# #HODL SENTIMENT

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**Abstract**

In this paper I propose a new proxy for investor attention in the cryptocurrency asset class that utilizes the combined sentiment of pump and dump chatrooms. In the sample of over 1000 cryptocurrencies over 3 years, I document a simple binary regime switching strategy on the one-factor cryptocurrency index that generates an annualized alpha in excess of 50% when compared to several factor benchmark models. An increase in pump and dump sentiment leads to a decrease in index returns in the following week, while GOOGLE SVI search proxies lead to increases in index returns over the same period. Although a strategy based on GOOGLE SVI proxies leads to positive and significant alpha relative to the one-factor index, I give evidence to suggest that the inclusion of a time series momentum factor explains the anomaly. Pump and Dump sentiment alpha appears to be an anomaly easily explained by common factors pervasive in the much-developed equity literature. The results point to the importance of alternative proxies for investor attention as the venues for investor communication change as well as defining sentiment based on vernacular used.

# 1. Introduction

With the recent advances of financial computing and increasing critics of the lack of physical backing in fiat currencies, the notion of a global digital currency has drawn considerable attention. Although the idea of a cryptocurrency has almost become ubiquitous in the global lexicon, the progress of such assets serving as a medium of exchange remains in a nascent stage. Yermack (2013) notes that bitcoin has achieved only scant consumer transaction volume and remains a speculative instrument. From an asset pricing perspective, it remains a question as to whether cryptocurrency represents a unique asset class. Liu and Tsyvinski (2018) find that cryptocurrencies cannot be explained by the common stock market, currencies, and macroeconomic factors. Similar to equities, Liu, Tsyvinski, and Wu (2019) find that a 3 factor model of the cryptocurrency market, size, and momentum captures the cross-section of returns. Although this an interesting result, the ability to short cryptocurrencies was not possible during most of the sample of the study. The most common way for sophisticated investors to short bitcoin is selling futures, which only became available on the CME on January 17, 2018. Nonetheless, valuing cryptocurrency assets is a worthwhile endeavor considering that the investment in such assets may represent a stake in future technology changes as well as representing a low-cost avenue for engaging in more nefarious market manipulation activities.

Surprisingly, there is not a significant amount of academic research on market manipulation, especially in the cryptocurrency space. Evidence of securities fraud is almost as old as securities markets themselves. "Bear raids" in which short-sellers released negative rumors about securities have their roots in 17th-century Dutch markets. From a theoretical perspective, Vila (1989) presents an example of information-based manipulation where the manipulator shorts the stock, releases false information, and then buys back the stock at a lower price. Benabou and Laroque (1992) give evidence to support that if a person has unreleased information about a stock and his statements are viewed as credible by investors, then one can profitably manipulate the stock price by making misleading statements. Allen and Gale (1992) develop an equilibrium model in which an uninformed manipulator can make a profit, provided investors attach a positive probability to the manipulator being an informed trader. Brunnermeier and Pederson (2005) find that predatory trading of large sophisticated investors undergoing force liquidation increases market illiquidity and may have spillover effects into other markets.

Rampant speculation, pump and dumps, and increased volatility of cryptocurrencies have drawn the attention of sophisticated investors and noise traders alike. Sockin and Xiong (2018) develop a theoretical framework in which informational frictions attenuate the risk of breakdown by decreasing price volatility and digital platform performance. Speculator sentiment in their model increases market fragility by decreasing users facilitating transactions for goods and services. The search for attention proxies has gained considerable interest in the recent finance literature. Da, Engelberg, and Gao (2011) use google search results to measure the attention of retail investors. Ben-Rephael, Da, and Israelsen create a measure, abnormal institutional investor attention (AIA), by using Bloomberg terminal data. Liu and Tsyvinski (2018) use GOOGLE SVI of the word "bitcoin" to find evidence of return predictability of cumulative coin market returns at a one-week to six-week time horizon. In addition, they find evidence of negative return predictability when using google searches of terms with negative connotations such as "Bitcoin Hack". Although Google may represent worldwide retail investor attention to cryptocurrency, there has been a lack of research on how other mediums such as chatrooms serve as a proxy for investor attention. If anomaly predictability decreases with publication as evidenced by McLean and Pontiff (2015), then it would be somewhat surprising to find GOOGLE SVI has higher return predictability relative to alternative proxies. In addition, GOOGLE SVI may contain some idiosyncratic component that is not related to actual noise trading such as general interest in technology. This paper will use several chatrooms that are attenuated to actual traders and evidence to provide a stronger return relative to other published proxies. Attention is a scarce resource and the chatroom venue serves as a direct revealed attention measure. In addition, I will establish that this proxy is not captured by commonly found anomalies in the equities literature with the creation of a multi-factor model that differs from the previous literature. Using factor models based on the cross-section of returns is not realistic given that much of the asset class can be explained. **Given that information is a scarce cognitive resource, sentiment derived from pump and dump chatrooms leads to incremental return predictability when compared to an unconditional factor model. Increases in sentiment lead to negative return predictability if increased retail attention leads to price reversal week over week.**

More formally an asset is determined overvalued or undervalued based on whether the observed price is above or below the fundamental implied price.

