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Predicting Bitcoin Returns

Price Momentum and Technical Indicators

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Research and Insights

Data Report

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Content

Executive Summary

Welcome to our Data Report on predictors of Bitcoin returns.

Key Takeaways

- We studied whether Bitcoin's returns can be predicted by price data and technical indicators over the period 11/5/2010 - 10/31/20 with regression analysis.
- Momentum is found in both Bitcoin daily return and weekly return, i.e., an increase in the current return possibly leads to a higher future return. The momentum effects are fairly strong and statistically significant.
- Major technical indicators show mixed performance in predicting 1-week and 2-week ahead cumulative returns:
    - Bearish SMA or EMA signals are somewhat effective at predicting future price performance, while bullish signals seen in moving averages are ineffective.
    - Surprisingly, an overbought signal in RSI tends to be accompanied by very strong future returns, contrary to the purpose of the RSI to detect reversal patterns.

Introduction

The forces and dynamics driving asset returns are always fascinating. Bitcoin, as an emerging asset class with a ten-year history, has experienced an unparalleled journey of booms and busts in the market. Since its price behavior often deviates from traditional assets such as stocks, bonds, and fiat currencies, investors are particularly interested in the potential drivers of Bitcoin's market value and returns.

In the hope of predicting Bitcoin returns, many investors endeavour to find methods to search for patterns in historical data. Traders utilize technical indicators to seek profits from the vigorous and volatile price action of Bitcoin. But does this information hold any power as a crystal ball for Bitcoin's future returns?

This article will examine the validity and predictive power of two of the most commonly used metrics among crypto traders, momentum and technical indicators.

Data of Bitcoin Return

In this study, the Bitcoin return data are constructed from the Bitcoin price data series, which is downloaded from the Messari website. Daily return is the return of buying a Bitcoin at 11:59:59 UTD today and selling it at 11:59:59 UTC one day later. Weekly return is the return of buying a Bitcoin at 11:59:59 UTC on Sunday and selling at the same time next Sunday. To put it simply, daily and weekly returns are respectively the daily and weekly percentage changes of the Bitcoin prices. The time series of Bitcoin price ranges from 11/05/2010 to 10/31/2020.

Table 1. Descriptive Statistics of Bitcoin Returns

Duration: 2010/11/5-2020/10/31	Daily Bitcoin Return (%)	Weekly Bitcoin Return (%)
Mean	0.45%	3.07%
Median	0.20%	1.42%
25% Quartile	-1.34%	-3.79%
75% Quartile	2.05%	8.12%
Minimum	-46.13%	-44.64%
Maximum	52.89%	98.10%
Standard Deviation	5.38%	15.24%
Skewness	0.65	1.82
Kurtosis	14.89	8.76

Table 1 shows the key statistics illustrating the overall performances and distributions of Bitcoin returns over the past decade. There are several prominent characteristics regarding Bitcoin returns:

- **High average returns:** The average daily and weekly Bitcoin returns are respectively 0.45% and 3.07%. These figures are really astounding as they beat most, if not all, popular stocks over the past decade.

- **High volatility:** The standard deviations, which measure the dispersion of data, are respectively 5.38% and 15.24% at daily and weekly frequencies, which are far higher than the mean returns. Notably, the minimum and maximum daily returns deviate from the mean by more than 100 times. All these statistics indicate a very high volatility in the price action of Bitcoin.

- **Positive skewness:** Daily and weekly returns are all positively skewed. As the right tail of the distribution is longer than the left, investors expect occasional huge gains relative to the mean.

- **High kurtosis:** Kurtosis, which measures the fatness of the tails of a distribution, indicates the chance of extreme events. As a rule of thumb, a kurtosis above 3 means that extreme events are more likely to happen than in the case of normal distribution. As for Bitcoin, the sample kurtoses are far above 3, indicating a high probability of extreme price actions.

Overview of Regression Analysis

In this article, we mainly adopt regression analysis to identify whether the Bitcoin return is related to its own past return and trading signals. The most basic form of regression is linear regression with only one independent variable. This form is based on a linear function: $\mathrm{y} = a + bx$. The variable y is the dependent variable and the variable x is the independent variable. The graph of such an equation is a straight line in an x-y plot. The constant a is the y-intercept of the line while the coefficient b is the slope measuring the steepness of the line. Linear regression is a practice that fits a straight line on data points. The purpose is to find a linear function of x that gives the best approximation or forecast of y through the least squares method.

