Investing in Times of Fintech Revolution: Ambiguity and Return Risk in Cryptocurrencies*

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Abstract

Rationally justifying Bitcoin markets' huge price fluctuations has remained a persistent challenge for both investors and researchers in this field. A primary reason is our potential weakness towards a robust quantification of unquantifiable risks or ambiguity in Bitcoin returns. This paper introduces a behavioural channel to offer the degree of ambiguity aversion as prominent source of abnormal returns from investment in Bitcoin markets. Using daily data over a period of ten years, we show that in general, Bitcoin investors depict an increasing aversion to ambiguity. Furthermore, we find that Bitcoin investors earn abnormal returns only when ambiguity is low. Robustness exercise reassures validity of our results.

JEL classification: C0; G1

Keywords: Bitcoin; Ambiguity; Abnormal returns

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1. Introduction

"But Bitcoin is an example of ambiguity, and the efficient market theory does not capture what is going on in the market for this cryptocurrency."

—— Robert Shiller[1]

"Bitcoin valuation is 'exceptionally ambiguous' ".

—— Robert Shiller[2]

1.1. Contextualisation

These quotes from Robert Shiller could hardly be more accurate in describing the aim of the present study, in which we attempt to answer the broad question of how ambiguity determines abnormal returns in virtual currencies, such as Bitcoin. Virtual currencies represent both the emergence of a new form of currency and a new payment technology to purchase goods and services. Among virtual currencies, Bitcoin has undoubtedly emerged as the most prominent new form of currency and a new payment technology to purchase goods and services (Dwyer, 2015; White et al., 2020). Due to its importance to the financial institutions, its susceptibility to large-scale price manipulations, and investors' increasing tendency of its choice over other established theory-backed assets (Trimborn and Härdle, 2017), ambiguity plays a major role in quantifying the magnitude of abnormal returns. This paper fills a gap in the literature by

[1] https://www.nytimes.com/2017/12/15/business/bitcoin-investing.html
[2] https://www.cnbc.com/2017/12/19/robert-shiller-bitcoin-valuation-is-exceptionally-ambiguous.html

rigorously studying the impact of ambiguity in Bitcoin returns in the spirit of Brenner and Izhakian's (2018).[3]

As the leading cryptocurrency, Bitcoin continues to draw high attention from investors, entrepreneurs, regulators and the general public. Many of the recent public discussions relating to Bitcoin have been triggered by the substantial changes in their prices (García-Monleón, et al., 2021), claims that the market for Bitcoin is a bubble without any fundamental value, and also concerns about evasion of regulatory and legal oversight (Akyildirim, 2020; Alexander and Heck, 2020). A large strand of literature attempts to understand market phenomena through the lens of the traditional neoclassical finance theories (Borri, 2019; Corbet et al, 2020l;). Specifically, Urquhart (2016) shows that Bitcoin returns do not follow the random walk model, based on which he concludes that the Bitcoin market exhibits a significant degree of inefficiency, particularly in the early years of its existence. In the time and frequency domains, Corbet et al. (2018) analyze the relationship between the return of three different cryptocurrencies and a variety of other financial assets, showing lack of relationships between crypto- and other assets. Liu and Tsyvinski (2020) investigate whether cryptocurrency pricing bears any similarity to stocks: however, none of the risk factors explaining movements in stock prices applies to cryptocurrencies in their sample. Moreover, movements in exchange rates, commodity prices, or macroeconomic factors of traditional significance for other assets play little to no role for most cryptocurrencies.

[3] Camerer and Weber, 1992 in an early effort provided evidence, theoretical explanations, and applications of research on ambiguity and subjective expected utility. Recent efforts include a design of a survey module by Cavatorta and Schroeder, 2019 to experimentally validate ambiguity preference that has wider applications for economics and finance.

All that apart, Bitcoin is an example of uncertainty and ambiguity, and the neoclassical theory fails to explain the behavior in the market for this cryptocurrency.[4] There has not been enough daily information coming in to rationally justify Bitcoin's huge price fluctuation. This type of uncertainty may arise for two reasons: (1) the technology is rather complicated and opaque to unsophisticated traders, and (2) the fundamental value of cryptocurrencies is unclear. As we highlighted above, even if it is strictly positive, it is likely to be derived from intangible factors and, as such, is rather uncertain. Therefore, we wish to extend our understanding of this cryptocurrency market from a behavioral finance perspective. This paper examines the role of the perspective of unquantifiable risk, or ambiguity in Bitcoin returns.

The notion of uncertainty has been investigated in the literature since the seminal works of Keynes (1921) and Knight (1921) from two perspectives: risk and ambiguity. While risk is a situation in which the beliefs of a decision maker (DM) are captured by a unique probability measure, ambiguity is a situation in which a DM's beliefs are not pinned down by a unique probability measure because of a lack of information(Snow 2010; Cavatorta and Schroder 2018). When investors choose between different assets, their knowledge of future returns is critical. When they are fully confident about the return of the investment, we can consider it a safe asset.

[4] A recurrent issue in financial theories is to study how agents make decisions on investments under risk. This is different from the concept of ambiguity, which is the subject of our study. While risk refers to situations where the perceived likelihoods of events can be represented by a unique probability distribution, ambiguity refers to situations where an agent's subjective knowledge about likelihoods of contingent events is consistent with multiple probability distributions. Importantly, the agent does not know what the precise distribution is.

In another recent study, Driouchi et al. (2018) investigate the behavior of US index put option holders during the pre-crisis and credit crunch period 2006–2008. They find evidence of ambiguity in the US index options market during 2006–2008 and measure the effect of ambiguity on realized index volatility that is implied directly from observed option prices. Based on portfolio data from a large financial institution in France, Bianchi and Tallon (2018) show that ambiguity averse investors are relatively more exposed to the French stock market than to the international stock market. This result implies that ambiguity aversion plays a significant role in explaining home bias in equity markets. Most research on ambiguity focuses on traditional financial assets while a few studies explore the role of ambiguity in the upcoming digital currency such as Bitcoin.

In this paper, we refer to ambiguity as uncertainty over the probability of potential future outcomes, while risk refers to uncertainty over those outcomes following Knight (1921). Specifically, we estimate ambiguity using five-minute Bitcoin returns based on the model of Brenner and Izhakian (2018). Our findings show that ambiguity plays an important role in Bitcoin returns; that is, investors take into account ambiguity when they price ambiguity. Our evidence further implies that investors show an increasing aversion to ambiguity.

We conduct a battery of robustness tests to verify our findings. For example, we use the forward-looking implied volatility from the S&P 500 index i.e. VIX in our regression model as VIX is used as a proxy for ambiguity in prior studies (e.g., Williams, 2015). We also control for higher moments including skewness and kurtosis. Further, we test for unstructureed attitude towards risk without imposing a specific functional form (e.g., constant relative risk aversion or constant absolute risk) over attitude towards risk.

In the spirit of Baker and Wulger (2006), we further examine the performance of Bitcoin returns conditional on ambiguity. Liu and Tsyvinski (2020) show that cryptocurrency returns cannot be explained by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama–French (1993) three-factor model (FF3FM), the Carhart (1997) momentum-extended FF3FM, and the Fama–French (2015) five-factor model (FF5FM). We first confirm their findings and further show that investors earn the abnormal returns of Bitcoins only when ambiguity is low but not when ambiguity is high.

1.2. Contribution

We contribute to the literature in several ways. First, we make a behavioural attempt at identifying the potential impact of ambiguity on asset pricing and the risk-return relationship. This is useful, because the use of Bitcoin, in a wider portfolio management strategy, has been shown to provide hedging benefits (Kajtazi and Moro, 2018; Atsalakis et al. 2019; Ma et al., 2020; Thampanya et al., 2020); yet Bitcoin markets are typically characterized by crashes (Fry and Cheah, 2016), excessive volatility (Katsiampa, 2017), and positive returns when the fundamental value is shown to be zero (Cheah and Fry, 2015). It is well known that traditional asset pricing models have difficulties in explaining the Bitcoin returns. Our study extends our understanding of the cryptocurrency market from a behavioral finance perspective, and we find that ambiguity plays an important role in explaining the abnormal returns of Bitcoin.

