Cross-sectional Momentum in Cryptocurrency Markets
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Abstract

There is substantial evidence supporting the existence of a short-term momentum anomaly in blockchain based digital assets. Specifically, those assets which perform best (worst) over a 30 day period tend to continue to outperform (underperform) over the subsequent 7 day period. Long-only momentum trading strategies that exploit this phenomenon have consistently delivered excess returns relative to our benchmark (Bitcoin). This paper reviews the evidence of price momentum in cryptocurrency markets, explores the construction of several applicable trading strategies and the potential explanations for the momentum effect.

Introduction

Beginning with Jegadeesh and Titman (1993), there exists an extensive exploration of the momentum effect across different asset classes and markets around the world. Momentum is perhaps the most persistent asset pricing anomaly across markets and time, and the most puzzling as there is no definitive explanation for this market inefficiency.

Traditional momentum strategies have been studied in cryptocurrency markets, with thus far inconclusive results and limited attention to whether these strategies can be profitably executed in a production trading environment. Grobys and Sapkota (2019) find no momentum in sample 2014-2018. Shen, Urquhart and Wang (2020) use a three factor model and find a reversal factor for the period 2013-2019. Jia, Goodell and Shen (2022) use a more recent sample period and find positive momentum. Fracassi and Kogan (2021) find positive momentum on shorter time frames (specifically 24 hours), possibly resulting from attention cryptocurrency markets give to popular websites quoting a rolling 24 hour percentage change in asset prices.

In this paper, we explore whether assets in the cryptocurrency market (“the assets”) that perform the best (worst) over various time periods tend to continue to outperform (underperform) over subsequent time periods. We outline a process for selecting accessible centralized and decentralized cryptocurrency exchanges, the construction of a universe of tradable assets and, given the fragmented nature of the crypto currency market, how we construct daily aggregated price and volume candles.

We contribute to the existing literature in two ways. First, we extend the investment universe and bring our analysis up to November of 2022. Second, we approach the problem from the perspective of fund managers, applying strict fundamental and liquidity-based filters to create a more realistic universe of spot cryptocurrencies.

Our analysis finds that there is a significant spread between top/bottom quintile returns across equally weighted portfolios constructed based on a 30 day lookback period and a 7 holding period. We find these results both in and out of sample during the time period from April 2018 to

November 2022. Included in our analysis is a look at the probable maximum portfolio size for a top quintile long only strategy based on available liquidity and portfolio turnover, and the portfolio's excess return to the performance of both our benchmark (Bitcoin) as well as an equally weighted and weekly rebalanced portfolio of all assets that meet our liquidity threshold.

Hypothesis

While the momentum effect is found across a wide range of asset classes and geographies, the reason for and time frame on which this asset pricing anomaly takes place is highly variable. A range of different variables discussed below, some unique to cryptocurrency markets, drove our initial hypothesis for why this anomaly exists and the optimal time frame on which we would find positive momentum to be in the range of one month.

Cryptocurrency market participants will be familiar with the concept of the "hot ball of money." The idea here pulls in a handful of our fundamental observations about cryptocurrency markets that are unique or extremely exacerbated relative to traditional markets.

Cryptocurrencies have very little intrinsic value in the sense that a long track record of market participants valuing these assets using a generally agreed upon set of fundamental variables does not exist. While you can produce a price-to-sales ratio or even a price-to-earnings ratio for some protocols, there is no reported evidence that these variables hold any explanatory power in the cross-section of cryptocurrency returns. Without some reasonably agreed upon framework for the fundamental valuation of these assets, there doesn't exist a set of investors that is willing to systematically buy (sell) assets when their valuations significantly deviate from the group.

Cryptocurrency markets are also extremely fragmented. Market participants across different legal jurisdictions have varying degrees of access to different centralized exchanges with varying levels of liquidity and different sets of listed assets. For example, US domiciled market participants can not access Binance which represents 75% of all volumes today. While decentralized exchanges do allow for relatively unfettered access to buy (sell) a wider range of assets, the data show that there is both significantly more market participants and significantly more transaction volume on centralized exchanges than decentralized exchanges. This market fragmentation can create limits to arbitrage as capital may be restricted from participating among regulatory or geographic boundaries.

Shorting cryptocurrencies across a wide range of assets with appropriate liquidity is also extremely difficult. Perpetual futures, a legitimate and significant innovation brought to financial markets by cryptocurrency market developers, have been successful at gaining enough liquidity to allow for hedging large beta risk, but liquidity in the long tail of assets is limited and highly concentrated on one centralized exchange (Binance). The limited number of market makers willing to provide constant liquidity to these markets in size also causes the funding rates for holding short positions to fluctuate wildly making it difficult to model the cost of carry for short positions. Liquid perpetual futures markets are often not available at the same time coins begin trading in the spot market as the creation of these markets is dependent on centralized and decentralized exchange teams approving their creation. Some legitimate speculation exists that overlapping relationships between protocol teams, their investors, and large centralized exchanges impact the timing of both spot and futures market listings for the purpose of controlling supply/demand characteristics of the market. DeFi lending markets for the long tail of coins (top 300) are very thin and require posting significant over collateralization for the borrow to effect the short position.

Cryptocurrency markets, we believe to no one's current surprise, are also rife with insider trading and market manipulation. Market moving variables such as when a specific coin will be listed on a large centralized exchange, when a protocol team will release news about a new version of its protocol or a change in its tokenomics, capital raises, investor cliff periods, airdrops, regulatory actions, large business development relationship announcements, developer incentivization programs and a host of other variables all take place with little to no regulatory oversight and massive imbalance in access to information across market participants. Wash trading, coordinated pump-and-dump schemes, and general manipulation are all well documented within the space. This imbalance is certainly not a secret and is widely taken into account by market participants bringing us back around to the core of our hypothesis.

