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Can Bitcoin Investors Profit from Predictions by Crypto Experts?

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ABSTRACT

Using a hand-collected dataset containing bullish, neutral, and bearish predictions for Bitcoin published by crypto experts, we show that neutral and bearish predictions are followed by negative abnormal returns whereas bullish predictions are not associated with nonzero abnormal returns. Based on all outstanding predictions, we compute prediction revisions relative to (i) the latest issued prediction and (ii) the outstanding consensus prediction. Downward revisions are followed by negative abnormal returns. We conclude that crypto experts are skilled information intermediaries on the Bitcoin market.

1. Introduction

Experts (e.g., analysts) can be information intermediaries who perform dual roles of information discovery and information interpretation (Ramnath et al., 2008). The value of expert predictions is studied extensively for stocks (Ramnath et al., 2008), for commodities, such as gold and silver (Fritsche et al., 2013), and for exchange rates (Pierdzioch and Rulke, 2015). For these asset classes, forecasts prove to be informative with respect to future price movements, thereby improving market efficiency (Davies & Canes, 1978). Cryptocurrencies represent an emerging asset class (Härdle et al., 2020) with Bitcoin being the largest of all cryptocurrencies. The characteristics of Bitcoin are significantly different from traditional securities (Klein et al., 2018). Bitcoin is an unregulated, decentralized, peer-to-peer cryptocurrency enabling users to process transactions through digital units of exchange. The market capitalization of Bitcoin was about USD 690 billion in May 2021 and is thereby the largest of all cryptocurrencies, representing around 46 percent of the total market capitalization of all cryptocurrencies.[1] Despite its relatively small market capitalization in comparison to traditional investment assets, research shows various kinds of investors could benefit from augmenting their portfolios with Bitcoin if liquidity is taken into account (Petukhina et al., 2021; Trimborn et al., 2019).

There is a large debate in the literature about the degree of market efficiency of Bitcoin (Urquhart, 2016; Jiang et al., 2018); this degree of efficiency is relevant for the potential value of predictions published by experts (Davies and Canes, 1978). We study the value

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[1] Data retrieved from https://coinmarketcap.com/charts/, downloaded May 28, 2021.

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Table 1
Summary statistics

Panel A: The annual number of experts, predictions, revisions, and consensus revisions									
	2013	2014	2015	2016	2017	2018	2019	2020	Total
Experts	7	9	6	18	37	42	26	14	119
Predictions	7	9	6	27	60	54	38	21	222
Bullish	6	5	4	22	38	31	30	17	153
Neutral	0	0	1	3	6	8	4	2	24
Bearish	1	4	1	2	16	15	4	2	45
Revisions	1	5	3	10	29	31	14	6	99
Upgrades	0	3	2	5	13	16	6	3	48
Downgrades	1	2	1	5	16	15	8	3	51
Consensus revisions	1	14	11	22	48	58	52	19	225
Upgrades	0	5	7	16	16	31	31	10	116
Downgrades	1	9	4	6	32	27	21	9	109

Panel B: Characteristics of the (0, 4) CAR					
	Mean	Standard deviation	Min	Max	N
Predictions					
Bullish	-0.011	0.119	-0.474	0.323	153
Neutral	-0.055	0.075	-0.192	0.065	24
Bearish	-0.070	0.147	-0.592	0.204	45
Revisions					
Upgrades	-0.008	0.120	-0.458	0.323	48
Downgrades	-0.060	0.104	-0.370	0.200	51
Consensus revisions					
Upgrades	-0.012	0.103	-0.458	0.323	116
Downgrades	-0.029	0.122	-0.592	0.246	109

of bullish, neutral, and bearish predictions by crypto experts for Bitcoin. To date, there is no prior research on the value of experts' predictions 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 De Smedt (2020), and Trimborn and Li (2021) 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 predictions and their revisions. We show that neutral and bearish predictions are followed by negative abnormal returns. Further, we observe that downward revisions of predictions (downward consensus revisions) are followed by significant negative abnormal returns of up to -5.99 (-2.90) percent. We therefore conclude that crypto experts are relevant information intermediaries on cryptocurrency markets and that they improve this market's efficiency.

