQ} - 1$

Similar to the MV CEQ Return, the retrieved number indicates the risk-free rate of return which an investor, in this setting with a power utility function, would require to be indifferent between holding the given risky portfolio or the risk-free asset.

A.4 Portfolio Returns – P-Values of Time-Series Diagnostics (2016-2024)

Portfolio Returns - P-Values of Time Series Diagnostics (2016-2024)

		Non-Crypto Portfolios				BTC Portfolios				CCI30 Portfolios			
		JB	*ADF*	*LB*	*ARCH*	*JB*	*ADF*	*LB*	*ARCH*	*JB*	*ADF*	*LB*	*ARCH*
ew	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.35	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.08 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.04 **	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.02 **	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew_bh	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.15	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew_bh	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.10 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew_bh	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.07 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew_bh	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.08 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ew_bh	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.06 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
gmv	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
gmv	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
gmv	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
gmv	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
gmv	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
minCVaR	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
minCVaR	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
minCVaR	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
minCVaR	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
minCVaR	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ERC	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ERC	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ERC	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ERC	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
ERC	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxDiv	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxDiv	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxDiv	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxDiv	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxDiv	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxR	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.05 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxR	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.05 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxR	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.11	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxR	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.06 *	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxR	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.13	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSR	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSR	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSR	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSR	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSR	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSTARR	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSTARR	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSTARR	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSTARR	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
maxSTARR	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
mv	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
mv	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
mv	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
mv	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
mv	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
bs-mv	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
bs-mv	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
bs-mv	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
bs-mv	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
bs-mv	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
crra	simple	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
crra	eq_fi	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
crra	gsci	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
crra	epra	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***
crra	all	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***	0.00 ***	0.01 ***	0.00 ***	0.00 ***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: ADF-tests have been performed with auto-selection of lags and the R-function is not able to plot p-values smaller than 0.01

Ljung-Box and ARCH-tests have been performed up to lag 30

Table 8: Portfolio Returns – P-Values of Time-Series Diagnostics (2016-2024)

A.5 Panel Regression Analysis – OLS Assumption Diagnostics

Regression Analysis: OLS Assumption Diagnostics

		Independence		**Homoscedasticity**		**Normality**	
Metric	Model	p-value	Conclusion	p-value	Conclusion	p-value	Conclusion
SR	Base Spec.	0.000	violated	0.000	violated	0.000	violated
SR	Crypto x YearFE	0.000	violated	0.000	violated	0.000	violated
SR	Crypto x StrategyFE	0.000	violated	0.000	violated	0.000	violated
SR	Crypto x AssetSpaceFE	0.000	violated	0.000	violated	0.000	violated
Sortino	Base Spec.	0.000	violated	0.000	violated	0.000	violated
Sortino	Crypto x YearFE	0.000	violated	0.000	violated	0.000	violated
Sortino	Crypto x StrategyFE	0.000	violated	0.000	violated	0.000	violated
Sortino	Crypto x AssetSpaceFE	0.000	violated	0.000	violated	0.000	violated
STARR	Base Spec.	0.000	violated	0.000	violated	0.000	violated
STARR	Crypto x YearFE	0.000	violated	0.000	violated	0.000	violated
STARR	Crypto x StrategyFE	0.000	violated	0.000	violated	0.000	violated
STARR	Crypto x AssetSpaceFE	0.000	violated	0.000	violated	0.000	violated
MV_CEQ	Base Spec.	0.000	violated	0.000	violated	0.000	violated
MV_CEQ	Crypto x YearFE	0.000	violated	0.000	violated	0.000	violated
MV_CEQ	Crypto x StrategyFE	0.000	violated	0.000	violated	0.000	violated
MV_CEQ	Crypto x AssetSpaceFE	0.000	violated	0.000	violated	0.000	violated
CRRA_CEQ	Base Spec.	0.000	violated	0.000	violated	0.000	violated
CRRA_CEQ	Crypto x YearFE	0.000	violated	0.000	violated	0.000	violated
CRRA_CEQ	Crypto x StrategyFE	0.000	violated	0.000	violated	0.000	violated
CRRA_CEQ	Crypto x AssetSpaceFE	0.000	violated	0.000	violated	0.000	violated

Independence is tested via Ljung-Box Test up to lag 21, Homoscedasticity is tested via ARCH-test up to lag 21, Normality is tested via Jarque-Bera Test

Table 9: Panel Regression Analysis – OLS Assumption Diagnostics

A.6 Schematic Diagram of Methodology Flow

The following visualization summarizes the main steps of the empirical process. The sequential execution assures consistency in the optimization and evaluation.

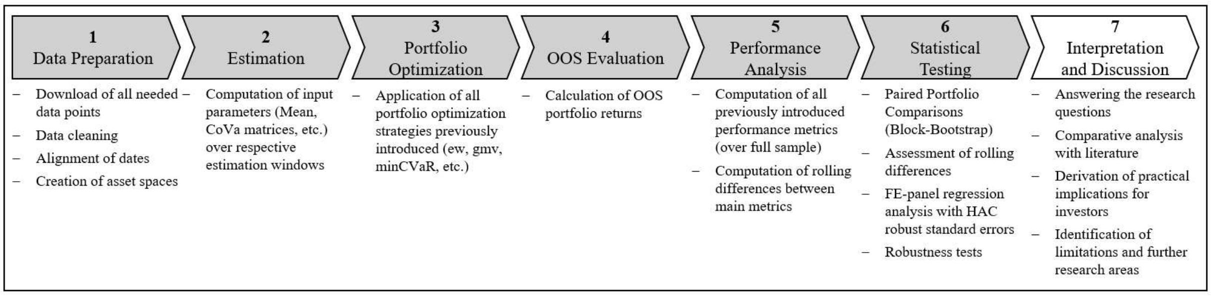

Figure 5: Chronological Sequence of Major Steps from the Empirical Analysis

A.7 QQ-Plots of the Individual Asset Returns (2015-2024)

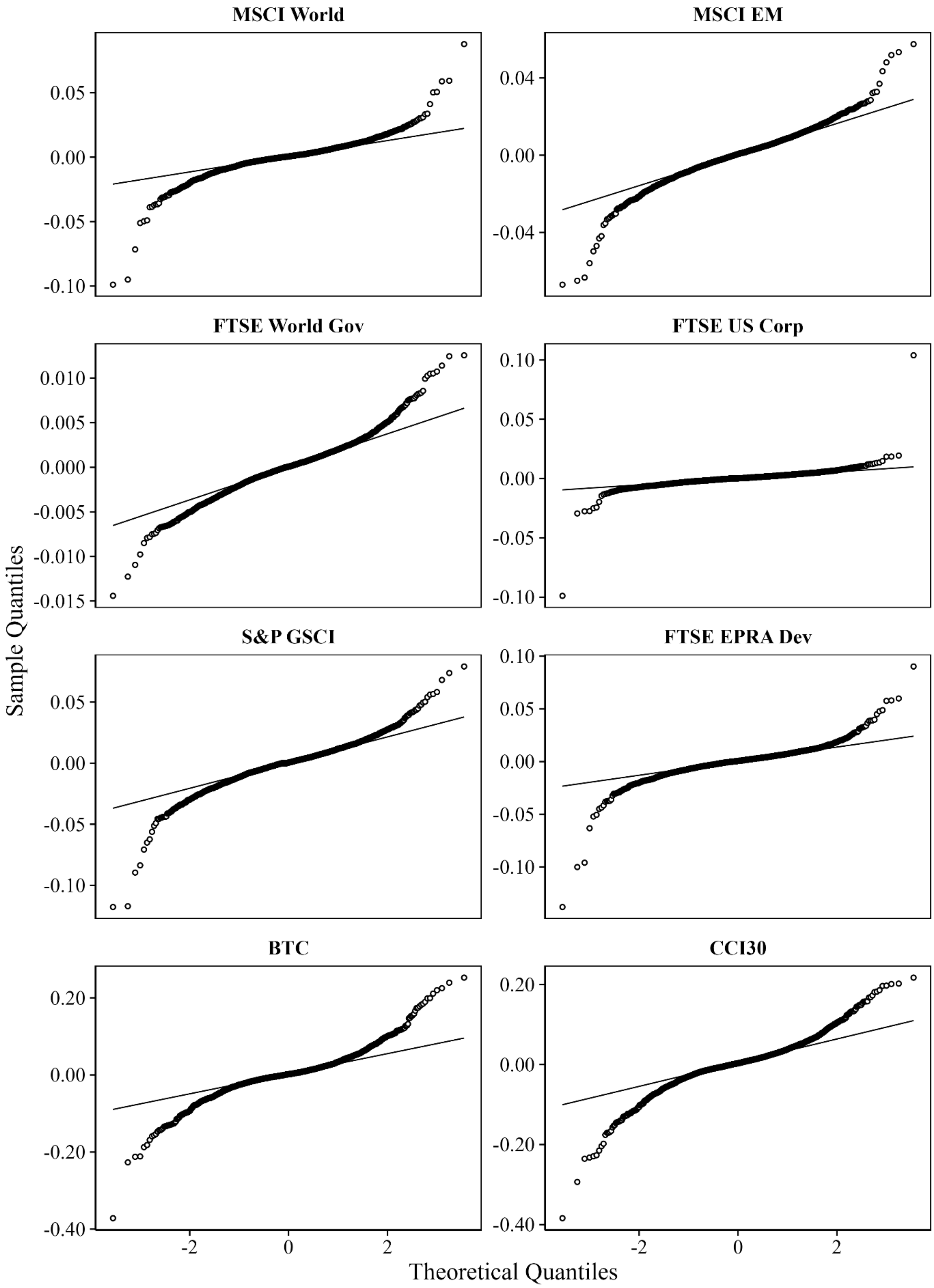

Figure 6: QQ-Plots of the Individual Asset Returns (2015-2024)

A.8 Plots of the Daily Individual Asset Return Series (2015-2024)

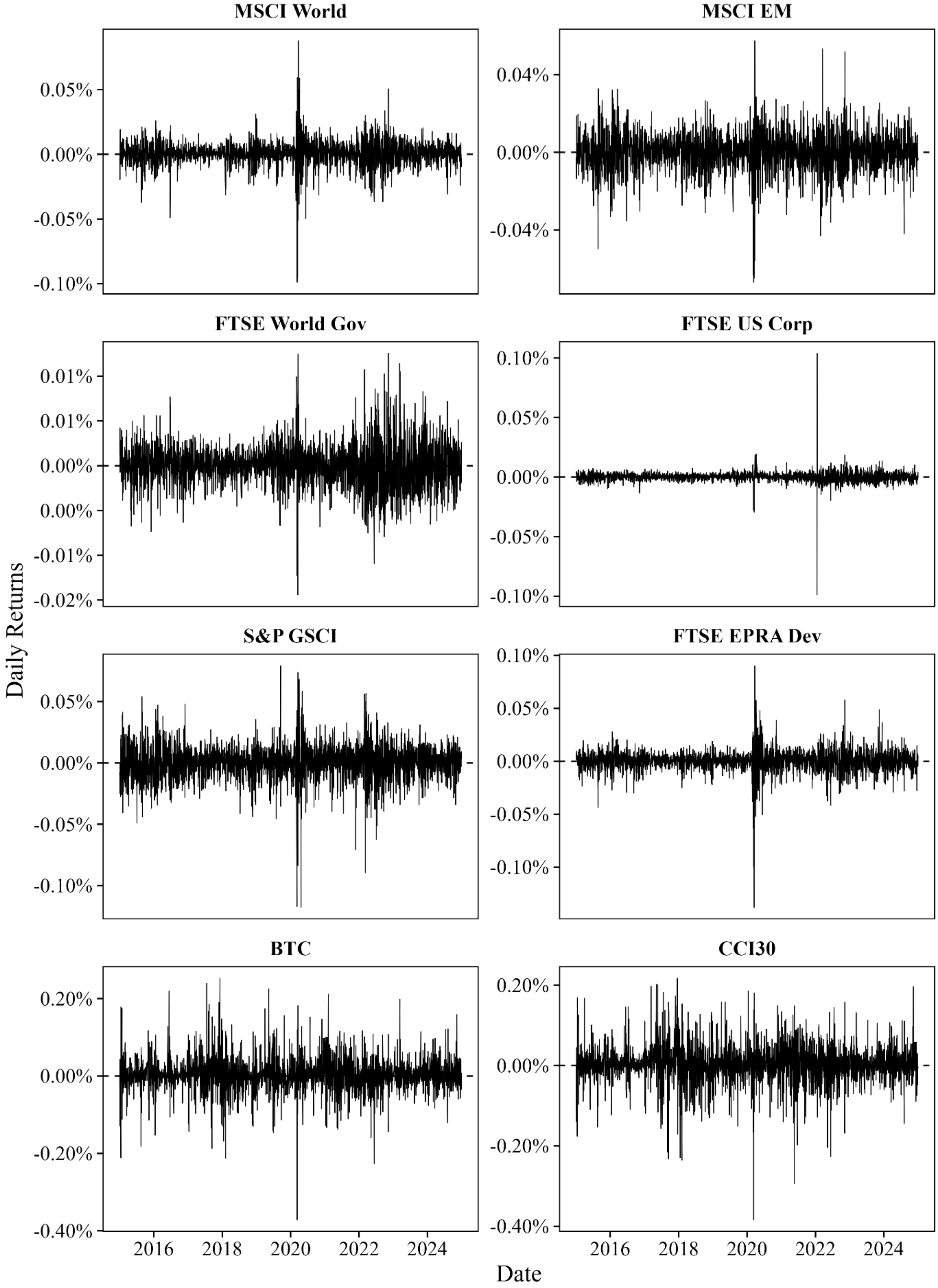

Figure 7: Plots of the Individual Asset Return Series (2015-2024)

A.9 ACF-Plots of the Individual Asset Returns

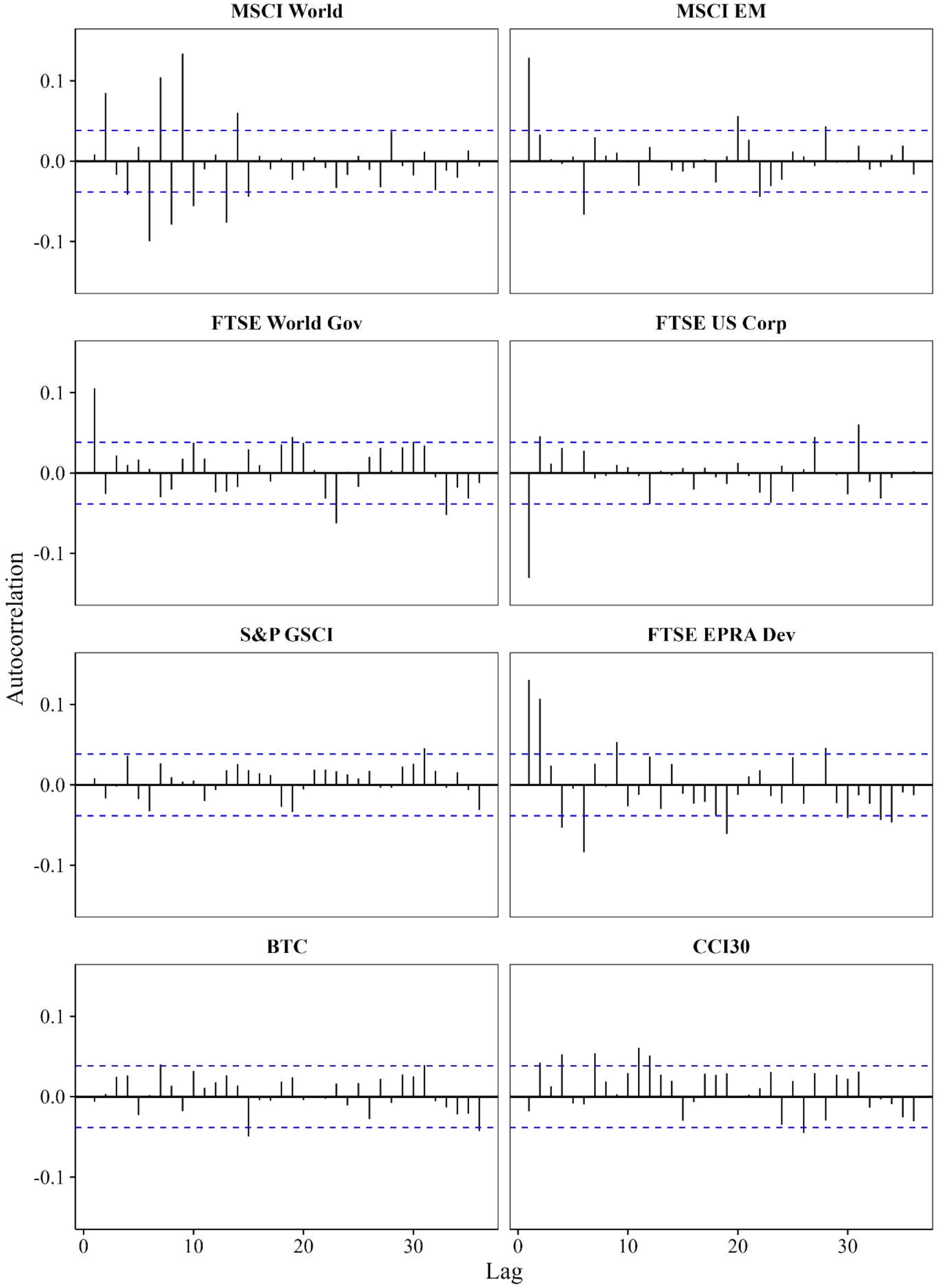

Figure 8: ACF-Plots of the Individual Asset Returns (up to Lag 36)

A.10 252-Day Rolling Correlation Plots between Crypto Assets and Traditional Assets

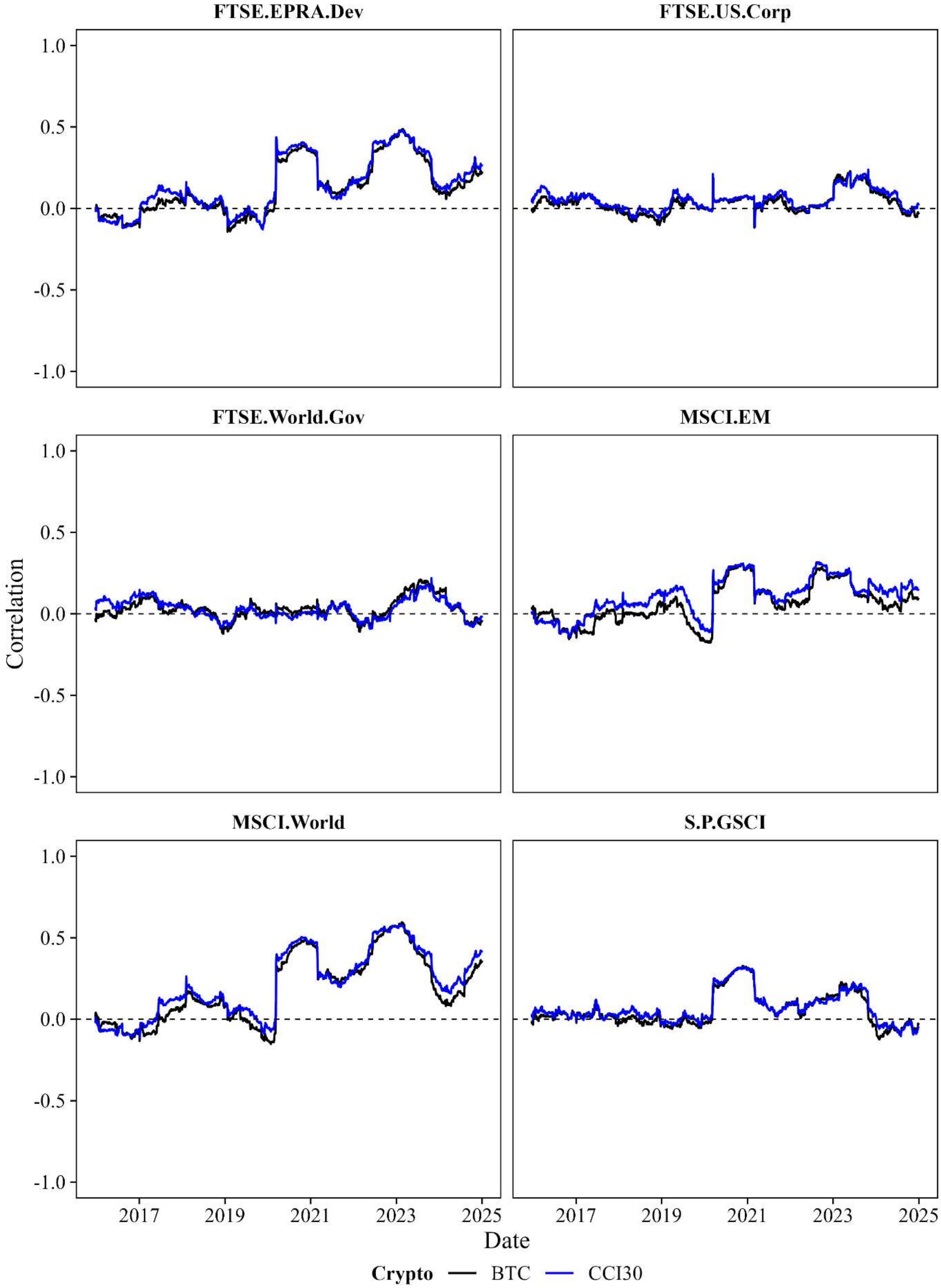

Figure 9: 252-Day Rolling Pearson Correlation Plots between Crypto Assets and Traditional Assets

A.11 Efficient Frontiers Across Asset Spaces

A.11.1 Mean-Variance Efficient Frontiers

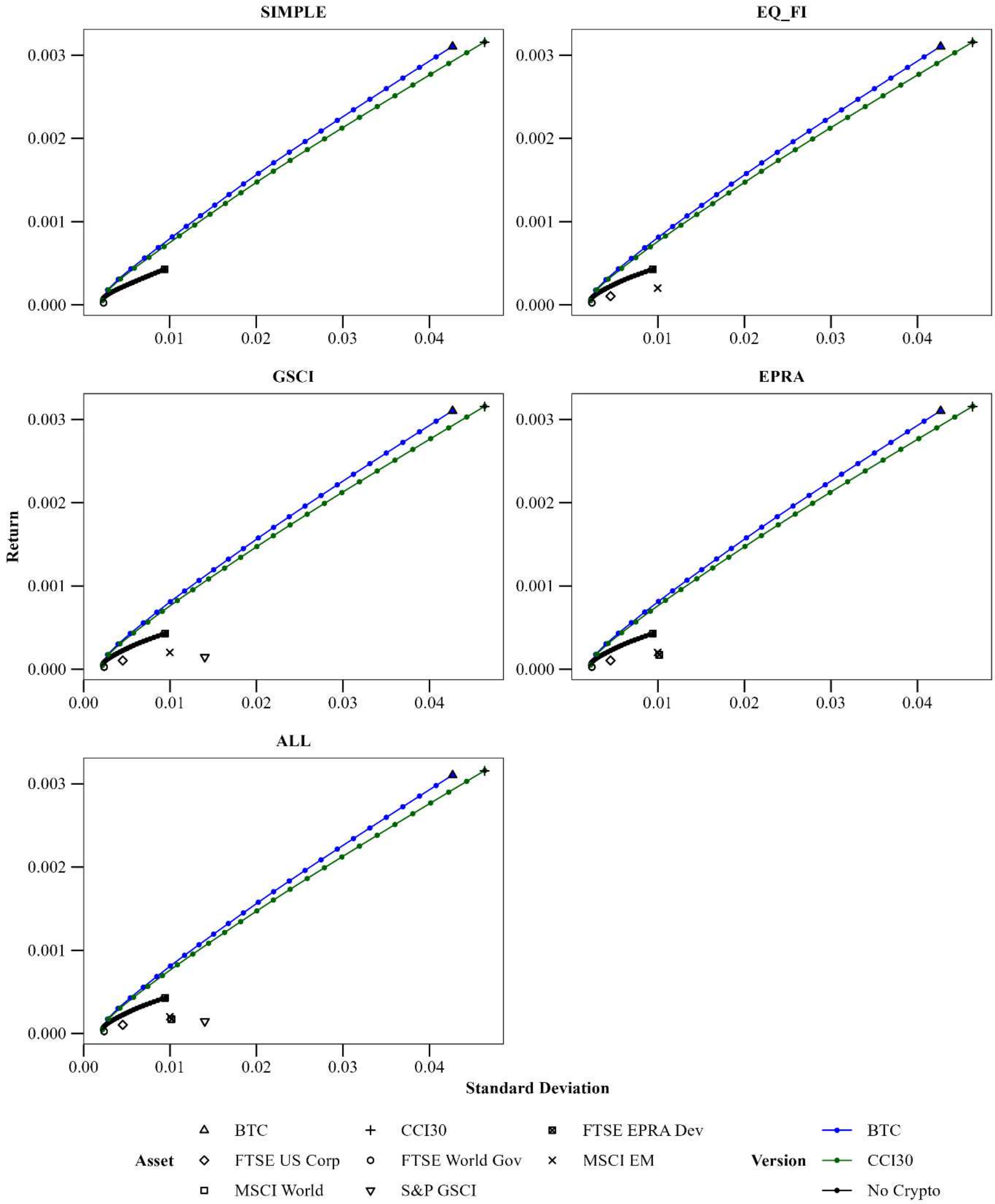

Figure 10: Efficient Frontiers – Mean-Variance Across Asset Spaces (Daily Data)

A.11.2 Mean-CVaR Efficient Frontiers

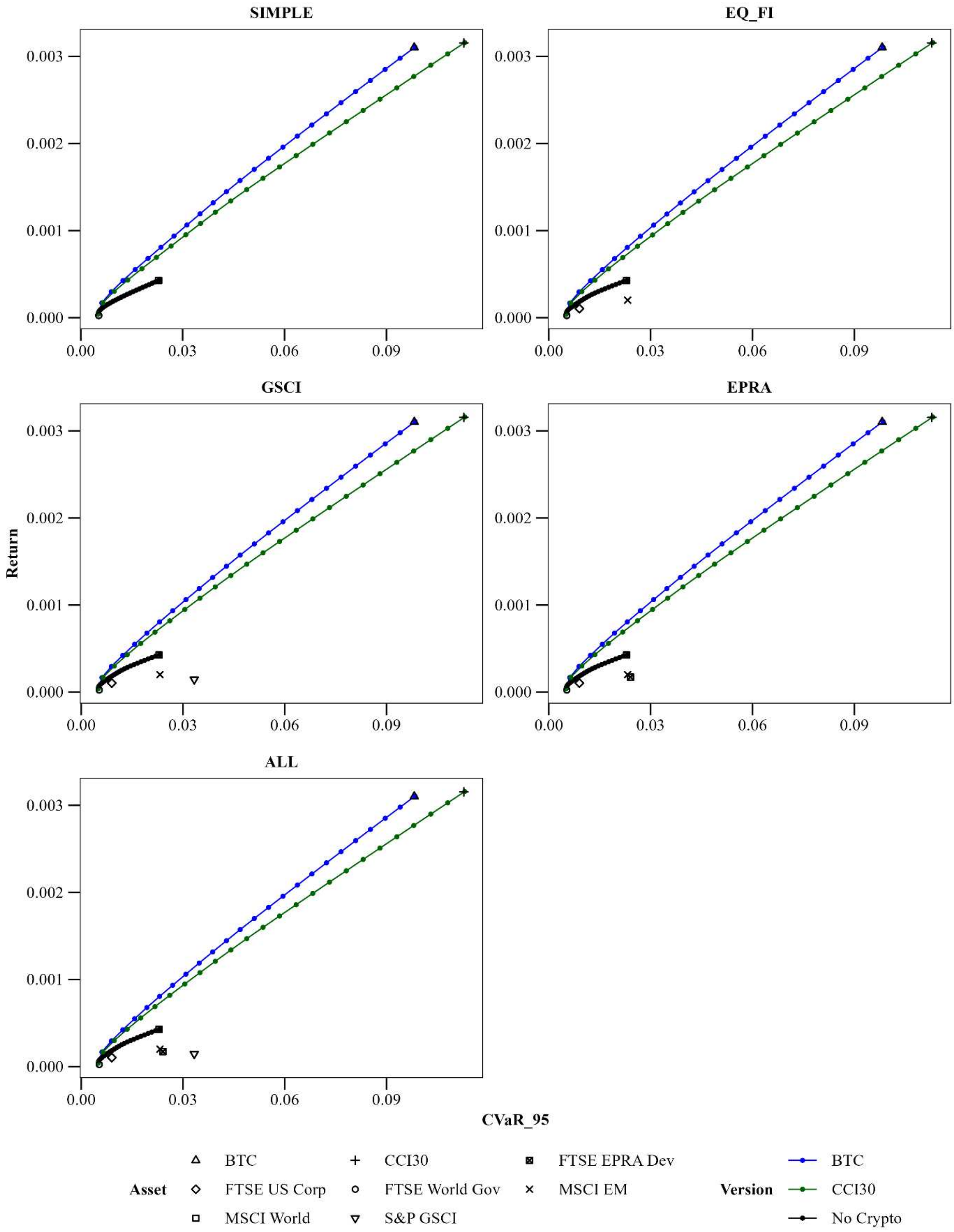

Figure 11: Efficient Frontiers – Mean-CVaR Across Asset Spaces (Daily Data)

A.12 Portfolio Weights: Average Crypto Allocation per Year Across Strategies

Portfolio Weights: Average Crypto Allocation per Year Across Strategies
(2016-2024) for Monthly Rebalancing

		CCI30										BTC									
Strategy	Asset Space	2016	2017	2018	2019	2020	2021	2022	2023	2024	**AVG.**	2016	2017	2018	2019	2020	2021	2022	2023	2024	**AVG.**
gmv	simple	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	**0.1%**	0.3%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.3%	**0.1%**
gmv	eq_fi	0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.2%	**0.0%**	0.3%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.4%	**0.1%**
gmv	epra	0.1%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.2%	**0.0%**	0.3%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.4%	**0.1%**
gmv	all	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.4%	**0.1%**	0.2%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.5%	**0.1%**
gmv	gsci	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.4%	**0.1%**	0.2%	0.0%	0.0%	0.2%	0.1%	0.0%	0.0%	0.0%	0.5%	**0.1%**
minCVaR	simple	0.7%	0.0%	0.2%	0.3%	0.2%	0.0%	0.0%	0.2%	0.0%	**0.2%**	0.6%	0.4%	0.1%	0.4%	0.0%	0.0%	0.1%	0.1%	0.2%	**0.2%**
minCVaR	eq_fi	0.6%	0.0%	0.1%	0.2%	0.1%	0.1%	0.0%	0.3%	0.0%	**0.2%**	0.7%	0.6%	0.0%	0.4%	0.0%	0.1%	0.0%	0.3%	0.2%	**0.3%**
minCVaR	epra	0.6%	0.0%	0.1%	0.2%	0.1%	0.1%	0.0%	0.3%	0.0%	**0.1%**	0.7%	0.6%	0.0%	0.4%	0.0%	0.0%	0.0%	0.3%	0.2%	**0.3%**
minCVaR	all	0.3%	0.0%	0.2%	0.2%	0.1%	0.1%	0.0%	0.1%	0.1%	**0.1%**	0.5%	0.3%	0.1%	0.4%	0.1%	0.0%	0.0%	0.1%	0.4%	**0.2%**
minCVaR	gsci	0.3%	0.0%	0.2%	0.2%	0.1%	0.1%	0.0%	0.1%	0.1%	**0.1%**	0.5%	0.3%	0.1%	0.4%	0.1%	0.1%	0.0%	0.1%	0.4%	**0.2%**
ERC	simple	20.0%	2.8%	3.8%	13.7%	24.2%	7.0%	4.7%	6.5%	5.8%	**9.8%**	20.5%	2.9%	4.4%	15.2%	23.4%	7.4%	6.7%	7.1%	6.0%	**10.4%**
ERC	eq_fi	0.0%	1.6%	2.8%	7.2%	2.3%	1.8%	2.9%	4.3%	4.3%	**3.0%**	0.0%	1.6%	3.3%	5.9%	2.5%	3.1%	3.5%	4.7%	4.6%	**3.2%**
ERC	epra	0.3%	2.1%	1.1%	4.3%	2.1%	2.3%	2.5%	3.9%	4.1%	**2.5%**	0.0%	2.1%	1.7%	0.7%	2.3%	2.6%	3.1%	4.3%	4.4%	**2.4%**
ERC	all	0.3%	2.0%	1.6%	3.8%	2.4%	3.3%	2.6%	3.4%	3.7%	**2.6%**	2.2%	2.1%	2.2%	0.6%	2.0%	3.7%	3.0%	3.8%	3.9%	**2.6%**
ERC	gsci	0.0%	3.6%	2.6%	5.2%	2.0%	3.2%	3.0%	3.7%	3.8%	**3.0%**	3.7%	1.5%	3.6%	4.9%	2.2%	4.5%	3.6%	4.1%	4.1%	**3.6%**
maxDiv	simple	3.6%	2.5%	1.3%	1.8%	2.2%	1.9%	3.4%	6.2%	6.0%	**3.2%**	3.4%	2.7%	1.4%	2.0%	2.2%	2.1%	3.9%	6.7%	6.3%	**3.4%**
maxDiv	eq_fi	3.6%	2.6%	1.3%	1.6%	2.3%	1.9%	3.0%	5.0%	5.5%	**3.0%**	3.5%	2.9%	1.6%	2.0%	2.4%	2.2%	3.7%	5.5%	5.9%	**3.3%**
maxDiv	epra	3.6%	2.6%	1.3%	1.7%	2.3%	1.9%	3.1%	5.1%	5.5%	**3.0%**	3.5%	2.9%	1.6%	2.1%	2.4%	2.1%	3.8%	5.6%	5.9%	**3.3%**
maxDiv	all	3.1%	2.3%	1.3%	1.7%	2.1%	1.6%	2.6%	4.1%	4.9%	**2.6%**	3.1%	2.6%	1.6%	2.0%	2.1%	1.8%	3.2%	4.5%	5.2%	**2.9%**
maxDiv	gsci	3.1%	2.3%	1.2%	1.6%	2.1%	1.7%	2.6%	4.0%	4.8%	**2.6%**	3.1%	2.6%	1.5%	1.9%	2.1%	1.9%	3.1%	4.4%	5.1%	**2.9%**
maxR	simple	100.0%	100.0%	83.3%	41.7%	100.0%	100.0%	16.7%	41.7%	100.0%	**75.9%**	100.0%	100.0%	83.3%	66.7%	100.0%	100.0%	8.3%	75.0%	100.0%	**81.5%**
maxR	eq_fi	100.0%	100.0%	83.3%	41.7%	91.7%	100.0%	16.7%	41.7%	100.0%	**75.0%**	100.0%	100.0%	83.3%	66.7%	91.7%	100.0%	8.3%	75.0%	100.0%	**80.6%**
maxR	epra	100.0%	100.0%	83.3%	41.7%	91.7%	100.0%	16.7%	41.7%	100.0%	**75.0%**	100.0%	100.0%	83.3%	66.7%	91.7%	100.0%	8.3%	75.0%	100.0%	**80.6%**
maxR	all	100.0%	100.0%	83.3%	41.7%	91.7%	100.0%	8.3%	41.7%	100.0%	**74.1%**	100.0%	100.0%	83.3%	66.7%	91.7%	100.0%	0.0%	75.0%	100.0%	**79.6%**
maxR	gsci	100.0%	100.0%	83.3%	41.7%	91.7%	100.0%	8.3%	41.7%	100.0%	**74.1%**	100.0%	100.0%	83.3%	66.7%	91.7%	100.0%	0.0%	75.0%	100.0%	**79.6%**
maxSR	simple	7.9%	16.9%	31.2%	0.3%	3.3%	19.8%	75.4%	35.3%	14.0%	**22.7%**	5.5%	12.8%	30.1%	0.9%	3.8%	21.1%	75.0%	47.2%	19.3%	**24.0%**
maxSR	eq_fi	7.9%	11.2%	30.0%	25.2%	3.5%	10.4%	75.4%	34.9%	13.7%	**23.6%**	5.5%	8.3%	29.1%	25.8%	3.9%	10.9%	66.7%	46.5%	18.6%	**23.9%**
maxSR	epra	8.0%	11.2%	30.1%	25.2%	3.5%	9.6%	75.4%	34.9%	13.7%	**23.5%**	5.6%	8.3%	29.3%	17.5%	3.9%	10.2%	66.6%	38.3%	18.6%	**22.0%**
maxSR	all	7.9%	11.1%	21.5%	33.5%	3.5%	8.3%	33.5%	34.9%	12.8%	**18.6%**	5.6%	8.2%	22.2%	25.9%	3.9%	9.1%	33.3%	38.3%	17.4%	**18.2%**
maxSR	gsci	7.8%	11.1%	21.4%	33.5%	3.5%	8.7%	33.6%	34.9%	12.7%	**18.6%**	5.5%	8.2%	22.1%	34.2%	3.9%	9.3%	33.3%	46.5%	17.4%	**20.0%**
maxSTARR	simple	7.2%	13.7%	13.8%	0.4%	4.4%	24.0%	0.2%	9.3%	16.4%	**9.9%**	5.0%	10.6%	17.8%	1.2%	5.3%	27.4%	8.3%	21.7%	21.0%	**13.1%**
maxSTARR	eq_fi	8.2%	12.2%	13.7%	0.3%	4.5%	10.9%	0.2%	8.9%	16.4%	**8.4%**	5.2%	7.7%	15.9%	1.3%	5.1%	12.1%	8.3%	21.1%	21.2%	**10.9%**
maxSTARR	epra	8.2%	12.2%	14.0%	0.4%	4.3%	7.5%	0.3%	9.0%	16.4%	**8.0%**	5.3%	7.7%	16.2%	1.2%	5.4%	10.0%	8.3%	21.1%	21.2%	**10.7%**
maxSTARR	all	8.2%	12.0%	3.8%	0.3%	4.3%	7.5%	0.0%	9.0%	14.6%	**6.6%**	5.2%	7.7%	5.7%	1.3%	4.8%	9.6%	0.0%	21.1%	19.6%	**8.3%**
maxSTARR	gsci	8.2%	12.0%	3.9%	0.3%	4.3%	8.7%	0.3%	8.9%	14.6%	**6.8%**	5.1%	7.7%	6.1%	1.1%	4.8%	10.2%	0.0%	21.1%	19.6%	**8.4%**
mv	simple	62.8%	80.0%	22.4%	3.2%	16.3%	41.2%	0.6%	8.6%	35.6%	**30.1%**	45.8%	63.0%	22.2%	14.7%	20.5%	44.1%	0.3%	21.1%	49.2%	**31.2%**
mv	eq_fi	61.5%	78.5%	22.0%	2.9%	15.7%	40.2%	0.6%	8.6%	35.6%	**29.5%**	45.3%	61.4%	21.9%	14.2%	20.2%	43.1%	0.3%	21.2%	49.2%	**30.7%**
mv	epra	61.3%	78.5%	22.0%	2.9%	15.7%	40.5%	0.8%	8.6%	35.6%	**29.5%**	45.0%	61.4%	21.9%	14.3%	20.2%	43.3%	0.3%	21.2%	49.2%	**30.8%**
mv	all	61.2%	78.5%	21.8%	2.9%	15.7%	39.1%	0.5%	8.6%	35.7%	**29.3%**	45.0%	61.4%	21.7%	14.3%	20.2%	41.5%	0.0%	21.2%	49.2%	**30.5%**
mv	gsci	61.5%	78.5%	21.8%	2.9%	15.7%	39.3%	0.5%	8.6%	35.7%	**29.4%**	45.2%	61.4%	21.7%	14.2%	20.2%	41.7%	0.0%	21.2%	49.2%	**30.5%**
bs-mv	simple	30.3%	61.7%	12.7%	0.8%	3.2%	25.1%	0.0%	2.3%	16.1%	**16.9%**	16.5%	45.4%	11.3%	3.7%	5.8%	26.9%	0.0%	8.7%	26.1%	**16.0%**
bs-mv	eq_fi	29.3%	59.5%	12.4%	1.6%	4.3%	23.9%	0.1%	2.1%	15.2%	**16.5%**	17.2%	44.6%	11.2%	6.1%	6.9%	25.6%	0.0%	7.9%	24.5%	**16.0%**
bs-mv	epra	29.5%	58.5%	12.0%	1.5%	6.3%	24.3%	0.2%	2.7%	15.7%	**16.7%**	17.7%	43.7%	10.8%	6.0%	8.8%	25.9%	0.0%	9.0%	24.9%	**16.3%**
bs-mv	all	30.0%	57.0%	12.2%	1.5%	7.0%	24.0%	0.1%	2.6%	15.2%	**16.6%**	18.3%	42.6%	11.4%	6.1%	9.7%	25.7%	0.0%	8.7%	23.9%	**16.3%**
bs-mv	gsci	30.6%	57.8%	12.6%	1.5%	5.7%	24.2%	0.2%	2.0%	14.7%	**16.6%**	18.5%	43.3%	11.7%	6.3%	8.5%	26.0%	0.1%	7.5%	23.5%	**16.2%**
crra	simple	96.7%	98.5%	33.6%	1.5%	22.9%	78.5%	0.2%	17.4%	80.4%	**47.7%**	91.4%	98.4%	38.9%	26.9%	33.4%	86.4%	0.2%	34.2%	96.1%	**56.2%**
crra	eq_fi	95.7%	96.0%	32.5%	1.3%	20.4%	77.0%	0.1%	16.5%	79.6%	**46.6%**	90.7%	96.5%	37.7%	26.1%	33.2%	84.3%	0.1%	33.8%	93.1%	**55.1%**
crra	epra	92.0%	95.5%	31.3%	1.1%	21.3%	75.0%	0.1%	16.6%	79.0%	**45.8%**	87.0%	95.2%	36.7%	25.2%	31.3%	81.9%	0.0%	32.9%	93.5%	**53.7%**
crra	all	93.7%	96.0%	32.3%	1.3%	21.5%	60.3%	0.3%	16.2%	78.5%	**44.5%**	87.4%	93.9%	36.2%	27.3%	31.8%	79.1%	0.9%	34.7%	92.2%	**53.7%**
crra	gsci	92.6%	96.0%	30.2%	1.4%	19.7%	63.3%	0.3%	17.5%	77.6%	**44.3%**	87.6%	96.3%	36.3%	24.4%	32.9%	78.6%	0.5%	33.3%	93.3%	**53.7%**