Humans possess a finite capacity to process the large amounts of information they are confronted with. Time is a scarce resource for decision makers. The rational inattention theory argues that some information may be evaluated less carefully, or even outright ignored. Or, alternatively, it may be optimal for investors to obtain news with limited frequency or limited accuracy. This can cause investors to over- or under-invest and could cause the persistence of trends. The speed of innovation within the space of cryptocurrencies has been so extreme, we believe that many speculators are exhibiting rational inattention, leading to the emergence of the momentum phenomenon. Rational inattention within cryptocurrency markets has become so extreme that market participants, in their self awareness of this extreme bias, have come to call the effect this produces the "hot ball of money" theory. We believe the momentum effect becomes self fulfilling as market participants attempt to front run the hot ball of money.

At any given time there are only a large handful of narratives impacting asset prices which the vast majority of market participants focus on collectively with their capital. These market narratives are aided by the fact that relative to traditional markets, cryptocurrency market participants are "very online", meaning they tend to participate in social media (Twitter, Reddit, etc.) extensively. Some examples of specific narratives that have driven significant amounts of capital into certain assets over the past 3 years include: Elon Musk talking about Dogecoin on Twitter, L1 protocols launching developer incentivization programs to grab TVL ("SoLunAvax"), DeFi summer and the associated farming of DeFi trading/lending protocols, NFTs (ArtBlock and generative art more generally), or Mark Zuckerberg renaming Facebook to Meta in order to focus on the metaverse.

This narrative rotation also has the effect of driving significant liquidity into protocols (total value locked) over a short period of time, producing a self-fulfilling effect in the fundamental viability of the protocol itself, further attracting investors to the protocol's token. This aligns with one of the core innovations of cryptocurrency markets being the ability to bootstrap liquidity within decentralized networks by incentivizing that liquidity with rewards in the form of tokens (protocol emissions). For those generally skeptical of this framework for bootstrapping liquidity, we do not see it as materially different from Uber highly subsidizing the cost to ride and amount paid to drivers, except in this case participants in the network are paid in protocol tokens instead of services. Cryptocurrency market participants are also incentivized to participate in protocols as liquidity providers where rewards are highest. The double edged sword here, and a variable that significantly contributes to our hypothesis, is that this protocol rewards chasing behavior that is not sticky and quickly rotates to the next narrative ("farming" opportunity). One of the legitimate criticisms for the significantly large valuations associated with some cryptocurrency protocol tokens is this lack of stickiness of liquidity and users, which can surge several orders of magnitude and completely collapse within months. Very few protocols have been able to organically attract longer term liquidity and users without unsustainable reward emissions. Another aspect of liquidity rewards emissions we feel may be contributing to the momentum effect is in the longer term structural aspect of the emissions schedules. While we don't present specific evidence in this paper, we do see more generally that protocols with a low float and high fully diluted valuation ("FDV") relative to their market cap (float * price), having a long term release of rewards emissions, tend to suffer from the constant sale of these emissions by liquidity farmers leading to these assets ending up consistently in the bottom quintile of 30 day returns.

Our last, and possibly main hypothesis for the existence of positive momentum in cryptocurrency markets is rooted in the idea that the development of these assets is so incredibly nascent. As the core technology develops, new tokenomic schemes are introduced, and consumer adoption takes place providing more liquidity to these networks, it is likely that a large set of assets eventually ascend in value. It would be a-historic for Bitcoin, the first incarnation of this specific technology, to be the eventual big winner in the space, when we have never seen the first incarnation of any technology in the modern era do so (AOL/Netscape vs Google/Facebook). As the core technology in the space is developed and applied to new protocols, market participants will likely continue to place bets by considerably marking up valuations well ahead of where these protocols might be valued if valuations were based on the relative fundamentals to Bitcoin and Ethereum (price to protocol staking rewards, number of monthly transactions, total dollar value of transactions, total unique wallets transacting, etc). And because innovation in this space is moving so quickly, the timeframe on which these bets are made, and closed, is significantly compressed relative to traditional markets.

For all of these reasons, we believe that the rotation of capital from active market participants (the hot ball of money) leads to significant positive momentum cross-sectionally over time frames associated with the lifecycle of these narratives. While we do not attempt to confirm the causal effect of these narratives in our paper, further research using social media data to quantify this effect may be able to prove its impact on the momentum factor in cryptocurrency markets.

As a caveat to our hypothesis above, we would like to submit that there is certainly a significant amount of hindsight bias in our analysis of the potential causal effects of the momentum factor. We have participated deeply in these markets and our views are certainly biased based on our prior experience. As well, compared to analyses of momentum in other asset classes, we are dealing with a very short sample period (less than 5 years) in an asset class that has and will continue to change considerably. The causal variables associated with the momentum effect we hypothesize today may not continue to impact cryptocurrency markets in perpetuity as market structure changes.

Data and Process

Despite on-chain transparency, identifying reliable data in the crypto ecosystem is a notoriously difficult endeavor. Price and volume data is provided by Nomics, which maintains a point-in-time database of cryptocurrency markets across a wide breadth of exchanges.

For quality control reasons, rather than use pre-generated aggregate open-high-low-close ("OHLC") data, we construct our own using only data from 57 major DeFi and CeFi exchanges. In doing so, we maintain a higher degree of confidence in the quality of the pricing data. Furthermore, this approach helps restrict our estimates of trading volume to only those venues we believe institutional investors would feel comfortable trading.