$$Sentiment_t = r_t - E[\hat{r}_t|Z_{t-1}] \tag{1}$$

Where $E[\hat{R}_t|Z_{t-1}]$ is the price implied from an alternative set of conditioning variables that give the expected conditional expected return. $R_t$ is the current return observed in the market. Any conditional return is measured with some error, thereby making all sentiment measures proxies for this process. In a more generalized notation, we can define sentiment. For the sake of simplicity, let us assume the proxy for conditional return is perfectly specified with a linear equation.

$$E[\hat{r}_t] = \beta_0 + \beta_1 Z_{t-1} + \epsilon \tag{2}$$

If $\beta_0$ and $\epsilon$ then we have a perfect measure of sentiment. If this is the case then if $E[\hat{r}_t|Z_{t-1}] < r_t$ then we buy the asset to take advantage of convergence. Otherwise, we sell it. This is the basis for the simple binary regime switching strategy to follow. Essentially, this proxy of sentiment we are creating in the following paper is just a proxy of this mispricing. Assuming a linear structure may not account for nonlinear features that change over time.

The more interesting question of this application of binary regime switching in the case where we make no assumptions about the underlying $Z_{t-1}$ or its distribution. By defining a different cost function we can minimize error of the signal rather the variance. We assume the following instead we have n weak learners for the sentiment misprcing, S:

$$\hat{S}_i = \sum_{i=1}^{n} \alpha_i k_i(x_i) \tag{3}$$

every expert classifier k can emit an opinion on each conditioning variable x.

$$x_i : k_i(x_i) \in -1, 1 \tag{4}$$

Essentially k is a function that maps the conditioning variable to the direction of predicted sentiment mispricing independent of other conditioning variables or learners. Each of these weak learners can be assigned a weight as reflected by the $\alpha$ parameter. The sign of $\hat{S}_i$ reflects the direction of mispricing as discussed above as determined by the weighted sum of the weak learners. Let us iterate m times to represent the assignment of weights to a new weak learner the minimizes the error between predicted sentiment and actual sentiment. Mathematically this is represented by the following:

$$\hat{S}_(m)(x_i) = \hat{S}_(m-1)(x_i) + \alpha_m k_m(x_i) \tag{5}$$

where $\alpha$ is the parameter. Let us define the exponential loss function below:

$$J = \sum_{i}^{N} e^{-S_i \hat{S}_(m)} \tag{6}$$

From the above equation, we can see that loss increases if the sign of $S_i$ and $\hat{S}_(m)$ are opposite. Meaning we misclassify sentiment. With algebra, one can rewrite the above as

$$J = \sum_{i}^{N} e^{-Si(\hat{S}_(m-1)(x_i)+\alpha_m k_m(x_i))} = w_i^m \sum_{i}^{N} e^{-S_i \alpha_m km} \tag{7}$$

$w_i^m$ is the weight assigned to each training point in set $x_i$ separated from the loss associated with signs. We can separate the points correctly classified from incorrectly classified with the transformation below:

$$J = \sum_{S_i = k_m(x_i)} w_i^{(m)} e^{-\alpha_m} + \sum_{S_i \neq k_m(x_i)} w_i^{(m)} e^{\alpha_m} \tag{8}$$

In doing this its clear to see minimizing the cost function is just minimizing the RHS of equation 8 with respect to $\alpha_m$. To do this just take the derivate of j with respect to the parameter and setting the equation to zero.

$$\frac{dJ}{d\alpha_m} = \frac{d(\sum_{S_i = k_m(x_i)} w_i^{(m)} e^{-\alpha_m} + \sum_{S_i \neq k_m(x_i)} w_i^{(m)} e^{\alpha_m})}{d\alpha_m} = 0 \tag{9}$$

$$0 = -\sum_{S_i = k_m(x_i)} w_i^{(m)} e^{-\alpha_m} + \sum_{S_i \neq k_m(x_i)} w_i^{(m)} e^{\alpha_m} \tag{10}$$

With algebra I solve for $\alpha_m$

$$\alpha_m = .5ln(\frac{\sum_{S_i = k_m(x_i)} w_i^{(m)}}{\sum_{S_i \neq k_m(x_i)} w_i^{(m)}}) \tag{11}$$

Thus, we have solved for weight of added classifier that minimizes the overall cost of the m-stage classifier. This is simply the AdaBoost algorithm by Freund and Schapire applied to the setting of sentiment mispricing. This proves that the addition of weak learners would improve the prediction of the set $S_{t-1}....S_{t-l}$ where l refers to the length of the training period. This prediction is conditioned on lagged proxies of sentiment $Proxies_{t-2}....Proxies_{t-l-1}$ such that we can now form the prediction sentiment in a binary setting.

$$S_t - \hat{S}_{t-1} = \epsilon \tag{12}$$

The empirical extension of this concept is the combination of different proxies to formulate a better conditional expectation of future sentiment mispricing. This is similar to the thought process of Baker and Wurgler (2007) as well as Huang, Jiang, Tu, and Zhou (2015), however, applying Adaboost makes no assumptions about the distribution of proxies of sentiment. More importantly, instead of capturing variation as done by Baker and Wurgler (2007), this methodology filters out idiosyncratic noise unrelated to formulated the conditional direction of sentiment mispricing. This is the first paper to combine text-based measurements using this type of methodology. The previous papers in this space concentrated on macroeconomic variable mispricing. The issue with this type of analysis is that it may pick up on systematic factors, hence there is a need to test the unconditional factor model against the returns associated with this binary regime switching strategy.

