Investing during a Fintech Revolution: Ambiguity and Return Risk in Cryptocurrencies*

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Abstract

Rationally justifying Bitcoin's immense price fluctuations has remained a persistent challenge for both investors and researchers in this field. A primary reason is our potential weakness toward robustly quantifying unquantifiable risks or ambiguity in Bitcoin returns. This paper introduces a behavioral channel to argue that the degree of ambiguity aversion is a prominent source of abnormal returns from investment in Bitcoin markets. Using data over a ten-year period, we show that Bitcoin investors exhibit, on average, an increasing aversion to ambiguity. Furthermore, investors are found to earn abnormal returns only when ambiguity is low. Robustness exercises reassure on the 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 pinpointing 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 trend in the form currency can take and a new payment technology in purchasing goods and services. Bitcoin has undoubtedly proven to be the most prominent in each case (Dwyer, 2015; Gillaizeau et al. 2019; White et al., 2020), with its growing centrality among financial institutions and increasing tendency to be the first choice over other established theory-backed assets (Trimborn and Härdle, 2018). Ambiguity plays a major role in quantifying the magnitude of abnormal returns. This paper fills a gap in the literature by rigorously studying the impact of ambiguity on Bitcoin returns in the spirit of Brenner and Izhakian (2018).[3]

[1]See https://www.nytimes.com/2017/12/15/business/bitcoin-investing.html

[2]See https://www.cnbc.com/2017/12/19/robert-shiller-bitcoin-valuation-is-exceptionally-ambiguous.html

[3]Camerer and Weber (1992), in an earlier effort, provide evidence, theoretical explanations, and applications of research on ambiguity and subjective expected utility. More recent efforts include a design of a survey

As the leading cryptocurrency, Bitcoin continues to draw wide attention from practitioners, regulators, and scholars. Many of the recent academic discussions on Bitcoin have been motivated by the substantial fluctuations in Bitcoin prices (García-Monleón et al., 2021), speculative bubbles and zero fundamental value (Cheah and Fry, 2016), and concerns about unstructured regulatory policy (Akyildirim et al., 2020; Alexander and Heck, 2020). A large strand of literature attempts to understand cryptocurrency market phenomena through the lens of the traditional neoclassical finance theories (Borri, 2019; Corbet et al., 2020). Specifically, Urquhart (2016) documents evidence of market inefficiency in the early years and improving market efficiency through time. Corbet et al. (2018b) investigate the relationship between cryptocurrencies and a variety of traditional financial assets and show that cryptocurrencies may offer diversification benefits for investors. Liu and Tsyvinski (2020) show that cryptocurrency returns have no exposure to commonly used stock market, macroeconomic, foreign exchange, and commodity market factors.[4] Lucey et al. (2021) introduce a new Cryptocurrency Uncertainty Index (UCRY) that captures policy and price uncertainty in cryptocurrency markets, showing the index to increase following major events such as cryptocurrency exchange hacks.

All that aside, Bitcoin usefully exemplifies uncertainty and ambiguity, and neoclassical theory fails to explain the market behavior for this cryptocurrency.[5] There has been inade-

module by Cavatorta and Schroeder (2019) to experimentally validate ambiguity preference that has wider applications for economics and finance.

[4]In a different context, Duan et al. (2019) show how macroeconomic variations can account for ambiguity and volatility in real estate markets.

[5]A recurrent issue across financial theories is the study of how agents make investment decisions under conditions of risk. This is distinct 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 the likelihoods of

quate empirical daily information to rationally explain Bitcoin's high volatility. As indicated by Giudici et al. (2019), the general uncertainty may arise both from unsophisticated investors finding blockchain technology opaque and complicated, and more importantly, from the fundamental value of cryptocurrencies remaining unclear.[6] It is difficult for investors to manage their cryptocurrency portfolios. Therefore, we attempt to extend our understanding of this market using a behavioral finance perspective. This paper examines the role of unquantifiable risk, or ambiguity, in Bitcoin returns.

Since the seminal studies of Keynes (1921) and Knight (1921), the concept of uncertainty has been analyzed from two distinct perspectives: *risk and ambiguity*. In the condition of risk, the beliefs of a decision-maker are captured by a well-defined probability distribution of possible outcomes. However, under the ambiguous condition, decision-makers beliefs on the probabilities of the outcome are unknown due to a lack of information (Snow, 2010; Cavatorta and Schroder, 2019). Epstein and Schneider (2008) investigate the impact of information quality on investor behaviors and show that ambiguity-averse investors tend to react more to negative than positive information. Kelsey et al. (2011) document that when momentum trading investors face ambiguity, they react differently to past winners and losers which creates an asymmetric momentum effect. Driouchi et al. (2018) investigate the lead-lag relationship between option and stock markets during the 2006-2008 subprime crisis. Their results suggest that ambiguity played an important role in the increased volatility of stock markets during the crisis. Bianchi and Tallon (2019) show that ambiguity averse investors exhibit a form of

contingent events is consistent with multiple probability distributions. Importantly, the agent does not know what the precise distribution is.

[6] Bitcoin prices are subject to speculation (Baur et al., 2018; Lee et al., 2020; Grobys and Junttila, 2021).

home bias, which leads to higher exposure to the domestic stock market and higher risk due to a lack of diversification.

Most research on ambiguity focuses on traditional financial assets while a few studies explore the role of ambiguity in emerging digital currencies such as Bitcoin.[7] Using an incentivized survey, Anantanasuwong et al. (2019) investigate ambiguity held toward traditional financial assets and cryptocurrency. Their findings suggest that individuals' perceptions of ambiguity levels differ according to asset type. Asano and Osaki (2020) explore the role of ambiguity aversion in portfolio allocation to show that as it rises it decreases the optimal proportion invested in ambiguous assets such as cryptocurrency.