In order for an asset to be considered for inclusion in the universe at each rebalance period, it must be listed on at least three exchanges, one of which must be a CeFi exchange. We use this filter for several reasons. While anyone can list any asset on a DeFi exchange, there is, at least ostensibly, a minimum filter for CeFi exchanges having to review and list assets on their platforms. Because most market maker activity takes place on CeFi exchanges, assets listed on CeFi typically have tighter spreads and the quality of the pricing data is usually better.

To avoid including fraudulent or meme-based tokens with anomalous volume spikes in our analysis, we decided to construct an indicator that defines consistent volume. In order for an asset to be considered for inclusion in the universe at each rebalance period, it must have had an average dollar volume traded of at least $5M for half of the previous 30 days.

The rebalance and trading of portfolios are performed on Thursday at midnight UTC. We assume the rebalance is instantaneous and frictionless, an unrealistic assumption that we will address later in the paper.

Our data contains approximately 30,000 unique assets but for this particular strategy, we narrowed that universe down using the parameter minimums we reasonably believed in. To that end, we were able to eliminate many assets based on just the volume and exchange requirements alone. Additionally, we spent time manually reviewing asset metadata and returns to exclude tokens that fell into specific categories. A few of those categories include: rebase tokens (e.g. OHM) and tokens with large transaction penalties (e.g. SAFEMOON).

Our full sample period for this analysis ranges from 2018-04-05 to 2022-11-06. We define the in-sample period to be 2018-04-05 to 2021-03-01 and the remainder as out-of-sample.

While our data set stretches back many years before the beginning of our sample period, our analysis is limited to after April 2018 based upon the definition of our investable universe and the need for a sufficient number of assets to exist to produce quintile portfolios.

Our aggregated price and volume candles only take into consideration CeFi and DeFi spot markets and do not consider price or volume from perpetual futures markets. In our analysis of available liquidity to execute these portfolios at specific sizes, we exclude this liquidity in order to avoid the necessary further accounting for funding rates. We have observed that in many cases perpetual futures liquidity in the long tail of coins, especially in the top quintile of 30 day momentum, is often considerably higher than spot markets, likely because of the increased attention to these assets by market participants and the availability of leverage. Further analysis of perpetual futures liquidity and funding rates may provide support for the implementation of portfolios at larger size.

We do not produce a time series of perpetual futures fund rates or DeFi borrow rates for short positions in the bottom quintile, nor do we attempt to ascertain whether markets for all of these potential positions even exist. Therefore, we do not attempt, in this specific paper, to produce long/short market neutral portfolios. Our benchmark for our long only top quintile portfolio is Bitcoin. Any mention of “excess return” means excess to the performance of Bitcoin. Along with our benchmark we also produce a weekly rebalanced equally weighted portfolio of all assets in our universe that meet our liquidity thresholds on each rebalance date.

We use Bitcoin as our benchmark instead of this equally weighted portfolio of all available assets for two main reasons, with one obviously large caveat. There has been and is now no product available to market participants that tracks our equally weighted portfolio of all available assets. While a sophisticated institution could have theoretically invested in this way, we’re highly certain none did. The most liquid 500 crypto assets are for the most part early stage startups with an extremely high failure rate, this is not the S&P 500 where turnover is 4% annually. As well, for many (we would say most) investors Bitcoin is still the asset that represents the cryptocurrency asset class and the easiest to invest in legally and operationally. Which brings us to our caveat. Using one asset as our benchmark absolutely introduces a tremendous amount of survivorship bias. While Bitcoin is the genesis asset of this asset class having been around over 13 years now, and represents roughly 40% of the overall market cap, its status as the benchmark with investors and in this paper speaks to its performance over that time period. Interestingly we would like to note that Ethereum (ETH), the second largest asset has outperformed Bitcoin by roughly an order of magnitude since its inception in 2015. One could easily argue ETH should be our benchmark given the sample period of this analysis. Regardless, the equally weighted portfolio as a benchmark does a strong theoretical job of demonstrating the excess return of the top quintile portfolio without the survivorship bias.

Our in-sample and out-of-sample analysis below does not initially include assumptions of transaction costs. In the Conclusions section of this paper we do include an analysis on the impact to returns at different assumptions of transaction cost. We structure our analysis in this way in order to show the impact of momentum on the returns of these quintile portfolios before factoring in the cost of trading on this anomaly and the excess return of the top quintile portfolio.

In-Sample Tests

We begin our in sample test by looking at returns associated with various permutations of look back and holding periods between 5 and 150 days. We find the greatest combination of monotonicity and top/bottom quintile return spread for return time frames between 10-35 days with a 7 day rebalance period, in line with our hypothesis.