## 2. Data

To investigate the effect of the sentiment of cryptocurrencies and index returns, we will utilize exchange data obtained directly from Coinbase, Gemini, and Binance. Data from these exchanges have been recorded over the past year. For an extended sample, data is scraped from CoinMarketCap. This data set is widely used by practitioners and academics alike. In addition to closing prices, we record daily trading volume as well as the number of coins that have been mined. The number of coins mined is used to create a market capitalization for each cryptocurrency by multiplying the number of coins by the current closing price. The period of study for the dataset is from 08/04/2013 to 04/09/2021. We concentrate the analysis on cryptocurrency/USD exchange rates. Data is collected every Friday of the month to give weekly returns. We exclude cryptocurrencies with less than one million in market capitalization and require all cryptocurrencies to have information for volume, price, and the number of minable coins. Returns are calculated on a simple percentage basis. It is imperative to note that the data source is survivorship bias-free.

To construct the sentiment index, data is obtained from telegram. We include the largest chatrooms by the number of participants as the source for our pump and dump sentiment indicator. Altcenter signals, crypto binance trading, cryptotrading bitcoin, fat pig signals, and crypto pumps binance are used. Further research will be done to include discord pump and dump chatrooms as well as Reddit. Image-based posts are not used in the construction of sentiment. The text of posts is compiled daily across all chatrooms with a bag of words model. We manually define words that positively relate to future returns to form a tonal dictionary. Although there is the existence of sentiment word lists such as Loughran-Mcdonald's sentiment word lists (2011), one must be careful to consider the typical vernacular used in chatrooms for pump and dumps is very different than 10-ks. Phrases like #TotheMoon, #PumpGang, and #HODL are commonplace in the pump and dump setting and positively relate to pump and dump sentiment, while I would be hard-pressed to find a firm that uses such informal language in a 10-K. In addition to teasing out the effects of the pump and dump sentiment, one may consider the use of the word bitcoin and cryptocurrency as a proxy for attention to cryptocurrency investment in general similar to Da, Engelberg, and Gao's GOOGLE SVI. As a comparison benchmark of my new attention proxy, I download the weekly SVI for the word bitcoin over the same period of the sentiment index.

# 3. Common Risk Factors in Cryptocurrency

To understand the incremental value add of a sentiment model one must first define the equilibrium based on arbitrage pricing theory. Factor analysis has received significant attention in empirical asset pricing. See Fama-French (1993) 3-factor model, Carhart (1997), Hou, Xue, Zhang (2014). In addition, time-series momentum and cross-sectional momentum have been anomalies that have seen significant research attention. See Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Moskowitz, Ooi, and Pedersen (2012), Asness, Moskowitz, and Pedersen(2013) for discussion of momentum applied to a factor setting. Liu, Tsyvinski, and Wu (2019) apply a similar methodology to the cryptocurrency space and form a cryptocurrency 3-factor model consisting of a cryptocurrency market factor (CMKT), a cryptocurrency size factor (CSMB), and a cryptocurrency momentum factor (CMOM). It stands to reason that the cryptocurrency asset class has similar asset pricing anomalies.

In this paper, we will construct similar indexes as Liu, Tsyvinski, and Wu (2019), however, we will investigate the zero investment constructed off excess returns of the risk-free rate. The issue with factors constructed on the cross-section of returns is that it does not represent real tradeable factors. Cryptocurrencies other than bitcoin cannot be short in a sizable manner for the period of sample. There is the existence of futures on the CME for bitcoin, which allow for short positions, however, futures do not provide a source of financing for a long-short strategy. In addition, instead of considering equal-weighted portfolios, we will form portfolios on value-weighted returns to not overweight small-cap cryptocurrencies that have significantly higher trading costs. Following the previous literature, most of the results to follow will be constructed by forming non-parametric ex-ante tercile sorts on a cryptocurrency characteristic such a momentum. Quartile results will also be done for a robustness check. The ex-post returns of each portfolio will be compared to an unconditional one-factor model to obtain the unexplained alpha consistent with the methodology of previous papers in the space.

### *3.1. Formation of Crypto Market Index*

To construct a simple weekly index for comparison of anomalies and returns of individual crypto assets, we first consider the universe of cryptos in the sample and form the value-weighted portfolio based on lagged one-week market capitalization. All weekly returns are taken in excess of the risk-free rate. In the figure below we plot the cumulative returns of the index along with widely known cryptocurrencies: bitcoin, ripple, and litecoin.