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 and that investors have 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 index from the S&P 500 (VIX) in our regression model as it is used as a proxy for ambiguity in prior studies (e.g., Williams, 2015). We control for higher moments, including skewness and kurtosis. We also test for unstructured attitude toward risk that does not impose a specific functional form (e.g., constant relative risk aversion or

[7]Previous studies on ambiguity mainly examine its role in equity markets (Anderson et al., 2009; Ulrich, 2013; Antoniou et al., 2015; Williams, 2015; Brenner and Izhakian, 2018). Antoniou et al. (2015) show that increases in ambiguity lead to outflows from equity markets. Brenner and Izhakian (2018) find that ambiguity-averse investors request a premium for bearing ambiguity in the U.S. stock market.

constant absolute risk) over attitude toward risk. Further, we conduct sub-sample analysis, control for information flow, and use an alternative sampling interval of the return series.

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, or the Fama–French (2015) five-factor model (FF5FM). We initially confirm their findings and proceed to demonstrate that investors earn abnormal returns of Bitcoin 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 behavioral 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, 2019; 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; Corbet et al., 2018a). It is widely accepted that traditional asset pricing models have difficulties in explaining Bitcoin returns. Our study extends our understanding of the cryptocurrency market using 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 research, primarily into attitudinal theory, such as aversion toward ambiguity, rather than the actual measurement of it. Indeed, only a few studies use market data to measure ambiguity; for example, Ulrich (2013) uses the 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 markets using Bitcoin data.

Our study has important implications for sustainability. By studying the uniquely ambiguous characteristic of Bitcoin, we aim to take into account, at least partially, "the dynamics" of this highly volatile currency to empower investors regardless of size with the required information to make optimal decisions regarding their choices. Our work has practical importance too. Not only individual investors but various funds have an increasing proclivity toward risk exposure with Bitcoin. This paper helps shed light on their investment decisions with Bitcoin: if investors can earn a risk premium after adjusting for systematic risk, then it is helpful to allocate their wealth to Bitcoin.[8] 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 policymakers. While Bitcoin markets are largely unregulated under current market conditions, policymakers can use our study to guide regulatory development. For example, they could use our method to estimate the ambiguity

[8]Huang et al. (2021) discuss in depth the "safe haven" hypothesis of Bitcoin and question whether Bitcoin is really a diversifier of risky investment.

of Bitcoin, in helping to identify potential market bubbles. They could also harness the ambiguity of Bitcoin to cool off trading in 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 have noted, ambiguity refers to situations where an agent's subjective knowledge about the likelihoods of contingent events is consistent with multiple probability distributions. We follow Izhakian (2020) 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 of probability, and $Var[\ ]$ is the variance of probability. While risk can be measured by the volatility of returns, ambiguity can be measured by the volatility of probabilities (Rothschild and Stiglitz, 1970). By construction, $\mho^2[r]$ is independent of risk, attitudes toward risk and/or attitude toward ambiguity, and it takes into account the variance of all the moments of the outcome distribution (Brenner and Izhakian, 2018).

Following Andersen et al. (2001), we use the five-minute Bitcoin prices to compute returns to minimize microstructure effects. For each day, we use the five-minute returns to calculate the daily mean (μ) and volatility (σ) of returns and normalize μ and σ based on the number of intraday observations. Following Scholes and Williams (1977), we estimate σ by taking into account the non-synchronous trading adjustment. 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, $r_{i,t}$, on day t.

Following Brenner and Izhakian (2018), we assume that the distribution of intraday Bitcoin returns is normal. Next, we calculate the cumulative probability of favorable returns ($P(r \geq r_f) = 1 - \Phi(r_f; \mu, \sigma)$) for each day. We consider any Bitcoin return greater than the risk-free rate to be favorable.

The Bitcoin return distribution is represented by a histogram. Specifically, we first separate daily returns ranging from -6% to $+6\%$ to 60 bins. Each bin is 0.2% width. Second, we estimate the probability of returns being in each bin. Third, we calculate the probability of returns being outside of -6% and $+6\%$. Fourth, we separately calculate the mean and variance of the probability for each of the 62 bins. Finally, we estimate the degree of Bitcoin ambiguity as

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

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

3. Data

We obtain data from multiple databases to construct our variables. Specifically, we collect Bitcoin price (in dollars) and volume between 2012 and 2019 from bitcoincharts.com. We obtain the number of trades from data.bitcoinity.org. 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.[9] 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.[10] We obtain the CBOE (Chicago Board Options Exchange) S&P 500 Volatility Index (VIX) from Wharton Research Data Services. The Bitcoin return is the difference between closing price on day t and day $t-1$ divided by closing price on day $t-1$.

The ambiguity measure of Bitcoin is based on the five-minute intraday returns. Panel A of Table 1 reports the summary statistics. The average of five-minute returns has a mean of 0.5% and the standard deviation has a mean of 4.3% in daily terms. Brenner and Izhakian (2018) highlight that high-frequency realized returns can be a poor proxy for long-run expected returns due to the large standard errors.

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

[10] See http://global-q.org/index.html. Hou et al. (2015) and Hou et al. (2021) provide detailed discussions on factor constructions.

Panel B of Table 1 continues to report the summary statistics in daily frequency. The daily Bitcoin return in excess of the 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 prior 30 average daily return, has a mean of 2.7%. The average probability of favorable returns is 0.540 similar to the favorable returns of S&P 500 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 August 2012, April 2013, January 2015, and February 2018, similar to the findings of Brenner and Izhakian (2018), who argue that this is because investors have concerns over high price (or low rates of return) periods due to "the correction" (a price drop after a price soar). This correction leads to high ambiguity, namely, the variance of the 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 exercise, we use the estimated expectations of the following four variables, namely the volatility of Bitcoin (σ), the average absolute deviation of Bitcoin returns from the mean (ϑ), the probability of favorable Bitcoin returns (P), and the degree of Bitcoin ambiguity ($\mho$). Following Andersen et al. (2003) and Brenner and Izhakian (2018), we estimate the expected volatility based on realized volatility using the coefficients obtained from the time-series autoregressive moving average ARMA(p, q) model with the minimal corrected Akaike information criterion (AICC):

$$ln\sqrt{\nu_t} = \Psi_0 + \epsilon_t + \sum_{i=1}^{p} \Psi_i ln\sqrt{\nu_{t-i}} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}, \tag{4}$$

where ν_t is the realized volatility on day t. We use the natural logarithm of volatility ($ln\sqrt{\nu_t}$) since $\sqrt{\nu}$ is skewed (Brenner and Izhakian, 2018). The expected volatility (ν_{t+1}^E) is then estimated as the fitted value from Eq. (4), i.e., $\nu_{t+1}^E = exp\Big(2\widehat{ln\sqrt{\nu_t}} + 2Var[u_t]\Big)$, 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 realized values.

