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F5: optimised crypto-currency investment strategies

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Crypto-currencies constitute an asset class characterised by high returns, high volatilities, and low correlations. Rational investment decisions in such a setting rely on portfolio-optimisation theory. At the same time, crypto-currency markets are not yet fully integrated with standard financial markets. Therefore, employing standard models of portfolio management can fail to incorporate critical information, unnecessarily loading up on unpriced risk, to capture priced return regularities, foregoing desired remunerated exposure, or to acknowledge the institutional environment, incurring gratuitously transaction costs. F5 provides an optimised investment strategy based on the main tenets of the state-of-the-art academic finance literature, and designed specifically for the setting of today's crypto-currency markets.

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"Nothing is more powerful than an idea whose time has come."

Victor Hugo[1]

1. Introduction

High realised returns of the most prominent crypto-currencies (cryptos) have attracted increasing investor attention, despite repeated downturns, continued sizable volatilities, as well as uncertainty about technological and legal backgrounds.[2]

Yet two additional critical factors have evolved in the decade since Nakamoto (2008)'s blockchain protocol introduced scarcity into the digital realm. Scarcity combined with the virtual tokens' intrinsic value arising from their potential to facilitate transactions – and power decentralised applications – has enabled a technological innovation to give rise to a novel asset class in financial markets.

The first factor is simply time: As the observable time horizon has grown to allow meaningful statistical analyses, investment in cryptos has turned from a quixotic fancy to its usual, proper science. The second factor is the maturation of the financial infrastructure in terms of trading venues, depository services, and also professional advice.

Despite swift recent progress, however, crypto markets still remain an emerging environment with a limited investor base. As with all financial innovation, initial market opaqueness and the lack of institutional investment opportunities slow capital inflows and delay the integration with established financial markets.

Indeed, crypto investment until recently effectively meant either holding coins directly, subjecting investors to high security requirements or risks, or alternatively entrusting individual coin holdings to online wallets, the reputation of which suffered from frequent cases of fraud or theft.

While theoretical research established the benefit of Bitcoin for portfolio diversification as early as Briere et al. (2013) and Eisl et al. (2015), there remained no practical way to hold a broader and optimised crypto portfolio with a regulated financial institution.

Only recently several approaches have become available that aim to capture the aggregate crypto market movement, for measurement or investment. However, no investment strategy based on state-of-the-art academic finance research and adapted to the specifics of crypto-currency markets has yet been developed. F5 does exactly that.

1.1. Relation to other crypto portfolios

Portfolios of crypto-currencies come in two forms: indices and investment strategies.

[1] This is a common yet loose translation of the original French "On résiste à l'invasion des armées; on ne résiste pas à l'invasion des idées." in Hugo (1877); it be noted that a somewhat more proximate quotation by Aimard (1861) pre-dates Hugo's commonly referenced publication: "Il y a quelque chose de plus puissant que la force brutale des baïonnettes: c'est l'idée dont le temps est venu et l'heure est sonnée."

[2] Also among economists, debate about whether to consider cryptos as currencies (Yermack, 2015), consider them harmful (Krugman, 2013), or advocate large-scale use by central banks (Barrdear and Kumhof, 2016), is still ongoing.

1.1.1. Indices

Reflecting the growing cross-section of traded cryptos, indices have been developed to capture the performance of "the crypto market" in general. While in principle every index defines an implicit investment strategy, they are not optimised for trading. In highly liquid stock markets, exchange-traded funds (ETFs) generate a means to invest (approximately) into indices, frequently relying extensively on the use of derivatives; in crypto markets, only physical replication would be possible, and hardly advisable.

By construction, an index is fully passive, and would not attempt to exclude assets based on information about the technology or the entity driving it. Stock markets rely on regulatory authorities to preclude fraudulent assets from being traded in the first place. Crypto investors who want to avoid scams, in contrast, need to ensure this themselves, unless they rely on a managed strategy.

Noteworthy indices include the Winklevoss index (WBBI), CCI30, and CRIX.

The Winklevoss index (Winkdex) is meant to accurately price one bitcoin and serves as the basis for the futures trading at the Chicago Board Options Exchange (CBOE). However, with only a single crypto as constituent, it does not aim to track the general crypto market – of which Bitcoin is becoming less and less representing – and is thus not meant to serve as the basis of a comprehensive crypto investment strategy.

The CCI30 constitutes a simple value-weighted average of the 30 largest cryptos with quarterly updated constituents and monthly rebalancing. The index applies a single adaptation to reflect specific properties of the crypto market, namely addressing the high volatility via exponentially-weighted moving average prices as the basis for calculating market capitalisations. It does not adjust the number of constituents, neither does it account for trading costs or liquidity concerns. While it is tracked by at least one passive fund, it is not an optimised trading strategy.

The CRypto-currency IndeX CRIX, developed by Trimborn and Härdle (2016), comes closest to a viable investment strategy, as it rebalances the weights of its constituents weekly, and the list of constituents monthly, while explicitly optimising their number. However, as an index its objective still is to reflect the broad crypto market, and so its construction includes additional cryptos whenever their price movements contain sufficiently additional information content; it has grown to exceed 60 cryptos at times, sometimes with heavy rebalancings at month-end. In essence, its aim is first statistical, second financial.

Moreover, none of the indices account for liquidity constraints in the fragmented exchanges where crypto trading takes place. Recent research (Trimborn et al., 2018) shows, when attempting to trade large amounts in small and illiquid cryptos, liquidity concerns can have first-order implications for performance.

1.1.2. Investment strategies

In contrast to indices, investment strategies are designed explicitly for trading. The most prominent crypto strategy is the C20 project: it has implemented a crypto token of its own in order to provide an ETF-like means to invest into a simple portfolio of the 20 largest cryptos. Effectively, it offers the analogue to a closed-end fund physically replicating a standard capped value-weighted index of a hard-coded number of constituents. This opens the potential for lower fees[3]; however, the focus clearly lies on the innovative implementation of a tokenised crypto investment. This strategy requires ex-ante funding, which in turn requires a simple and pre-determined investment strategy, rather than the approach of active fund management, where reputational capital is built up via a performance history and incentives remain aligned due to the possibility of investors to withdraw their funds.

In summary, depending on an investor's situation and preferences, different investment vehicles will be best suited; but for a large group of investors the standard financial-industry procedure of delegating investment decisions in complicated markets to active and professional investment managers, within a clearly established legal framework, is the preferred approach.

After all, not only are smart contract markets still immature; more importantly, incomplete contracts and unforeseeable events generate value from a legally responsible entity managing and backing the investment strategy (the DAO incident in 2016 providing the strongest case in point). While such a trusted third party appears anathema to some crypto enthusiasts, a trusted third party also means that there exists a party with reputation at stake (thus avoiding nothing-at-stake problems), ensuring its incentives to tackle potential upcoming challenges – a commitment which is key in a rapidly evolving regulatory environment, as the markets for cryptos.

In the realm of active investment, various strategies have been or are being offered; almost all offer either some variation of a high-frequency arbitrage strategy, or are based on "technical analysis."

As far as technical analysis is concerned, in short, rational investors stay clear of it. Notwithstanding continued popularity among non-professionals, similar to homeopathy, decades of innumerous studies according to academic standards have failed to provide evidence of any merits. Such strategies' appeal must be considered purely psychological and extends from other asset types to cryptos, which this time are no different.

In principle, short-term arbitrage strategies exploiting temporary inefficiencies in such fragmented and rapidly developing markets are not improbable. Thus opportunities for highly sophisticated traders to generate abnormal returns (alpha) are not unlikely; however, the proposition that these traders would raise large amounts from uninformed retail investors in order to then leave a significant share[4] of the gains, is.

