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Tail behavior of Bitcoin, the dollar, gold and the stock market index ☆

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A R T I C L E I N F O

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A B S T R A C T

This paper studies whether Bitcoin can be classified as a currency, a commodity or an investment asset. Inspired by the movement that tail behavior is the key feature to determine the property of asset and for market participants to perceive the asset, I compare the tail behavior of daily return on Bitcoin to that of daily return on the US dollar, gold and the stock market index. Based on the conditional autoregressive Value at Risk proposed by Engle and Manganelli (2004), I find the similarity of the tail behavior between Bitcoin and the dollar, the stock market index with respect to contemporaneous correlation. Additionally, the tail of stock market return turns out to be associated with the risk premium on Bitcoin's return while Bitcoin is proved to be the element of the time-varying investment opportunity set on the basis of Merton's (1973) ICAPM setting. These findings suggest that Bitcoin is traded as an alternative for a medium of exchange and a means of investment, being far from a commodity.

1. Introduction

Although it has been over ten years since Bitcoin was introduced by Nakamoto (2008) to the financial market, we still cannot clearly define the identity of Bitcoin. Since Bitcoin has comprehensive and overlapping features with other major asset classes, such as the dollar, gold, stocks and bonds, it is still controversial whether Bitcoin is a kind of a currency, a commodity or an investment asset. Bitcoin has been touted as an alternative to fiat money because Bitcoin is accepted as payment for goods and services worldwide. Meanwhile, Bitcoin seems to be perceived as an investment asset by economic actors because it is gradually added to their investment portfolios. The facts that Bitcoin is the reward of mining and its supply is restricted indicate Bitcoin appears to be the digital version of commodity to store the value. Due to its ambiguity, Bitcoin status has become a main research topic among financial scholars. For the classification of Bitcoin, many prior studies compare Bitcoin to conventional assets by employing the time series of assets' returns and volatilities. However, this stream of research lacks an exhaustive understanding of Bitcoin because assets are also characterized by higher order statistical moments, specifically tail behavior. It is not surprising that all financial variables are distinguished in terms of not only their first and second moments but also their higher moments.[1] This article attempts to address this gap by exploring the tail behavior of Bitcoin and other assets.

☆ The views expressed in this paper are solely those of the author and do not reflect official positions of the Bank of Korea.

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[1] It is a well-known fact that even simple stock market return is not easily defined by only the value of mean and variance. For Bitcoin, the skewness of Bitcoin is found to be negative in Takaishi (2018).

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The recent pioneering works of identification on Bitcoin are Dyhrberg (2016a), Baur et al. (2018a) and Baur et al. (2018b). With the sufficient sample size and robust methodology, these studies reveal the relationship between Bitcoin and conventional assets. Dyhrberg (2016a) shows that the GARCH estimation results prove the similarities between Bitcoin and gold, the dollar. She concludes that Bitcoin is somewhere between a commodity and a currency. Baur et al. (2018a), however, rebut this statement with the new approach. They suggest the general correlation analysis and asymmetric GARCH model with the extended sample period to prove that there is no similarity between Bitcoin and gold, the dollar. Baur et al. (2018b) enlarge the scope of the assets and conclude that Bitcoin is different from all traditional assets, such as currency, equity, bond, energy and precious metal. Note that it is the return and/or volatility processes by which they compare Bitcoin to gold, the equity and the dollar, and so on. Other articles are also on the basis of the mean and variance to uncover the nature of Bitcoin. Bouri et al. (2017a) investigate the return-volatility relationship of Bitcoin and find the similarity between Bitcoin and gold. Tiwari et al. (2019) employ seven GARCH specifications to model Bitcoin and report the difference of significance in the model specifications between Bitcoin and the stock market index. Both Corbet et al. (2018) and Guesmi et al. (2019) examine return and volatility transmissions across Bitcoin and a variety of other financial assets, such as the dollar, gold, the stock and the bond, for analyzing the interconnectedness among them. Panagiotidis et al. (2018) and Panagiotidis et al. (2019) estimate dynamics of Bitcoin's return using stock market returns, exchange rates, gold and oil returns. Klein et al. (2018) concentrate on the volatility behavior to find the distinction between Bitcoin and gold. Using daily return series of equity indices, represented by six equity ETFs, and five main cryptocurrencies including Bitcoin, Kristjanpoller et al. (2020) find the asymmetric multifractality in the cross-relationship between Bitcoin and equity ETFs.

This paper focuses on the tail behaviors of Bitcoin, the US dollar, gold and stock market index in order to check if Bitcoin is a currency, a commodity or an investment asset. Tail behavior of asset is the key feature to define what kind of financial intrument it is and what role it has on the market. It is a well-known and proven fact that economic agents has growingly recognized the tail risk of the market. Throughout the series of global and international impacts of economic and financial crises, households, firms and regulatory authorities have been keen on the tail behavior of the economic variables. This leads to the phenomenon that the investors' demand for the asset, described as the asset's risk premium, is dictated by the tail behavior of economic and financial variables. Recently, researchers have hypothesized that heavy-tailed shocks to economic fundamentals help explain certain asset's behavior that has proved otherwise difficult to reconcile with traditional macro-finance theory. Following the work of Barro (2006), rare disaster hypothesis shows that economic model matches a number of focal asset pricing moments when incorporating tail risk into the model. Bollerslev et al. (2015), Andersen et al. (2015), Kelly and Jiang (2014) and many others argue that tail risk measures have explanatory power for the risk premium on the time-series of asset's return.[2] In Giovannetti (2013), tail risk commands the risk premium in the equilibrium derived from the standard consumption-investment intertemporal problem when an representative agent maximizes the quantile of the utility distribution instead of the expected utility. In this sense, tail behavior and its statistical property define not only the economic situation and but also the corresponding variables.

The chief obstacle to the investigation of tail movement is a viable measure of tail risk — tail risk for the return on Bitcoin, the dollar, gold, the stock market index over time. Kelly and Jiang (2014) organize the literature on the estimation of tail risk. There are two current approaches to measuring tail risk dynamics for assets' returns. The first one is based on option price data. Examples of the option-based approach include Bakshi et al. (2003), who study risk-neutral skewness and kurtosis of stock returns, Bollerslev et al. (2009), who examine how the variance risk premium relates to the equity premium, and Backus et al. (2011) and Gao and Song (2015), who infer disaster risk premia from options. The second one is based on high frequency data exemplified by Engle and Manganelli (2004). Different from the option-based approach, Engle and Manganelli's (2004) method does not need brisk derivatives market. Futhermore, since the key factor for specification of tail risk is the underlying persistence in high frequency return data, this approach can be applied to any return series reducing misspecification bias.[3] I, therefore, estimate the time series of conditional Value at Risk (VaR) following Engle and Manganelli (2004), named as conditional autoregressive Value at Risk (CAViaR). After the time-series of conditional 1% and 5% VaR for the return on Bitcoin, the dollar, gold and the stock market index are obtained, the similarity and difference of them are examined based on these conditional processes.

I first implement the unconditional correlation analysis and find that Bitcoin is classified as an instrument for a medium of exchange and the investment. Based on the correlations between the daily CAViaR of Bitcoin's return and that of return on the dollar, gold and the stock market index, the CAViaR of Bitcoin[4] has a strong correlation with that of the dollar and the stock market index as no correlation with gold is there. Interestingly enough, the correlations between the CAViaR of Bitcoin and that of the dollar and the stock market index are negative, which tells us that Bitcoin is the alternative instrument for payment and investment.

For a deeper understanding, the relationship between the risk premium of Bitcoin's return and the tail risk of the dollar, gold and the stock market index is investigated. The risk premium of Bitcoin's return, reflecting economic actors' demand for Bitcoin, should be associated with the tail of the dollar, gold and the stock market index if Bitcoin is the alternative instru-

[2] Given that tail movement of asset's returns is governed by higher statistical moments, Kinateder and Papavassiliou (2019) can also be the example of the risk premium generated by tail risk. They find that realized kurtosis is the dominant predictor of subsequent bond returns.

[3] Note that Engle and Manganelli (2004) choose two individual stock returns, daily stock returns of General Motors and IBM, to conduct empirical studies.

[4] The CAViaR of Bitcoin is interchangeable with the CAViaR of Bitcoin's return hearafter. In the same way, the CAViaR of the dollar, gold or the stock market index is the CAViaR of return on the corresponding asset.

ment for them. I run single predictive regressions of Bitcoin's return on the tail of the dollar, gold and the stock market return. Consistent with the results of unconditional contemporaneous correlation analysis, tail of the stock market return is closely linked with the risk premium of Bitcoin's return, negatively forecasting Bitcoin's return over several horizons. In other words, market participants are willing to increase the portion of Bitcoin in their wealth when the stock market index is in extreme circumstances.