2. Data and Methodology

2.1. Crypto experts and their predictions

Currently, there is no institution that tracks predictions by crypto experts. Therefore, we meticulously compiled a dataset containing predictions published by these experts. Since Bitcoin is the largest of all cryptocurrencies and because there are relatively little predictions published for other cryptocurrencies, we decided to focus on Bitcoin predictions only. We used the following procedure to screen crypto experts 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 screened the two Bitcoin communities BitcoinTalk and Bitcoin Subreddit that are advertised on bitcoin.org for analyses made by Bitcoin experts identified in the first step. Third, for these experts we also searched both Google and Twitter for additional reports that were not covered in the first and second steps. Fourth and last, we scanned articles published on Bitcoin Obituaries for predictions. This procedure ensures that the impact of selection or survivorship bias is minimized; to illustrate, our dataset also reflects predictions by less successful experts that ceased to operate.

The selection procedure for crypto experts ensured that we include only experts that were relatively well-known at the time of the publication of a prediction. These experts are typically independent experts that are not affiliated with banks or other financial institutions, although some of the experts have a background as stock analyst. Predictions could be either bullish (i.e., the expert expects a price increase), neutral (i.e., the expert expects the price to move sideways), or bearish (i.e., the expert expects a price decrease). The expert's prediction therefore is a discrete variable similar to recommendations by stock analysts to buy, hold, or sell stocks. We only include predictions that were accompanied with a justification. Justifications are typically shorter than those in stock analyst reports, and they are sometimes communicated in the form of a tweet only. The predictions are based on fundamental factors and/or technical factors. Examples of fundamental determinants are a Bitcoin halving and the current state of the general financial market. Technical

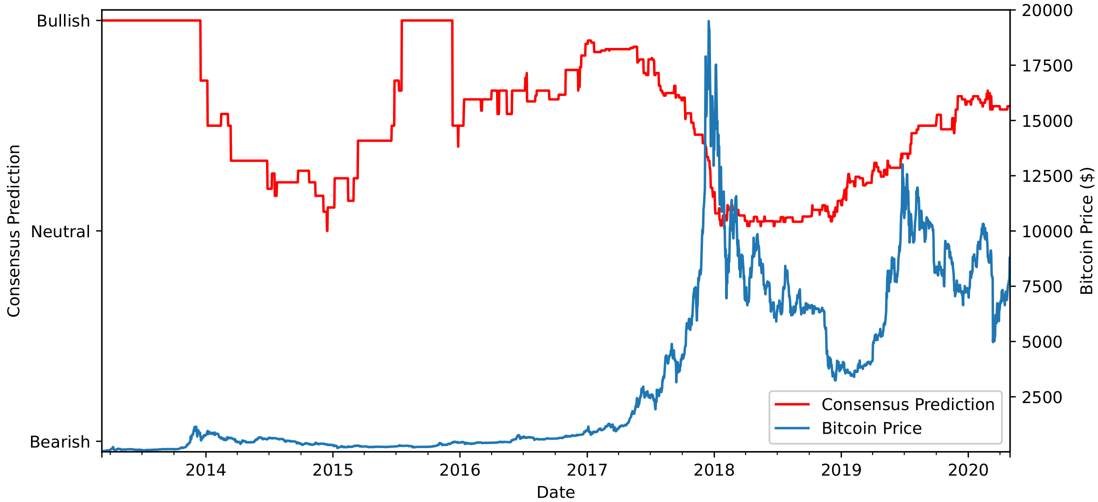

Figure 1. Consensus prediction and Bitcoin price.

factors comprise, among others, trend analyses such as the Elliott wave theory. We used an inter-rater reliability analysis method where all three authors interpreted the direction of all identified predictions independently. Expert reports without a clearly predicted direction of prices (i.e., reports where we disagreed about the implied direction of Bitcoin prices) were excluded from our analysis. Experts sometimes published both a short-term prediction (e.g., coming week or month) and a longer-term prediction. In these cases, we used the shorter-term prediction only.