Our regression results presented in the following sections cover the estimates of the slope coefficients and the corresponding t-statistics based on the regular standard error. A slope coefficient b is interpreted as the followings: if the independent variable x increases by 1, the dependent variable increases by a magnitude of b. Bitcoin return is the dependent variable of interest in our study. As the unit of Bitcoin return is in percentage, Bitcoin return increases by $b \times p$ percentage points if the independent variable x increases by p units.

The t-statistic is the coefficient divided by its standard error. The standard error can be interpreted as a measure of the precision with which the regression coefficient is measured. If a slope coefficient is large compared to its standard error, then it has a high probability to be different from 0. This involves the concept of hypothesis testing. The null hypothesis is that the coefficient is not different from zero; the alternative hypothesis is that the coefficient is different from zero.

The p-value is the probability of obtaining the t-statistic at least as extreme as the observed result of a hypothesis test, assuming that the null hypothesis is true. The rule of thumb is that: if the p-value of the corresponding t-statistic is smaller than the critical value (e.g. 5%), it rejects the null hypothesis that the coefficient is not different from zero, and such result is statistically significant. Following the common practice of econometric studies, the critical values adopted in in our study are 1%, 5% and 10%, and we highlight the statistically significant results.

Price Momentum

Methodology

Momentum in finance generally refers to the notion that rising prices tend to continue rising further whereas falling prices tend to fall further. From a time-series perspective, a more formal definition of momentum is that the past returns positively impact the future returns.

With an impressive uptrend in 2020, Bitcoin seems like the best proof of the momentum theories. In what follows, we try to examine whether Bitcoin returns exhibit momentum effects in our full sample period, i.e. 11/5/2010-10/31/2020 with regression analysis.

To check whether momentum exists, we regress the return $\boldsymbol{r_t}$ in period t versus its past returns $\boldsymbol{r_{t-h}}$ in period t-h, i.e., lagged by h periods. The period t is in day or week in our study.

$$r_t = \alpha + \beta \cdot r_{t-h} + \varepsilon_t$$

The return variables r_t and r_{t-h} here measure the excess returns of Bitcoin above and beyond the risk-free rate, which is proxied by the three-month Treasury bill rate.

We can also examine the predictive power of the pure direction of the past return:

$$r_t = \alpha + \beta \cdot sign(r_{t-h}) + \varepsilon_t$$

$sign(r_{t-h})$ equals +1 if the past return is positive, and -1 if the past return is negative. The coefficient β measures how the average present return varies when the past return is different from zero. If β is statistically significantly greater than zero, the positive past return predicts a higher average present return than the negative past return, and vice versa. And 2β stands for the average difference between the present returns following the positive past returns and those following the negative past returns. It is obtained from the following arithmetic:

$$(r_t|sign(r_{t-h}) = 1) - (r_t|sign(r_{t-h}) = -1) = \beta - (-\beta) = 2\beta$$

A Note on Interpreting Regression Results

If β is statistically significant and greater than zero, then the recent returns have an impact on future returns, which supports the existence of momentum in Bitcoin returns. If β is statistically significant and negative, then the present return is negatively correlated with the past return. This indicates that the signal is a negative indicator.

Results and Analysis

Table 2. Regression Results: Momentum of Daily Returns

	Number of Days Lagged						
	1-day (t-1)	2-day (t-2)	3-day (t-3)	4-day (t-4)	5-day (t-5)	6-day (t-6)	7-day (t-7)
Panel A. Using the past return r_{t-h} as the independent variable							
β	0.0159 (0.969)	**-0.0381**** **(-2.327)**	0.0086 (1.49)	0.0136 (0.833)	**0.0817***** **(5.026)**	**0.0768***** **(4.726)**	**-0.0292*** **(-1.797)**
Panel B. Using the sign of past return $sign(r_{t-h})$ as the independent variable							
β	**0.2360***** **(2.670)**	0.0862 (0.977)	-0.0992 (-1.128)	**0.1476*** **(1.680)**	**0.2031**** **(2.311)**	**0.2415***** **(2.748)**	0.0397 (0.452)

$*$ p-value < 0.1, $**$ p-value < 0.05, $***$ p-value < 0.01; t-statistics in parentheses

Table 2 illustrates the regression results of daily returns using the full sample period, which supports the existence of momentum in Bitcoin daily returns. Here are the main findings:

- **The 5-day and 6-day lagged returns (r_{t-5} , r_{t-6}) are relatively strong positive predictors of the present return r_t.**
  In other words, we find that bitcoin returns from 5-6 days ago are the best at predicting returns in the immediate future. Their slope estimates β are statistically significant, as the p-values are smaller than our critical values as listed in Panel A. If r_{t-5} and r_{t-6} respectively increase by one standard deviation (5.38 percent points (pp) as shown in Table 1), r_t increases by 0.44 (=5.38 ×0.0817) pp and 0.41 (=5.38×0.0768) pp correspondingly.

