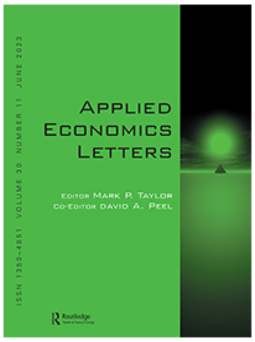

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The profitability of Bollinger Bands trading bitcoin futures

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ABSTRACT

We explore whether investors would receive excess profits by round-turn trading (hereafter referred to as trading) Bitcoin futures based on Bollinger Bands trading strategy (BBTS). Since investors are suggested to first buy (then sell) Bitcoin futures as oversold (overbought) signals emitted by the BBTS (i.e. penetrating lower (upper) Bollinger Bands regarded as a buying (selling) signal), we aim to explore whether investors would have better returns by trading such futures according to the BBTS. Results show that the average holding period return (AHPR) is over 20% for trading Bitcoin futures following the BBTS. Furthermore, after we adjust the 60-day moving average (MA) instead of the 20-day MA for the BBTS, the AHPR is above 50%. It is noted that if the margin could be deemed as an investment amount, its rate of return would be much higher than the 50% for trading Bitcoin futures.

KEYWORDS

Bitcoin futures; Bollinger Bands trading strategy (BBTS); average holding period return (AHPR); contrarian strategies

JEL CLASSIFICATION

G02; G11; G14

Introduction

Due to the innovation, transparency, and simplicity, cryptocurrency has drawn much interest from media and investors recently (Masciandaro 2018). Based on blockchain technology, cryptocurrency essentially is a subset of the class of digital currency (Lee 2015). The cryptocurrency market has not only grown exponentially in market value (Ji et al. 2019) but has also quickly become an important constituent of the global financial market (Gajardo, Kristjanpoller, and Minutolo 2018). Indeed, there are various cryptocurrencies in the market and Bitcoin seems to have received most of the attention from investors (Dwyer 2015).

As accounted for over 40% of the total capital of cryptocurrencies, Bitcoin could be regarded as one of the most popular cryptocurrencies and has considerable trading volume in futures markets (Katsiampa 2017). As originally introduced in 2008 (Nakamoto 2008), Bitcoin came into existence in 2009 (Makarov and Schoar 2020). Designed as a payment system for providing an archival function (Howell, Niessner, and Yermack 2020), Bitcoin is a digital asset schemed to work as a medium of exchange (Ali et al. 2014). As ElBahrawy et al. (2017) revealed, users can send and receive Bitcoins with the joint confirming for the transactions in a decentralized and transparent way. With the authorized passcode, people can transfer Bitcoins electronically to anywhere in the world without depending on counterparties (Athey et al., 2016). Furthermore, the returns of Bitcoin are internally determined by buyers as well as sellers and are not affected by fundamental economic factors (Baek and Elbeck 2015). In sum, Bitcoin can be deemed as a panacea to substitute financial institutions (Kerner 2014) and an alternative to cash (Evans-Pughe 2012).

In the real world, people expect to create more profit by investing. Therefore, they utilize diverse methods to achieve this goal. However, the prices of stocks might be influenced by numerous factors, which results in the difficulty of forecasting the future prices of stocks. For instance, fiscal policies would affect the stock market, indicating that the increase in the public deficit would push stock market indices to go down and vice versa (Foresti and Napolitano 2017). Wang and Guo (2020) also disclose that investors' behaviour and policy shocks could result in serious variations in a certain financial market.