1.2. A research-based, long-term strategy

F5 fills the gap of professional intermediated investment management for the asset class of crypto-currencies: it is constructed to provide fund management for cryptos. There-

[3] However, the concrete implementation of C20 cannot be considered a discount vehicle: beyond the annual management fee of 0.50%, only 87% of the ICO proceeds actually were distributed to investors; 7.5% to the management team.

[4] Berk and Green (2004) show theoretically how in settled markets skillful fund managers can appropriate all α they generate, keeping uninformed investors at reservation values of 0 outperformance.

fore it is optimised for long-term investors who seek to participate in the general development of cryptos, while ensuring a dynamic optimisation of the holdings within their crypto engagement.

Having an active fund manager can be critical in a nascent market characterised by little regulatory screening and repeated occurrences of scams. As the example of BitConnect has shown, unsophisticated investors can fall prey to fraudulent schemes to an extent inflating a coin's market capitalisation above 2.7 billion USD before it collapses. When information about a crypto's deficiencies is publicly accessible, as was the case with BitConnect, professional investors can avoid losses.

At the same time, research on mutual fund managers shows they can be prone to excess trading, reducing performance due to transaction costs. In crypto markets, where trading costs and market impact (slippage) can still loom much larger, a low trading frequency is thus of key importance.

2. The Investment Strategy – Principles

Any investment strategy based on academic findings will start with the presumption of efficient markets free from arbitrage opportunities, and then pursue active management based on empirical regularities with respect to two dimensions: First, when there are limits to arbitrage; and second, to gain exposure to priced, systematic risk factors.

2.1. Investment Philosophy

The F5 investment philosophy is based on "efficiently inefficient" crypto markets (Pedersen, 2015) – efficient enough to preclude simple mechanistic trading strategies from outperforming consistently (i.e., by more than luck), yet inefficient enough to compensate skillful management for its information with expected positive risk-adjusted excess returns on its trading strategy. This way, the information is eventually incorporated into market prices (Grossman and Stiglitz, 1980).

However, even in the absence of superior information on individual assets, maintaining a rational portfolio is imperative for efficient investment: only regular rebalancing can optimise the benefits of diversification by avoiding idiosyncratic risk (Markowitz, 1952).

Therefore, the philosophy combines both perspectives as state-of-the-art portfolio theory does: holdings are optimised for their contribution to portfolio risk and return, while explicitly incorporating additional information via correspondingly over- or underweight positions.

2.2. Portfolio Optimisation

The underlying portfolio optimisation manages the diversification benefits, which are sizable for crypto portfolios (Eisl et al., 2015) because correlations are low – in two ways: First, the generally comparatively low correlation between most crypto returns, as depicted in Table 1, implies that a crypto investment in only one or very few coins is inefficient. Second, as correlations are particularly low with respect to returns of traditional financial assets, as visible in Table 2, an ever-increasing number of academics recommends holding at least some positive part of investable wealth in cryptos.[5]

Table 1: Correlations of daily returns of major crypto-currencies (by market cap).

	ETH	XRP	BCH	LTC	EOS	BNB	XLM	TRX
Period 2016-01-01 until 2018-12-07								
BTC	0.441	0.269	0.441	0.578	0.451	0.491	0.334	0.429
ETH		0.249	0.552	0.416	0.537	0.431	0.281	0.443
XRP			0.369	0.329	0.394	0.254	0.510	0.381
BCH				0.479	0.466	0.283	0.305	0.254
LTC					0.466	0.405	0.345	0.358
EOS						0.353	0.373	0.432
BNB							0.264	0.299
XLM								0.280
Period 2017-01-01 until 2017-12-31								
BTC	0.355	0.107	0.021	0.369	0.243	0.384	0.222	0.279
ETH		0.110	0.276	0.343	0.390	0.320	0.194	0.335
XRP			0.130	0.213	0.203	0.079	0.474	0.193
BCH				0.159	0.229	0.113	0.065	0.011
LTC					0.277	0.236	0.273	0.220
EOS						0.206	0.216	0.334
BNB							0.109	0.256
XLM								0.109
Period 2018-01-01 until 2018-12-07								
BTC	0.812	0.655	0.778	0.831	0.673	0.617	0.652	0.558
ETH		0.733	0.776	0.821	0.688	0.544	0.689	0.536
XRP			0.640	0.687	0.642	0.441	0.719	0.544
BCH				0.778	0.662	0.514	0.596	0.462
LTC					0.670	0.593	0.619	0.479
EOS						0.482	0.595	0.501
BNB							0.447	0.314
XLM								0.408

All portfolio-optimisation methods fall into two categories: first, the classical approach since Markowitz (1952) estimates the distribution of asset returns, and then uses these estimates to derive the optimal portfolio. In theory, this is simple: After all, given the return distribution (including all co-moments), calculating the optimal portfolio weights is straightforward. However, in practice producing reliable estimates of out-of-sample returns is challenging, and in the last decades the academic literature has demonstrated how sensitive portfolio performance tends to be with respect to unavoidable estimation

[5]Note, however, that cryptos' correlation coefficients tend to exhibit sizable time-series variation.

Table 2: Daily-return correlations between major crypto-currencies and standard financial investments (3 stock-market indices, a commodity index, and the gold price) for the period 2016-01-01 to 2018-12-07.

	BTC	ETH	XRP	BCH	LTC	EOS	BNB	XLM
DAX	0.020	0.037	0.087	0.012	0.051	0.053	0.038	0.066
SnP.500	0.037	0.060	0.068	-0.041	0.075	0.039	0.026	0.089
MSCI_World	0.039	0.067	0.079	-0.024	0.078	0.056	0.032	0.094
Commodities_USCI	0.010	0.051	0.072	0.103	0.052	0.038	0.054	0.069
Gold	0.020	0.023	0.009	0.035	0.001	0.071	0.040	-0.015
USD.EUR	0.051	0.001	-0.039	0.038	0.075	0.036	0.040	0.000

Table 3: Distributional properties of daily returns of major crypto-currencies deviate strongly from normality: numbers for the period 2016-01-01 to 2018-12-07.

	BTC	ETH	XRP	BCH	LTC	EOS	BNB	XLM	TRX
skewness	0.31	0.80	8.00	1.65	2.41	6.16	2.80	4.08	4.17
excess.kurtosis	5.10	4.31	135.29	8.56	19.19	88.33	20.84	36.01	32.23

error in return distributions.

Therefore, recent advances in portfolio theory have developed a second category of approaches. Acknowledging the difficulty in robustly estimating out-of-sample moments of return distributions, they completely sidestep the problem by optimising the portfolio weights directly.

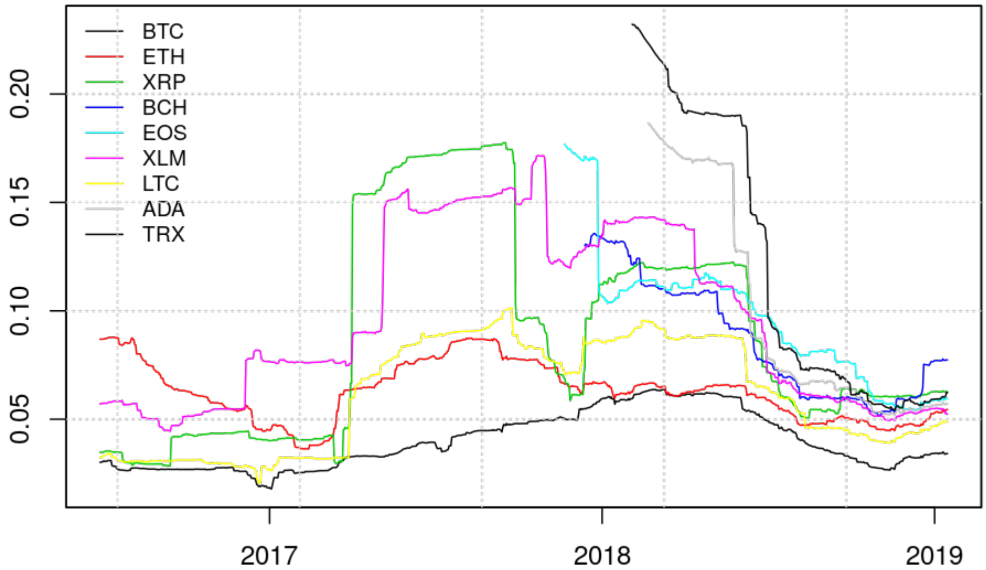
This circumvents two critical issues: on the one hand the explicit estimation of covariances and higher-order co-moments,[6] and on the other hand the effects of parameter instability over time. While useful for stocks, both advantages turn out particularly valuable in crypto markets: first, returns are even more leptokurtic (i.e., deviate even further from a normal distribution; see for instance Elendner et al. (2017) as well as Table 3), and second, subject to more pronounced parameter instability. This is already visible in simple rolling-window volatility plots, see Figure 1.