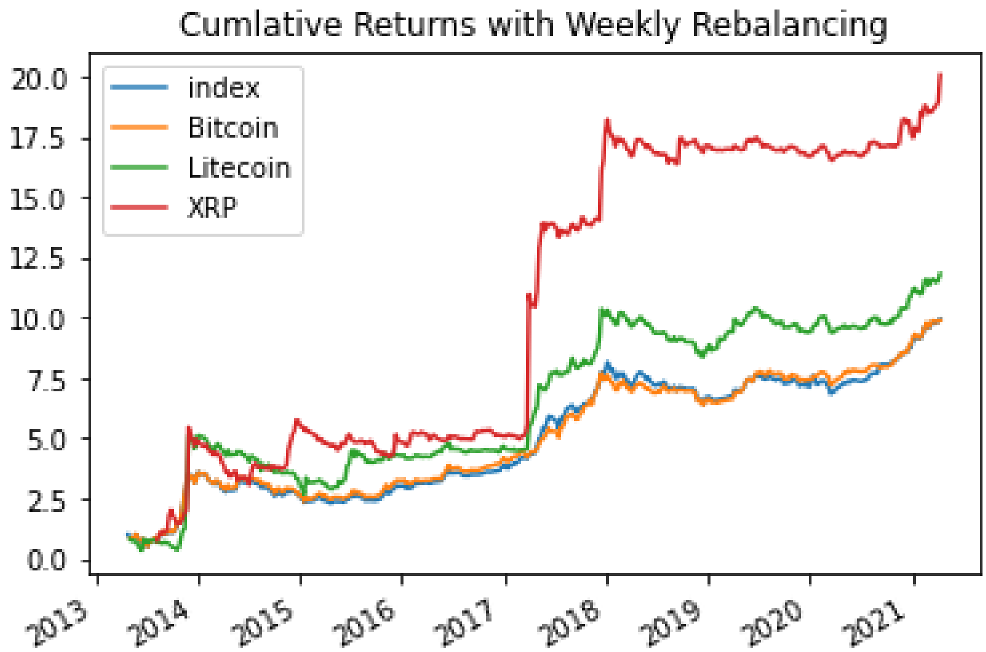


Fig. 1. Investor Sentiment

As an example of the strength of the crypto index at explaining returns, I output the results of the time-series regressions of bitcoin, ripple, and litecoin against the index and a time-invariant intercept. The simple regression follows the form below:

$$R_{it} = \beta_0 \left(R_{Mt} - RF_t\right) + \alpha_i \tag{13}$$

Standard errors are corrected for autocorrelation with Newey West standard errors with lag 1.

Table 1: Bitcoin Regression Results

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 0.0026 | 0.002 | 1.192 | 0.233 | -0.002 | 0.007 |
| **index** | 0.8742 | 0.045 | 19.555 | 0.000 | 0.787 | 0.962 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 210.156 | **Durbin-Watson:** | 1.880 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 5742.326 |
| **Skew:** | -1.596 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 21.054 | **Cond. No.** | 8.11 |

Table 2: Ripple Regression Results

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 0.0208 | 0.014 | 1.482 | 0.138 | -0.007 | 0.048 |
| **index** | 1.1949 | 0.242 | 4.947 | 0.000 | 0.722 | 1.668 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 628.889 | **Durbin-Watson:** | 1.940 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 190761.736 |
| **Skew:** | 8.657 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 109.120 | **Cond. No.** | 8.13 |

Table 3: Ethereum Regression Results

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | 0.0203 | 0.011 | 1.812 | 0.070 | -0.002 | 0.042 |
| **index** | 0.9621 | 0.099 | 9.700 | 0.000 | 0.768 | 1.157 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 210.888 | **Durbin-Watson:** | 1.611 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 3146.279 |
| **Skew:** | 2.768 | **Prob(JB):** | 0.00 |
| **Kurtosis:** | 18.098 | **Cond. No.** | 8.54 |

Interestingly enough all three main cryptocurrencies have fairly normal coefficients with betas between .8 and 1.2 when using the value-weighted index. None of the 3 major cryptocurrencies have significant alpha at the 5% level. Bitcoin has a lower beta than one similar to what would be expected from large-cap equity. To test whether there is a premium unexplained by the index across the universe of cryptocurrencies, the Famma Macbeth (1973) regression is performed.

Table 4: Fama Macbeth Regression of Crypto Universe

| | mean | std_error | tstat |
|---|---|---|---|
| intercept | 0.03 | 0.02 | 1.37 |
| index | 0.01 | 0.01 | 0.99 |

As evidenced by the insignificant t-stat of the intercept, the crypto index does not have a time-invariant risk premium unexplained by the simple one-factor model nor is there a risk premium relative to the index pointing to its strength of explaining returns.

# 4. Characteristic Portfolio Sorts

To improve our factor model, we form a variety of non-parametric sorts on common factors known in the equity literature. At each point t in the sample, we sort the cross-section on an ex-ante characteristic to form tercile and quartile portfolios. t refers to time. The portfolios are then weighted by the lagged market capitalization to evaluate the ex-post return. Each portfolio's return will be reported in excess of the one-factor returns with t-stats. Clearly, it does not make sense to report unadjusted return t-stats with a null value of zero considering the major bull market in the asset class. In an additional test of performance, I will include the unconditional alpha of the portfolio's unadjusted return against the simple factor model. In all tables to follow the higher portfolio number represents a higher value of the ex-ante sorted characteristic.

## *4.1. Cross-Sectional Momentum*

In the results below we report the cross-sectional momentum results sorted on yearly, one month, and one month average daily mean returns similar to Jegadeesh and Titman (1993). Portfolios are rebalanced weekly.