Besides, some studies report that stock markets would be efficient, meaning that all available information is reflected completely in stock markets

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(Fama 1965, 1970). In other words, investors might not be able to predict the future prices of stocks based on the efficient market hypothesis (EMH) and, as a result, can hardly make excess returns by trading stocks (Latif et al. 2011). However, this viewpoint seems challenged by the overreaction hypothesis (Caporale and Plastun 2019) and the herding behaviours (Ballis and Drakos 2020) for cryptocurrency markets since investors may overreact to news released due to their excessive self-confidence (Chuang and Lee 2006; Saedi and Rezaein 2019). Thus, some investors might predict future prices of stocks by taking technical analysis into account (Yu et al. 2013). As studies reported, contrarian strategies might be proper for some technical indicators because of the overreaction hypothesis (Borgards and Czudaj 2021) and momentum strategies might be appropriate for other technical indicators owing to the trend-following concerns (King and Koutmos 2021) for cryptocurrency markets. To sum up, technical analysis remains popular among practitioners, despite the continuing debate on its profitability.

As regards technical analysis, the moving average (MA) trading strategies are widely explored in the literature but the Bollinger Bands trading strategy (BBTS) seems rarely explored in the related studies. According to Liao et al. (2021), the BBTS assumes that prices will continue to move in the direction of the penetration; that is, penetration of the upper (lower) BBTS suggests that prices will continue to move higher (lower). Since past studies show that the BBTS could grasp sudden price fluctuations (Leung and Chong 2003), the profitability for employing the BBTS may come from the contrarian wisdom of BBTS (Ni et al. 2020) that short-term contrarian profits obtained by adopting the BBTS would persist even after adjusting for market frictions. Thus, we employ Bitcoin futures, the most popular cryptocurrency, as our target and explore whether adopting the BBTS would exploit profits for trading such futures.

We argue that this study would contribute to the existing literature in several aspects. First, we endeavour to explore whether investors would have a better return in trading Bitcoin, the most popular cryptocurrency, by employing the BBTS, one of the most prevalent trading strategies in investment securities, which seems rarely explored in the existing literature. Second, because stock prices rebounded likely to occur after stock price overreaction according to the wisdom of the BBTS, we illustrate that trading Bitcoin futures would generate profits, even considerable profits, which seem seldom disclosed in the relevant studies. Third, we argue that, if history may often repeat itself, our revealed results might encourage many investors to trade Bitcoin futures because investors might have satisfactory profits by trading such futures.

The rest of this paper is organized as follows. Section 2 introduces the data and methodology. The second 3 presents the empirical results and analyses. Section 4 provides our concluding remarks.

Data and methodology

Data

We collect daily data for Bitcoin futures over the period 2016–2020 from Datastream and then explore whether investors would generate profits by trading such futures according to the BBTS.

Bollinger bands trading strategy

The BBTS would set an X-standard deviation (2-standard deviation in general) above and below the n-day MA (20- day MA in general) of historical closing prices (Bollinger 2002) as the upper (lower) Bollinger Bands. Investors are suggested to adopt contrarian strategies as the penetration of the upper (lower) Bollinger Bands is remitted because such penetration indicates an overreaction price with a strong possibility of an impending trend reversal, which presents a sell (buy) signal.

Cumulative holding period returns and average holding period return

Since we explore whether investors can generate profits by trading such futures following the BBTS, we measure Holding Period Returns per trade (HPRi), Cumulative Holding Period Return (CHPR), and Average Holding Period Return (AHPR) for evaluating the performance of trading Bitcoin futures.

HPRi is measured by the first buying Bitcoin futures as the buying signals emitted by lower Bollinger Bands, and then selling such futures when the selling signals occurred by upper Bollinger Bands for trade i. The HPRi is computed by the following formula.

$$HPRi = (\alpha i/\beta i) - 1 \tag{1}$$

where αi = closing Bitcoin futures index at selling day for trade i,

βi = closing Bitcoin futures index at buying day for trade i.

We then calculate CHPR by summing up HPRi from i = 1 (the first trade) to n (the final trade) as shown below.

$$CHPR = \sum_{i=1}^{n} HPR_i \tag{2}$$

where i = 1 to n (total number of trades).

Afterwards, we can derive AHPR by the following equation.

$$AHPR = (CHPR/n) \tag{3}$$

where n = total number of trades.