For this reason classical approaches nowadays always apply some shrinkage to the μ/σ estimation. Still, the latest academic literature finds no clear best practice and generally remains skeptical regarding out-of-sample performance (e.g., DeMiguel et al. (2009b)).

Today's state-of-the-art portfolio optimisation thus belongs to the second category, taking the opposite approach of directly optimising the weights. Rather than imposing assumptions about statistical properties of the joint distribution of individual returns, this approach instead directly models investor utility from the ultimately resulting single

[6] This must not be misunderstood to imply higher moments can be ignored: modern portfolio optimisation naturally does consider higher moments, albeit indirectly, insofar as they impact portfolio returns.

Figure 1: Volatilities of daily returns in rolling windows of 180 days length for major crypto-currencies for the time period as of 2016 until 2018-12-07. Both time-series instability as well as the sizable impact of outliers are clearly visible.



portfolio return. The weights are then determined by the solution of this optimisation. In this spirit, F5 is based on the framework of Brandt et al. (2009) as follows.

Let $r_{p,\,t+1}$ denote the return from time t to time $t+1$ of the entire portfolio consisting of cryptos $i = 1, \ldots, N_t$, with their individual returns for the period denoted $r_{i,\,t+1}$, respectively.

Let $w_{i,\,t}$ denote the weight of crypto i in the portfolio at the beginning of period t. Since we consider a fully invested, crypto-only portfolio, its return

$$r_{p,\,t+1} = \sum_{i=1}^{N_t} w_{i,\,t}\, r_{i,\,t+1}. \tag{1}$$

With $\mathbb{E}_t\left[\cdot\right]$ denoting time-t conditional expectation and $u\left(\cdot\right)$ the investor's utility function, the optimisation problem thus amounts to

$$\max_{w_{i,\,t}} \mathbb{E}_t\left[u\left(r_{p,\,t+1}\right)\right] = \max_{w_{i,\,t}} \mathbb{E}_t\left[u\left(\sum_{i=1}^{N_t} w_{i,\,t}\, r_{i,\,t+1}\right)\right], \tag{2}$$

where the solution to the maximisation problem determines the optimal weights $w_{i,\,t}$. These weights are parametrised as a function of two components: first, the weights of a benchmark portfolio $\bar{w}_{i,\,t}$, and second, of crypto characteristics $\hat{x}_{i,\,t}$.

While the approach of Brandt et al. (2009) can accommodate also more involved functions for the weights, we employ their standard setup with a linear function:

$$w_{i,t} = \bar{w}_{i,t} + \frac{1}{N_t}\theta^\top \hat{x}_{i,t} \tag{3}$$

Thereby, the first summand represents a purely passive benchmark, e.g., a simple value-weighted or equally-weighted portfolio. The second summand reflects the active investment decisions to over- and underweight different cryptos with respect to the benchmark, based on their characteristics $\hat{x}_{i,t}$, which are standardised cross-sectionally to have zero mean and unit standard variation, as well as a parameter vector θ to be estimated.

2.3. Active Management

This clear separation of investment positions into a passive background component and an active decision part is a strong advantage over the more traditional approach of estimating return distributions and then calculating directly the holdings. Especially in crypto markets, with recurrent periods of both extreme drawdowns and extreme performance, it is critical to be able to pinpoint when heavy gains or losses were driven by general market movements.

At the same time, crypto markets provide a particularly important role for the manager, as the opacity and technicality of the markets allow for information advantages. For instance, avoiding scams requires the manager to exclude fraudulent coins from the investment universe. More generally, however, the central part of active management amounts to determining the characteristics $\hat{x}_{i,t}$ which the optimisation is based on: both the choice of variables and their precise construction drive the active return component. He is also responsible for determining the degree of conservatism vs. aggressiveness of the strategy by his parametrisation of $u(\cdot)$.

The concrete weights $w_{i,t}$, however, then follow from Equation (3), enforcing consistency across all invested coins and investment discipline by preventing deviations in individual positions that are not founded in underlying fundamentals.

As a result of the optimisation in Equation (2), the optimal θ^* provides one coefficient per risk factor, not per investable coin. This also precludes the curse of dimensionality.

2.3.1. Risk factors

The question is not *whether* to account for characteristics: Asset-pricing theory (APT) has established systematic relations between asset characteristics and expected returns that are both theoretically substantiated risk factors and to large extent empirically documented across virtually all asset classes, from stocks and bonds to commodities to currencies. The question is *how* these insights apply to the specific setting of crypto markets.

The standard workhorse model in financial economics is the so-called 4-factor model: MKT, the first factor goes back to Markowitz (1952) and should capture the aggregate market return; SMB and HML, factors two and three by Fama and French (1992), capture a size and a value premium, respectively; WML, the fourth factor called momentum, introduced by Carhart (1997), rigorously captures the stylised fact that winning assets tend to continue to gain for a while, as losing assets tend to depreciate further.

Exposure to risk factors is compensated via higher expected returns. Since our optimisation framework automatically determines exposures via θ, what needs to be established is which factors apply to crypto markets.

MKT, commonly instrumented via national stock-market indices, raises the question which market is relevant? The international nature of cryptos suggest a global index; however, correlations with stock market indices are surprisingly low for most cryptos (cf. also Table 2), independently of the choice of index, and often not significantly different from zero. This is indicative of still limited links to traditional financial markets. For practical purposes, it simplifies the problem as this factor can be omitted. However, once financial-market integration proceeds sufficiently, the market factor will need to be included.

HML refers to the relation of returns to the ratio of market to book value of firms. Book values, however, are not applicable to cryptos. While studies of currency markets sometimes try to salvage the concept via interest-rate parity arguments, the inexistence of liquid markets for riskless interest rates in cryptos precludes this approach, too. We thus drop HML from consideration.

SMB denotes the size factor based on market capitalisation, which in principle can be established for cryptos. (See, however, the discussion about market capitalisation in a crypto context in Section 2.4.2.) However, the distribution of market capitalisations of cryptos is severely more skewed than for listed stocks: since setting up yet another coin is close to costless, a huge amount of cryptos exist with arbitrarily low to no market value. Moreover, introducing an arbitrary threshold of "minimum market cap" for coins to be considered does not help, as small coins prove infeasible for institutional investment: not only do they often not (yet) meet minimum requirements regarding proof of concept and security environment, their low liquidity alone precludes meaningful investments. In effect, therefore, a professionally managed crypto fund can invest only in (comparatively) "large" cryptos.

WML, the momentum factor, is constructed to capture the tendency of increasing asset prices to increase further, as well as of dropping asset prices to be more likely to continue their decline than to recover in the short- to mid-term. Its returns are those to a (hypothetical) net-zero-investment portfolio going long on winner assets (highest past returns) and short on loser assets (lowest past returns).