Note: Weights are calculated based on retrieved weights for rebalancing points. Weight drifts between rebalancing dates are not considered.

Table 10: Portfolio Weights: Average Crypto Allocation per Year, Strategy and Asset Space

Note: This table is based on portfolios under a long-only constraint, using the described rolling window approach and a monthly rebalancing frequency. Weight drifts between rebalancing periods are not considered.

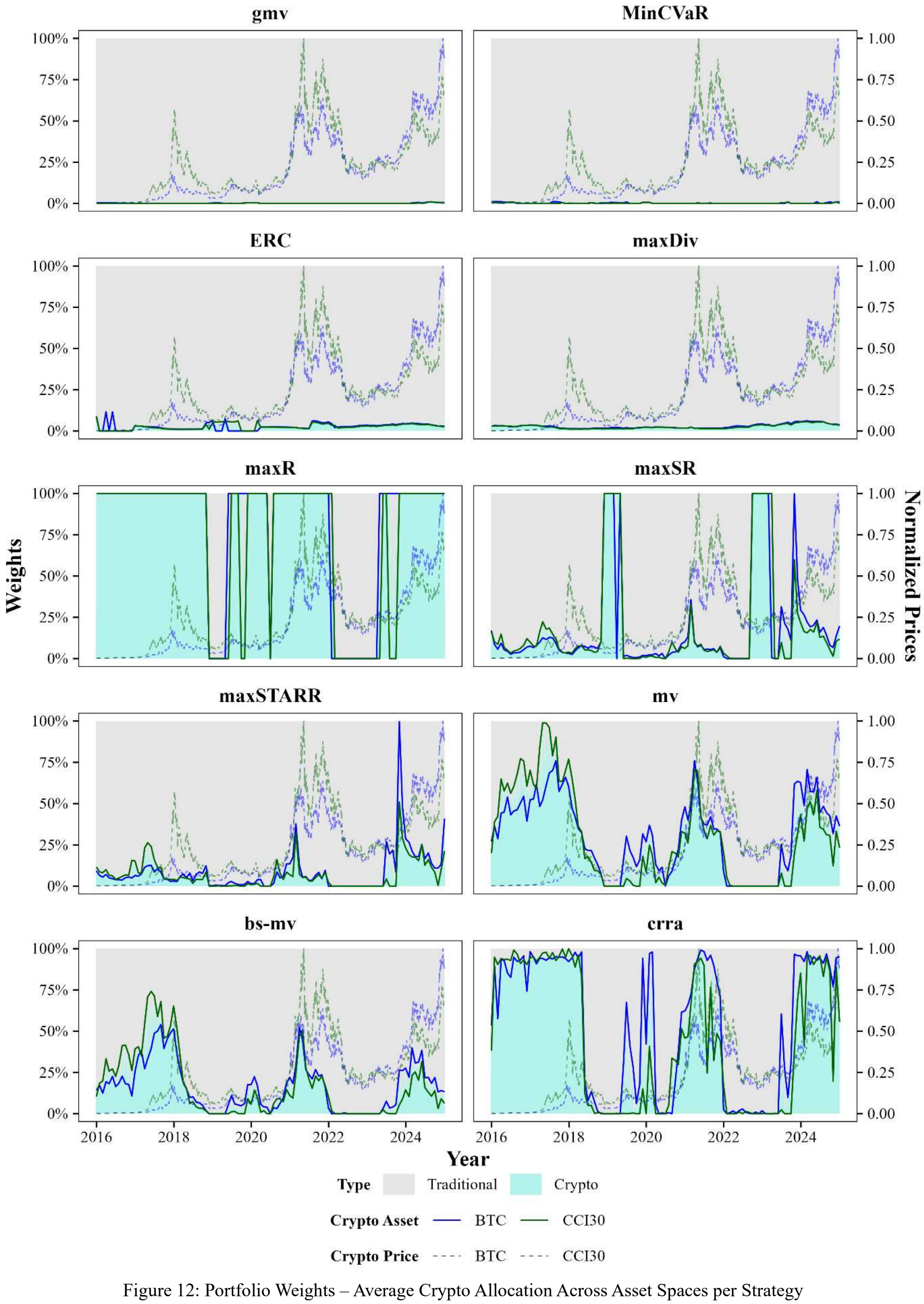

Figure 12: Portfolio Weights – Average Crypto Allocation Across Asset Spaces per Strategy
Including Normalized Crypto Prices

Note: This plot is based on portfolios under a long-only constraint, using the described rolling window approach and a monthly rebalancing frequency. Weight drifts between rebalancing periods are not considered.

A.13 Portfolio Comparisons Traditional vs. CCI30

Portfolio Comparison: Traditional vs. CCI30 Across Strategies

Descriptive Statistics (2016-2024) for Monthly Rebalancing

		Annual Mean		Annual StdDev		Skewness		Excess Kurt.	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	0.062	0.356 ***	0.076	0.274 ***	-0.946	-0.532	14.156	7.092
ew	eq_fi	0.056	0.238 ***	0.073	0.178 ***	-1.106	-0.684	12.510	8.476
ew	gsci	0.060	0.213 ***	0.083	0.159 ***	-1.301	-0.839	11.617	8.904
ew	epra	0.054	0.207 ***	0.085	0.162 ***	-1.384	-0.904	18.192	10.248
ew	all	0.058	0.190 ***	0.089	0.148 ***	-1.625	-1.077	17.304	10.924
ew_bh	simple	0.072	0.700 **	0.089	0.695 ***	-0.840	-0.605	11.719	6.112
ew_bh	eq_fi	0.060	0.624 **	0.081	0.661 ***	-1.007	-0.653	10.548	6.239
ew_bh	gsci	0.061	0.597 **	0.087	0.649 ***	-1.142	-0.671	9.872	6.316
ew_bh	epra	0.057	0.596 **	0.090	0.649 ***	-1.314	-0.672	16.440	6.308
ew_bh	all	0.058	0.573 **	0.092	0.638 ***	-1.478	-0.688	15.793	6.380
gmv	simple	0.013	0.013	0.038	0.038 *	-0.386	-0.425	7.051	7.422
gmv	eq_fi	0.012	0.013	0.037	0.037	-0.538	-0.588	6.892	7.391
gmv	gsci	0.013	0.013	0.036	0.036	-0.575	-0.622	7.375	7.847
gmv	epra	0.012	0.013	0.037	0.037	-0.543	-0.593	6.873	7.369
gmv	all	0.013	0.013	0.036	0.036	-0.579	-0.626	7.362	7.831
minCVaR	simple	0.012	0.013	0.038	0.038	-0.367	-0.443	6.714	7.487
minCVaR	eq_fi	0.010	0.011	0.038	0.038	-0.240	-0.236	6.603	6.373
minCVaR	gsci	0.010	0.011	0.037	0.037 **	-0.349	-0.354	6.662	6.560
minCVaR	epra	0.010	0.011	0.038	0.038	-0.268	-0.260	6.651	6.431
minCVaR	all	0.010	0.011	0.037	0.037 *	-0.367	-0.371	6.666	6.576
ERC	simple	0.021	0.166 ***	0.043	0.153 ***	-0.687	-1.753	10.667	33.412
ERC	eq_fi	0.032	0.057	0.048	0.100 ***	-1.202	-2.253	18.180	43.793
ERC	gsci	0.024	0.061	0.092	0.107 ***	-3.173	-2.071	53.917	29.562
ERC	epra	0.029	0.048	0.053	0.097 ***	-1.367	-3.615	18.168	79.378
ERC	all	0.026	0.051	0.083	0.102 ***	-5.598	-4.062	121.406	68.181
maxDiv	simple	0.027	0.055 ***	0.043	0.050 ***	-0.699	-0.755	10.846	10.980
maxDiv	eq_fi	0.028	0.056 ***	0.046	0.051 ***	-1.140	-1.059	16.864	11.468
maxDiv	gsci	0.026	0.052 ***	0.045	0.049 ***	-0.945	-1.027	11.855	10.214
maxDiv	epra	0.028	0.056 ***	0.046	0.052 ***	-1.123	-1.046	18.017	11.712
maxDiv	all	0.026	0.052 ***	0.045	0.049 ***	-0.953	-1.029	12.514	10.341
maxR	simple	0.068	0.769 ***	0.112	0.676 ***	-0.703	-0.553	4.371	8.125
maxR	eq_fi	0.054	0.746 ***	0.120	0.674 ***	-0.614	-0.556	2.842	8.213
maxR	gsci	0.104	0.766 **	0.158	0.678 ***	-0.856	-0.559	8.176	7.992
maxR	epra	0.046	0.742 ***	0.119	0.674 ***	-0.660	-0.555	2.659	8.219
maxR	all	0.100	0.766 **	0.160	0.678 ***	-0.853	-0.559	7.803	7.988
maxSR	simple	0.070	0.113	0.104	0.317 ***	-0.136	-1.372	5.770	27.811
maxSR	eq_fi	0.048	0.092	0.099	0.318 ***	-0.221	-1.081	6.822	29.096
maxSR	gsci	0.049	0.250 **	0.132	0.266 ***	-0.679	1.106	10.747	26.537
maxSR	epra	0.044	0.099	0.098	0.317 ***	-0.246	-1.093	7.025	29.514
maxSR	all	0.040	0.241 **	0.126	0.263 ***	-0.760	1.153	9.515	27.611
maxSTARR	simple	0.041	0.145	0.095	0.183 ***	-0.586	-1.586	5.673	33.536
maxSTARR	eq_fi	0.019	0.093	0.088	0.157 ***	-0.760	-2.208	7.653	47.560
maxSTARR	gsci	0.042	0.156 **	0.116	0.147 ***	-1.037	-0.097	11.871	10.972
maxSTARR	epra	0.032	0.097	0.083	0.154 ***	-0.829	-2.326	9.520	51.006
maxSTARR	all	0.029	0.146 **	0.111	0.142 ***	-1.161	-0.066	12.020	11.579
mv	simple	0.057	0.493 **	0.087	0.385 ***	-0.683	-0.238	5.338	21.279
mv	eq_fi	0.059	0.480 **	0.094	0.379 ***	-0.596	-0.194	3.644	20.744
mv	gsci	0.096	0.522 **	0.138	0.388 ***	-1.013	-0.196	13.542	18.353
mv	epra	0.054	0.478 **	0.095	0.379 ***	-0.687	-0.192	3.900	20.765
mv	all	0.082	0.509 **	0.139	0.388 ***	-1.012	-0.189	13.159	18.319
bs-mv	simple	0.050	0.346 **	0.070	0.291 ***	-0.709	-0.213	6.096	29.378
bs-mv	eq_fi	0.043	0.326 **	0.077	0.281 ***	-0.772	-0.202	5.347	28.147
bs-mv	gsci	0.063	0.346 **	0.102	0.282 ***	-1.297	-0.220	15.895	25.480
bs-mv	epra	0.049	0.332 **	0.078	0.278 ***	-0.685	-0.150	5.085	27.606
bs-mv	all	0.061	0.342 **	0.100	0.278 ***	-1.363	-0.172	14.847	25.492
crra	simple	0.058	0.658 ***	0.095	0.530 ***	-0.631	-0.378	4.625	12.568
crra	eq_fi	0.057	0.641 **	0.104	0.519 ***	-0.644	-0.390	3.374	12.620
crra	gsci	0.111	0.679 ***	0.145	0.509 ***	-0.897	-0.349	9.851	12.404
crra	epra	0.047	0.638 **	0.103	0.511 ***	-0.720	-0.414	3.400	12.905
crra	all	0.082	0.646 ***	0.147	0.508 ***	-0.948	-0.348	9.804	12.137

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 11: Portfolio Comparison: Traditional vs. CCI30 Across Strategies – Descriptive Statistics

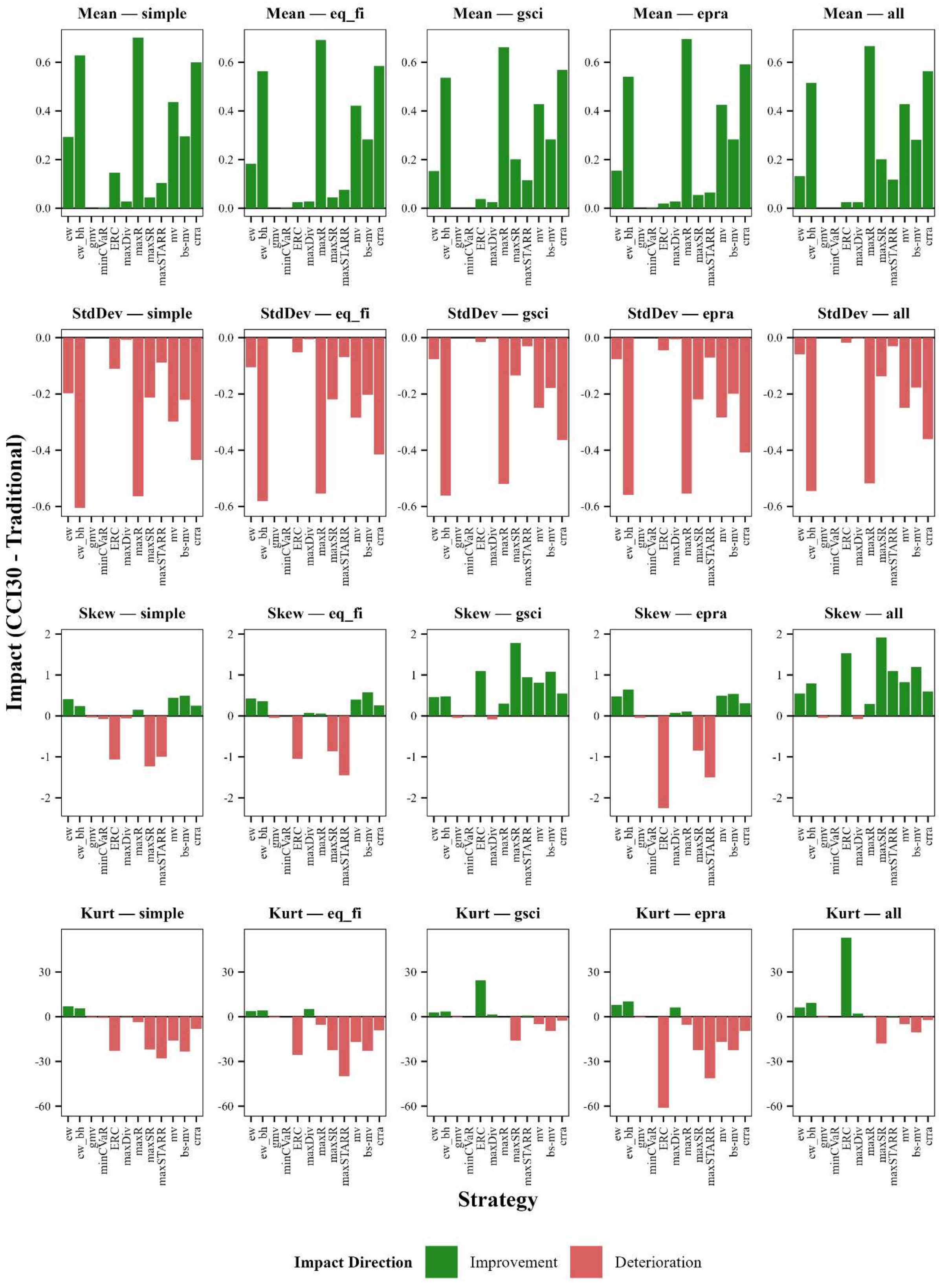

Figure 13: Performance Impact of Crypto Inclusion (CCI30) by Strategy and Asset Space – Descriptive Statistics

Note: Differences of Performance Measures that indicate a weaker performance when higher (e.g. Standard Deviation) are multiplied by -1 in the plots. The displayed differences are calculated based on the previous table.

Portfolio Comparison: Traditional vs. CCI30 Across Strategies

Tail Risk Measures (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	Max. Drawdown Trad.	Max. Drawdown CCI30	CVaR95 Trad.	CVaR95 CCI30	Downside Dev Trad.	Downside Dev CCI30
ew	simple	0.200	0.499 ***	0.012	0.041 ***	0.055	0.190 ***
ew	eq_fi	0.229	0.364 *	0.011	0.027 ***	0.053	0.125 ***
ew	gsci	0.235	0.323	0.013	0.024 ***	0.062	0.113 ***
ew	epra	0.244	0.352	0.013	0.024 ***	0.063	0.115 ***
ew	all	0.265	0.311	0.013	0.022 ***	0.067	0.106 ***
ew_bh	simple	0.218	0.898 ***	0.014	0.107 ***	0.064	0.492 ***
ew_bh	eq_fi	0.240	0.887 ***	0.012	0.103 ***	0.059	0.471 ***
ew_bh	gsci	0.240	0.881 ***	0.013	0.102 ***	0.065	0.463 ***
ew_bh	epra	0.253	0.881 ***	0.014	0.101 ***	0.066	0.463 ***
ew_bh	all	0.270	0.876 ***	0.014	0.100 ***	0.069	0.456 ***
gmv	simple	0.169	0.169	0.006	0.006	0.027	0.027
gmv	eq_fi	0.177	0.177	0.005	0.005	0.027	0.027
gmv	gsci	0.159	0.159	0.005	0.005	0.026	0.026
gmv	epra	0.178	0.178	0.005	0.005	0.027	0.027
gmv	all	0.160	0.160	0.005	0.005	0.026	0.026
minCVaR	simple	0.170	0.172	0.005	0.006	0.027	0.027
minCVaR	eq_fi	0.185	0.185	0.005	0.005	0.027	0.027
minCVaR	gsci	0.167	0.171	0.005	0.005	0.026	0.027
minCVaR	epra	0.185	0.185	0.005	0.006	0.027	0.027
minCVaR	all	0.170	0.173	0.005	0.005	0.027	0.027
ERC	simple	0.172	0.362	0.007	0.023 ***	0.031	0.111 ***
ERC	eq_fi	0.196	0.335	0.007	0.015 ***	0.035	0.076 ***
ERC	gsci	0.350	0.350	0.014	0.017 ***	0.072	0.082 ***
ERC	epra	0.206	0.368	0.008	0.014 **	0.039	0.076 ***
ERC	all	0.319	0.371	0.011	0.015 ***	0.067	0.081 ***
maxDiv	simple	0.172	0.186	0.007	0.007 ***	0.031	0.035 ***
maxDiv	eq_fi	0.197	0.211	0.007	0.007 ***	0.033	0.036 ***
maxDiv	gsci	0.157	0.171	0.007	0.007 ***	0.033	0.035 ***
maxDiv	epra	0.200	0.216	0.007	0.008 ***	0.034	0.037 ***
maxDiv	all	0.161	0.176	0.007	0.007 ***	0.033	0.036 ***
maxR	simple	0.290	0.955 ***	0.018	0.105 ***	0.082	0.470 ***
maxR	eq_fi	0.292	0.953 ***	0.020	0.105 ***	0.089	0.470 ***
maxR	gsci	0.324	0.953 ***	0.026	0.105 ***	0.117	0.473 ***
maxR	epra	0.305	0.953 ***	0.019	0.105 ***	0.089	0.470 ***
maxR	all	0.321	0.953 ***	0.026	0.105 ***	0.119	0.473 ***
maxSR	simple	0.258	0.745 ***	0.016	0.051 ***	0.073	0.237 ***
maxSR	eq_fi	0.300	0.706 ***	0.016	0.051 ***	0.071	0.235 ***
maxSR	gsci	0.239	0.431 *	0.022	0.039 ***	0.097	0.171 ***
maxSR	epra	0.303	0.687 ***	0.016	0.051 ***	0.070	0.234 ***
maxSR	all	0.258	0.434	0.022	0.038 ***	0.093	0.169 ***
maxSTARR	simple	0.290	0.505	0.016	0.027 **	0.069	0.134 ***
maxSTARR	eq_fi	0.346	0.531	0.015	0.023 **	0.066	0.118 **
maxSTARR	gsci	0.285	0.279	0.020	0.023 ***	0.087	0.102 ***
maxSTARR	epra	0.260	0.524	0.014	0.023 **	0.061	0.116 **
maxSTARR	all	0.254	0.283	0.019	0.023 ***	0.084	0.099 ***
mv	simple	0.221	0.570 ***	0.014	0.056 ***	0.063	0.258 ***
mv	eq_fi	0.240	0.588 ***	0.015	0.055 ***	0.068	0.254 ***
mv	gsci	0.241	0.604 ***	0.023	0.057 ***	0.102	0.261 ***
mv	epra	0.237	0.600 ***	0.015	0.055 ***	0.070	0.254 ***
mv	all	0.262	0.616 ***	0.023	0.057 ***	0.103	0.261 ***
bs-mv	simple	0.201	0.462 **	0.011	0.041 ***	0.050	0.195 ***
bs-mv	eq_fi	0.215	0.466 **	0.012	0.040 ***	0.056	0.189 ***
bs-mv	gsci	0.186	0.484 **	0.017	0.041 ***	0.076	0.190 ***
bs-mv	epra	0.212	0.459 **	0.012	0.039 ***	0.056	0.186 ***
bs-mv	all	0.188	0.478 **	0.017	0.040 ***	0.075	0.187 ***
crra	simple	0.242	0.701 ***	0.015	0.083 ***	0.069	0.361 ***
crra	eq_fi	0.247	0.702 ***	0.017	0.081 ***	0.076	0.353 ***
crra	gsci	0.266	0.680 ***	0.024	0.078 ***	0.107	0.345 ***
crra	epra	0.280	0.692 ***	0.017	0.080 ***	0.077	0.348 ***
crra	all	0.312	0.705 ***	0.025	0.078 ***	0.110	0.345 ***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 12: Portfolio Comparison: Traditional vs. CCI30 Across Strategies – Drawdown and Tail Risk

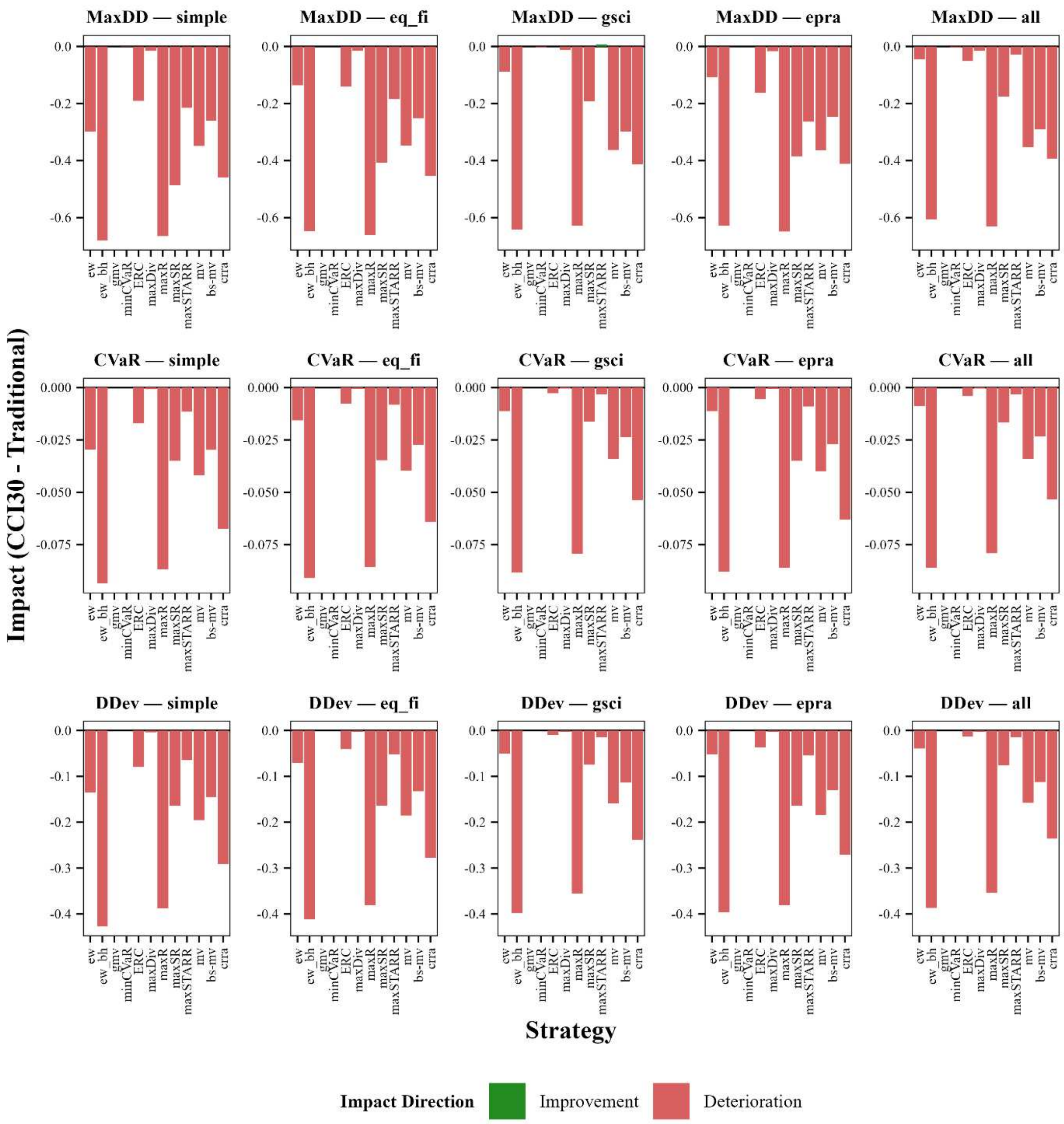

Figure 14: Performance Impact of Crypto Inclusion (CCI30) by Strategy and Asset Space – Drawdown and Tail Risk

Note: Differences of Performance Measures that indicate a weaker performance when higher (e.g. Maximum Drawdown) are multiplied by -1 in the plots. The displayed differences are calculated based on the previous table.

Portfolio Comparison: Traditional vs. CCI30 Across Strategies

Risk-Reward Measures (2016-2024) for Monthly Rebalancing

		Sharpe Ratio		Adj. SR		Sortino Ratio		STARR	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	0.582	0.715 *	0.413	0.562	0.777	1.767 *	0.015	0.032 *
ew	eq_fi	0.410	0.678 **	0.343	0.516	0.684	1.756 *	0.013	0.033 *
ew	gsci	0.490	0.696 **	0.382	0.504	0.666	1.721 **	0.013	0.032 **
ew	epra	0.374	0.664 **	0.302	0.473	0.554	1.641 **	0.011	0.031 **
ew	all	0.428	0.679 **	0.322	0.454	0.581	1.605 **	0.012	0.031 **
ew_bh	simple	0.649	0.658	0.457	0.542	0.825	1.385	0.016	0.025
ew_bh	eq_fi	0.435	0.635	0.367	0.525	0.701	1.284	0.014	0.023
ew_bh	gsci	0.485	0.625	0.394	0.517	0.645	1.247	0.013	0.023
ew_bh	epra	0.390	0.626	0.316	0.518	0.572	1.247	0.011	0.023
ew_bh	all	0.423	0.617	0.329	0.511	0.562	1.216	0.011	0.022
gmv	simple	-0.119	-0.114	-0.119	-0.114	-0.217	-0.207	-0.004	-0.004
gmv	eq_fi	-0.119	-0.115	-0.120	-0.116	-0.228	-0.219	-0.004	-0.004
gmv	gsci	-0.118	-0.111	-0.119	-0.112	-0.210	-0.197	-0.004	-0.004
gmv	epra	-0.118	-0.114	-0.119	-0.114	-0.226	-0.217	-0.004	-0.004
gmv	all	-0.117	-0.110	-0.118	-0.111	-0.210	-0.197	-0.004	-0.004
minCVaR	simple	-0.133	-0.111	-0.133	-0.112	-0.244	-0.207	-0.005	-0.004
minCVaR	eq_fi	-0.167	-0.148	-0.167	-0.148	-0.317	-0.285	-0.006	-0.006
minCVaR	gsci	-0.179	-0.160	-0.179	-0.160	-0.308	-0.278	-0.006	-0.005
minCVaR	epra	-0.165	-0.146	-0.165	-0.146	-0.320	-0.286	-0.006	-0.006
minCVaR	all	-0.183	-0.163	-0.183	-0.163	-0.320	-0.288	-0.006	-0.006
ERC	simple	0.049	0.644 ***	0.049	0.152	0.077	1.328 **	0.001	0.025 **
ERC	eq_fi	0.209	0.345	0.194	0.225	0.367	0.500	0.007	0.010
ERC	gsci	0.061	0.284 *	0.058	0.228	0.077	0.519	0.002	0.010
ERC	epra	0.168	0.268	0.158	0.161	0.273	0.380	0.005	0.008
ERC	all	0.111	0.297	0.092	0.163	0.115	0.400	0.003	0.009
maxDiv	simple	0.168	0.462 ***	0.163	0.390	0.278	1.004 ***	0.005	0.019 ***
maxDiv	eq_fi	0.149	0.423 ***	0.142	0.355	0.264	0.999 ***	0.005	0.019 ***
maxDiv	gsci	0.155	0.441 ***	0.149	0.371	0.234	0.928 ***	0.005	0.018 ***
maxDiv	epra	0.147	0.420 ***	0.141	0.353	0.261	0.991 ***	0.005	0.019 ***
maxDiv	all	0.141	0.431 ***	0.136	0.365	0.214	0.913 ***	0.004	0.018 ***
maxR	simple	0.349	0.606 *	0.327	0.497	0.599	1.595	0.011	0.028
maxR	eq_fi	0.248	0.597 *	0.240	0.491	0.396	1.546 *	0.007	0.027 *
maxR	gsci	0.521	0.620	0.434	0.505	0.727	1.579	0.013	0.028
maxR	epra	0.190	0.593 **	0.185	0.489	0.303	1.538 *	0.006	0.027 *
maxR	all	0.494	0.621	0.421	0.505	0.679	1.580	0.012	0.028
maxSR	simple	0.570	0.213	0.518	0.191	0.693	0.399	0.012	0.007
maxSR	eq_fi	0.311	0.213	0.299	0.193	0.406	0.314	0.007	0.006
maxSR	gsci	0.326	0.869 *	0.298	0.282	0.313	1.345 *	0.005	0.024 **
maxSR	epra	0.272	0.239	0.263	0.212	0.366	0.343	0.006	0.006
maxSR	all	0.230	0.819 *	0.219	0.316	0.228	1.306 **	0.004	0.023 **
maxSTARR	simple	0.204	0.360	0.198	0.261	0.328	0.946	0.006	0.018
maxSTARR	eq_fi	0.001	0.227	0.001	0.185	0.002	0.629	0.000	0.013
maxSTARR	gsci	0.221	0.531 ***	0.207	0.458	0.263	1.335 **	0.005	0.023 **
maxSTARR	epra	0.143	0.242	0.139	0.189	0.210	0.673	0.004	0.014
maxSTARR	all	0.109	0.485 ***	0.106	0.427	0.122	1.272 **	0.002	0.022 **
mv	simple	0.388	0.549 **	0.358	0.391	0.605	1.834	0.011	0.034
mv	eq_fi	0.363	0.539 *	0.342	0.395	0.586	1.815	0.010	0.033
mv	gsci	0.596	0.600 *	0.417	0.423	0.755	1.929	0.013	0.035
mv	epra	0.318	0.537 **	0.301	0.394	0.502	1.808	0.009	0.033
mv	all	0.517	0.582 **	0.397	0.421	0.611	1.878	0.011	0.034 *
bs-mv	simple	0.409	0.486 *	0.372	0.337	0.617	1.678	0.011	0.032
bs-mv	eq_fi	0.279	0.463 **	0.264	0.340	0.435	1.625	0.008	0.031
bs-mv	gsci	0.495	0.512 *	0.362	0.360	0.577	1.720	0.010	0.032
bs-mv	epra	0.340	0.481 *	0.318	0.347	0.533	1.679	0.010	0.032
bs-mv	all	0.504	0.514 *	0.368	0.363	0.567	1.726	0.010	0.032
crra	simple	0.368	0.616 *	0.344	0.470	0.564	1.771	0.010	0.031
crra	eq_fi	0.311	0.613 **	0.297	0.468	0.500	1.761	0.009	0.030
crra	gsci	0.617	0.667	0.464	0.488	0.855	1.910	0.015	0.034
crra	epra	0.231	0.622 **	0.223	0.466	0.369	1.779 *	0.007	0.031 *
crra	all	0.465	0.625 *	0.390	0.479	0.577	1.815 *	0.010	0.032 *

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on Ledoit & Wolf for SR and a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21 for other measures.