Second, our study is related to general studies which have focused mainly on the theoretical aspects of attitudes toward (aversion to) ambiguity, rather than on the actual measurement of ambiguity. Only a few studies used market data to measure ambiguity; for example, Ulrich (2013) uses entropy of inflation and Williams (2015) uses the Volatility Index (VIX). Following Brenner and Izhakian (2018), we explore the importance of ambiguity in the cryptocurrency market using Bitcoin data.

Our study has important implications for sustainability. By studying the unique ambiguous feature of Bitcoin, we aim to at least partially take into account "the dynamics" of this highly volatile currency. This way, we aim to empower investors — small or big, to be able to make informed decisions regarding their choices. Moreover, our proposal has practical importance too. Not only individual investors but various funds—such as Crypto Fund AG—have risk exposure to Bitcoin. This paper helps to shed light on their investment decisions on Bitcoin. If investors can indeed earn the risk premium after adjusting for systematic risk, then it is helpful to allocate their wealth to Bitcoin. However, if the risk premium is conditional on ambiguity as shown in our results, caution should be exercised by investors in "real-time" trading because the risk premium becomes insignificant during periods of high ambiguity.

Our work also has important implications for policy makers. While Bitcoin markets are largely unregulated under current market conditions, policy makers can use our study to guide regulations if they plan to implement these in the future. For example, policy makers can use our method to estimate the ambiguity of Bitcoin which can help to identify potential market bubbles. They can also use the ambiguity of Bitcoin to cool-off trading in the Bitcoin markets.

The remainder of the paper proceeds as follows. Section 2 discusses the construction of the ambiguity measure. Section 3 describes the data while section 4 reports the main empirical results and performs various robustness tests. Section 5 concludes the paper.

2. The ambiguity measure

As we noted before, ambiguity refers to situations where an agent's subjective knowledge about likelihoods of contingent events is consistent with multiple probability distributions, there has been an evolution in the way we measure ambiguity, focusin in particular, on the way we embed information. For the purpose of our paper, we follow Izhakian (2018) and define ambiguity as

$$\mho^2[r] = \int E[\varphi(r)]Var[\varphi(r)]dr, \tag{1}$$

where r is the Bitcoin return, $\varphi(r)$ is the marginal probability, $E[]$ is the expectation, and $Var[]$ is the variance. While risk can be measured by the volatility of returns, $\mho^2[r]$ captures the fact that ambiguity can be measured by the volatility of probabilities (Rothschild and Stiglitz, 1970). By construction, $\mho^2[r]$ is independent of risk, attitudes towards risk and/or attitude towards ambiguity and takes into account the variance of all the moments of the outcome distribution (Brenner and Izhakian, 2018).

In line with Andersen et al. (2001), we use five-minutes intervals price to compute returns to minimize microstructure effects. For each day we use five-minute returns to compute the normalized (by the number of intraday observations) daily mean (μ) and variance of the return

(σ), respectively. Following Scholes and Williams (1977), we estimate σ by taking into account the adjustment for nonsynchronous trading. Specifically, σ is computed as

$$\sigma_t^2 = \sum_{i=1}^{N_t} (r_{i,t} - E[r_{i,t}])^2 + \sum_{i=2}^{N_t} (r_{i,t} - E[r_{i,t}])(r_{i,t-1} - E[r_{i,t-1}]), \tag{2}$$

where there are N_t five-minute returns, $r_{i,t}$, in day t.

Following Brenner and Izhakian (2018), we assume that the intraday returns are normally distributed. We then compute for each day the cumulative probability of favorable returns (gain), $P(r \geq r_f) = 1 - \Phi(r_f; \mu, \sigma)$, where any return greater than the risk-free rate is considered favorable.

We represent each daily return distribution by a histogram. Specifically, we divide the range of daily returns, from -6% to +6%, into 60 intervals (bins), each of width 0.2%. For each day, we compute the probability of the return being in each bin. In addition, we compute the probability of the return being lower than -6% and higher than +6%. We then compute the mean and the variance of the probabilities for each of the 62 bins separately. Finally, we estimate the degree of ambiguity of each month using the following discrete form

$$\begin{aligned} \mho^2[r] &= \frac{1}{\omega(1-\omega)} \times \Bigg\{ E\big[\Phi(r_0; \mu, \sigma)\big] Var\big[\Phi(r_0; \mu, \sigma)\big] \\ &+ \sum_{i=1}^{60} E\big[\Phi(r_i; \mu, \sigma) - \Phi(r_{i-1}; \mu, \sigma)\big] \times Var\big[\Phi(r_i; \mu, \sigma) - \Phi(r_{i-1}; \mu, \sigma)\big] \\ &+ E\big[1 - \Phi(r_{60}; \mu, \sigma)\big] Var\big[1 - \Phi(r_{60}; \mu, \sigma)\big] \Bigg\}, \end{aligned} \tag{3}$$

where $r_0 = -0.06$ and $\omega = r_1 - r_{i-1} = 0.002$. The ambiguity in day t is the rolling mean of Eq. (3) over 30 days.

3. Data

We collect daily Bitcoin data including closing price, high price, low price (all prices are in dollars), and volume (between 13/09/2011 and 30/11/2019) from bitcoincharts.com. We download the daily excess market returns ($MKTRF$), size factor (SMB), book-to-market factor (HML), profitability factor (RMW), investment factor (CMA), momentum factor (UMD), and treasury bill rate (RF) from Kenneth French's website.[5] We download the daily q-factors including the size factor (ME), investment factor (I/A), return-on-equity factor (ROE), and expected growth factor (EG) from global-q.org.[6] We download the CBOE (Chicago Board Options Exchange) Volatility Index from Wharton Research Data Services. We use the CBOE S&P 500 Volatility Index (VIX). The Bitcoin return is the difference between closing price at day t and day $t-1$ divided by closing price at day $t-1$. We obtain five-minute bitcoin data from Bitcoincharts.

The ambiguity measure of Bitcoin is based on the five-minute intra-day returns. Panel A of Table 1 reports the summary statistics. The average of five-minute returns is 0.5%, the standard deviation is 4.2%, and the Sharpe ratio is 24.2% in terms of daily returns. Brenner and Izhakian (2018) highlight that the high frequency realized returns can be a poor proxy for long run expected return due to the large standard errors.

[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[6]http://global-q.org/index.html. Hou et al. (2015) and Hou et al. (2019, 2020) provide detailed discussions on factor constructions.

Panel B of Table 1 continues to report the summary statistics in daily frequencies. The daily Bitcoin return in excess of risk-free rate is 0.4%. Our risk measure, the standard deviation of the prior 30 daily returns (σ), has a mean of 3.8%. Another risk measure, the absolute deviation ($\vartheta = E\big[\ |\ r - E[r]\ |\ \big]$) which is the average absolute daily deviation of returns from the rolling prior 30 average daily return, has a mean of 2.7%. The average of favorable returns is 0.540 similar to the favorable returns of US equity index as in Brenner and Izhakian (2018). The average degree of ambiguity ($\mho$) is 1.173. Figure 1 plots the time-series of realized Bitcoin ambiguity and excess returns from February 2012 to November 2019. As can be seen, some high ambiguity periods are related to low Bitcoin returns and price crashes including the periods of August 2012, April 2013, January 2015, and February 2018, similar to the findings of Brenner and Izhakian (2018). Brenner and Izhakian (2018) argue that this is because investors have concerns over high price (low rates of return) period due to "the correction" (a price drop after a price soar). This correction leads to high ambiguity, i.e., the variance of probability of a price drop. Panel C of Table 1 reports the correlation between key variables. The favorable probability is positively related to returns, consistent with Brenner and Izhakian (2018).

4. Empirical results

4.1. Estimating expected values

In our empirical tests, we use the estimated expectations of the following four variables, namely, the volatility (σ), the average absolute deviation of returns from the expected return (ϑ), the probability of favorable returns (P), and the degree of ambiguity ($\mho$). Following

Andersen et al. (2003) and Brenner and Izhakian (2018), we estimate the expected volatility based on realized volatility using the coefficients estimated by the time-series autoregressive moving average ARMA(p, q) model with the minimal corrected Akaike information criterion (AICC):

$$ln\sqrt{\nu_t} = \Psi_0 + \epsilon_t + \Psi_1 ln\sqrt{\nu_{t-1}} + \theta_1 \epsilon_{t-1}, \tag{4}$$

where ν_t is realized volatility in day t. We use the natural logarithm of volatility ($ln\sqrt{\nu_t}$) to avoid negative expected volatility estimates as ν_t is skewed following Brenner and Izhakian (2018). The expected volatility (ν^E_{t+1}) is then estimated as the fitted value from Eq. (4), i.e., $\nu^E_{t+1} = e^{2\widehat{ln\sqrt{\nu_t}} + Var[u_t]}$, where $Var[u_t]$ is the variance of error term. For each day, we use a rolling window regression with the prior 365 days to estimate Eq. (4). Similarly, we estimate the expected absolute deviation, ϑ, using its monthly realized values, to obtain its expectation of ϑ^E.