With some adaptations regarding the specification of the investment universe, this factor can be constructed for cryptos, does not depend on size, and turns out to be empirically highly relevant in explaining crypto returns. This fits well with one standard interpretation of WML, namely the delayed incorporation of information into prices – certainly as big a challenge in crypto markets as in traditional financial markets.

We thus include one classical risk factor constructed specifically for the crypto market in $\hat{x}_{i,t}$. Effectively, this leads to over- and underweighting coins in relation to their exposure to the crypto-WML factor.

Recently, in independent research Yale economists Liu and Tsyvinski (2018) have confirmed the important role of momentum in crypto-asset pricing. F5 is the first to build an investable asset based on this return regularity.

2.3.2. A-priori information

Additional variables in the vector $\hat{x}_{i,t}$ can reflect management views on technological, legal, or other aspects that may not be fully priced into current coin prices, but do not merit the complete exclusion of coins. Currently F5 does not employ additional factors.

2.3.3. Objects of active management decisions

Beyond the construction of $\hat{x}_{i,t}$, the set of active decisions encompasses the choice of N_t, of $u(\cdot)$, of rebalancing times, and also which passive benchmark to start out from.

Regarding N_t, the choice is particularly relevant in crypto markets, as additional considerations affect the decision whether to trade in given coins – including which coins it is traded against, at which exchanges, wallet security, multisig status, etc. The flagship F5 index is built with a time-invariant $N = 12$.

Regarding $u(\cdot)$, the choice should best represents investors' preferences while still retaining analytical parsimony and tractability. The flagship F5 index employs a specification built around a classical parameter of risk aversion γ.

Rebalancing times are discussed in detail in Section 3.1, as F5 employs a range of mechanisms to reduce turnover while approximating optimal positions. This is critical given the comparatively large trading costs and low liquidity in crypto markets.

The choice of the benchmark warrants discussion.

2.4. Baseline Benchmark

As pointed out, our framework models deviations from a baseline benchmark; this raises the question which benchmark strategy to set. The most common choice definitely lies in using value-weighting across a fixed number of assets. Also CRIX value-weights, albeit over an optimised number of constituents.

2.4.1. Robustness over convention: equally-weighted baseline

However, most crypto-market indices (including CRIX) are not explicitly optimised for investment purposes. In such a setting, the findings of DeMiguel et al. (2009b) become particularly pronounced, and F5 builds on this strand of research by taking a $1/N_t$ strategy as the starting point. Even in the most-efficient markets it has repeatedly been shown to perform remarkably well out-of-sample; in fact, on a risk-adjusted level it is often hard to beat. The reason lies in the fact that the strategy is immune to overfitting – a concern of particular relevance in the context of crypto-currencies, where return distributions exhibit particularly severe changes (over time) of parameter estimates (seen also in Figure 1).

2.4.2. Issues with value-weighted crypto portfolios

Two additional arguments support an equally-weighted baseline benchmark: First, the heavy skewness of market capitalisations across coins makes value-weighting unattractive: In an unrestricted setting, the resulting portfolio returns will be driven to the largest extent soley by the returns of BTC and ETH; in the restricted setting, the weights of the most valuable cryptos will effectively be pinned to w^{max} at all times. In both settings, there remains little room for an optimising strategy to generate additional value.[7]

Second, with an equally-weighted benchmark the strategy's real-time target weights do not directly rely on estimates of market capitalisation.[8] This is not merely a statistical problem, but a serious economic issue: market capitalisation (defined as price per coin × coins outstanding) is, despite being most popular, an economically problematic metric: It does not account for pre-mined coins or coins held by founders; it does not account for lost or burnt coins; and most importantly, it does not account for growth rates of coins. Expected inflation, however, critically depends on the long-run expectation of coins outstanding.[9] Relying on a baseline benchmark that does not depend on market-capitalisation estimates prevents those problems from influencing the strategy.

Finally, it is important to point out that the equal weights refer to the *baseline weights* – the actual weights of the F5 strategy will naturally be notably different, due to the use of the momentum factor and the characteristics $\hat{x}_{i,t}$. Depending on the parameterisation (including γ), there can be sizable deviations from the baseline benchmark.

2.5. Holding Constraints

While the exposition so far has dealt with target weights, actual portfolio weights need to be restricted: First from below at least at zero, in order to reflect the infeasibility of efficient short sales in crypto markets, or even at $w^{min} > 0$ if the investment decisions *which* coins to invest in and *how much* to invest per coin should be decoupled (a condition fostering the optimisation as well as the intuition about portfolio formation). Second possibly from above at w^{max}, in order to meet regulatory requirements precluding concentration risk. The constrained weights are thus defined as

$$w^c_{i,t} = \frac{\min[\max[w^{min},\, w_{i,t}],\, w^{max}]}{\sum_{j=1}^{N_t} \min[\max[w^{min},\, w_{j,t}],\, w^{max}]}, \tag{4}$$

[7]For instance, the crypto20 token becomes an equally-weighted index for up to 60–70% of its holdings due to its cap around 10%. Incidentally, this actually helps its performance.

[8]The separate question of when coins become significant enough to merit inclusion in the index is based on market capitalisation and leads to an indirect effect via the rare events of additions to or removals of coins from the index.

[9]Considering the long-run maximum supply does not help, as it approaches ∞ for many coins.

where rescaling with the denominator ensures that $\sum_{i=1}^{N_t} w_{i,t}^c = 1$.

Currently weights are subject to a uniform $w^{min} = 2\%$ and no w^{max}, but the framework presented can easily accommodate more sophisticated restrictions, e.g., constraining portfolio norms (DeMiguel et al., 2009a).

2.6. Rebalancing

As the strategy is optimised for the long run, rebalancings should not occur too frequently, in order to economise on transaction costs. Given current trading costs, the goal is an average half-life of positions of several months.

Details about the operationalisation of determining rebalancing dates, traded coins and the sizes of position changes are provided in Section 3.

3. The Investment Strategy – Operationalisation

To make the portfolio optimisation operational, some management choices are needed; so are certain assumptions. Ultimately, also the assumptions should be considered as part of the active management decisions that pertain to the fund manager, with investors evaluating directly his portfolio's risk-adjusted performance. The basic manager choices encompass:

- the number of constituents of the strategy N_t,
- the choice of coins for investment (and thus effectively a linear ranking of the investment universe) at a given coin-choice frequency,
- the (potentially higher) frequency of rebalancing within the set of invested coins,
- which risk factors to include into consideration,
- and the starting date and initial value of the investment.

Since an F5 index is defined for every combination of those five choices, this whitepaper effectively presents a *family* of factor-based investment strategies optimised for crypto markets. The so-called "flagship F5 index" simply denotes the first and foremost instance.

Furthermore, a strategy is parametrised by:

- risk-and-return preferences $u(\cdot)$, in particular risk aversion γ,
- the specification of the investable coin universe over time,
- the precise construction of the momentum factor (and further factors, if any) and the corresponding individual coin characteristics $\hat{x}_{i,t}$,
- the rebalancing thresholds confining the no-trade region ("smart rebalancing").

With those parameters chosen (and continuously updated) by management, an F5 strategy is constructed via the following iterative 7-step procedure:

1. Starting with the initialisation date, determine the sequence of coin-choice dates.

2. At each such date, establish the investment universe as well as a linear ordering over all its coins, setting the top N_t to be the constituents until the next date.[10]

3. For each day, calculate the momentum factor, and consequently each invested coin's standardised characteristics $\hat{x}_{i,t}$.

4. Based on those dynamically updated values, run the optimisation from Equation (2) to find the optimal θ^*, which in turn determines the optimal target weights $w_{i,t}$, and if constraints apply $w^c_{i,t}$.[11]

5. Determine the set of rebalancing dates,[12] and verify at each whether the discrepancy between evolved, effective weights and target weights is large enough to merit rebalancing trades.