We applied the above procedure to identify experts and their predictions to the period of January 2012 to March 2020. For this period, we identified 119 different experts that in total issued 222 predictions (153 bullish, 24 neutral, and 45 bearish). Table 1 presents our summary statistics. Panel A gives an annual decomposition of the number of experts, forecasts and revisions. In line with Bitcoin popularity the numbers are typically higher for the second half of our sample period. Panel B presents the CARs for the (0, 4) period following forecasts and revisions. Bullish forecasts, upgrades, and consensus upgrades all exhibit CARs around -1%. The more negative forecasts and revisions come with more negative CARs. In addition to Table 1, it is worth noting that our most active expert issued 16 predictions and the least active expert issued 1 prediction. Among our sample of experts are researchers, analysts, investors, and prominent Twitter users, such as Andrew Left, Charles Bovaird, Justin Sun, Josh Rager, and “Dave the Wave”. We provide the full sample in the online appendix.

2.2. Prediction revisions

We compute upward and downward revisions by comparing a newly issued prediction to the most recently published prediction by any expert in our sample. If the most recently published prediction was bullish (bearish) and the new prediction is bearish (bullish), then we categorize this new prediction as a downward (upward) revision. For this procedure, we identify 48 upward revisions and 51 downward revisions, see Table 1 for a breakdown per year. As a robustness check, we follow Barber et al. (2001) in constructing a consensus prediction that is recomputed every time a crypto expert initiates coverage, changes the prediction, or drops coverage. If an expert does not update his prediction within 12 months from the publication date, we consider it as dropped coverage. We treat consensus increases as upward revisions and decreases as downward revisions. We identify 116 upward consensus revisions and 109 downward consensus revisions, also see Table 1. Figure 1 depicts both the consensus prediction and the Bitcoin price for our sample period. The average consensus prediction is in between a bullish and a neutral prediction (1.47, if bullish, neutral, and bearish are coded as 1, 2, and 3). This implies that crypto experts are on average optimistic regarding future Bitcoin prices, which is in line with security analysts (Barber et al., 2001).

2.3. Bitcoin abnormal returns

We retrieve Bitcoin prices from www.coinmarketcap.com. We compute observed 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). It is common practice in event studies to compute abnormal returns by controlling observed returns for expected returns. The latter are determined by a benchmark and the asset’s sensitivity to it. If a clear benchmark is absent, the literature (e.g., Jensen and Johnson, 1995; Schnusenberg and Madura, 2001) resorts to the mean-adjusted model to arrive at abnormal returns. In our main tests, we follow this approach in computing Bitcoin abnormal returns, and we subtract the mean Bitcoin return of our estimation window ($\widehat{R}_t$) from our observed Bitcoin returns during our event window, $AR_t = R_t - \widehat{R}_t$. As estimation window, we use the period (-54, -6). All our reported results are robust to using alternative specifications of abnormal returns, such as

Table 2
Returns surrounding bullish, neutral, and bearish predictions with standard errors in parentheses. The asterisks *, and ** represent significance levels of 5%, and 1%, respectively.

	Bullish			Neutral			Bearish		
	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	-0.28			0.26			0.31		
	(0.39)			(0.90)			(0.76)		
-3	-0.06			0.86			-0.73		
	(0.34)			(0.85)			(0.90)		
-2	-0.33			1.09			-0.97		
	(0.37)			(1.13)			(0.89)		
-1	-0.31			-0.85			-1.33		
	(0.47)			(0.99)			(0.83)		
0	-0.72			-1.84			-2.94**		
	(0.54)			(0.90)			(0.94)		
1	0.39	-0.33		-1.27	-3.12*		-2.46*	-5.40**	
	(0.47)	(0.68)		(0.62)	(1.12)		(1.08)	(1.49)	
2	-0.58	-0.91	-0.19	-1.05	-4.17**	-2.32*	0.32	-5.08**	-2.14
	(0.39)	(0.83)	(0.61)	(0.76)	(1.30)	(0.96)	(1.07)	(1.73)	(1.28)
3	-0.50	-1.41	-0.69	-0.72	-4.89**	-3.05**	-1.65*	-6.72**	-3.78**
	(0.44)	(1.01)	(0.82)	(0.71)	(1.23)	(0.98)	(0.82)	(1.90)	(1.45)
4	0.36	-1.05	-0.33	-0.58	-5.47**	-3.63**	-0.26	-6.98**	-4.04*
	(0.39)	(0.96)	(0.79)	(0.70)	(1.53)	(1.12)	(1.30)	(2.19)	(2.14)

using a different estimation window (e.g., -365, -6) and to using different abnormal returns methods (e.g., autoregressive model of order 1).[2]

Similar to the stock analyst 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 (e.g., 24/7 trading), we allow for a longer event window consisting of four pre-event days (for which we do not expect significant abnormal 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 predictions. For these investors, we study cumulative returns for the post-event window separately. We present our findings in tables throughout this paper. The online appendix contains a graphical representation of all our findings.