We also estimate expected ambiguity using ARMA(p, q) similar to the method used to estimate the expected volatility. Specifically, we estimate the expected ambiguity based on realized ambiguity using the coefficients estimated by the time-series model:

$$ln\mho_t = \Psi_0 + \epsilon_t + \Psi_1 ln\mho_{t-1} + \theta_1 \epsilon_{t-1}, \tag{5}$$

where $\mho_t$ is realized ambiguity in day t. The expected ambiguity ($\mho^E_{t+1}$) is then estimated as the fitted value from Eq. (5), i.e., $\mho^E_{t+1} = e^{2\widehat{ln\mho_t} + Var[u_t]}$, where $Var[u_t]$ is the variance of error term. Further, we estimate expected probability of unfavorable returns using ARMA(p, q). Specifically, we estimate the expected ambiguity based on realized ambiguity using the coefficients estimated by the time-series model:

$$lnQ_t = \Psi_0 + \epsilon_t + \Psi_1 lnQ_{t-1} + \theta_1 \epsilon_{t-1}, \tag{6}$$

where $Q_t = \frac{P_t}{1-P_t}$ and P_t is realized probability of favorable returns in day t. The expected probability (P^E_{t+1}) is then estimated as the fitted value from Eq. (6), i.e., $Q^E_{t+1} = \frac{e^{2\widehat{lnQ_t}+0.5Var[u_t]}}{1-e^{2\widehat{lnQ_t}+0.5Var[u_t]}}$, where $Var[u_t]$ is the variance of error term.

Panel A of Table 2 reports summary statistics of estimated values of volatility, absolute deviation, the probability of favorable returns, and ambiguity. Each value is obtained from the fitted value from the ARMA model discussed above. Compared with the realized values in Panel B of Table 1, we find that the variation of expected values are generally smaller than the corresponding realized values. This is similar to Brenner and Izhakian (2018).

4.2. Main empirical tests

We now turn to test the impact of ambiguity on returns using the following empirical design. The expected probability is between 0.368 and 0.768. We divide this range into 37 equal bins of 0.01 each,indexed by i.[7] For example, the first bin is from 0.38 to 0.39. The few values lower that 0.38 are indexed as $i = 1$, while the few values higher than 0.75 are index as $i = 37$. We construct a dummy variable for each probability bin. Specifically, the dummy variable

[7] Brenner and Izhakian (2018) also use bins of 0.01 each.

(D_i) is equal to one if the expected probability of favorable returns in a day t belongs to bin i, and zero otherwise. The empirical model is described by:

$$\begin{aligned} r_{t+1} - r_{f,t+1} &= \alpha + \gamma \cdot \nu_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E \\ &+ \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t \end{aligned} \tag{7}$$

where P_t^E is the midpoint of probability bin i. It is worth noting that the attitude toward ambiguity varies when the expected probability of favorable returns changes, while the attitude towards risk remains constant.

The coefficients from Eq. (7) can be written as $\eta(P^E) = \hat{\eta} + \hat{\eta}_i$, which represents investors' attitude towards ambiguity conditional on the expected probability of favorable returns (P^E) falling into bin i. A negative value of $\eta(P^E)$ means that investors show ambiguity-loving behavior which leads to a negative ambiguity premium, while a positive value means that investors show ambiguity-averse behavior which leads to a positive ambiguity premium. Further, a high $\hat{\eta}_i$ falling into the bins of low probabilities of favorable returns implies an increasing pursuit of ambiguity, while a high $\hat{\eta}_i$ falling into the bins of high probabilities of favorable returns implies an increasing aversion to ambiguity.

We run both ordinary least square (OLS) and weighted least square (WLS) regressions to test Eq. (7). Specifically, in the WLS regressions, the weights are inversely proportional to the sum of the estimated risk and the estimated ambiguity, i.e., $\frac{1}{\sqrt{\nu_t^E + \mho_t^E}}$ following French, Schwert, and Stambaugh (1987) and Brenner and Izhakian (2018).

Table 3 reports the OLS and WLS regressions results. In the first specification, expected volatility, as a measure of risk, is the only independent variable. It has a positive coefficient, consistent with the well-known facts that high risk is related to high returns. We then introduce expected ambiguity in the subsequent regressions. We first focus exclusively on expected ambiguity. We find that it is insignificant, consistent with Brenner and Izhakian (2018). Next, we investigate the effect of expected ambiguity on returns conditional on attitude toward ambiguity as specified by Eq. (7). The ambiguity coefficient in high probability bins of favorable returns (e.g., η_{34}) is significant, indicating that Bitcoin investors have increasing aversion towards ambiguity.

4.3. Robustness: Alternative volatility measures

In this subsection, we use alternative volatility measures rather than the expected volatility in our regressions. Cheah, Luo, Zhang, and Sung (2020) show that the forward-looking implied volatility (VIX) from S&P index options can predict Bitcoin returns. Cao, Wang, and Zhang (2005) and Garlappi, Uppal, and Wang (2007) suggest the role of the volatility of mean in ambiguity. Following these work, we use the VIX index and the volatility of mean. Consistent with our previous tests, we use the expected average volatility, $VOLM^E$, which is estimated from an ARMA (p,q) model of the realized standard deviation of the prior 30 daily average returns. Average returns are the rolling average over the prior 30 days. Specifically, we examine the role of ambiguity based on the following two equations:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VIX_t + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \varepsilon_t. \quad (8)$$

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VOLM_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \varepsilon_t. \quad (9)$$

Table 4 reports the results under alternative volatility measures. The effect of ambiguity on returns is robust to the alternative risk measures. Specifically, the ambiguity coefficient in high probability bins of favorable returns (e.g., η_{34}) remains significant, which provides support for increasing aversion towards ambiguity of Bitcoin investors.

4.3.1. Higher-order moments

In this section, we conduct further robustness tests by taking into account higher order moments; namely, skewness, kurtosis, and volatility of volatility. Prior studies show that higher moments play an important role in asset prices. Kelly and Jiang (2014) and Bollerslev et al. (2015) show that skewness is related to tail and crash risk. Jondeau et al. (2019) find that average skewness can predict stock market returns. Cheah et al. (2020) examine the role of skewness and kurtosis in Bitcoin return predictability. Brandt and Kang (2004) and Brenner and Izhakian (2018) argue that ambiguity can be related to volatility of volatility. Following these studies, we run the following equation to take into account skewness ($Skew$), kurtosis ($Kurt$), and volatility of volatility ($VOLV$)

$$
\begin{aligned}
r_{t+1} - r_{f,t+1} &= \alpha + \gamma \cdot \nu_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) \\
&+ \beta_1 \cdot Skew_t^E + \beta_2 \cdot Kurt_t^E + \beta_3 \cdot VOLV_t^E + \varepsilon_t. \qquad (10)
\end{aligned}
$$

Consistent with our prior tests, we use the expected values which are estimated from ARMA (p,q) models. Table 5 reports the results, showing the effect of ambiguity on returns after controlling for expected skewness ($Skew^E$), kurtosis ($Kurt^E$), and volatility of volatility ($VOLV^E$). Consistent with prior results, we again find that Bitcoin investors have increasing aversion towards ambiguity.

4.4. Robustness: Unstructured risk attitudes

Following Brenner and Izhakian (2018), in this subsection we test a further discrete model where attitudes towards ambiguity depending on wealth and risk attitudes contain a finite number of values. Specifically, we divide the wealth range (the logarithm of gross Bitcoin return in excess of risk-free rate) into nine equal bins of 0.5 each, indexed by i. For example, the first bin is from 0.5 to 5. The few values lower that 0.5 are indexed as $i = 1$, while the few values higher than 5 are indexed as $i = 9$. The number of wealth bins is consistent with the number of expect probability bins as in Eq. (7).