We also estimate expected ambiguity using ARMA(p, q) similar to the method for the expected volatility estimates. Specifically, we calculate the expected ambiguity based on realized ambiguity using the coefficients obtained from the following time-series model:

$$ln\mho_t = \Psi_0 + \epsilon_t + \sum_{i=1}^{p} \Psi_i ln\mho_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}, \tag{5}$$

where $\mho_t$ is the realized ambiguity on day t. The expected ambiguity ($\mho_{t+1}^E$) is then estimated as the fitted value from Eq. (5), i.e., $(\mho_{t+1}^2)^E = exp\Big(2\widehat{ln\mho_t} + 2Var[u_t]\Big)$, where $Var[u_t]$ is the variance of the error term.

Further, we estimate the expected probability of unfavorable returns using ARMA(p, q). Specifically, we estimate the expected ambiguity based on realized ambiguity using the coefficients obtained from the following time-series model:

$$lnQ_t = \Psi_0 + \epsilon_t + \sum_{i=1}^{p} \Psi_i lnQ_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}, \tag{6}$$

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

Panel A of Table 2 reports summary statistics of the expected values of volatility, absolute deviation, 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 is generally smaller than for the corresponding realized values, similar to Brenner and Izhakian (2018).

4.2. Main empirical tests

We now turn to investigate 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.[11] For example, the first bin is from 0.38 to 0.39. The few values lower than 0.38 are indexed as $i = 1$, while the few values higher than 0.75 are indexed as $i = 37$.

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

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

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

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 toward risk remains constant.

The coefficients from Eq. (7) can be written as $\eta(P_i^E) = \hat{\eta} + \hat{\eta_i}$, which captures the investor's attitude toward ambiguity conditional on the expected probability of favorable returns (P^E) falling into bin i. A negative value of $\eta(P_i^E)$ means that investors show ambiguity-loving behaviors, which lead to a negative ambiguity premium, while a positive value means that investors show ambiguity-averse behaviors, which lead 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, we set the weights to be inversely related to the risk and ambiguity estimates, i.e., $\frac{1}{\sqrt{\nu_t^E + \mho_t^E}}$, following French et al. (1987) and Brenner and Izhakian (2018).

Table 3 reports the results from the OLS and WLS regressions. In the first specification, the expected volatility, as a measure of risk, is the only independent variable. It has a positive coefficient, consistent with the well-known fact that high risk is related to high returns. We then add the expected ambiguity to the subsequent regressions. We first focus exclusively on the expected ambiguity and 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 bins of high probability of favorable returns (e.g., η_{34}) is significant, indicating that Bitcoin investors have an increasing aversion to ambiguity.

4.3. Robustness exercise

(i) Alternative volatility measures

In this subsection, we use alternative measures of volatility in our regressions. Cheah et al. (2020) show that the forward-looking implied volatility (VIX) from S&P index options can predict Bitcoin returns. Cao et al. (2005) and Garlappi et al. (2007) suggest the role of the volatility of mean in ambiguity. Following these studies, 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:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VIX_t + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t. \quad (8)$$

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VOLM_t^E + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t. \quad (9)$$

Table 4 reports the results under these alternative volatility measures. The effect of ambiguity on returns is robust to alternative risk measures. Specifically, the coefficient of ambiguity in bins of high probability of favorable returns (e.g., η_{34}) remains significant.

Higher-order moments

In this subsection, 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 the volatility of volatility. Following these studies, we run the following regression to take into account skewness ($Skew$), kurtosis ($Kurt$), and volatility of volatility ($VOLV$):

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot \nu_t^E + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right)$$
$$+ \quad \beta_1 \cdot Skew_t^E + \beta_2 \cdot Kurt_t^E + \beta_3 \cdot VOLV_t^E + \varepsilon_t. \qquad (10)$$

Consistent with our prior tests, we use the expected values 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 our main results, we again find that Bitcoin investors have an increasing ambiguity aversion.

(ii) Unstructured risk attitudes

Following Brenner and Izhakian (2018), in this subsection, we test a further discrete model where attitudes toward 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 the risk-free rate) into ten equal bins of 0.5 each, indexed by i. For example, the first bin is from 0.5 to 1. The few values lower than 0.5 are indexed as $i = 1$, while the few values higher than 5.5 are indexed as $i = 10$.

We then generate a dummy variable for each wealth bin. If the wealth on a given 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 wealth into account,

$$
\begin{aligned}
r_{t+1} - r_{f,t+1} &= \alpha + \gamma \cdot \nu_t^E + \sum_{j=2}^{10} \gamma_j \cdot \left(C_{j,t} \times w_j \times \nu_t^E \right) + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) \\
&+ \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t, \qquad (11)
\end{aligned}
$$

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-averse behaviors, which implies a positive risk premium.

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

(iii) Sub-sample differences

In this subsection, we conduct a sub-sample analysis. Specifically, we divide our sample into two sub-samples before and after April 2014. Table 7 reports the results. We find that the results of the sub-samples are similar to those of the full sample.

(iv) Controlling for information flow

Previous studies highlight the importance of information flow in trading (e.g., Copeland, 1976; Chan and Fong, 2006; Celik, 2013; Ahadzie and Jeyasreedharan, 2020). Following these studies, we conduct a further robustness test after controlling for the information arrival rate. Specifically, we measure information flow using trading volume (TV), number of trades (NT), average trade size (ATS), and vol-trade (VT), following Ahadzie and Jeyasreedharan (2020). Table 8 shows that our results are consistent after controlling for information flow.

(v) Ten-minute return series

In this subsection, we check whether our results are robust to the alternative sampling interval of a high-frequency return series (e.g., Hansen and Lunde, 2006; Bollerslev et al., 2008). Specifically, we use a ten-minute return series of Bitcoin. Table 9 shows that our results remain robust. Our finding is similar to that of Yarovaya and Zieba (2020). They compare the differences in linkage between return and volume of the top-30 most tradable cryptocurrencies, using 5-, 10-, 25-, 60-minute, and daily data. Their sample includes Bitcoin, and according to their results, 5-minute data capture the highest amount of volatility, demonstrate stronger correlations coefficients between returns and trading volume, while the results of the Granger causality test demonstrate no differences in results for 5-, 20-, 30-, 45-, or 60-minute intraday data.