In other words, we explore whether investors trading Bitcoin futures would generate profits by measuring the HPR per trade following Equation (1), the CHPR according to Equation (2), and the AHPR based on Equation (3).

According to the traditional BBTS, upper or lower Bollinger Bands would be measured as 2 standard deviations (SDs) over or below 20-day MA. In this study, we further decrease 2 SDs to 1.5 SDs, even 1 SD, and use 10-day as well as 60-day MA to conduct the empirical tests. By doing so, we may find out whether the CHPR and AHPR would be affected by decreasing SD and the shorter as well as the longer MA. We argue that the above concerns might increase the flexibility of utilizing the BBTS by employing different parameters.

Empirical results and analyses

Descriptive statistics

By collecting the daily data of Bitcoin futures from Datastream, Table 1 presents that the difference between the maximum and minimum of Bitcoin futures is rather wide and the SD is also pretty high. This phenomenon indicates that the movement of Bitcoin futures is quite volatile. Besides, as plotted with these daily data, Figure 1 shows a peak that occurred around the beginning of 2018 and a sharp increase at the end of the data period (i.e. the year 2020).

Table 1 reports the means, standard deviations (SD), coefficient of variation (CV), median, minima, and maxima of Bitcoin futures prices over the data period 2016–2020.

Table 1. Descriptive statistics.

Crypto Currencies	Sample	Mean	SD	CV	Median	Min.	Max.
Bitcoin futures	1824	6135.05	4762.74	77.63%	6410.25	364.33	29374.15

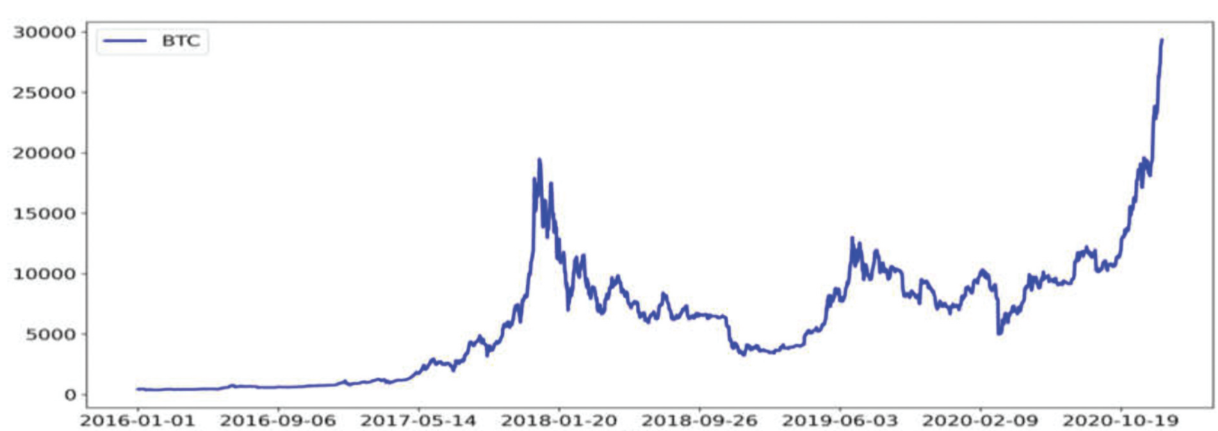

Figure 1. The trend of the bitcoin prices from 2016 to 2020.

Empirical results

By employing daily data of Bitcoin futures over the data period 2016–2020, we measure the CHPR, the number of trades, and AHPR for trading such futures according to the BBTS. As mentioned earlier, after decreasing 2 SDs to 1.5 SDs and even 1 SD as well as using 10-day MA and 60-day MA in this study, we not only reveal the HPR and AHPR of trading Bitcoin futures by employing the BBTS but also disclose more information related to such trades with the use of different parameters for the BBTS (i.e. using different SDs and/or different day MAs).