In addition, I examine if Bitcoin is the subject of investment based on the capital asset pricing model (CAPM). To this end, I check the significance and the magnitude of risk price related to Bitcoin's return based on the framework of Merton's (1973) intertemporal capital asset pricing model (ICAPM). If Bitcoin is another investment vehicle for investors, the investment opportunity set comprises the return on investment assets including the return on Bitcoin. According to the theory of the ICAPM, state variables forecasting the movement of components in the investment opportunity set are priced in an innovation way. I check if the state variable predicting the return on Bitcoin is priced on the Fama–French 25 portfolios sorted by size and book-to-market. The lagged value of the return on Bitcoin is used as a state variable.[5,6] Depending on the framework of ICAPM, this article finds that risk price related to Bitcoin is not priced. However, the magnitude of risk price related to Bitcoin is considerable when compared to that of size, momentum and value factor from Fama and French (1993), Carhart (1997) which are also not priced on the selected test asset with the daily sample. Futhermore, the t-statistics for the risk price of Bitcoin are also comparable to those of benchmark risk factors. These results imply the likelihood that Bitcoin is regarded as the tool of the investment for economic actors to accumulate and dispose of wealth.

To the best of my knowledge, it is novel to compare financial variables based on the tail behavior. This can be a complement to the extant research analyzing only with the mean and variance. Not only that, it should be borne in mind that defining and classifying Bitcoin is closely linked with the job uncovering how market participants perceive Bitcoin. To address a demand-side viewpoint, checking the risk premium of Bitcoin in the predictive regression and verifying the significance of the risk price related to Bitcoin based on the framework of ICAPM seem to be an imperative step to check if Bitcoin can be the investment asset for investors who want to hedge their sequence of wealth and consumption during the lifetime. Indeed, Feng et al. (2018),[7] Shahzad et al. (2019) and Bouri et al. (2020) [8] also compare the tail movement of Bitcoin to that of the stock market index and gold, but they just investigate the direct cross-correlation of time series, which do not consider the viewpoint of market participants. In my article, the relationship between risk premium of Bitcoin and the tail behaviors of other assets and the risk price of Bitcoin in the ICAPM clarify that Bitcoin acts and is regarded as an alternative for stocks in market participants' demand sense.

The rest of the paper is organized as follows. Section 2 provides a review of the literature on identification of Bitcoin. Section 3 presents the econometric model for the estimation of the CAViaR of return on Bitcoin, the dollar, gold and the stock market index. Section 4 describes the data set and the empirical results. The risk price related to Bitcoin in ICAPM setting is reported in Section 5. Section 6 presents conclusion.

2. Related studies

Uncovering and classifying Bitcoin are challenging tasks, and which remain unsettled. The debate on the identity of Bitcoin has continued to ascend because of its wide usability. The literature disagrees on whether Bitcoin fulfils the criteria of a currency, a commodity or an investment asset. Whelan (2013) argues that Bitcoin is more similar to the currency. According to Whelan (2013), Bitcoin is the currency because it is a globally accepted medium of exchange. Cuthbertson (2015) states that there are more than 100,000 retailers accepting Bitcoin as payments for goods and services. Polasik et al. (2015) also view it as a medium of exchange since the demand arising from the transactional needs of users drives up prices in the regression of Bitcoin on variables capturing the demand and the supply of Bitcoin. Based on the global survey of merchants, they also mention that Bitcoin has widely dispersed users for online transactions. Bouoiyour and Selmi (2015) reveal the usefulness of Bitcoin in trade transactions investigating long-run cointegration between Bitcoin price and the monetary velocity, the price of gold and Shanghai market index. An interesting paper by Koutmos (2018) examines the empirical linkages between Bitcoin's returns and transaction activity, proxied by the total number of unique Bitcoin addresses. Unique address refers to an identifier which serves as a possible destination for a Bitcoin payment. The bivariate VAR models employed in this paper show strong linkages between Bitcoin's returns with its transaction activities. In addition, Bitcoin can be classified as the fiat currency such as the dollar and the euro in that Bitcoin has no or limited the intrinsic value. Van Wijk (2013) finds that the euro-dollar exchange rate has a significant effect on the value of Bitcoin in the long run relying on error correction model. Similar results are reported by Ennis (2013). Using a GARCH analysis, he reports that Bitcoin returns are statistically

[5] Due to the non-persistency of Bitcoin's return as presented in Table 1, the return of Bitcoin itself automatically becomes the state variable. This is consistent with the fact that the stock market return itself is the priced risk factor in the framework of ICAPM.

[6] Finding predictors for the return on Bitcoin is beyond the scope of this paper. The predictor for the return on Bitcoin can be the future research for the field of forecasting of time series.

[7] In this paper, conditional VaR is estimated by the combination of extreme value theory and ARMA-GARCH model. This method is with a stronger assumption and not empirically convincing when considering the large number of potential polynomials in mean and variance equation.

[8] These two papers employ the approach of Han et al. (2016) that measures the directional quantile dependence between two time series. Since this method does not contain the specification describing the persistence in tail behavior, this relies on large sample sizes for the validity. Recall that the sample size of Bitcoin is still small due to its recent emergence.

independent of equity and bond markets while it acts as a hedge for the euro supporting the idea that Bitcoin is an alternative monetary asset. Hazlett and Luther (2019) demonstrate that transactions are routinely conducted with Bitcoin serving as the medium of exchange. They use the market capitalizations of government-issued monies as an estimate of their respective demands and show that the demand for Bitcoin, similarly measured, is comparable to the demand for many government-issued monies. Only six of the government-issued monies[9] had a market capitalization greater than the market capitalization of Bitcoin. However, Bitcoin can be used for the payment not based on the creditability of government, but on the private trust. Bitcoin is traded in a decentralized peer-to-peer payment network.

On the other hand, there are many properties Bitcoin shares with gold. Like the dollar and the euro, Bitcoin and gold are also one of the instruments of international payment. They do not have nationality and are not controlled by a government. Unlike the currency, however, both Bitcoin and gold derive most of their value from the fact that they are scarce and costly to extract. This feature enables them to act as a store of value, being classified as a commodity. Selgin (2015) puts an emphasis on the fact that Bitcoin is not just contingently but absolutely scarce, which defines Bitcoin as a synthetic commodity money. By employing threshold GARCH model, Dyhrberg (2016b) argues that Bitcoin possesses some of the same hedging abilities as gold. This is confirmed by Bouri et al. (2017a) who investigate the return-volatility relationship of Bitcoin and find the similarity between Bitcoin and gold. Based on an asymmetric GARCH framework, their results show that Bitcoin has a safe-haven property somewhat similar to gold. Shahzad et al. (2019) also claim that Bitcoin and gold have a similarity in their safe-haven properties for the stock market index. Ji et al. (2019) suggest that Bitcoin is a substitute for gold showing that an increase in gold price decreases demand for cryptocurrency, and therefore weakens the return connectedness of return spillover for the cryptocurrency market. Different from gold, Bitcoin, however, has no intrinsic value and exists only in the virtual market without tangibility. Al-Khazali et al. (2018) reject the claim that Bitcoin and gold are similar. They demonstrate that the return and volatility of gold react to macroeconomic news whereas those of Bitcoin do not mostly react in a similar manner. Also, Bitcoin is often characterized as a speculative bubble by many scholars.[10] The big price fluctuations hamper Bitcoin to serve as a store of value. To illustrate this point, Geuder et al. (2019) study the Bitcoin price with focus on identifying and analyzing bubble behavior. They confirm the existence of frequent bubble periods in Bitcoin prices. This is supported by Baek and Elbeck (2015) who conclude that Bitcoin returns are not driven by fundamental economic factors but by speculative motives.

Other studies state that the motivation of buying and selling Bitcoin is the risk management by reforming investors' portfolios. Investors can hedge their downside risk of their wealth by adjusting the amount of Bitcoin as they have done with other investment assets, such as stocks and bonds. Put differently, Bitcoin is the element of the time-varying investment opportunity set and has the risk premium proportional to its capability of hedging against the economic fluctuations. Brière et al. (2015) provide evidence that inclusion of Bitcoin in an investment portfolio offers significant diversification benefits in terms of risk-return trade-off. Bouri et al. (2017b) examine whether Bitcoin can act as an alternative financial instrument for major world stock indices, bonds, oil, gold, and the dollar. Like Brière et al. (2015), the empirical results show that Bitcoin has an investment attractiveness as Bitcoin's returns are inversely covarying with returns on Chinese stocks and Asia Pacific stocks. Kristoufek (2015) also reveals that Bitcoin possesses properties of investment asset by finding drivers of the Bitcoin's price. Glaser et al. (2014) highlight that Bitcoin is treated as a financial investment asset rather than a currency, acting as a means of investing or borrowing in the financial market. They apply ARCH and GARCH estimation approach, and document that it is not Bitcoin network volume but Bitcoin trading volume which is closely linked with the new user's attention. MacDonell (2014) shows that Bitcoin values are strongly susceptible to the CBOE volatility index in ARMA modelling, suggesting that Bitcoin values are connected with investor behavior rather than consumer spending behavior. Similarly, Wang et al.'s (2016) cointegation analysis and vector error correction model indicate that stock price index have a negative impact on Bitcoin price.

