Can Bitcoin Investors Profit from Buy, Hold, and Sell Recommendations by Crypto Analysts?*

Dirk F. Gerritsen[1], Rick A. C. Lugtigheid[1], Thomas Walther[1,2,†]

[1] Utrecht School of Economics, Utrecht University, The Netherlands
[2] Faculty of Business and Economics, Technische Universität Dresden, Germany

Abstract

Using a hand-collected dataset containing buy, hold, and sell recommendations for Bitcoin published by crypto analysts, we show that hold and sell recommendations are followed by negative abnormal returns whereas buy recommendations are not associated with nonzero abnormal returns. Based on all outstanding recommendations, we compute recommendation changes relative to (i) the latest issued recommendation and (ii) the outstanding consensus recommendation. Downgrades are followed by negative abnormal returns. We conclude that crypto analysts are skilled information intermediaries on the Bitcoin market.

Keywords: Bitcoin, Analysts, Analyst recommendations, Market efficiency
JEL Classifications: G14, G24

* We are thankful to Elie Bouri, Andrew Urquhard, and Simon Trimborn for their valuable suggestions on a former version of this manuscript.
† Corresponding author's e-mail: t.walther@uu.nl.

1 Introduction

Bitcoin is an unregulated, decentralized, peer-to-peer cryptocurrency enabling users to process transactions through digital units of exchange. There is a large debate in the literature about the degree of market efficiency of Bitcoin (Urquhart, 2016; Jiang et al., 2018), which is relevant for the potential value of Bitcoin recommendations published by crypto analysts (Davies and Canes, 1978). Because the characteristics of Bitcoin are significantly different from traditional securities (Klein et al., 2018), analysts employ various techniques to construct their recommendations (e.g., fundamental, sentiment, technical, and trend analysis).

Analysts are information intermediaries who perform dual roles of information discovery and information interpretation (Ramnath et al., 2008). They are experts in discovering information from non-public or neglected sources (Grossman & Stiglitz, 1980) and add value through their superior capabilities in interpreting and analyzing public information (Cooper et al., 2001). Analysts communicate information through reports containing, i.a., a recommendation to buy, hold, or sell the respective asset. The value of predictions is studied extensively for stocks and other asset classes (Ramnath et al., 2008). Forecasts prove to be informative with respect to future price movements, thereby improving market efficiency (Davies & Canes, 1978). We study the value of buy, hold, and sell recommendations by crypto analysts for Bitcoin. To date, there is no prior research on recommendations for crypto assets.

In related literature, Hudson and Urquhart (2019) and Gerritsen et al. (2020) show that technical analysis can be used to predict Bitcoin prices. Moreover, Bouri and Gupta (2019), Kraaijeveld and Smedt (2020), and Trimborn et al. (2020) find that Twitter and other crowd sentiment have predictive power for returns of Bitcoin and other cryptocurrencies. In addition, various studies determine key driving factors to forecast Bitcoin markets (Kristoufek, 2015; Walther et al., 2019).