- **The 2-day and 7-day lagged returns (r_{t-2} , r_{t-7}) are negative predictors of the present return r_t.**
  The slope estimates can be interpreted similarly as the positive predictors. If r_{t-2} and r_{t-7} respectively increase by one standard deviation, r_t decreases by 0.21 (=5.38 ×0.0381) pp and 0.16 (=5.38×0.0292) pp correspondingly. This indicates volatility and quick reversals in the price action of Bitcoin.

- **The signs of 1-day, 4-day, 5-day and 6-day lagged returns are positive predictors of the present return r_t.**
  As shown in Panel B, their slope estimates carry statistical significances. If r_{t-1}, r_{t-4}, r_{t-5} and r_{t-6} are positive returns, in comparison to their negative counterparts, the present return r_t increases by 0.472 (=2×0.236) pp, 0.295 pp, 0.406 pp and 0.483 pp respectively.

Table 3. Regression Results: Momentum of Weekly Returns

	Number of Weeks Lagged						
	1-week (t-1)	2-week (t-2)	3-week (t-3)	4-week (t-4)	5-week (t-5)	6-week (t-6)	7-week (t-7)
Panel A. Using the past return r_{t-h} as the independent variable							
β	**0.1810*** (4.192)**	**0.2178*** (5.076)**	**0.1906*** (4.412)**	0.0704 (1.609)	**0.1048** (2.403)**	0.0416 (0.949)	0.0414 (0.944)
Panel B. Using the sign of past return $sign(r_{t-h})$ as the independent variable							
β	**1.6767** (2.492)**	**1.9054*** (2.832)**	**2.0068*** (2.981)**	**1.1766* (1.742)**	1.0326 (1.525)	0.7751 (1.142)	0.7148 (1.051)
$*$ p-value < 0.1, $**$ p-value < 0.05, $***$ p-value < 0.01; t-statistics in parentheses							

Table 3 illustrates the regression results of weekly returns using the full sample period. The continuation of momentum in weekly returns is even more persistent and obvious than in daily returns. Here are the main findings:

- **The 1-week, 2-week, 3-week and 5-week lagged returns (r_{t-1}, r_{t-2}, r_{t-3}, r_{t-5}) are relatively strong positive predictors of the present return r_t.**
  If r_{t-1}, r_{t-2}, r_{t-3} and r_{t-5} respectively increase by one standard deviation (15.2 pp as shown in Table 1), r_t increases by 2.75 (=15.2 ×0.181) pp, 3.31 pp, 2.90 pp, 1.59 pp correspondingly.

- **The signs of 1-week, 2-week, 3-week and 4-week lagged returns are positive predictors of the present return r_t.**
  If r_{t-1}, r_{t-2}, r_{t-3} and r_{t-4} are positive returns, in comparison to their negative counterparts, the present return r_t increases by 3.35 (=2×1.6767) pp, 3.81 pp, 4.01 pp and 2.35 pp respectively.

Technical Indicators

Indicators and Trading Signals

Technical analysis is the study of historical price charts and market statistics, with the aim of predicting price movements. Many market participants utilize various technical indicators to spot trend patterns and corresponding profit opportunities.

We now move on to explore whether certain popular technical indicators can act as reliable predictors of Bitcoin returns. The following briefly describes the indicators included in our study, and we adopt the common practice on the choice of timeframes for the technical indicator.

Simple Moving Average (SMA)

The purpose of calculating moving averages of asset prices is to help smooth out the price data and facilitate the discovery of trends and patterns. A k-day SMA refers to the simple mean of the closing prices in k nearest days. For evaluating shorter-term trends, the timeframes are usually 5, 10 and 20 days, while the medium-term and long-term timeframes are 50, 100 and 200 days.

$$SMA_t = (P_t + P_{t-1} + \cdots + P_{t-(k+1)})/k$$

Exponential Moving Average (EMA)

EMA is a variation of SMA that places greater weightings on recent prices. As seen in the following formula, a k-day EMA has a weight ω on the current price and a weight 1-ω on the EMA in the previous period.