(vi) 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, or 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 the performance of Bitcoin returns varies during periods of high and low ambiguity.

Ambiguity is an important representation of uncertain knowledge. Financial literature has shown that ambiguous signals can convey both good and bad news. The level of ambiguity can vary over time; a high level of ambiguity is associated with environments in which investors have a great deal of uncertainty in interpreting the details of news, both good or bad. That is, the precision of the news in investors' minds could rate anywhere from very low to very high. When ambiguity is low, investors are more certain of how informative news may be for the stock market, and they have a greater sense of precision around possible outcomes. Ex-ante, we might expect that ambiguity is high at identifiable times of greater uncertainty, such as the 2008 financial crisis (Brenner and Izhakian, 2018). At other times, such as before this when the economy was relatively stable, we might expect lower levels of ambiguity.

To test the performance of Bitcoin returns, we use 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. (2021) five-factor model (q5FM). Specifically, we run the following time-series regressions:

$$r_t - r_{f,t} \;=\; \alpha + \beta_m f_{MKT,t} + \varepsilon_t, \tag{12}$$

$$r_t - r_{f,t} \;=\; \alpha + \beta_m f_{MKT,t} + \beta_s f_{SMB,t} + \beta_h f_{HML,t} + \varepsilon_t, \tag{13}$$

$$r_t - r_{f,t} \;=\; \alpha + \beta_m f_{MKT,t} + \beta_s f_{SMB,t} + \beta_h f_{HML,t} + \beta_w f_{WML,t} + \varepsilon_t, \tag{14}$$

$$r_t - r_{f,t} \;=\; \alpha + \beta_m f_{MKT,t} + \beta_s f_{SMB,t} + \beta_h f_{HML,t} + \beta_r f_{RMW,t} + \beta_c f_{CMA,t} + \varepsilon_t, \tag{15}$$

$$r_t - r_{f,t} \;=\; \alpha + \beta_m f_{MKT,t} + \beta_{me} f_{ME,t} + \beta_{roe} f_{ROE,t} + \beta_{ia} f_{IA,t} + \beta_{eg} f_{EG,t} + \varepsilon_t, \tag{16}$$

where R_t is the day-t return of Bitcoin, $R_{f,t}$ 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 (Hou et al., 2021) size factor, $f_{ROA,t}$ is the day-t value of the HMXZ profitability factor, $f_{I/A,t}$ 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 10 reports the performance of Bitcoin returns under various asset pricing models over the full 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 loading (i.e., the coefficients of risk factors, β) is insignificant, indicating that well-known equity risk factors have difficulties in explaining Bitcoin returns.

Panels B and C of Table 10 report the performance of Bitcoin returns under various asset pricing models during periods of high and low ambiguity. High (or low) ambiguity periods are defined as those above (or 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 model is used. 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.

Brenner and Izhakian (2018) show that high ambiguity can be associated with high prices and low returns during periods of significant economic, social, and political events (such as Brexit or the U.S. presidential elections). Similarly, we find that the abnormal returns of Bitcoin during periods of high ambiguity are insignificant while they become significant during periods of low ambiguity. Overall, our results indicate that ambiguity plays an important role in understating the performance of Bitcoin.

5. Conclusion

Investors invariably face a choice between known and unknown risks. Therefore, an ambiguity-averse investor would rather choose an alternative where the probability distribution of an investment outcome is known over, one where it is unknown. This paper studies the important role of ambiguity in Bitcoin returns, an asset that has captured investor attention like no other in recent times. Because virtual currencies like Bitcoin tend not to conform to conventional asset pricing theoretical frameworks and hence their returns cannot be easily theoretically predicted, alternative tools are needed to characterize the observed abnormalities in their returns. We spotlight the timeless case of ambiguity, contextualized through the design of an improved methodological underpinning that employs the value of information, to understand the extent the degree of ambiguity aversion may contribute to the variable magnitudes of abnormal returns.

Following the approach set out by Brenner and Izhakian (2018), we find that Bitcoin investors have an increasing aversion to ambiguity, and such a characterization helps in quantifying the extent of abnormal returns of Bitcoin. We examine the performance of Bitcoin returns conditional on ambiguity. Specifically, 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 periods of low ambiguity, irrespective of the asset price models employed. Our results are robust to alternative measures of volatility in Bitcoin prices, higher-order moments (such as skewness) that determine asset prices, design of a further discrete model where attitudes toward ambiguity depend on wealth and risk attitudes, sub-sample tests, inclusion of information flow, and alternative sample frequency of returns.

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Table 1 **Descriptive statistics**

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

RET: Bitcoin returns;

σ: volatility;

ϑ: absolute deviation;

P: probability of favorable returns;

$\mho$: ambiguity.

Panel A reports the summary statistics of intraday returns. μ^{5m} is the daily mean of five-minute Bitcoin returns. σ^{5m} is the daily standard deviation of five-minute Bitcoin returns. Panel B reports the daily summary statistics. RET is the daily Bitcoin returns. σ is the standard deviation of the prior 30 daily Bitcoin returns. ϑ is the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. P is the average daily probability of favorable Bitcoin returns. We consider a Bitcoin return as favorable if it is greater than the risk-free rate and estimate the probability using the daily mean and variance of returns based on the five-minute Bitcoin returns. $\mho$ is the square root of the variance of Bitcoin favorable returns probability over the prior 30 days. Panel C reports the correlations.

Panel A: Intraday descriptive statistics					
	μ^{5m}	σ^{5m}	$\frac{\mu^{5m}}{\sigma^{5m}}$		
Mean	0.005	0.043	0.200		
Stdev	0.062	0.066	3.677		
Median	0.003	0.031	0.108		
Skewness	13.278	22.956	49.301		
Kurtosis	455.503	833.145	2595.886		
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: expected volatility;

ϑ^E: expected absolute deviation;

P^E: expected probability of favorable returns;

$\mho^E$: expected ambiguity.