We then generate a dummy variable for each wealth bin. If the wealth in a give day t belongs to bin j, the dummy variable $C_{j,t}$ is equal to one and zero otherwise. Specifically, we run the following equation to take into account wealth,

$$r_{t+1}-r_{f,t+1} = \alpha+\gamma\cdot\nu_t^E+\sum_{j=2}^{9}\gamma_j\cdot\left(C_{j,t}\times w_j\times\nu_t^E\right)+\eta\cdot(\mho_t^2)^E\times\vartheta_t^E+\sum_{i=2}^{9}\eta_i\cdot\left(D_{i,t}\times P_t^E\times(\mho_t^2)^E\times\vartheta_t^E\right)+\varepsilon_t, \tag{11}$$

where w_j is the midpoint of wealth bin j. It is worth noting that risk attitudes in the model can comove with the wealth. $\gamma+\gamma_j$ captures Bitcoin investors' attitudes toward risk conditional on the wealth w falling into wealth bin j. If the sum is negative, it indicates that investors exhibit risk-loving behaviors which implies a negative risk premium. Conversely, if the sum is positive, it indicates that investors exhibit risk-verse behaviors which implies a positive risk premium.

Table 6 reports the results. We find that $\gamma+\gamma_j$ is positive. Thus, investors exhibit risk-verse behaviors and result in a positive risk premium. Further, Bitcoin investors still have increasing aversion towards ambiguity according to the ambiguity coefficient in high probability bins of favorable returns.

4.5. Performance of Bitcoin returns conditional on ambiguity

Liu and Tsyvinski (2020) show that cryptocurrency returns cannot be explained by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama–French (1993) three-factor model (FF3FM), the Carhart (1997) momentum-extended FF3FM, and the Fama–French (2015) five-factor model (FF5FM). In the spirit of Baker and Wulger (2006), we examine the performance of Bitcoin returns conditional on ambiguity. Hibbert and Stan (2020) examine the pricing of ambiguity in the cross-sectional stock returns of various portfolios. Following these studies, we examine whether ambiguity helps us to understand the performance of Bitcoin returns.

We measure the performance of Bitcoin returns based on several asset pricing models including the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), the Fama–French (1993) three-factor model (FF3FM), the Carhart (1997) momentum-extended FF3FM, the Fama–French (2015) five-factor model (FF5FM), and the Hou et al. (2020) five-factor model (q5FM). Specifically, we run the following time-series regressions:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \varepsilon_{i,t}, \tag{12}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \varepsilon_{i,t}, \tag{13}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,w} f_{WML,t} + \varepsilon_{i,t}, \tag{14}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,s} f_{SMB,t} + \beta_{i,h} f_{HML,t} + \beta_{i,r} f_{RMW,t} + \beta_{i,c} f_{CMA,t} + \varepsilon_{i,t}, \tag{15}$$

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,m} f_{MKT,t} + \beta_{i,me} f_{ME,t} + \beta_{i,roe} f_{ROE,t} + \beta_{i,ia} f_{IA,t} + \beta_{i,eg} f_{EG,t} + \varepsilon_{i,t}, \tag{16}$$

where $R_{i,t}$ is the day-t return of portfolio i, $R_{f,t}$ is the risk-free rate for day t, $f_{MKT,t}$ is the day-t value of the market factor, $f_{SMB,t}$ is the day-t value of the Fama–French (FF) size factor, $f_{HML,t}$ is the day-t value of the FF book-to-market factor, $f_{WML,t}$ is the day-t value of the momentum factor, $f_{RMW,t}$ is the day-t value of the FF profitability factor, $f_{CMA,t}$ is the day-t value of the FF investment factor, $f_{ME,t}$ is the day-t value of the HMXZ (i.e., Hou et al., 2020) size factor, $f_{ROA,t}$ is the day-t value of the HMXZ profitability factor, and $f_{I/A,t}$ is the day-t value of the HMXZ investment factor, and $f_{EG,t}$ is the day-t value of the HMXZ expected growth factor.

Panel A of Table 7 reports the performance of the Bitcoin returns under various asset pricing models over the whole sample period. Consistent with Liu and Tsyvinski (2020), we find that the abnormal return (α) of Bitcoin is significantly positive under the CAPM, the FF3M, the momentum-extended FF3FM, the FF5FM, and the q5FM. For example, the abnormal return of Bitcoin under the FF5FM is 0.004 ($t = 4.26$). Further, the risk loadings (i.e., the coefficients of risk factors, β) are all insignificant, indicating that well-known equity risk factors have difficulties in explaining the Bitcoin returns. This is similar to the findings of Cheah et al. (2020) which show that equity risk factors have no predictive power on Bitcoin returns.

Panels B and C of Table 7 report the performance of the Bitcoin returns under various asset pricing models over high and low ambiguity periods. High ambiguity periods are those above the median of ambiguity while low ambiguity period are those below the median of ambiguity. As can be seen, Bitcoin investors earn insignificant abnormal returns during high ambiguity periods. The premium is only present during low ambiguity periods no matter which asset pricing mode is tested. For example, the abnormal return of Bitcoin under the FF5FM during high ambiguity periods is 0.002 ($t = 1.02$) while it is 0.006 ($t = 7.37$) during low ambiguity periods. Comparing the performance over the full periods with that during low ambiguity periods, we find that the abnormal return is even more pronounced. Overall, our results indicate that ambiguity plays an important role in understating the Bitcoin performance.

5. Conclusion

Investors invariably face a choice between known risks over unknown risks and therefore, an ambiguity-averse investor would rather choose an alternative where the probability distribution of an investment outcome is known over one where the probabilities that are unknown. This paper studies, to the best of our knowledge the first time, the important role of ambiguity in Bitcoin returns, an investment portfolio that has caught investors' attention like none other in recent times. Because virtual currencies like Bitcoin, do not conform to conventional asset pricing theory and hence their returns cannot be theoretically predicted, at least partially, alternative tools are needed to characterize observed abnormalities in their returns. We bring in the classical case of ambiguity, contextualised through a design of improved methodological underpinning that employs value of information, to understand the extent the degree of ambiguity aversion contributes to the variable magnitudes of abnormal returns.

Following the approach set out by Brenner and Izhakian (2018) and Baker and Wulger (2006), we find that Bitcoin investors have increasing aversion towards ambiguity, and such a characterisation helps in quantifying the extent of the abnormal returns of Bitcoin. We examine the performance of Bitcoin returns conditional on ambiguity. Towards this we use several asset pricing models and distinguish the performance of Bitcoin returns between high and low ambiguity periods. An important finding from this exercise is that Bitcoin investors earn very low abnormal returns during periods of high ambiguity in contrast to the period of low ambiguity irrespective of the asset price models we employ. Our results are robust to alternative measures of volatility in Bitcoin prices, higher order moments (such as skewness) that determine asset prices, and design of a further discrete model where attitude towards ambiguity depends on wealth and risk attitudes.

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Table 1 **Descriptive statistics**

This table reports descriptive statistics and correlations for the following variables of Bitcoin:

RET: daily Bitcoin returns;

σ: daily volatility;

ϑ: daily absolute deviation;

P: daily probability;

$\mho$: daily ambiguity.

Panel A reports the intra-day summary statistics. The mean return, μ^{5m}, is the daily average five-minute returns. The return standard deviation, σ^{5m}, is the daily standard deviation of five-minute returns. Panel B reports the daily summary statistics. The return, RET, is the daily returns of Bitcoin. The volatility, σ, is the standard deviation of the prior 30 daily returns. The absolute deviation, ϑ, is the average absolute daily deviation of returns from the rolling prior 30 average daily returns. The mean probability, P, is the average daily probability of favorable returns over a month. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. Probabilities are based on the daily mean and variance of returns computed from the five-minute returns. Ambiguity, $\mho$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Panel B reports the correlations of the estimated expected values.