Return timeframe	Rebalance timeframe	1	2	3	4	5	5-1 Spread
5	7	-31.35%	-2.37%	46.90%	68.25%	49.28%	80.64%
10	7	-29.37%	-6.22%	45.11%	46.66%	76.49%	105.87%
15	7	-17.04%	-3.23%	28.73%	44.82%	77.02%	94.07%
20	7	-17.55%	8.74%	9.65%	80.45%	52.30%	69.85%
25	7	-17.48%	3.21%	23.29%	52.07%	64.72%	82.19%
30	7	-13.86%	12.72%	26.45%	84.35%	69.17%	83.03%
35	7	-12.59%	14.83%	47.01%	66.21%	73.46%	86.05%
45	7	0.41%	9.04%	37.77%	49.73%	34.79%	34.38%
60	7	10.12%	18.09%	18.85%	48.82%	38.80%	28.69%
90	7	17.10%	27.28%	51.41%	3.71%	62.83%	45.73%
120	7	36.86%	22.70%	57.08%	32.20%	7.96%	-28.90%
150	7	25.10%	93.55%	-4.42%	21.48%	36.70%	11.60%
5	14	-2.60%	9.01%	29.25%	58.66%	48.29%	50.89%
10	14	-3.73%	37.69%	10.59%	37.10%	54.11%	57.84%
15	14	9.21%	14.44%	28.62%	47.60%	35.84%	26.63%
20	14	-14.65%	44.57%	45.66%	53.89%	18.77%	33.42%
25	14	-8.07%	44.97%	45.64%	54.78%	10.65%	18.72%
30	14	-13.43%	42.36%	61.23%	54.18%	11.79%	25.22%
35	14	9.05%	24.15%	59.63%	43.79%	7.11%	-1.94%
45	14	9.05%	41.12%	57.46%	34.61%	5.72%	-3.33%
60	14	9.26%	16.82%	17.13%	48.69%	37.65%	28.38%
90	14	16.91%	26.15%	33.32%	3.05%	61.50%	44.60%
120	14	32.32%	21.80%	46.31%	30.50%	6.90%	-25.43%
150	14	23.74%	61.92%	-6.71%	21.04%	35.71%	11.97%

Evaluating this table there seems to be a range of stability between 15-35 day lookback with a 7 day rebalance. As 30 days aligns with the typical monthly cycle, and most popular crypto web sites quote a rolling 30 day return, we choose these parameters to further continue our analysis below.

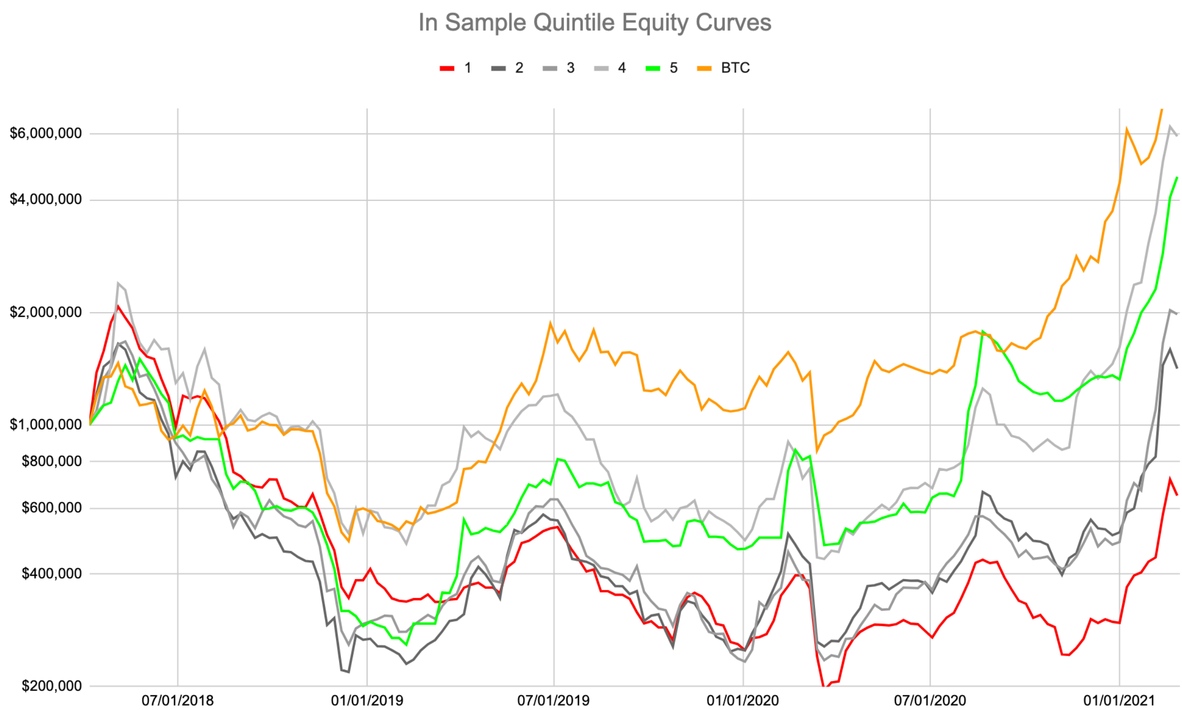
To test for the influence of outlier trades in our universe, we perform subsample analysis. Specifically, at the beginning of each strategy backtest, we randomly subsample ⅔ of our investable universe and only consider those assets at each rebalance. We performed 20 different subsamples in the in-sample period and 10 in the out-of-sample. Results of our subsample analysis confirm that the initial results are robust to universe selection and not reliant on the performance of any given outlier asset or trade.

	Quintiles				
Run	1	2	3	4	5
1	-12.33%	21.26%	51.30%	58.83%	91.06%
2	-3.96%	11.94%	4.13%	101.95%	90.21%
3	-7.10%	13.43%	90.17%	29.70%	58.32%
4	-18.07%	14.30%	44.60%	94.24%	14.70%
5	-12.04%	3.16%	38.55%	61.16%	80.03%
6	-20.39%	-4.98%	33.18%	35.03%	49.12%
7	-19.69%	23.65%	42.03%	39.94%	150.70%
8	-23.55%	25.58%	40.84%	33.16%	135.42%
9	-17.98%	28.98%	75.61%	25.87%	92.44%
10	-27.87%	59.52%	24.11%	61.24%	55.92%
11	8.66%	-26.68%	31.19%	50.85%	68.73%
12	-11.17%	15.44%	29.43%	83.50%	63.35%
13	-5.47%	36.81%	19.79%	64.38%	41.68%
14	-30.84%	32.48%	8.77%	48.51%	101.27%
15	10.63%	-5.70%	29.20%	57.49%	115.31%
16	-18.43%	18.22%	35.83%	61.40%	56.41%
17	-19.91%	-17.54%	94.73%	26.16%	76.37%
18	-6.66%	-10.05%	54.09%	81.17%	95.29%
19	-20.00%	22.85%	35.31%	27.68%	223.93%
20	-24.11%	7.51%	56.98%	30.07%	111.47%
Average	-12.73%	16.65%	45.61%	56.82%	98.84%

We also look at the impact of rebalancing on different days of the week. Our analysis confirms that the initial results are robust to rebalance day selection.