Table 5: Value Weighted: Yearly Momentum

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | 0.41 | 0.37 | 0.71 | 0.01 | 0.36 | 0.85 | 0.0 |
| Port 2 | 0.15 | 0.33 | 0.75 | 0.00 | 0.41 | 0.93 | 0.0 |
| Port 3 | 0.70 | 0.81 | 0.42 | 0.01 | 0.50 | 1.06 | 0.0 |

Table 6: Value Weighted: Monthly Momentum

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.30 | -0.51 | 0.61 | -0.00 | 0.88 | 0.92 | 0.0 |
| Port 2 | -0.24 | -0.53 | 0.60 | -0.00 | 0.68 | 0.97 | 0.0 |
| Port 3 | 1.25 | 1.81 | 0.07 | 0.01 | 0.07 | 0.99 | 0.0 |

Table 7: Value Weighted: Bi-Weekly Momentum

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -1.69 | -2.85 | 0.00 | -0.01 | 0.01 | 0.89 | 0.0 |
| Port 2 | -0.15 | -0.35 | 0.72 | 0.00 | 0.91 | 0.92 | 0.0 |
| Port 3 | 1.99 | 2.22 | 0.03 | 0.02 | 0.03 | 1.00 | 0.0 |

Table 8: Value Weighted: Weekly Momentum

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.89 | -1.45 | 0.15 | -0.01 | 0.16 | 0.95 | 0.0 |
| Port 2 | 0.03 | 0.08 | 0.93 | 0.00 | 0.70 | 0.96 | 0.0 |
| Port 3 | 2.72 | 2.33 | 0.02 | 0.03 | 0.01 | 1.05 | 0.0 |

In line with what has been documented in the previous literature, I find evidence of significant momentum when using value-weighted returns. The returns momentum relationship is monotonic at all time horizons. Alpha is significant for the top tercile portfolios at a 5% significance level. For the weekly top tercile portfolio, the mean excess return is an economically significant 141.44% a year. Considering that the costs of trading on Coinbase are .2% a trade, it seems likely the portfolio's returns are not solely due to not taking into account trading costs.

## 4.2. *Small Cap Effect*

The long-term tendency for small market equities to outperform large-cap equities as measured by market capitalization is the well-documented ”small-cap” effect. Small-cap cryptocurrencies known as altcoins may be fundamentally different from large-cap cryptocurrencies and may also earn a risk premium similar to equities. The table below plots the results of sorting on lagged market capitalization.

Table 9: Value Weighted: Market Cap

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | 3.55 | 4.24 | 0.00 | 0.04 | 0.00 | 1.01 | 0.0 |
| Port 2 | 0.66 | 1.03 | 0.30 | 0.01 | 0.23 | 0.96 | 0.0 |
| Port 3 | 0.03 | 0.81 | 0.42 | 0.00 | 0.51 | 1.00 | 0.0 |

From the above table, I find evidence to support large market capitalization coins earning significantly less returns than small-cap altcoins. The small-cap portfolio earns 3.55% a week (tstat 4.24) which equates to over 180% a year over the index. Trading costs may be significantly higher for these coins as bid-ask spreads are quite large.

## 4.3. *Volatility Sorted Portfolios*

The low-volatility anomaly documented by Chan, Karceski, and Lakonishok (1999), and Jangannathan and Ma (2003) refers to the observation that low-volatility stocks have higher returns than high-volatility stocks in most markets studied. This is highly counterintuitive since from a theoretical perspective as we expect evidence of a risk-return tradeoff. I report the results for the single sorts on ex-ante volatility using the yearly standard deviation of returns as well as the six-month calculation,

Table 10: Value Weighted: Yearly Volatility

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.15 | -0.48 | 0.63 | 0.00 | 0.36 | 0.84 | 0.0 |
| Port 2 | 0.96 | 1.18 | 0.24 | 0.01 | 0.32 | 1.06 | 0.0 |
| Port 3 | 1.09 | 1.20 | 0.23 | 0.01 | 0.32 | 1.10 | 0.0 |

Table 11: Value Weighted: Six month Volatility

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.20 | -0.66 | 0.51 | 0.00 | 0.38 | 0.83 | 0.0 |
| Port 2 | 0.56 | 0.89 | 0.37 | 0.01 | 0.34 | 0.99 | 0.0 |
| Port 3 | 1.07 | 1.17 | 0.24 | 0.01 | 0.27 | 1.03 | 0.0 |

Contrary to what is documented in other asset classes I find that ex-ante volatility has a monotonic relationship with the ex-post return. Although none of the returns are significantly different from zero when adjusting for the one-factor index returns, clearly returns are increasing in volatility sorts. In addition, unconditional alpha is not significant and beta is increasing in volatility.

## *4.4. Lottery Demand*

Bali, Cakici, and Whitelaw (2011) show that a preference for lottery-based stocks results in a negative and significant relationship between the maximum daily return over the past one month (MAX) and expected stock returns. In addition, one can consider skewness as an alternative proxy for preference for extreme positive returns. It may be possible that skewness relates to the overreaction of investors to positive news if the value of a cryptocurrency is correlated with future transactional value or acceptance of blockchain technology. Given that the irrationality of lottery demand is attributed to noise traders, one would expect stronger observed relationships in the crypto space given the lack of institutional dominance. Using investment in Grayscale trusts as a proxy for institutional investment, it is confirmed that hedge funds only began to invest in the space in 2018. The results are shown below for sorting on the yearly skew and monthly max.

Table 12: Value Weighted: Yearly Skew

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.16 | -0.46 | 0.65 | 0.00 | 0.31 | 0.81 | 0.0 |
| Port 2 | 0.58 | 0.91 | 0.36 | 0.01 | 0.29 | 0.96 | 0.0 |
| Port 3 | 0.47 | 0.56 | 0.58 | 0.00 | 0.67 | 1.06 | 0.0 |

Table 13: Value Weighted: Monthly Max

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.36 | -0.70 | 0.48 | -0.00 | 0.86 | 0.88 | 0.0 |
| Port 2 | 1.33 | 1.72 | 0.09 | 0.01 | 0.08 | 1.03 | 0.0 |
| Port 3 | 0.65 | 0.77 | 0.44 | 0.00 | 0.60 | 1.08 | 0.0 |

Surprisingly, there is no significant relationship that can be inferred from above. Quartile results do no show any monotonic relationships as well. The results may be inconclusive given that weekly returns are used. Daily returns would be needed to replicate Bali (2011).