There are several papers which assert that Bitcoin exhibits intrinsic attributes not related to conventional assets. Using a network VAR approach, Giudici and Abu-Hashish (2019) find that correlations between the prices of Bitcoin and the prices of conventional assets are low. Ji et al. (2018) who use the directed acyclic graph (DAG) approach to determine the contemporaneous causal relations between Bitcoin and stocks, gold and the dollar, also conclude that Bitcoin is isolated, and no specific asset plays a key role in affecting the Bitcoin market. Stavroyiannis and Babalos (2017) rely on a variety of econometric approaches, such as asymmetric GARCH and full BEKK model, and investigate the dynamic properties of Bitcoin, the S&P 500 index and gold. They conclude that Bitcoin does not hold any of the attributes the stock market index and gold have.

The above literature presents an incomplete picture of the identity of Bitcoin because tail behaviors of assets are not accounted for. Futhermore, prior studies have not dealt with the viewpoint on how economic actors see Bitcoin. Thus, this is where I seek to contribute. Using the CAViaR, the regression analysis of risk premium on Bitcoin's return, and the framework of ICAPM, the characteristics of Bitcoin are investigated in depth.

[9] United States dollar, Russian ruble, Hong Kong dollar, Brazilian real, South Korean won, Czech koruna

[10] Robert J. Shiller wrote that Bitcoin was the best current example of a speculative bubble. Nouriel Roubini has called Bitcoin the "mother of all bubbles."

3. Conditional autoregressive value at risk

This section presents how to estimate the series of conditional VaR by CAViaR specifications using daily returns on the price index, following Engle and Manganelli (2004).[11] The key idea of the CAViaR is the recognition of the persistent quantile of the return. CAViaR is obtained by modeling the quantile of daily return directly with four specifications. First, general CAViaR specification is the following:

$$f_t(\beta) = \beta_0 + \sum_{i=1}^{q} \beta_{1,i} f_{t-i}(\beta) + \sum_{j=1}^{r} \beta_{2,j}\, l(x_{t-j}) \tag{1}$$

where β is a vector of unknown parameters and x is a vector of observable variables. $p = q + r + 1$ is the dimension of β and l is a function of a finite number of lagged values of observables. The autoregressive terms $\beta_{1,i} f_{t-i}(\beta)$ ensure that the quantile changes "smoothly" over time. The roles of $l(x_{t-j})$ is to link $f_t(\beta)$ to observable variables that belong to the information set. The unknown parameters are estimated by regression quantiles, as introduced by Koenker and Bassett (1978). Engle and Manganelli (2004) suggest four specifications of CAViaR processes as follows.

$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 |y_{t-1}| \tag{2}$$
$$f_t(\beta) = \beta_1 + \beta_2 f_{t-1}(\beta) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \tag{3}$$
$$f_t(\beta) = \left(\beta_1 + \beta_2 f_{t-1}^2(\beta) + \beta_3 y_{t-1}^2\right)^{1/2} \tag{4}$$
$$f_t(\beta) = f_{t-1}(\beta_1) + \beta_1 \left\{ [1 + exp(G[y_{t-1} - f_{t-1}(\beta_1)])]^{-1} - \theta \right\} \tag{5}$$

where θ is 1% and 5% associated with VaR in this paper.[12] I use the notation $(x)^+ = max(x, 0)$, $(x)^- = -min(x, 0)$. From top to bottom, four specifications are called Symmetric absolute value, Asymmetric slope, Indirect GARCH(1,1) and Adaptive, respectively. I proceed the empirical verification only with the Asymmetric slope since it makes the most use of the information set.[13] As a proxy for the information set, the lagged return, y_{t-1}, is used following Engle and Manganelli (2004). In Asymmetric slope specification, β_1 and β_2 are constant and the coefficient on the lagged VaR, respectively. Two coefficients, β_3 and β_4 allow the response to positive and negative returns to be different. Because VaR is usually reported as a positive number, estimated VaR is set to be positive. The high value of estimated VaR means high tail risk.

4. Data and empirical results

Following the works of Dyhrberg (2016a) and Baur et al. (2018a), Bitcoin price data is obtained from Coindesk Price index. A control group consists of the price index of the dollar, gold and the stock market. For the price index of gold, the gold bullion USD/troy ounce rate (Gold Cash) and the CMX gold futures 100 oz rate in USD (Gold Future) are adopted. For the currency, the dollar-euro exchange rate (USD/EUR FX) and the dollar-pound exchange rate (USD/GBP FX) are chosen. The Financial Times Stock Exchange Index (FTSE 100) and the Morgan Stanley Capital International world equity index (MSCI World) represent the equity market index in the financial market where investors freely trade for portfolio management. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. All variables are daily observations from October 1, 2013 to June 30, 2019 due to the data availability of Bitcoin. The prices of these assets are plotted in Fig. 1.

The return on these price index and descriptive statistics for return series are presented in Table 1. In the second column, Bitcoin shows the highest mean return, 0.432. Conversely, other financial assets show mean returns ranging from −0.014 to 0.025. The mean return of Bitcoin is about 17 times larger than that of MSCI World which is the second highest. The standard deviations of returns also provide a striking picture in which the standard deviation of Bitcoin's returns is about at least six times larger than that of returns on other financial assets. This result is consistent with Yermack (2014) and Dwyer (2015). Bitcoin's returns also show the highest figures of minimum and maximum in absolute value. As indicated by Baur et al. (2018a), Bitcoin thus seems to be nowhere near the dollar, gold and the stock market based on the first and second moments.

However, Bitcoin is not at the top in terms of skewness and kurtosis. The values of these two moments of Bitcoin's return are considerable and similar across assets. The skewness of Bitcoin's return is 0.399 which is in the middle of asset's skewnesses spectrum in absolute value. When it comes to kurtosis, all financial assets show similar figures ranging from about 4 to 9, except for USD/GBP FX. Note that the values of kurtosis are too considerable to be neglected. Additionally, the results of Jarque–Bera test in the eighth column signal that analysis of all data should go beyond examining the first two moments. These findings appear that Bitcoin and other financial assets are linked and send a warning to us again, leading to the need of analysis on the tail behavior of financial assets.

To address this, I estimated 1% and 5% daily VaRs of return on price index in the way described in Section 3. 1% and 5% VaRs of Bitcoin's return are plotted in Fig. 2, and 1% VaRs and 5% VaRs of returns on other assets are plotted in Figs. 3 and 4, respectively. The amplitude of CAViaR of Bitcoin is the largest and the CAViaRs of stock market returns, FTSE 100 and MSCI

[11] The use of more frequent daily data rather than monthly data would improve the estimation precision.

[12] It should be noted that the conventional choice of the confidence level for the tail risk is 95% and 99%, which correspond to the 1% and 5% VaR.

[13] Qualitatively similar results are obtained with the rest of the specifications: Symmetric absolute slope, Indirect GARCH(1,1) and Adaptive.