Day of the Week	1	2	3	4	5
Monday	44.41%	16.01%	33.67%	33.64%	65.68%
Tuesday	31.05%	-14.73%	54.23%	47.08%	63.92%
Wednesday	16.18%	17.65%	18.64%	62.00%	77.87%
Thursday	-13.86%	12.72%	26.45%	84.35%	69.17%
Friday	-20.60%	14.58%	82.95%	42.59%	83.83%
Saturday	-7.27%	11.29%	37.25%	58.71%	73.65%
Sunday	23.20%	12.23%	46.87%	65.88%	45.21%
Average	14.77%	10.83%	45.51%	57.81%	69.20%

While our top quintile portfolio produces an 69.17% annualized return, and our equally weighted portfolio returns 36.32%, Bitcoin outperforms both at 96.99%.



Out-of-Sample Tests

We find statistically consistent results out of sample to our in sample tests when looking at quintile returns associated with look back and rebalance periods, with one exception. In our out of sample period the longer 14 day rebalance period performs similarly to the shorter 7 day rebalance period, whereas this was not the case in sample.

Return timeframe	Rebalance timeframe	1	2	3	4	5	5 - 1 Spread
5	7	-57.11%	-34.51%	-54.00%	-24.94%	0.52%	57.63%
10	7	-54.96%	-35.63%	-46.36%	-22.92%	0.29%	55.25%
15	7	-56.71%	-39.71%	-53.30%	-25.71%	0.43%	57.14%
20	7	-53.30%	-32.51%	-46.75%	-27.09%	-0.06%	53.24%
25	7	-53.05%	-33.84%	-52.03%	-22.06%	0.56%	53.60%
30	7	-58.32%	-39.88%	-54.38%	-28.78%	-2.35%	55.97%
35	7	-54.97%	-21.98%	-40.56%	-26.58%	-16.78%	38.19%
45	7	-48.04%	-17.82%	-28.63%	-43.75%	-15.18%	32.86%
60	7	-39.65%	-7.86%	-28.06%	-44.49%	-28.38%	11.27%
90	7	-16.23%	-37.46%	-25.30%	-30.72%	-32.75%	-16.53%
120	7	-13.07%	-29.38%	-36.03%	-40.25%	-11.61%	1.46%
150	7	-21.25%	-28.58%	-36.32%	-18.14%	-26.80%	-5.55%
5	14	-56.43%	-27.46%	-46.50%	-24.29%	0.85%	57.28%
10	14	-47.35%	-32.70%	-39.08%	-15.92%	2.13%	49.48%
15	14	-56.21%	-30.83%	-46.34%	-16.77%	4.30%	60.51%
20	14	-51.68%	-27.33%	-45.92%	-26.49%	2.03%	53.71%
25	14	-48.73%	-33.56%	-45.37%	-13.26%	5.30%	54.03%
30	14	-51.32%	-34.91%	-42.78%	-21.79%	3.13%	54.45%
35	14	-53.92%	-16.44%	-33.03%	-22.76%	-10.39%	43.52%
45	14	-43.14%	-16.11%	-22.13%	-37.57%	-8.73%	34.41%
60	14	-38.17%	-3.69%	-20.30%	-37.54%	-21.32%	16.84%
90	14	-8.78%	-32.22%	-23.03%	-22.72%	-24.26%	-15.48%
120	14	-5.03%	-26.17%	-32.75%	-35.81%	-9.95%	-4.93%
150	14	-21.08%	-27.92%	-32.27%	-9.77%	-23.34%	-2.26%