Table 13: Portfolio Comparison: Traditional vs. CCI30 Across Strategies – Risk-Adjusted Returns

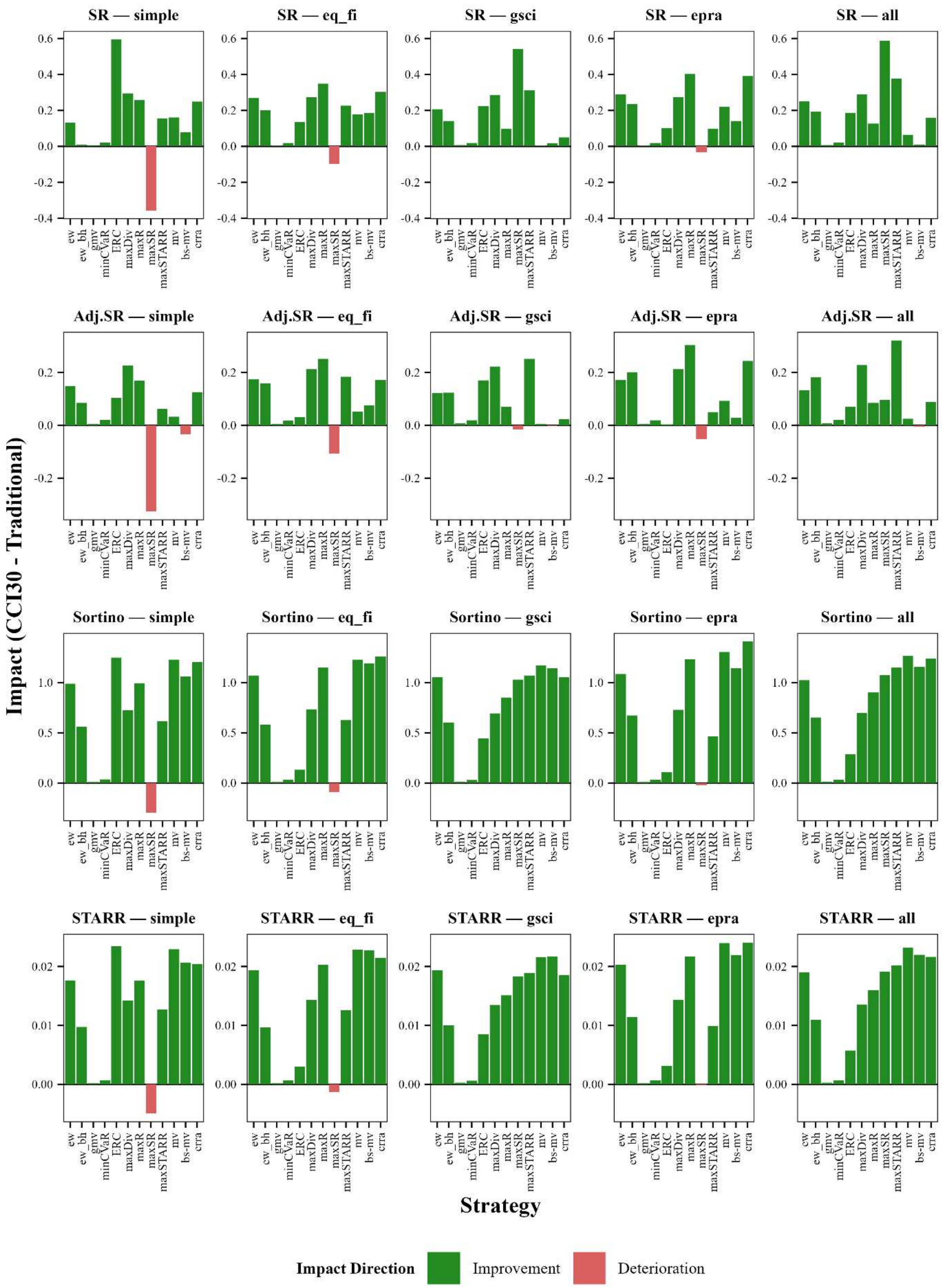

Figure 15: Performance Impact of Crypto Inclusion (CCI30) by Strategy and Asset Space – Risk-Adjusted Returns

Note: The displayed differences are calculated based on the previous table.

Portfolio Comparison: Traditional vs. CCI30 Across Strategies

Utility based Measures (2016-2024) for Monthly Rebalancing

		MV CEQ		CRRA CEQ	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30
ew	simple	0.055	0.275 *	0.055	0.273 *
ew	eq_fi	0.049	0.210 **	0.049	0.210 **
ew	gsci	0.051	0.192 **	0.051	0.191 **
ew	epra	0.044	0.183 **	0.044	0.182 **
ew	all	0.047	0.170 **	0.047	0.169 **
ew_bh	simple	0.062	-0.024	0.062	-0.068
ew_bh	eq_fi	0.052	-0.032	0.052	-0.071
ew_bh	gsci	0.050	-0.035	0.050	-0.072
ew_bh	epra	0.046	-0.035	0.046	-0.072
ew_bh	all	0.046	-0.036	0.046	-0.071
gmv	simple	0.010	0.011	0.010	0.011
gmv	eq_fi	0.010	0.011	0.010	0.011
gmv	gsci	0.011	0.011	0.011	0.011
gmv	epra	0.010	0.011	0.010	0.011
gmv	all	0.011	0.011	0.011	0.011
minCVaR	simple	0.010	0.011	0.010	0.011
minCVaR	eq_fi	0.008	0.009	0.008	0.009
minCVaR	gsci	0.008	0.009	0.008	0.009
minCVaR	epra	0.008	0.009	0.008	0.009
minCVaR	all	0.008	0.009	0.008	0.009
ERC	simple	0.018	0.140 **	0.018	0.139 **
ERC	eq_fi	0.029	0.043	0.029	0.042
ERC	gsci	0.012	0.045	0.011	0.044
ERC	epra	0.026	0.034	0.026	0.033
ERC	all	0.016	0.036	0.016	0.035
maxDiv	simple	0.025	0.052 ***	0.025	0.052 ***
maxDiv	eq_fi	0.025	0.053 ***	0.025	0.053 ***
maxDiv	gsci	0.024	0.049 ***	0.024	0.049 ***
maxDiv	epra	0.025	0.053 ***	0.025	0.053 ***
maxDiv	all	0.023	0.049 ***	0.023	0.049 ***
maxR	simple	0.051	0.087	0.050	0.038
maxR	eq_fi	0.033	0.065	0.033	0.018
maxR	gsci	0.069	0.079	0.068	0.030
maxR	epra	0.025	0.062	0.025	0.014
maxR	all	0.063	0.079	0.063	0.031
maxSR	simple	0.055	-0.037	0.055	-0.045
maxSR	eq_fi	0.033	-0.058	0.033	-0.065
maxSR	gsci	0.023	0.154	0.023	0.156
maxSR	epra	0.031	-0.051	0.031	-0.058
maxSR	all	0.016	0.147	0.016	0.148 *
maxSTARR	simple	0.028	0.100	0.028	0.098
maxSTARR	eq_fi	0.007	0.058	0.007	0.056
maxSTARR	gsci	0.022	0.131 **	0.021	0.131 **
maxSTARR	epra	0.021	0.063	0.021	0.062
maxSTARR	all	0.010	0.122 **	0.010	0.122 **
mv	simple	0.047	0.311	0.047	0.302
mv	eq_fi	0.047	0.303	0.047	0.296
mv	gsci	0.070	0.346	0.069	0.338
mv	epra	0.041	0.301	0.041	0.293
mv	all	0.054	0.328	0.054	0.321
bs-mv	simple	0.044	0.245	0.044	0.242
bs-mv	eq_fi	0.035	0.231	0.035	0.228
bs-mv	gsci	0.048	0.255	0.048	0.252
bs-mv	epra	0.041	0.241	0.041	0.239
bs-mv	all	0.048	0.254	0.047	0.252
crra	simple	0.045	0.267	0.045	0.243
crra	eq_fi	0.042	0.268	0.042	0.246
crra	gsci	0.082	0.336	0.082	0.316
crra	epra	0.032	0.280	0.031	0.258
crra	all	0.051	0.296	0.051	0.277

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 14: Portfolio Comparison: Traditional vs. CCI30 Across Strategies – Utility

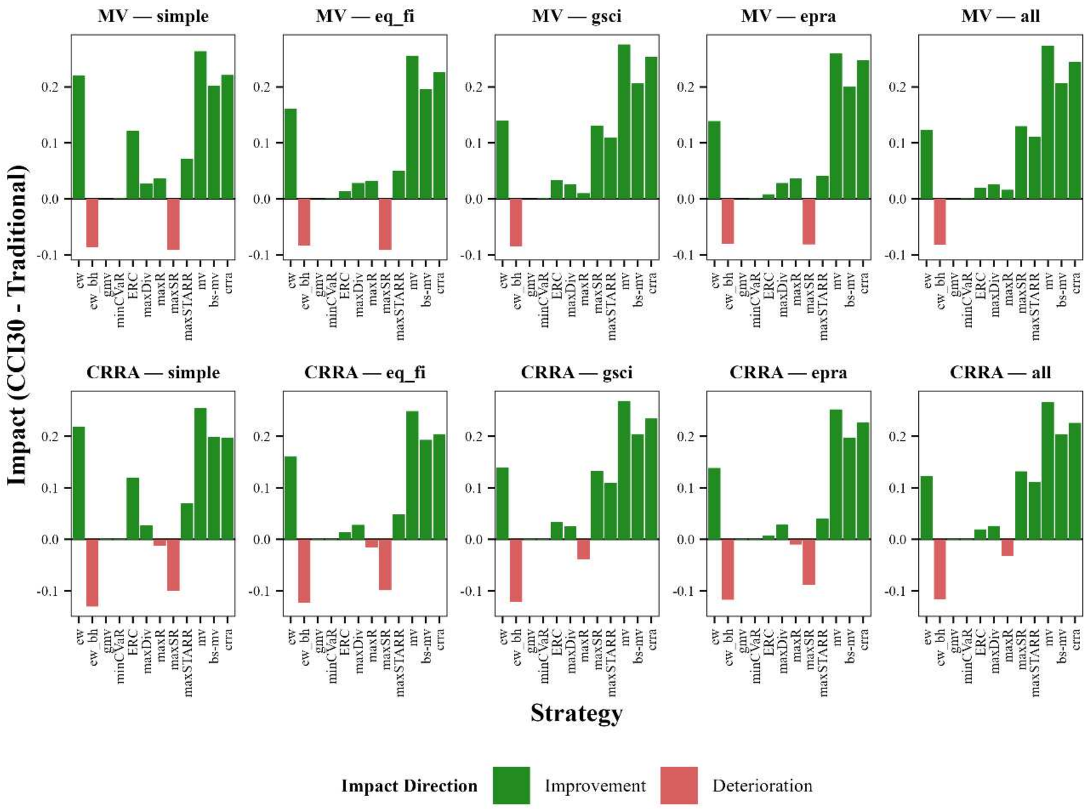

Figure 16: Performance Impact of Crypto Inclusion (CCI30) by Strategy and Asset Space – Utility

Note: The displayed differences are calculated based on the previous table.

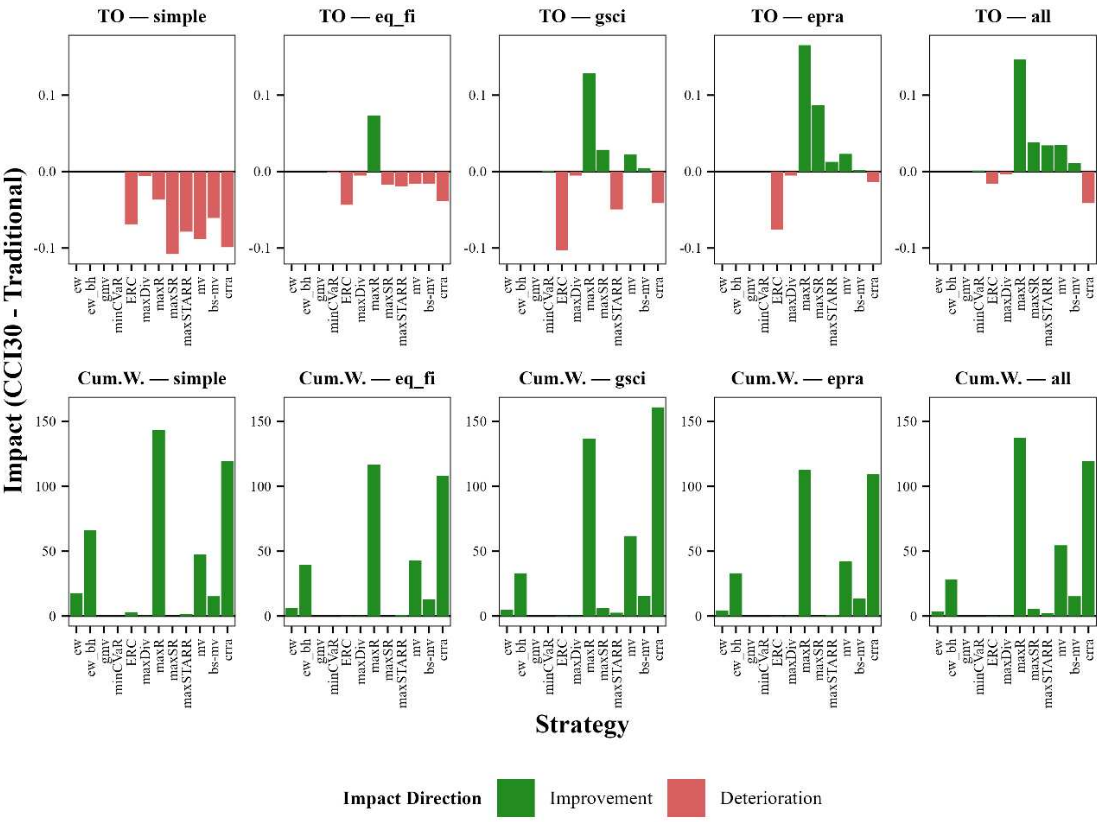

Figure 17: Performance Impact of Crypto Inclusion (CCI30) by Strategy and Asset Space – Other Metrics

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. Turnover) are multiplied by -1 in the plots. The displayed differences are calculated based on the following table.

Portfolio Comparison: Traditional vs. CCI30 Across Strategies
Other Metrics (2016-2024) for Monthly Rebalancing

		Turnover		Cum. Wealth		IR
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	
ew	simple	-	-	0.733	18.302	1.249
ew	eq_fi	-	-	0.636	6.941	1.266
ew	gsci	-	-	0.695	5.479	1.270
ew	epra	-	-	0.592	5.098	1.266
ew	all	-	-	0.648	4.289	1.269
ew_bh	simple	-	-	0.888	66.808	0.745
ew_bh	eq_fi	-	-	0.701	40.291	0.670
ew_bh	gsci	-	-	0.697	33.690	0.639
ew_bh	epra	-	-	0.634	33.637	0.649
ew_bh	all	-	-	0.643	28.929	0.622
gmv	simple	0.022	0.022	0.116	0.119	0.294
gmv	eq_fi	0.030	0.030	0.115	0.117	0.240
gmv	gsci	0.034	0.034	0.121	0.124	0.289
gmv	epra	0.032	0.032	0.115	0.117	0.240
gmv	all	0.035	0.035	0.121	0.124	0.289
minCVaR	simple	0.033	0.033	0.109	0.119	0.357
minCVaR	eq_fi	0.086	0.088	0.088	0.097	0.350
minCVaR	gsci	0.067	0.066	0.093	0.101	0.332
minCVaR	epra	0.088	0.089	0.087	0.097	0.383
minCVaR	all	0.069	0.068	0.089	0.098	0.364
ERC	simple	0.053	0.122	0.206	3.206	1.068
ERC	eq_fi	0.030	0.073	0.330	0.619	0.288
ERC	gsci	0.071	0.174	0.204	0.674	0.662
ERC	epra	0.033	0.109	0.299	0.489	0.226
ERC	all	0.109	0.125	0.237	0.532	0.474
maxDiv	simple	0.017	0.023	0.280	0.645	1.238
maxDiv	eq_fi	0.067	0.072	0.281	0.659	1.325
maxDiv	gsci	0.071	0.077	0.267	0.602	1.360
maxDiv	epra	0.078	0.084	0.280	0.661	1.326
maxDiv	all	0.082	0.086	0.260	0.599	1.374
maxR	simple	0.294	0.330	0.778	144.327	0.974
maxR	eq_fi	0.404	0.330	0.546	117.314	0.939
maxR	gsci	0.367	0.239	1.349	138.219	0.904
maxR	epra	0.532	0.367	0.431	113.302	0.939
maxR	all	0.404	0.257	1.243	138.845	0.912
maxSR	simple	0.131	0.239	0.819	0.778	-0.009
maxSR	eq_fi	0.375	0.392	0.490	0.459	-0.008
maxSR	gsci	0.443	0.414	0.456	6.380	0.815
maxSR	epra	0.492	0.405	0.447	0.558	0.028
maxSR	all	0.466	0.428	0.348	5.836	0.798
maxSTARR	simple	0.260	0.339	0.412	2.307	0.640
maxSTARR	eq_fi	0.451	0.470	0.148	1.116	0.517
maxSTARR	gsci	0.378	0.428	0.384	2.859	1.344
maxSTARR	epra	0.432	0.419	0.300	1.205	0.464
maxSTARR	all	0.489	0.455	0.236	2.529	1.375
mv	simple	0.180	0.269	0.645	48.097	1.258
mv	eq_fi	0.364	0.380	0.663	43.568	1.229
mv	gsci	0.392	0.370	1.238	62.978	1.306
mv	epra	0.459	0.436	0.583	42.809	1.236
mv	all	0.456	0.421	0.960	55.648	1.292
bs-mv	simple	0.191	0.252	0.557	15.911	1.107
bs-mv	eq_fi	0.352	0.368	0.456	13.410	1.089
bs-mv	gsci	0.425	0.421	0.711	16.310	1.145
bs-mv	epra	0.419	0.417	0.535	14.306	1.113
bs-mv	all	0.466	0.455	0.692	15.909	1.150
crra	simple	0.228	0.327	0.643	120.111	1.202
crra	eq_fi	0.390	0.429	0.617	108.678	1.193
crra	gsci	0.380	0.421	1.538	162.460	1.273
crra	epra	0.500	0.514	0.475	109.731	1.235
crra	all	0.458	0.499	0.941	120.118	1.231

Note: Turnover is reported on a monthly basis without consideration of the weight drift between rebalancing periods.
IR is calculated using the non-crypto portfolio as the benchmark.

Table 15: Portfolio Comparison: Traditional vs. CCI30 Across Strategies – Other Metrics

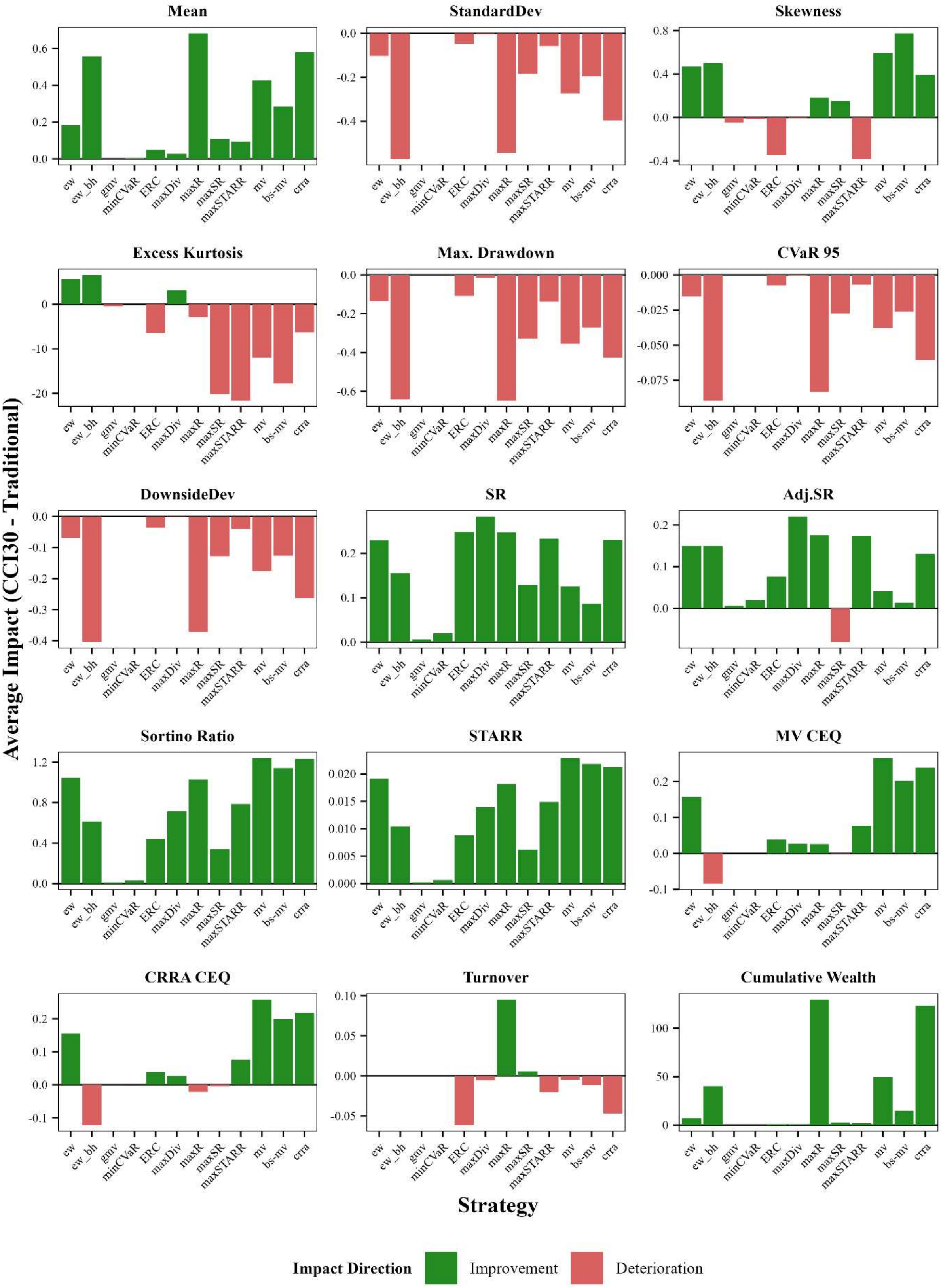

Figure 18: Average Impact of Adding CCI30 on Performance Measures Across Asset Spaces

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. Standard Deviations) are multiplied by -1 in the plots. The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

A.14 Panel Regression Analysis – Base Model

Regression Analysis: Base Model
Trad. and CCI30 Portfolios

Variable	SR Coeff.	Sortino Coeff.	STARR Coeff.	MV_CEQ Coeff.	CRRA CEQ Coeff.
Intercept	0.107 ***	0.302 ***	0.106 ***	0.001 ***	0.001 ***
Crypto	0.008 **	0.054 ***	0.018 ***	0.000 ***	0.000 ***
StrategyFE_ew_bh	0.000	0.010	0.005	-0.000 *	-0.000 *
StrategyFE_gmv	-0.057 ***	-0.134 ***	-0.051 ***	-0.000 ***	-0.000 ***
StrategyFE_minCVaR	-0.064 ***	-0.151 ***	-0.057 ***	-0.000 ***	-0.000 ***
StrategyFE_ERC	-0.006	-0.016	-0.006	-0.000 ***	-0.000 ***
StrategyFE_maxDiv	-0.003	-0.007	-0.004	-0.000 ***	-0.000 ***
StrategyFE_maxR	-0.005	0.001	0.001	-0.000	-0.000
StrategyFE_maxSR	0.008	0.006	0.003	-0.000 ***	-0.000 ***
StrategyFE_maxSTARR	0.003	-0.014	-0.005	-0.000 ***	-0.000 ***
StrategyFE_mv	0.002	0.007	0.002	0.000	0.000
StrategyFE_bs-mv	-0.009	-0.015	-0.006	0.000	0.000
StrategyFE_crra	0.007	0.028	0.010	0.000	0.000
YearFE_2017	0.161 ***	0.432 ***	0.152 ***	0.002 ***	0.002 ***
YearFE_2018	-0.141 ***	-0.254 ***	-0.095 ***	-0.002 ***	-0.002 ***
YearFE_2019	0.046 ***	0.068 ***	0.025 ***	-0.000 ***	-0.000 ***
YearFE_2020	0.054 ***	0.126 ***	0.044 ***	-0.000 ***	-0.001 ***
YearFE_2021	-0.012	-0.106 ***	-0.037 ***	-0.000	-0.000
YearFE_2022	-0.195 ***	-0.360 ***	-0.134 ***	-0.002 ***	-0.002 ***
YearFE_2023	-0.079 ***	-0.130 ***	-0.049 ***	-0.000 ***	-0.000 ***
YearFE_2024	-0.036 ***	-0.138 ***	-0.047 ***	-0.000	-0.000
AssetSpaceFE_eq_fi	0.002	0.015	0.004	-0.000	-0.000
AssetSpaceFE_gsci	0.006	0.011	0.004	0.000	0.000
AssetSpaceFE_epra	-0.000	0.012	0.004	-0.000	-0.000
AssetSpaceFE_all	0.003	0.005	0.002	-0.000	-0.000
Adj.R²	0.145	0.099	0.103	0.060	0.058

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Panel Regression Analysis – Base Model

A.15 Panel Regression Analysis – Crypto x AssetSpaceFE

Regression Analysis: Crypto x AssetSpaceFE
Trad. and CCI30 Portfolios

Variable	SR Coeff.	Sortino Coeff.	STARR Coeff.	MV_CEQ Coeff.	CRRA CEQ Coeff.
Intercept	0.107 ***	0.295 ***	0.103 ***	0.001 ***	0.001 ***
Crypto	0.007	0.069 ***	0.023 ***	0.000 **	0.000 *
AssetSpaceFE_eq_fi	0.002	0.026	0.009	-0.000	-0.000
AssetSpaceFE_gsci	0.005	0.023	0.008	0.000	0.000
AssetSpaceFE_epra	-0.001	0.020	0.007	-0.000	-0.000
AssetSpaceFE_all	0.001	0.010	0.004	-0.000	-0.000
StrategyFE_ew_bh	0.000	0.010	0.005	-0.000 *	-0.000 *
StrategyFE_gmv	-0.057 ***	-0.134 ***	-0.051 ***	-0.000 ***	-0.000 ***
StrategyFE_minCVaR	-0.064 ***	-0.151 ***	-0.057 ***	-0.000 ***	-0.000 ***
StrategyFE_ERC	-0.006	-0.016	-0.006	-0.000 ***	-0.000 ***
StrategyFE_maxDiv	-0.003	-0.007	-0.004	-0.000 ***	-0.000 ***
StrategyFE_maxR	-0.005	0.001	0.001	-0.000	-0.000
StrategyFE_maxSR	0.008	0.006	0.003	-0.000 ***	-0.000 ***
StrategyFE_maxSTARR	0.003	-0.014	-0.005	-0.000 ***	-0.000 ***
StrategyFE_mv	0.002	0.007	0.002	0.000	0.000
StrategyFE_bs-mv	-0.009	-0.015	-0.006	0.000	0.000
StrategyFE_crra	0.007	0.028	0.010	0.000	0.000
YearFE_2017	0.161 ***	0.432 ***	0.152 ***	0.002 ***	0.002 ***
YearFE_2018	-0.141 ***	-0.254 ***	-0.095 ***	-0.002 ***	-0.002 ***
YearFE_2019	0.046 ***	0.068 ***	0.025 ***	-0.000 ***	-0.000 ***
YearFE_2020	0.054 ***	0.126 ***	0.044 ***	-0.000 ***	-0.001 ***
YearFE_2021	-0.012	-0.106 ***	-0.037 ***	-0.000	-0.000
YearFE_2022	-0.195 ***	-0.360 ***	-0.134 ***	-0.002 ***	-0.002 ***
YearFE_2023	-0.079 ***	-0.130 ***	-0.049 ***	-0.000 ***	-0.000 ***
YearFE_2024	-0.036 ***	-0.138 ***	-0.047 ***	-0.000	-0.000
Crypto x AssetSpaceFE_eq_fi	-0.002	-0.022	-0.008	-0.000	-0.000
Crypto x AssetSpaceFE_gsci	0.001	-0.024	-0.008	0.000	0.000
Crypto x AssetSpaceFE_epra	0.002	-0.016	-0.006	-0.000	-0.000
Crypto x AssetSpaceFE_all	0.003	-0.011	-0.005	0.000	0.000
Adj. R²	0.145	0.099	0.103	0.060	0.058

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Panel Regression Analysis Including Interaction Term – Crypto x AssetSpaceFE

A.16 Robustness Tests – RQ1

(1) When substituting CCI30 with BTC, the differences between traditional and crypto-enhanced portfolios remain broadly similar for the descriptive statistics, with the key distinction that also minCVaR significantly enhances mean returns and increases standard deviations consistently. The differences in drawdown and tail risk measures are also broadly comparable, with additional significant increases when using minCVaR (CVaR, downside deviation) and maxSTARR (maximum drawdown) and fewer increases when using maxSR (maximum drawdown). This translates to minCVaR yielding significant improvements in risk-adjusted return measures when using BTC. Utility-based approaches show less significant improvements, even though the observed measures are still constantly higher than those of traditional portfolios. Utility-based measures again show the main differences in comparison to the CCI30 portfolios for the minCVaR strategy, now exhibiting consistent significant improvements of MV and CRRA CEQ at least at the 10% significance level. Additionally, maxSR and maxSTARR yield slightly better results in specific asset spaces. Turnover and IR behave similarly between both scenarios, while cumulative wealth is notably higher for utility-based approaches and maxR when CCI30 is used. Overall, it can be said that the observed patterns mainly persist across this robustness check. MinCVaR joins the pool of strategies that significantly benefit from crypto enhancement and utility-based approaches display slightly more modest improvements when BTC is added.

(2) When assessing whether CCI30 improves returns differently when a weekly rebalancing frequency is applied, more statistically significant increases in mean returns are observed for the ERC and maxSTARR strategies, while maxSR shows fewer significant increases. Standard deviations remain relatively similar, with additional increases in specific asset spaces when constructing portfolios via gmv or minCVaR. While CVaR patterns are mainly similar, fewer and weaker significant increases of the maximum drawdown are observed for mv and bs-mv. At the same time, maxSR portfolios exhibit more significant increases in this metric. Downside deviation increases significantly when using gmv and minCVaR in specific asset spaces, which was not the case in the monthly rebalanced setting. Looking at risk-adjusted return metrics, the main differences are (1) maxSTARR now exhibits consistently improved metrics in terms of SR, Sortino Ratio and STARR, (2) maxR, mv, and crra improve metrics on a significant level for more asset spaces, and (3) maxSR does not exhibit significant improvements anymore. Utility-based measures display more significant improvements for the maxSTARR strategy except in the eq_fi asset space. As in the monthly setting, turnover increases strongly once crypto assets are added. For most strategies, these increases demonstrate a much larger magnitude. Cumulative wealth also increases in most scenarios, however, to a smaller extent than turnover. In summary, while potentially offering some benefits in risk-adjusted and utility-based metrics, weekly rebalancing does not change the previously derived results strongly besides for maxSTARR, which performs significantly better when rebalancing is performed with this frequency. The heavily increased turnover, however, indicates that increased transaction costs most likely outweigh those potential benefits.

Mainly the same differences which have been found between monthly and weekly rebalancing also apply when comparing monthly and daily rebalancing. Evaluating the risk-adjusted return measures, maxSTARR, maxR, mv and crra still improve more significantly with daily rebalancing, but not as strongly as in the weekly setting. Additionally, maxSR does not improve the results significantly anymore, even though the direction of the difference remains similar. Utility-based measures are even more similar between monthly and daily than between monthly and weekly. The other metrics, namely turnover, cumulative wealth and IR, exhibit similar differences.

(3) When using an expanding window instead of a rolling window, mean returns and standard deviations increase more consistently for several additional strategies, namely gmv, minCVaR, maxSR, maxSTARR. The downside and tail risk measures behave similarly, with more significant increases in maximum drawdown for ERC and less significant increases for maxSR. This leads to gmv and minCVaR consistently improving SR, Sortino Ratio and STARR and adjusted SR in certain asset spaces when using an expanding window, which was not observable for the rolling windows. Additionally, maxSR and maxSTARR show more significant improvements, while maxR and crra now display non-significant performance reductions for some previously improved measures. Furthermore, utility-based measures exhibit more significant improvements for gmv, minCVaR, maxSR and maxSTARR. Turnover indicates that using an expanding window consistently requires less trading than the rolling window approach. Cumulative wealth increases more for risk-based approaches, maxR and maxSR, whereas utility-based approaches show fewer differences in cumulative wealth. Overall, it can be thus said that crypto assets can also enhance portfolios under an expanding window, leaving the overall conclusion unchanged. Nevertheless, some strategies significantly benefit in this setting, while others are harmed.

(4) After introducing an additional gens constraint in the form of $\boldsymbol{\omega} \geq a\mathbf{1}$ with $a \in [0, {}^{1}/_{N}]$, and setting $a = 0.5\ {}^{1}/_{N}$ for both, the traditional and the crypto-enhanced portfolios, the results show several differences. Mean returns and standard deviations are consistently increased across all strategy/asset space combinations. Also, downside and tail risk measures are more consistently increased across strategies due to the minimum weight assigned to crypto assets. In terms of risk-adjusted returns, the additional constraint leads to consistent significant increases for gmv and minCVaR, and significant increases in some asset additional asset spaces for ERC, maxSTARR and crra in terms of SR, Sortino Ratio and STARR. For the bs-mv strategy, the results slightly weaken and even display a significant decrease in the gsci and all asset space compared to significant increases before introducing the new constraint. An even more advantageous picture for the additional constraint can be observed for utility-based measures. Gmv, minCVaR, ERC, maxSR, maxSTARR, mv, bs-mv and crra exhibit a higher number of significant increases in both MV and CRRA CEQ returns. While turnover still increases through the addition of crypto assets in most scenarios, the magnitude of these increases is considerably lower. Cumulative wealth generally increases by a smaller extent for maxR, bs-mv and crra, while it increases considerably stronger for all purely risk-based approaches, maxSR and maxSTARR. IRs remain positive in almost all scenarios. To conclude, it can be said that the previously derived results mainly hold and are even enhanced in several scenarios once a gens constraint is introduced.

(5) So far, all results have been evaluated in a frictionless setting. Since this thesis focuses on evaluating the potential of crypto assets in portfolio optimization in a real-world setting, a proxy for transaction costs is introduced. To account for the costs caused by rebalancing portfolios, the return series of each strategy is adjusted proportional to that strategy's turnover at each rebalancing date as follows:

$$r_t^{adj} = r_t - c \times TO_t \tag{A6}$$

Where TO_t is defined as the sum of absolute changes in asset weights between two rebalancing dates, and c is set to 50 basis points (bps) following DeMiguel et al. (2009). Setting c equal to 50 bps can be considered somewhat conservative, as transaction costs during the OOS period of this thesis were lower for many assets. However, crypto assets, especially around the beginning of the OOS period, could even exceed transaction costs of 50 bps. The weight drift between rebalancing dates is not considered and returns on non-rebalancing dates remain unadjusted. In this context, it needs to be highlighted that such an ex-post introduction of transaction cost implies that the formed portfolios are not optimal in the setting with frictions, as they are estimated without accounting for them in any specific manner.