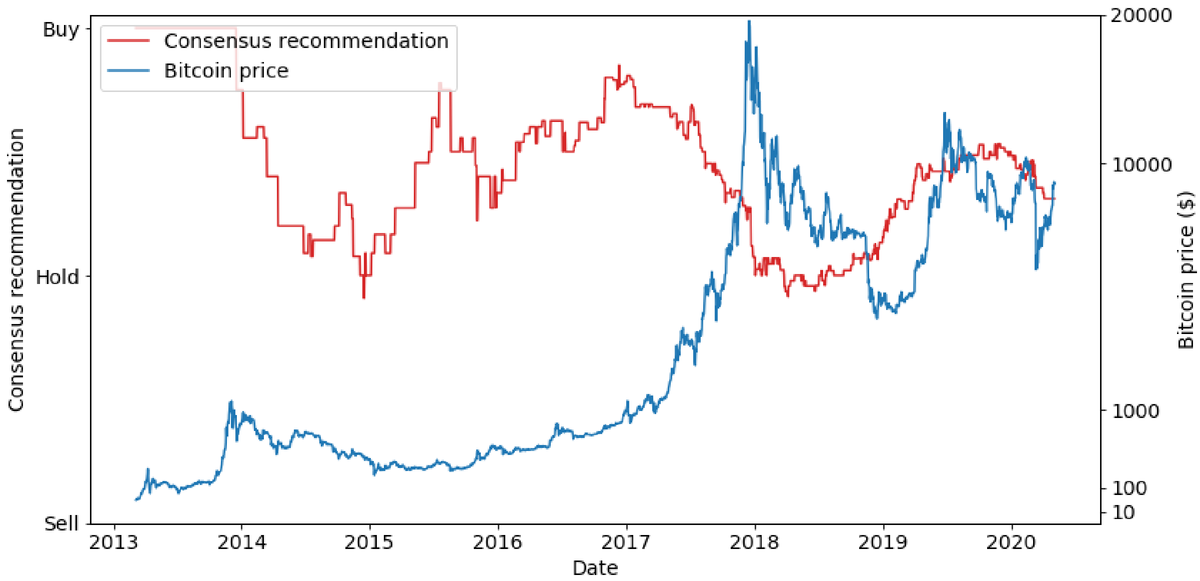
We contribute to the literature by investigating the value of recommendations and their revisions. We show that hold and sell recommendations are followed by negative abnormal returns. Further, we observe that downgrades (consensus downgrades) are followed by significant negative abnormal returns of up to -4.29 (-2.57) percent.

2 Data and Methodology

We hand-collected a large sample of Bitcoin recommendations issued from January 2012 to March 2020.[1] We identified 132 different analysts and in total 279 recommendations (178 buy, 31 hold, and 70 sell recommendations).

We use two different procedures to compute revisions. First, we follow Barber et al. (2001) in constructing a consensus recommendation that is recomputed every time a crypto analyst initiates coverage, changes the recommendations, or drops coverage. If an analyst does not update his recommendations within 12 months from the publication date, we consider it as dropped coverage. We treat consensus increases as upgrades and decreases as downgrades. Figure 1 depicts both the consensus recommendation and the Bitcoin price for our sample period. The average consensus recommendation is in between a buy and a hold recommendation (1.56, if buy, hold, and sell are coded as 1, 2, and 3). This implies that crypto analysts are on average optimistic regarding future Bitcoin prices, which is in line with security analysts (Barber et al., 2001). We identify 138 consensus upgrades and 141 consensus downgrades.

Figure 1. Consensus recommendation and Bitcoin price.



Second, we compute upgrades and downgrades by comparing a newly issued recommendation to the most recently published recommendation by any analyst. This analysis differs in two ways from our consensus analysis. First, a recommendation reiteration by an analyst can lead to an upgrade or downgrade if a contrasting recommendation was published by another analyst in the period between those two recommendations. Second, dropped

[1] Please see the online appendix for the exact procedure.

recommendations do not play a role in this analysis. For this procedure, we identify 71 upgrades and 77 downgrades.

We retrieve Bitcoin prices from www.coinmarketcap.com. We compute daily log-returns as follows: $R_t = \ln\left(\frac{B_t}{B_{t-1}}\right)$, where B_t is the closing price of day *t* (UTC). We calculate abnormal returns by subtracting the mean Bitcoin return of our estimation window ($\hat{R}_t$) from our observed Bitcoin returns during our event window: by $AR_t = R_t - \hat{R}_t$. As estimation window, we use the period (-54, -6). Similar to the analysts literature, we study the cumulative abnormal returns (CAR) as of the event day, i.e. $CAR_{t,t+m} = \sum_{s=0}^{m} AR_{t+s}$. Event studies commonly consider event windows of (-2, 2). Given the possibility of other market dynamics relative to stocks, we allow for a longer event window consisting of four pre-event days (for which we do not expect significant returns), the event day, and four post-event days. We expect the strongest findings for the event day. We include the post-event period since we know that not all investors respond instantaneously to recommendations. For these investors, we study cumulative returns for the post-event window separately.[2]