6. If so, determine which coins to trade and respective trade sizes in a tradeoff minimising the number of coins traded, the trade size per coin, and the discrepancy between rebalanced and target weights.[13]

7. Monitor the evolution of the regularly rebalanced weights, the implied portfolio value, and all relevant crypto-currency markets, in order to trigger active changes if unforeseen risks or opportunities arise.

As should be clearly visible, the procedure is designed with its efficient practical implementation in mind. The individual steps are further detailed in the following expositions. For an evaluation of how the flagship F5 strategy has performed in the past, see Section 5.

[10] In contrast to the trading desk's implementation of the strategy, the F5 index does take into account slippage in the index calculation. Large trading requirements due to in- or divestments into new or from old coin positions may thus lead to a certain tracking error. By monitoring slippage across marketplaces, the trading desk can, however, potentially mitigate price effects by spreading trades across time and exchanges.

[11] While the constraints may be less important for equal- or value-weighted indices, an unconstrained momentum strategy is likely to suggest coins for short-selling. Given today's crypto-currency market structure, F5 a long-only strategy with $w^{min} \geq 0$.

[12] The potential for different frequencies for coin choices and rebalancings within the coin set reflects the circumstance that adding another crypto-currency to the set of traded assets often represents a significantly higher effort than trading across established positions.

[13] Including this consideration into the F5 index construction mitigates to a large degree the trading desk's tension to achieve efficient rebalancing without incurring too high tracking error. Moreover, not trading in all invested coins is also a measure mitigating operational risk.

3.1. Coin Choice and Rebalancing Times

While indices are calculated continuously, a trading strategy must take into account that trading is costly and its frequency needs to be chosen such that it trades off transaction costs with tracking errors. Therefore, not all days may be chosen to be eligible for rebalancings. Rebalancings fall into two categories: trades of given positions towards target allocations, or changes in the coins of which the portfolio is composed. Correspondingly, F5 distinguishes two types of rebalancing dates: first, those when the ranking of coins eligible for investment is updated, potentially leading to the liquidation of existing and establishment of new positions; and second those when the allocation of existing positions is rebalanced across coins.

Due to trading costs and market frictions in crypto markets still significantly in excess of traditional financial markets, as well as the long-run perspective taken, the flagship F5 strategy is starting with a quarterly frequency for both types. With expected reductions in fees, the rebalancing frequency can be increased easily; an increase of the coin choice frequency may follow. Since rebalancings imply on average significantly lower trade sizes than position changes, a higher frequency of rebalancings versus changes of invested coins can make sense.

3.2. Investment Universe and Constituent Count

While to many crypto investors CoinMarketCap.com appears the conclusive list of coins available for investment, several additional aspects need to be taken into account. First, the platform does not screen coins like stock exchanges screen companies before listing their shares. Therefore, many fraudulent coins have been included in the major crypto platforms, some at times reaching billion-euro market capitalisations.[14] While the ultimate viability of a crypto can often be hard to evaluate, and no guarantee against a coin being written off completely is possible, many scams can be identified by experts in advance. Such coins are blacklisted from the F5 investment universe.

Furthermore, certain coins are not designed to be investment assets. For instance, tether is explicitly engineered to preclude any capital gains, as it is pegged to the USD.[15] Thus, it would expose investors to risk (of the peg breaking) with no upside potential; therefore such coins are excluded from the investment universe.

Moreover, coins also need to be allow for frictionless inclusion in trading and security systems. This hard requirement can lead to management excluding certains coins based on legal or technical reasons from the investment universe.

Finally, due to transaction-cost reasons, only a limited number of coins can be managed efficiently.[16] Consequently, a linear order needs to be defined, according to which the

[14] BitConnect was likely the most infamous case of a crypto clearly identified and called out as a Ponzi scheme by numerous experts well in advance of its collapse – which came after market capitalisation intermittently ballooned beyond two billion euro.

[15] Since F5 is denominated in €, technically holding tether would entail non-zero returns, but clearly a crypto-currency strategy is neither intended nor meaningfully employed for trading on fiat exchange rates.

[16] For instance, CRIX has had months with the constituent list expanding to as many as 60 coins, and

first N_t coins are included in the index.

Despite the limitations addressed in Section 2.4.2, F5 does follow the crypto community's common practice of considering market capitalisation as the basis of ranking a coin's prominence. However, the volatility of coin prices (and potentially, though of lesser concern, of the number of coins outstanding) induces serious fluctuations of point-in-time values. To preclude daily spikes from influencing the composition of the index, an exponentially-weighted moving average is taken as the basis for the ranking, calculated over a rolling window of fixed length, chosen such as to provide sufficient local stability of the ranking but still allow young coins that acquire a sizable market share quickly to enter the investment set early. For this purpose, the window length is reduced for coins not yet traded before. However, a minimal history length is required in order to allow estimation of coin characteristics.

3.3. The Momentum Factor and Coin Characteristics

As detailed in Section 2.3.1, among the risk factors of the standard asset-pricing 4-factor model, only the momentum factor is relevant for crypto-currency returns. The following details the construction of the crypto-specific WML factor, describes its properties, and documents its relevance for the major crypto-currencies' returns.

In analogy to Carhart's (1997) construction for stock markets, the crypto-WML factor is defined as the return on a virtual portfolio going long winner assets and going short loser assets. Winners respectively losers are defined as the top resp. bottom three deciles of assets ranked by their past returns (the 4 deciles around the median do not enter the factor construction).

In stock markets, all listed shares are commonly taken as the asset universe to be ranked; in crypto markets, for the reasons explained in Section 3.2, it is not meaningful to include all coins "listed" on any of the common overview platforms. Consequently, the WML factor is constructed based on the top 100 coins of the coin universe as detailed in Section 3.2. In line with the stock-market literature, portfolios are formed on a monthly basis,[17] while the 12/2 period of past returns considered is adjusted to reflect the higher parameter instability and the swifter changes in the investment environment in crypto markets.

Figure 2 displays the evolution of the crypto-WML factor as a (hypothetical) investment of 1000 at the beginning of 2017. It is visible that in calm periods, crypto markets exhibit reversal rather than momentum, with past losers outperforming past winners. In contrast, in turbulent times as the end of 2017 and the first quarter of 2018, the return differential of momentum assets becomes remarkable strong and stable. This emphasises the importance of handling time variation in return distributions. However, the momentum factor is *not* an investment strategy – due to its heavy reliance on short sales it is not investable at all – but a proxy construction aimed at capturing a regularity in

contracting again heavily in the following months. While this was optimal from a statistical point of view, it is impractical to implement in practice.

[17] While cryptos are indeed traded every calendar day, based on the finding of liquidity effects concerning Sundays in Elendner (2018), portfolios are always formed on the first Monday each month.

Figure 2: The value of a factor-mimicking portfolio for the crypto momentum factor, starting at 1000 at 2017-01-01. The crypto momentum factor is based on a virtual portfolio with long positions in the top three deciles on past crypto returns ("winners") and short on the bottom three deciles ("losers"). Note that since short positions cannot be established efficiently for many crypto-currencies, the factor-mimicking portfolio is not a tradable strategy. Instead, it captures a priced risk factor in the cross-section of crypto returns.

individual coins' returns.

The (raw) characteristics of coins are thus their relation of their returns to those of the crypto-WML factor in a standard APT regression (Ross, 1976). To illustrate the currently quite strong common factor in crypto-currency returns, Table 4 details momentum β's for the top coins in the recent period of August 2018. They range from insignificantly different from 0 to as high as 1.34. For investment purposes, the characteristics are estimated within a somewhat longer rolling window via a Fama and MacBeth (1973) approach. The resulting characteristics are depicted in Figure 3, which shows these loadings to both co-move across coins, as well as to evolve significantly over time, reaching as high as 1 and as low as -1.5 for the most pronounced coins.