All statistically significant differences between traditional and crypto-enhanced portfolios remain unchanged when comparing mean returns and standard deviations. However, the absolute differences are mostly reduced once we move to the setting that includes the transaction cost approximation. The differences in drawdown and tail risk measures remain similar in most scenarios apart from bs-mv in the epra asset space, where maximum drawdown does not increase significantly once the returns are adjusted. In absolute terms, maximum drawdowns exhibit increases, whereas CVaR and downside deviation remain somewhat similar in a large set of strategy/asset space combinations. For risk-adjusted return measures, the strategies offer notably more significant improvements through crypto assets with higher statistical significance once we account for transaction costs. This case applies to maxSR, maxSTARR, mv, bs-mv and crra, which now also broadly improve Sortino Ratios and STARRs. Even though the absolute values of MV and CRRA CEQ returns are consistently lower, the significant differences between traditional and crypto-enhanced portfolios persist. MaxSR now even yields additional significant improvements. Turnover is not affected by the transaction cost approximation in this thesis. Cumulative wealth in absolute terms and the observed differences compared to traditional portfolios are mainly lower. In summary, while absolute values and differences for many measures decrease, the statistically significant differences mainly remain and even increase for certain measures in certain strategy/asset space combinations. Overall, the observed patterns persist across the robustness test of introducing transaction costs.

Tables with the detailed results of all conducted robustness tests can be downloaded under the following link:

Download Link – Robustness Tests RQ1

A.17 Pre- Post-COVID Comparisons – Traditional vs. CCI30

Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies

Descriptive Statistics for Monthly Rebalancing

		Pre-COVID								Post-COVID							
		Annual Mean		Annual StdDev		Skewness		Excess Kurt.		Annual Mean		Annual StdDev		Skewness		Excess Kurt.	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	0.071	0.499 **	0.051	0.279 **	-0.571	0.098	3.913	5.591	0.076	0.278 **	0.080	0.255 **	-0.087	-0.543	3.119	3.626
ew	eq_fi	0.077	0.344 **	0.054	0.177 **	-0.355	0.145	2.033	6.235	0.062	0.187 **	0.076	0.167 **	-0.289	-0.570	3.383	3.271
ew	gsci	0.067	0.295 **	0.066	0.155 **	-0.266	0.082	1.809	5.788	0.091	0.191 *	0.084	0.150 *	-0.388	-0.577	2.878	3.002
ew	epra	0.078	0.303 **	0.058	0.152 **	-0.409	0.131	2.914	6.267	0.066	0.169 **	0.087	0.154 **	-0.112	-0.526	2.733	3.043
ew	all	0.070	0.266 **	0.065	0.137 **	-0.310	0.070	2.565	5.701	0.089	0.174 *	0.089	0.141 *	-0.321	-0.562	2.713	2.900
ew_bh	simple	0.073	0.842	0.055	0.698	-0.624	-0.214	3.737	4.691	0.097	0.648 **	0.097	0.667 **	-0.162	-0.585	2.519	4.529
ew_bh	eq_fi	0.076	0.706	0.058	0.650	-0.399	-0.286	1.644	5.200	0.074	0.621 **	0.085	0.649 **	-0.270	-0.608	2.292	4.665
ew_bh	gsci	0.066	0.658	0.068	0.633	-0.342	-0.313	1.593	5.384	0.092	0.613 *	0.089	0.642 *	-0.300	-0.615	1.815	4.709
ew_bh	epra	0.077	0.659	0.060	0.632	-0.441	-0.314	2.492	5.404	0.074	0.611 **	0.093	0.642 **	-0.157	-0.616	2.244	4.712
ew_bh	all	0.068	0.619	0.067	0.616	-0.370	-0.339	2.342	5.576	0.089	0.603 *	0.093	0.635 *	-0.254	-0.623	2.001	4.758
gmv	simple	0.041	0.042	0.024	0.024	-0.440	-0.444	1.799	1.805	-0.007	-0.007	0.044	0.044	0.230	0.228	1.915	1.907
gmv	eq_fi	0.042	0.042	0.024	0.024	-0.406	-0.411	1.790	1.795	-0.007	-0.007	0.042	0.042	0.064	0.062	1.497	1.491
gmv	gsci	0.041	0.041	0.024	0.024	-0.360	-0.365	1.718	1.724	-0.005	-0.004	0.041	0.041	0.072	0.069	1.736	1.730
gmv	epra	0.042	0.042	0.024	0.024	-0.406	-0.411	1.790	1.795	-0.007	-0.007	0.042	0.042	0.055	0.053	1.500	1.495
gmv	all	0.041	0.041	0.024	0.024	-0.360	-0.365	1.718	1.724	-0.005	-0.004	0.041	0.041	0.065	0.062	1.744	1.738
minCVaR	simple	0.045	0.047	0.024	0.024	-0.507	-0.478	2.025	1.888	-0.011	-0.011	0.043	0.043	0.301	0.302	1.431	1.430
minCVaR	eq_fi	0.045	0.047	0.024	0.024	-0.417	-0.411	1.868	1.758	-0.013	-0.013	0.043	0.043	0.281	0.278	1.490	1.486
minCVaR	gsci	0.040	0.042	0.025	0.025	-0.264	-0.268	1.646	1.588	-0.007	-0.007	0.042	0.042	0.257	0.256	1.855	1.826
minCVaR	epra	0.045	0.047	0.024	0.024	-0.418	-0.411	1.866	1.758	-0.013	-0.013	0.043	0.043	0.243	0.244	1.574	1.576
minCVaR	all	0.040	0.042	0.025	0.025	-0.266	-0.268	1.640	1.586	-0.008	-0.007	0.042	0.042	0.224	0.223	1.936	1.913
ERC	simple	0.043	0.177 **	0.026	0.105 **	-0.551	0.001	2.716	5.633	0.011	0.206 ***	0.049	0.148 ***	0.087	-0.326	3.069	10.868
ERC	eq_fi	0.059	0.124	0.029	0.094	-0.335	-0.645	1.994	5.403	0.023	0.043 **	0.055	0.060 **	-0.484	-0.515	10.809	7.492
ERC	gsci	0.078	0.137	0.083	0.108	-0.389	-0.253	8.029	4.547	0.031	0.051	0.054	0.070	-0.272	-0.654	8.629	7.847
ERC	epra	0.059	0.114 *	0.031	0.071 *	-0.409	-0.551	2.318	8.006	0.022	0.042	0.059	0.065	-0.340	-0.197	7.404	2.721
ERC	all	0.076	0.109	0.048	0.080	-1.035	-0.502	25.984	5.769	0.029	0.060 **	0.057	0.072 **	-0.230	-0.464	6.523	5.197
maxDiv	simple	0.049	0.092 ***	0.026	0.033 ***	-0.470	0.013	2.647	3.107	0.018	0.034	0.049	0.055	0.070	0.057	3.051	2.866
maxDiv	eq_fi	0.056	0.100 ***	0.028	0.035 ***	-0.336	0.088	2.066	2.942	0.015	0.031	0.052	0.056	-0.518	-0.377	10.523	4.113
maxDiv	gsci	0.051	0.091 ***	0.029	0.035 ***	-0.260	-0.037	1.675	2.394	0.019	0.033 *	0.050	0.053 *	-0.197	-0.230	5.458	2.715
maxDiv	epra	0.056	0.100 ***	0.028	0.035 ***	-0.346	0.068	2.049	2.891	0.015	0.031	0.053	0.057	-0.522	-0.391	11.985	4.839
maxDiv	all	0.051	0.091 ***	0.029	0.035 ***	-0.266	-0.050	1.649	2.342	0.018	0.033 *	0.051	0.054 *	-0.213	-0.260	6.284	3.219
maxR	simple	0.046	0.913 *	0.083	0.728 *	-0.786	-0.155	6.234	5.218	0.106	0.717 ***	0.129	0.593 ***	-0.578	-0.446	2.877	6.232
maxR	eq_fi	0.065	0.923 *	0.100	0.727 *	-0.543	-0.158	3.206	5.231	0.078	0.664 **	0.129	0.590 **	-0.472	-0.454	2.099	6.383
maxR	gsci	0.039	0.923 *	0.113	0.727 *	-1.101	-0.158	5.487	5.231	0.195	0.702 **	0.187	0.598 **	-0.763	-0.465	6.848	5.946
maxR	epra	0.055	0.924 *	0.105	0.727 *	-0.644	-0.158	2.574	5.225	0.071	0.656 **	0.125	0.589 **	-0.497	-0.452	2.213	6.405
maxR	all	0.029	0.924 *	0.117	0.727 *	-1.100	-0.158	4.540	5.225	0.195	0.702 **	0.187	0.598 **	-0.763	-0.465	6.848	5.946
maxSR	simple	0.057	0.139	0.067	0.259	-0.438	-0.615	10.108	28.431	0.088	0.101	0.128	0.364	-0.086	-1.528	3.405	23.789
maxSR	eq_fi	0.071	0.172	0.064	0.281	-0.361	0.359	8.872	27.333	0.048	0.046	0.119	0.351	-0.026	-1.679	4.331	27.547
maxSR	gsci	0.033	0.363 **	0.099	0.278 **	-0.302	2.350	15.295	27.762	0.083	0.180	0.153	0.257	-0.702	-0.234	8.311	24.556
maxSR	epra	0.064	0.173	0.064	0.281	-0.451	0.357	8.388	27.292	0.048	0.058	0.116	0.349	-0.034	-1.708	4.612	28.200
maxSR	all	0.024	0.362 **	0.100	0.278 **	-0.352	2.342	14.920	27.662	0.074	0.164	0.143	0.252	-0.815	-0.230	7.282	26.671
maxSTARR	simple	0.040	0.155	0.066	0.187	-1.167	-2.777	12.998	51.703	0.051	0.149	0.113	0.180	-0.425	-0.438	3.275	14.981
maxSTARR	eq_fi	0.030	0.132	0.058	0.184	-0.875	-2.921	13.411	54.302	0.028	0.083	0.104	0.128	-0.509	-0.168	4.728	3.288
maxSTARR	gsci	0.015	0.223 **	0.069	0.122 **	-2.613	1.551	25.464	30.732	0.075	0.124 *	0.146	0.165 *	-0.785	-0.586	7.246	4.904
maxSTARR	epra	0.038	0.136	0.056	0.184	-1.254	-2.917	10.123	54.122	0.046	0.087	0.097	0.122	-0.490	-0.220	6.832	4.994
maxSTARR	all	0.020	0.221 **	0.067	0.121 **	-3.040	1.569	26.207	30.917	0.047	0.106 *	0.139	0.157 *	-0.845	-0.627	7.383	4.888
mv	simple	0.073	0.905 **	0.066	0.488 **	-1.224	0.060	8.798	14.064	0.063	0.182	0.098	0.268	-0.277	-2.153	2.948	30.525
mv	eq_fi	0.088	0.894 **	0.079	0.479 **	-0.723	0.114	3.706	13.824	0.059	0.175	0.100	0.264	-0.310	-2.135	2.762	28.999
mv	gsci	0.072	0.885 **	0.091	0.481 **	-1.295	0.109	7.094	13.666	0.143	0.263	0.167	0.286	-0.880	-1.657	10.789	18.439
mv	epra	0.073	0.884 **	0.084	0.480 **	-0.762	0.118	3.387	13.758	0.062	0.179	0.099	0.263	-0.434	-2.163	3.535	29.448
mv	all	0.057	0.876 **	0.095	0.481 **	-1.223	0.114	5.982	13.596	0.129	0.246	0.166	0.286	-0.896	-1.657	11.032	18.517
bs-mv	simple	0.070	0.694 **	0.054	0.383 **	-1.609	0.016	14.404	17.696	0.042	0.071	0.080	0.179	-0.364	-2.987	3.508	47.134
bs-mv	eq_fi	0.084	0.681 **	0.064	0.368 **	-0.755	0.058	6.028	17.227	0.029	0.058	0.081	0.174	-0.372	-3.092	3.227	47.228
bs-mv	gsci	0.073	0.661 **	0.074	0.362 **	-1.181	0.075	7.354	16.867	0.076	0.113	0.119	0.188	-1.174	-2.515	14.686	33.035
bs-mv	epra	0.084	0.669 **	0.065	0.364 **	-0.758	0.092	5.753	17.137	0.040	0.079	0.082	0.173	-0.256	-2.872	3.028	42.076
bs-mv	all	0.071	0.648 **	0.073	0.358 **	-1.117	0.114	6.636	16.877	0.074	0.117	0.115	0.184	-1.273	-2.490	14.067	32.006
crra	simple	0.068	1.171 ***	0.070	0.615 ***	-0.995	-0.020	6.826	9.808	0.068	0.269	0.109	0.447	-0.347	-1.282	2.741	15.304
crra	eq_fi	0.083	1.148 **	0.088	0.601 **	-0.565	-0.039	2.770	9.993	0.067	0.261	0.111	0.441	-0.429	-1.277	2.733	14.896
crra	gsci	0.073	1.144 **	0.097	0.592 **	-1.276	0.011	6.544	9.957	0.178	0.338	0.174	0.429	-0.755	-1.274	7.850	14.180
crra	epra	0.059	1.119 **	0.093	0.592 **	-0.647	-0.059	2.389	10.090	0.070	0.279	0.106	0.432	-0.484	-1.304	3.112	15.810
crra	all	0.043	1.118 **	0.104	0.595 **	-1.204	-0.022	5.349	9.615	0.150	0.296	0.172	0.422	-0.827	-1.255	8.496	13.897

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 18: Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies – Descriptive Statistics

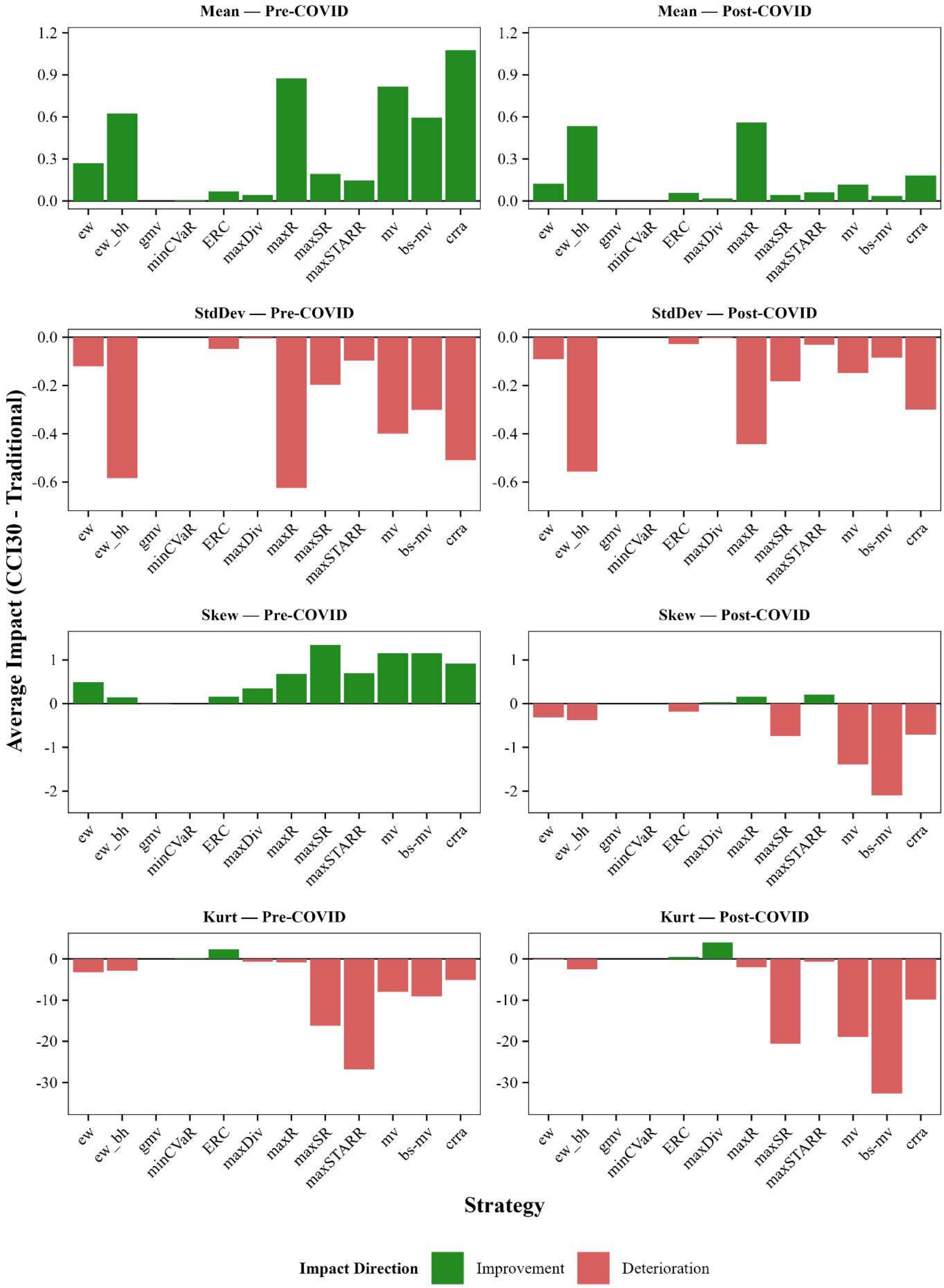

Figure 19: Average Impact of Adding CCI30 Pre- and Post-COVID – Descriptive Statistics

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. Standard Deviations) are multiplied by -1 in the plots. The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies

Tail Risk Measures for Monthly Rebalancing

		Pre-COVID						Post-COVID					
		Max. Drawdown		CVaR95		Downside Dev		Max. Drawdown		CVaR95		Downside Dev	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	0.086	0.499 ***	0.008	0.040 ***	0.036	0.181 ***	0.200	0.450 ***	0.012	0.039 ***	0.055	0.180 ***
ew	eq_fi	0.108	0.356 ***	0.008	0.025 ***	0.037	0.114 ***	0.229	0.364 *	0.011	0.025 ***	0.053	0.118 ***
ew	gsci	0.124	0.313 **	0.010	0.022 ***	0.046	0.101 ***	0.155	0.285 **	0.012	0.022 ***	0.058	0.105 ***
ew	epra	0.101	0.304 **	0.008	0.021 ***	0.040	0.098 ***	0.243	0.352 *	0.012	0.023 ***	0.060	0.109 ***
ew	all	0.115	0.274 **	0.010	0.019 ***	0.046	0.089 ***	0.176	0.286 *	0.013	0.021 ***	0.062	0.099 ***
ew_bh	simple	0.099	0.898 ***	0.009	0.107 ***	0.039	0.477 ***	0.218	0.820 ***	0.014	0.101 ***	0.067	0.473 ***
ew_bh	eq_fi	0.125	0.887 ***	0.009	0.102 ***	0.041	0.449 ***	0.240	0.814 ***	0.012	0.098 ***	0.059	0.461 ***
ew_bh	gsci	0.138	0.881 ***	0.010	0.100 ***	0.048	0.439 ***	0.164	0.810 ***	0.013	0.097 ***	0.062	0.456 ***
ew_bh	epra	0.116	0.881 ***	0.009	0.100 ***	0.042	0.438 ***	0.251	0.811 ***	0.013	0.097 ***	0.064	0.457 ***
ew_bh	all	0.128	0.876 ***	0.010	0.098 ***	0.047	0.429 ***	0.182	0.807 ***	0.013	0.096 ***	0.065	0.452 ***
gmv	simple	0.038	0.038	0.004	0.004	0.016	0.016	0.169	0.169	0.006	0.006	0.031	0.031 *
gmv	eq_fi	0.038	0.038	0.004	0.004	0.016	0.016	0.177	0.177	0.006	0.006	0.030	0.030
gmv	gsci	0.037	0.037	0.003	0.003	0.016	0.016	0.159	0.159	0.006	0.006	0.029	0.029
gmv	epra	0.038	0.038	0.004	0.004	0.016	0.016	0.178	0.178	0.006	0.006	0.030	0.030
gmv	all	0.037	0.037	0.003	0.003	0.016	0.016	0.160	0.160	0.006	0.006	0.029	0.029
minCVaR	simple	0.036	0.036	0.004	0.004	0.017	0.017	0.170	0.170	0.006	0.006	0.030	0.030
minCVaR	eq_fi	0.036	0.036	0.004	0.004	0.017	0.017	0.178	0.176	0.006	0.006	0.030	0.030 *
minCVaR	gsci	0.039	0.039	0.004	0.004	0.017	0.017	0.155	0.156	0.006	0.006	0.029	0.029 *
minCVaR	epra	0.036	0.036	0.004	0.004	0.017	0.017	0.179	0.177	0.006	0.006	0.030	0.030
minCVaR	all	0.039	0.039	0.004	0.004	0.017	0.017	0.159	0.159	0.006	0.006	0.030	0.030
ERC	simple	0.034	0.164 *	0.004	0.016 ***	0.018	0.069 ***	0.172	0.243	0.007	0.023 ***	0.034	0.100 ***
ERC	eq_fi	0.048	0.134	0.004	0.014 ***	0.019	0.066 ***	0.196	0.210	0.008	0.008 ***	0.039	0.043 ***
ERC	gsci	0.121	0.216	0.013	0.016 **	0.058	0.074 ***	0.164	0.176	0.008	0.010 ***	0.038	0.050 ***
ERC	epra	0.046	0.080	0.004	0.010 ***	0.021	0.048 ***	0.206	0.231	0.008	0.009 ***	0.042	0.046 ***
ERC	all	0.060	0.095	0.007	0.012 ***	0.033	0.056 ***	0.177	0.177	0.008	0.010 ***	0.040	0.051 ***
maxDiv	simple	0.034	0.037	0.004	0.004 ***	0.018	0.021 ***	0.172	0.186	0.007	0.008 ***	0.034	0.038 ***
maxDiv	eq_fi	0.047	0.060	0.004	0.005 ***	0.019	0.022 ***	0.197	0.211	0.008	0.008 *	0.037	0.040 *
maxDiv	gsci	0.043	0.057	0.004	0.005 ***	0.019	0.022 ***	0.157	0.171	0.007	0.008 **	0.036	0.038 *
maxDiv	epra	0.048	0.060	0.004	0.005 ***	0.019	0.022 ***	0.200	0.216	0.008	0.008 **	0.038	0.041 *
maxDiv	all	0.043	0.056	0.004	0.005 ***	0.020	0.022 ***	0.161	0.176	0.007	0.008 **	0.036	0.038 *
maxR	simple	0.183	0.948 ***	0.015	0.114 ***	0.062	0.494 ***	0.290	0.621 ***	0.020	0.089 ***	0.093	0.406 ***
maxR	eq_fi	0.262	0.945 ***	0.017	0.114 ***	0.074	0.494 ***	0.290	0.621 ***	0.020	0.089 ***	0.094	0.405 ***
maxR	gsci	0.296	0.945 ***	0.020	0.114 ***	0.087	0.494 ***	0.239	0.619 ***	0.030	0.089 ***	0.135	0.412 ***
maxR	epra	0.225	0.945 ***	0.017	0.114 ***	0.078	0.494 ***	0.305	0.636 ***	0.019	0.089 ***	0.090	0.405 ***
maxR	all	0.260	0.945 ***	0.020	0.114 ***	0.091	0.494 ***	0.239	0.619 ***	0.030	0.089 ***	0.135	0.412 ***
maxSR	simple	0.180	0.603 ***	0.011	0.041 ***	0.048	0.189 ***	0.258	0.672 ***	0.019	0.059 ***	0.089	0.274 ***
maxSR	eq_fi	0.140	0.614 ***	0.010	0.043 ***	0.045	0.194 ***	0.299	0.665 ***	0.018	0.057 ***	0.084	0.266 ***
maxSR	gsci	0.228	0.431 *	0.017	0.037 ***	0.072	0.161 ***	0.239	0.386	0.025	0.040 ***	0.111	0.180 ***
maxSR	epra	0.151	0.613 ***	0.010	0.043 ***	0.045	0.194 ***	0.303	0.641 ***	0.018	0.057 ***	0.082	0.265 ***
maxSR	all	0.258	0.434	0.017	0.037 ***	0.073	0.161 ***	0.239	0.386	0.024	0.039 ***	0.105	0.177 ***
maxSTARR	simple	0.202	0.505	0.011	0.027 *	0.050	0.144 **	0.290	0.298	0.018	0.026 **	0.082	0.125 **
maxSTARR	eq_fi	0.228	0.529	0.010	0.027 *	0.044	0.142 **	0.282	0.268	0.017	0.019 *	0.076	0.089 **
maxSTARR	gsci	0.285	0.251	0.012	0.017 *	0.056	0.075 **	0.239	0.239	0.024	0.026 **	0.107	0.118 ***
maxSTARR	epra	0.180	0.524 *	0.010	0.027 *	0.042	0.142 **	0.201	0.212	0.015	0.018 ***	0.069	0.084 ***
maxSTARR	all	0.249	0.249	0.012	0.017 **	0.055	0.075 **	0.254	0.239	0.024	0.025 **	0.103	0.114 ***
mv	simple	0.104	0.535 ***	0.011	0.071 ***	0.048	0.313 ***	0.221	0.435 *	0.015	0.042 ***	0.069	0.200 ***
mv	eq_fi	0.177	0.548 ***	0.013	0.070 ***	0.057	0.306 ***	0.240	0.449 *	0.016	0.041 ***	0.072	0.198 ***
mv	gsci	0.208	0.566 ***	0.016	0.070 ***	0.069	0.307 ***	0.241	0.387	0.027	0.045 **	0.121	0.211 **
mv	epra	0.182	0.557 ***	0.014	0.070 ***	0.062	0.306 ***	0.237	0.435	0.015	0.041 ***	0.070	0.197 ***
mv	all	0.223	0.574 ***	0.016	0.070 ***	0.073	0.308 ***	0.241	0.387	0.027	0.045 **	0.121	0.212 **
bs-mv	simple	0.090	0.462 ***	0.009	0.055 ***	0.040	0.247 ***	0.201	0.344	0.012	0.028 **	0.056	0.138 **
bs-mv	eq_fi	0.129	0.448 ***	0.010	0.053 ***	0.046	0.236 ***	0.215	0.358	0.012	0.027 **	0.058	0.135 **
bs-mv	gsci	0.156	0.456 ***	0.013	0.052 ***	0.055	0.233 ***	0.182	0.293	0.019	0.030 **	0.087	0.143 **
bs-mv	epra	0.125	0.442 ***	0.010	0.052 ***	0.046	0.233 ***	0.212	0.343	0.012	0.027 **	0.058	0.133 **
bs-mv	all	0.155	0.447 ***	0.012	0.051 ***	0.055	0.230 ***	0.179	0.280	0.018	0.029 **	0.085	0.140 **
crra	simple	0.113	0.701 ***	0.011	0.094 ***	0.051	0.396 ***	0.242	0.610 ***	0.017	0.073 ***	0.077	0.328 ***
crra	eq_fi	0.205	0.702 ***	0.014	0.091 ***	0.063	0.387 ***	0.244	0.601 ***	0.017	0.072 ***	0.079	0.324 ***
crra	gsci	0.207	0.680 ***	0.017	0.089 ***	0.074	0.380 ***	0.231	0.589 ***	0.028	0.068 ***	0.125	0.314 ***
crra	epra	0.221	0.692 ***	0.015	0.090 ***	0.069	0.382 ***	0.246	0.593 ***	0.016	0.070 ***	0.076	0.316 ***
crra	all	0.251	0.677 ***	0.018	0.090 ***	0.080	0.383 ***	0.233	0.584 ***	0.028	0.067 ***	0.126	0.309 ***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 19: Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies – Drawdown and Tail Risk

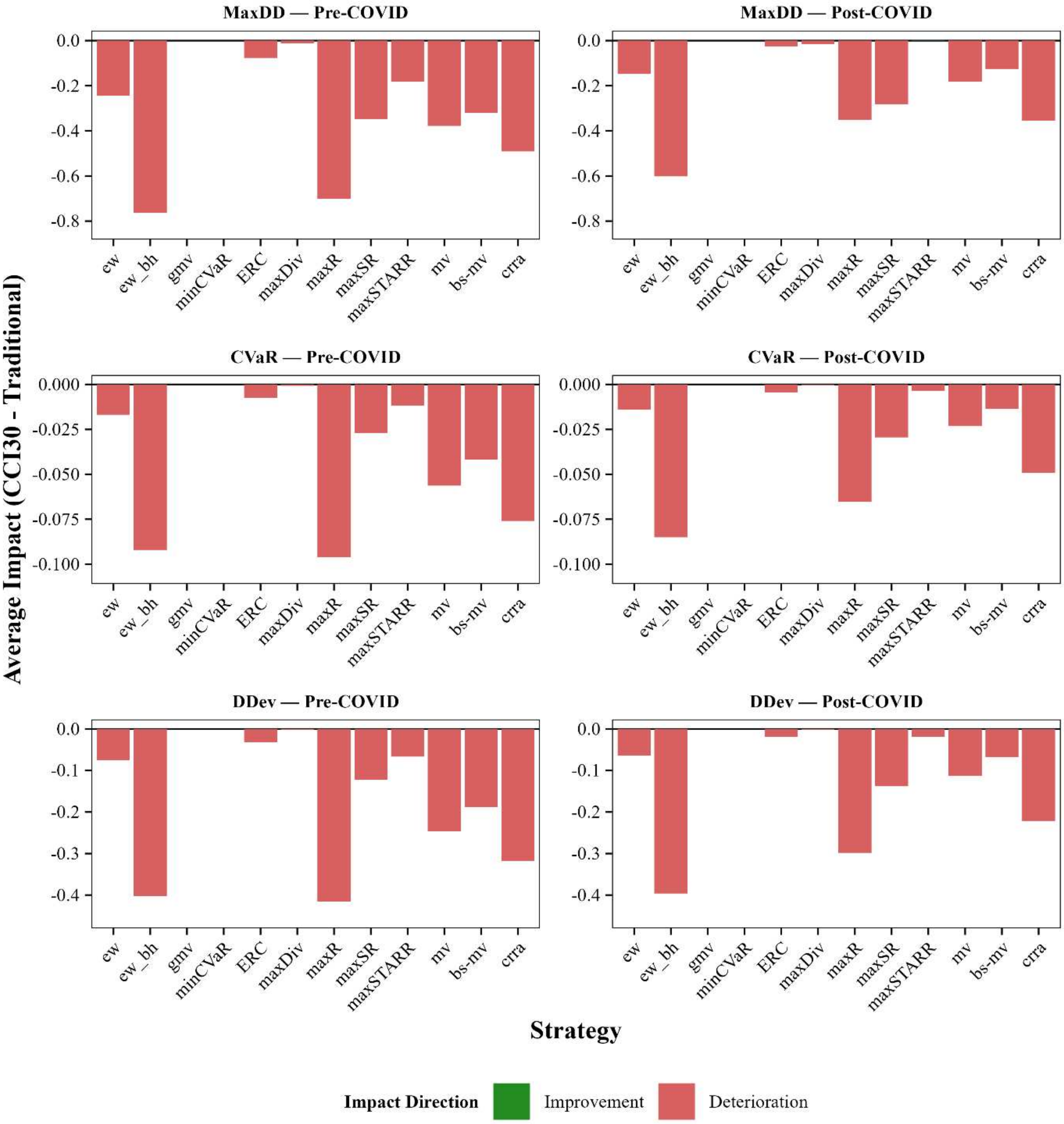

Figure 20: Average Impact of Adding CCI30 Pre- and Post-COVID – Downside and Tail Risk

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. MaxDD) are multiplied by -1 in the plots. The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies

Risk-Reward Measures for Monthly Rebalancing

		Pre-COVID								Post-COVID							
		Sharpe Ratio		Adj. SR		Sortino Ratio		STARR		Sharpe Ratio		Adj. SR		Sortino Ratio		STARR	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	1.512	0.898	0.732	0.743	1.624	2.682	0.030	0.048	0.479	0.670	0.462	0.585	0.925	1.406	0.018	0.026
ew	eq_fi	1.142	0.929	0.940	0.741	1.713	2.908	0.033	0.053	0.304	0.583	0.296	0.524	0.723	1.375	0.014	0.026
ew	gsci	0.987	0.915 *	0.872	0.742	1.174	2.802	0.023	0.051	0.563	0.673	0.522	0.593	1.138	1.575	0.022	0.030
ew	epra	1.284	0.971	0.916	0.753	1.617	2.966	0.031	0.054	0.314	0.555	0.308	0.507	0.690	1.325	0.014	0.025
ew	all	1.138	0.956 *	0.915	0.759	1.243	2.848	0.024	0.052	0.511	0.637	0.483	0.569	1.039	1.505	0.020	0.029
ew_bh	simple	1.435	0.690	0.759	0.609	1.521	1.738	0.027	0.031	0.613	0.705	0.579	0.591	1.072	1.318	0.021	0.025
ew_bh	eq_fi	1.053	0.644	0.899	0.566	1.562	1.544	0.030	0.027	0.370	0.696	0.359	0.581	0.835	1.292	0.016	0.024
ew_bh	gsci	0.903	0.626	0.808	0.550	1.105	1.470	0.021	0.026	0.562	0.693	0.533	0.579	1.084	1.289	0.021	0.024
ew_bh	epra	1.188	0.628	0.911	0.551	1.510	1.475	0.029	0.026	0.359	0.692	0.352	0.578	0.771	1.283	0.015	0.024
ew_bh	all	1.044	0.612	0.866	0.538	1.173	1.413	0.022	0.025	0.509	0.689	0.488	0.575	1.000	1.280	0.019	0.024
gmv	simple	1.008	1.016	0.858	0.862	1.715	1.747	0.032	0.033	-0.576	-0.572	-0.549	-0.546	-0.987	-0.980	-0.021	-0.021
gmv	eq_fi	0.992	1.000	0.854	0.858	1.759	1.791	0.033	0.033	-0.556	-0.553	-0.544	-0.540	-1.013	-1.006	-0.021	-0.021
gmv	gsci	0.977	0.983	0.854	0.857	1.710	1.735	0.032	0.033	-0.563	-0.554	-0.547	-0.539	-0.951	-0.935	-0.020	-0.019
gmv	epra	0.992	1.000	0.854	0.858	1.759	1.791	0.033	0.033	-0.550	-0.546	-0.538	-0.534	-1.007	-0.999	-0.021	-0.021
gmv	all	0.977	0.983	0.854	0.857	1.710	1.735	0.032	0.033	-0.557	-0.547	-0.542	-0.534	-0.948	-0.932	-0.020	-0.019
minCVaR	simple	1.155	1.172	0.913	0.937	1.911	2.057	0.035	0.038	-0.683	-0.683	-0.642	-0.643	-1.121	-1.122	-0.024	-0.024
minCVaR	eq_fi	1.055	1.082	0.887	0.910	1.895	2.016	0.035	0.037	-0.709	-0.701	-0.665	-0.658	-1.192	-1.180	-0.025	-0.025
minCVaR	gsci	0.950	0.985	0.852	0.880	1.617	1.737	0.031	0.033	-0.650	-0.649	-0.612	-0.611	-1.026	-1.022	-0.022	-0.022
minCVaR	epra	1.055	1.082	0.887	0.910	1.894	2.016	0.035	0.037	-0.680	-0.674	-0.642	-0.637	-1.189	-1.177	-0.025	-0.025
minCVaR	all	0.949	0.985	0.852	0.880	1.612	1.735	0.031	0.033	-0.641	-0.638	-0.605	-0.603	-1.038	-1.032	-0.022	-0.022
ERC	simple	1.329	1.357	0.900	0.771	1.630	2.378	0.030	0.041	-0.218	0.565 ***	-0.216	0.468	-0.373	1.813 ***	-0.007	0.032 ***
ERC	eq_fi	1.266	1.277	1.010	0.635	2.369	1.685	0.046	0.030	-0.011	0.193 **	-0.011	0.188	-0.022	0.440 **	0.000	0.009 **
ERC	gsci	1.103	0.799	0.579	0.676	1.129	1.670	0.019	0.031	0.093	0.318	0.092	0.297	0.172	0.526	0.003	0.010
ERC	epra	1.296	1.509	0.974	0.160	2.186	2.082	0.042	0.039	-0.018	0.181	-0.018	0.179	-0.036	0.392	-0.001	0.008
ERC	all	1.189	1.554	-0.868	0.456	1.930	1.734	0.038	0.031	0.067	0.427 *	0.067	0.397	0.124	0.708 *	0.002	0.014 *
maxDiv	simple	1.358	1.411 ***	0.938	1.056	2.026	3.814 **	0.038	0.072 ***	-0.092	0.116	-0.092	0.116	-0.171	0.246	-0.003	0.005
maxDiv	eq_fi	1.248	1.289 ***	0.995	1.054	2.298	4.003 **	0.044	0.075 **	-0.123	0.078	-0.124	0.078	-0.236	0.174	-0.005	0.004
maxDiv	gsci	1.239	1.311 ***	1.041	1.079	1.967	3.539 **	0.038	0.068 **	-0.085	0.123 *	-0.085	0.122	-0.143	0.245	-0.003	0.005
maxDiv	epra	1.250	1.294 ***	0.994	1.055	2.285	3.969 **	0.043	0.074 **	-0.119	0.080	-0.120	0.079	-0.228	0.178	-0.005	0.004
maxDiv	all	1.247	1.317 ***	1.046	1.083	1.955	3.510 **	0.038	0.067 **	-0.094	0.114 *	-0.094	0.113	-0.158	0.231	-0.003	0.005
maxR	simple	0.352	0.559	0.325	0.513	0.539	1.821	0.009	0.031	0.467	0.851	0.434	0.638	0.882	1.706	0.016	0.031
maxR	eq_fi	0.390	0.569	0.369	0.520	0.711	1.843	0.013	0.032	0.356	0.848	0.342	0.632	0.572	1.576	0.010	0.029
maxR	gsci	0.187	0.569	0.179	0.520	0.309	1.843	0.005	0.032	1.174	0.941	0.541	0.667	1.265	1.643	0.023	0.030
maxR	epra	0.337	0.571	0.321	0.522	0.538	1.845	0.010	0.032	0.296	0.828	0.287	0.625	0.517	1.557	0.010	0.028
maxR	all	0.121	0.571 *	0.118	0.522	0.182	1.845	0.003	0.032	1.174	0.941	0.541	0.667	1.265	1.643	0.023	0.030
maxSR	simple	0.723	0.239	0.524	0.217	0.912	0.670	0.016	0.012	0.607	0.216	0.570	0.194	0.721	0.281	0.013	0.005
maxSR	eq_fi	1.004	0.436	0.566	0.353	1.294	0.821	0.023	0.015	0.214	0.069	0.212	0.068	0.282	0.083	0.005	0.002
maxSR	gsci	0.228	1.044 *	0.218	0.153	0.279	2.176	0.005	0.038 *	0.654	1.405	0.508	-1.514 *	0.527	0.861	0.009	0.015
maxSR	epra	0.883	0.442	0.581	0.355	1.122	0.828	0.020	0.015	0.206	0.112	0.204	0.107	0.286	0.127	0.005	0.002
maxSR	all	0.117	1.039 *	0.116	0.167	0.154	2.165 *	0.003	0.037 *	0.592	1.137	0.481	-0.546	0.468	0.788	0.008	0.014
maxSTARR	simple	0.334	0.308	0.292	0.201	0.542	0.986	0.009	0.021	0.198	0.564	0.195	0.429	0.324	0.991	0.006	0.019
maxSTARR	eq_fi	0.195	0.264	0.186	0.188	0.406	0.664	0.007	0.018	0.035	0.396	0.035	0.383	0.058	0.654	0.001	0.012
maxSTARR	gsci	0.023	0.615 ***	0.023	0.415	0.050	2.784 **	0.001	0.049 **	0.628	0.855	0.502	0.656	0.478	0.840	0.008	0.015
maxSTARR	epra	0.314	0.274	0.280	0.191	0.595	0.866	0.011	0.018	0.227	0.460	0.220	0.432	0.323	0.744	0.006	0.014
maxSTARR	all	0.072	0.608 ***	0.069	0.415	0.145	2.765 **	0.003	0.049 **	0.280	0.658 *	0.262	0.554	0.220	0.720 *	0.004	0.013 *
mv	simple	0.913	0.814	0.463	0.505	1.238	2.854	0.022	0.050	0.341	0.556	0.331	0.227	0.563	0.788	0.010	0.015
mv	eq_fi	0.748	0.812	0.616	0.516	1.308	2.882	0.023	0.050	0.307	0.542	0.299	0.246	0.489	0.761	0.009	0.015
mv	gsci	0.532	0.794 *	0.426	0.521	0.862	2.835	0.015	0.049	0.910	0.983	0.453	-0.010	0.975	1.126	0.017	0.021
mv	epra	0.585	0.800 *	0.513	0.519	0.976	2.848	0.018	0.050	0.332	0.561	0.319	0.232	0.535	0.786	0.010	0.015
mv	all	0.382	0.783 **	0.338	0.523	0.610	2.802	0.011	0.049	0.919	0.915	0.439	0.095	0.862	1.046	0.015	0.019
bs-mv	simple	1.156	0.799	-0.130	0.425	1.436	2.756	0.026	0.049	0.205	0.326	0.201	0.205	0.318	0.339	0.006	0.007
bs-mv	eq_fi	0.982	0.800	0.622	0.439	1.551	2.828	0.027	0.050	0.062	0.255	0.062	0.189	0.090	0.248	0.002	0.005
bs-mv	gsci	0.722	0.787	0.504	0.452	1.096	2.783	0.019	0.050	0.600	0.705	0.399	0.018	0.589	0.620	0.011	0.012
bs-mv	epra	0.985	0.797	0.633	0.445	1.526	2.813	0.027	0.050	0.180	0.369	0.178	0.216	0.275	0.411	0.005	0.008
bs-mv	all	0.697	0.780	0.513	0.458	1.068	2.764	0.019	0.049	0.644	0.699	0.401	0.043	0.586	0.660	0.011	0.013
crra	simple	0.740	0.905 *	0.533	0.600	1.081	2.923	0.019	0.049	0.357	0.603	0.345	0.386	0.566	0.747	0.010	0.013
crra	eq_fi	0.610	0.906	0.549	0.591	1.110	2.931	0.020	0.049	0.334	0.593	0.322	0.389	0.531	0.732	0.010	0.013
crra	gsci	0.499	0.899 **	0.412	0.599	0.813	2.979	0.014	0.050	1.066	0.973	0.530	0.229	1.227	1.000	0.022	0.018
crra	epra	0.395	0.896 **	0.372	0.586	0.669	2.894	0.012	0.049	0.360	0.648	0.344	0.378	0.603	0.805	0.011	0.014
crra	all	0.229	0.864 **	0.215	0.603	0.378	2.882 *	0.007	0.049 *	1.098	0.831	0.467	0.355	1.000	0.878	0.018	0.016

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on Ledoit & Wolf for SR and a two-tailed block-bootstrapping procedure with 1 000 replications andblock-length 21 for other measures.

Table 20: Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies – Risk-adjusted Returns

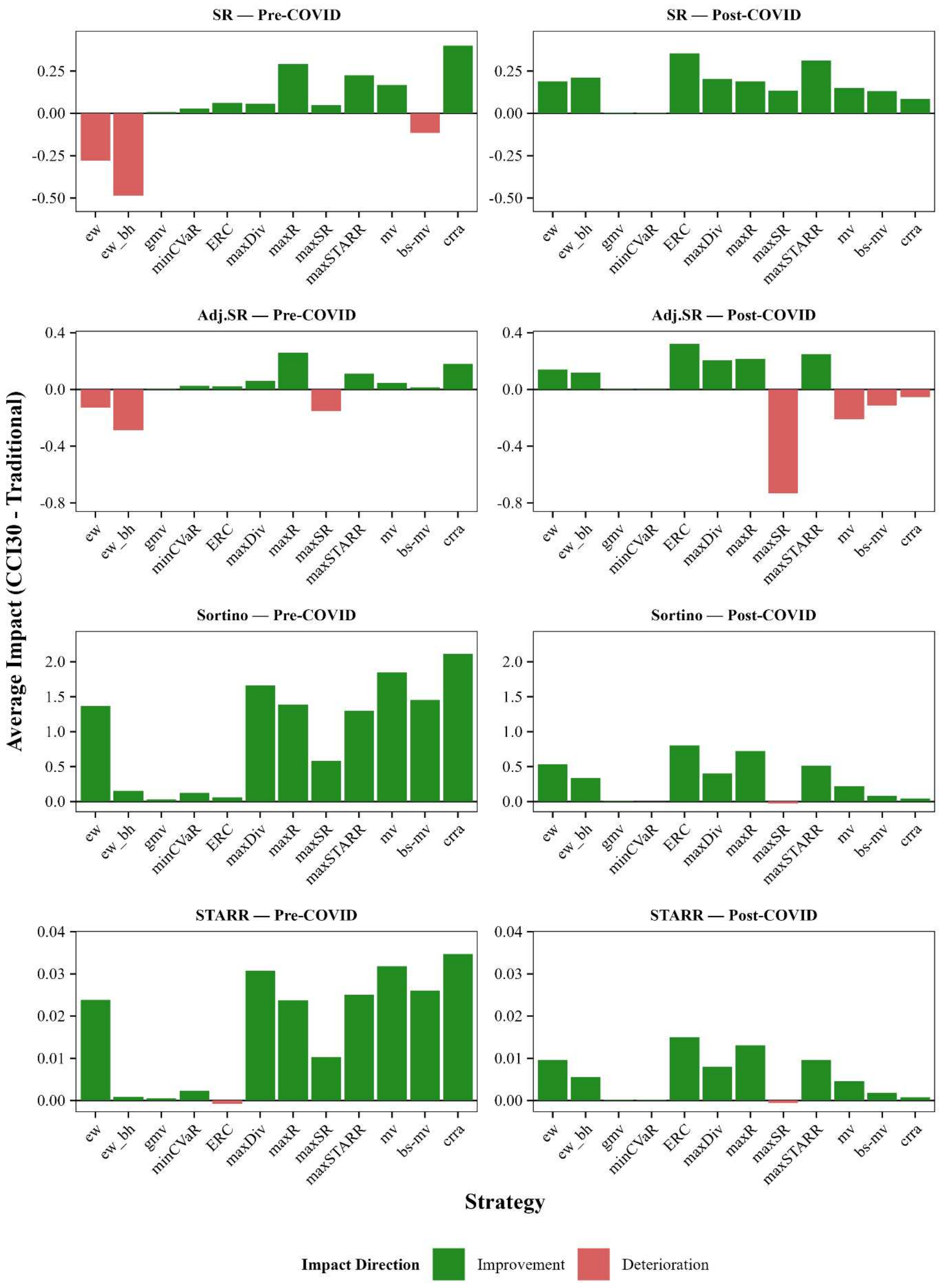

Figure 21: Average Impact of Adding CCI30 Pre- and Post-COVID – Risk-Adjusted Returns

Note: The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

Pre- Post-COVID Comp: Traditional vs. CCI30 Across Strategies

Utility based Measures for Monthly Rebalancing

		Pre-COVID				Post-COVID			
		MV CEQ		CRRA CEQ		MV CEQ		CRRA CEQ	
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30	Trad.	CCI30
ew	simple	0.070	0.466 *	0.070	0.466 *	0.068	0.198	0.068	0.196
ew	eq_fi	0.075	0.346 *	0.075	0.346 *	0.055	0.157	0.055	0.156
ew	gsci	0.063	0.296 *	0.063	0.296 *	0.084	0.170	0.084	0.170
ew	epra	0.076	0.308 *	0.076	0.308 *	0.056	0.143	0.056	0.142
ew	all	0.065	0.269 **	0.065	0.269 **	0.080	0.155	0.080	0.155
ew_bh	simple	0.070	0.117	0.070	0.093	0.086	-0.019	0.086	-0.052
ew_bh	eq_fi	0.074	0.075	0.074	0.053	0.065	-0.012	0.065	-0.043
ew_bh	gsci	0.061	0.059	0.061	0.038	0.083	-0.005	0.083	-0.036
ew_bh	epra	0.074	0.062	0.074	0.041	0.063	-0.008	0.063	-0.039
ew_bh	all	0.064	0.051	0.064	0.031	0.079	-0.002	0.079	-0.033
gmv	simple	0.041	0.042	0.041	0.042	-0.010	-0.010	-0.010	-0.010
gmv	eq_fi	0.042	0.042	0.042	0.042	-0.010	-0.010	-0.010	-0.010
gmv	gsci	0.041	0.041	0.041	0.041	-0.007	-0.007	-0.007	-0.007
gmv	epra	0.042	0.042	0.042	0.042	-0.010	-0.010	-0.010	-0.010
gmv	all	0.041	0.041	0.041	0.041	-0.007	-0.007	-0.007	-0.007
minCVaR	simple	0.045	0.048	0.045	0.048	-0.014	-0.014	-0.014	-0.014
minCVaR	eq_fi	0.045	0.047	0.045	0.047	-0.016	-0.015	-0.016	-0.015
minCVaR	gsci	0.040	0.042	0.040	0.042	-0.010	-0.009	-0.010	-0.009
minCVaR	epra	0.045	0.047	0.045	0.047	-0.016	-0.016	-0.016	-0.016
minCVaR	all	0.040	0.042	0.040	0.042	-0.010	-0.010	-0.010	-0.010
ERC	simple	0.043	0.175 **	0.043	0.175 **	0.007	0.189 ***	0.007	0.189 ***
ERC	eq_fi	0.059	0.117	0.059	0.117	0.019	0.038 **	0.019	0.038 **
ERC	gsci	0.070	0.127	0.070	0.127	0.027	0.044	0.027	0.044
ERC	epra	0.060	0.112	0.060	0.112	0.017	0.037	0.017	0.037
ERC	all	0.075	0.105	0.075	0.105	0.024	0.054 *	0.024	0.054 *
maxDiv	simple	0.049	0.095 ***	0.049	0.095 ***	0.015	0.029	0.015	0.029
maxDiv	eq_fi	0.056	0.103 ***	0.056	0.103 ***	0.011	0.027	0.011	0.027
maxDiv	gsci	0.051	0.094 ***	0.051	0.094 ***	0.015	0.030	0.015	0.030
maxDiv	epra	0.056	0.104 ***	0.056	0.104 ***	0.011	0.027	0.011	0.027
maxDiv	all	0.051	0.094 ***	0.051	0.094 ***	0.014	0.029	0.014	0.029
maxR	simple	0.037	0.126	0.036	0.099	0.085	0.209	0.085	0.183
maxR	eq_fi	0.051	0.138	0.051	0.111	0.054	0.153	0.054	0.128
maxR	gsci	0.021	0.138	0.020	0.111	0.154	0.181	0.153	0.155
maxR	epra	0.039	0.139	0.039	0.112	0.049	0.144	0.049	0.120
maxR	all	0.008	0.139	0.008	0.112	0.154	0.181	0.153	0.155
maxSR	simple	0.051	0.040	0.051	0.037	0.066	-0.093	0.066	-0.106
maxSR	eq_fi	0.067	0.055	0.067	0.055	0.027	-0.129	0.027	-0.142
maxSR	gsci	0.018	0.281 *	0.018	0.287 *	0.049	0.083	0.049	0.082
maxSR	epra	0.059	0.057	0.059	0.056	0.028	-0.118	0.028	-0.130
maxSR	all	0.009	0.279 *	0.009	0.285 *	0.044	0.071	0.044	0.069
maxSTARR	simple	0.034	0.107	0.034	0.104	0.032	0.105	0.032	0.104
maxSTARR	eq_fi	0.026	0.085	0.026	0.082	0.012	0.060	0.012	0.060
maxSTARR	gsci	0.008	0.222 **	0.008	0.223 **	0.045	0.087	0.044	0.086
maxSTARR	epra	0.034	0.089	0.034	0.086	0.033	0.067	0.033	0.067
maxSTARR	all	0.014	0.220 **	0.014	0.220 **	0.018	0.072 *	0.018	0.072 *
mv	simple	0.068	0.728	0.068	0.716	0.050	0.077	0.050	0.069
mv	eq_fi	0.081	0.731	0.081	0.722	0.045	0.072	0.045	0.065
mv	gsci	0.061	0.712	0.061	0.703	0.106	0.150	0.106	0.143
mv	epra	0.064	0.713	0.064	0.704	0.048	0.078	0.048	0.071
mv	all	0.044	0.695	0.044	0.686	0.091	0.131	0.091	0.124
bs-mv	simple	0.068	0.605	0.068	0.600	0.033	0.023	0.033	0.020
bs-mv	eq_fi	0.081	0.612	0.081	0.608	0.020	0.012	0.020	0.009
bs-mv	gsci	0.067	0.590	0.067	0.587	0.056	0.062	0.056	0.059
bs-mv	epra	0.080	0.600	0.080	0.596	0.030	0.034	0.030	0.032
bs-mv	all	0.065	0.577	0.065	0.574	0.056	0.068	0.056	0.066
crra	simple	0.063	0.826	0.063	0.799	0.052	-0.031	0.052	-0.052
crra	eq_fi	0.074	0.831	0.074	0.804	0.049	-0.030	0.049	-0.050
crra	gsci	0.060	0.853	0.060	0.831	0.142	0.064	0.142	0.045
crra	epra	0.047	0.809	0.047	0.783	0.055	-0.002	0.055	-0.022
crra	all	0.027	0.796	0.027	0.774	0.111	0.030	0.111	0.012

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21.

Table 21: Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies – Utility

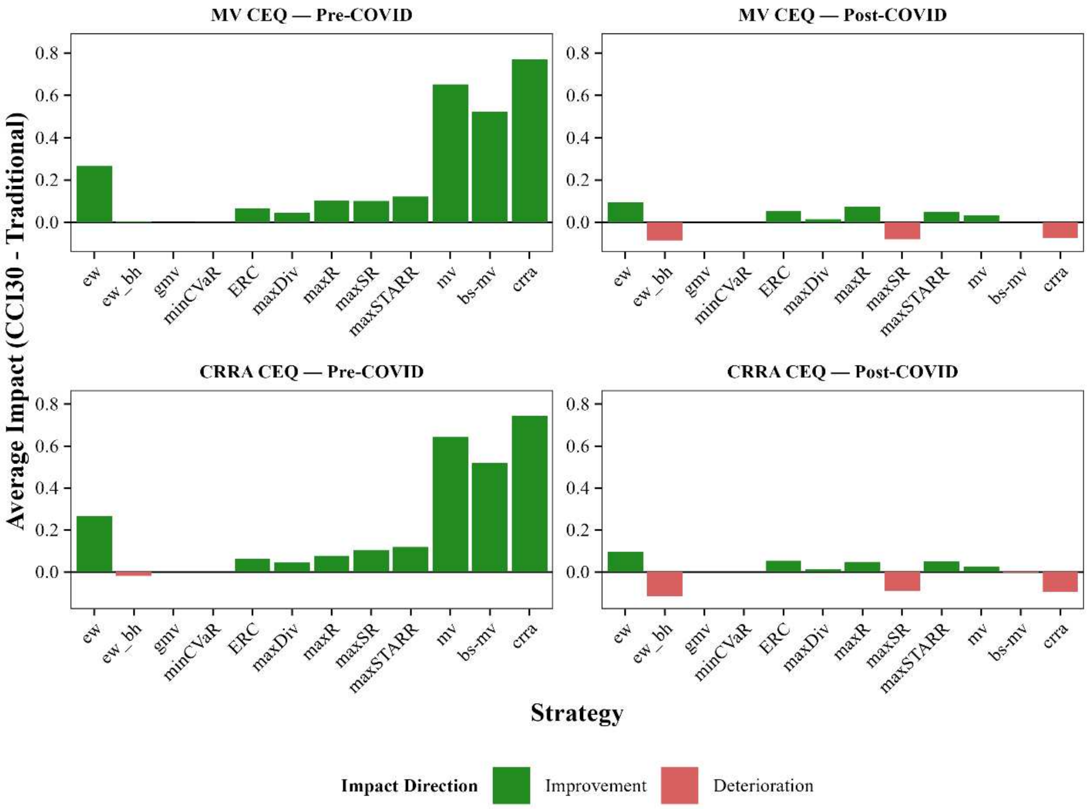

Figure 22: Average Impact of Adding CCI30 Pre- and Post-COVID – Utility

Note: The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

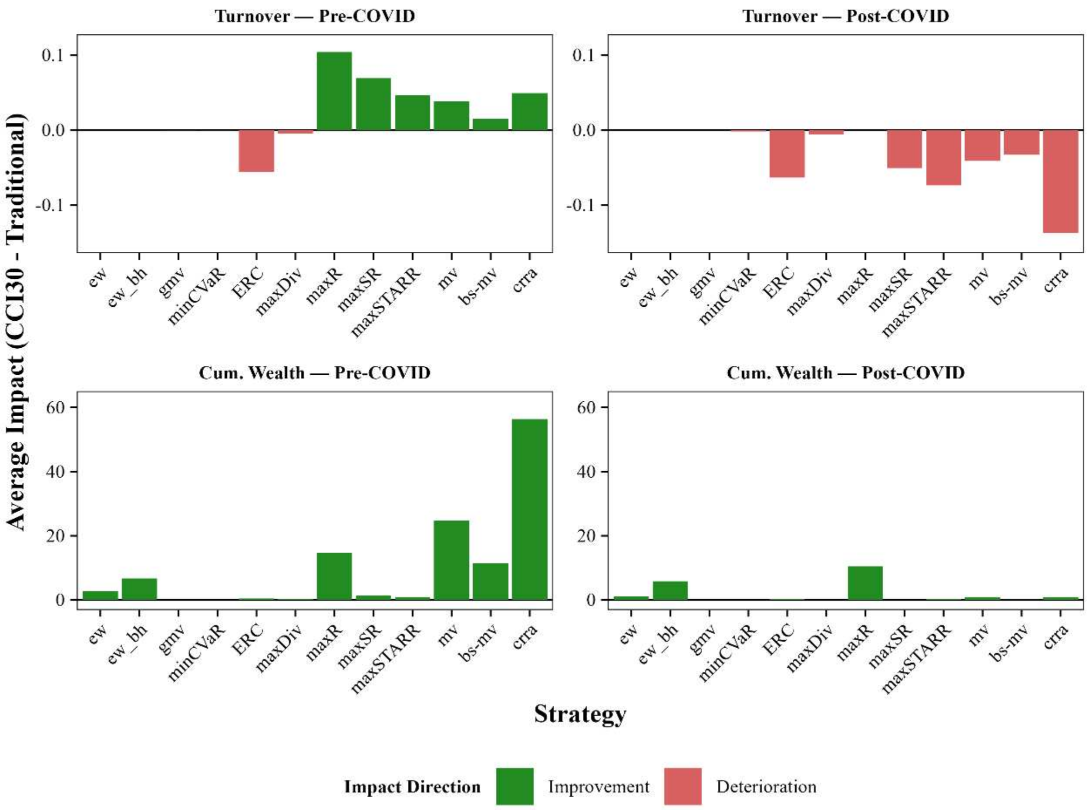

Figure 23: Average Impact of Adding CCI30 Pre- and Post-COVID – Other Metrics

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. Turnover) are multiplied by -1 in the plots. The displayed differences are the average differences across asset spaces from the comparison of traditional vs. CCI30 portfolios with monthly rebalancing.

Pre- Post-COVID Comp.: Traditional vs. CCI30 Across Strategies
Other Metrics for Monthly Rebalancing

		Pre-COVID					Post-COVID				
		Turnover		Cum. Wealth		IR	Turnover		Cum. Wealth		IR
Strategy	Asset Space	Trad.	CCI30	Trad.	CCI30		Trad.	CCI30	Trad.	CCI30	
ew	simple	-	-	0.345	6.000	1.860	-	-	0.428	2.338	0.910
ew	eq_fi	-	-	0.377	3.011	1.827	-	-	0.341	1.347	0.943
ew	gsci	-	-	0.318	2.311	1.818	-	-	0.538	1.417	0.927
ew	epra	-	-	0.380	2.431	1.814	-	-	0.357	1.166	0.939
ew	all	-	-	0.331	1.963	1.808	-	-	0.520	1.245	0.927
ew_bh	simple	-	-	0.351	11.424	1.063	-	-	0.574	6.925	0.671
ew_bh	eq_fi	-	-	0.372	7.012	0.861	-	-	0.413	6.351	0.682
ew_bh	gsci	-	-	0.311	5.854	0.809	-	-	0.543	6.234	0.648
ew_bh	epra	-	-	0.374	5.907	0.796	-	-	0.410	6.150	0.679
ew_bh	all	-	-	0.323	5.073	0.755	-	-	0.520	6.041	0.650
gmv	simple	0.018	0.018	0.189	0.192	0.806	0.022	0.023	-0.039	-0.038	0.276
gmv	eq_fi	0.027	0.028	0.192	0.195	0.784	0.028	0.028	-0.040	-0.039	0.304
gmv	gsci	0.032	0.032	0.187	0.189	0.690	0.031	0.031	-0.026	-0.024	0.385
gmv	epra	0.027	0.028	0.192	0.195	0.784	0.032	0.032	-0.039	-0.038	0.304
gmv	all	0.032	0.032	0.187	0.189	0.690	0.034	0.034	-0.026	-0.024	0.385
minCVaR	simple	0.039	0.038	0.208	0.221	0.739	0.023	0.024	-0.057	-0.057	-0.071
minCVaR	eq_fi	0.128	0.129	0.208	0.218	0.675	0.034	0.039	-0.067	-0.065	0.181
minCVaR	gsci	0.085	0.085	0.184	0.194	0.727	0.037	0.037	-0.038	-0.037	0.041
minCVaR	epra	0.128	0.129	0.208	0.218	0.678	0.038	0.041	-0.067	-0.066	0.245
minCVaR	all	0.085	0.085	0.183	0.194	0.731	0.041	0.042	-0.041	-0.040	0.124
ERC	simple	0.066	0.078	0.198	1.068	1.445	0.039	0.160	0.049	1.612	1.536
ERC	eq_fi	0.024	0.089	0.279	0.655	0.798	0.030	0.032	0.112	0.226	1.002
ERC	gsci	0.085	0.192	0.373	0.739	0.913	0.033	0.135	0.154	0.268	0.456
ERC	epra	0.027	0.117	0.283	0.602	1.001	0.032	0.076	0.107	0.218	0.632
ERC	all	0.142	0.146	0.373	0.566	0.618	0.035	0.082	0.144	0.330	0.762
maxDiv	simple	0.019	0.021	0.228	0.475	2.291	0.012	0.020	0.086	0.171	0.643
maxDiv	eq_fi	0.065	0.069	0.265	0.524	2.270	0.061	0.067	0.069	0.156	0.725
maxDiv	gsci	0.071	0.076	0.240	0.468	2.252	0.066	0.071	0.090	0.170	0.767
maxDiv	epra	0.069	0.075	0.265	0.525	2.262	0.079	0.084	0.070	0.157	0.725
maxDiv	all	0.075	0.082	0.240	0.468	2.244	0.082	0.084	0.086	0.168	0.775
maxR	simple	0.320	0.320	0.199	14.296	1.192	0.246	0.351	0.620	13.115	1.083
maxR	eq_fi	0.280	0.240	0.289	15.010	1.191	0.421	0.421	0.408	9.979	0.984
maxR	gsci	0.400	0.240	0.150	15.010	1.221	0.246	0.246	1.398	11.919	0.857
maxR	epra	0.400	0.280	0.231	15.082	1.207	0.561	0.456	0.365	9.559	0.967
maxR	all	0.480	0.280	0.098	15.082	1.236	0.246	0.246	1.398	11.919	0.857
maxSR	simple	0.214	0.253	0.260	0.563	0.217	0.053	0.225	0.484	0.176	-0.160
maxSR	eq_fi	0.420	0.370	0.338	0.753	0.256	0.307	0.385	0.222	-0.082	-0.179
maxSR	gsci	0.478	0.377	0.125	2.960	1.273	0.386	0.421	0.420	1.054	0.396
maxSR	epra	0.494	0.380	0.299	0.763	0.283	0.467	0.400	0.222	-0.026	-0.145
maxSR	all	0.513	0.393	0.083	2.941	1.273	0.400	0.434	0.365	0.912	0.357
maxSTARR	simple	0.216	0.273	0.172	0.783	0.616	0.300	0.398	0.243	0.917	0.697
maxSTARR	eq_fi	0.470	0.467	0.129	0.627	0.523	0.410	0.443	0.120	0.443	0.673
maxSTARR	gsci	0.466	0.431	0.056	1.488	2.129	0.275	0.395	0.375	0.721	0.713
maxSTARR	epra	0.556	0.422	0.166	0.652	0.503	0.297	0.386	0.228	0.481	0.583
maxSTARR	all	0.596	0.482	0.080	1.467	2.081	0.373	0.403	0.201	0.587	0.874
mv	simple	0.177	0.261	0.347	26.598	2.328	0.154	0.249	0.334	1.041	0.403
mv	eq_fi	0.371	0.324	0.429	25.826	2.297	0.298	0.366	0.306	0.980	0.399
mv	gsci	0.401	0.335	0.332	24.746	2.291	0.326	0.338	0.885	1.962	0.479
mv	epra	0.490	0.421	0.342	24.759	2.286	0.374	0.388	0.324	1.027	0.408
mv	all	0.504	0.409	0.249	23.754	2.282	0.357	0.371	0.761	1.727	0.457
bs-mv	simple	0.208	0.261	0.335	12.762	2.099	0.171	0.232	0.211	0.307	0.107
bs-mv	eq_fi	0.387	0.347	0.414	12.343	2.101	0.283	0.346	0.136	0.229	0.114
bs-mv	gsci	0.412	0.383	0.346	11.364	2.089	0.396	0.412	0.401	0.594	0.200
bs-mv	epra	0.440	0.405	0.412	11.749	2.074	0.364	0.388	0.198	0.366	0.194
bs-mv	all	0.471	0.444	0.336	10.792	2.060	0.423	0.424	0.395	0.632	0.247
crra	simple	0.218	0.219	0.321	61.886	2.617	0.209	0.397	0.358	1.263	0.276
crra	eq_fi	0.339	0.298	0.397	58.058	2.576	0.348	0.466	0.346	1.209	0.270
crra	gsci	0.408	0.317	0.333	58.542	2.651	0.289	0.447	1.232	2.314	0.252
crra	epra	0.482	0.433	0.258	52.642	2.564	0.436	0.515	0.372	1.453	0.326
crra	all	0.487	0.420	0.172	51.917	2.574	0.352	0.495	0.943	1.739	0.216

Note: Turnover is reported on a monthly basis without consideration of the weight drift between rebalancing periods. IR is calculated using the non-crypto portfolio as the benchmark.

Table 22: Pre- Post-COVID Comparison: Traditional vs. CCI30 Across Strategies – Other Metrics

A.18 Rolling Comparison of Performance Measures

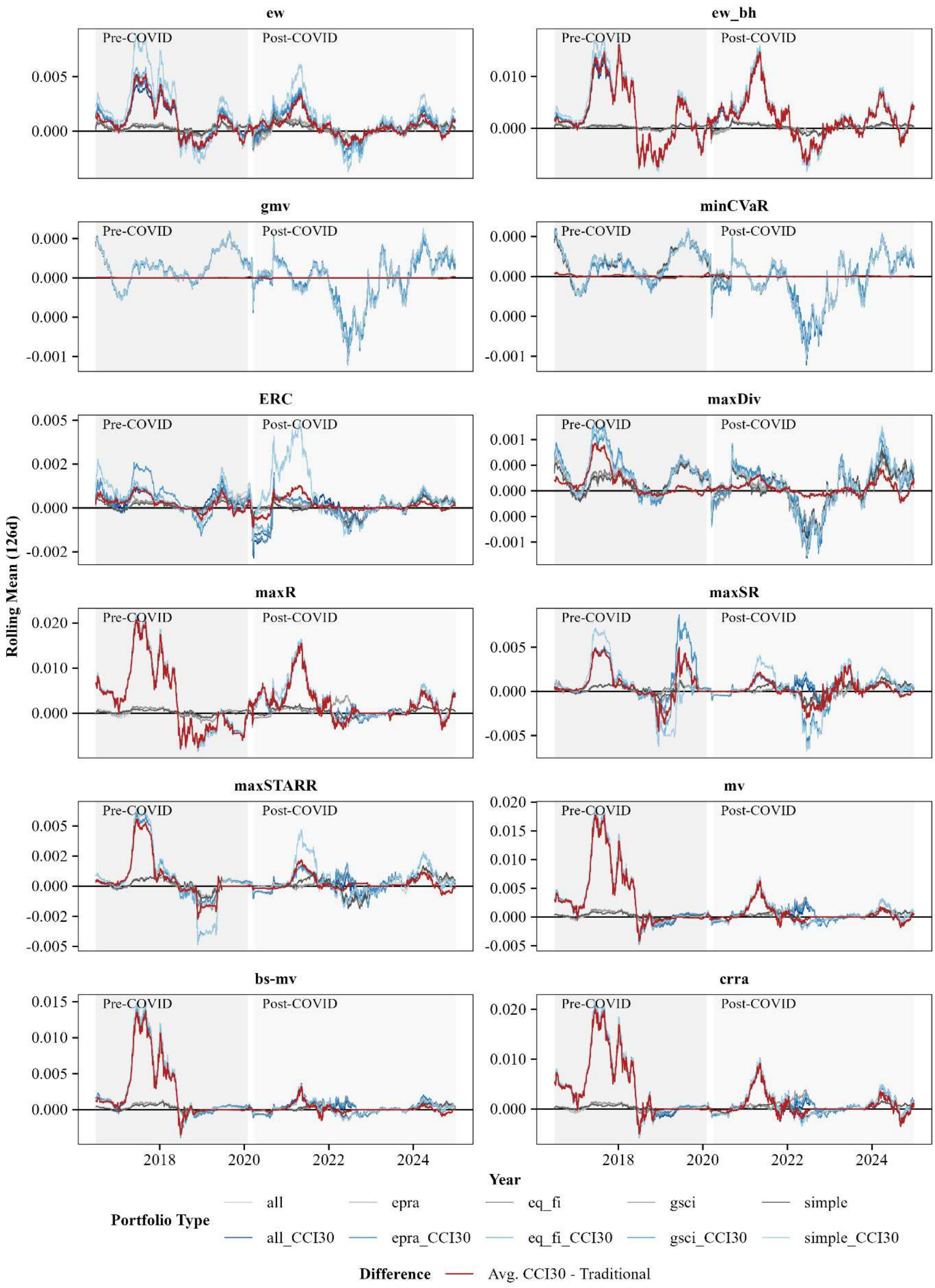

Figure 24: Rolling 126-Day Daily Mean Returns Across Strategies and Asset Spaces for Traditional vs. CCI30

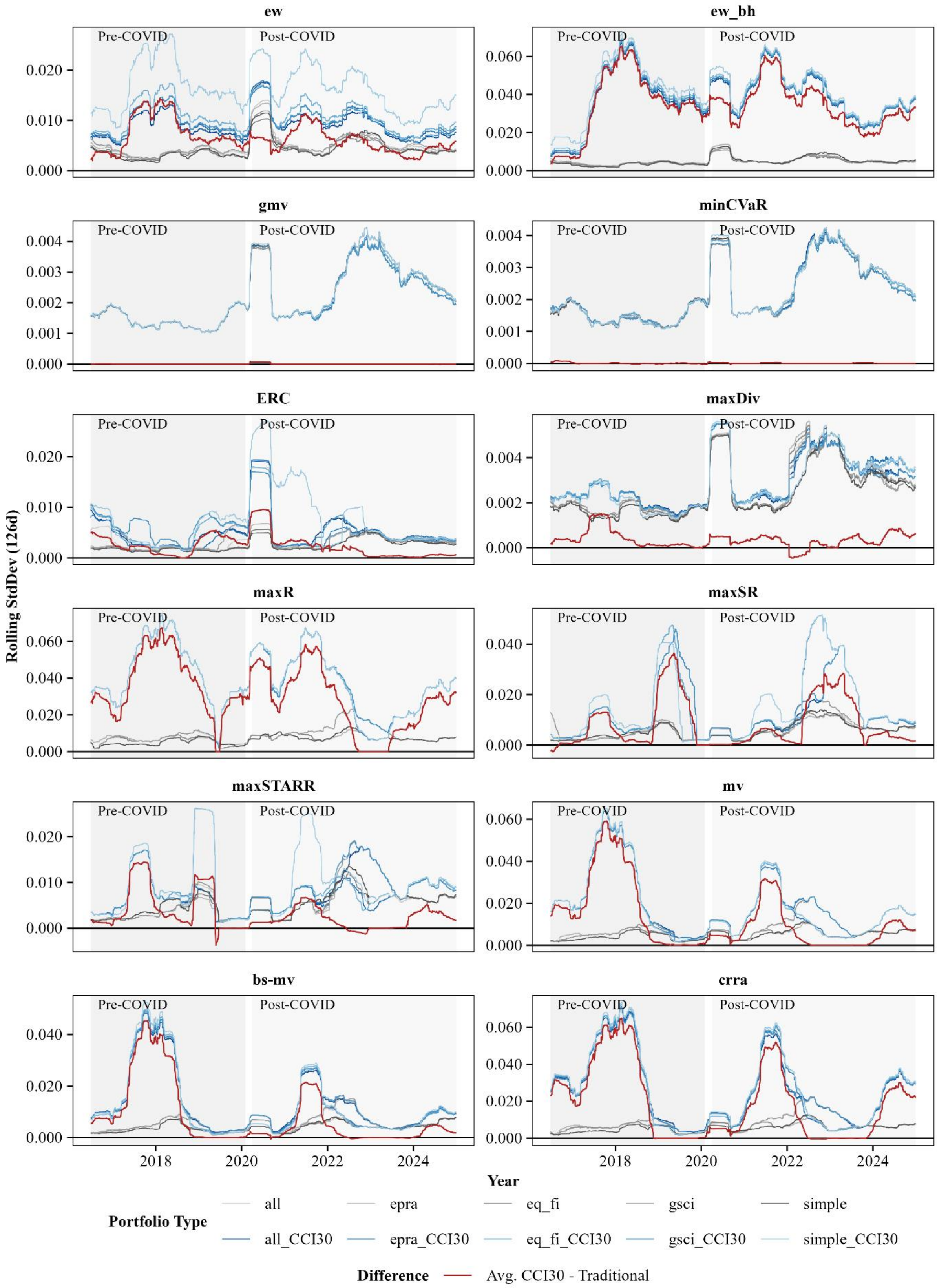

Figure 25: Rolling 126-Day Daily Std.Dev. Across Strategies and Asset Spaces for Traditional vs. CCI30