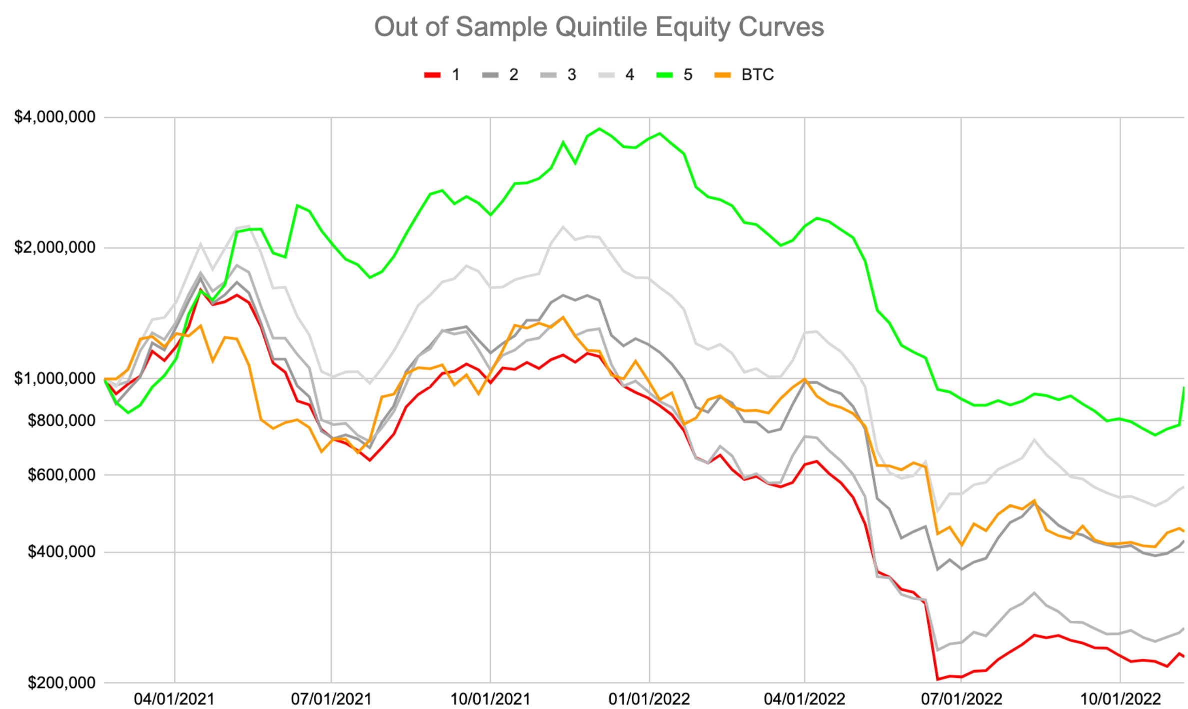
Subsample:

Run	1	2	3	4	5
1	-51.39%	-32.27%	-51.01%	-23.77%	0.48%
2	-57.17%	-36.81%	-50.91%	-27.69%	0.89%
3	-49.63%	-38.90%	-50.79%	-25.55%	-0.78%
4	-49.02%	-37.24%	-47.26%	-27.02%	1.20%
5	-54.23%	-34.65%	-52.26%	-26.45%	-1.00%
6	-50.09%	-38.59%	-45.51%	-24.19%	2.34%
7	-56.45%	-38.22%	-51.45%	-22.87%	2.41%
8	-49.97%	-38.48%	-52.29%	-27.74%	-0.86%
9	-49.19%	-35.87%	-46.37%	-21.55%	-0.08%
10	-50.46%	-35.39%	-46.70%	-23.93%	0.91%

Rebalance day of the week:

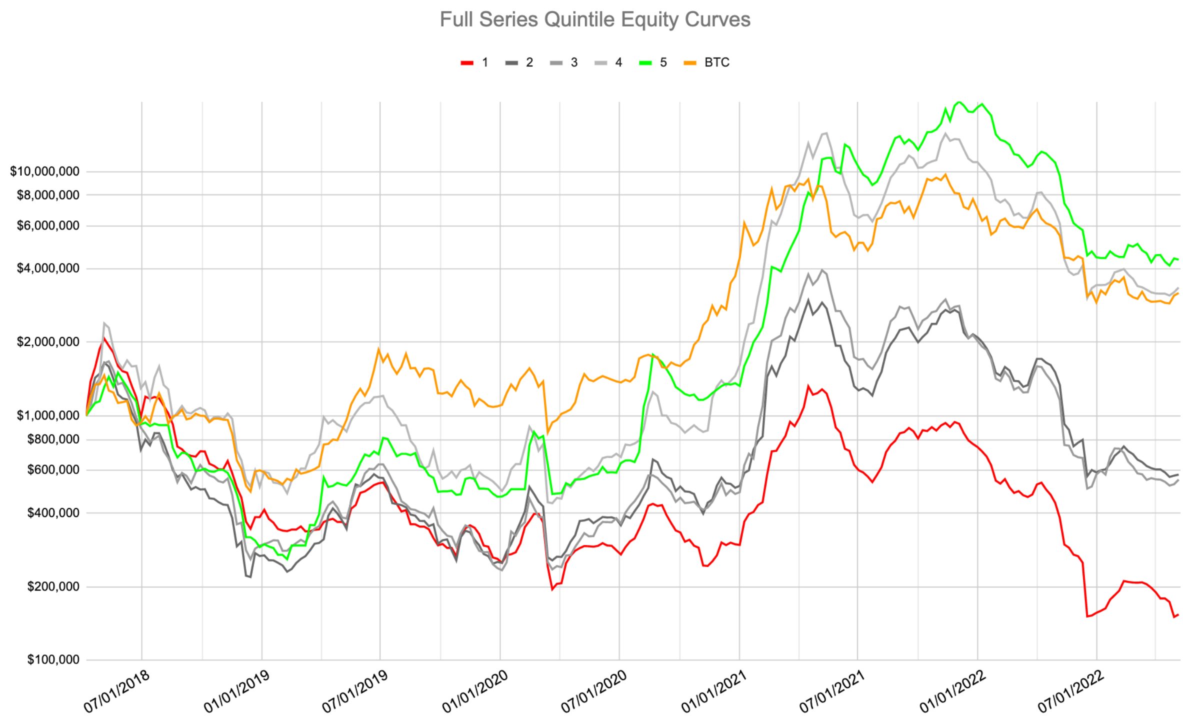
Day of the Week	1	2	3	4	5
Monday	-54.72%	-42.35%	-54.24%	-24.13%	1.17%
Tuesday	-55.43%	-42.28%	-53.37%	-26.96%	1.35%
Wednesday	-54.23%	-41.53%	-52.92%	-26.29%	0.71%
Thursday	-58.32%	-39.88%	-54.38%	-28.78%	-2.35%
Friday	-63.92%	-33.59%	-36.90%	-35.10%	-13.65%
Saturday	-57.03%	-29.13%	-41.08%	-30.89%	-7.37%
Sunday	-58.00%	-29.58%	-33.96%	-27.61%	-12.62%
Average	-57.30%	-36.74%	-46.25%	-28.49%	-4.55%

The top quintile portfolio returns -2.35% annualized, the equally weighted portfolio returns -29.93% annualized and Bitcoin underperforms both returning -37.82% annualized during the out of sample period.