These raw characteristics are calculated for all coins in the investment universe. In line with the methodology of Brandt et al. (2009), they are standardised to zero mean and unit standard deviation for those N_t constituent coins at the respective investment intervals. It is with respect to these standardised characteristics weights, in accordance

Table 4: Coefficients and t-statistics for the top coins' β's with respect to the crypto-WML factor for August 2018.

	BTC	ETH	XRP	BCH	LTC	EOS	BNB	XLM	TRX
β^{WML}	0.33	0.76	1.34	0.84	0.63	0.84	0.92	0.41	1.29
t-stat	1.92	2.93	3.56	2.79	2.35	1.99	3.08	1.35	3.43

with Equation (3), are chosen such as to maximise expected utility.

3.4. Risk Aversion and optimal θ^*

Our optimisation approach requires an explicit view on investor utility. Of course, portfolio-management approaches that do not rely on utility functions cannot side-step the need to take a stance on risk-return tradeoffs, at least if they want to pin down a concrete, implementable investment plan rather than outline an infinite set of potentially efficient allocations. We therefore consider it actually preferable to take an explicit view on risk aversion, amenable to economic intuition. (Which risk preferences are implied by maximising expected returns under some conditional VaR constraint?)

We follow the academic standard and employ a utility function with constant relative risk aversion (CRRA) over crypto wealth, parametrised by a single γ coefficient of risk aversion:

$$u\left(r_{p,\,t+1}\right) = \frac{\left(1 + r_{p,\,t+1}\right)^{1-\gamma}}{1-\gamma} \tag{5}$$

This has the advantage that preferences about higher moments are incorporated in a very parsimonious way. Moreover, γ is subject to clear economic intuition and the implied risk preferences can be compared to other financial markets.

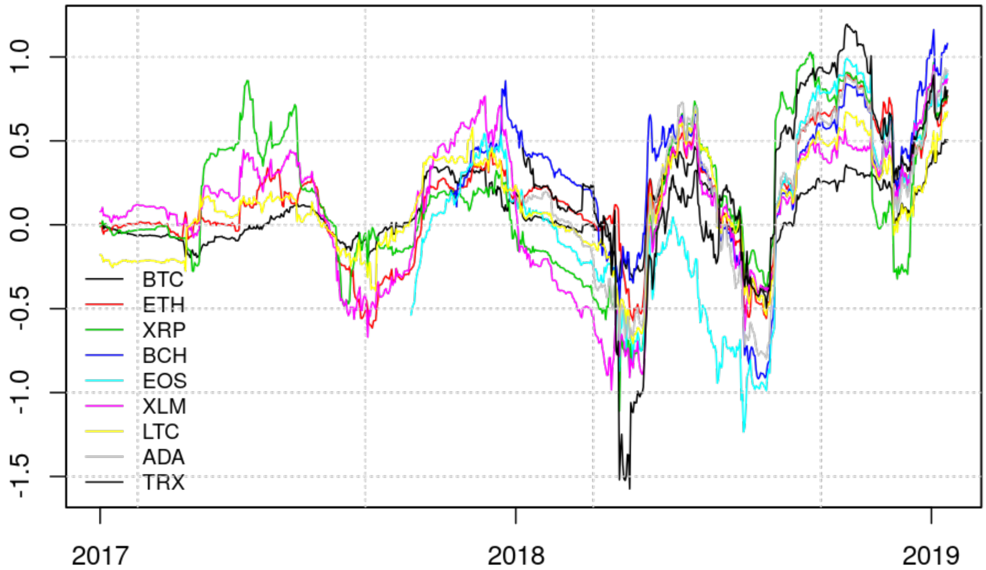
It is important to point out that we neither claim nor need this utility function to be an accurate representation of each investor's utility: rather, it should be considered a structured way for the manager to parametrise the risk-return tradeoff on which he is making an active decision.

3.5. Smart Rebalancing

At any rebalancing date, the investment strategy's target weights are compared with the actual current weights as evolved due to the individual coins' returns since the last rebalancing. While a standard index would change all positions to match the target holdings, from the perspective of an investment strategy it is desirable to minimise trading: both in terms of the number of coins as well as in terms of the trade sizes.

Consequently, F5 employs a rebalancing algorithm in order to minimise trading needs while ensuring positions sufficiently close to target allocations. It is based on soft and hard thresholds below and above each target weight: only coins with weights outside the interval delineated by the hard thresholds are traded back towards their targets; to

Figure 3: Current top 9 coins' β with respect to the crypto-WML factor for the period starting on 2017-01-01 (or later, depending on coin maturity).



limit the trade size, the adjustment proceeds only to the (weaker) soft threshold at the same side of the target.

Since F5 is a pure crypto-currency strategy, it does not keep any fiat currency cash holdings, and required coin purchases need to be financed by coin sales, and proceeds from sales invested via purchases. The rebalancing algorithm proceeds in an iterative procedure, compensating with position changes of coins in order of their distance to their targets with opposite sign. If balancing trades would lead to positions crossing any coin's target weight, the set of compensating coins is broadened and the trade sizes distributed proportionally to the respective deviations from target weights. This ensures the most overweighted coins compensate for required purchases, and the most underweighted positions are increased in response to sales.

Consequently, rebalancings will usually only affect a subset of positions. If no position lies outside its hard thresholds, a potential rebalancing dates is passed up without trading activity. The no-trade region reflects the presence of transaction costs. For sufficiently broad rebalancing thresholds, the frequency of (candidate) rebalancing dates can be significantly increased, with many of the days skipping any trading.

The reduction in trading activity, while maintaining a close proximity to the strategy's target weights, does not directly affect the strategy's returns as calculated before fees; its purpose is to generate value by avoiding fees.

4. Data

The technical terminology in this section is explained in Appendix A.

Data are obtained directly from crypto exchanges via their APIs. Seven exchanges are monitored: binance, bitfinex, bittrex, gdax, hitbtc, kraken, and poloniex. Our queries include lists of all traded pairs, daily OHLC data[18] for all pairs, regular transcripts of tradehistories, as well as regular snapshots of the orderbooks.

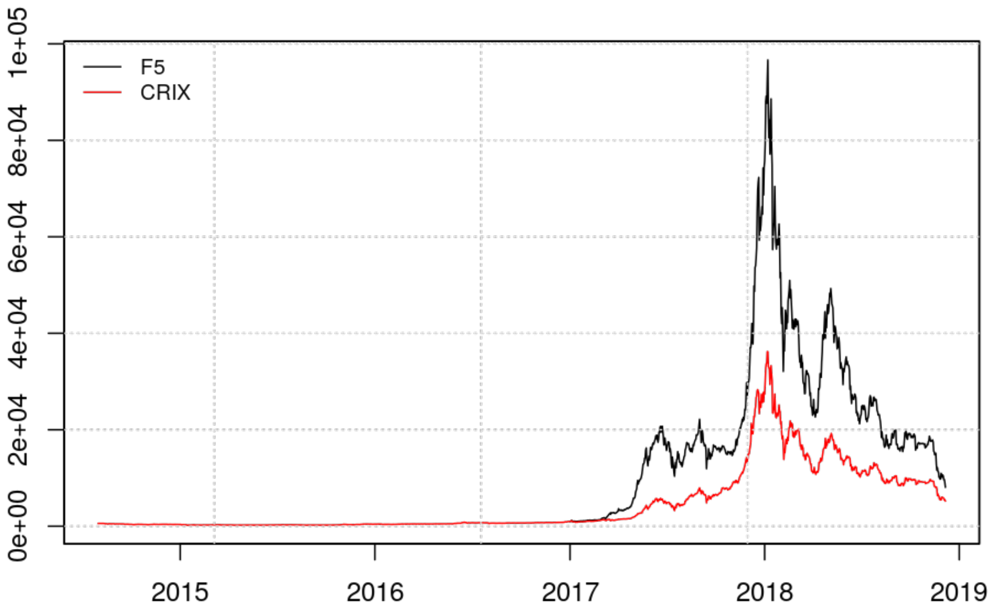
Additionally, we obtain aggregate crypto-market data from coinmarketcap on an hourly basis, as well as the standard CRypto IndeX CRIX.