$$EMA_t = \omega \cdot P_t + (1-\omega) \cdot EMA_{t-1}, \text{ where } \omega = 2/(k+1)$$

Moving Average Convergence Divergence (MACD)

MACD is a trend indicator that usually tracks the difference between a shorter-term 12-day EMA and a longer-term 26-day EMA. Technical analysts tend to compare the MACD series against the signal line, which is the 9-day EMA series of the MACD. A bullish crossover occurs when the MACD crosses above the signal line, whereas a bearish crossover occurs when the MACD falls below the signal line.

$$MACD_t(12{,}26) = 12\text{-}day\ EMA_t - 26\text{-}day\ EMA_t$$

Relative Strength Index (RSI)

RSI is an oscillator that is calculated by dividing the average of gains by the average of losses in the past 14 days. It is normalized such that the value fluctuates between 0 and 100. An asset is considered overbought when its RSI is above 70 and oversold when below 30.

$$14\text{-}\,\text{day } RSI_t = 100 - 100/[(1 + (\text{Average of Gains}/\text{Average of Losses}))]$$

Table 4 summarizes the general rules of thumb on the trading signals generated from the above indicators. **Put simply, a bullish/overbought signal indicates the price will go upward whereas a bearish/oversold signal indicates the price will go downward.** Our study mainly examines the crossover-type signals as people generally believe that crossovers help predict strong breakouts and breakdowns in price actions, and they have clear-cut rules to follow.

Table 4. Trading Signals of Technical Indicators

Indicators	Trading Signals
Moving Averages	**Price Crossovers** Bullish signal: P_t crosses above MA_t (e.g. P_t crosses above 50-day MA_t or 50-day MA_t) Bearish signal: P_t crosses below MA_t (e.g. P_t crosses below 50-day MA_t or 50-day MA_t) **MA Crossovers** Bullish signal: short-term MA_t crosses above long-term MA_t (e.g. 10-day MA_t or EMA_t crosses above 50-day MA_t) Bearish signal: short-term MA_t crosses above long-term MA_t (e.g. 10-day MA_t crosses above 50-day MA_t) Remarks: MA_t can be either SMA_t or EMA_t
Moving Average Convergence Divergence	**Signal Line Crossovers** Bullish signal: $MACD_t$ crosses above 9-day EMA_t of $MACD_t$ Bearish signal: $MACD_t$ falls below 9-day EMA_t of $MACD_t$
Relative Strength Index	**Index Range** Oversold signal: 14-day RSI_t < 30 Overbought signal: 14-day RSI_t > 70

Methodology

The following regression can provide a check on the predictive abilities of the indicators against the no-signal cases:

$$r_{t+h} = \alpha + \beta \cdot bullsignal_t + \gamma \cdot bearsignal_t + \varepsilon_t$$

We assume investors buy and hold Bitcoin for certain time once the signal is observed, so the return variable r_{t+h} measures the cumulative return from the current period to h periods ahead. In our study, we consider one-week and two-week cumulative returns.

$bullsignal_t$ and $bearsignal_t$ are dummy variables respectively indicating the incidence of bullish/oversold and bearish/overbought signals. There are 3 cases:

- **No-signal case: If there are no signals at all, both $bullsignal_t$ and $bearsignal_t$ equal 0.**
  The intercept α measures the average return of the no-signal cases.

- **Bullish case: If a bullish/oversold signal exists in time t, $bullsignal_t$ equals 1 and $bearsignal_t$ equals 0.**
  The slope coefficient β measures the difference between the average bullish signal return and the average no-signal return.