3 Results

3.1 Recommendation level

Our results for recommendations are presented in Table 1 and Figure 2. Figure 2 shows that there is no pre-event trend in Bitcoin prices before analyst recommendations. Table 1 confirms this observation as there are no statistically significant returns for individual days during the period (-4, -1). Measuring as of the event day, we find no clear pattern for returns following buy recommendations. For hold and sell recommendations, the event day exhibits negative abnormal returns of -2.67 percent and -1.89 percent, respectively. Sell recommendations are associated with additional negative and significant abnormal returns (at 10%) on days 1 and 3. All windows as of the event day (i.e., (0, 1) to (0, 4)) are associated with significant negative CARs after hold and sell recommendations.[3] In addition (1, 4) is strongly negative after sell recommendations.

[2] All results are robust to using a different estimation window, for example (-365, -6) or different abnormal returns method (AR(1)).
[3] Our findings are robust for a restricted sample where we exclude 2020 and the turmoil surrounding the outbreak of Covid-19.

Figure 2. CARs around the publication of a recommendation

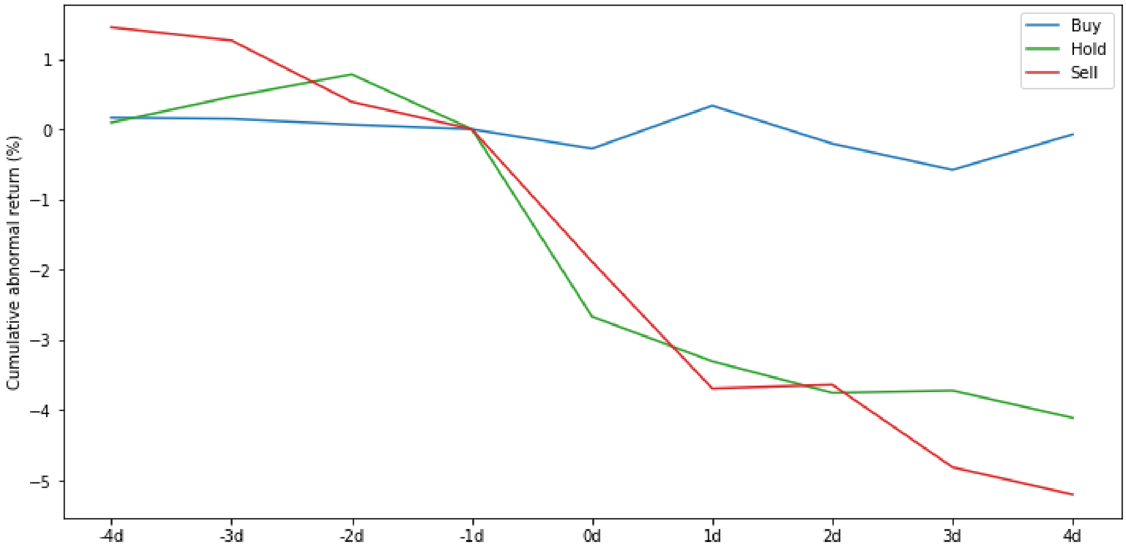


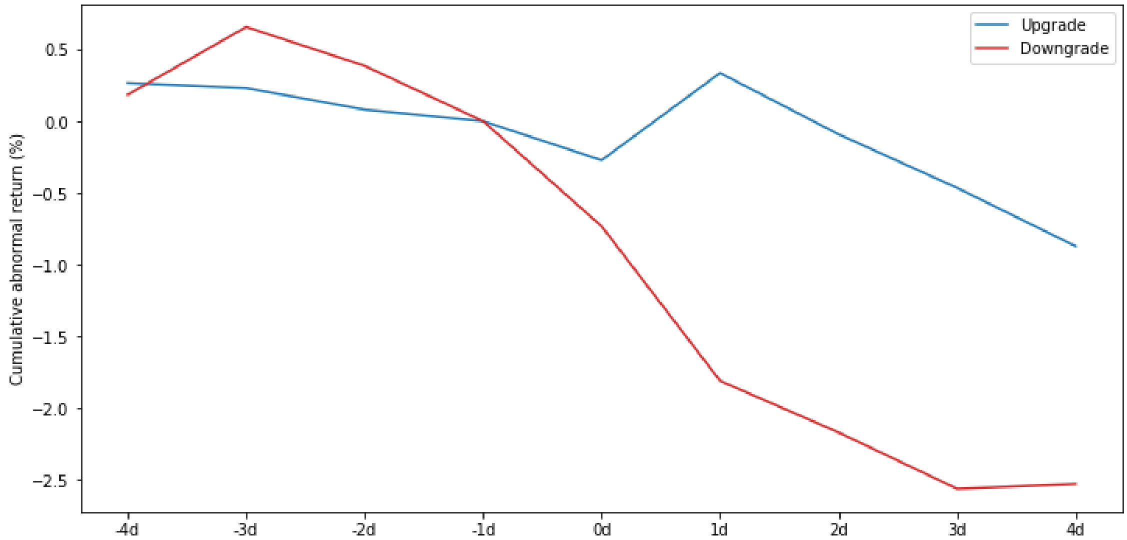
Table 1. Returns surrounding buy, hold, and sell recommendations with standard errors in parentheses. The asterisks *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Buy			Hold			Sell		
	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1
-4	-0.20			-0.19			0.21		
	(0.36)			(0.79)			(0.55)		
-3	-0.02			0.37			-0.19		