For backtesting, we supplement our data with hourly OHLC data by cryptodatadownload and complete tradehistories provided by kaiko.

Data about traditional financial assets stem from Yahoo Finance and the Federal Reserve Bank of St. Louis (FRED).

5. Quantitative Evaluation

Figure 4: Portfolio value of the F5 index' investment strategy when initialised at 1000 on 2017-01-01. The CRIX is the most-common benchmark index for cryptos, and depicted rescaled to the same starting value.



[18]Not all exchanges provide explicit APIs for OHLC data, but for most daily high and low prices are available via API, and all provide daily "closing" prices – while, naturally, crypto markets do not "close" in the historical sense of suspending trading.

To evaluate risks and opportunities of the F5 investment strategy, this section explores the hypothetical performance of an F5 portfolio starting with the value of 1000 on 2017-01-01 in a backtesting exercise. In order to preclude hindsight bias, no dynamic management decisions are included in this evaluation; F5 is determined based on the standard parametrisation alone. The portfolio value of the index is shown in Figure 4, together with the benchmark index CRIX, also rescaled to a value of 1000 at the starting date.

It is clearly visible that the momentum strategy outperforms particularly in the heated period at the end of 2017, when increased exposure to high-momentum coins led to particularly pronounced gains; as the flip side of the same coin, the crash at the beginning of 2018 war participated in disproportionately strongly, too, leading to larger losses than the benchmark suffered. However, the momentum strategy detected the changes in risk-factor exposures, and via updates of its positions at subsequent coin-choice and rebalancing dates, mitigated the development. As of 2018-12-06, it still stands at a 55 % premium over CRIX.

5.1. Rebalancings

If F5 had maintained a quarterly rebalancing frequency since inception on 2017-01-01, a constant constituent count of $N_t = 12$ coins would have led to investments into a total of 27 cryptos, 5 of which (BTC, ETH, XRP, LTC, DASH) would have been held from the start as detailed in Table 6.

5.2. Weights

While changes in the investment set necessarily require trading, whenever a coin remains in the investment set across a rebalancing time point, despite the fact that the probability of its weight matching exactly the target weight being virtually zero, due to the smart rebalancing procedure, it may or may not be traded. With quarterly rebalancing dates, the start-of-2017-vintage of F5

Out of 64 potential weight adjustments, 17 (that is 27 %) could be omitted without too large deviations from target weights. Table 7 details rebalancings as absolute percentage point changes in weights per rebalancing date. Table 8 gives more details about the distribution of *target* weights over the same time period, while Table 9 reports the same for effective weights.

5.3. Performance

In Table 5, various common risk measures are depicted for F5, the benchmark index CRIX, and investments into an equally-weighted, two-constituent BTX-and-ETH portfolio, as well as investments into those two coins directly.

While an investment in CRIX would be slightly less risky, daily expected returns are 15 basis points lower. Therefore, the F5 Sharpe ratio is notably higher. Compared to the equally-weighted BTC/ETH portfolio, for F5 expected returns are higher, while volatility lower. Also, while Values-at-Risk turn out comparable, the conditional VaR is

Table 5: Performance and risk measures for F5 and alternative crypto investments for the period from 2017-01-01 until 2018-12-07. 50BTC/50ETH denote a portfolio of half Bitcoin and half Ethereum. VaR_x denotes the Value-at-Risk at the x% level. CVar_x denotes the conditional VaR at the x% level.

	F5	CRIX	50BTC/50ETH	BTC	ETH
exp. returns	0.47	0.39	0.43	0.28	0.53
returns_clean	833.34	1260.93	551.46	338.33	1603.63
returns_clean_pa	217.85	190.70	163.86	92.13	250.05
volatility	5.68	4.51	5.97	4.51	6.28
Sharpe_ratio	8.03	8.34	7.54	6.43	8.80
max_drawdown	91.82	87.92	91.68	82.50	93.46
upside_frequ	54.61	58.12	51.77	54.60	51.09
VaR_5	-8.95	-6.99	-8.21	-6.65	-8.53
VaR_1	-15.68	-14.22	-16.02	-12.71	-15.35
CVaR_5	-13.26	-11.42	-10.38	-9.41	-10.64
CVaR_1	-19.86	-14.22	-28.76	-18.50	-26.83

slightly milder at the 5% level, but considerably harsher at the 1% level as compared to F5.

We can conclude that – as expected of a crypto-currency strategy – F5 constitutes a risky investment. It is designed for investors who take a bullish long-term view on the asset class of crypto-currencies, as due to the impossibility of efficient large short positions and the absence of liquid derivatives markets, the opportunities for hedging are still limited for now.[19] At the same time, the F5 momentum strategy provides outperformance in comparison to the benchmark index or comparable investment products. Most importantly, its solid basis in state-of-the-art robust portfolio optimisation techniques is designed to reduce its vulnerability to unexpected future events, while maintaining a strong performance potential.

6. Conclusion

After almost a decade since the introduction of blockchain technology, crypto-currencies have evolved to a novel asset class. While crypto assets exhibit high volatility, their return properties make them an attractive addition to diversified portfolios (Petukhina et al., 2018). So far, however, no investment vehicle existed to allow investors to participate in crypto exposure via an optimised investment strategy. We propose the first state-of-the-art, long-term investment strategy as the basis for active intermediated investment management in cryptos: F5.

[19]The BTC futures at the CME is the one noteworthy exception, but addresses only the Bitcoin price.

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Appendix A Definitions and Terms

API Application Programming Interface, online information source that can be queried by a computer algorithm, as provided by crypto exchanges about their trading data

asset umbrella term for either coin, fiat, or strategy

crypto individual crypto-currency (e.g., BTC, ETH, ...), which is priced by the ratio at which it is trading in pairs

coin synonymous with crypto

exchange trading venue which is offering the possibility to exchange certain assets against pre-defined alternative assets, i.e., a set of traded pairs

fiat central-bank-issued, official government (fiat) currency which is legal tender (EUR, USD, ...); often base asset in traded pairs

index the value of a trading strategy, denominated in some base asset

OHLC panel data consisting of Open/High/Low/Close prices for a traded pair over a regular frequency, commonly daily

orderbook list of committed bid and ask offers that can be executed immediately by taking the opposite leg, albeit at some slippage, at any one point in time

pair short for "trading pair," a market for the interchange of two assets, quoted as the amount that one unit of the target asset is exchanged for in terms of the base asset, for instance BTCEUR trading BTC against EUR or ETCBTC for the price of ether in bitcoins

slippage the price impact a larger order can have, in particular in less liquid pairs; more precisely the magnitude in percent of the detrimental change of the mid price, triggered by a given (potential) trade

source information provider, can be an exchange or any other provider; supplies the data to calculate and evaluate a strategy

strategy an investment strategy is effectively a time-varying weights vector over assets which is always summing to 1: at any point, the weight defines what fraction of the strategy's wealth is invested into which asset; when priced in terms of some base asset, its value is an index

tradehistory exhaustive chronological list of all individual trades executed for a pair on an exchange over a given time interval

Appendix B Details on F5 Weights and Trades

Table 6: Investment-set changes of the F5 index as started on 2017-01-01 with quarterly rebalancings. +1 denotes a coin's addition, −1 its divestment, and 0 its continued presence as an F5 constituent.