Panel A: Intra-day descriptive statistics					
	μ^{5m}	σ^{5m}	$\frac{\mu^{5m}}{\sigma^{5m}}$		
Mean	0.005	0.042	0.242		
Stdev	0.062	0.069	4.005		
Median	0.003	0.030	0.120		
Skewness	13.278	23.627	41.265		
Kurtosis	455.503	848.383	1909.015		
Panel B: Daily descriptive statistics					
	RET	σ	ϑ	P	$\mho$
Mean	0.004	0.038	0.027	0.543	1.173
Stdev	0.045	0.024	0.017	0.069	0.701
Medium	0.002	0.033	0.023	0.539	0.996
Skewness	0.047	2.237	2.203	0.405	0.877
Kurtosis	17.120	10.846	10.513	2.839	2.958
Panel C: Correlation					
	RET	σ	ϑ	P	$\mho$
σ	0.031	1.000			
ϑ	0.031	0.978	1.000		
P	0.191	0.197	0.202	1.000	
$\mho$	-0.060	0.738	0.764	-0.210	1.000

Table 2 **Descriptive statistics of expected values**

This table reports descriptive statistics and correlations for the following variables of Bitcoin:

σ^E: daily expected volatility;

ϑ^E: daily expected absolute deviation;

P^E: daily expected probability;

$\mho^E$: daily expected ambiguity.

Panel A reports the summary statistics. For each day, the expected values are estimated based only on their realized values over the prior 365 days and using the ARMA(p, q) model with the minimal AICC. The expected volatility, σ^E, is the standard deviation of the prior 30 daily returns. The expected absolute deviation ϑ^E is estimated from the average absolute daily deviation of returns from the rolling prior 30 average daily returns. The expected ambiguity, $\mho^E$, is estimated from the realized ambiguity, where ambiguity $\mho^E$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Probabilities of returns are based on the daily mean and variance of returns computed from five-minute returns. The expected probability of favorable returns, P^E, is estimated from the rolling averages of the daily probabilities of favorable returns over the prior 30 days. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. Panel B reports the correlations of the estimated expected values.

Descriptive statistics				
	σ^E	ϑ^E	P^E	$\mho^E$
Mean	0.002	0.001	0.542	1.998
Stdev	0.003	0.002	0.070	2.208
Medium	0.001	0.001	0.535	1.087
Skewness	4.888	4.275	0.506	1.635
Kurtosis	31.899	26.391	2.903	5.212
Correlation				
	σ^E	ϑ^E	P^E	$\mho^E$
ϑ^E	0.956	1.000		
P^E	0.258	0.248	1.000	
$\mho^E$	0.580	0.654	-0.188	1.000

Table 3 **Main OLS and WLS regression tests**

The table reports the results of the tests of the main model. Panels A and B report the results obtained using OLS and WLS regressions in the following equation:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot \nu_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t.$$

The estimated expected value of each variable at time t is the out-of-sample fitted value of the ARMA(p, q) model with the minimal AICC over its realized values over the prior 365 days. The expected volatility, σ^E, is the standard deviation of the prior 30 daily returns. The expected absolute deviation ϑ^E is estimated from the average absolute daily deviation of returns from the rolling prior 30 average daily returns. The expected ambiguity, $\mho^E$, is estimated from the realized ambiguity, where ambiguity $\mho^E$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Probabilities of returns are based on the daily mean and variance of returns computed from five-minute returns. The expected probability of favorable returns, P^E, is estimated from the rolling averages of the daily probabilities of favorable returns over the prior 30 days. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. The dummy variable (D_i) is equal to one if the expected probability of favorable returns in a day t belongs to bin i, and zero otherwise. In Panel B, the weights are inversely proportional to the sum of the estimated risk and the estimated ambiguity. The numbers in parentheses are t-statistics.

	Panel A: OLS			Panel B: WLS		
α	0.002	0.003	0.002	0.003	0.004	0.003
	(2.15)	(2.28)	(1.95)	(3.16)	(3.66)	(3.04)
γ	0.420		0.535	0.460		0.246
	(1.53)		(0.56)	(1.32)		(0.22)
θ		0.000			-0.000	
		(0.47)			(-0.08)	
η			-0.091			-0.082
			(-0.77)			(-0.44)
η_2			0.554			0.590
			(1.32)			(0.90)
η_3			0.077			0.049
			(0.22)			(0.09)
η_4			0.188			0.182
			(0.60)			(0.37)
η_5			0.409			0.375
			(1.40)			(0.82)
η_6			0.146			0.142
			(0.51)			(0.32)
η_7			0.173			0.113
			(0.63)			(0.26)
η_8			0.210			0.162
			(0.75)			(0.37)
η_9			0.200			0.155
			(0.76)			(0.38)
η_{10}			0.318			0.287
			(1.25)			(0.72)
η_{11}			0.056			0.025
			(0.23)			(0.07)
η_{12}			0.167			0.154
			(0.69)			(0.40)
η_{13}			0.192			0.182
			(0.80)			(0.48)

Table 3 (Continued)

	Panel A: OLS			Panel B: WLS		
η_{14}			0.116			0.090
			(0.50)			(0.25)
η_{15}			0.180			0.156
			(0.78)			(0.43)
η_{16}			0.048			0.017
			(0.21)			(0.05)
η_{17}			0.218			0.220
			(0.97)			(0.62)
η_{18}			0.184			0.175
			(0.85)			(0.52)
η_{19}			0.190			0.183
			(0.89)			(0.55)
η_{20}			0.131			0.121
			(0.63)			(0.37)
η_{21}			0.161			0.148
			(0.78)			(0.46)
η_{22}			0.090			0.086
			(0.43)			(0.26)
η_{23}			0.092			0.087
			(0.46)			(0.28)
η_{24}			0.118			0.118
			(0.59)			(0.38)
η_{25}			0.659			0.582
			(3.18)			(1.83)
η_{26}			0.399			0.424
			(1.96)			(1.34)
η_{27}			0.036			0.004
			(0.17)			(0.01)
η_{28}			-0.147			-0.136
			(-0.74)			(-0.45)
η_{29}			-0.156			-0.162
			(-0.79)			(-0.54)
η_{30}			-0.031			0.026
			(-0.16)			(0.09)
η_{31}			0.199			0.210
			(1.03)			(0.71)
η_{32}			0.314			0.323
			(1.67)			(1.13)
η_{33}			0.056			0.085
			(0.30)			(0.30)
η_{34}			1.594			1.657
			(6.33)			(4.80)
η_{35}			0.000			0.096
			(0.00)			(0.30)
η_{36}			-0.067			-0.003
			(-0.23)			(-0.01)
η_{37}			-0.403			-0.287
			(-1.43)			(-0.81)
Adj-R^2	0.0005	-0.0003	0.0726	0.0006	-0.0000	0.0335

Table 4 **VIX and expected average volatility regression tests**

The table reports the results obtained using OLS in the following equations:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VIX_t + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \varepsilon_t.$$

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VOLM_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \varepsilon_t.$$

The estimated expected value of each variable at time t is the out-of-sample fitted value of the ARMA(p, q) model with the minimal AICC over its realized values over the prior 365 days. VIX is the value of VIX index. The expected average volatility, $VOLM^E$, is estimated from the realized standard deviation of the prior 30 daily average returns and average returns are the rolling average over the prior 30 days. The expected absolute deviation ϑ^E is estimated from the average absolute daily deviation of returns from the rolling prior 30 average daily returns. The expected ambiguity, $\mho^E$, is estimated from the realized ambiguity, where ambiguity $\mho^E$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Probabilities of returns are based on the daily mean and variance of returns computed from five-minute returns. The expected probability of favorable returns, P^E, is estimated from the rolling averages of the daily probabilities of favorable returns over the prior 30 days. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. The dummy variable (D_i) is equal to one if the expected probability of favorable returns in a day t belongs to bin i, and zero otherwise. The numbers in parentheses are t-statistics.