Panel A reports the summary statistics. Based on the ARMA(p, q) model with the minimal AICC, we estimate the expected values using their realized values over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable Bitcoin returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. Panel B reports the correlations of 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 main model. Panels A and B report the results obtained from the following OLS and WLS regressions:

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

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. θ is the coefficient obtained from regressing Bitcoin excess returns on the expected ambiguity. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. 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 from the OLS and WLS regressions in the following equations:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VIX_t + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t.$$

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot VOLM_t^E + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t.$$

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. VIX is the value of the VIX index. $VOLM^E$ is the expected average volatility obtained from the realized standard deviation of the prior 30 daily average Bitcoin returns and average Bitcoin returns are the rolling average over the prior 30 days. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. The numbers in parentheses are t-statistics.

	VIX				$VOLM^E$			
	Panel A: OLS		Panel B: WLS		Panel A: OLS		Panel B: 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 from the OLS and WLS regressions in the following equation:

$$\begin{aligned} r_{t+1} - r_{f,t+1} &= \alpha + \gamma \cdot \nu_t^E + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) \\ &+ \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \beta_1 \cdot Skew_t^E + \beta_2 \cdot Kurt_t^E + \beta_3 \cdot VOLV_t^E + \varepsilon_t. \end{aligned}$$

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. $Skew^E$ is the expected skewness obtained from the realized skewness of the prior 30 daily returns. $Kurt^E$ is the expected kurtosis obtained from the realized kurtosis of the prior 30 daily returns. $VOLV^E$ is the expected volatility of volatility obtained from the realized volatility of volatility of the prior 30 daily returns. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. 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 from the OLS and WLS regressions in the following equation:

$$r_{t+1} - r_{f,t+1} = \alpha + \gamma \cdot \nu_t^E + \sum_{j=2}^{10} \gamma_j \cdot \left(C_{j,t} \times w_j \times \nu_t^E \right) + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t.$$

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign the dummy variable $C_j = 1$ if the wealth w on that day falls in the range j of wealth, and zero otherwise. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. 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 **Sub-sample analysis**

The table reports the results of the tests of the main model based on two sub-samples. Panels A and B report the results obtained from the OLS and WLS regressions in the following equation:

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

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. The numbers in parentheses are t-statistics.

	Sub-sample before April 2014						Sub-sample after April 2014					
	Panel A: OLS			Panel B: WLS			Panel A: OLS			Panel B: WLS		
α	0.009	0.013	0.013	0.013	0.016	0.015	0.001	0.002	0.001	0.002	0.002	0.002
	(1.97)	(2.28)	(2.45)	(3.05)	(3.52)	(3.14)	(0.93)	(1.34)	(0.57)	(1.99)	(2.11)	(2.04)
γ	0.015		0.248	-0.146		0.779	0.604		1.270	0.050		-1.031
	(0.03)		(0.12)	(-0.21)		(0.28)	(0.97)		(0.93)	(0.07)		(-0.72)
θ		-0.001			-0.002							
		(-0.84)			(-1.26)			(0.78)			(0.41)	
η			0.266			0.246			-0.092			-0.069
			(1.02)			(0.63)			(-0.92)			(-0.44)
η_2									0.555			0.597
									(1.56)			(1.08)
η_3									0.076			0.047
									(0.25)			(0.10)
η_4									0.187			0.181
									(0.71)			(0.44)
η_5									0.374			0.343
									(1.51)			(0.89)
η_6			-0.562			-0.568			0.050			0.067
			(-0.87)			(-0.59)			(0.20)			(0.18)
η_7			-0.863			-0.852			0.218			0.148
			(-1.38)			(-0.91)			(0.92)			(0.40)
η_8			-0.856			-0.952			0.311			0.347
			(-1.36)			(-1.02)			(1.26)			(0.91)
η_9			-0.839			-0.881			0.236			0.229
			(-1.39)			(-0.98)			(1.05)			(0.65)
η_{10}			-0.485			-0.534			0.303			0.292
			(-0.80)			(-0.59)			(1.40)			(0.87)
η_{11}			-0.742			-0.758			0.047			0.043
			(-1.32)			(-0.90)			(0.22)			(0.13)
η_{12}			-0.637			-0.659			0.158			0.174
			(-1.06)			(-0.74)			(0.76)			(0.54)
η_{13}			-0.723			-0.796			0.189			0.214
			(-1.13)			(-0.85)			(0.93)			(0.67)

Table 7 (Continued)

	Sub-sample before April 2014						Sub-sample after April 2014					
	OLS			WLS			OLS			WLS		
η_{14}			-0.717			-0.737			0.112			0.108
			(-1.16)			(-0.81)			(0.56)			(0.35)
η_{15}			-0.690			-0.774			0.177			0.178
			(-1.06)			(-0.82)			(0.90)			(0.58)
η_{16}			-1.177			-1.230			0.052			0.050
			(-1.48)			(-1.15)			(0.27)			(0.17)
η_{17}			-0.478			-0.484			0.210			0.258
			(-0.97)			(-0.65)			(1.05)			(0.84)
η_{18}			-0.504			-0.514			0.209			0.230
			(-1.07)			(-0.73)			(1.12)			(0.79)
η_{19}			-0.467			-0.461			0.207			0.226
			(-1.01)			(-0.66)			(1.06)			(0.75)
η_{20}			-0.502			-0.499			0.107			0.130
			(-1.11)			(-0.73)			(0.58)			(0.46)
η_{21}			-0.459			-0.457			0.068			0.129
			(-1.03)			(-0.68)			(0.33)			(0.43)
η_{22}			-0.513			-0.521			0.062			0.119
			(-1.14)			(-0.77)			(0.30)			(0.40)
η_{23}			-0.496			-0.489			-0.066			0.034
			(-1.14)			(-0.75)			(-0.32)			(0.11)
η_{24}			-0.460			-0.453			0.052			0.126
			(-1.07)			(-0.70)			(0.26)			(0.43)
η_{25}			0.235			0.238			0.324			0.364
			(0.53)			(0.35)			(1.59)			(1.25)
η_{26}			-0.184			-0.183			0.570			0.798
			(-0.43)			(-0.28)			(1.97)			(2.13)
η_{27}			-0.543			-0.528			0.037			0.023
			(-1.16)			(-0.75)			(0.18)			(0.08)
η_{28}			-0.723			-0.729			0.146			0.089
			(-1.73)			(-1.17)			(0.53)			(0.26)
η_{29}			-0.698			-0.710			-0.347			-0.356
			(-1.69)			(-1.16)			(-0.95)			(-0.87)
η_{30}			-0.594			-0.576			0.564			0.732
			(-1.46)			(-0.95)			(1.35)			(1.58)
η_{31}			-0.342			-0.353			3.287			3.302
			(-0.85)			(-0.59)			(2.05)			(2.46)
η_{32}			-0.213			-0.225			0.784			0.556
			(-0.54)			(-0.38)			(0.73)			(0.56)
η_{33}			-0.461			-0.465						
			(-1.17)			(-0.80)						
η_{34}			1.046			1.015						
			(2.17)			(1.48)						
η_{35}			-0.569			-0.566						
			(-1.24)			(-0.88)						
η_{36}			-0.660			-0.714						
			(-1.21)			(-0.99)						
η_{37}			-0.982			-0.965						
			(-1.90)			(-1.38)						
Adj-R^2	-0.0023	-0.0007	0.1179	-0.0008	0.0032	0.0291	-0.0000	-0.0002	0.0102	-0.0003	-0.0002	0.0022