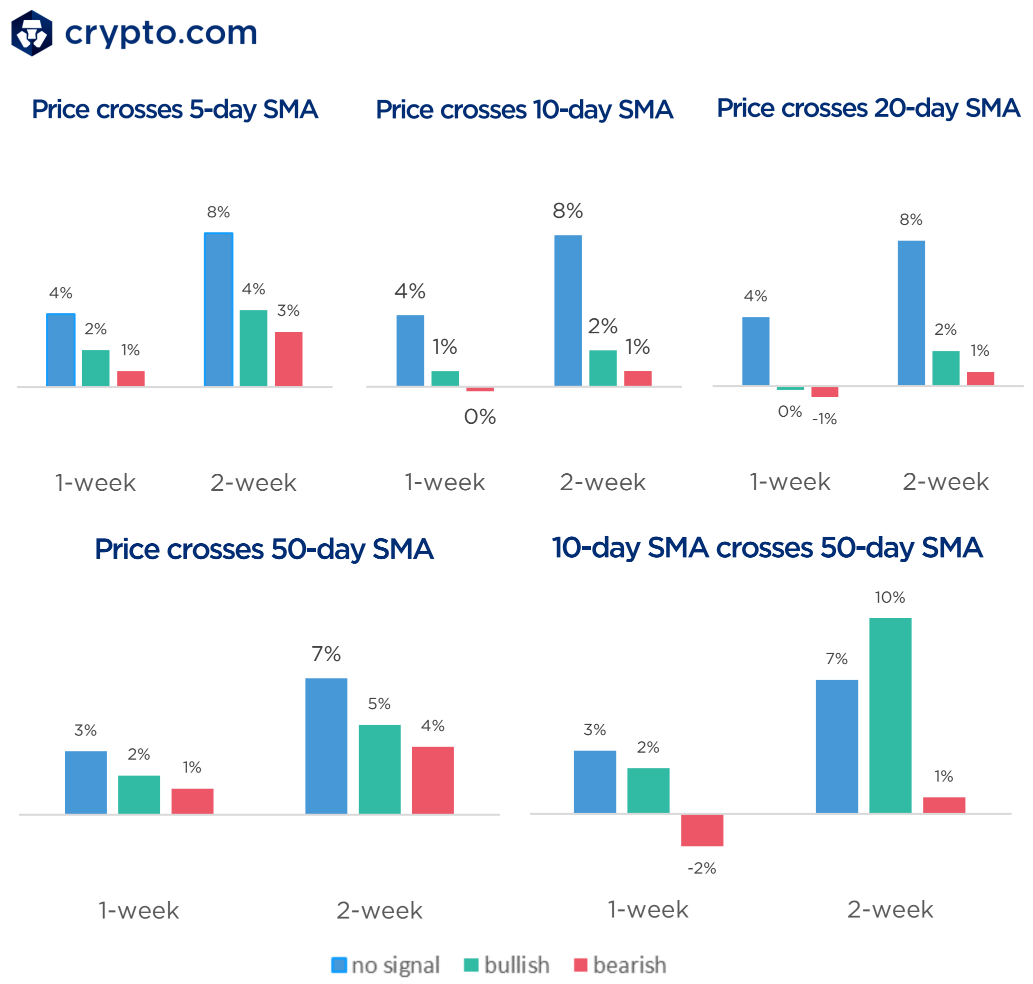
- **Bearish case: If a bearish/overbought signal exists in time t, $bullsignal_t$ equals 0 and $bearsignal_t$ equals 1.**
  The slope coefficient γ measures the difference between the average bearish signal return and the average no-signal return.

If β or γ is statistically significantly different from 0, then the average return ahead of the signal is statistically significantly different from that of the no-signal case with magnitudes of β or γ.

In ideal cases, β should be larger than 0 while γ should be smaller than 0, i.e. the bullish signal return outperforms the no-signal return while the bearish signal return underperforms the no-signal return.

Results and Analysis

Chart 1. Average 1-Week and 2-Week Cumulative Returns Following SMA Signals



Source: Crypto.com Research, Messari

We present the results in both charts and regression tables. The charts present the average 1-week and 2-week cumulative returns following different types of signals. In case you find the information of the regression tables too hard to grasp, the charts can also give you an overview of the signals' performance.

First, we observed interesting results regarding SMA trading signals (Chart 2 and Table 5).

- **All the bullish SMA signals, except for 10-day SMA crossing above 50-day SMA, substantially underperform the no-signal cases in terms of 1-week and 2-week ahead cumulative returns.**

- From Table 5, we can observe that the β estimates are less than zero in most cases. This means that the average 1-week and 2-week cumulative returns following the bullish signals underperform the corresponding returns in no-signal cases. And the differences are statistically significant for both 1-week and 2-week returns following prices crossing below 5-day, 10-day, and 20-day SMA. This contradicts the ideal case that bullish signals can forecast higher future returns than usual.

  As for 10-day SMA crossing above 50-day SMA (Panel E), its 2-week cumulative return beats that of the no-signal case by 3.22 pp on average, but the difference is statistically insignificant.

- **All the bearish SMA signals substantially underperform the no-signal cases in terms of 1-week and 2-week ahead cumulative returns.** All the γ estimates are negative, implying that the average 1-week and 2-week cumulative returns following all the bearish signals underperform the corresponding returns in no-signal cases. And such differences are statistically significant for both 1-week and 2-week returns following price crossing below 5-day, 10-day, and 20-day SMA. This is consistent with the ideal case that bearish signals can forecast lower future returns than usual.