### *4.5. Illiquidity and Stock Returns*

Amihud (2002) gives evidence that expected market illiquidity positively predicts positive stock excess return resulting in an illiquidity premium. The measure is constructed by taking the ratio of weekly return converted to a daily return over 24 hr volume. The results are show below

Table 14: Value Weighted: illiq

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | 0.38 | 0.60 | 0.55 | 0.00 | 0.70 | 1.07 | 0.00 |
| Port 2 | 0.52 | 0.93 | 0.35 | 0.01 | 0.38 | 1.01 | 0.00 |
| Port 3 | 6.28 | 1.09 | 0.28 | 0.03 | 0.30 | 2.35 | 0.05 |

As expected, we see that investors demand a higher return for illiquid cryptocurrencies with the higher tercile portfolio return being almost 6% higher than the lowest tercile portfolio. The returns seem to be captured by the extremely high beta of the one-factor model. Alpha is positive but still insignificant.

## *4.6. Portfolios Constructed from Rolling Regressions Parameters*

The negative relation between returns and idiosyncratic volatility documented in Ang, Hodrick, and Xing (2006) is investigated. In addition, we perform the sorts on alpha and beta similar to Frazzini and Pederson (2014).

Table 15: Value Weighted: Yearly Alpha

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.33 | -0.68 | 0.50 | 0.00 | 0.86 | 0.84 | 0.0 |
| Port 2 | 0.55 | 0.89 | 0.38 | 0.01 | 0.21 | 0.88 | 0.0 |
| Port 3 | 0.12 | 0.21 | 0.83 | 0.00 | 0.69 | 0.97 | 0.0 |

Table 16: Value Weighted: Yearly Beta

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | 0.34 | 0.55 | 0.58 | 0.01 | 0.07 | 0.69 | 0.0 |
| Port 2 | 0.44 | 0.61 | 0.54 | 0.00 | 0.41 | 0.98 | 0.0 |
| Port 3 | 0.30 | 0.44 | 0.66 | 0.00 | 0.85 | 1.07 | 0.0 |

Table 17: Value Weighted: Yearly Idiosyncratic Volatility

| | Return | t-stat | p-value | Alpha | p-value Alpha | Beta | p-value Beta |
|---|---|---|---|---|---|---|---|
| Port 1 | -0.27 | -0.84 | 0.40 | 0.00 | 0.52 | 0.83 | 0.0 |
| Port 2 | 1.12 | 1.33 | 0.19 | 0.01 | 0.17 | 0.97 | 0.0 |
| Port 3 | 1.09 | 1.19 | 0.24 | 0.01 | 0.33 | 1.12 | 0.0 |

None of the above sorts appear to have significant results as measured by the t-stat and p-value of alpha. Sorts on idiosyncratic volatility indicate there is no unidentified systematic factor. Surprisingly we do not find that sorting ex-ante beta predicts future returns in any capacity, but it does predict future unconditional beta. I will leave this to future research.

## 5. Time Series Momentum

Contrary to cross-sectional momentum where one typically buys the winner and shorts the losers, instead, I consider the portfolios dependent on the time-series momentum documented by Moskowitz and Pederson (2012). This type of anomaly is well documented across equities, currencies, commodities, and sovereign bonds.

Table 18: Time Series Momentum

| | Return | t-stat | p-value | Alpha | p-value Alpha |
|---|---|---|---|---|---|
| Yearly Momentum | -0.28 | -1.001 | 0.317 | 0.001 | 0.515 |
| Monthly Momentum | -0.31 | -0.853 | 0.394 | 0.005 | 0.033 |
| Bi-Weekly Momentum | -0.13 | -0.357 | 0.721 | 0.008 | 0.002 |
| Weekly Momentum | -0.41 | -1.202 | 0.230 | 0.004 | 0.110 |

Contrary to previous literature's results time-series momentum does not appear to be very profitable in the cryptocurrency asset class as evidenced by negative returns across all horizons in the above table. Bi-weekly momentum appears to have a positive and significant alpha at a one percent level, however, the index adjusted return is negative and not statistically different from zero. Momentum seems to exist only in equally weighted portfolios and is most likely unprofitable if traded in any sort of economic size. This makes sense intuitively considering since there are fewer cryptocurrencies in the stock universe and price information is far easier to obtain now than what has been seen historically in the equity space. It may be possible that heterogeneous expectations of conditional returns are have decreased variance relative to equities due to the lack of fundamentals driving cryptocurrencies. Overall, we can conclude that similar to the Famma French 3 Factor model of the index, I find that a similar result when looking at cryptocurrencies. There exists a small-cap and momentum premium, however, instead of forming SMB (small-minus-big) and UMD (up-minus-down) we will use S (small) and U (up) to reflect the inability to short. In general, we can conclude from the above results that cryptocurrencies are far more efficient than what many people would initially think. Many of the anomalies that are found in the equity space are not found in this particular asset class.