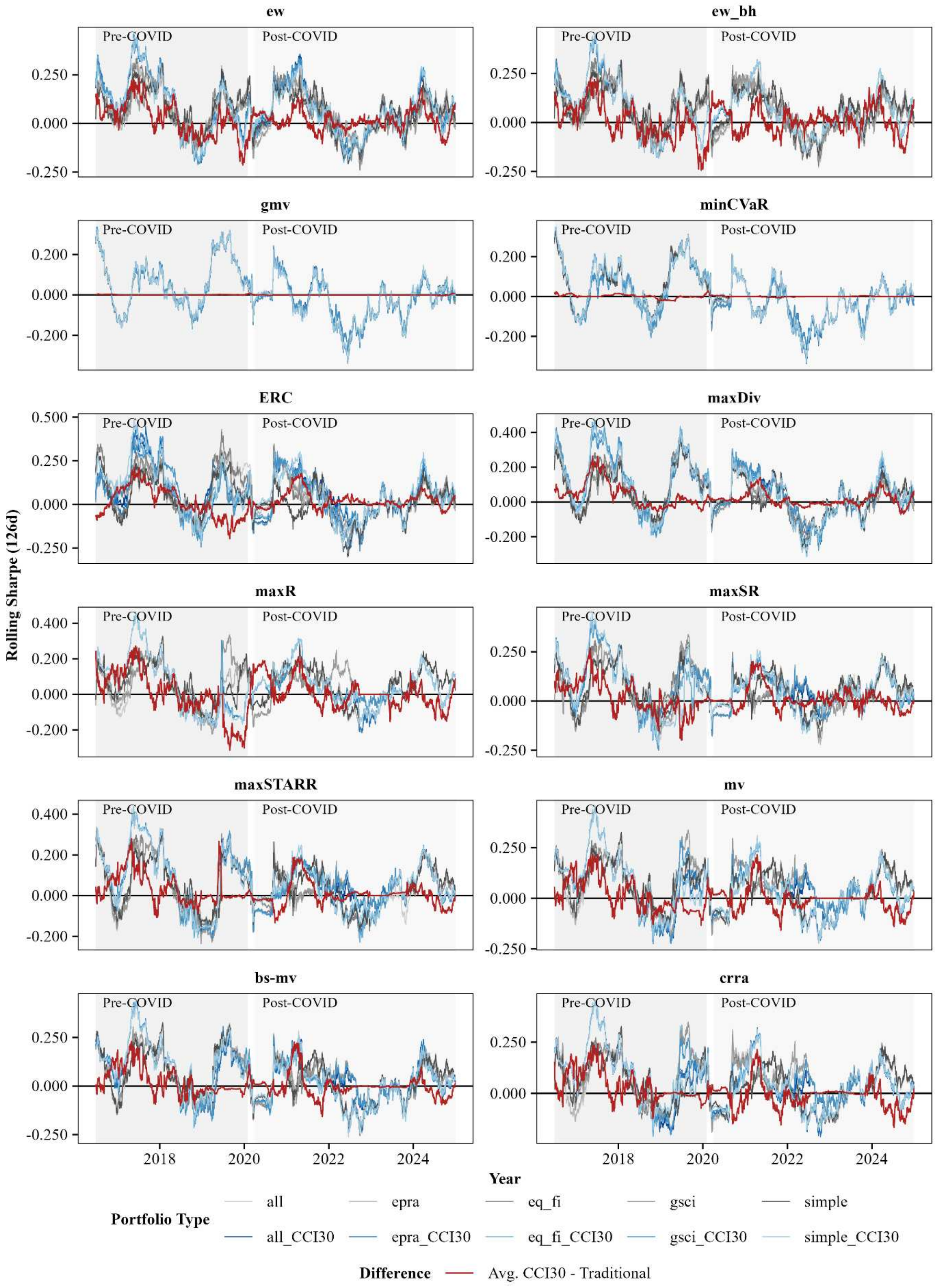

Figure 26: Rolling 126-Day Daily SR Across Strategies and Asset Spaces for Traditional vs. CCI30

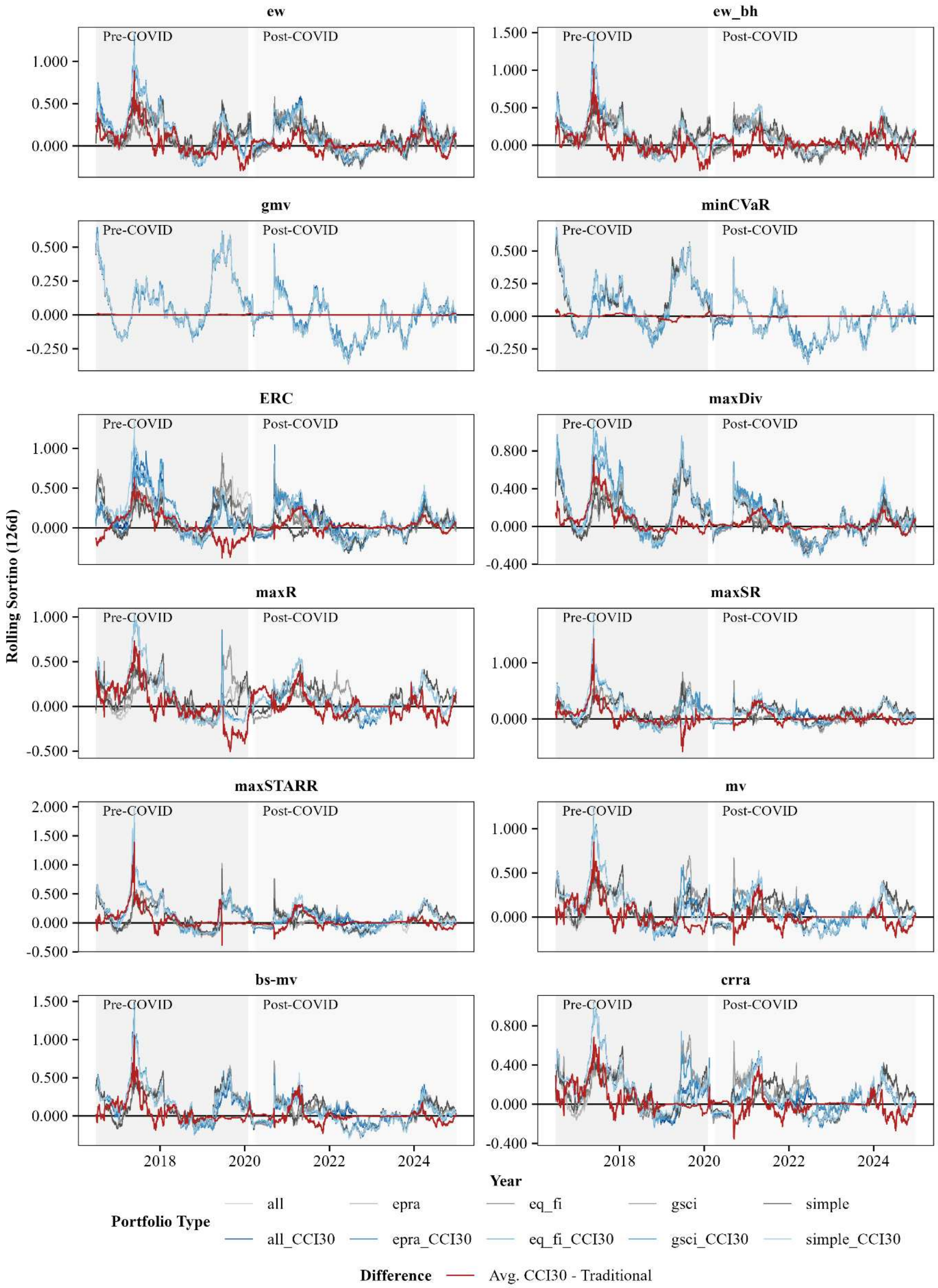

Figure 27: Rolling 126-Day Daily Sortino Across Strategies and Asset Spaces for Traditional vs. CCI30

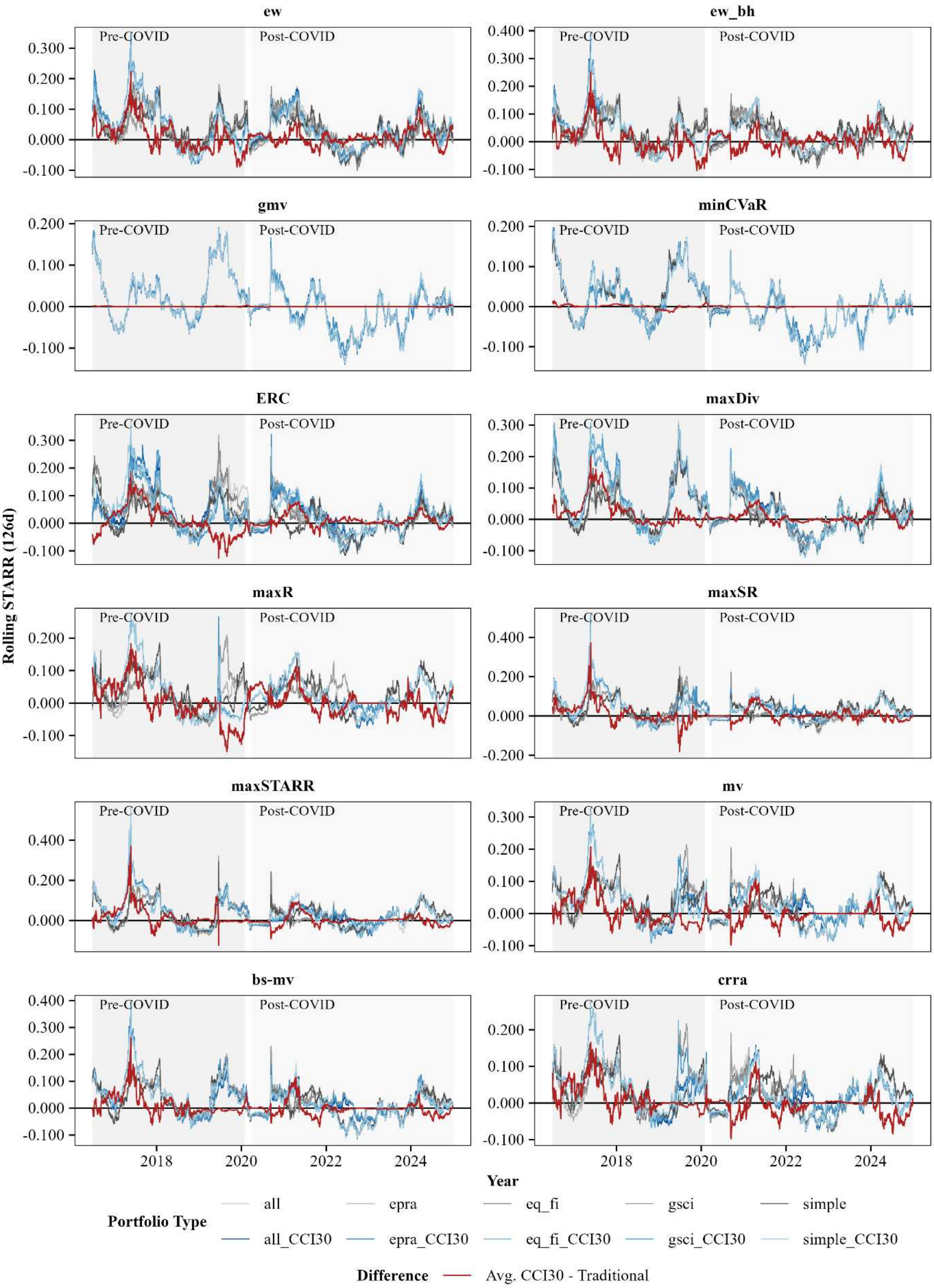

Figure 28: Rolling 126-Day Daily STARR Across Strategies and Asset Spaces for Traditional vs. CCI30

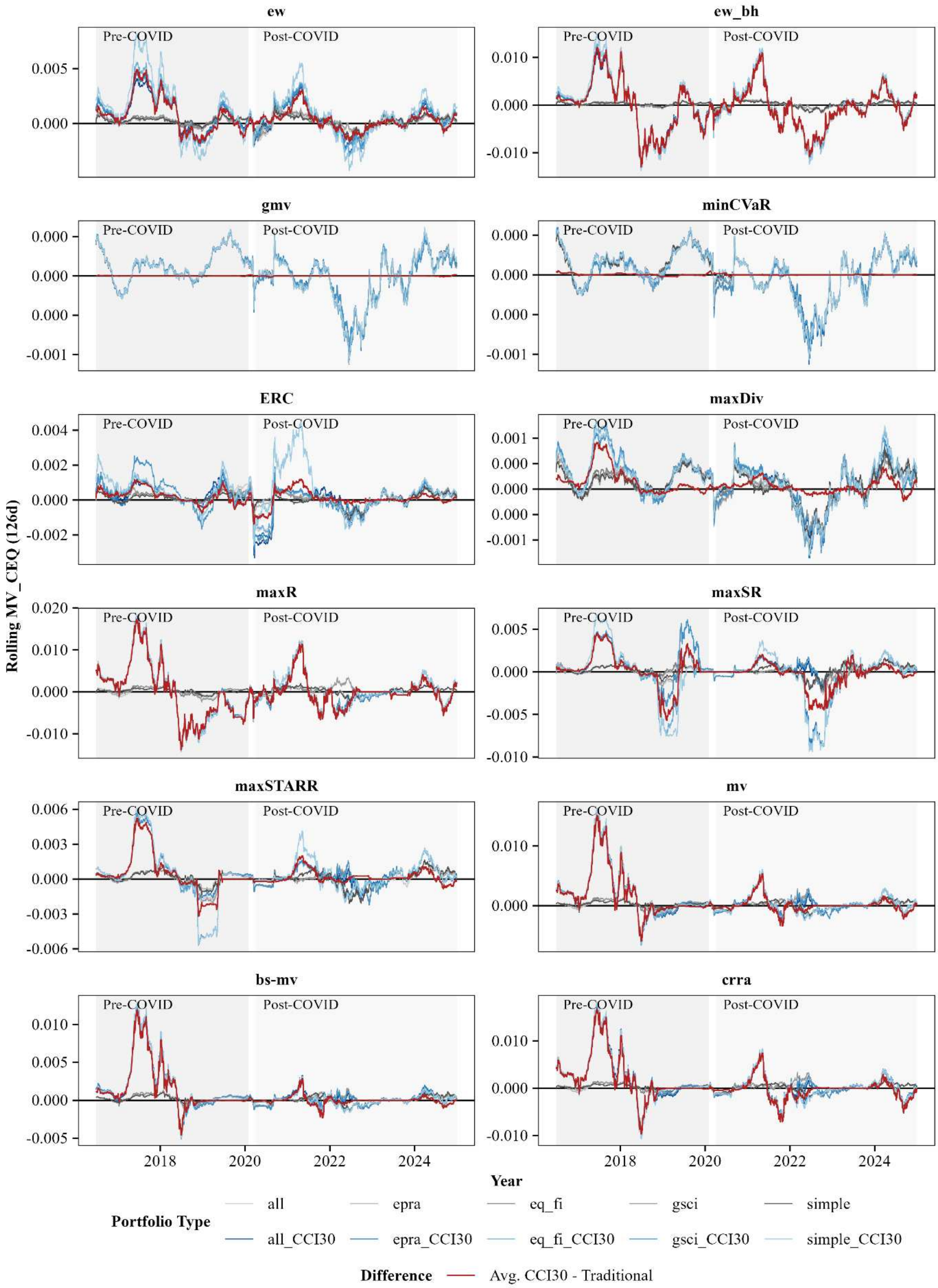

Figure 29: Rolling 126-Day Daily MV CEQ Returns Across Strategies and Asset Spaces for Traditional vs. CCI30

Note: MV CEQ Returns are calculated based on a risk aversion of $\gamma = 3$

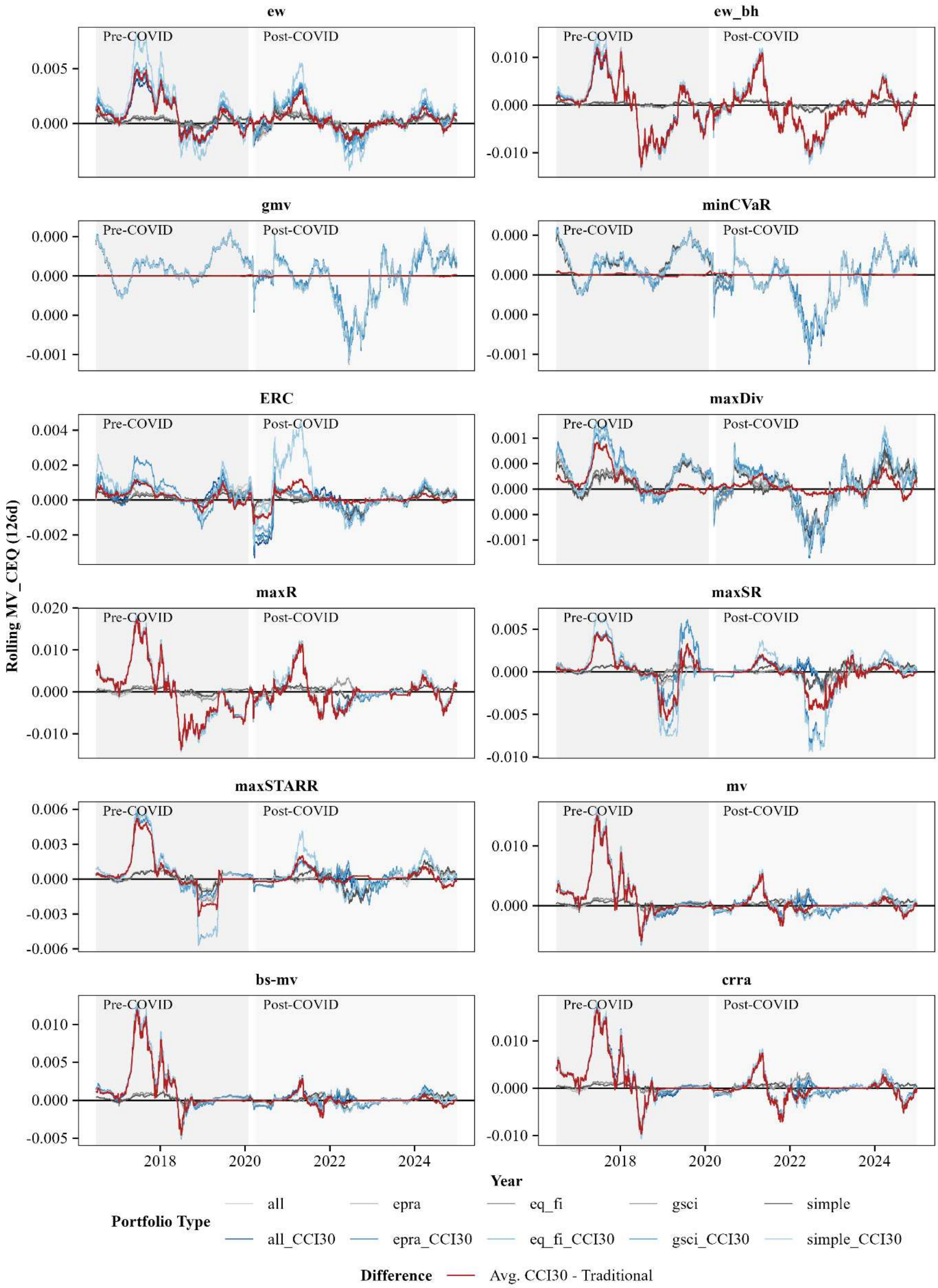

Figure 30: Rolling 126-Day Daily CRRA CEQ Return Across Strategies and Asset Spaces for Traditional vs. CCI30

Note: CRRA CEQ Returns are calculated based on a risk aversion of $\gamma = 3$

A.19 Panel Regression Analysis – Crypto x YearFE

Regression Analysis: Crypto x YearFE
Trad. and CCI30 Portfolios

	SR	Sortino	STARR	MV_CEQ	CRRA CEQ
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Intercept	0.088 ***	0.257 ***	0.090 ***	0.000 ***	0.000 ***
Crypto	0.045 ***	0.146 ***	0.050 ***	0.001 ***	0.001 ***
YearFE_2017	0.125 ***	0.211 ***	0.077 ***	0.000 ***	0.000 ***
YearFE_2018	-0.083 ***	-0.096 ***	-0.039 ***	-0.000 ***	-0.000 ***
YearFE_2019	0.093 ***	0.190 ***	0.067 ***	0.000 ***	0.000 ***
YearFE_2020	0.071 ***	0.180 ***	0.061 ***	-0.000 **	-0.000 **
YearFE_2021	-0.006	-0.052 ***	-0.017 **	0.000 *	0.000 *
YearFE_2022	-0.169 ***	-0.278 ***	-0.107 ***	-0.001 ***	-0.001 ***
YearFE_2023	-0.057 ***	-0.036	-0.017 *	0.000 ***	0.000 ***
YearFE_2024	-0.010	-0.075 ***	-0.025 ***	0.000 ***	0.000 ***
StrategyFE_ew_bh	0.000	0.010	0.005	-0.000 *	-0.000 *
StrategyFE_gmv	-0.057 ***	-0.134 ***	-0.051 ***	-0.000 ***	-0.000 ***
StrategyFE_minCVaR	-0.064 ***	-0.151 ***	-0.057 ***	-0.000 ***	-0.000 ***
StrategyFE_ERC	-0.006	-0.016	-0.006	-0.000 ***	-0.000 ***
StrategyFE_maxDiv	-0.003	-0.007	-0.004	-0.000 ***	-0.000 ***
StrategyFE_maxR	-0.005	0.001	0.001	-0.000	-0.000
StrategyFE_maxSR	0.008	0.006	0.003	-0.000 ***	-0.000 ***
StrategyFE_maxSTARR	0.003	-0.014	-0.005	-0.000 ***	-0.000 ***
StrategyFE_mv	0.002	0.007	0.002	0.000	0.000
StrategyFE_bs-mv	-0.009	-0.015	-0.006	0.000	0.000
StrategyFE_crra	0.007	0.028	0.010	0.000	0.000
AssetSpaceFE_eq_fi	0.002	0.015	0.004	-0.000	-0.000
AssetSpaceFE_gsci	0.006	0.011	0.004	0.000	0.000
AssetSpaceFE_epra	-0.000	0.012	0.004	-0.000	-0.000
AssetSpaceFE_all	0.003	0.005	0.002	-0.000	-0.000
Crypto x YearFE_2017	0.073 ***	0.442 ***	0.150 ***	0.004 ***	0.004 ***
Crypto x YearFE_2018	-0.116 ***	-0.317 ***	-0.111 ***	-0.003 ***	-0.003 ***
Crypto x YearFE_2019	-0.094 ***	-0.245 ***	-0.083 ***	-0.001 ***	-0.001 ***
Crypto x YearFE_2020	-0.034 **	-0.108 ***	-0.035 **	-0.001 ***	-0.001 ***
Crypto x YearFE_2021	-0.012	-0.109 ***	-0.039 ***	-0.001 **	-0.001 **
Crypto x YearFE_2022	-0.053 ***	-0.165 ***	-0.055 ***	-0.002 ***	-0.002 ***
Crypto x YearFE_2023	-0.043 **	-0.187 ***	-0.064 ***	-0.001 ***	-0.001 ***
Crypto x YearFE_2024	-0.053 ***	-0.125 ***	-0.044 ***	-0.001 ***	-0.001 ***
Adj. R^2	0.153	0.119	0.121	0.094	0.091

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Panel Regression Analysis Including Interaction Term – Crypto x YearFE

A.20 Robustness Tests – RQ2

(1) When BTC is used instead of CCI30, mean returns increase in more scenarios post-COVID, but the average increase is 8.4 pp smaller. Standard deviations increase by a lower extent and in fewer scenarios post-COVID. Similar to the CCI30 portfolios, the BTC portfolios exhibit increased downside and tail risk measures in almost all scenarios in both subperiods, but by a lower magnitude post-COVID. When using BTC, more of these increases are of statistical significance. Risk-adjusted return measures increase in most scenarios in both subperiods. However, these increases are only statistically significant for certain strategies in either of the periods, which again is similar to the results obtained with CCI30. Additionally, also in this setting, SRs increase stronger post-COVID, while Sortino Ratios and STARRs increase stronger pre-COVID. Utility-based measures still increase in most considered scenarios, but generally by a lower extent than when adding CCI30. The observed differences between the pre- and post-COVID periods are thus smaller when BTC is used. The results for turnover, cumulative wealth, and IRs are mainly similar. Therefore, the core results hold, even though minor differences between using BTC and CCI30 can be observed. Adding BTC can improve the performance pre- and post-COVID similarly to adding CCI30. However, different strategies yield the best improvements, and different magnitudes can be observed between the periods.

Tables with the detailed results of the conducted robustness test can be downloaded under the following link:

Download Link – Robustness Test RQ2

A.21 Strategy Comparison – EW vs. All Within CCI30

Strategy Comparison: EW vs. All Within CCI30

Descriptive Statistics (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	Mean			StdDev			Skew	Kurt
ew	simple	0.356			0.274			-0.532	7.092
gmv	simple	0.013	***	▽	0.038	***	△	-0.425	7.422
minCVaR	simple	0.013	***	▽	0.038	***	△	-0.443	7.487
ERC	simple	0.166	**	▽	0.153	***	△	-1.753	33.412
maxDiv	simple	0.055	***	▽	0.050	***	△	-0.755	10.980
maxR	simple	0.769	**	△	0.676	***	▽	-0.553	8.125
maxSR	simple	0.113	**	▽	0.317		▽	-1.372	27.811
maxSTARR	simple	0.145	**	▽	0.183	***	△	-1.586	33.536
mv	simple	0.493		△	0.385	***	▽	-0.238	21.279
bs-mv	simple	0.346		▽	0.291		▽	-0.213	29.378
crra	simple	0.658	**	△	0.530	***	▽	-0.378	12.568
ew	eq_fi	0.238			0.178			-0.684	8.476
gmv	eq_fi	0.013	***	▽	0.037	***	△	-0.588	7.391
minCVaR	eq_fi	0.011	***	▽	0.038	***	△	-0.236	6.373
ERC	eq_fi	0.057	***	▽	0.100	***	△	-2.253	43.793
maxDiv	eq_fi	0.056	***	▽	0.051	***	△	-1.059	11.468
maxR	eq_fi	0.746	**	△	0.674	***	▽	-0.556	8.213
maxSR	eq_fi	0.092		▽	0.318	***	▽	-1.081	29.096
maxSTARR	eq_fi	0.093	**	▽	0.157		△	-2.208	47.560
mv	eq_fi	0.480	*	△	0.379	***	▽	-0.194	20.744
bs-mv	eq_fi	0.326		△	0.281	***	▽	-0.202	28.147
crra	eq_fi	0.641	**	△	0.519	***	▽	-0.390	12.620
ew	gsci	0.213			0.159			-0.839	8.904
gmv	gsci	0.013	***	▽	0.036	***	△	-0.622	7.847
minCVaR	gsci	0.011	***	▽	0.037	***	△	-0.354	6.560
ERC	gsci	0.061	***	▽	0.107	***	△	-2.071	29.562
maxDiv	gsci	0.052	***	▽	0.049	***	△	-1.027	10.214
maxR	gsci	0.766	**	△	0.678	***	▽	-0.559	7.992
maxSR	gsci	0.250		△	0.266	***	▽	1.106	26.537
maxSTARR	gsci	0.156		▽	0.147		△	-0.097	10.972
mv	gsci	0.522	**	△	0.388	***	▽	-0.196	18.353
bs-mv	gsci	0.346		△	0.282	***	▽	-0.220	25.480
crra	gsci	0.679	***	△	0.509	***	▽	-0.349	12.404
ew	epra	0.207			0.162			-0.904	10.248
gmv	epra	0.013	***	▽	0.037	***	△	-0.593	7.369
minCVaR	epra	0.011	***	▽	0.038	***	△	-0.260	6.431
ERC	epra	0.048	***	▽	0.097	***	△	-3.615	79.378
maxDiv	epra	0.056	***	▽	0.052	***	△	-1.046	11.712
maxR	epra	0.742	**	△	0.674	***	▽	-0.555	8.219
maxSR	epra	0.099		▽	0.317	***	▽	-1.093	29.514
maxSTARR	epra	0.097	*	▽	0.154		△	-2.326	51.006
mv	epra	0.478	**	△	0.379	***	▽	-0.192	20.765
bs-mv	epra	0.332		△	0.278	***	▽	-0.150	27.606
crra	epra	0.638	**	△	0.511	***	▽	-0.414	12.905
ew	all	0.190			0.148			-1.077	10.924
gmv	all	0.013	***	▽	0.036	***	△	-0.626	7.831
minCVaR	all	0.011	***	▽	0.037	***	△	-0.371	6.576
ERC	all	0.051	***	▽	0.102	***	△	-4.062	68.181
maxDiv	all	0.052	***	▽	0.049	***	△	-1.029	10.341
maxR	all	0.766	***	△	0.678	***	▽	-0.559	7.988
maxSR	all	0.241		△	0.263	***	▽	1.153	27.611
maxSTARR	all	0.146		▽	0.142		△	-0.066	11.579
mv	all	0.509	**	△	0.388	***	▽	-0.189	18.319
bs-mv	all	0.342		△	0.278	***	▽	-0.172	25.492
crra	all	0.646	**	△	0.508	***	▽	-0.348	12.137

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21. △ indicates improvement, ▽ indicates deterioration

Table 24: Strategy Comparison: EW vs. Other Strategies Within CCI30 – Descriptive Statistics

Strategy Comparison: EW vs. All Within CCI30

Tail Risk Measures (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	Max. Drawdown		CVaR95		Downside Dev	
ew	simple	0.499		0.041		0.190	
gmv	simple	0.169 ***	△	0.006 ***	△	0.027 ***	△
minCVaR	simple	0.172 ***	△	0.006 ***	△	0.027 ***	△
ERC	simple	0.362	△	0.023 ***	△	0.111 ***	△
maxDiv	simple	0.186 ***	△	0.007 ***	△	0.035 ***	△
maxR	simple	0.955 ***	▽	0.105 ***	▽	0.470 ***	▽
maxSR	simple	0.745 *	▽	0.051	▽	0.237	▽
maxSTARR	simple	0.505	▽	0.027 ***	△	0.134 **	△
mv	simple	0.570	▽	0.056 **	▽	0.258 **	▽
bs-mv	simple	0.462	△	0.041	△	0.195	▽
crra	simple	0.701 *	▽	0.083 ***	▽	0.361 ***	▽
ew	eq_fi	0.364		0.027		0.125	
gmv	eq_fi	0.177 **	△	0.005 ***	△	0.027 ***	△
minCVaR	eq_fi	0.185 **	△	0.005 ***	△	0.027 ***	△
ERC	eq_fi	0.335	△	0.015 ***	△	0.076 ***	△
maxDiv	eq_fi	0.211 **	△	0.007 ***	△	0.036 ***	△
maxR	eq_fi	0.953 ***	▽	0.105 ***	▽	0.470 ***	▽
maxSR	eq_fi	0.706 **	▽	0.051 ***	▽	0.235 ***	▽
maxSTARR	eq_fi	0.531	▽	0.023	△	0.118	△
mv	eq_fi	0.588 **	▽	0.055 ***	▽	0.254 ***	▽
bs-mv	eq_fi	0.466	▽	0.040 **	▽	0.189 ***	▽
crra	eq_fi	0.702 ***	▽	0.081 ***	▽	0.353 ***	▽
ew	gsci	0.323		0.024		0.113	
gmv	gsci	0.159 **	△	0.005 ***	△	0.026 ***	△
minCVaR	gsci	0.171 **	△	0.005 ***	△	0.027 ***	△
ERC	gsci	0.350	▽	0.017 ***	△	0.082 ***	△
maxDiv	gsci	0.171 **	△	0.007 ***	△	0.035 ***	△
maxR	gsci	0.953 ***	▽	0.105 ***	▽	0.473 ***	▽
maxSR	gsci	0.431	▽	0.039 ***	▽	0.171 **	▽
maxSTARR	gsci	0.279	△	0.023	△	0.102	△
mv	gsci	0.604 ***	▽	0.057 ***	▽	0.261 ***	▽
bs-mv	gsci	0.484	▽	0.041 ***	▽	0.190 ***	▽
crra	gsci	0.680 ***	▽	0.078 ***	▽	0.345 ***	▽
ew	epra	0.352		0.024		0.115	
gmv	epra	0.178 **	△	0.005 ***	△	0.027 ***	△
minCVaR	epra	0.185 **	△	0.006 ***	△	0.027 ***	△
ERC	epra	0.368	▽	0.014 ***	△	0.076 ***	△
maxDiv	epra	0.216 **	△	0.008 ***	△	0.037 ***	△
maxR	epra	0.953 ***	▽	0.105 ***	▽	0.470 ***	▽
maxSR	epra	0.687 **	▽	0.051 ***	▽	0.234 ***	▽
maxSTARR	epra	0.524	▽	0.023	△	0.116	▽
mv	epra	0.600 **	▽	0.055 ***	▽	0.254 ***	▽
bs-mv	epra	0.459	▽	0.039 **	▽	0.186 ***	▽
crra	epra	0.692 ***	▽	0.080 ***	▽	0.348 ***	▽
ew	all	0.311		0.022		0.106	
gmv	all	0.160 *	△	0.005 ***	△	0.026 ***	△
minCVaR	all	0.173 *	△	0.005 ***	△	0.027 ***	△
ERC	all	0.371	▽	0.015 ***	△	0.081 ***	△
maxDiv	all	0.176 **	△	0.007 ***	△	0.036 ***	△
maxR	all	0.953 ***	▽	0.105 ***	▽	0.473 ***	▽
maxSR	all	0.434	▽	0.038 ***	▽	0.169 ***	▽
maxSTARR	all	0.283	△	0.023	▽	0.099	△
mv	all	0.616 ***	▽	0.057 ***	▽	0.261 ***	▽
bs-mv	all	0.478	▽	0.040 ***	▽	0.187 ***	▽
crra	all	0.705 ***	▽	0.078 ***	▽	0.345 ***	▽

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21. △ indicates improvement, ▽ indicates deterioration

Table 25: Strategy Comparison: EW vs. Other Strategies Within CCI30 – Drawdown and Tail Risk