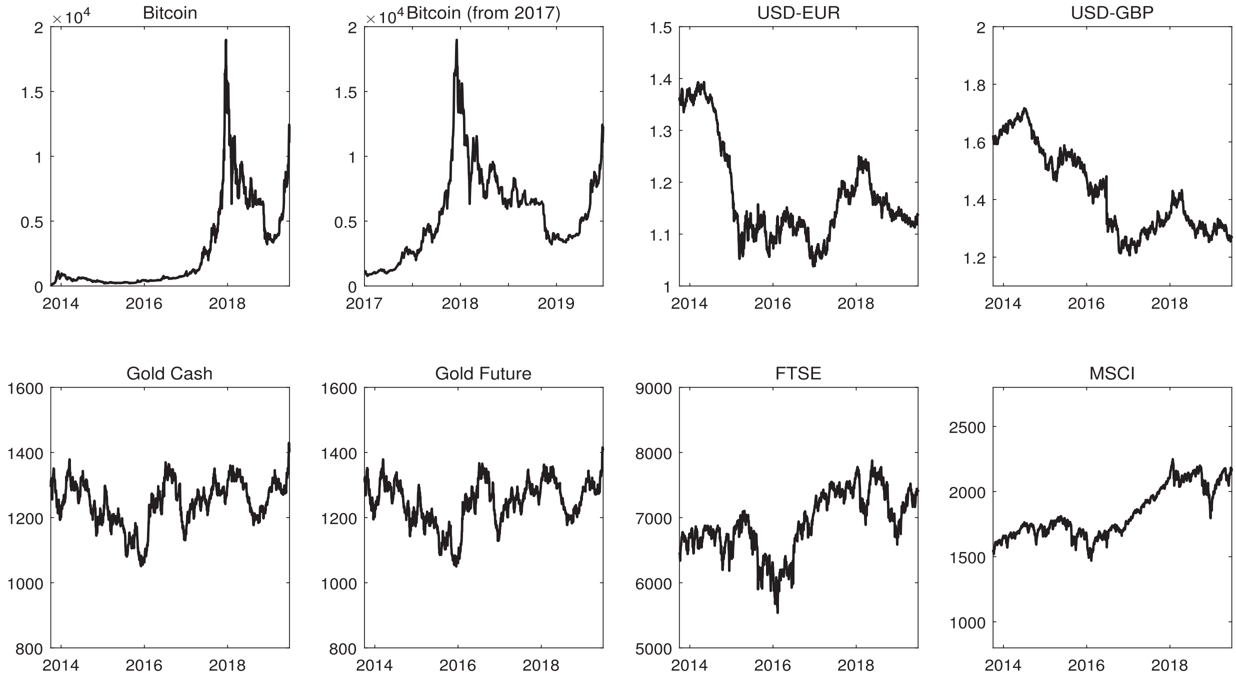

Fig. 1. This figure plots the price of Bitcoin, the dollar, gold and the stock market index. Bitcoin price data is obtained from Coindesk Price index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. The sample period is from October 1, 2013 to June 30, 2019.

Table 1

Summary statistics. This table reports descriptive statistics for the return on Bitcoin, the dollar, gold and the stock market index. Bitcoin price data is obtained from Coindesk Price index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. The data are all daily, from October 1, 2013 to June 30, 2019. The table reports mean, standard deviation, skewness, kurtosis, minimum, maximum, Jarque–Bera test statistics and first order autocorrelation of daily returns. For the test results of Jarque–Bera and first order autocorrelation, significance levels at 90%, 95%, and 99% are denoted by one, two and three stars, respectively.

	Mean	SD	Skew	Kurt	Min	Max	Jarque–Bera	AR(1)
Bitcoin	0.432	5.002	0.399	8.726	−24.759	35.849	2086.221***	0.020
USD/EUR FX	−0.010	0.502	0.079	5.492	−2.234	2.634	389.329***	−0.006
USD/GBP FX	−0.014	0.572	−1.738	29.683	−7.976	2.802	45195.142***	0.043*
Gold Cash	0.007	0.772	0.195	4.396	−2.890	3.800	131.022***	0.039
Gold Future	0.010	0.834	0.325	5.939	−3.350	4.605	565.493***	−0.053**
FTSE 100	0.013	0.828	−0.131	5.695	−4.667	3.577	457.573***	0.012
MSCI World	0.025	0.682	−0.634	7.188	−4.904	3.087	1194.870***	0.160***

World, are the highest in frequency. Comparing the time hitting the peak and trough, CAViaR of Bitcoin appears to be more similar to that of stock market return than that of the dollar and gold. But, when it comes to the frequency, CAViaR of Bitcoin is covarying with that of USD/GBP FX and Gold Cash. For the CAViaRs of USD/EUR FX and Gold future, the persistencies of them look higher than those of other assets as being different from CAViaR of Bitcoin.

In Table 2, all of the estimation results for parameters of CAViaR specification are reported. In general, all 1% and 5% VaRs of assets are stably estimated based on the significance of coefficients on lagged VaRs (β_2). All CAViaRs of returns on assets show the significant autoregressive term, which is consistent with the persistency of tail behavior. However, the coefficients in front of information set (β_3, β_4) show the different significance across assets, which implies their dissimilarity.

First, the results of specification for 1% VaR are examined (Panel A). While the CAViaR of Bitcoin shows the statistically significant coefficients on both the maximum and the minimum of lagged return[14] based on the corresponding one-sided p values, CAViaRs of other assets are not alike in the sensitivity to this information set. At the 5% level of significance level, the coefficients of the maximum of lagged return (β_3) are significant only for the CAViaRs of Bitcoin, USD/EUR FX and USD/GBP FX. At the 1% level of significance, the coefficients of the maximum of lagged return are significant for the CAViaR of Bitcoin and

[14] To be more specific, the maximum of lagged return should be written as the maximum value between the lagged return and zero. For the sake of brevity, I abbreviate hereafter.

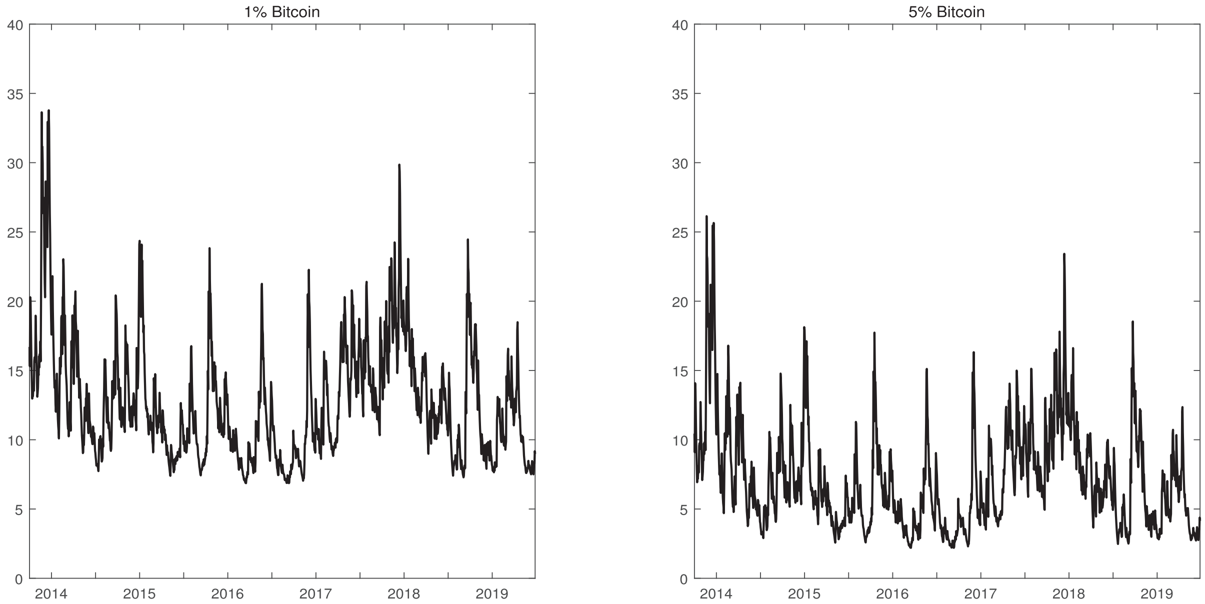

Fig. 2. This figure plots estimated 1% and 5% CAViaRs of Bitcoin's return. Bitcoin price data is obtained from Coindesk Price index. The sample period is from October 1, 2013 to June 30, 2019.