Table 8 **Tests after controlling for information flow**

The table reports the results of the tests after controlling for information flow. Panels A and B report the results obtained from the OLS and WLS regressions in the following equation:

$$r_{t+1} - r_{f,t+1} = \alpha + \beta IF + \gamma \cdot \nu_t^E + \eta \cdot \left((\mho_t^2)^E \times \vartheta_t^E \right) + \sum_{i=2}^{37} \eta_i \cdot \left(D_{i,t} \times P_t^E \times (\mho_t^2)^E \times \vartheta_t^E \right) + \varepsilon_t.$$

IF is the information flow measured by the natural logarithm of trading volume (TV), number of trades (NT), average trade size (ATS), and vol-trade (VT). We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. The numbers in parentheses are t-statistics.

	Panel A: OLS				Panel B: WLS			
	TV	NT	ATS	VT	TV	NT	ATS	VT
α	-0.015	0.005	0.012	0.011	-0.016	0.005	0.021	0.012
	(-1.27)	(2.32)	(0.73)	(1.63)	(-1.71)	(3.20)	(1.51)	(2.25)
β	0.002	-0.001	-0.001	-0.000	0.002	-0.001	-0.001	-0.001
	(1.49)	(-1.45)	(-0.58)	(-1.29)	(2.07)	(-1.67)	(-1.28)	(-1.70)
γ	0.470	0.481	0.467	0.451	-0.006	0.395	0.276	0.377
	(0.49)	(0.50)	(0.49)	(0.47)	(-0.01)	(0.35)	(0.25)	(0.33)
η	-0.094	-0.086	-0.090	-0.087	-0.087	-0.078	-0.081	-0.078
	(-0.80)	(-0.73)	(-0.76)	(-0.74)	(-0.47)	(-0.42)	(-0.44)	(-0.42)
η_2	0.537	0.559	0.555	0.558	0.569	0.596	0.593	0.596
	(1.28)	(1.33)	(1.32)	(1.33)	(0.87)	(0.91)	(0.91)	(0.91)
η_3	0.084	0.071	0.077	0.074	0.061	0.043	0.051	0.045
	(0.24)	(0.20)	(0.22)	(0.21)	(0.11)	(0.08)	(0.09)	(0.08)
η_4	0.192	0.185	0.190	0.187	0.190	0.178	0.186	0.181
	(0.62)	(0.59)	(0.61)	(0.60)	(0.39)	(0.36)	(0.38)	(0.37)
η_5	0.403	0.411	0.410	0.411	0.372	0.375	0.376	0.375
	(1.38)	(1.41)	(1.40)	(1.41)	(0.81)	(0.82)	(0.82)	(0.82)
η_6	0.136	0.150	0.146	0.149	0.135	0.145	0.142	0.144
	(0.48)	(0.53)	(0.51)	(0.52)	(0.30)	(0.33)	(0.32)	(0.32)
η_7	0.169	0.176	0.173	0.175	0.112	0.114	0.113	0.114
	(0.61)	(0.64)	(0.63)	(0.63)	(0.26)	(0.26)	(0.26)	(0.26)
η_8	0.204	0.210	0.209	0.209	0.160	0.160	0.158	0.159
	(0.73)	(0.75)	(0.75)	(0.75)	(0.37)	(0.37)	(0.37)	(0.37)
η_9	0.198	0.203	0.202	0.203	0.158	0.155	0.157	0.156
	(0.75)	(0.77)	(0.77)	(0.77)	(0.39)	(0.38)	(0.38)	(0.38)
η_{10}	0.318	0.320	0.319	0.320	0.292	0.286	0.288	0.287
	(1.25)	(1.26)	(1.26)	(1.26)	(0.73)	(0.72)	(0.72)	(0.72)
η_{11}	0.058	0.055	0.056	0.056	0.033	0.022	0.024	0.022
	(0.23)	(0.22)	(0.23)	(0.22)	(0.08)	(0.06)	(0.06)	(0.06)
η_{12}	0.170	0.166	0.167	0.166	0.163	0.148	0.152	0.149
	(0.70)	(0.68)	(0.69)	(0.68)	(0.43)	(0.39)	(0.40)	(0.39)
η_{13}	0.193	0.194	0.194	0.195	0.189	0.180	0.183	0.181
	(0.81)	(0.81)	(0.81)	(0.81)	(0.50)	(0.48)	(0.49)	(0.48)

Table 8 (Continued)