We measure the performance of trading Bitcoin futures according to BBTS and then derive CHPR and AHPR according to Equations (2) and (3). In addition, we also present the number of trades, average duration day, and maximum duration day for diverse strategies designed in this study based on Equation (4) to (6).

Table 2 shows that the AHPR is over 20% when trading Bitcoin futures following the BBTS (i.e. 20-day MA and 2-SD). However, the AHPR is more than 50% while adjusting to 60-day MA and 2 SDs. We argue that such high returns might result from the upward trend shown at the end of the data period.

As further compared for the CHPR and AHPR in diverse cases, Tables 2 also reports that as compared with the strategy (20, 2) suggested by the BB trading rule, AHPRs decrease but CHPRs increase for the strategies (20, 1.5), (60, 1.5), (60, 1), and (10, 2). This result might be caused by the evidence that decreasing SD would increase the number of trades, thereby likely increasing CHPR. Furthermore, it is noted that if the margin amount is regarded as an investment amount, the AHPR would be much more impressive for market participants.

Further investigation

Based on the forecasting studies of Diebold (e.g. Diebold and Lopez 1996; Diebold and Rudebusch 1989; Diebold and Kilian 2000, etc.), Diebold and Lopez (1996) indicated that forecasts are of great importance and are widely used in economics and finance to access and compare the accuracy of forecasts; Diebold and Rudebusch (1989) showed the persistence in U.S. aggregate output by employing the estimation of integrated ARIMA models because of providing better low-frequency approximations; and Diebold and Kilian (2000) indicated that unit-root tests are useful for selecting forecasting models, which might be due to that ARIMA models are one of the most general class of models for forecasting a time series which can be made to be stationary by differencing if necessary.

As such, regarding the prediction models, the appropriateness of a prediction model is measured by minimizing the root mean square error (RMSE), which is mainly based on the perspective of minimizing error variance (i.e. RMSE); however, this study is to endeavour to find how to maximize CHPR and maximum AHPR by setting different parameter for BB trading rules, which is mainly from the investment perspective.

However, as for the possible similarity between our study and prediction models, we argue that the concern of in-sample and out-of-sample might be taken into account for both. For example, As for ARIMA models, we would use in-sample data to fit

Table 2. CHPR and AHPR of trading bitcoin futures from 2016 to 2020.

(1)	(2)	(3)	(4)	(5)	(6)
BBTS	CHPR (%)	No. of Trades	AHPR (%)	Average Duration Day	Maximum Duration Day
(20, 2)	635.25%	30	21.18%	53	175
(20, 1.5)	788.99%	58	13.60%	29	158
(20, 1)	560.27%	76	7.37%	23	108
(60, 2)	633.22%	12	52.77%	110	348
(60, 1.5)	673.91%	22	30.63%	69	332
(60, 1)	743.42%	30	24.78%	51	205
(10, 2)	673.36%	42	16.03%	41	178
(10, 1.5)	480.38%	100	4.80%	18	89
(10, 1)	380.55%	137	2.78%	14	82

Table 3. CHPR and AHPR of trading bitcoin futures from 2016 to 2019.

(1)	(2)	(3)	(4)	(5)	(6)
BBTS	CHPR (%)	No. of Trades	AHPR (%)	Average Duration Day	Maximum Duration Day
(20, 2)	549.44%	26	21.13%	51	168
(20, 1.5)	728.41%	51	14.28%	28	158
(20, 1)	516.86%	65	7.95%	22	108
(60, 2)	662.09%	11	60.19%	110	348
(60, 1.5)	626.30%	20	31.32%	62	332
(60, 1)	708.62%	26	27.25%	48	205
(10, 2)	595.23%	35	17.01%	41	178
(10, 1.5)	348.94%	81	4.31%	18	89
(10, 1)	350.81%	108	3.25%	14	82

Table 4. CHPR and AHPR of trading bitcoin futures from 2020 to 2020.