- **The bullish SMA signals outperform the bearish SMA signals.**
  The coefficient estimates of the bullish signals are generally higher, or less negative, than those of the bearish counterparts. In other words, the returns following the bullish signals outperform the returns following the bearish ones.

  For instance, regarding price crossing 5-day SMA (Panel A), the 1-week return and 2-week return following the bullish signals are 1.10 pp and 1.13 pp higher than those following the bearish signals.

Table 5. Regression Results: Testing Signals of SMA

	Time Horizons of Cumulative Returns	
Coefficients	1-week	2-week
Panel A. Price crosses 5-day SMA		
α (no signal)	3.7909***	8.0098***
β (bullish)	**-1.8658**** (-2.197)**	**-4.0108***** (-2.774)**
γ (bearish)	**-2.9691***** (-3.494)**	**-5.1395***** (-3.555)**
Panel B. Price crosses 10-day SMA		
α (no signal)	3.7242***	7.8862***
β (bullish)	**-2.9144***** (-2.789)**	**-5.9956***** (-3.371)**
γ (bearish)	**-3.955***** (-3.785)**	**-7.0689***** (-3.975)**
Panel C. Price crosses 20-day SMA		
α (no signal)	3.5948***	7.5677***
β (bullish)	**-3.7791***** (-2.912)**	**-5.7342***** (-2.592)**
γ (bearish)	**-4.1506***** (-3.199)**	**-6.8258***** (-3.086)**
Panel D. Price crosses 50-day SMA		
α (no signal)	3.3036***	7.0959***
β (bullish)	-1.2665 (-0.702)	-2.4288 (-0.790)
γ (bearish)	-1.9445 (-1.075)	-3.5613 (-1.152)
Panel E. 10-day SMA crosses 50-day SMA		
α (no signal)	3.2860***	6.9782***
β (bullish)	-0.9126 (-0.346)	3.2166 (0.713)
γ (bearish)	**-4.9694*** (-1.857)**	-6.1098 (-1.338)

* p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01; t-statistics in parentheses.
Remarks: Results are generally robust to Newey-West standard errors.