Strategy Comparison: EW vs. All Within CCI30

Risk-Reward Measures (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	Sharpe Ratio		Adj. SR		Sortino Ratio		STARR	
ew	simple	0.715		0.562		1.767		0.032	
gmv	simple	-0.114 ***	▽	-0.114 *	▽	-0.207 ***	▽	-0.004 ***	▽
minCVaR	simple	-0.111 ***	▽	-0.112 *	▽	-0.207 ***	▽	-0.004 ***	▽
ERC	simple	0.644	▽	0.152	▽	1.328	▽	0.025	▽
maxDiv	simple	0.462 *	▽	0.390	▽	1.004	▽	0.019	▽
maxR	simple	0.606	▽	0.497	▽	1.595	▽	0.028	▽
maxSR	simple	0.213 ***	▽	0.191	▽	0.399 ***	▽	0.007 ***	▽
maxSTARR	simple	0.360 *	▽	0.261	▽	0.946	▽	0.018	▽
mv	simple	0.549	▽	0.391	▽	1.834	△	0.034	△
bs-mv	simple	0.486	▽	0.337	▽	1.678	▽	0.032	▽
crra	simple	0.616	▽	0.470	▽	1.771	△	0.031	▽
ew	eq_fi	0.678		0.516		1.756		0.033	
gmv	eq_fi	-0.115 ***	▽	-0.116	▽	-0.219 ***	▽	-0.004 ***	▽
minCVaR	eq_fi	-0.148 ***	▽	-0.148 *	▽	-0.285 ***	▽	-0.006 ***	▽
ERC	eq_fi	0.345 ***	▽	0.225	▽	0.500 **	▽	0.010 **	▽
maxDiv	eq_fi	0.423 **	▽	0.355	▽	0.999 *	▽	0.019 *	▽
maxR	eq_fi	0.597	▽	0.491	▽	1.546	▽	0.027	▽
maxSR	eq_fi	0.213 ***	▽	0.193	▽	0.314 **	▽	0.006 **	▽
maxSTARR	eq_fi	0.227 **	▽	0.185	▽	0.629 *	▽	0.013 *	▽
mv	eq_fi	0.539	▽	0.395	▽	1.815	△	0.033	△
bs-mv	eq_fi	0.463	▽	0.340	▽	1.625	▽	0.031	▽
crra	eq_fi	0.613	▽	0.468	▽	1.761	△	0.030	▽
ew	gsci	0.696		0.504		1.721		0.032	
gmv	gsci	-0.111 ***	▽	-0.112	▽	-0.197 ***	▽	-0.004 ***	▽
minCVaR	gsci	-0.160 ***	▽	-0.160 *	▽	-0.278 ***	▽	-0.005 ***	▽
ERC	gsci	0.284 **	▽	0.228	▽	0.519 ***	▽	0.010 **	▽
maxDiv	gsci	0.441 **	▽	0.371	▽	0.928 **	▽	0.018 *	▽
maxR	gsci	0.620	▽	0.505	△	1.579	▽	0.028	▽
maxSR	gsci	0.869	△	0.282	▽	1.345	▽	0.024	▽
maxSTARR	gsci	0.531	▽	0.458	▽	1.335	▽	0.023	▽
mv	gsci	0.600	▽	0.423	▽	1.929	△	0.035	△
bs-mv	gsci	0.512	▽	0.360	▽	1.720	▽	0.032	▽
crra	gsci	0.667	▽	0.488	▽	1.910	△	0.034	△
ew	epra	0.664		0.473		1.641		0.031	
gmv	epra	-0.114 ***	▽	-0.114	▽	-0.217 ***	▽	-0.004 ***	▽
minCVaR	epra	-0.146 ***	▽	-0.146	▽	-0.286 ***	▽	-0.006 ***	▽
ERC	epra	0.268 **	▽	0.161	▽	0.380 **	▽	0.008 **	▽
maxDiv	epra	0.420 *	▽	0.353	▽	0.991 *	▽	0.019	▽
maxR	epra	0.593	▽	0.489	△	1.538	▽	0.027	▽
maxSR	epra	0.239 ***	▽	0.212	▽	0.343 **	▽	0.006 **	▽
maxSTARR	epra	0.242 **	▽	0.189	▽	0.673	▽	0.014	▽
mv	epra	0.537	▽	0.394	▽	1.808	△	0.033	△
bs-mv	epra	0.481	▽	0.347	▽	1.679	△	0.032	△
crra	epra	0.622	▽	0.466	▽	1.779	△	0.031	▽
ew	all	0.679		0.454		1.605		0.031	
gmv	all	-0.110 ***	▽	-0.111	▽	-0.197 ***	▽	-0.004 ***	▽
minCVaR	all	-0.163 ***	▽	-0.163	▽	-0.288 ***	▽	-0.006 ***	▽
ERC	all	0.297 **	▽	0.163	▽	0.400 **	▽	0.009 **	▽
maxDiv	all	0.431 **	▽	0.365	▽	0.913 *	▽	0.018 *	▽
maxR	all	0.621	▽	0.505	△	1.580	▽	0.028	▽
maxSR	all	0.819	△	0.316	▽	1.306	▽	0.023	▽
maxSTARR	all	0.485	▽	0.427	▽	1.272	▽	0.022	▽
mv	all	0.582	▽	0.421	▽	1.878	△	0.034	△
bs-mv	all	0.514	▽	0.363	▽	1.726	△	0.032	△
crra	all	0.625	▽	0.479	△	1.815	△	0.032	△

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: Significance based on Ledoit & Wolf for SR and a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21 for other measures. △ indicates improvement, ▽ indicates deterioration

Table 26: Strategy Comparison: EW vs. Other Strategies Within CCI30 – Risk-Adjusted Returns

Strategy Comparison: EW vs. All Within CCI30

Utility based Measures (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	MV CEQ		CRRA CEQ	
ew	simple	0.275		0.273	
gmv	simple	0.011 **	▽	0.011 **	▽
minCVaR	simple	0.011 **	▽	0.011 **	▽
ERC	simple	0.140	▽	0.139	▽
maxDiv	simple	0.052 *	▽	0.052 *	▽
maxR	simple	0.087	▽	0.038	▽
maxSR	simple	-0.037 ***	▽	-0.045 ***	▽
maxSTARR	simple	0.100	▽	0.098 *	▽
mv	simple	0.311	△	0.302	△
bs-mv	simple	0.245	▽	0.242	▽
crra	simple	0.267	▽	0.243	▽
ew	eq_fi	0.210		0.210	
gmv	eq_fi	0.011 ***	▽	0.011 **	▽
minCVaR	eq_fi	0.009 ***	▽	0.009 **	▽
ERC	eq_fi	0.043 **	▽	0.042 **	▽
maxDiv	eq_fi	0.053 **	▽	0.053 **	▽
maxR	eq_fi	0.065	▽	0.018	▽
maxSR	eq_fi	-0.058 **	▽	-0.065 **	▽
maxSTARR	eq_fi	0.058 **	▽	0.056 **	▽
mv	eq_fi	0.303	△	0.296	△
bs-mv	eq_fi	0.231	△	0.228	△
crra	eq_fi	0.268	△	0.246	△
ew	gsci	0.192		0.191	
gmv	gsci	0.011 ***	▽	0.011 ***	▽
minCVaR	gsci	0.009 ***	▽	0.009 ***	▽
ERC	gsci	0.045 ***	▽	0.044 ***	▽
maxDiv	gsci	0.049 **	▽	0.049 **	▽
maxR	gsci	0.079	▽	0.030	▽
maxSR	gsci	0.154	▽	0.156	▽
maxSTARR	gsci	0.131	▽	0.131	▽
mv	gsci	0.346	△	0.338	△
bs-mv	gsci	0.255	△	0.252	△
crra	gsci	0.336	△	0.316	△
ew	epra	0.183		0.182	
gmv	epra	0.011 **	▽	0.011 **	▽
minCVaR	epra	0.009 **	▽	0.009 **	▽
ERC	epra	0.034 ***	▽	0.033 **	▽
maxDiv	epra	0.053 **	▽	0.053 **	▽
maxR	epra	0.062	▽	0.014	▽
maxSR	epra	-0.051 **	▽	-0.058 **	▽
maxSTARR	epra	0.063	▽	0.062 *	▽
mv	epra	0.301	△	0.293	△
bs-mv	epra	0.241	△	0.239	△
crra	epra	0.280	△	0.258	△
ew	all	0.170		0.169	
gmv	all	0.011 **	▽	0.011 **	▽
minCVaR	all	0.009 ***	▽	0.009 **	▽
ERC	all	0.036 ***	▽	0.035 ***	▽
maxDiv	all	0.049 **	▽	0.049 **	▽
maxR	all	0.079	▽	0.031	▽
maxSR	all	0.147	▽	0.148	▽
maxSTARR	all	0.122	▽	0.122	▽
mv	all	0.328	△	0.321	△
bs-mv	all	0.254	△	0.252	△
crra	all	0.296	△	0.277	△

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Significance based on a two-tailed block-bootstrapping procedure with 1 000 replications and block-length 21. △ indicates improvement, ▽ indicates deterioration

Table 27: Strategy Comparison: EW vs. Other Strategies Within CCI30 – Utility

Strategy Comparison: EW vs. All Within CCI30

Other Metrics (2016-2024) for Monthly Rebalancing

Strategy	Asset Space	Turnover	Cum. Wealth		IR
ew	simple	-	18.302		-
gmv	simple	0.022	0.119	▽	-1.352
minCVaR	simple	0.033	0.119	▽	-1.349
ERC	simple	0.122	3.206	▽	-1.012
maxDiv	simple	0.023	0.645	▽	-1.312
maxR	simple	0.330	144.327	△	0.739
maxSR	simple	0.239	0.778	▽	-1.202
maxSTARR	simple	0.339	2.307	▽	-1.099
mv	simple	0.269	48.097	△	0.587
bs-mv	simple	0.252	15.911	▽	-0.087
crra	simple	0.327	120.111	△	0.829
ew	eq_fi	-	6.941		-
gmv	eq_fi	0.030	0.117	▽	-1.389
minCVaR	eq_fi	0.088	0.097	▽	-1.391
ERC	eq_fi	0.073	0.619	▽	-1.343
maxDiv	eq_fi	0.072	0.659	▽	-1.328
maxR	eq_fi	0.330	117.314	△	0.791
maxSR	eq_fi	0.392	0.459	▽	-0.806
maxSTARR	eq_fi	0.470	1.116	▽	-1.086
mv	eq_fi	0.380	43.568	△	0.937
bs-mv	eq_fi	0.368	13.410	△	0.408
crra	eq_fi	0.429	108.678	△	1.006
ew	gsci	-	5.479		-
gmv	gsci	0.034	0.124	▽	-1.379
minCVaR	gsci	0.066	0.101	▽	-1.387
ERC	gsci	0.174	0.674	▽	-1.410
maxDiv	gsci	0.077	0.602	▽	-1.336
maxR	gsci	0.239	138.219	△	0.857
maxSR	gsci	0.414	6.380	△	0.077
maxSTARR	gsci	0.428	2.859	▽	-0.482
mv	gsci	0.370	62.978	△	1.158
bs-mv	gsci	0.421	16.310	△	0.653
crra	gsci	0.421	162.460	△	1.233
ew	epra	-	5.098		-
gmv	epra	0.032	0.117	▽	-1.325
minCVaR	epra	0.089	0.097	▽	-1.327
ERC	epra	0.109	0.489	▽	-1.377
maxDiv	epra	0.084	0.661	▽	-1.245
maxR	epra	0.367	113.302	△	0.815
maxSR	epra	0.405	0.558	▽	-0.634
maxSTARR	epra	0.419	1.205	▽	-0.871
mv	epra	0.436	42.809	△	1.003
bs-mv	epra	0.417	14.306	△	0.612
crra	epra	0.514	109.731	△	1.074
ew	all	-	4.289		-
gmv	all	0.035	0.124	▽	-1.313
minCVaR	all	0.068	0.098	▽	-1.323
ERC	all	0.125	0.532	▽	-1.420
maxDiv	all	0.086	0.599	▽	-1.253
maxR	all	0.257	138.845	△	0.883
maxSR	all	0.428	5.836	△	0.149
maxSTARR	all	0.455	2.529	▽	-0.392
mv	all	0.421	55.648	△	1.135
bs-mv	all	0.455	15.909	△	0.753
crra	all	0.499	120.118	△	1.134

Note: Turnover is reported on a monthly basis without consideration of the weight drift between rebalancing periods. IR is calculated using the ew portfolio as the benchmark. △ indicates improvement, ▽ indicates deterioration

Table 28: Strategy Comparison: EW vs. Other Strategies Within CCI30 – Other Metrics

A.22 Average Differences in Performance Metrics EW vs. All

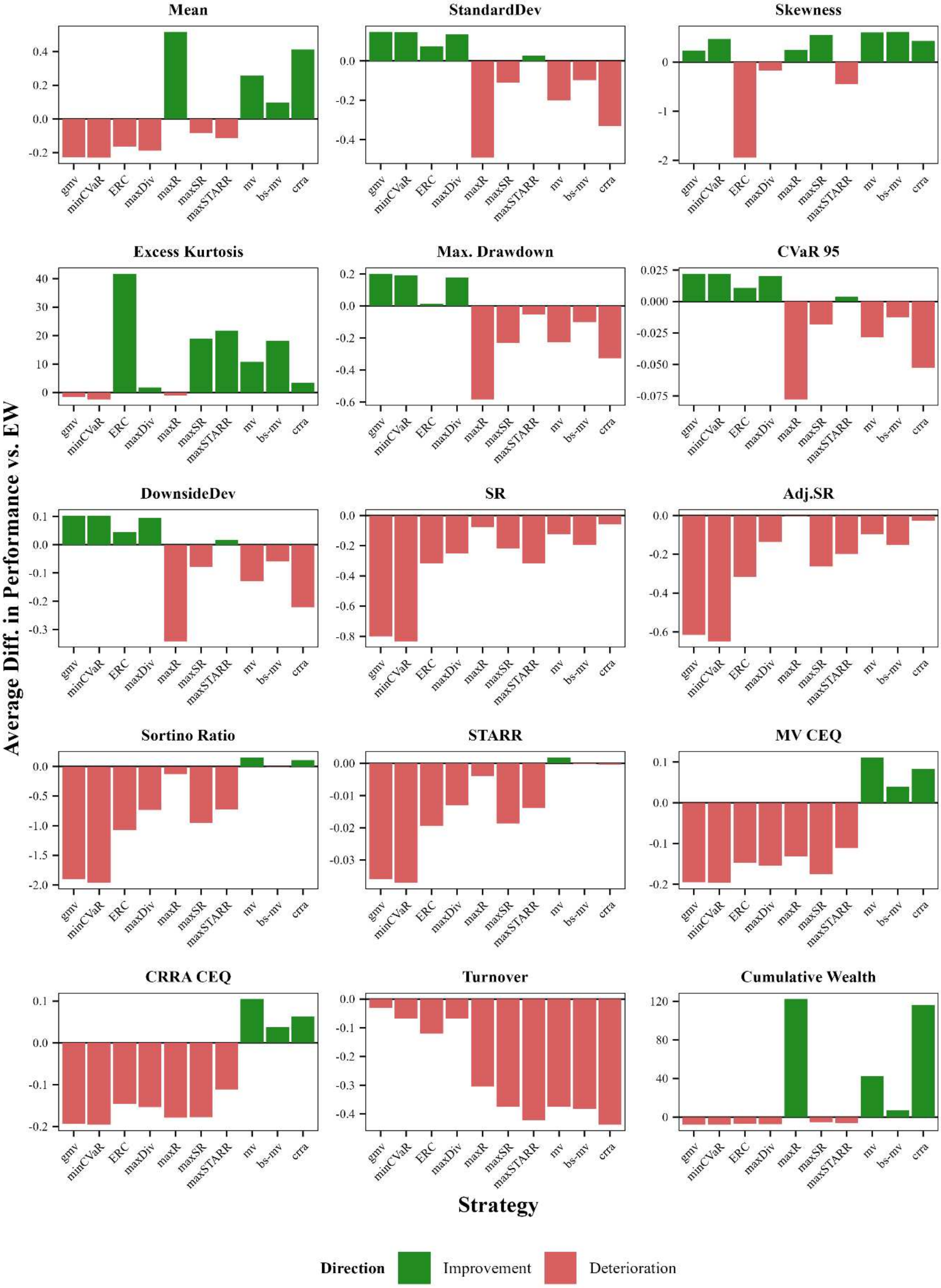

Figure 31: Average Difference of Performance Measures to EW per Strategy across Asset Spaces

Note: Differences of Performance Measures that indicate weaker performance when higher (e.g. Standard Deviation) are multiplied by -1 in the plots. The displayed differences are the average differences across asset spaces from the comparison of ew vs. each other strategy within CCI30 portfolios with monthly rebalancing.

A.23 Panel Regression Analysis – Crypto x StrategyFE

Regression Analysis: Crypto x StrategyFE

Trad. and CCI30 Portfolios

Variable	SR Coeff.	Sortino Coeff.	STARR Coeff.	MV_CEQ Coeff.	CRRA CEQ Coeff.
Intercept	0.107 ***	0.303 ***	0.106 ***	0.001 ***	0.001 ***
Crypto	0.008	0.052	0.018	0.001 ***	0.001 ***
StrategyFE_ew_bh	0.004	-0.001	0.001	0.000	0.000
StrategyFE_gmv	-0.054 ***	-0.110 ***	-0.042 ***	-0.000 **	-0.000 **
StrategyFE_minCVaR	-0.061 ***	-0.126 ***	-0.048 ***	-0.000 **	-0.000 **
StrategyFE_ERC	-0.010	-0.012	-0.005	-0.000	-0.000
StrategyFE_maxDiv	-0.013	-0.026	-0.010	-0.000	-0.000
StrategyFE_maxR	0.005	0.002	0.002	0.000	0.000
StrategyFE_maxSR	0.007	0.007	0.003	-0.000	-0.000
StrategyFE_maxSTARR	0.001	-0.007	-0.001	-0.000	-0.000
StrategyFE_mv	0.004	-0.005	-0.001	0.000	0.000
StrategyFE_bs-mv	-0.011	-0.033	-0.011	-0.000	-0.000
StrategyFE_crra	0.007	0.017	0.006	0.000	0.000
YearFE_2017	0.161 ***	0.432 ***	0.152 ***	0.002 ***	0.002 ***
YearFE_2018	-0.141 ***	-0.254 ***	-0.095 ***	-0.002 ***	-0.002 ***
YearFE_2019	0.046 ***	0.068 ***	0.025 ***	-0.000 ***	-0.000 ***
YearFE_2020	0.054 ***	0.126 ***	0.044 ***	-0.000 ***	-0.001 ***
YearFE_2021	-0.012	-0.106 ***	-0.037 ***	-0.000	-0.000
YearFE_2022	-0.195 ***	-0.360 ***	-0.134 ***	-0.002 ***	-0.002 ***
YearFE_2023	-0.079 ***	-0.130 ***	-0.049 ***	-0.000 ***	-0.000 ***
YearFE_2024	-0.036 ***	-0.138 ***	-0.047 ***	-0.000	-0.000
AssetSpaceFE_eq_fi	0.002	0.015	0.004	-0.000	-0.000
AssetSpaceFE_gsci	0.006	0.011	0.004	0.000	0.000
AssetSpaceFE_epra	-0.000	0.012	0.004	-0.000	-0.000
AssetSpaceFE_all	0.003	0.005	0.002	-0.000	-0.000
Crypto x StrategyFE_ew_bh	-0.006	0.022	0.008	-0.001 *	-0.001 *
Crypto x StrategyFE_gmv	-0.007	-0.048	-0.018	-0.001 ***	-0.001 ***
Crypto x StrategyFE_minCVaR	-0.006	-0.049	-0.017	-0.001 ***	-0.001 ***
Crypto x StrategyFE_ERC	0.008	-0.008	-0.004	-0.000 **	-0.000 **
Crypto x StrategyFE_maxDiv	0.020	0.038	0.012	-0.000 ***	-0.000 ***
Crypto x StrategyFE_maxR	-0.021	-0.001	-0.000	-0.000	-0.000
Crypto x StrategyFE_maxSR	0.002	-0.001	-0.000	-0.001 ***	-0.001 ***
Crypto x StrategyFE_maxSTARR	0.003	-0.014	-0.007	-0.000	-0.000
Crypto x StrategyFE_mv	-0.005	0.024	0.006	0.000	0.000
Crypto x StrategyFE_bs-mv	0.004	0.036	0.010	0.000	0.000
Crypto x StrategyFE_crra	0.000	0.023	0.007	0.000	0.000
Adj. R^2	0.145	0.099	0.103	0.061	0.060

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 29: Panel Regression Analysis Including Interaction Term – Crypto x StrategyFE

A.24 Robustness Tests – RQ3

(1) When BTC is used instead of CCI30, hardly any substantial differences are observable in the descriptive statistics. The only notable differences are, that maxSTARR now exhibits more significant negative differences for mean returns and bs-mv displays a significantly lower standard deviation in the simple asset space. Most of the previously derived results regarding drawdown and tail risk measures are also confirmed. The main differences observable are (1) minCVaR does not outperform in terms of maximum drawdown in gsci and all anymore, (2) maxSR does not underperform in terms of maximum drawdown in eq_fi, (3) maxSTARR underperforms in maximum drawdown for epra and does not outperform in terms of CVaR and downside deviation in simple, and (4) bs-mv outperforms for downside deviation in simple but underperforms for maximum drawdown in gsci and all. Similarly to before, no strategy which significantly outperforms in any risk-adjusted return measure can be observed. Furthermore, one can still observe a significant underperformance from all risk-based approaches across almost all asset spaces, with only minor changes in the observed differences. The same holds for utility-based measures, where no significant outperformance is exhibited, and risk-based approaches consistently underperform compared to ew. Since the results of the other metrics (turnover, cumulative wealth, and IR) also do not change strongly, one can conclude that the previously derived results hold for portfolios where BTC is added as the crypto asset.

(2) The observed results change stronger when compared to the ew_bh strategies instead of ew. No strategy can significantly outperform in terms of mean returns anymore, with some (maxSR, maxSTARR and bs-mv) even significantly underperforming. However, several additional strategies outperform in terms of standard deviation, namely maxR, maxSR, maxSTARR, mv, and crra, since ew_bh exhibits higher volatility than ew with rebalancing. This is also observable for drawdown and tail risk measures, where no significant underperformance for any other strategy is observable, while several strategies join the 'outperformance' bracket. For risk-adjusted return measures, crra outperforms ew_bh at the 10% level for SRs, and the set of observable nonsignificant improvements in terms of SRs, Sortino Ratios and STARRs grew. The underperformances for risk-based approaches persist, however, with lower or no significance in certain strategy/asset space combinations. CRRA CEQ returns are significantly higher than for ew_bh when applying mv and crra across all asset spaces, and MV CEQ returns are higher in all but the simple asset space. Furthermore, all significant underperformances for utility-based metrics vanished. Regarding other metrics (turnover, cumulative wealth and IR), no substantial differences compared to the setting when comparing to ew can be observed. In summary, ew_bh gets more seriously challenged by other strategies, but there is still no strategy that can consistently outperform across all metric categories, even though utility-based approaches like mv and crra outperform in many metrics.

Tables with the detailed results of all conducted robustness tests can be downloaded under the following link: Download Link – Robustness Tests RQ3

A.25 Methodology DCC-GARCH Models

A.25.1 Theoretical Background

Recent literature applied various approaches to model crypto assets' returns and volatility. Munim et al. (2019) find that ARIMA models are well-suited to model crypto returns and partly even outperform neural network models. Regarding univariate volatility forecasts, previous researchers came to different conclusions and provided varying recommendations for the choice of the best-suiting models. Amongst the best-performing models are e.g. regular GARCH, Integrated GARCH (iGARCH), Exponential GARCH (eGARCH), Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) and Threshold GARCH (TGARCH), often in a simple (1,1) specification. Many more sophisticated models fail to deliver more reliable forecasts consistently. However, they mainly agree that the underlying distribution should consider heavy tails, e.g. via a t-student distribution (Bergsli et al., 2022; Chu et al., 2017; Fung et al., 2022; Köchling, Schmidtke, & Posch, 2020; Kumar, Jilowa, & Deokar, 2024; Queiroz & David, 2024). Other papers extend the previous results to a multivariate space and find DCC-GARCH models to be well-suited to model several crypto assets or a combination of traditional and crypto assets (Candila, 2021; Guesmi et al., 2019).

A.25.2 Model Formulations

All model formulations used in this thesis will be listed below. Those models are used, as they were found to be well suited by previous literature (compare section A.25.1). For all models, Y_t is the time-series value at time t, ϕ_0 is the constant term of the ARMA model, ϕ_i are the coefficients of the autoregressive terms, θ_i are the coefficients of the moving average terms, ϵ_t are the white noise error terms (i.i.d. with zero mean and variance σ^2), σ_t^2 is the conditional variance at time t, ω is the long-term average variance, α_1 is the coefficient for the lagged squared residual (ARCH term), β_1 is the coefficient for the lagged conditional variance (GARCH term), Z_{t-1} are the standardized residuals, γ_1 is the asymmetry term which allows different impacts for positive and negative shocks, $I_{(\epsilon_{t-1}<0)}$ is the indicator function for asymmetry, H_t is the time-varying covariance matrix, D_t is the diagonal matrix of time-varying standard deviations from a GARCH model, R_t is the time-varying correlation matrix and a and b are parameters that control the dynamics of the conditional correlations. In ARMA models, p is the autoregressive component, and q is the moving average component, whereas p and q denote the GARCH and ARCH terms in the GARCH models.

ARMA (p, q)

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t \tag{A7}$$

GARCH (1,1)

Following Bollerslev (1986), the GARCH(1,1) is defined as:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{A8}$$

iGARCH(1,1)

Following Engle and Bollerslev (1986), the iGARCH(1,1) is defined similarly to the standard GARCH(1,1) from Equation A8, but with the additional constraint of:

$$\alpha_1 + \beta_1 = 1 \tag{A9}$$

eGARCH(1,1)

Following Nelson (1991), the eGARCH(1,1) is defined as:

$$\ln(\sigma_t^2) = \omega + \alpha_1(|Z_{t-1}| - \mathbb{E}[|Z_{t-1}|]) + \gamma_1 Z_{t-1} + \beta_1 \ln(\sigma_{t-1}^2) \tag{A10}$$

GJR-GARCH(1,1)

Following Glosten et al. (1993), the GJR-GARCH(1,1), which allows asymmetric shocks, is defined as:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 I(\epsilon_{t-1} < 0)\epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{A11}$$

TGARCH(1,1)

Following Zakoian (1994), the TGARCH(1,1) is defined as:

$$\sigma_t = \omega + \alpha_1 |\epsilon_{t-1}| + \gamma_1 I(\epsilon_{t-1} < 0)|\epsilon_{t-1}| + \beta_1 \sigma_{t-1} \tag{A12}$$

This specification is very similar to the GJR-GARCH from Equation A11, but instead of using the squared shocks, it uses absolute shocks.

DCC-GARCH(1,1)

Following Engle (2002), the DCC-GARCH(1,1) for multivariate volatilities is defined as:

$$X_t = H_t^{1/2} Z_t,$$

$$Z_t \sim N(0,1) \quad (A13)$$

$$H_t = D_t R_t D_t \quad (A14)$$

Where each individual series is modelled as a univariate GARCH process and the dynamics of the correlations are captured by:

$$Q_t = (1 - a - b)Q + aZ_{t-1}Z_{t-1}^{\top} + bQ_{t-1} \quad (A15)$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \quad (A16)$$

A.25.3 Rolling Window Estimation Routine

The following steps are performed at each rebalancing to retrieve the mean and covariance forecasts based on a rolling 252-day window. The routine is performed for all asset spaces separately and subsequently used in the portfolio optimizations:

(1) An ARIMA model is fitted for each asset.
(2) For each asset, all five univariate GARCH models are fitted, using the previously derived ARIMA models as the mean term.
(3) Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values from the fitted GARCH models, the best GARCH model per asset per rebalancing date is identified.
(4) An LB and an ARCH test (with lag 21) are performed on the standardized residuals.
(5) A multivariate DCC-GARCH is estimated using the previously identified best-fitting univariate GARCH models for each asset.
(6) A one-day ahead forecast of the mean vector and covariance matrix is retrieved using the DCC-GARCH.

All GARCH models are implemented with a (1,1) specification and under a t-student distribution. The LB and ARCH tests provide evidence that the standardized residuals are mostly white noise, as they typically show no remaining serial correlation or ARCH effects.

The ARMA models are fitted with the *auto.arima* function from the R-package *forecast*, whereas univariate GARCH models are fitted with the R-package *rugarch* and the DCC-GARCH is fitted with the R-package *rmgarch* (Galanos, 2022; Galanos & Kley, 2024; Hyndman et al., 2025).

A.26 Download Link of Further Comparisons

Download Link – Further Comparisons

A.27 Cumulative Wealth Path Comparisons

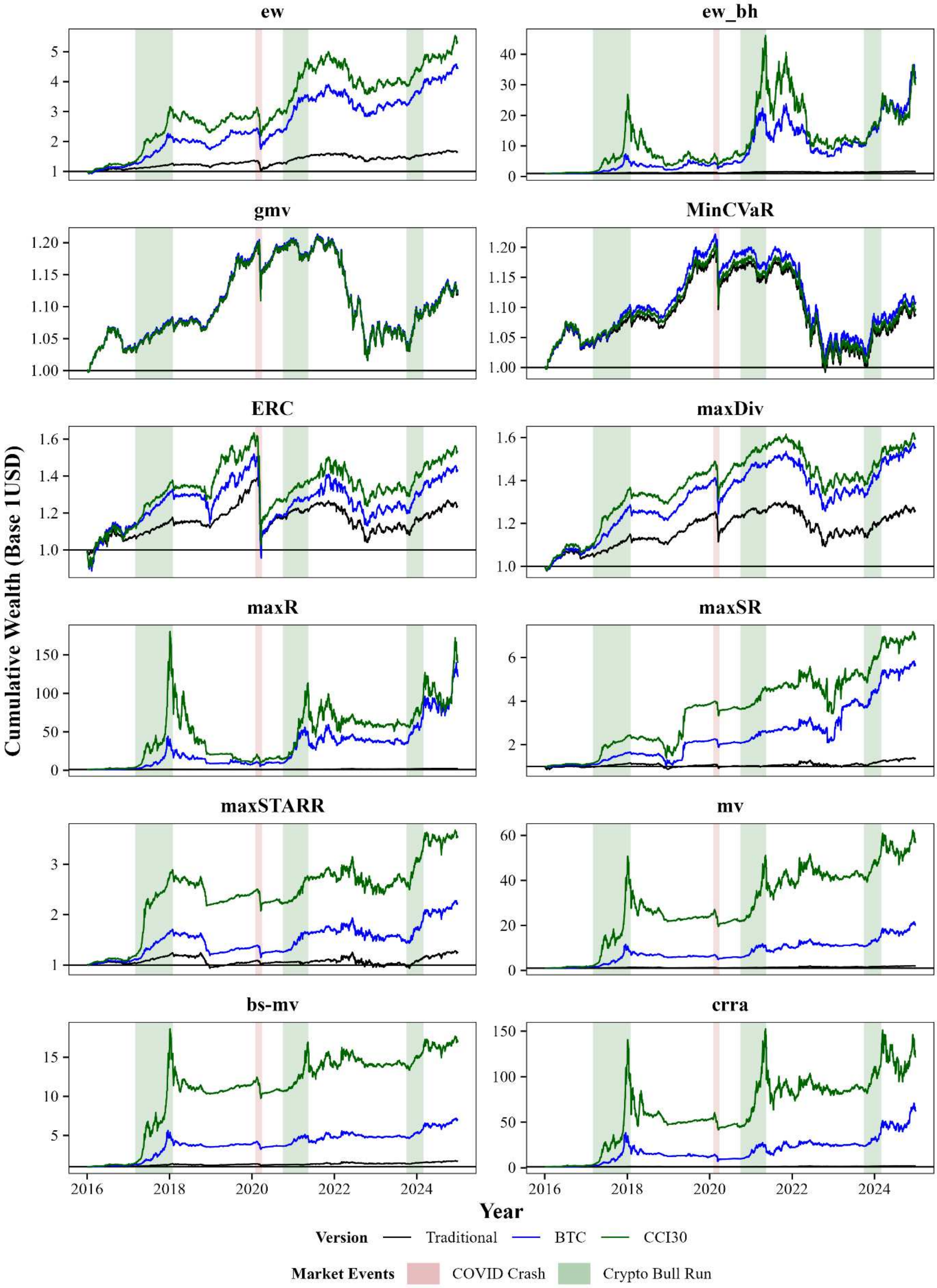

Figure 32: Cumulative Wealth Path Comparison of Strategies in the 'all' Asset Space
Note: The shaded green areas reflect prominent, observable long-term upwards movement of CCI30 and BTC prices and are not derived from a formal model.

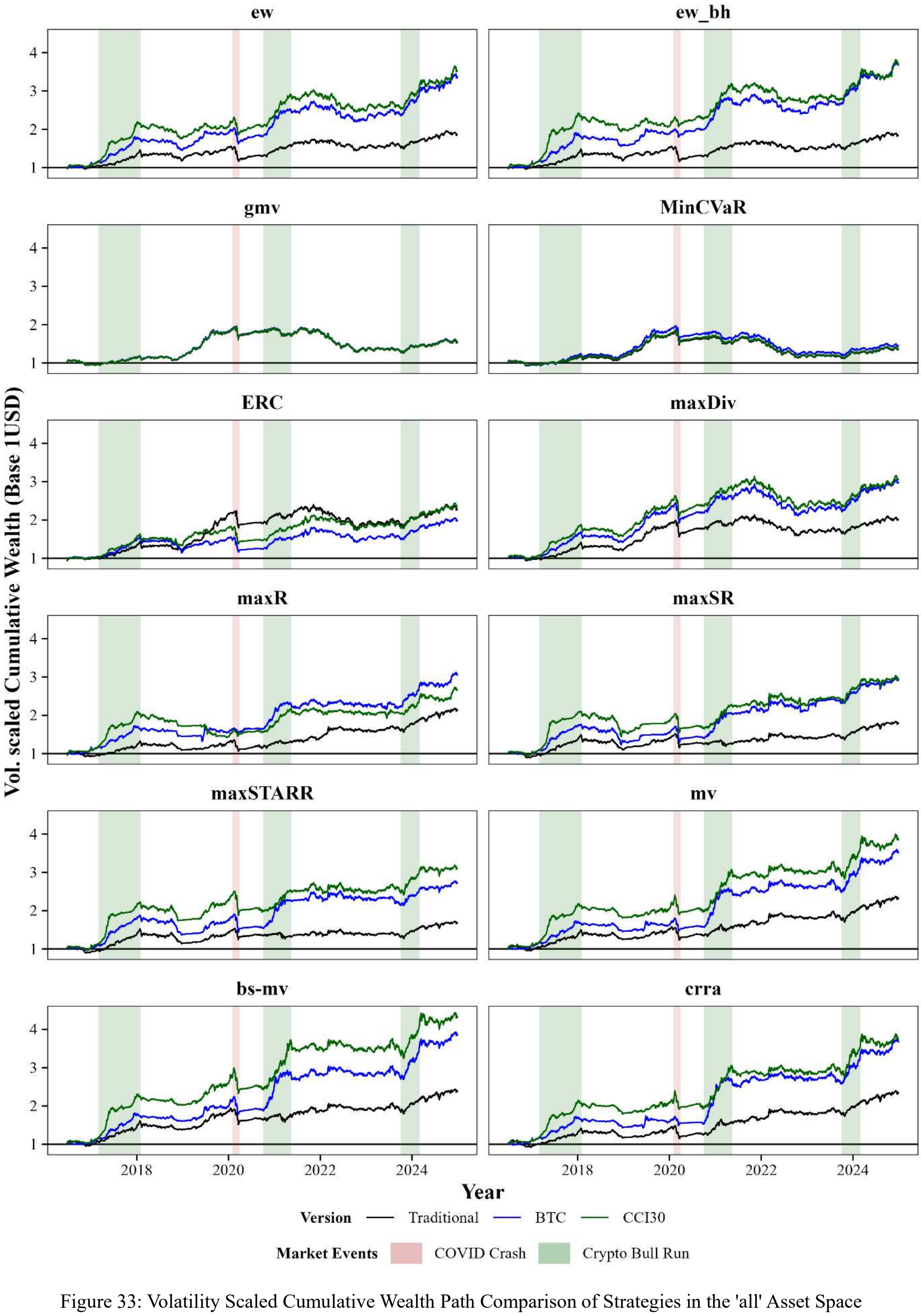

Figure 33: Volatility Scaled Cumulative Wealth Path Comparison of Strategies in the 'all' Asset Space

Note: Returns are adjusted based on 126-Day realized rolling volatility and scaled to a common annual volatility level of 10%. The shaded green areas reflect prominent, observable long-term upwards movement of CCI30 and BTC prices and are not derived from a formal model.

A.28 Download Link of Differences in Performance Metrics and CCI30 Price

Download Link – Differences in Performance Metrics and CCI30 Price

A.29 List of Comparable Assets for Indices Used

Asset used	Comparable Asset Name	Type	ISIN/CUSIP	Fund Size*
Traditional Assets				
MSCI.World	iShares Core MSCI World UCITS ETF	ETF	IE00B4L5Y983	107 356
MSCI.EM	iShares MSCI EM UCITS ETF	ETF	IE00B0M63177	5 173
FTSE.World.Gov.	iShares Global Govt Bond UCITS ETF	ETF	IE00B3F81K65	2 833
FTSE.US.Corp	iShares $ Corp Bond UCITS ETF	ETF	IE0032895942	8 104
S.P.GSCI	iShares S&P GSCI Commodity-Indexed Trust	Commodity Pool	46428R107	907
FTSE.EPRA.Dev.	HSBC FTSE EPRA NAREIT Developed UCITS ETF USD	ETF	IE00B5L01S80	1 446
Crypto Assets				
CCI30	n/a	n/a		-
BTC	iShares Bitcoin Trust ETF	ETF	46438F101	69 314

* in million USD, as of 4th of June 2025

Figure 34: List of Comparable Assets for Indices Used in Portfolio Optimization

The assets and information have been retrieved directly from iShares (2025a; 2025b; 2025c; 2025d; 2025e; 2025f) and HSBC (2025). Similar ETFs tracking the performance of such indices also exist from other asset managers. The products from iShares and HSBC have been selected, as their issued ETFs are amongst the largest per respective asset.