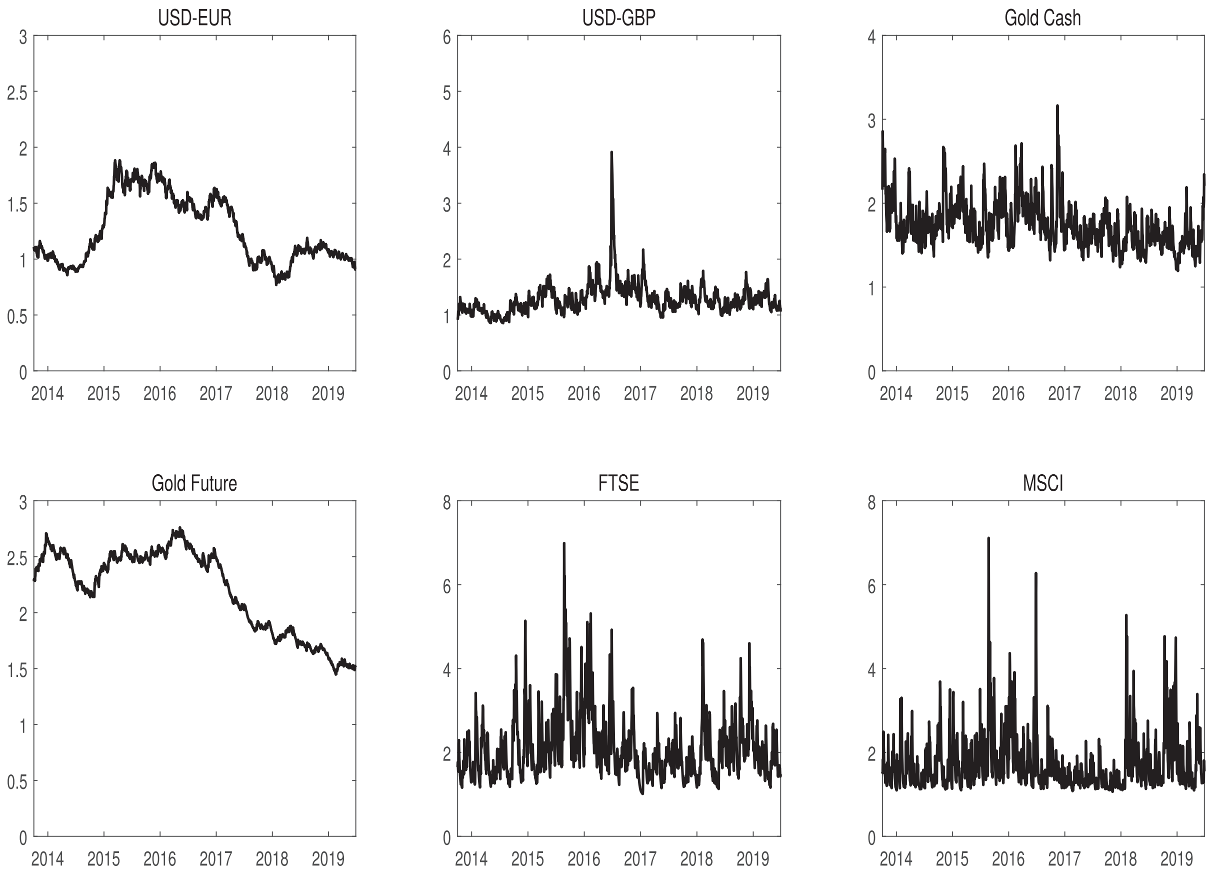

Fig. 3. This figure plots estimated 1% CAViaRs of return on the dollar, gold and the stock market index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. The sample period is from October 1, 2013 to June 30, 2019.

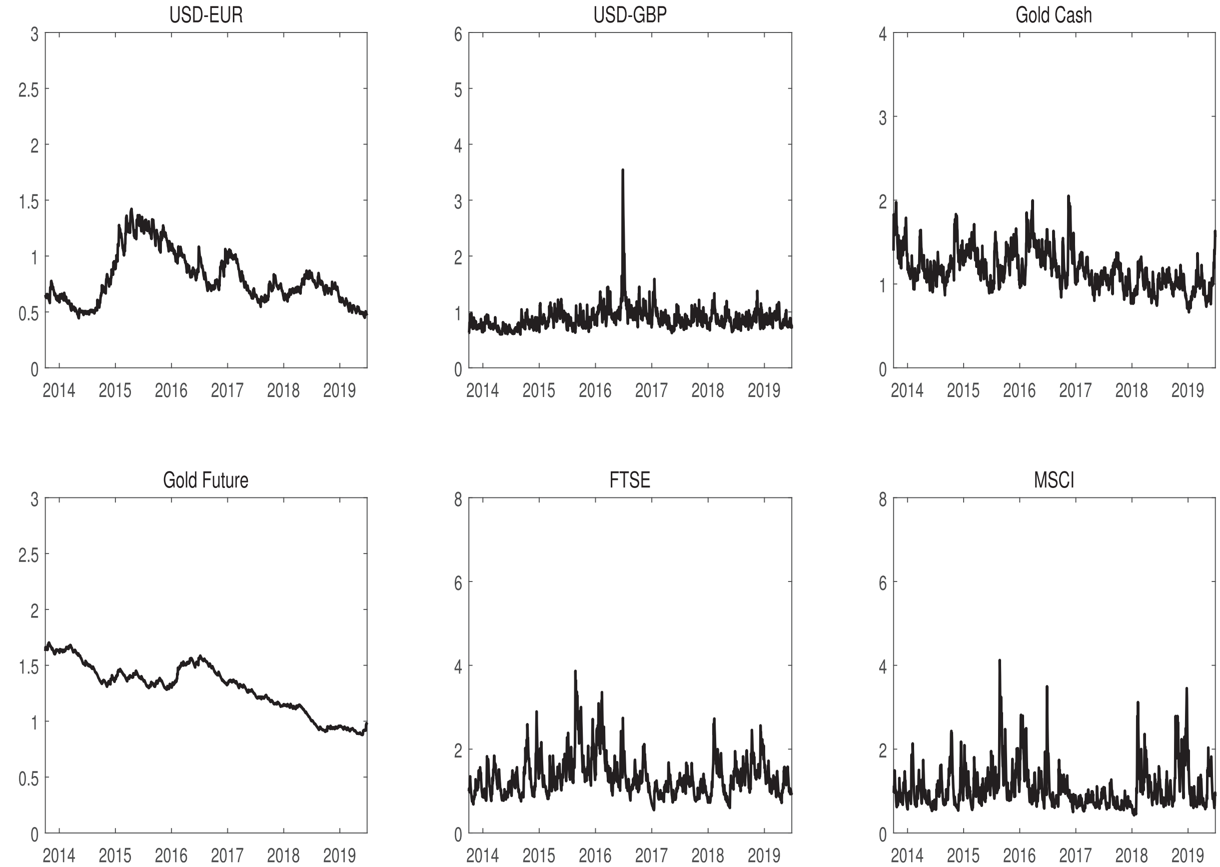

Fig. 4. This figure plots estimated 5% CAViaRs of return on the dollar, gold and the stock market index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. The sample period is from October 1, 2013 to June 30, 2019.

USD/EUR FX. As for the coefficient of minimum of lagged return (β_4), all assets but Gold future are significant at the 1%, 5% and 10% level of significance.

As for the 5% VaRs (Panel B), the results are similar to those of 1% VaR. All CAViaRs are persistent on the basis of significant coefficients on the lagged VaRs. As the coefficient on the maximum of lagged return for Bitcoin is significant, the only coefficient for the USD/GBP FX is also statistically significant at the 5% level of significance. The coefficients of USD/EUR FX, Gold cash, Gold Future, FTSE 100 and MSCI World are not statistically significant. At the 5% level of significance, the coefficients of all but Gold future on the minimum of lagged return are significant. To sum up, Bitcoin is close to a currency and an investment asset, being not a kind of a commodity.

To comb through the characteristics of Bitcoin, following Baur et al. (2018a), I conduct the unconditional contemporaneous correlation analysis for CAViaR of Bitcoin and other six variables. The results are in Table 3. The comparison of 1% VaRs is in Panel A, and that of 5% VaRs is in Panel B. The lower triangular figures are the values of correlation coefficients. The upper triangular figures are corresponding p-values testing the hypothesis that there is no relationship between the observed phenomena (null hypothesis). For the 1% VaR, CAViaR of Bitcoin has no correlation with Gold Cash and Gold Future. The correlation coefficients are 0.029 and −0.044 which are not statistically significant at the 5% level of significance. Moreover, the absolute values of correlation coefficients for Gold Cash and Gold Future are small relative to those of other subjects. The correlations between 1% VaR of Bitcoin and the dollar, the stock market are statistically significant at the 1% level of significance. The correlation coefficients of the currency, USD/EUR FX and USD/GBP FX, are −0.299 and −0.220, respectively. The correlation coefficients of the stock market, FTSE 100 and MSCI World, are −0.194 and −0.131, respectively. Note that the statistically significant correlation coefficients in Panel A are all negative. This points the capability of Bitcoin to be the alternative instrument for a currency and an investment asset. Bitcoin's tail behaves well when the value of a currency or an investment asset depreciates extremely, described by the increase in VaR.

In Panel B, the same empirical verification process is conducted using 5% VaRs. The results are almost the same as the results in Panel A. The only difference is that the correlation between VaR of Bitcoin and VaR of Gold Future becomes statistically significant. However, the value of correlation coefficient is still trivial relative to correlation coefficients for a currency and an investment asset. The correlation coefficient of Gold Future is about a half of that of a currency and an investment asset and lower than 0.1. Consistent with the results in Panel A, the correlations between VaR of Bitcoin and

Table 2
Estimates and relevant statistics for the 1% and 5% CAViaRs. This table presents the values of the estimated parameters, the corresponding standard errors, (one-sided) *p* values and the values of the regression quantile objective funtions (RQ) when computing the series of CAViaR of return on the price index of Bitcoin, the dollar, gold and the stock market. Bitcoin price data is obtained from Coindesk Price index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. Asymmetric slope specification is adopted for all variables. Panel A is about 1% VaR estimates and Panel B is about 5% VaR estimates. The sample period is from October 1, 2013 to June 30, 2019.