(1)	(2)	(3)	(4)	(5)	(6)
BBTS	CHPR (%)	No. of Trades	AHPR (%)	Average Duration Day	Maximum Duration Day
(20, 2)	232.71%	4	58.18%	78	175
(20, 1.5)	199.55%	7	28.51%	46	118
(20, 1)	193.57%	11	17.60%	31	98
(60, 2)	473.63%	1	473.63%	293	293
(60, 1.5)	207.28%	2	103.64%	149	199
(60, 1)	203.89%	4	50.97%	149	197
(10, 2)	234.53%	7	33.50%	57	118
(10, 1.5)	170.22%	19	8.96%	19	54
(10, 1)	37.41%	29	1.29%	13	51

an ARIMA and then use this fitting ARIMA model to predict whether the out-of-sample data would be still matched, which can be evaluated by measuring its root mean square error (RMSE) to assess whether this model is appropriate. Similarly, we can measure the average HPR by employing either in-sample data (i.e. using 2016–2019 data) or out-of-sample data (i.e. using 2020 data only). As such, we might be able to compare the performance of the in-sample data period with that of the out-of-sample data period.

We thus find that the results shown in Table 3 are similar to those of Table 2, representing that AHPRs (using 2016–2020 data) in Table 2 are similar to AHPRs (using 2016–2019 data) in Table 3. However, because of the sharp upward trend in the year 2020 shown in Figure 1, most AHPRs in Table 4 (using out-of-sample data) are higher than those in Table 3 (using in-sample data). Even so, the performance ranking from high to low is 2 SDs, 1.5 SDs, and 1 SDs for x-day MA (including 20-day, 60-day, and 10-day MA) for both tables (i.e. Table 3 and Table 4). In other words, the ranking from high to low is the same for employing either in-sample data (i.e. using 2016–2019 data) or out-of-sample data (i.e. using 2020 data only) even though there is a sharp upward trend for the year 2020. Based on in-sample and out-of-sample wisdom of prediction models, we thus employ this wisdom for further investigation, which may shed new light on this study.

Conclusion

In recent years, cryptocurrencies have received much more attention from investors. Due to the high percentage of total capital, Bitcoin definitely is regarded as one the most popular cryptocurrencies. Besides, encouraged by the wide use of technical analysis, we are motivated to investigate if investors could earn more profit for trading Bitcoin by applying Bollinger Bands trading strategy, one of the most prevalent trading strategies in investment securities. In this study, we explore whether investors would create profits by buying Bitcoin futures as the penetration of the lower Bollinger Bands occurred and selling such futures when the penetration of the upper Bollinger Bands emitted. The results reveal that investors might have considerable AHPR, which implies that contrarian trading strategies might be proper for trading Bitcoin futures according to the BBTS.

Furthermore, we argue that this study may have valuable implications for investors. First, we propose that investors might generate profits and even higher profits following the BBTS, implying the BBTS might be worthy for investors to trade Bitcoin futures. Second, investors might obtain diverse profitable outcomes by employing the BBTS with concerning dissimilar SDs or employing different-day MA, indicating that investors might analyse these possible outcomes with big data analytics in advance.

Regarding the possible shortcomings of this study, although we set three SDs and three MA lines in this study, we still need to find out more outcomes with big data analytics by employing diverse SDs and/or different day MAs. By doing so, we may provide more beneficial evidence for investors to trade such futures. Therefore, for future studies, we believe that the results might be more reliable and trustworthy if the data can be extended broadly. Besides, we might explore if the results would be different between the bear market period and the bull market period. Additionally, we might further employ intraday data to explore the above issues because many investors trading index futures, such as Bitcoin futures, might not prefer holding a long period due to the rather high leverage risk of trading such futures.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from Min-Yuh Day on reasonable request at myday@gm.ntpu.edu.tw.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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