	(0.31)			(0.73)			(0.66)		
-2	-0.08			0.32			-0.87		
	(0.35)			(1.07)			(0.64)		
-1	-0.06			-0.78			-0.39		
	(0.48)			(0.91)			(0.65)		
0	-0.28			-2.67***			-1.89**		
	(0.42)			(0.93)			(0.94)		
1	0.61	0.34		-0.64	-3.30**		-1.80*	-3.69***	
	(0.38)	(0.58)		(0.73)	(1.24)		(0.82)	(1.19)	
2	-0.54	-0.21	0.07	-0.45	-3.75***	-1.09	0.05	-3.64***	-1.75*
	(0.36)	(0.72)	(0.56)	(0.78)	(1.33)	(1.08)	(0.76)	(1.34)	(0.88)
3	-0.37	-0.58	-0.30	0.03	-3.72**	-1.05	-1.17*	-4.81***	-2.93***
	(0.40)	(0.90)	(0.75)	(0.59)	(1.40)	(1.16)	(0.55)	(1.35)	(0.93)
4	0.51	-0.07	0.20	-0.39	-4.11**	-1.44	-0.39	-5.20***	-3.31**
	(0.34)	(0.85)	(0.71)	(0.89)	(1.65)	(1.53)	(0.89)	(1.65)	(1.30)

3.2 Recommendation revisions

By studying recommendation revisions, we explicitly acknowledge the potential value of the arrival of new information to investors. Figure 3 and Table 2 indicate that there are no meaningful abnormal returns prior to consensus upgrades and downgrades. Event and post-event returns for upgrades are not different from zero either. Following downgrades, we report a significant abnormal return of -1.00 percent on day 1. Both the CARs as of day 0 and 1 are negative and significant.

Figure 3. Cumulative mean-adjusted return around consensus recommendation revisions.



The results for the second revision analysis are presented in Table A1 in the appendix. For upgrades, the results are similar to those of consensus revisions. For downgrades, the results are stronger. The event-day abnormal return for a downgrade is -1.22 percent. The CAR is -4.29 percent for the window (0, 4) and -3.07 percent for the window (1, 4).