	Panel A: VIX				Panel B: $VOLM^E$			
	OLS		WLS		OLS		WLS	
α	0.010	0.011	0.011	0.011	0.002	0.002	0.003	0.003
	(2.59)	(2.77)	(3.14)	(3.14)	(2.02)	(1.95)	(3.06)	(3.05)
VIX	-0.043	-0.053	-0.048	-0.050				
	(-1.76)	(-2.14)	(-2.17)	(-2.23)				
$VOLM^E$					0.495	0.406	0.505	-0.031
					(1.56)	(0.38)	(1.24)	(-0.02)
η_2		0.556		0.592		0.554		0.591
		(1.32)		(0.91)		(1.32)		(0.90)
η_3		0.074		0.048		0.077		0.049
		(0.21)		(0.09)		(0.22)		(0.09)
η_4		0.183		0.177		0.188		0.182
		(0.59)		(0.36)		(0.60)		(0.37)
η_5		0.416		0.385		0.410		0.377
		(1.43)		(0.84)		(1.40)		(0.82)
η_6		0.151		0.145		0.147		0.145
		(0.53)		(0.33)		(0.52)		(0.33)
η_7		0.172		0.111		0.174		0.115
		(0.62)		(0.26)		(0.63)		(0.27)
η_8		0.215		0.164		0.212		0.166
		(0.77)		(0.38)		(0.76)		(0.38)
η_9		0.194		0.148		0.203		0.159
		(0.74)		(0.36)		(0.77)		(0.39)
η_{10}		0.309		0.276		0.320		0.290
		(1.22)		(0.69)		(1.26)		(0.73)
η_{11}		0.050		0.017		0.059		0.029
		(0.20)		(0.04)		(0.24)		(0.07)
η_{12}		0.156		0.142		0.170		0.158
		(0.64)		(0.37)		(0.70)		(0.41)
η_{13}		0.177		0.165		0.195		0.186
		(0.74)		(0.44)		(0.81)		(0.50)

Table 4 (Continued)

	Panel A: VIX				Panel B: $VOLM^E$			
	OLS		WLS		OLS		WLS	
η_{14}		0.098		0.070		0.118		0.093
		(0.42)		(0.19)		(0.50)		(0.25)
η_{15}		0.167		0.141		0.182		0.158
		(0.72)		(0.39)		(0.79)		(0.44)
η_{16}		0.034		0.003		0.049		0.020
		(0.15)		(0.01)		(0.22)		(0.06)
η_{17}		0.203		0.203		0.220		0.224
		(0.90)		(0.58)		(0.98)		(0.64)
η_{18}		0.170		0.157		0.188		0.181
		(0.79)		(0.46)		(0.87)		(0.53)
η_{19}		0.177		0.166		0.193		0.188
		(0.83)		(0.50)		(0.91)		(0.56)
η_{20}		0.121		0.106		0.135		0.127
		(0.58)		(0.33)		(0.65)		(0.39)
η_{21}		0.151		0.133		0.166		0.155
		(0.74)		(0.42)		(0.81)		(0.48)
η_{22}		0.083		0.070		0.097		0.095
		(0.40)		(0.22)		(0.46)		(0.29)
η_{23}		0.085		0.074		0.096		0.095
		(0.43)		(0.24)		(0.48)		(0.30)
η_{24}		0.112		0.104		0.123		0.126
		(0.57)		(0.34)		(0.62)		(0.41)
η_{25}		0.652		0.566		0.665		0.590
		(3.18)		(1.79)		(3.22)		(1.85)
η_{26}		0.394		0.409		0.402		0.433
		(1.95)		(1.30)		(1.97)		(1.36)
η_{27}		0.024		-0.018		0.044		0.013
		(0.11)		(-0.06)		(0.20)		(0.04)
η_{28}		-0.141		-0.145		-0.136		-0.122
		(-0.73)		(-0.49)		(-0.69)		(-0.40)
η_{29}		-0.147		-0.169		-0.144		-0.147
		(-0.78)		(-0.57)		(-0.74)		(-0.49)
η_{30}		-0.025		0.017		-0.020		0.039
		(-0.13)		(0.06)		(-0.10)		(0.13)
η_{31}		0.206		0.204		0.210		0.223
		(1.10)		(0.70)		(1.10)		(0.76)
η_{32}		0.327		0.321		0.326		0.339
		(1.82)		(1.15)		(1.76)		(1.19)
η_{33}		0.077		0.088		0.072		0.104
		(0.44)		(0.32)		(0.39)		(0.37)
η_{34}		1.637		1.667		1.618		1.687
		(7.19)		(5.17)		(6.58)		(4.97)
η_{35}		0.029		0.095		0.025		0.124
		(0.14)		(0.32)		(0.11)		(0.39)
η_{36}		-0.027		0.000		-0.031		0.032
		(-0.10)		(0.00)		(-0.11)		(0.09)
η_{37}		-0.360		-0.276		-0.369		-0.254
		(-1.40)		(-0.85)		(-1.37)		(-0.75)
Adj-R^2	0.0008	0.0743	0.0017	0.0352	0.0006	0.0726	0.0005	0.0335

Table 5 **Tests after controlling for higher moments**

The table reports the results of the tests of the main model after controlling for higher moments. Panels A and B report the results obtained using OLS and WLS regressions in the following equation:

$$\begin{aligned} r_{t+1} - r_{f,t+1} &= \alpha + \gamma \cdot \nu_t^E + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E \\ &+ \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \beta_1 \cdot Skew_t^E + \beta_2 \cdot Kurt_t^E + \beta_3 \cdot VOLV_t^E + \varepsilon_t. \end{aligned}$$

The estimated expected value of each variable at time t is the out-of-sample fitted value of the ARMA(p, q) model with the minimal AICC over its realized values over the prior 365 days. The expected volatility, σ^E, is the standard deviation of the prior 30 daily returns. The expected absolute deviation ϑ^E is estimated from the average absolute daily deviation of returns from the rolling prior 30 average daily return. The expected ambiguity, $\mho^E$, is estimated from the realized ambiguity, where ambiguity $\mho^E$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Probabilities of returns are based on the daily mean and variance of returns computed from five-minute returns. The expected probability of favorable returns, P^E, is estimated from the rolling averages of the daily probabilities of favorable returns over the prior 30 days. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. The dummy variable (D_i) is equal to one if the expected probability of favorable returns in a day t belongs to bin i, and zero otherwise. The expected skewness, $Skew^E$, is estimated from the realized skewness of the prior 30 daily returns. The expected skewness, $Kurt^E$, is estimated from the realized kurtosis of the prior 30 daily returns. The expected volatility of volatility, $VOLV^E$, is estimated from the realized volatility of volatility of the prior 30 daily returns. In Panel B, the weights are inversely proportional to the sum of the estimated risk and the estimated ambiguity. The numbers in parentheses are t-statistics.

	Panel A: OLS			Panel B: WLS		
α	0.002	0.004	0.011	0.003	0.004	-0.050
	(1.72)	(1.80)	(0.27)	(2.51)	(2.35)	(-1.13)
γ	-1.121	-1.072	-1.256	-1.541	-1.370	-2.138
	(-1.53)	(-1.38)	(-1.01)	(-2.54)	(-2.16)	(-2.27)
$Skew^E$	0.001			0.000		
	(0.69)			(0.39)		
$Kurt^E$		-0.000			-0.000	
		(-1.04)			(-0.97)	
$VOLV^E$			-0.009			0.052
			(-0.22)			(1.19)
η	-0.056	-0.061	-0.057	-0.028	-0.032	-0.028
	(-0.49)	(-0.53)	(-0.49)	(-0.16)	(-0.18)	(-0.16)
η_2	0.325	0.324	0.324	0.214	0.214	0.216
	(0.78)	(0.78)	(0.78)	(0.33)	(0.33)	(0.34)
η_3	0.029	0.028	0.028	-0.022	-0.022	-0.018
	(0.08)	(0.08)	(0.08)	(-0.04)	(-0.04)	(-0.03)
η_4	0.195	0.193	0.193	0.149	0.148	0.156
	(0.65)	(0.64)	(0.64)	(0.32)	(0.32)	(0.34)
η_5	0.262	0.258	0.257	0.154	0.150	0.160
	(0.91)	(0.90)	(0.89)	(0.35)	(0.34)	(0.37)
η_6	0.095	0.088	0.090	0.028	0.022	0.031
	(0.34)	(0.32)	(0.32)	(0.06)	(0.05)	(0.07)
η_7	0.021	0.016	0.018	-0.082	-0.086	-0.081
	(0.08)	(0.06)	(0.07)	(-0.20)	(-0.21)	(-0.20)
η_8	0.164	0.158	0.158	0.078	0.071	0.086
	(0.60)	(0.58)	(0.58)	(0.19)	(0.17)	(0.21)
η_9	0.155	0.150	0.152	0.053	0.048	0.063
	(0.61)	(0.59)	(0.59)	(0.14)	(0.12)	(0.16)
η_{10}	0.181	0.176	0.177	0.099	0.093	0.112
	(0.73)	(0.71)	(0.71)	(0.26)	(0.25)	(0.30)
η_{11}	-0.039	-0.046	-0.045	-0.109	-0.116	-0.093
	(-0.16)	(-0.19)	(-0.18)	(-0.30)	(-0.32)	(-0.25)