Chart 2. Average 1-Week and 2-Week Returns Following EMA Signals

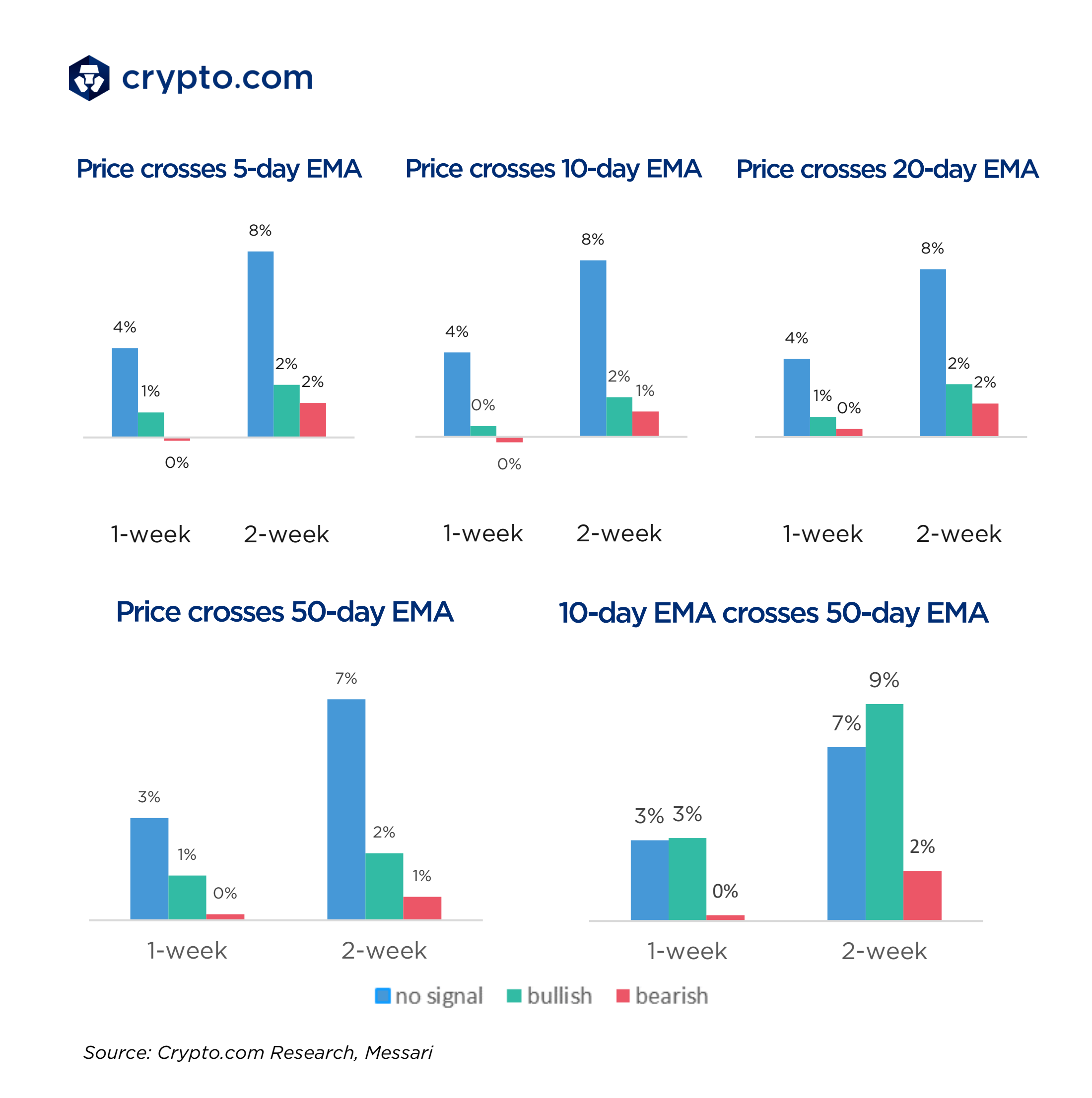


Chart 3 and Table 6 illustrate the results regarding EMA:

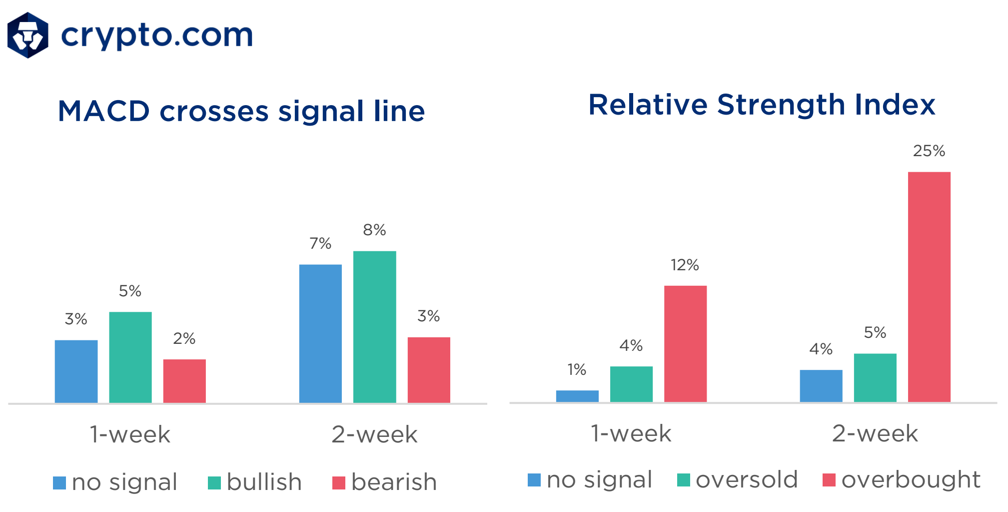
- **The performance of EMA signals largely follows the above main findings using SMA signals.**
- **Despite statistical insignificance, 10-day EMA crossing 50-day EMA crossing signal line perform ideally in predicting returns.** As observed in Chart 2 and Panel E of Table 6, for both 1-week and 2-week returns, the bullish signals outperform the no-signal cases whereas the bearish signals underperform the no-signal case.