Table 2. Returns surrounding consensus recommendation revision with standard errors in parentheses. The asterisks *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Upgrade			Downgrade		
	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1
-4	-0.02			0.18		
	(0.35)			(0.39)		
-3	0.00			0.43		
	(0.35)			(0.40)		
-2	-0.21			-0.22		
	(0.36)			(0.42)		
-1	-0.08			-0.38		
	(0.40)			(0.42)		
0	-0.28			-0.72		
	(0.39)			(0.55)		
1	0.54	0.26		-1.00**	-1.72**	
	(0.36)	(0.51)		(0.48)	(0.70)	
2	-0.42	-0.16	0.12	-0.36	-2.09**	-1.37**
	(0.30)	(0.59)	(0.47)	(0.48)	(0.83)	(0.62)
3	-0.32	-0.48	-0.20	-0.45	-2.53***	-1.81***
	(0.41)	(0.79)	(0.65)	(0.40)	(0.87)	(0.66)
4	-0.34	-0.82	-0.54	-0.04	-2.57**	-1.85**
	(0.32)	(0.82)	(0.70)	(0.52)	(1.02)	(0.82)

4 Discussion & Conclusion

We find that hold and sell recommendations are associated with negative CARs in the period following the recommendation. Recommendations to buy Bitcoin do not result in statistically significant abnormal returns. For recommendation revisions, we find that only downgrades are statistically and economically relevant. The finding that negative news has a more pronounced impact than positive is consistent with Soroka (2006).

We conclude that crypto analysts are an important contributor to price discovery on the Bitcoin market and that their recommendations improve the market's efficiency. Our results support the findings of Trimborn et al. (2020) who find that cryptocurrency experts sentiment carries valuable information.

Our study undertakes a first step in estimating the value of Bitcoin recommendations. The long-standing literature on security analysts studies target prices (Brav and Lehavy, 2003) and the textual justification of the recommendation (Huang et al., 2014) as well. Future research can address these for crypto analysts. In addition, the effect of different market regimes is a further avenue for research.[4]

[4] In unreported tests, we confirm our results especially in bear markets, but the current sample is too small to make valid conclusions.

Literature

Barber, B., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns. *The Journal of Finance*, *56*(2), 531-563. doi: 10.1111/0022-1082.00336.

Bouri, E., Gupta, R. (2019). Predicting Bitcoin Returns: Comparing the Roles of Newspaper- and Internet Search-Based Measures of Uncertainty. *Finance Research Letters*, forthcoming. doi: 10.1016/j.frl.2019.101398.

Brav, A., & Lehavy, R. (2003). An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. *The Journal of Finance*, *58*(5), 1933-1967. doi: 10.1111/1540-6261.00593.

Cooper, R. A., Day, T. E., & Lewis, C. M. (2001). Following the leader: a study of individual analysts' earnings forecasts. *Journal of Financial Economics*, *61*(3), 383-416. doi: 10.1016/S0304-405X(01)00067-8.

Davies, P. L., & Canes, M. (1978). Stock prices and the publication of second-hand information. *Journal of Business*, *51*(1), 43-56.

Gerritsen, D. F., Bouri, E., Ramezanifar, E., & Roubaud, D. (2019). The profitability of technical trading rules in the Bitcoin market. *Finance Research Letters, 34*. doi: 10.1016/j.frl.2019.08.011.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, *70*(3), 393-408.

Huang, A. H., Zang, A. Y., & Zheng, R. (2014). Evidence on the information content of text in analyst reports. *The Accounting Review*, *89*(6), 2151-2180. doi: 10.2308/accr-50833.

Hudson, R., Urquhart, A. (2019). Technical trading and cryptocurrencies. *Annals of Operations Research*, forthcoming. doi: 10.1007/s10479-019-03357-1.

Jiang, Y., Nie, H., & Ruan, W. (2018). Time-varying long-term memory in Bitcoin market. *Finance Research Letters*, *25*, 280-284. doi: 10.1016/j.frl.2017.12.009.