3. Results

3.1. Predictions

Our results for predictions are presented in Table 2 and Figure A1 in our online appendix. Table 2 shows that there is no pre-trend in Bitcoin prices prior to predictions by experts, 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 bullish predictions. For bearish predictions, the event day exhibits negative abnormal returns of -2.94 percent. Bearish predictions are associated with additional negative and significant abnormal returns (at the 5%-level) 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 neutral and bearish predictions.[3] In addition, most cumulative abnormal returns starting as of day 1 are negative and statistically significant following both neutral and bearish predictions.

The findings in Table 2 suggest that both bearish and neutral predictions are viewed by investors as a negative signal. In a univariate regression setting, we regress the CAR on a dummy taking the value of one if a prediction is either neutral or bearish and zero if the predictions is bullish. We apply this to both the (0, 4) and the (1, 4) periods. The slope coefficients are statistically significant in both cases (results available upon request), indicating that Bitcoin returns are significantly more negative after bearish and neutral predictions than after bullish predictions.

[2] In addition, the results of our main tests are also largely robust to using raw returns instead of abnormal returns and cumulative raw returns instead of cumulative abnormal returns.

[3] In terms of robustness, we consider three alternatives. First, in terms of sample selection, we exclude 2020 and the turmoil surrounding the outbreak of Covid-19; our findings are robust (see Table A3 in the Online Appendix). Second, we collected a sample of negative Bitcoin events from www.tradingview.com (as per May 11, 2021) and checked to which extent our findings are driven by negative fundamental Bitcoin news. See Table A2 in the Online Appendix for a list of events. We conclude that these events had a negligible effect on our findings (see Table A3). Third, we consider the sign test as a nonparametric alternative. We apply this test for hold and sell recommendations together, and we find that the test statistic remains significant for the period (0, 4) but renders insignificant (p = 0.12) for the period (1, 4). See Table A3 in the Online Appendix.

Table 3
Returns surrounding prediction revisions with standard errors in parentheses. The asterisks *, and ** represent significance levels of 5% and 1%, respectively.

	Upward revision			Downward revision		
	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1
-4	0.06			-0.06		
	(0.76)			(0.70)		
-3	-0.70			-0.51		
	(0.71)			(0.78)		
-2	-1.38			0.19		
	(0.93)			(0.74)		
-1	-0.89			-1.13		
	(0.74)			(0.70)		
0	-2.43			-1.75*		
	(1.29)			(0.74)		
1	0.73	-1.70		-2.09**	-3.84**	
	(0.81)	(1.36)		(0.84)	(1.19)	
2	0.15	-1.55	0.88	-1.05	-4.89**	-3.14**
	(0.64)	(1.55)	(0.96)	(0.87)	(1.34)	(0.94)
3	0.79	-0.76	1.67	-1.64	-6.53**	-4.78**
	(0.62)	(1.73)	(1.10)	(0.73)	(1.44)	(1.05)
4	0.00	-0.76	1.67	0.54	-5.99**	-4.24**
	(0.75)	(1.73)	(1.15)	(0.61)	(1.46)	(1.19)

Table 4
Returns surrounding consensus prediction revision with standard errors in parentheses. The asterisks * and ** represent significance levels of 5% and 1%, respectively.