Table 5 (Continued)

	Panel A: OLS			Panel B: WLS		
η_{12}	0.113	0.108	0.109	0.054	0.049	0.071
	(0.48)	(0.45)	(0.46)	(0.15)	(0.13)	(0.20)
η_{13}	0.098	0.091	0.093	0.035	0.027	0.051
	(0.42)	(0.39)	(0.40)	(0.10)	(0.08)	(0.14)
η_{14}	0.061	0.055	0.057	0.002	-0.004	0.016
	(0.27)	(0.24)	(0.25)	(0.01)	(-0.01)	(0.05)
η_{15}	0.053	0.043	0.048	-0.030	-0.040	-0.015
	(0.22)	(0.18)	(0.20)	(-0.09)	(-0.11)	(-0.04)
η_{16}	0.016	0.006	0.011	-0.047	-0.056	-0.032
	(0.07)	(0.03)	(0.05)	(-0.14)	(-0.17)	(-0.09)
η_{17}	0.138	0.129	0.134	0.097	0.088	0.106
	(0.63)	(0.58)	(0.61)	(0.29)	(0.26)	(0.32)
η_{18}	0.087	0.078	0.082	0.033	0.024	0.043
	(0.41)	(0.37)	(0.39)	(0.10)	(0.07)	(0.13)
η_{19}	0.114	0.105	0.108	0.065	0.057	0.079
	(0.55)	(0.51)	(0.52)	(0.21)	(0.18)	(0.25)
η_{20}	0.052	0.042	0.046	0.005	-0.004	0.016
	(0.25)	(0.21)	(0.23)	(0.02)	(-0.01)	(0.05)
η_{21}	0.061	0.051	0.056	0.005	-0.005	0.015
	(0.30)	(0.25)	(0.28)	(0.02)	(-0.02)	(0.05)
η_{22}	0.041	0.028	0.035	-0.013	-0.025	-0.008
	(0.20)	(0.14)	(0.18)	(-0.04)	(-0.08)	(-0.03)
η_{23}	0.085	0.070	0.079	0.038	0.024	0.044
	(0.43)	(0.36)	(0.40)	(0.13)	(0.08)	(0.15)
η_{24}	-0.034	-0.048	-0.040	-0.063	-0.078	-0.058
	(-0.17)	(-0.25)	(-0.20)	(-0.21)	(-0.26)	(-0.19)
η_{25}	0.552	0.540	0.546	0.444	0.431	0.458
	(2.72)	(2.66)	(2.69)	(1.46)	(1.42)	(1.51)
η_{26}	0.311	0.293	0.305	0.294	0.277	0.293
	(1.56)	(1.48)	(1.53)	(0.98)	(0.93)	(0.98)
η_{27}	-0.095	-0.113	-0.102	-0.173	-0.191	-0.161
	(-0.45)	(-0.53)	(-0.48)	(-0.56)	(-0.62)	(-0.52)
η_{28}	-0.198	-0.220	-0.205	-0.233	-0.255	-0.237
	(-1.03)	(-1.14)	(-1.07)	(-0.81)	(-0.89)	(-0.83)
η_{29}	-0.214	-0.238	-0.222	-0.260	-0.284	-0.266
	(-1.13)	(-1.26)	(-1.18)	(-0.93)	(-1.01)	(-0.95)
η_{30}	-0.046	-0.064	-0.054	-0.010	-0.029	-0.002
	(-0.23)	(-0.32)	(-0.26)	(-0.03)	(-0.10)	(-0.01)
η_{31}	0.111	0.089	0.103	0.086	0.064	0.088
	(0.58)	(0.47)	(0.54)	(0.30)	(0.23)	(0.31)
η_{32}	0.213	0.187	0.204	0.182	0.157	0.177
	(1.15)	(1.01)	(1.11)	(0.67)	(0.57)	(0.65)
η_{33}	-0.010	-0.039	-0.018	-0.036	-0.064	-0.048
	(-0.05)	(-0.21)	(-0.10)	(-0.14)	(-0.24)	(-0.18)
η_{34}	0.891	0.857	0.884	0.913	0.880	0.876
	(4.31)	(4.14)	(4.27)	(3.11)	(2.99)	(2.98)
η_{35}	0.011	-0.036	0.004	0.096	0.049	0.046
	(0.05)	(-0.15)	(0.02)	(0.31)	(0.16)	(0.15)
η_{36}	-0.476	-0.535	-0.482	-0.531	-0.591	-0.613
	(-1.50)	(-1.68)	(-1.50)	(-1.40)	(-1.55)	(-1.60)
η_{37}	-0.406	-0.449	-0.417	-0.320	-0.370	-0.319
	(-1.44)	(-1.59)	(-1.49)	(-0.93)	(-1.07)	(-0.92)
Adj-R^2	0.0080	0.0079	0.0079	0.0085	0.0085	0.0085

Table 6

Unstructured risk attitude

The table reports the results of the tests of the risk attitude model. Panels A and B report the results obtained using OLS and WLS regressions in the following equation:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot \nu_t^E + \sum_{j=2}^{9} \gamma_j \cdot \left(C_{j,t} \times w_j \times \nu_t^E\right) + \eta \cdot (\mho_t^2)^E \times \vartheta_t^E + \sum_{i=2}^{9} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E\right) + \varepsilon_t.$$

The estimated expected value of each variable at time t is the out-of-sample fitted value of the ARMA(p, q) model with the minimal AICC over its realized values over the prior 365 days. The expected volatility, σ^E, is the standard deviation of the prior 30 daily returns. The expected absolute deviation ϑ^E is estimated from the average absolute daily deviation of returns from the rolling prior 30 average daily return. The expected ambiguity, $\mho^E$, is estimated from the realized ambiguity, where ambiguity $\mho^E$, is the square root of variance of the daily probabilities of returns over the prior 30 days. Probabilities of returns are based on the daily mean and variance of returns computed from five-minute returns. The expected probability of favorable returns, P^E, is estimated from the rolling averages of the daily probabilities of favorable returns over the prior 30 days. A return is considered favorable if it is greater than the risk-free rate, where returns are assumed to be normally distributed. The dummy variable (C_j) is equal to one if the wealth w in that day falls in the range of j of wealth and zero otherwise. The dummy variable (D_i) is equal to one if the expected probability of favorable returns in a day t belongs to bin i, and zero otherwise. In Panel B, the weights are inversely proportional to the sum of the estimated risk and the estimated ambiguity. The numbers in parentheses are t-statistics.

	Panel A: OLS	Panel B: WLS
α	0.004	0.004
	(2.71)	(3.63)
γ	3.668	6.602
	(1.41)	(2.56)
γ_2	-2.918	-5.638
	(-1.46)	(-2.85)
γ_3	-1.877	-3.149
	(-1.29)	(-2.14)
γ_4	-2.887	-4.623
	(-2.32)	(-3.59)
γ_5	-1.441	-2.325
	(-1.47)	(-2.33)
γ_6	-1.212	-2.086
	(-1.58)	(-2.74)
γ_7	-3.152	-4.165
	(-3.32)	(-4.39)
γ_8	-0.097	-0.586
	(-0.12)	(-0.65)
γ_9	-0.793	-1.468
	(-1.36)	(-2.43)
γ_{10}	-1.061	-1.634
	(-2.11)	(-3.27)
η	-0.088	-0.077
	(-0.75)	(-0.41)
η_2	0.559	0.604
	(1.33)	(0.93)
η_3	0.073	0.040
	(0.21)	(0.07)
η_4	0.185	0.174
	(0.60)	(0.36)
η_5	0.421	0.373
	(1.44)	(0.82)
η_6	0.152	0.125
	(0.53)	(0.28)
η_7	0.186	0.111
	(0.67)	(0.26)
η_8	0.224	0.150
	(0.80)	(0.35)
η_9	0.228	0.167
	(0.86)	(0.41)