	Bitcoin	USD/EUR FX	USD/GBP FX	Gold Cash	Gold Future	FTSE 100	MSCI World
Panel A: 1% VaR							
β_1	0.969	0.000	0.087	0.177	−0.002	0.167	0.355
Standard errors	0.597	0.002	0.078	0.092	0.005	0.061	0.095
p values	0.052	0.461	0.134	0.027	0.321	0.003	0.000
β_2	0.839	0.997	0.869	0.824	0.994	0.836	0.655
Standard errors	0.065	0.003	0.074	0.053	0.006	0.039	0.104
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β_3	0.224	−0.031	0.191	0.138	0.014	−0.016	0.109
Standard errors	0.055	0.009	0.113	0.097	0.030	0.194	0.266
p values	0.000	0.000	0.045	0.076	0.324	0.466	0.341
β_4	0.482	0.053	0.223	0.311	0.036	0.626	0.920
Standard errors	0.187	0.010	0.030	0.090	0.037	0.128	0.442
p values	0.005	0.000	0.000	0.000	0.163	0.000	0.019
RQ	225.173	22.006	28.730	32.822	37.396	36.799	33.383
Panel B: 5% VaR							
β_1	0.282	0.001	0.118	0.040	−0.001	0.055	0.076
Standard errors	0.151	0.002	0.033	0.028	0.002	0.035	0.019
p values	0.031	0.336	0.000	0.072	0.275	0.056	0.000
β_2	0.817	0.978	0.764	0.894	0.997	0.907	0.857
Standard errors	0.048	0.010	0.078	0.047	0.004	0.055	0.043
p values	0.000	0.000	0.000	0.000	0.000	0.000	0.000
β_3	0.203	0.009	0.175	0.104	0.015	−0.045	−0.061
Standard errors	0.085	0.018	0.107	0.065	0.011	0.107	0.084
p values	0.008	0.317	0.050	0.055	0.084	0.336	0.234
β_4	0.474	0.081	0.275	0.187	0.000	0.287	0.414
Standard errors	0.102	0.028	0.141	0.096	0.012	0.113	0.109
p values	0.000	0.002	0.026	0.026	0.495	0.006	0.000
RQ	788.538	80.672	90.170	117.877	136.969	134.582	112.832

Table 3
Contemporaneous correlations of 1% and 5% CAViaRs. The table reports the correlation matrix of 1% VaRs (Panel A) and 5% VaRs (Panel B). Bitcoin price data is obtained from Coindesk Price index. Gold Cash, USD/EUR FX and USD/GBP FX are sourced from Federal Reserve Economic Data. Gold Future, FTSE 100 and MSCI World are available on Bloomberg terminal. The matrix consists of two parts. The lower triangular values are the coefficients of correlation. The upper triangular values are p-values for the corresponding coefficients, testing the hypothesis that there is no relationship between the observed phenomena (null hypothesis). The sample period is from October 1, 2013 to June 30, 2019.

	Bitcoin	USD/EUR FX	USD/GBP FX	Gold Cash	Gold Future	FTSE 100	MSCI World
Panel A: 1% VaR							
Bitcoin	1.000	0.000	0.000	0.263	0.085	0.000	0.000
USD/EUR FX	−0.299	1.000	0.000	0.000	0.000	0.000	0.000
USD/GBP FX	−0.220	0.353	1.000	0.000	0.000	0.000	0.000
Gold Cash	0.029	0.307	0.170	1.000	0.000	0.000	0.665
Gold Future	−0.044	0.631	0.160	0.482	1.000	0.000	0.203
FTSE 100	−0.194	0.284	0.207	0.095	0.128	1.000	0.000
MSCI World	−0.131	0.145	0.199	0.011	0.033	0.772	1.000
Panel B: 5% VaR							
Bitcoin	1.000	0.000	0.000	0.168	0.003	0.000	0.000
USD/EUR FX	−0.206	1.000	0.000	0.000	0.000	0.000	0.000
USD/GBP FX	−0.191	0.276	1.000	0.000	0.141	0.000	0.000
Gold Cash	0.036	0.317	0.209	1.000	0.000	0.000	0.614
Gold Future	0.078	0.187	0.038	0.541	1.000	0.403	0.006
FTSE 100	−0.191	0.350	0.202	0.110	−0.022	1.000	0.000
MSCI World	−0.164	0.211	0.252	−0.013	−0.071	0.816	1.000

VaR of a currency and an investment asset are negative. Taken together, regardless of the level of confidence for VaR, 1% VaR and 5% VaR, Bitcoin can be classified as a currency and an investment asset as being an substitutive instrument for them.

This empirical finding is inconsistent with the evidence from Dyhrberg (2016a) and Baur et al. (2018a). Using the mean and volatility of return on Bitcoin, a currency and gold, Dyhrberg (2016a) argues that Bitcoin can be classified as something between the dollar and gold on a scale from pure medium of exchange advantages to pure store of value advantages whereas Baur et al. (2018a) find no relationship between Bitcoin and other subjects. The above findings also differ from previous claims that Bitcoin is similar to gold due to their safe-haven properties (Dyhrberg, 2016b; Bouri et al., 2017a; Shahzad et al., 2019) and an increase in gold price decreases the demand for Bitcoin (Ji et al., 2019). In fact, the results in this paper are somewhat consistent with those of Al-Khazali et al. (2018) because Bitcoin and gold appear not to share the factors that affect their tail behaviors. The findings are also consistent with prior observations that Bitcoin's demand is linked with its transaction activity (Bouoiyour and Selmi, 2015; Koutmos, 2018; Hazlett and Luther, 2019) or investing activity (Kristoufek, 2015; Glaser et al., 2014). Given the negative relationship between Bitcoin and conventional assets (Ennis, 2013; Bouri et al., 2017b), my results extend the existing literature in that there are significantly negative relationship between Bitcoin and the dollar, the stock market with respect to tail movement. In light of this, the finding that tail risk of Bitcoin is inversely covarying with that of a currency and an investment asset entitles Bitcoin to be the hedging tool for them in the financial market.

To support the notion that Bitcoin acts as an alternative way for market participants to hedge the tail risk of a currency and an investment asset, I additionally run the predictive regression of Bitcoin's return on the tail movement of the dollar, gold and the stock market return. The following is the specification of short- and long-horizon single predictive regression.

$$r_{t,t+q} = \beta_1 + \beta_2 Tail_t + e_{t,t+q} \tag{6}$$

where $r_{t,t+q} = r_{t+1} + \cdots + r_{t+q}$ is the continuously compounded Bitcoin's return over q periods (from $t+1$ to $t+q$), and $e_{t,t+q}$ denotes a forecasting error with zero conditional mean.[15] $Tail_t$ is the CAViaRs of the dollar, gold and the stock market.

The sign of the slope coefficient, β_2, indicates whether a given tail of a currency, a commodity or an investment asset dictates positive or negative risk premium related to Bitcoin, and the associated t-statistic indicates whether this effect is statistically significant. I use forecasting horizons of 1, 7, 14, 21, 28, 42, 60 days ahead. The statistical significance of the regression coefficients is evaluated by using both Newey and West (1987) and Hansen and Hodrick (1980) asymptotic standard errors with q lags. The risk premium of Bitcoin's return should be associated with the tail risk of the considered assets once Bitcoin functions as an alternative financial instrument for the selected subjects. Since risk premium is the representation of the demand from market participants, the increase of tail risk in a currency, a commodity and an investment asset must be connected with the low risk premium of Bitcoin. Bitcoin will be preferable for traders and practitioners in such instances. The expected empirical results, thus, are the negative coefficients on the CAViaR of the dollar and the stock market in the predictive regression.

Tables 4 and 5 report the results of preditive regressions of Bitcoin's return on the subject's 1% VaR and 5% VaR, respectively. For the 1% VaR, the tail of the stock market return commands the risk premium of Bitcoin, implying that an increase in the tail risk of the stock market return generates an incentive for market participants to demand Bitcoin. The slope coefficients for FTSE 100 are negatively significant at the 10% level of significance for 7, 14 and 21 horizons, and those for MSCI World are also negatively significant between 7 and 42 horizons and adjusted R^2 are impressive ranging from 0.007 to 0.018. In contrast, the tails of a currency and a commodity have nothing to do with the risk premium of Bitcoin. The coefficients of USD/EUR FX, USD/GBP FX, Gold Cash and Gold Future are insignificant over the whole horizon.