	Upward consensus revisions			Downward consensus revisions		
	AR	CAR as of t=0	CAR as of t=1	AR	CAR as of t=0	CAR as of t=1
-4	-0.16			0.32		
	(0.39)			(0.47)		
-3	-0.06			0.39		
	(0.38)			(0.47)		
-2	-0.33			0.19		
	(0.39)			(0.48)		
-1	0.39			-0.79		
	(0.40)			(0.49)		
0	-0.72			-0.54		
	(0.57)			(0.51)		
1	0.47	-0.24		-1.13*	-1.66*	
	(0.42)	(0.62)		(0.53)	(0.76)	
2	-0.35	-0.59	0.13	-0.37	-2.03*	-1.49*
	(0.33)	(0.71)	(0.51)	(0.55)	(0.90)	(0.71)
3	-0.23	-0.82	-0.10	-0.84	-2.87**	-2.34*
	(0.44)	(0.88)	(0.70)	(0.51)	(1.03)	(0.82)
4	-0.37	-1.19	-0.48	-0.03	-2.90*	-2.36*
	(0.38)	(0.95)	(0.78)	(0.62)	(1.17)	(0.96)

3.2. Prediction revisions

By studying prediction revisions, we explicitly acknowledge the potential value of the arrival of new information to investors. The results for the main revision analysis are presented in Table 3 and Figure A2. For upward revisions, we do not witness significant abnormal returns. For downward revisions, we observe a persistently negative effect on Bitcoin prices. The event-day abnormal return for a downward revision is -1.75 percent. Also on the day following the downward revisions, the abnormal return is large (-2.09 percent), a finding that is both economical and statistically highly significant. The CAR is -5.99 percent for the window (0, 4) and -4.24 percent for the window (1, 4).[4] We additionally test in a univariate regression setting if downward revisions are associated with more negative CARs than upward revisions. We regress the CARs for the (0, 4) and the (1, 4) periods on a dummy that takes the value of one for downward revisions and zero for upward revisions (results available upon request). In both specifications, the slope coefficient is statistically significant.

The results for the second revision analysis (i.e., consensus revisions) are presented in Table 4 and Figure A3 in the online appendix. Both the table and the figure indicate that there are no meaningful abnormal returns prior to either upward or downward consensus

[4] As a robustness check, we perform the nonparametric sign test, and results (see Table A6 in the Online Appendix) are statistically significant for both the (0, 4) and the (1, 4) periods.

revisions. Event and post-event returns for upward revisions are not different from zero either. Following downward revisions, we report a significant abnormal return of -1.13 percent on day 1. All CARs as of both day 0 and 1 are negative and significant after downward revisions. Also here, we regress the CARs for the (0, 4) and the (1, 4) periods on a dummy that takes the value of one for downward consensus revisions and zero for upward consensus revisions. The slope coefficient is negative but statistically insignificant. In sum, the results for the consensus revision analysis are of a somewhat smaller significance, both in terms of statistical significance and in terms of economic significance. This can partly be explained by consensus revisions due to coverage dropping; these revisions are changes are not covered in any media outlet and are therefore generally unnoticed.

4. Discussion & Conclusion

We find that neutral and bearish predictions are associated with negative CARs in the period following the prediction. Bullish predictions do not result in statistically significant abnormal returns. For revisions in predictions, we find that only downward revisions are statistically and economically relevant. A possible explanation for the fact that bullish predictions are not associated with positive abnormal returns are the potentially conflicting interests among experts. Investors potentially factor in the possibility that experts issuing bullish predictions are motivated by their own holdings in Bitcoin. Conversely, neutral and especially bearish predictions are more likely to be independent of the expert's own holdings since short positions in Bitcoin were either impossible (until December 2017) or costly to obtain (from January 2018). Additionally, our finding that negative news has a more pronounced impact than positive is consistent with Soroka (2006).

We conclude that crypto experts are an important contributor to price discovery on the Bitcoin market and that especially their non-positive predictions improve the market's efficiency. Our results support the findings of Trimborn and Li (2021) who find that cryptocurrency experts sentiment carries valuable information.

Our study undertakes a first step in estimating the value of Bitcoin expert predictions. 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 experts. In addition, the effect of different market regimes is a further avenue for research.[5]

CRediT authorship contribution statement

Dirk F. Gerritsen: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – review & editing. **Rick A. C. Lugtigheid:** Methodology, Software, Formal analysis, Resources, Data curation, Writing – original draft. **Thomas Walther:** Validation, Data curation, Writing – review & editing, Visualization, Project administration, Supervision.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102266.

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