# 6. Alternative Sentiment Data

If the alpha of a strategy is proportional to costs of information acquisition, let us consider an alternative data domain in which we may be able to form a long-only strategy that outperforms the one-factor index. We develop a new measure of the abnormal pump and dump sentiment that is different from other attention proxies such as the GOOGLE SVI. To test whether there is a potential trading strategy that profits off sentiment we form a simple binary regime switching strategy on the week over week sentiment change. If lagged sentiment is increasing, the strategy invests in risk-free security. While if lagged sentiment is decreasing, the strategy goes long the crypto market index by financing the position with the risk-free security. Please see the figure below for the cumulative returns of the strategy throughout the sample compared with the actual returns of the index.


Fig. 2. Sentiment Index Strategy

Clearly, the strategy dominates the index on a risk-adjusted basis from the picture above. In the table below please see the results of the time series regression of the strategy against the one-factor model as well other factor models. Substituting cross-sectional momentum vs bi-weekly momentum does not substantially change the interpretation of the results.

Table 19: Sentiment Index Strategy

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **index** | 0.4973 | 0.079 | 6.320 | 0.000 | 0.343 | 0.652 |
| **constant** | 0.0120 | 0.005 | 2.547 | 0.011 | 0.003 | 0.021 |

Table 20: Sentiment Index Strategy Two-Factor

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Index** | 0.5582 | 0.110 | 5.057 | 0.000 | 0.342 | 0.775 |
| **Momentum** | -0.1482 | 0.161 | -0.918 | 0.359 | -0.465 | 0.168 |
| **constant** | 0.0122 | 0.005 | 2.617 | 0.009 | 0.003 | 0.021 |

Table 21: Sentiment Index Strategy Three-Factor

| | coef | std err | z | P> \|z\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **Index** | 0.5499 | 0.106 | 5.209 | 0.000 | 0.343 | 0.757 |
| **Momentum** | -0.1319 | 0.155 | -0.849 | 0.396 | -0.436 | 0.173 |
| **Small Cap** | -0.0799 | 0.061 | -1.300 | 0.194 | -0.200 | 0.041 |
| **constant** | 0.0135 | 0.005 | 2.949 | 0.003 | 0.005 | 0.022 |

The results indicate that the simple binary regime switching strategy results in a significant 1.2% per week over the sample. The alpha is significant at a 5% level but not at a 1% level. The inclusion of the bi-weekly momentum factor results in the increased significance of alpha as the strategy as the strategy's returns load negatively on the momentum factor. The three-factor also fails to explain the alpha of the sentiment-based strategy. The significance of the alpha is increased to .3%.

Although there appears to be a profitable strategy associated with investor sentiment, it may be that the sentiment found has no incremental value add relative to the well-known proxies in the literature. Monthly GOOGLE SVI is used as a test of robustness. The simple binary regime switching strategy that maximizes unconditional alpha is the opposite in signal of the investor sentiment strategy suggesting overreaction when sentiment is increasing. We long the index if sentiment is increasing while investing in the risk-free security is sentiment is decreasing.

Table 22: SVI Strategy

| | **coef** | **std err** | **z** | **P> \|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **index** | 0.5776 | 0.073 | 7.958 | 0.000 | 0.435 | 0.72 |
| **constant** | 0.0088 | 0.004 | 1.975 | 0.048 | 0.003 | 0.018 |

Table 23: SVI Strategy Two Factor

| | **coef** | **std err** | **z** | **P> \|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **index** | 0.3721 | 0.118 | 3.163 | 0.002 | 0.141 | 0.603 |
| **Momentum** | 0.3895 | 0.141 | 2.753 | 0.006 | 0.112 | 0.667 |
| **constant** | 0.0052 | 0.004 | 1.159 | 0.247 | -0.004 | 0.014 |

From the above, we see the sentiment strategy based on GOOGLE SVI underperforms the sentiment based on pump and dump chatrooms. Although the strategy remains positive and significant at a 5% level for the one-factor model, the inclusion of the momentum factor renders the time-invariant intercept not significantly different from zero. GOOGLE SVI sentiment positively loads on momentum with a coefficient of approximately .4. In untabulated results, it is found that using weekly GOOGLE SVI with weekly rebalancing results in less alpha relative to the results shown above.

# 7. AdaBoost Combined Sentiment Prediction

To see if I can improve on the simple binary regime switching strategy on the previous sentiment indicators, I will implement the AdaBoost algorithm in python. The 3 features to be included are the sentiment based on pump and dump, GOOG SVI, and bi-weekly time-series momentum. For the choice of classifier, one could choose any machine learning model. In the results below a Decision Tree was used. In addition, one could also greedily search features and splitting thresholds as well. The choice of lookback for training the machine learning algorithm is arbitrary, however, I find the 24 month lookback period performs optimally.

Table 24: AdaBoost Strategy

| | | | |
|---|---|---|---|
| **Dep. Variable:** | backtest | **R-squared:** | 0.600 |
| **Model:** | OLS | **Adj. R-squared:** | 0.597 |
| **Method:** | Least Squares | **F-statistic:** | 54.44 |
| **Date:** | Fri, 07 May 2021 | **Prob (F-statistic):** | 1.14e-11 |
| **Time:** | 15:46:58 | **Log-Likelihood:** | 218.92 |
| **No. Observations:** | 147 | **AIC:** | -433.8 |
| **Df Residuals:** | 145 | **BIC:** | -427.9 |
| **Df Model:** | 1 | | |

| | **coef** | **std err** | **z** | **P> \|z\|** | **[0.025** | **0.975]** |
|---|---|---|---|---|---|---|
| **Index** | 0.5934 | 0.080 | 7.379 | 0.000 | 0.436 | 0.751 |
| **constant** | 0.0097 | 0.005 | 2.148 | 0.032 | 0.001 | 0.019 |

The combined strategy performs better than the GOOGLE SVI and time-series momentum strategy, however, the results lag the binary strategy based only on the pump and dump sentiment. Alpha is still significant at a 5% level. The cumulative returns of the strategy are shown in the figure below.