For the 5% VaR, the results are maintained. The tail of an investment asset solely dictates the risk premium of Bitcoin's return. While the slope coefficients of USD/EUR FX, USD/GBP FX, Gold Cash and Gold Future are insignificant over the whole horizon at the 10% level of significance, coefficients of FTSE 100 are negatively significant for 7 and 14 horizons. In the case of MSCI World, the slope coefficients are negatively significant between 7 and 42 horizons with the remarkable adjusted R^2, ranging from 0.013 to 0.028. In sum, the initial claim that Bitcoin is the substitutive tool for an investment asset is bolstered by the predictive regression analysis since the risk premium of Bitcoin's return are explained by the tail behavior of the stock market return. Inconsistent with the contempaneous correlation analysis, however, the relationship between Bitcoin and a currency is not adamantly supported.

This evidence corroborates in part Brière et al. (2015) who assert that investors benefit from inclusion of Bitcoin in an investment portfolio because they can enjoy the diversification effects in terms of risk-return trade-off. My results also support Wang et al. (2016) and Bouri et al. (2017b), who document the inverse relationship between Bitcoin and the stock market index. In fact, my findings provide a broader picture in that Bitcoin acts as the suitable diversifier for stock indices against extreme downside risk of portfolios. More importantly, investigation on the relationship between the risk premium of Bitcoin and tail risk of the stock market index sheds light on the investors' perception that Bitcoin is an alternative for stocks. These results are not captured by Stavroyiannis and Babalos (2017), Ji et al. (2018) and Giudici and Abu-Hashish (2019) who find no connectedness between Bitcoin and the stock market index based only on the first and second moments of assets.

5. Bitcoin and the ICAPM

In order to get a more detailed view that Bitcoin can be defined as an investment asset, this paper further examines whether Bitcoin is one of elements in the investment opportunity set. On a practical level, I check if the risk price related to Bitcoin's return is priced in the ICAPM setting.

[15] Due to the high frequency of data, daily returns on risk free asset are assumed to be constant.

Table 4
Predictive regressions of Bitcoin's return on 1% CAViaRs of the dollar, gold and the stock market. This table reports the results for single predictive regressions of Bitcoin's return on 1% CAViaR series of the dollar, gold and the stock market at horizons of 1, 7, 14, 21, 28, 42 and 60 days ahead. The slope estimates are presented in the first row, Newey and West (1987) t-ratios (in parentheses) and Hansen and Hodrick (1980) (in brackets) t-ratios computed with the corresponding lags are in the second and the third row, respectively. The adjusted coefficient of determination ($adj.R^2$) statistics are in the fourth row. The sample period is from October 1, 2013 to June 30, 2019.

Predictor	q = 1	q = 7	q = 14	q = 21	q = 28	q = 42	q = 60
USD/EUR FX	−0.035	−0.128	0.362	1.614	3.642	10.313	20.781
	(−0.085)	(−0.050)	(0.071)	(0.211)	(0.359)	(0.703)	(1.037)
	[−0.085]	[−0.042]	[0.059]	[0.176]	[0.296]	[0.583]	[0.903]
$Adj.R^2$	0.000	0.000	0.000	0.000	0.001	0.006	0.018
USD/GBP FX	−0.128	−1.157	−0.616	−0.149	1.934	6.444	16.977
	(−0.332)	(−0.578)	(−0.154)	(−0.023)	(0.202)	(0.463)	(0.896)
	[−0.338]	[−0.490]	[−0.127]	[−0.019]	[0.170]	[0.414]	[0.858]
$Adj.R^2$	0.000	0.000	0.000	0.000	0.000	0.002	0.010
Gold Cash	0.542	1.899	4.885	9.400	15.295	16.548	27.215
	(1.096)	(0.685)	(0.809)	(0.891)	(0.974)	(0.815)	(1.337)
	[1.126]	[0.567]	[0.657]	[0.738]	[0.848]	[0.765]	[1.380]
$Adj.R^2$	0.001	0.001	0.004	0.008	0.016	0.012	0.025
Gold Future	−0.020	0.029	0.493	0.722	0.503	0.316	2.400
	(−0.062)	(0.013)	(0.112)	(0.109)	(0.056)	(0.023)	(0.118)
	[−0.062]	[0.011]	[0.092]	[0.089]	[0.045]	[0.018]	[0.098]
$Adj.R^2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000
FTSE 100	−0.151	−1.806	−3.171	−4.656	−5.238	−6.785	−5.102
	(−0.974)	(−1.920)	(−1.747)	(−1.670)	(−1.454)	(−1.400)	(−0.867)
	[−0.988]	[−1.642]	[−1.445]	[−1.428]	[−1.248]	[−1.291]	[−0.850]
$Adj.R^2$	0.001	0.009	0.011	0.015	0.014	0.016	0.007
MSCI World	−0.150	−1.854	−3.133	−5.093	−6.758	−8.400	−7.624
	(−0.739)	(−1.690)	(−1.865)	(−2.167)	(−2.210)	(−1.931)	(−1.314)
	[−0.795]	[−1.481]	[−1.613]	[−1.918]	[−1.895]	[−1.759]	[−1.195]
$Adj.R^2$	0.000	0.007	0.008	0.014	0.017	0.018	0.011

Table 5
Predictive regressions of Bitcoin's return on 5% CAViaRs of the dollar, gold and the stock market. This table reports the results for single predictive regressions of Bitcoin's return on 5% CAViaR series of the dollar, gold and the stock market at horizons of 1, 7, 14, 21, 28, 42 and 60 days ahead. The slope estimates are presented in the first row, Newey and West (1987) t-ratios (in parentheses) and Hansen and Hodrick (1980) (in brackets) t-ratios computed with the corresponding lags are in the second and the third row, respectively. The adjusted coefficient of determination ($adj.R^2$) statistics are in the fourth row. The sample period is from October 1, 2013 to June 30, 2019.

Predictor	q = 1	q = 7	q = 14	q = 21	q = 28	q = 42	q = 60
USD/EUR FX	−0.308	−2.345	−4.148	−5.147	−5.256	−2.676	4.633
	(−0.640)	(−0.816)	(−0.706)	(−0.554)	(−0.414)	(−0.148)	(0.186)
	[−0.647]	[−0.682]	[−0.582]	[−0.456]	[−0.342]	[−0.124]	[0.163]
$Adj.R^2$	0.000	0.001	0.002	0.002	0.001	0.000	0.001
USD/GBP FX	−0.183	−1.935	−1.999	−2.857	−0.423	3.823	17.460
	(−0.353)	(−0.764)	(−0.444)	(−0.436)	(−0.043)	(0.264)	(0.825)
	[−0.359]	[−0.678]	[−0.381]	[−0.365]	[−0.037]	[0.239]	[0.791]
$Adj.R^2$	0.000	0.001	0.000	0.000	0.000	0.000	0.006
Gold Cash	0.582	2.562	7.127	12.866	19.031	21.509	33.648
	(1.033)	(0.730)	(0.865)	(0.891)	(0.931)	(0.865)	(1.271)
	[1.059]	[0.589]	[0.683]	[0.728]	[0.801]	[0.800]	[1.263]
$Adj.R^2$	0.001	0.002	0.006	0.011	0.018	0.016	0.028
Gold Future	0.360	3.115	7.225	10.281	12.824	13.895	14.654
	(0.575)	(0.659)	(0.681)	(0.618)	(0.572)	(0.451)	(0.376)
	[0.570]	[0.518]	[0.543]	[0.497]	[0.464]	[0.376]	[0.333]
$Adj.R^2$	0.000	0.002	0.005	0.006	0.007	0.006	0.004
FTSE 100	−0.375	−3.506	−6.101	−8.479	−9.697	−12.079	−9.640
	(−1.538)	(−2.195)	(−1.817)	(−1.605)	(−1.412)	(−1.325)	(−0.870)
	[−1.548]	[−1.812]	[−1.467]	[−1.342]	[−1.200]	[−1.205]	[−0.853]
$Adj.R^2$	0.001	0.013	0.017	0.020	0.019	0.020	0.009
MSCI World	−0.401	−3.290	−5.976	−8.851	−11.240	−13.022	−13.266
	(−1.595)	(−2.176)	(−2.285)	(−2.302)	(−2.227)	(−1.859)	(−1.428)
	[−1.659]	[−1.844]	[−1.906]	[−1.990]	[−1.932]	[−1.736]	[−1.348]
$Adj.R^2$	0.002	0.013	0.018	0.024	0.028	0.026	0.020

Table 6

Cross-sectional regressions of ICAPM with Bitcoin and benchmark factor models on the 25 test assets. This table reports the estimation results for ICAPM with Bitcoin's return (BIT-ICAPM) and benchmark factor models when the test assets are the 25 Fama–French portfolios sorted by size and book-to-market. The estimation procedure is the two-pass regression approach following Fama and MacBeth (1973). The full-sample factor loadings, which are the independent variables in the regressions, are computed in one multiple time-series regression. The benchmark factor models include the CAPM, the Fama and French (1993) three-factor model (FF3) and the Carhart (1997) four-factor model (FF4). For each factor model, the estimates of the risk prices are in the first row. From the second to the fourth row, t-statistics are reported. The first set of t-statistics, indicated by $t-stat_{FM}$, stands for the Fama and MacBeth (1973) t-statistics. The second set, indicated by $t-stat_{SH}$, adjusts for errors-in-variables and follows Shanken (1992). The third set of t-statistics, indicated by $t-stat_{PM}$, accounts for the potential model misspecification and follows Kan et al. (2013). The Adjusted R^2 is the cross-sectional goodness-of-fit measure and follows Jagannathan and Wang (1996). The table examines the sample period from October 1, 2013 to June 30, 2019.