Table 6 (Continued)

	Panel A: OLS	Panel B: WLS
η_{10}	0.352	0.305
	(1.38)	(0.77)
η_{11}	0.093	0.050
	(0.38)	(0.13)
η_{12}	0.223	0.206
	(0.91)	(0.54)
η_{13}	0.236	0.222
	(0.98)	(0.59)
η_{14}	0.154	0.122
	(0.65)	(0.33)
η_{15}	0.216	0.184
	(0.93)	(0.51)
η_{16}	0.090	0.052
	(0.39)	(0.14)
η_{17}	0.252	0.252
	(1.12)	(0.72)
η_{18}	0.221	0.210
	(1.02)	(0.62)
η_{19}	0.215	0.197
	(1.00)	(0.59)
η_{20}	0.156	0.140
	(0.74)	(0.43)
η_{21}	0.183	0.161
	(0.89)	(0.50)
η_{22}	0.120	0.119
	(0.57)	(0.37)
η_{23}	0.113	0.103
	(0.56)	(0.33)
η_{24}	0.138	0.143
	(0.69)	(0.46)
η_{25}	0.698	0.615
	(3.34)	(1.93)
η_{26}	0.414	0.446
	(2.02)	(1.41)
η_{27}	0.045	-0.004
	(0.21)	(-0.01)
η_{28}	-0.132	-0.152
	(-0.66)	(-0.50)
η_{29}	-0.137	-0.174
	(-0.69)	(-0.58)
η_{30}	-0.015	-0.010
	(-0.08)	(-0.03)
η_{31}	0.218	0.183
	(1.11)	(0.61)
η_{32}	0.344	0.348
	(1.81)	(1.21)
η_{33}	0.076	0.066
	(0.40)	(0.23)
η_{34}	1.265	1.062
	(3.51)	(2.60)
η_{35}	0.059	0.145
	(0.25)	(0.45)
η_{36}	-0.005	0.046
	(-0.02)	(0.12)
η_{37}	0.545	0.707
	(1.33)	(1.53)
Adj-R^2	0.0768	0.0410

Table 7 **Abnormal returns**

This table reports the performance of Bitcoin returns under various asset pricing models. $f_{MKT,t}$ is the day-t value of the market factor, $f_{SMB,t}$ is the day-t value of the Fama–French size factor, $f_{HML,t}$ is the day-t value of the Fama–French book-to-market factor, $f_{WML,t}$ is the day-t value of the momentum factor, $f_{RMW,t}$ is the day-t value of the Fama–French profitability factor, $f_{CMA,t}$ is the day-t value of the Fama–French investment factor, $f_{ME,t}$ is the day-t value of the HXZ (i.e., Hou, Mo, Xue, and Zhang, 2020) size factor, $f_{ROA,t}$ is the day-t value of the HXZ profitability factor, and $f_{I/A,t}$ is the day-t value of the HXZ investment factor, and $f_{EG,t}$ is the day-t value of the HXZ expected growth factor. The numbers in parentheses are t-statistics.

	Panel A: Full period					Panel B: High ambiguity					Panel C: Low ambiguity				
α	0.004	0.004	0.004	0.004	0.004	0.001	0.001	0.001	0.002	0.001	0.006	0.006	0.006	0.006	0.006
	(4.20)	(4.22)	(4.21)	(4.26)	(4.20)	(0.89)	(0.92)	(0.92)	(1.02)	(0.97)	(7.34)	(7.38)	(7.38)	(7.34)	(7.38)
$f_{MKT,t}$	0.036	0.040	0.042	0.000		0.060	0.069	0.070	-0.033		-0.011	-0.031	-0.035	-0.009	
	(0.35)	(0.39)	(0.40)	(0.00)		(0.37)	(0.42)	(0.43)	(-0.18)		(-0.11)	(-0.28)	(-0.31)	(-0.08)	
$f_{SMB,t}$		-0.005	0.003	-0.038			-0.118	-0.100	-0.222			0.164	0.156	0.189	
		(-0.03)	(0.02)	(-0.21)			(-0.38)	(-0.32)	(-0.69)			(0.94)	(0.88)	(1.07)	
$f_{HML,t}$		0.097	0.118	0.209			0.087	0.149	0.389			0.106	0.089	0.028	
		(0.54)	(0.59)	(0.93)			(0.28)	(0.42)	(1.00)			(0.62)	(0.47)	(0.13)	
$f_{WML,t}$			0.033					0.091					-0.029		
			(0.23)					(0.36)					(-0.22)		
$f_{RMW,t}$				-0.145					-0.379					0.113	
				(-0.50)					(-0.74)					(0.41)	
$f_{CMA,t}$				-0.310					-0.815					0.162	
				(-0.85)					(-1.24)					(0.48)	
$f_{ME,t}$					-0.006					-0.176					0.224
					(-0.03)					(-0.55)					(1.28)
$f_{ROE,t}$					-0.072					0.011					-0.234
					(-0.25)					(0.02)					(-0.88)
$f_{IA,t}$					0.047					-0.524					0.670
					(0.14)					(-0.91)					(2.19)
$f_{EG,t}$					0.000					-0.435					0.488
					(0.00)					(-0.77)					(1.51)
Adj-R^2	-0.0003	-0.0009	-0.0012	-0.0013	-0.0017	-0.0006	-0.0019	-0.0025	-0.0017	-0.0025	-0.0007	-0.0013	-0.0020	-0.0024	0.0006

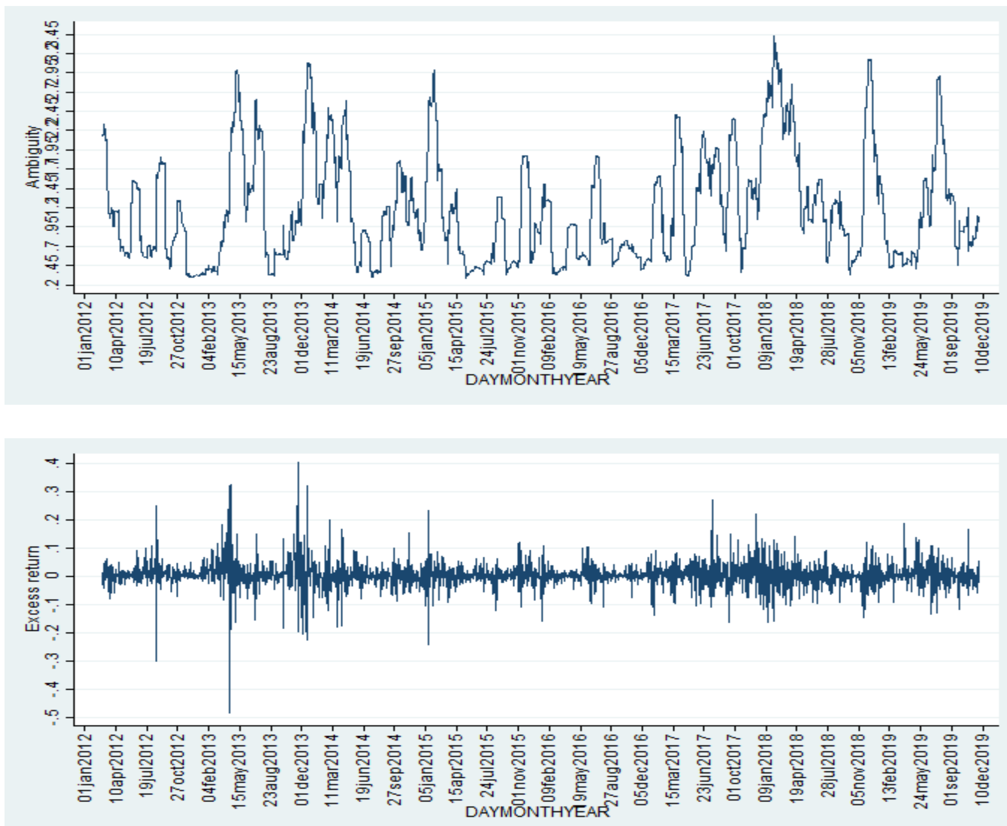

Fig. 1. Time series of Bitcoin ambiguity and excess return

This figure plots the time series patterns of realized Bitcoin ambiguity and excess returns from February 2012 to November 2019.