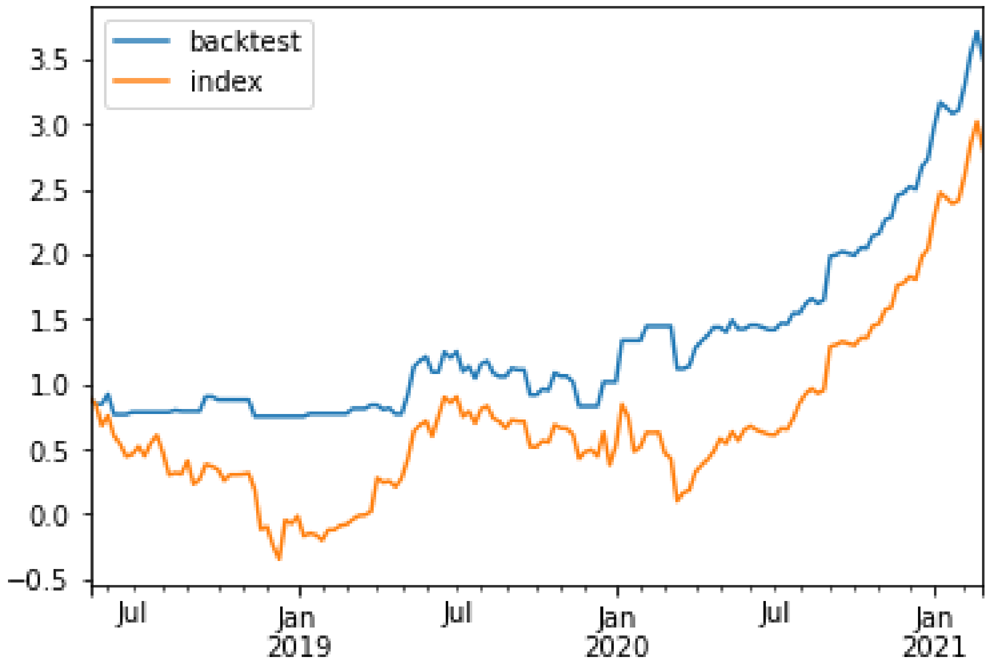


Fig. 3. Combined Sentiment

Clearly, from the above picture, one can see that the alpha of the sentiment strategy comes from Jul 2018 to Jul 2019, where bitcoin was flat over the year. Interestingly enough the combined sentiment strategy does not participate in Jan 2019 to Jul 2019 period where the index recovered from its drawdown. Overall cumulative return with weekly re-balancing shows the two strategies have similar ending cumulative returns, however, the sentiment strategy has far superior risk-adjusted performance that can be capitalized upon with sufficient use of leverage.

# 8. Reversal of Alpha

In the table below I investigate whether there is reversal in the sentiment strategy. Please note the reversal alpha is annualized in the table below. I choose to look at unconditional alpha due to the strategy being low beta in general.

Table 25: Annualized AdaBoost Strategy Reversal

| | reversal alpha |
|---|---|
| 1 | 0.55 |
| 2 | 0.45 |
| 3 | -0.09 |

Interestingly enough the alpha becomes negative after 3 weeks. After this period we do see the alpha increase as the sentiment is a short-term indicator that is based on weekly changes. One can conclude that the one-week holding period is optimal but one would not see significantly lower alpha if two weeks were chosen.

## *8.1. Minor Notes General Trading Costs*

Given the above results, it is not apparent whether the alpha exists outside trading costs. Although an alpha over 40% a year seems relatively large, however, if we assumed trading costs of .25% per trade (.5% roundtrip cost) the p-value of the alpha drops below the 10% level of significance to 14%. The assumption of fees of .25% per trade reflects the costs of trading on Gemini, which is on the high side of major exchanges. Coinbase for example has a fixed fee of .2%. Many other exchanges have maker-taker fees where you earn a rebate for being paid passively or the ability to have lower fees with higher trading volume. The addition of adding fees due to crossing the spread makes the strategy harder to implement as well. Since there is no low-cost implementable crypto index ETF, alpha would be preserved if one considered alpha relative to a fee-adjusted crypto index.

## 9. Conclusions

The results in the contents of this paper give evidence of cross-sectional momentum, time-series momentum, and small-cap abnormal performance that can be explained by a value-weighted crypto index. Traditional proxies for attention such as the Google SVI are not strong predictors of future returns and captured by a two-factor model with a momentum factor. Sentiment based on pump and dump chatrooms has a much stronger relationship with ex-post returns. The documented simple binary regime switching strategy has an annualized alpha of over 50%. Results are robust to an unconditional two-factor model and three-factor model. The paper gives additional evidence of why the venue of communication's vernacular needs to be taken into consideration in the creation of a proxy for attention. The combination of factors utilized AdaBoost performs better than the combination of strategies utilizing each conditioning variable, however, it underperforms the strategy utilizing only the pump and dump sentiment.

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