A.30 Average Performance Measures per Strategy (CCI30)

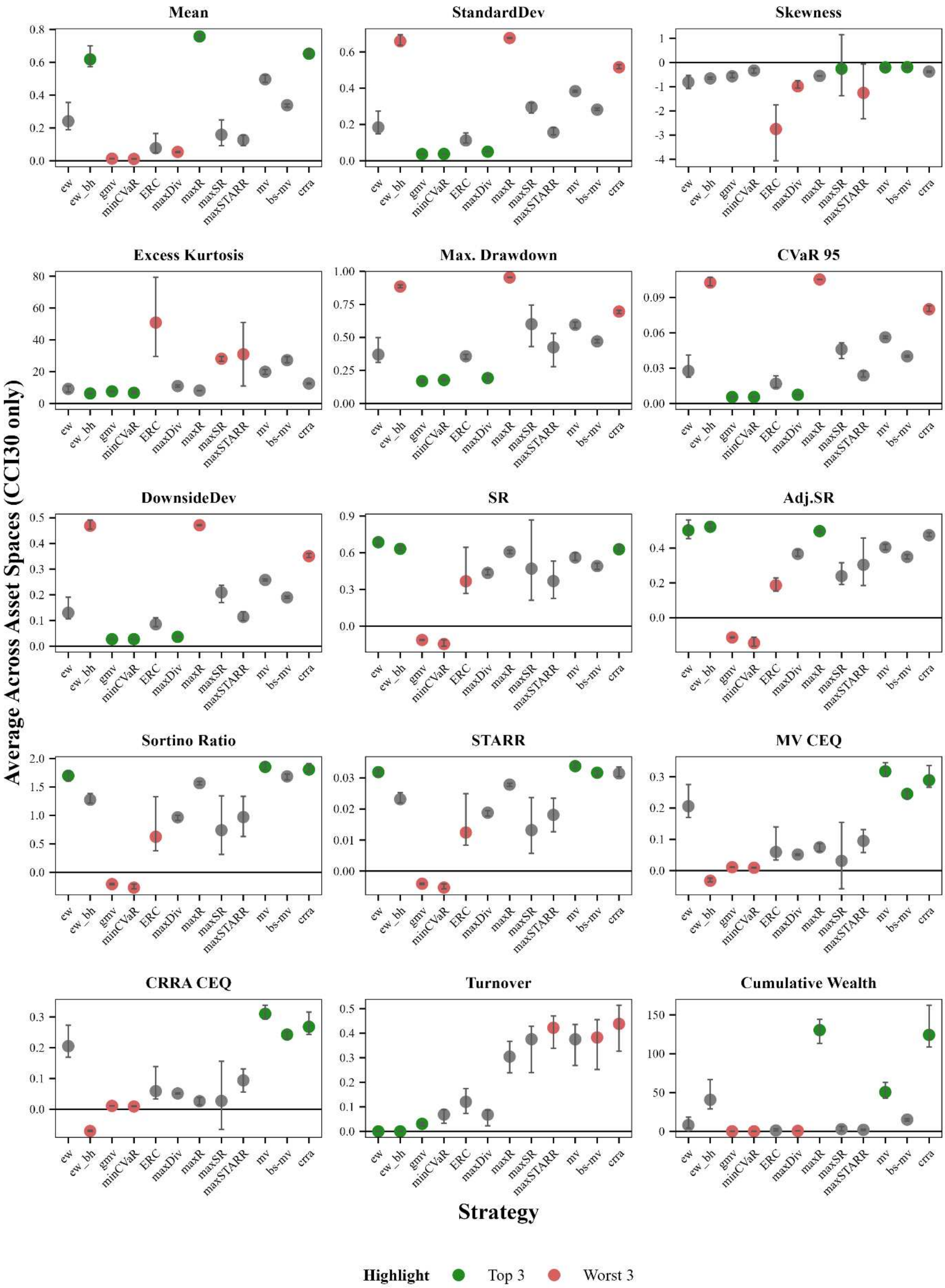

Figure 35: Average Performance Measures per Strategy Within CCI30 Portfolios

Note: Error-Bars indicate Max. and Min. values observed in specific asset spaces while dots represent the average across all asset spaces. Ranking (Top 3 and Worst 3) is based on average values.

A.31 Average Performance Measures Under Different Risk Aversions

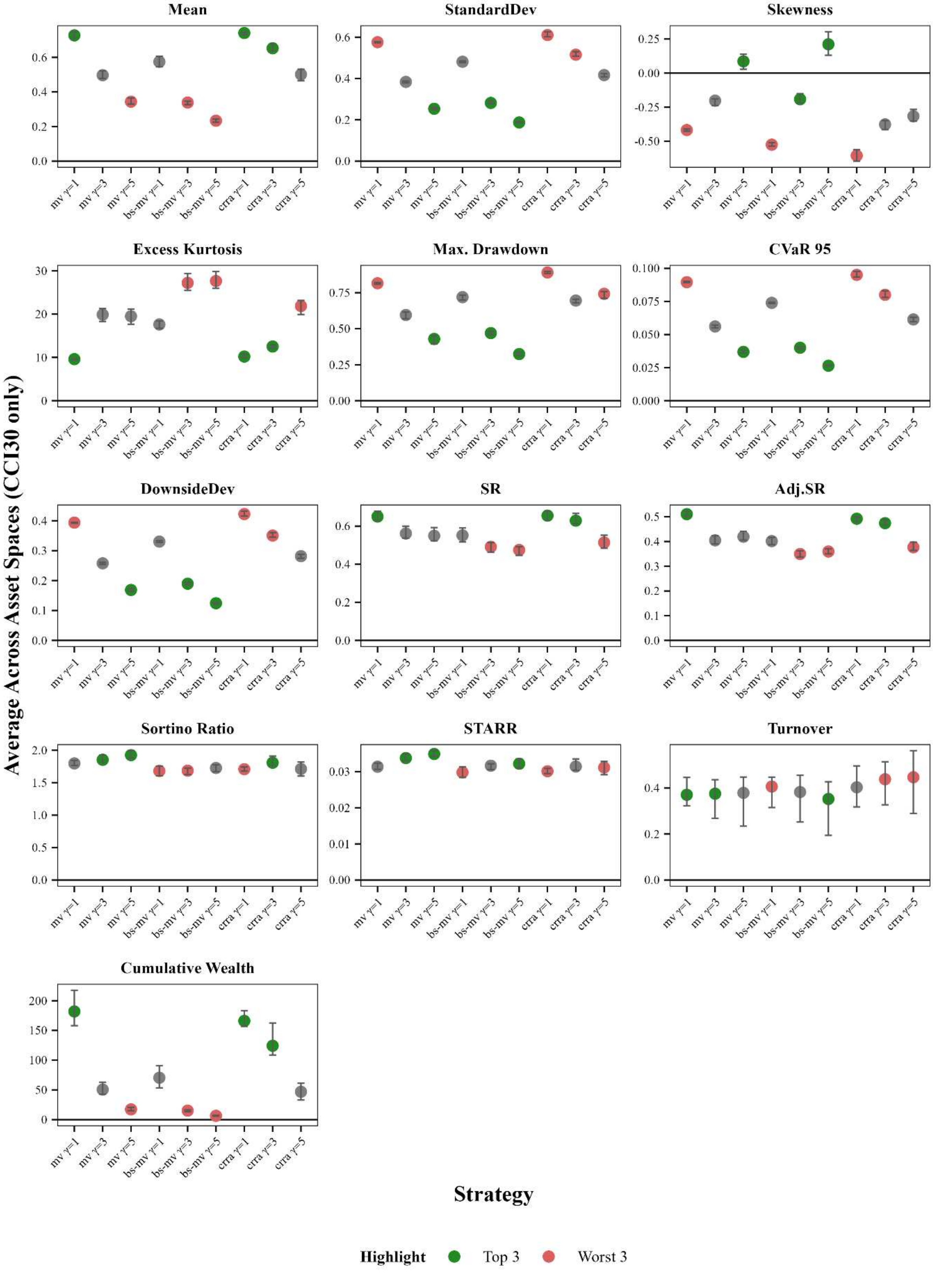

Figure 36: Average Performance Measures for Utility-based Strategies Within CCI30 Portfolios Under Different Risk Aversions

Note: Error-Bars indicate Max. and Min. values observed in specific asset spaces while dots represent the average across all asset spaces. Ranking (Top 3 and Worst 3) is based on average values.

A.32 Average CEQ Returns Under Different Risk Aversions

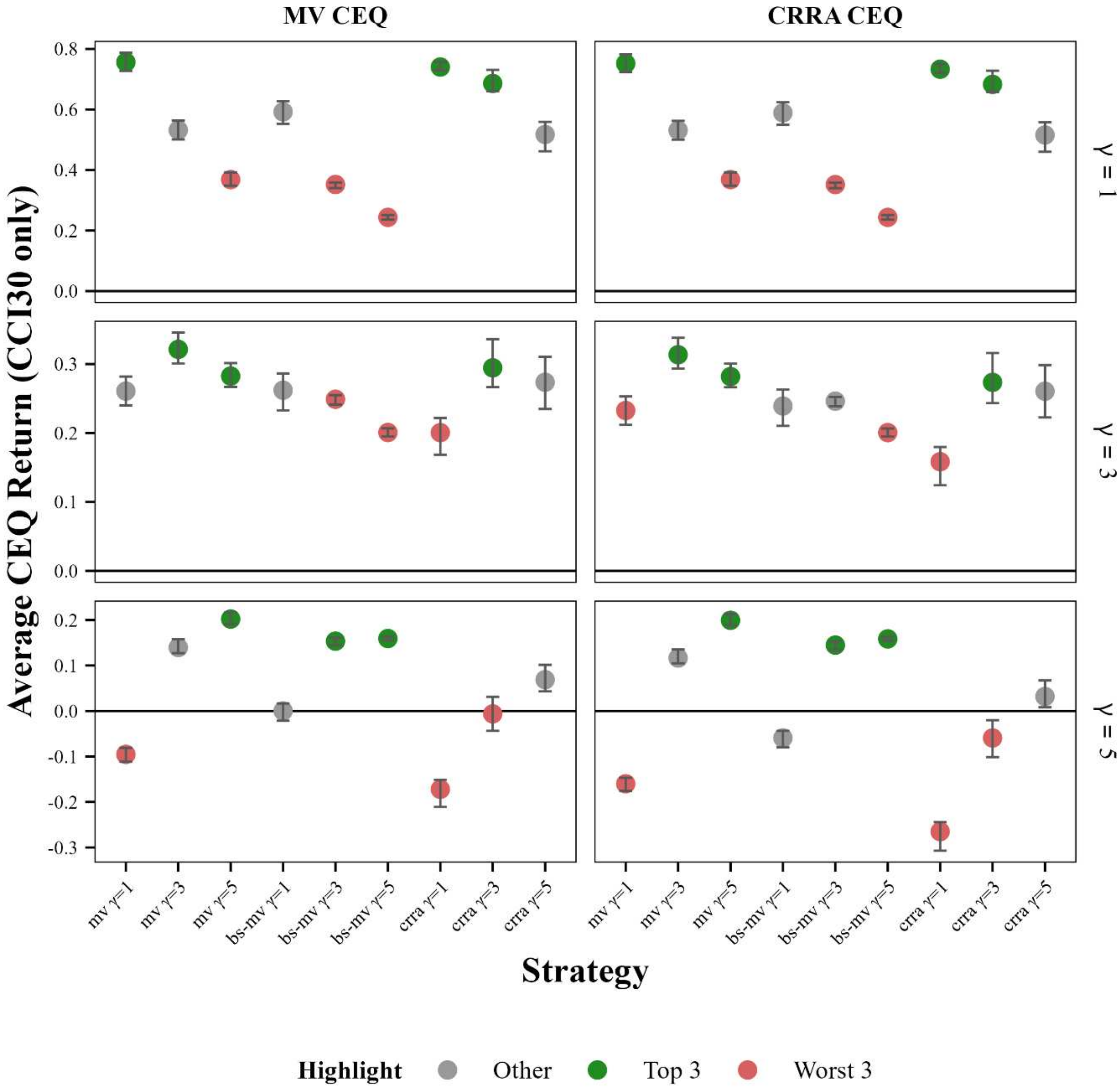

Figure 37: Average CEQ Return Measures for Utility-based Strategies Within CCI30 Portfolios Under Different Risk Aversions

Note: Error-Bars indicate Max. and Min. values observed in specific asset spaces while dots represent the average across all asset spaces. Ranking (Top 3 and Worst 3) is based on average values.

A.33 Cumulative Wealth Paths Under Different Risk Aversions

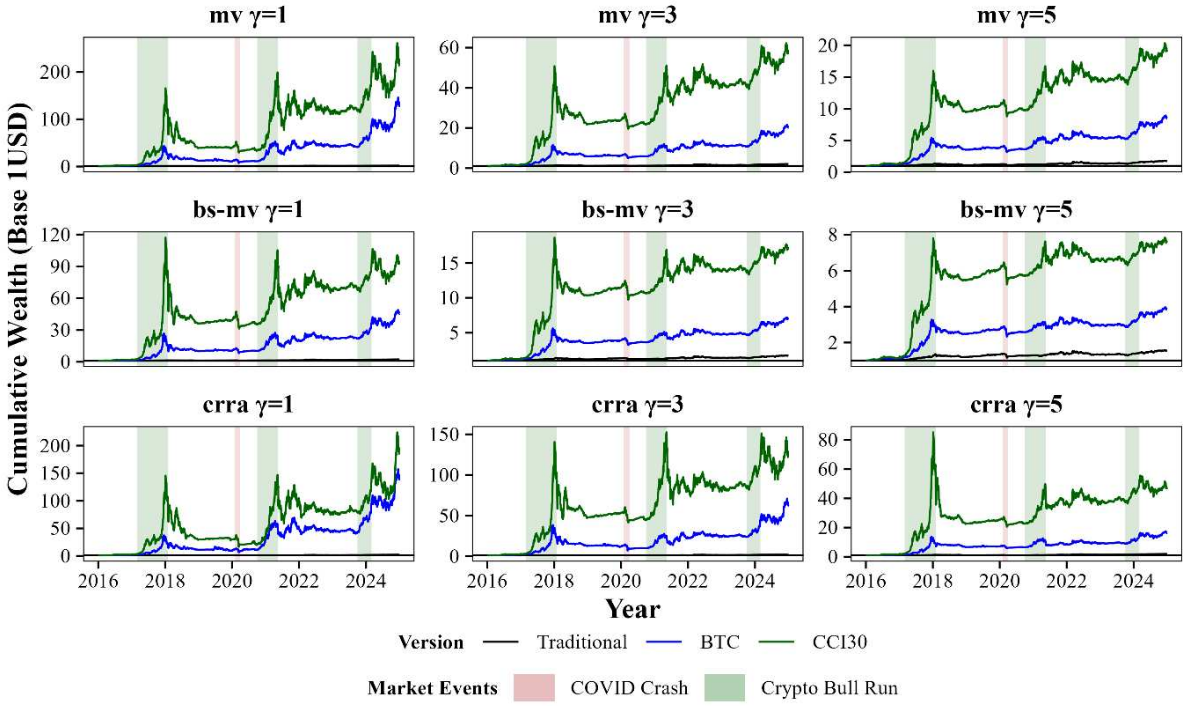

Figure 38: Cumulative Wealth Path Comparison of Utility-based Strategies in the 'all' Asset Space Under Different Levels of Risk Aversion

Note: The shaded green areas reflect prominent, observable long-term upwards movement of CCI30 and BTC prices and are not derived from a formal model.

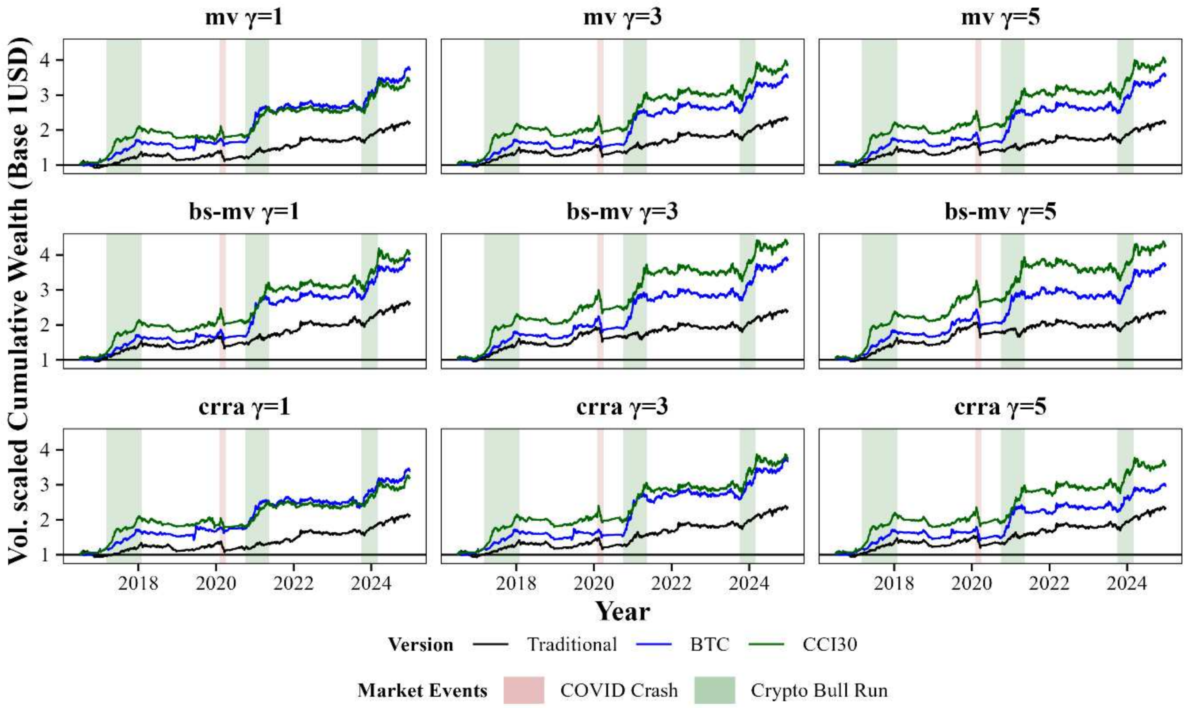

Figure 39: Volatility Adjusted Cumulative Wealth Path Comparison of Utility-based Strategies in the 'all' Asset Space Under Different Levels of Risk Aversion

Note: Returns are adjusted based on 126-Day realized rolling volatility and scaled to a common annual volatility level of 10%. The shaded green areas reflect prominent, observable long-term upwards movement of CCI30 and BTC prices and are not derived from a formal model.

A.34 Explorative Explanatory Regressions

Note: This section is purely explorative, was conducted out of personal interest beyond the RQs and thus does not claim to be methodologically rigorous.

To identify potential drivers of the time-varying crypto-inclusion effects, explanatory regressions on the rolling differences in three risk-adjusted return measures, namely SR, Sortino Ratio and STARR, are conducted for all strategies except ew_bh, gmv and minCVaR. The ew_bh, gmv and minCVaR strategies are excluded, as they either only serve as a benchmark (ew_bh) and are not considered classical optimizations or hardly allocate to crypto assets, thus showing only minor differences. The differences are calculated as the difference between monthly rebalanced CCI30 and traditional portfolios over a 21-day window. The window has been selected as it approximately matches the monthly rebalancing frequency. As this section is purely explorative and results are typically similar across asset spaces, the regressions are only performed for the all asset space.

A.34.1 Variable Selection Based on Theoretical Rational

All explanatory variables are based on a theoretical rationale and target a dimension that potentially influences the over- or underperformance of crypto-enhanced portfolios. The following variables are used to explain performance differences:

CCI30 Mean Return (21-Day Rolling): The CCI30 mean return over a 21-day rolling window, subsequently referred to as CCI30_Mean, is supposed to capture short-term momentum in the crypto asset. This could increase investor attention and thus lead to outperformance from crypto-enhanced portfolios. The idea is based on the momentum effect, which can be observed in crypto markets according to Liu et al. (2022).

CCI30 Volatility (21-Day Rolling): The CCI30 Volatility, subsequently referred to as CCI30_Vol, indicates times of turmoil in crypto assets, which could lead to more cautious investors and thus reduced interest in crypto assets and increased interest in more stable, traditional assets. This is supported by the fact that crypto assets are proven to exhibit volatility clustering (Corbet et al., 2019).

CCI30 – MSCI World Correlation (21-Day Rolling): The 21-day rolling correlation between CCI30 and MSCI World (the non-crypto asset that typically correlates most with CCI30 within our sample), subsequently called Corr, indicates the potential diversification benefits from adding a crypto asset. The expected sign of the coefficient is negative, as a higher correlation causes smaller expected diversification benefits.

VIX (21-Day Rolling Average): The VIX is used as a proxy for overall market uncertainty and is retrieved from Yahoo Finance (2025). During such crises, investors could either search for more stable assets leading to underperformance of crypto-enhanced portfolios or seek diversification across asset classes. Previous literature supports both. While some studies indicate that crypto assets serve as a hedge during crises (Baur et al., 2018a; Bouri et al., 2020; Dwita Mariana et al., 2021; Dyhrberg, 2016a; Dyhrberg, 2016b), others contradict (Gorman & Hughen, 2024; Nguyen, 2022).

COVID-19 Dummy: To be able to directly assess whether the performance difference varied between the largest and broadest market crash within the sample period (highest drawdowns), a dummy variable for the COVID-19 crisis (subsequently named COVID), which takes 1 for each date from February 1, 2020 to March 31, 2020 is introduced.

Ex-Post Regime Indicator (Bull = 1, Bear = 2): Crypto assets tend to display different regimes with substantial differences in their return characteristics (Figà-Talamanca, Focardi, & Patacca, 2021) that do not necessarily match regimes of other asset classes. The rationale behind the inclusion of this variable is that crypto-enhanced portfolios are expected to outperform during bullish crypto regimes. In contrast, they are expected to outperform less (or underperform) during bearish crypto regimes.

This explanatory variable is constructed based on the methodology in Figà-Talamanca et al. (2021). They argue that models allowing either two or three regimes based on a Hidden Markov Model (HMM) best represent crypto assets' behavior. Thus, this thesis applies a univariate two-state Gaussian HMM on the 21-day rolling mean return of the CCI30 using the R-package *depmixS4* (Visser & Speekenbrink, 2021). The model assumes that the 21-day rolling mean return process r_i is conditionally normally distributed given the regime:

$$r_t | S_t = i \sim N(\mu_i, \sigma_i^2) \qquad (A17)$$

where each regime i has a distinct mean μ_i and variance σ_i^2.

The estimation of the HMM is performed via maximum likelihood, and the optimal sequence of states is extracted ex-post using the Viterbi algorithm. As a result, the most probable regime for each date (1=bullish, 2=bearish) is returned. Even though the returns in this thesis do not exactly follow a normal distribution in each state, the model captures the large up- and downward movements well (see Figure 47):

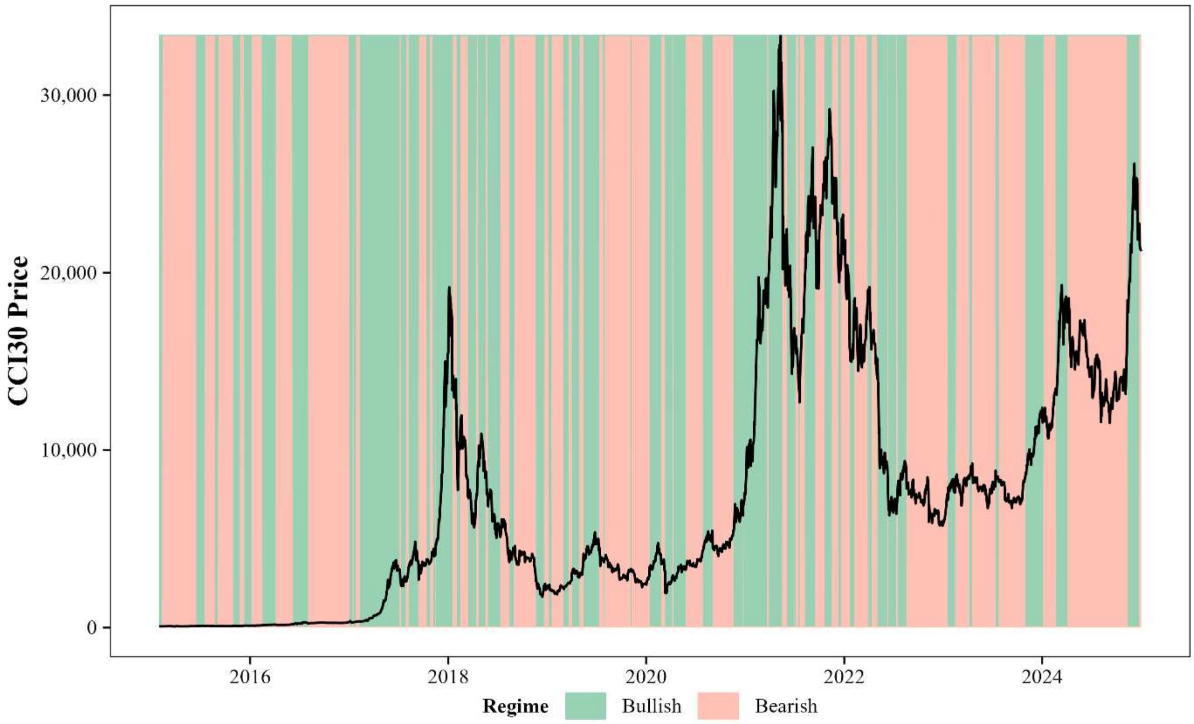

Figure 40: Ex-Post Regime Based on 2-State HMM

Google Trends Index for "Bitcoin": This variable, subsequently referred to as GoogleTrends, is included to represent retail investors' attention and thus capture the behavioral finance aspect of crypto investment. Previous literature shows that investor attention has a positive impact on crypto prices. Thus, a positive relationship is assumed (Kristoufek, 2015; Urquhart, 2017). The variable is downloaded from Google Trends (2025) in overlapping 90-day periods and subsequently normalized.

BTC – USD Trading Volume (21-Day Rolling Average): The trading volume (subsequently named BTC_Volume), on the one hand, reflects the actual investor interest that is translated into actual transactions and, on the other hand, serves as a liquidity proxy. It potentially indicates ease of trading, lower transaction costs and more robust price discovery. Increased actual investor interest and reduced transaction costs are assumed to contribute to outperformance positively.

A.34.2 Variable Retention and Model Specification

Variable Retention: To ensure that only the explanatory variables that add value to the models are retained, a stepwise variable importance analysis, based on different model fit metrics (adjusted R^2, AIC and BIC) is performed. In an initial step, a complete model, using all theoretically justified explanatory variables, is estimated. Subsequently, each explanatory variable is dropped individually, and the resulting model is compared to the complete model. As all variables can be considered valuable (exclusion leads to lower adjusted R^2 or higher AIC/BIC), at least for some strategies, all variables are retained.

Model Specification: The framework is designed to explain 21-day rolling differences in each strategy's three main risk-adjusted return metrics i (SR, Sortino and STARR). The strategy is denoted by s and the dependent variables are defined as:

$$Y_t^{(i,s)} = Metric_t^{CCI30(i,s)} - Metric_t^{Trad(i,s)} \qquad (A18)$$

Adding the explanatory variables (as named in section A.34.1), we get the full model specification per strategy s and metric i in the form of:

$$Y_t^{(i,s)} = \beta_0 + \beta_1 CCI30_{Mean_t} + \beta_2 CCI30_{Vol_t} + \beta_3 Corr_t + \beta_4 VIX_t + \beta_5 COVID_t + \beta_6 Regime_t + \beta_7 GoogleTrends_t + \beta_8 BTC\_Volume_t \qquad (A19)$$

The explanatory variables are aligned in dates to ensure synchronous evaluation. The regressions are run per strategy and metric and produce a set of coefficients that enable assessment of the drivers of outperformance or underperformance per strategy and metric.

A.34.3 OLS Assumption Diagnostics and Estimation Method

Even though this section is only explorative, the same OLS assumption diagnostics and estimation method as described in section 3.7 are applied. Additionally, the stationarity of the underlying time series is assessed via an Augmented Dickey Fuller (ADF) test. As the underlying dataset is significantly smaller, these regressions use *vcovHAC* instead of *NeweyWest* to introduce HAC-robust variance-covariance matrices. *VcovHAC* is used with the default specifications, which applies a quadratic spectral kernel, automatic bandwidth selection following Andrews (1991) and no prewithening. Furthermore, the pairwise correlation between all variables (besides the COVID-Dummy) and the Variance Inflation Factors for each model are calculated to ensure multicollinearity is not a concern.

A.34.4 Results

The following three Tables (30-32) show the main regression results across strategies. The previously described variable retention results and the results of the OLS assumption diagnostics can be downloaded under the following link:

Download Link – OLS Assumption Diagnostics (Explanatory Regressions)

Explanatory Regressions: Sharpe Ratio Differences
CCI30 - Traditional in asset space 'all'

	ew	ERC	maxDiv	maxR	maxSR	maxSTARR	mv	bs-mv	crra
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Intercept	0.103 *	0.017	0.110 ***	0.074	0.035	-0.014	0.060	0.057	0.053
CCI30_Mean	12.742 ***	6.685 ***	7.808 ***	12.224 ***	9.114 ***	7.575 ***	11.035 ***	10.175 ***	10.132 ***
CCI30_Vol	-2.255 ***	-0.642	-0.677 **	-1.721	-1.571 *	-1.435 *	-2.858 ***	-2.624 ***	-2.747 ***
Corr	0.065	0.141 ***	0.035 *	0.050	0.057	-0.002	0.100 *	0.065	0.061
VIX	0.004	0.000	-0.000	0.004	0.004	0.004 *	0.005 **	0.004 *	0.005 **
COVID	0.254 ***	-0.147 **	0.098 ***	0.427 ***	0.072 **	0.086 ***	0.254 ***	0.184 ***	0.245 ***
Regime	-0.066 ***	-0.026	-0.052 ***	-0.084 **	-0.037 *	-0.008	-0.047 *	-0.041 *	-0.037
GoogleTrend	0.000	0.002 **	-0.000	0.001	0.001	0.002 **	0.003 *	0.003 *	0.003 *
BTC_Volume	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000 **	-0.000 *	-0.000 **
Adj. R^2	0.590	0.393	0.699	0.357	0.409	0.345	0.450	0.474	0.350

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 30: Explorative Explanatory Regressions – Sharpe Ratio Differences

Explanatory Regressions: Sortino Ratio Differences
CCI30 - Traditional in asset space 'all'

	ew	ERC	maxDiv	maxR	maxSR	maxSTARR	mv	bs-mv	crra
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Intercept	0.388 *	0.263	0.501 ***	0.533	0.265	0.055	0.254	0.303	0.221
CCI30_Mean	29.947 ***	17.832 ***	18.127 ***	36.358 ***	24.975 ***	20.766 ***	33.307 ***	29.553 ***	31.859 ***
CCI30_Vol	-5.543 **	-0.928	-2.710 **	-4.464	-3.910	-4.093	-6.587 *	-6.191 *	-7.011 *
Corr	0.167	0.480 **	0.167	0.175	0.169	0.055	0.242	0.108	0.286
VIX	0.010	-0.003	-0.002	-0.001	0.009	0.012 **	0.011	0.009	0.009
COVID	0.534 ***	-0.171	0.220 ***	0.891 ***	0.441 ***	0.442 ***	0.619 ***	0.490 ***	0.634 ***
Regime	-0.223 ***	-0.149	-0.200 ***	-0.273 *	-0.143	-0.057	-0.138	-0.147	-0.085
GoogleTrend	0.010	0.000	-0.004	0.014	0.002	0.004	0.019	0.018	0.020 *
BTC_Volume	-0.000 ***	-0.000	-0.000	-0.000 **	-0.000 **	-0.000 **	-0.000 ***	-0.000 ***	-0.000 ***
Adj. R^2	0.389	0.120	0.346	0.292	0.278	0.215	0.313	0.308	0.258

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 31: Explorative Explanatory Regressions – Sortino Ratio Differences

Explanatory Regressions: STARR Differences
CCI30 - Traditional in asset space 'all'

	ew	ERC	maxDiv	maxR	maxSR	maxSTARR	mv	bs-mv	crra
Variable	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
Intercept	0.096	0.077	0.170 ***	0.171	0.080	0.017	0.060	0.093	0.047
CCI30_Mean	10.841 ***	6.196 ***	6.425 ***	13.132 ***	8.989 ***	7.406 ***	11.638 ***	10.351 ***	11.211 ***
CCI30_Vol	-1.728 *	-0.202	-0.889 **	-1.440	-1.256	-1.407	-2.145	-2.157 *	-2.380 *
Corr	0.065	0.165 **	0.066 *	0.057	0.065	0.027	0.084	0.036	0.095
VIX	0.004 *	-0.001	-0.001	0.000	0.003	0.004 **	0.004	0.004	0.004
COVID	0.199 ***	-0.063	0.091 ***	0.333 ***	0.175 ***	0.176 ***	0.241 ***	0.163 **	0.242 ***
Regime	-0.069 **	-0.049	-0.068 ***	-0.093 *	-0.043	-0.016	-0.039	-0.050	-0.023
GoogleTrend	0.003	0.000	-0.001	0.005	0.000	0.001	0.007	0.006	0.007 *
BTC_Volume	-0.000 ***	-0.000	-0.000	-0.000 **	-0.000 **	-0.000 *	-0.000 ***	-0.000 ***	-0.000 ***
Adj. R^2	0.386	0.130	0.338	0.298	0.288	0.213	0.309	0.311	0.257

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 32: Explorative Explanatory Regressions – STARR Differences

Table 30 shows that all strategies exhibit a positive intercept, indicating that CCI30-enhanced portfolios generally outperform their traditional counterparts regarding SR. This outperformance is, however, not constantly significant across strategies. Furthermore, it shows that the coefficients for CCI30_Mean are positive and highly significant across all strategies, suggesting that crypto momentum is a key driver of SR differences. In contrast, CCI30_Vol's coefficients are negative and significant for almost all strategies. Thus, the SR-difference is typically severely decreased during high crypto volatility. This is unsurprising, as the SR is a direct function of mean excess returns and volatility. Therefore, it could be expected that mean returns and volatility of crypto assets strongly influence the rolling SR differences between traditional and crypto-enhanced portfolios. The effects of Corr are mixed and are mainly insignificant at any reasonable level except for ERC, maxDiv and mv, which exhibit significantly larger positive differences when correlations are high. The coefficients for the VIX are typically small but positive and significant for maxSTARR, mv, bs-mv and crra. This indicates that these strategies benefit more from crypto inclusion in volatile market environments. The COVID dummy is positive and significant for nearly all strategies (besides ERC), suggesting that crypto-enhanced portfolios outperformed stronger during the COVID-19 crisis. Bearish regimes (Regime = 2) are connected to lower SR differences across all strategies, however, not in a significant manner for ERC, maxSTARR and crra. Lastly, increases in GoogleTrend typically slightly increase the SR differences, while BTC_Volume slightly decreases them. The coefficients for these two variables are not consistently significant.

The results for Sortino Ratio and STARR mainly exhibit similar patterns with slightly different magnitudes and levels of statistical significance. Adjusted R^2 values range from 0.120 to 0.699. This indicates that for some strategies a large portion of the variation is explained, while for others a large portion of the variation is left unexplained. A more detailed exploration, potentially including additional control variables and a broader empirical set-up, is left for future research.

A.35 Download Link of Paired Portfolio Comparison with Different Parameters

Download Link – Paired Portfolio Comparison with Different Parameters

A.36 Download Link of R-Scripts used

Download Link – R-Scripts

A.37 Download Link of Base-Data

Download Link – Base-Data

A.38 Artificial Intelligence Declaration

I acknowledge the use of Artificial Intelligence (AI) to improve the text quality and support R-coding. An AI tool was employed for language refinement, including improving clarity, facilitating translation purposes, and setting up and adapting R-scripts. All contents derived from AI were reviewed and edited to ensure accuracy and adherence to academic standards.