Table 6. Regression Results: Testing Signals of EMA

	Time Horizons of Cumulative Returns	
Coefficients	**1-week**	**2-week**
Panel A. Price crosses 5-day EMA		
α (no signal)	4.0214***	8.3881***
β (bullish)	**-2.8872** (-3.355)**	**-6.0090*** (-4.100)**
γ (bearish)	**-4.1640*** (-4.834)**	**-6.8250*** (-4.656)**
Panel B. Price crosses 10-day EMA		
α (no signal)	3.8054***	7.9608***
β (bullish)	**-3.3167*** (-3.290)**	**-6.1827*** (-3.604)**
γ (bearish)	**-4.0512*** (-4.019)**	**-6.8212*** (-3.976)**
Panel C. Price crosses 20-day EMA		
α (no signal)	3.5234***	7.5620***
β (bullish)	**-2.6093*** (-2.108)**	**-5.1804** (-2.458)**
γ (bearish)	**-3.1521** (-2.546)**	**-6.0452*** (-2.868)**
Panel D. Price crosses 50-day EMA		
α (no signal)	3.3654***	7.2691***
β (bullish)	-1.8910 (-1.127)	**-5.0630* (-1.766)**
γ (bearish)	**-3.1685* (-1.878)**	**-6.4907** (-2.253)**
Panel E. 10-day EMA crosses 50-day EMA		
α (no signal)	3.2480***	6.9749***
β (bullish)	0.0779 (0.027)	1.7380 (0.343)
γ (bearish)	-3.0213 (-1.006)	-4.9583 (-0.966)

* p-value < 0.1, ** p-value < 0.05, *** p-value < 0.01; t-statistics in parentheses
Remarks: Results are generally robust to Newey-West standard errors.

Chart 3. Average 1-Week and 2-Week Cumulative Returns Following MACD and RSI Signals



Source: Crypto.com Research, Messari

Chart 3 and Table 7 illustrate the results regarding MACD and RSI:

- **Like 10-day EMA crossing 50-day EMA, MACD crossing signal line performs ideally in predicting returns, but the results lack statistical significance.**

Intriguingly, RSI works in an opposite way versus how it is intended:

- **Overbought signals strongly outperform the oversold signals and the no-signal cases.**
  The γ estimates are far larger than the α and β estimates, indicating that overbought signals where RSI >70 tend to be followed by much higher returns.

  Specifically, the 1-week and 2-week cumulative returns following the overbought signals beat the no-signal cases by 11.14 pp and 21.15 pp respectively (Panel B of Table 7). This implies that the Bitcoin price tends to continue its uptrend even it has risen for numerous days, and the RSI overbought signal fails to predict when the uptrend ends.

Table 7. Regression Results: Testing Signals of MACD and RSI

	Time Horizons of Cumulative Returns	
Coefficients	1-week	2-week
Panel A. MACD crosses signal line		
α (no signal)	3.2501***	7.1113***
β (bullish)	1.4364 (0.909)	0.6725 (0.248)
γ (bearish)	-0.9907 (-0.625)	-3.7204 (-1.3740)
Panel B. RSI		
α (no signal)	1.3319***	3.5037***
β (oversold)	**2.5556*** **(1.761)**	1.7483 (0.713)
γ (overbought)	**11.1380***** **(15.434)**	**21.1074***** **(17.261)**

$*$ p-value < 0.1, $**$ p-value < 0.05, $***$ p-value < 0.01; t-statistics in parentheses
Remarks: Results are generally robust to Newey-West standard errors.

Summary

Conclusion

Key Takeaways

- We studied whether Bitcoin's returns can be predicted by price data and technical indicators over the period 11/5/2010 - 10/31/20 with regression analysis.
- Momentum is found in both Bitcoin daily return and weekly return, i.e., an increase in the current return possibly leads to a higher future return. The momentum effects are fairly strong and statistically significant.
- Major technical indicators show mixed performance in predicting 1-week and 2-week ahead cumulative returns:
    - Bearish SMA or EMA signals are somewhat effective at predicting future price performance, while bullish signals seen in moving averages are ineffective.
    - Surprisingly, an overbought signal in RSI tends to be accompanied by very strong future returns, contrary to the purpose of the RSI to detect reversal patterns.

Limitations and Caveats

Although we have concluded the above results, we would still like to highlight some limitations of our study:

- The estimates and statistical significance of the regression results are limited by and subject to the specification of the models and the sample durations. For example, we have not included potential economic factors in the models, and their presence can impact the estimates of our existing coefficients.

- We only adopt simple rules and assumptions regarding the technical signals for illustration, and they can be far from real trading situations. Further fine-tuning and back-testing are needed for identifying profitable strategies.

- Our study is time sensitive. Altering the sample durations will very likely lead to different results. Readers should interpret the results with caution.

- This study’s conclusions are drawn using historical data, which do not accurately reflect potential future returns and correlation. Readers should note that the results do not constitute as any investment advice.

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