Conclusions

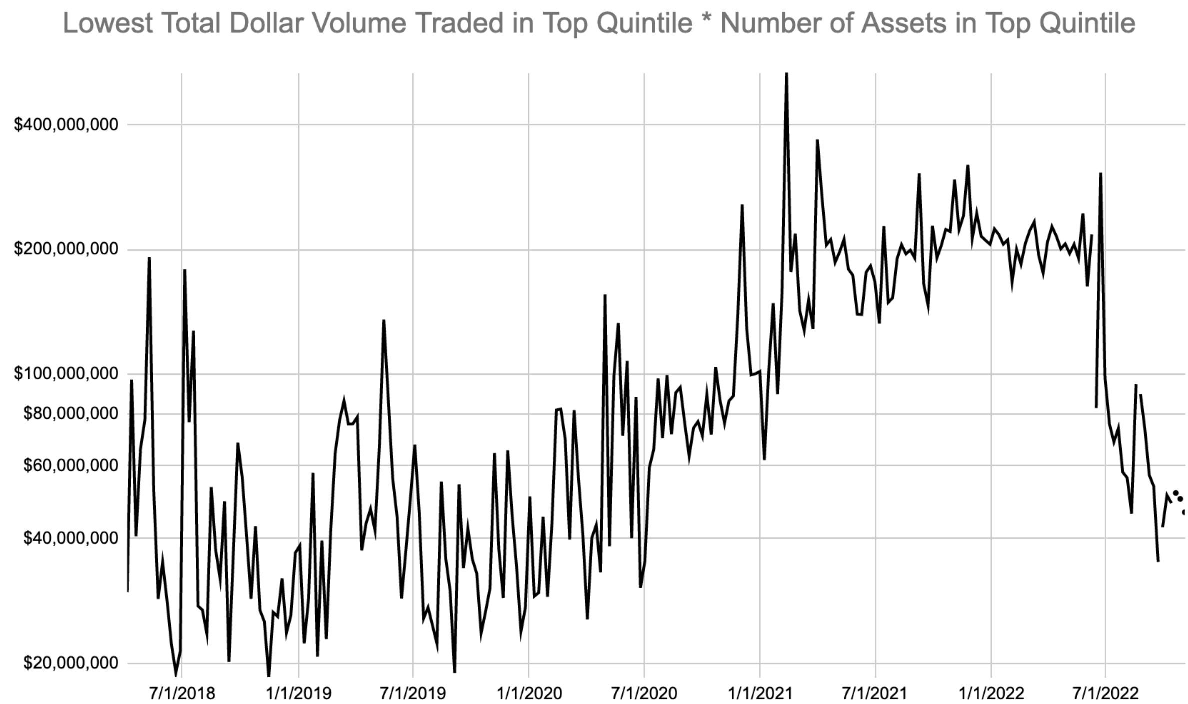
When analyzing the full time series of our experiment, we find robust and economically large evidence of momentum consistent with our hypothesis in- and out-of-sample. Over the full sample period, the top quintile 30 day look back and 7 day rebalance portfolio produces a 37.8% annualized return relative to the bottom quintile at -33.8%, the equal weighted portfolio at 11.7% and Bitcoin at 28.7%.



Within this paper, we assumed zero transaction costs and market impact. While unrealistic, actual trading costs vary dramatically over time, venue, and market, making them difficult to estimate. As a final step of our analysis, we ran our strategy for varying levels of costs and find that an assumed trading cost of 125 basis points would cause the top quintile to underperform the benchmark. At the time of writing, both maker and taker fees are 10 basis points (for regular users) on Binance, 10 for maker and 20 for taker (for trades between $100k and $1 million) on Coinbase Pro, and 30 basis points on both Uniswap and Sushi Swap.

Market impact has the potential to be a significant cost, particularly for the fat tail of less liquid markets. The size of the trade will be a key consideration for impact costs, which has important implications for the potential capacity of our strategy.

In the exhibit below, we plot the average 20-day dollar volume for the least liquid market in the top quintile portfolio multiplied by the number of assets in the top quintile portfolio. By using the least liquid market as our constraining factor, this metric establishes a maximum portfolio capacity under the assumption we are willing to trade 100% of the available average volume for the least liquid market.



To firmly establish capacity, further study is warranted. Specifically:

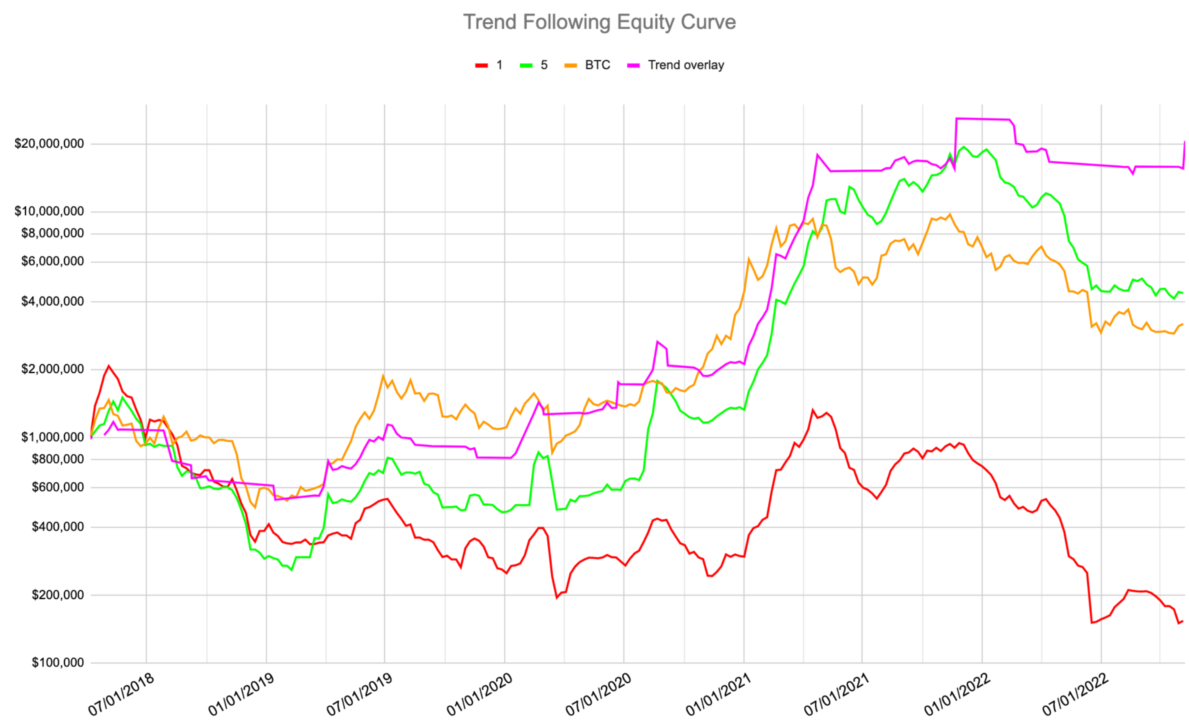
- The ability to enter and exit low liquidity trades patiently (e.g. generating signals every Thursday at midnight UTC and trading throughout the remainder of the day)
- The impact of liquidity-weighting portfolio holdings, or further liquidity screening, on returns
- The ability and cost of execution through OTC desks

If we assume an average trading cost (both explicit and impact) of 50 basis points, in-sample and out-of-sample annualized returns for the top quintile portfolio are reduced by 30 percentage points and 12 percentage points respectively.

While our analysis has demonstrated a significant spread between top/bottom quintile portfolios using a basic incarnation of the momentum factor, and the aggregate returns from our full sample are considerable, the max drawdown of the top quintile portfolio is still eye popping. On multiple occasions during our full sample the portfolio draws down more than 75%. No matter how much one considers themself a true believer in the long term growth of the cryptocurrency asset class and the ability for the underlying technology to fulfill the promise associated with the hype it has generated over the past decade, there is no escaping the fact that a portfolio which draws down at these thresholds every few years is not only a tough sell to investors, but tough to stick with from a behavioral perspective. While this paper is not meant to demonstrate the efficacy of trend following strategies applied to the cryptocurrency asset class, something we may choose to publish in the future, we still wanted to demonstrate the impact of a basic trend following model on excess returns and max drawdown when applied to our top quintile portfolio. We use a 5,50 day exponential moving average crossover for the price of Bitcoin to signal the top quintile portfolio (invest at the close on a cross of the 5 above the 50, go to cash at the close on a cross of the 5 below the 50).

The top quintile portfolio with the trend following overlay produces a 93.3% annualized return over the full sample period relative to a 37.8% return for the basic top quintile portfolio and Bitcoin at 28.7%. The max drawdown for the top quintile portfolio with the trend following overlay also falls to 45% from 75%.

While our cross-sectional momentum analysis results clearly show investors should avoid buying underperforming names individually, we believe similar causal effects are at play in regards to the efficacy of trend following strategies like the one above which manage the overall beta exposure of a portfolio. In the simplest terms, investing in liquid crypto markets is largely about avoiding coins that are going down and going to cash when the largest coins (BTC/ETH) are in downtrends.



Our belief is that the effects associated with the causal variables in our hypothesis will persist for quite some time, likely a decade or more, until the significant convexity associated with investing in new protocols decreases meaningfully. This will also likely coincide with the potential addressable market for cryptocurrency use and ownership being saturated, existing protocols being able to serve demand effectively at reasonable transaction prices, regulatory regimes being erected, access to these markets becoming more evenly distributed, and the ability to effect short positions becoming more widely accessible at reasonable costs. At that point in time we will likely see a lengthening in the term structure associated with the momentum effect, from 30 days to something more approaching equity markets (12 months).

There are several topics we'd like to highlight which are natural extensions of the research we've published here, some of which we have done extensive internal work on at Starkiller Capital and may publish at a future date, and others we have yet to explore. In this paper we only look at one very basic form of momentum. There are many flavors of momentum, some which may be more suited to capturing the behavioral and market structure of the momentum factor for cryptocurrency markets we outlined in our hypothesis. We've specifically chosen the most simplistic incarnation of momentum here for academic purposes. Exploring the covariance between momentum and time series momentum is another associated line of research. Given the top/bottom quintile return spread in our work here, an exploration of the feasibility in acquiring short positions and the cost to do so in order to effect a market neutral portfolio should yield a further understanding of why the potential inability to short cryptocurrency assets leads to the momentum anomaly. In exploring the feasibility of producing a market neutral portfolio we may find other market neutral opportunities associated with an imbalance in aggregate perpetual futures funding rates for the long and short sides of the portfolio.