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105-116. doi: 10.1016/j.irfa.2018.07.010.

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public Twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*(C). doi: 10.1016/j.intfin.2020.101188.

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, *10*(4), e0123923. doi: 10.1371/journal.pone.0123923.

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, *24*(1), 34-75. doi: 10.1016/j.ijforecast.2007.12.006.

Soroka, S. N. (2006). Good news and bad news: Asymmetric responses to economic information. *The Journal of Politics*, *68*(2), 372-385. doi: 10.1111/j.1468-2508.2006.00413.x

Trimborn, S., Chen, Y., Li, Y. (2020). Investing with cryptocurrencies - On the informative effects of experts sentiment. Unpublished Manuscript.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, *148*, 80-82. doi: 10.1016/j.econlet.2016.09.019

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility–A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money*, *63*, 101133. doi: 10.1016/j.intfin.2019.101133

Can Bitcoin Investors Profit from Buy, Hold, and Sell Recommendations by Crypto Analysts?

Online appendix

Data and Methodology: Screening crypto analysts

We used the following procedure to screen crypto analysts that cover Bitcoin. First, we searched for news articles containing Bitcoin price, analyst, or predict* (incl. prediction, predicted, etc.) published by world-leading business news outlets such as Bloomberg and CNBC, and by Bitcoin-specific news agencies to which bitcoin.org refers, such as Coindesk, Cointelegraph, and Bitcoinist. We continued with adding agencies to the point that news agencies did not cover reports that were not covered by others already. Second, we searched both Google and Twitter for reports published by analysts identified in the first step. Third, we examined three Bitcoin communities BitcoinTalk, Bitcoin Subreddit (which are advertised on bitcoin.org) and Bitcoin TradingView. These websites provide the opportunity to post analyses or discuss analyses made by established Bitcoin analysts. Fourth, we scanned articles published on Bitcoin Obituaries for investment recommendations.

We include only well-known crypto analysts that wrote an extensive justification. Per platform, the eligibility criteria differed. All analysts mentioned by news agencies are included. For Twitter, we used various "100 most influential people in crypto" or "10 analysts you must follow" type of lists that were published by news agencies. An analyst must have had at least 30k followers to be included in our analysis. Although this threshold is admittedly arbitrary, analysts with fewer followers hardly make it to top-10 or top-100 lists. For TradingView, we considered the top-3 analysts on that platform, for whom we included the most liked recommendation for each month. We used Subreddit and BitcoinTalk forums to make sure that we did not miss analyst recommendations that were frequently discussed. On these platforms we sorted by upvotes and likes, respectively.

Written reports without a predicted clear direction of prices were excluded from our analysis. If the analyst was optimistic about the future price development even though the type of recommendation was not explicitly stated, we labeled it as 'buy'. Similarly, we labeled pessimistic views as 'sell'.

Additional Tables

Table A1. Returns surrounding recommendation revision with standard errors in parentheses. The asterisks *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively.

	Upgrade			Downgrade		
	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1
-4	0.24			0.10		
	(0.60)			(0.50)		
-3	-0.46			-0.26		
	(0.51)			(0.63)		
-2	-1.41			-0.35		
	(0.67)			(0.68)		
-1	-1.56			-0.78		
	(0.87)			(0.59)		
0	-1.24			-1.22**		
	(0.81)			(0.56)		
1	0.60	-0.64		-1.51**	-2.72***	
	(0.57)	(0.91)		(0.71)	(0.94)	
2	-0.01	-0.65	0.58	-0.26	-2.98***	-1.76**
	(0.47)	(1.05)	(0.73)	(0.68)	(0.99)	(0.77)
3	0.30	-0.36	0.88	-1.07	-4.05***	-2.83***
	(0.57)	(1.29)	(0.94)	(0.53)	(1.06)	(0.83)
4	0.41	0.06	1.29	-0.25	-4.29***	-3.07***
	(0.55)	(1.20)	(0.98)	(0.58)	(1.18)	(1.07)