	Panel A: OLS				Panel B: WLS			
	TV	NT	ATS	VT	TV	NT	ATS	VT
η_{14}	0.120	0.119	0.118	0.119	0.100	0.090	0.092	0.091
	(0.51)	(0.51)	(0.50)	(0.51)	(0.27)	(0.24)	(0.25)	(0.25)
η_{15}	0.184	0.180	0.181	0.181	0.166	0.153	0.156	0.154
	(0.80)	(0.78)	(0.79)	(0.78)	(0.46)	(0.42)	(0.43)	(0.42)
η_{16}	0.049	0.052	0.051	0.053	0.023	0.019	0.023	0.021
	(0.21)	(0.23)	(0.22)	(0.23)	(0.07)	(0.05)	(0.07)	(0.06)
η_{17}	0.222	0.212	0.217	0.214	0.230	0.211	0.216	0.211
	(0.98)	(0.94)	(0.96)	(0.95)	(0.65)	(0.60)	(0.61)	(0.60)
η_{18}	0.190	0.181	0.184	0.182	0.187	0.168	0.173	0.168
	(0.88)	(0.84)	(0.85)	(0.84)	(0.55)	(0.49)	(0.51)	(0.50)
η_{19}	0.194	0.184	0.190	0.186	0.194	0.173	0.180	0.174
	(0.91)	(0.87)	(0.89)	(0.87)	(0.58)	(0.52)	(0.54)	(0.52)
η_{20}	0.136	0.127	0.131	0.128	0.134	0.112	0.118	0.112
	(0.65)	(0.61)	(0.63)	(0.61)	(0.41)	(0.34)	(0.36)	(0.34)
η_{21}	0.164	0.157	0.161	0.158	0.159	0.139	0.146	0.140
	(0.80)	(0.76)	(0.78)	(0.77)	(0.49)	(0.43)	(0.45)	(0.44)
η_{22}	0.094	0.089	0.091	0.090	0.097	0.080	0.085	0.080
	(0.45)	(0.42)	(0.44)	(0.43)	(0.30)	(0.24)	(0.26)	(0.25)
η_{23}	0.093	0.089	0.092	0.090	0.095	0.081	0.086	0.081
	(0.46)	(0.45)	(0.46)	(0.45)	(0.30)	(0.26)	(0.27)	(0.26)
η_{24}	0.121	0.115	0.118	0.116	0.129	0.111	0.116	0.111
	(0.61)	(0.58)	(0.59)	(0.58)	(0.42)	(0.36)	(0.37)	(0.36)
η_{25}	0.654	0.665	0.663	0.666	0.581	0.586	0.588	0.588
	(3.16)	(3.21)	(3.20)	(3.22)	(1.82)	(1.84)	(1.84)	(1.84)
η_{26}	0.401	0.397	0.399	0.397	0.432	0.418	0.421	0.418
	(1.97)	(1.95)	(1.96)	(1.95)	(1.36)	(1.32)	(1.33)	(1.32)
η_{27}	0.032	0.045	0.041	0.046	0.002	0.011	0.011	0.012
	(0.15)	(0.21)	(0.19)	(0.21)	(0.01)	(0.03)	(0.03)	(0.04)
η_{28}	-0.144	-0.149	-0.146	-0.147	-0.122	-0.148	-0.141	-0.147
	(-0.73)	(-0.75)	(-0.73)	(-0.74)	(-0.40)	(-0.49)	(-0.46)	(-0.48)
η_{29}	-0.149	-0.159	-0.155	-0.157	-0.144	-0.175	-0.168	-0.175
	(-0.76)	(-0.81)	(-0.79)	(-0.80)	(-0.48)	(-0.58)	(-0.56)	(-0.58)
η_{30}	-0.027	-0.034	-0.029	-0.032	0.039	0.012	0.021	0.013
	(-0.14)	(-0.17)	(-0.15)	(-0.16)	(0.13)	(0.04)	(0.07)	(0.04)
η_{31}	0.203	0.196	0.201	0.198	0.224	0.197	0.206	0.198
	(1.05)	(1.01)	(1.04)	(1.03)	(0.76)	(0.67)	(0.70)	(0.67)
η_{32}	0.319	0.309	0.316	0.312	0.341	0.306	0.318	0.307
	(1.70)	(1.65)	(1.68)	(1.66)	(1.19)	(1.07)	(1.11)	(1.07)
η_{33}	0.059	0.053	0.058	0.056	0.103	0.067	0.078	0.068
	(0.31)	(0.28)	(0.31)	(0.29)	(0.36)	(0.24)	(0.27)	(0.24)
η_{34}	1.591	1.589	1.597	1.593	1.674	1.628	1.647	1.630
	(6.32)	(6.31)	(6.34)	(6.33)	(4.85)	(4.72)	(4.77)	(4.72)
η_{35}	-0.003	-0.006	0.004	-0.001	0.108	0.069	0.089	0.072
	(-0.01)	(-0.02)	(0.02)	(-0.00)	(0.34)	(0.22)	(0.28)	(0.22)
η_{36}	-0.081	-0.072	-0.064	-0.068	0.004	-0.033	-0.016	-0.032
	(-0.27)	(-0.24)	(-0.21)	(-0.23)	(0.01)	(-0.09)	(-0.04)	(-0.09)
η_{37}	-0.422	-0.394	-0.390	-0.388	-0.287	-0.301	-0.279	-0.295
	(-1.50)	(-1.40)	(-1.38)	(-1.38)	(-0.81)	(-0.85)	(-0.79)	(-0.83)
Adj-R^2	0.0731	0.0731	0.0724	0.0729	0.0347	0.0341	0.0337	0.0342

Table 9 **Tests of ten-minute return series**

The table reports the results of the tests of ten-minute return series. Panels A and B report the results obtained from the OLS and WLS regressions in the following equation:

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

We obtain the expected value estimates of each variable on day t from the fitted value of the ARMA(p, q) model with the minimal AICC over the prior 365 days. σ^E is the expected standard deviation of the prior 30 daily Bitcoin returns. ϑ^E is the expected absolute deviation obtained from the average absolute daily deviation of Bitcoin returns from the rolling prior 30 average daily returns. $\mho^E$ is the expected ambiguity obtained from the realized Bitcoin ambiguity. P^E is the expected probability of favorable returns obtained from the rolling average of the daily probabilities of favorable Bitcoin returns over the prior 30 days. We consider a Bitcoin return as favorable if it is greater than the risk-free rate. We assign $D_i = 1$ if the expected probability of favorable Bitcoin returns on day t belongs to bin i, and zero otherwise. In Panel B, we set the weights to be inversely related to the risk and ambiguity estimates. The numbers in parentheses are t-statistics.