Model	Factors					$Adj.R^2$
BIT-ICAPM	γ_0	γ_M	γ_{BIT}			
Estimate	0.016	0.023	−2.391			0.245
$t-stat_{FM}$	0.440	0.535	−1.119			
$t-stat_{SH}$	0.399	0.496	−1.013			
$t-stat_{PM}$	0.412	0.499	−0.910			
CAPM	γ_0	γ_M				
Estimate	0.023	0.014				0.018
$t-stat_{FM}$	0.582	0.307				
$t-stat_{SH}$	0.582	0.307				
$t-stat_{PM}$	0.572	0.303				
FF3	γ_0	γ_M	γ_{SMB}	γ_{HML}		
Estimate	0.024	0.023	−0.011	−0.017		0.665
$t-stat_{FM}$	0.845	0.632	−0.806	−1.239		
$t-stat_{SH}$	0.843	0.632	−0.805	−1.239		
$t-stat_{PM}$	0.835	0.629	−0.805	−1.240		
FF4	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_{MOM}	
Estimate	0.016	0.032	−0.012	−0.017	0.061	0.716
$t-stat_{FM}$	0.572	0.885	−0.835	−1.207	1.359	
$t-stat_{SH}$	0.570	0.882	−0.835	−1.206	1.354	
$t-stat_{PM}$	0.566	0.884	−0.834	−1.207	1.319	

According to the Merton's (1973) ICAPM, the investment opportunity set is nothing but the mixture of individual investment assets. The key idea of the ICAPM is the recognition of the risks in the time-varying investment opportunity set available to investors. In response, investors would hold hedging portfolios to minimize the impact of the unexpected future changes in the investment opportunity set because the investment opportunity set determines the level of utility. The state variables, elements of vector X in Merton's (1973) ICAPM, are defined as the variables that drive the variations of the instantaneous mean returns and volatilities of the instantaneous return processes for individual risky assets. Therefore, the state variable for the Bitcoin's return should be priced in an innovation way if Bitcoin is the member of the investment opportunity set.[16] In other words, Bitcoin is one of the investment assets.

The cross-sectional regression estimation results for ICAPM are reported in Table 6. This table also reports the estimation results for benchmark factor models, such as CAPM, Fama and French (1993) three-factor model and Carhart (1997) four-factor model. The test assets are the 25 Fama–French portfolios sorted by size and book-to-market. The sample period is from October 1, 2013 to June 30, 2019. The estimation procedure is the two-pass regression approach following Fama and MacBeth (1973). For each factor model, three t-statistics are reported for the conservative judgement. The first set of t-statistics, indicated by $t-stat_{FM}$, stands for the Fama and MacBeth (1973) t-statistics. The second set, denoted by $t-stat_{SH}$, adjusts for errors-in-variables and follows Shanken (1992). The third set of t-statistics, indicated by $t-stat_{PM}$, accounts for the potential model misspecification and follows Kan et al. (2013). The Adjusted R^2 is the cross-sectional goodness-of-fit measure and follows Jagannathan and Wang (1996).

As expected, the empirically poor performance of CAPM is exhibited with the low adjusted R^2. The risk price of market portfolio is small and statistically insignificant. Meanwhile, it is unexpected that the risk price related to Bitcoin is not significantly priced even based on the Fama and MacBeth's (1973) t-statistic. However, it should be noted that the value of risk price is considerable in comparison to that of size, value and momentum factor (SMB, HML and MOM) in benchmark factor models. This figure, −2.391, is the largest risk price among the risk factors. Also, as t-statistics for size, value and momemtum factors are also insignificant, the values of t-statistics for the risk price related to Bitcoin, ranging from −0.9 to −1.1, is tolerable. The t-statistics for risk factors in benchmark factor models are also around one in absolute value. Note that risk factors in benchmark factor models are the most renowned risk factors in asset pricing literature. The insignificance of risk prices may be due to the short sample period used in this analysis. The adjusted R^2 is also comparable to that of benchmark factor models once one takes into account the number of factors and the origin of the factors in ICAPM.[17] These findings sug-

[16] The variable itself becomes the risk factor when the variable is too noisy to find the predictor. Bitcoin's return is the case.

[17] Risk factor in ICAPM is derived from the economic equilibrium whereas risk factor constructed by characteristics in the benchmarket factor models is contrived only for the explanation of risk premium.

gest that Bitcoin behaves like an investment asset and is used as a hedging instrument for the time varying utility by investors in the market.

6. Conclusion

This paper contributes to the ongoing efforts to define what kind of Bitcoin is. The existing analyses demonstrate that Bitcoin has similarities with a currency, a commodity and an investment asset since it has some of their statistical properties based on the first and second moment. This paper tries to answer the question on the basis of the tail behaviors of Bitcoin, the dollar, gold and the stock market index. Motivated by the movement that tail behavior is the key feature to determine the property of an asset and for market participants to recognize an asset, I compare the tail behavior of daily return of Bitcoin to that of the dollar, gold and the stock market index. Based on the estimated conditional autoregressive Value at Risk proposed by Engle and Manganelli (2004), the similarities between Bitcoin and the dollar, the stock market index are revealed. While the contemporaneous correlation between Bitcoin and gold is small and not statistically significant, the correlations between Bitcoin and the dollar, the stock maket index are large enough and negatively significant. The significance of correlation suggests that Bitcoin is a kind of a currency and an investment asset. Not only that, the sign of the correlation proves that Bitcoin functions as an alternative financial instrument for the dollar and the stock market.

In order for Bitcoin to be reinforced as an alternative tool for a currency and an investment asset, I run the single predictive regression of Bitcoin's return on the tails of the dollar, gold and the stock market index. As a result, the tail of stock market return turns out to be associated with the risk premium on Bitcoin's return. When the tail risk of the stock market return is high, investors' demand for Bitcoin rises. To sum up, these findings suggest that Bitcoin has a place on the market as an alternative for the means of exchange and investment of wealth, being far from commodity.

In addition, I check if Bitcoin is one of elements in the investment opportunity set on the framework of Merton's (1973) ICAPM. The analyses of contemporaneous correlation and predictive regression claim that the usage of Bitcoin is another instrument for investment asset. If this is the case, risk price related to Bitcoin's return should be priced in the ICAPM setting. The cross-sectional regression estimation results illustrate the Bitcoin's capability of alternative product for investment asset. The risk price related to Bitcoin's return is considerably large and its t-statistics are not deniable when compared to those of empirically successful risk factors, size, value and momentum factors. As Bitcoin is the element of the time-varying investment opportunity set investors face for their portfolio management, it functions as an investment asset like stocks and bonds.

The findings in this paper involve potential implications for practitioners, traders and governments. If Bitcoin is recognized as a means of payment, monetary authority should monitor it for the stable status of his or her own original currency in a new multiple currency regime. According to Gresham's law, the new payment instrument not backed by the existing currency becomes an emerging threat to the authority of monetary policy.[18] Bitcoin can also be the tool for the investment. For investors, Bitcoin would be the innovative way of storing the value, diversifying the portfolio allocation and even making a new profit like creating spread trades. Central bankers will benefit from considering Bitcoin as part of their foreign reserves because it can prevent huge loss in their portfolios consisting of conventional assets. However, investors should be concerned about the likelihood that, due to the non-existence of intrinsic value, the value of Bitcoin can be dramatically collapsed once investors realize that the price of Bitcoin deviates from its true value. This is well illustrated by the example of Tulip Mania in the 17th century. If this is the case, policymaker, perhaps, might impose the new regulations for the safe and stable financial transaction of Bitcoin as he or she did on other investment assets, such as circuit breaker and short-selling restriction.

With the evidence that tail behavior is the crucial feature for distinguishing assets, future research may consider the common factors determining the relationship between the tail of Bitcoin and that of the dollar, stock market index. Given that Bitcoin can be the alternative for investment asset in the tail sense, It also would be interesting to evaluate the change of efficient frontier in three-dimensional space, which is the mean–variance-skewness efficient frontier, when Bitcoin is considered as the element of the investment opportunity set.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.intfin.2020.101202.

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[18] Gresham's law states that bad currency will quickly dominate good currency in circulation.

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