	2017-01	2017-04	2017-07	2017-10	2018-01	2018-04	2018-07	2018-10
BTC	1	0	0	0	0	0	0	0
ETH	1	0	0	0	0	0	0	0
XRP	1	0	0	0	0	0	0	0
LTC	1	0	0	0	0	0	0	0
ETC	1	0	0	0	-1			
STEEM	1	-1	1	-1				
DASH	1	0	0	0	0	0	0	0
REP	1	0	-1					
MAID	1	0	-1					
XEM	1	0	0	0	0	0	-1	
WAVES	1	-1	1	-1				
DGD	1	-1						
GNT		1	-1					
DCR		1	-1					
ICN		1	-1					
STRAT			1	-1				
BTS			1	-1				
XLM			1	-1	1	0	0	0
MIOTA				1	0	0	0	0
NEO				1	-1	1	0	0
OMG				1	-1			
QTUM				1	-1			
LSK				1	-1			
BCH					1	0	0	0
ADA					1	0	0	0
TRX					1	0	0	0
EOS					1	-1	1	0

Table 7: Weight changes at quarterly rebalancings for F5 initialised on 2017-01-01. Missing entries indicate that the respective coin was not part of the portfolio at that quarter-start. Entries of 0 indicate that due to the smart-rebalancing procedure, the coin's weight was considered close enough to its target weight to not merit any adjustment of its position.

	2017-01	2017-04	2017-07	2017-10	2018-01	2018-04	2018-07	2018-10
BTC	14.22	0.00	0.98	3.76	-0.46	0.00	0.00	-6.50
ETH	9.26	0.00	-3.98	-9.96	0.46	0.00	5.61	0.00
XRP	11.95	-6.00	-12.19	5.67	-31.66	5.68	0.00	3.85
LTC	3.00	4.48	-2.11	4.24	-4.17	0.00	2.53	-2.78
ETC	13.91	0.00	2.71	3.37	-6.40			
STEEM	3.00	-0.83	9.45	-7.71				
DASH	9.32	-8.31	6.26	-0.52	7.02	0.00	-0.95	-7.94
REP	3.00	4.00	-3.01					
MAID	3.70	8.31	-5.44					
XEM	12.56	-11.38	0.00	-9.72	6.33	0.00	-4.58	
WAVES	10.64	-4.48	9.67	-12.60				
DGD	5.43	-3.17						
GNT		11.38	-14.26					
DCR		3.00	-1.69					
ICN		3.00	-3.95					
STRAT			3.00	-2.00				
BTS			3.00	-1.09				
XLM			11.55	-5.84	3.00	5.43	5.16	-17.77
MIOTA				9.96	-1.33	0.00	-6.65	7.94
NEO				3.00	-1.43	3.00	10.22	7.97
OMG				12.60	-5.22			
QTUM				3.00	-3.47			
LSK				3.86	-3.98			
BCH					15.98	-3.00	-10.22	0.00
ADA					8.19	3.62	-4.11	0.00
TRX					9.31	0.00	0.00	2.78
EOS					7.84	-14.73	3.00	12.46

Table 8: Descriptives of *target weights* (per coin) of the F5 strategy starting 2017-01-01. Numbers are in percent, q_x denotes the x% quantile; $w^{min} = 2\%$.

	min	q_25	mean	std. dev.	median	q_75	max
BTC	3.00	3.00	7.22	4.58	5.91	10.23	20.89
ETH	3.00	5.42	9.43	4.43	9.82	12.70	23.49
XRP	3.00	8.30	11.11	5.03	10.78	14.34	28.26
LTC	3.00	3.00	8.27	4.78	8.60	11.73	24.15
ETC	8.34	9.95	11.97	2.58	11.50	13.63	23.73
STEEM	3.00	3.00	6.79	4.46	3.65	10.47	17.92
DASH	3.00	3.00	7.05	4.18	6.80	10.31	19.59
REP	3.00	3.49	8.39	4.03	9.28	11.58	16.30
MAID	3.00	8.73	10.42	3.13	10.51	12.11	17.63
XEM	3.00	3.00	7.24	6.46	3.95	10.29	42.53
WAVES	3.00	3.00	5.54	3.75	3.00	8.98	16.51
DGD	4.49	9.58	11.24	2.93	11.07	12.83	18.00
GNT	3.00	9.77	11.61	2.59	11.45	13.02	18.85
DCR	3.00	3.00	3.00	0.00	3.00	3.00	3.00
ICN	3.00	3.00	3.58	1.74	3.00	3.00	10.31
STRAT	3.00	3.00	3.00	0.00	3.00	3.00	3.00
BTS	3.00	3.00	4.19	3.06	3.00	3.00	14.62
XLM	3.00	3.00	8.57	5.38	8.88	12.34	24.13
MIOTA	3.00	4.78	9.12	4.83	8.80	12.29	27.78
NEO	3.00	3.00	9.68	5.11	9.60	13.34	21.40
OMG	3.00	3.00	6.14	3.86	4.46	8.48	17.65
QTUM	3.00	3.00	4.80	3.36	3.00	4.21	16.23
LSK	3.00	3.00	5.32	4.00	3.00	6.67	15.55
BCH	3.00	3.00	5.83	4.56	3.00	8.42	28.77
ADA	3.00	3.00	7.67	4.02	8.01	10.29	22.50
TRX	3.00	3.00	9.89	4.94	10.59	12.96	23.22
EOS	3.00	3.00	9.77	5.44	10.96	14.62	19.73

Table 9: Descriptives of *effective weights* (per coin) of the F5 strategy starting 2017-01-01. Numbers are in percent, q_x denotes the x% quantile.

	min	q_25	mean	std. dev.	median	q_75	max
BTC	1.67	4.79	7.41	3.40	6.88	10.72	16.03
ETH	2.50	5.07	9.08	4.54	7.19	12.70	23.57
XRP	2.50	7.28	11.21	7.05	8.58	14.30	47.92
LTC	0.91	4.65	6.34	2.76	5.85	7.80	18.33
ETC	4.73	8.52	10.33	2.38	10.12	11.82	17.91
STEEM	0.59	1.97	4.78	3.06	4.68	7.26	10.59
DASH	1.93	10.35	12.64	5.85	13.27	15.99	35.75
REP	2.04	2.70	3.49	1.30	3.00	3.53	6.73
MAID	1.89	4.10	5.91	3.00	5.21	6.28	13.54
XEM	1.69	4.93	9.31	5.20	8.78	13.36	23.72
WAVES	4.56	8.82	9.67	2.27	10.23	11.10	14.23
DGD	2.62	3.66	4.42	0.84	4.47	5.16	6.21
GNT	8.50	12.24	14.09	2.30	14.33	15.43	19.79
DCR	1.33	1.67	2.26	0.80	1.93	2.99	4.18
ICN	1.10	1.46	2.17	0.92	2.00	2.48	4.74
STRAT	1.95	2.54	2.81	0.44	2.68	3.15	3.74
BTS	1.03	1.50	1.90	0.55	1.95	2.27	3.37
XLM	2.82	4.81	9.72	6.05	8.89	10.77	23.59
MIOTA	2.67	7.02	9.32	4.48	9.94	10.81	31.86
NEO	1.09	2.42	7.05	5.50	3.00	11.64	17.17
OMG	4.22	5.35	7.83	2.53	7.70	10.20	12.60
QTUM	1.15	2.46	2.64	0.64	2.73	2.99	4.05
LSK	2.11	3.16	3.56	0.71	3.64	3.92	5.33
BCH	2.00	4.36	9.99	5.78	11.85	15.53	19.27
ADA	2.76	3.35	5.86	2.46	4.81	8.39	10.93
TRX	3.99	5.64	6.99	1.71	6.69	8.36	11.35
EOS	2.37	2.72	9.03	5.46	10.94	14.05	16.26