	Panel A: OLS			Panel B: WLS		
α	0.002	0.003	0.003	0.003	0.003	0.003
	(2.15)	(2.18)	(2.43)	(3.11)	(3.58)	(3.19)
γ	0.420		0.107	0.455		0.017
	(1.53)		(0.11)	(1.28)		(0.01)
θ		0.000			-0.000	
		(0.66)			(-0.00)	
η			-0.044			-0.005
			(-0.37)			(-0.03)
η_2			-1.129			-1.246
			(-0.38)			(-0.39)
η_3			0.092			0.001
			(0.27)			(0.00)
η_4			0.219			0.119
			(0.74)			(0.27)
η_5			0.175			0.075
			(0.59)			(0.17)
η_6			-0.036			-0.113
			(-0.13)			(-0.26)
η_7			0.149			0.028
			(0.54)			(0.07)
η_8			0.035			-0.085
			(0.13)			(-0.21)
η_9			0.175			0.073
			(0.68)			(0.19)
η_{10}			0.108			0.010
			(0.43)			(0.03)
η_{11}			0.051			-0.045
			(0.21)			(-0.12)
η_{12}			0.018			-0.058
			(0.07)			(-0.16)
η_{13}			0.109			0.037
			(0.46)			(0.10)

Table 9 (Continued)

	Panel A: OLS			Panel B: WLS		
η_{14}			0.064			-0.020
			(0.28)			(-0.06)
η_{15}			0.048			-0.031
			(0.20)			(-0.09)
η_{16}			-0.022			-0.111
			(-0.10)			(-0.32)
η_{17}			0.108			0.051
			(0.49)			(0.15)
η_{18}			0.104			0.029
			(0.49)			(0.09)
η_{19}			0.096			0.036
			(0.45)			(0.11)
η_{20}			0.079			0.008
			(0.38)			(0.03)
η_{21}			0.100			0.036
			(0.49)			(0.12)
η_{22}			0.040			-0.032
			(0.20)			(-0.11)
η_{23}			0.051			-0.004
			(0.26)			(-0.01)
η_{24}			0.016			-0.009
			(0.07)			(-0.03)
η_{25}			0.401			0.313
			(2.04)			(1.06)
η_{26}			0.258			0.207
			(1.02)			(0.59)
η_{27}			-0.062			-0.116
			(-0.31)			(-0.39)
η_{28}			-0.200			-0.234
			(-0.99)			(-0.78)
η_{29}			-0.155			-0.213
			(-0.82)			(-0.76)
η_{30}			0.074			0.027
			(0.37)			(0.09)
η_{31}			0.098			0.081
			(0.50)			(0.28)
η_{32}			0.195			0.152
			(1.07)			(0.56)
η_{33}			-0.015			-0.057
			(-0.08)			(-0.21)
η_{34}			1.443			1.512
			(5.87)			(4.49)
η_{35}			0.103			0.198
			(0.43)			(0.63)
η_{36}			-0.259			-0.303
			(-0.93)			(-0.89)
η_{37}			-0.109			-0.017
			(-0.40)			(-0.05)
Adj-R^2	0.0005	-0.0002	0.0535	0.0004	-0.0002	0.0235

Table 10 **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 HMXZ (Hou et al., 2021) size factor, $f_{ROA,t}$ is the day-t value of the HMXZ profitability factor, $f_{I/A,t}$ 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. The numbers in parentheses are t-statistics.

	Panel A: Full sample					Panel B: High ambiguity periods					Panel C: Low ambiguity periods				
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

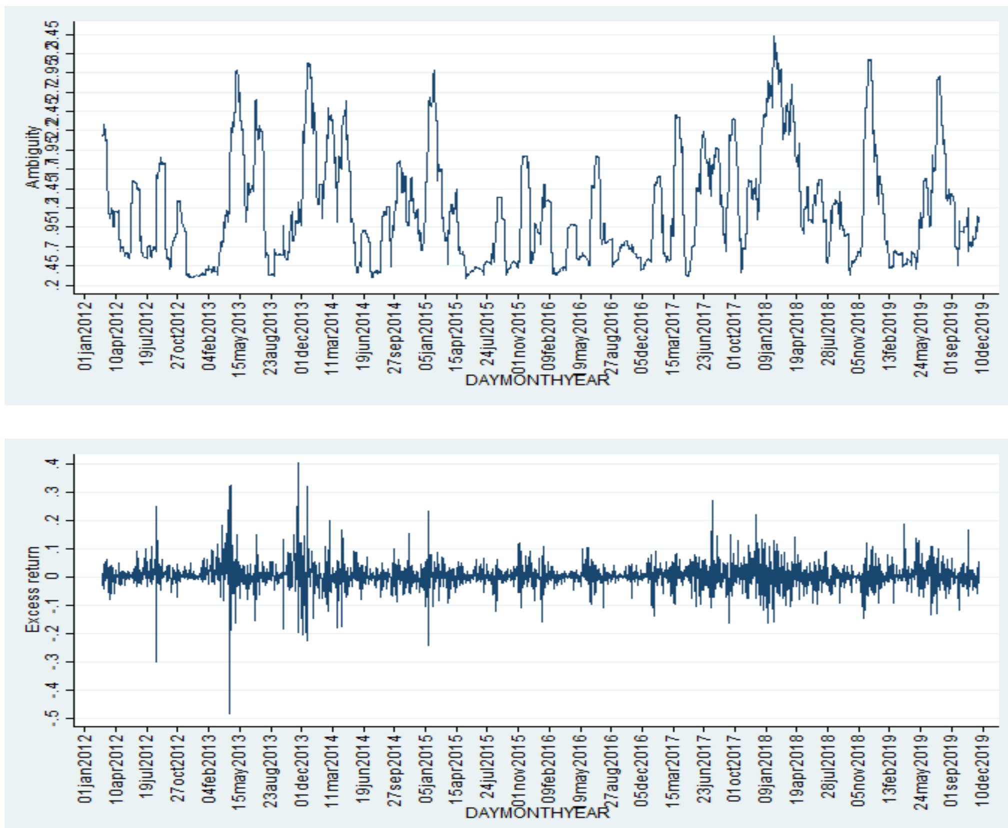

Fig. 1. Time series of Bitcoin ambiguity and excess returns

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