Does the speculative frenzy in bitcoin spread to the stock market? *

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Abstract

We find that the speculative frenzy in bitcoin affects stock prices. Stocks that have non-fundamental return co-movement with bitcoin exhibit temporary over-valuation and subsequent return reversal that exceeds −1% per month. Instrumental variables analysis using Tether flows and authorizations supports a causal interpretation of our findings. Overall, the evidence is consistent with the rapid spread of speculative interest in high skewness strategies from the social transmission of ideas and suggests that investors may evaluate these stocks in a way that is consistent with the predictions of prospect theory.

JEL Classification: G12; G14

Keywords: Cryptocurrency; social transmission bias; prospect theory

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Abstract

We find that the speculative frenzy in bitcoin affects stock prices. Stocks that have non-fundamental return co-movement with bitcoin exhibit temporary over-valuation and subsequent return reversal that exceeds −1% per month. Instrumental variables analysis using Tether flows and authorizations supports a causal interpretation of our findings. Overall, the evidence is consistent with the rapid spread of speculative interest in high skewness strategies from the social transmission of ideas and suggests that investors may evaluate these stocks in a way that is consistent with the predictions of prospect theory.

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1. Introduction

Bitcoin and cryptocurrencies have gained widespread acceptance as an investible asset class. These new securities can potentially provide portfolio diversification benefits because cryptocurrencies have little or no exposure to common risk factors (Borri, 2019; Liu and Tsyvinksi, 2021; Liu, Tsyvinksi, and Wu, 2021). However, cryptocurrencies are also a catalyst for speculative activity (Yermack, 2015; Biais, Bisiere, Bouvard, Casamatta, and Menkveld, 2020). Token prices appear to move for non-fundamental reasons such as memes on social media or scheduled pump and dump trading events (Li, Shin, and Wang, 2021). In a recent 2021 Bank of America survey, 74% of asset managers believe that bitcoin is in bubble territory.[1]

This study examines whether the speculative frenzy in bitcoin and cryptocurrencies spreads to the equity market. Although cryptocurrency returns are orthogonal to stock market factors, it is unknown whether fluctuations in cryptocurrency can affect stock prices. Speculative interest in high-skewness strategies can spread rapidly (Hirshleifer, 2021; Han, Hirshleifer, and Walden, 2021) when investors form distorted beliefs from experiencing or observing the volatility and skewness of cryptocurrency returns. These investors may seek out and drive up the prices of similar securities with low probability high upside outcomes. In this paper, we identify excessive correlated trading between bitcoin and a set of highly speculative stocks. These non-fundamental demand shocks produce temporary overvaluation and subsequent return reversals. Additional tests suggest that investors evaluate these stocks in a way that is consistent with the key features of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1982; Grinblatt and Han, 2005; Barberis, Mukherjee, and Wang, 2016; Barberis, Jin, and Wang, 2021).

Correlated trading between bitcoin and individual stocks can arise for two reasons. First, return co-movement can reflect common risk exposures or fundamental cash flow shocks. Second, non-fundamental co-movement may arise from speculative trading. The latter creates

[1] See for example, When Elon Musk tweets, crypto prices move. Vox Recode, 2021, Jun 14, and Nearly 3 in 4 professional investors in Bank of America survey see bitcoin as a bubble, CNBC 2021, Apr 13.

excessive *non-directional* co-movement among these securities. Extreme positive co-movement can arise from concurrent capital flows into bitcoin and speculative securities while extreme negative co-movement can occur when speculators rotate between bitcoin and speculative stocks.[2] Our study focuses on non-fundamental return co-movement. To operationalize the analysis, we estimate the return co-movement between bitcoin and U.S. individual stocks over the past three months and create a measure called *BTC sensitivity* that computes the absolute value of the co-movement estimate. In this regard, our empirical approach shares similarities with studies of market contagion (Bae, Karoyli, and Stulz, 2003). To ensure that *BTC sensitivity* is unrelated to fundamental blockchain exposure, we drop all stocks that report any use of bitcoin or blockchain technology (Autore, Clarke, and Jiang, 2020).

Our speculative trading hypothesis has two clear and testable implications. The first observable feature is a share price run-up due to non-fundamental trading. Second, if speculative demand bids up prices sufficiently above intrinsic value, we expect a predictable return reversal.

Figure 1 illustrates the main result. We create a long-short portfolio that buys high *BTC sensitivity* and shorts low *BTC sensitivity* stocks. Consistent with our predictions, the portfolio experiences a price run-up during the initial three-month formation period and a sharp reversal over the next six months. The extended return reversal is evidence against possible risk theories or explanations based on common cash flow or discount rate shocks. Using sorts, we find that the long-short portfolio produces a monthly Carhart four-factor alpha of −1.34% (t-stat = −5.38). After confining the sample to only stocks with significant *BTC sensitivity* estimates, the negative *BTC sensitivity* premium sharply increases to −2.16% (t-stat = −4.32).

[Figure 1 here]

The economic effects are large. We estimate $920 million in mispricing each month on average relative to a characteristics-adjusted benchmark (Daniel, Grinblatt, Titman, and Wermers, 1997). Using a binned scatterplot of Fama-MacBeth (1973) cross-sectional regressions,

[2] Bitcoin is treated as property under U.S. tax law and not subject to wash trading rules. A popular trading strategy is to tax loss harvest cryptocurrencies to offset stock gains, which can also produce excess co-movement.

we show that high *BTC sensitivity* stocks are overpriced because the negative *BTC sensitivity* premium is driven by the underperformance of *BTC sensitivity* stocks in the highest bins and not the outperformance of *BTC sensitivity* stocks in the lowest bins.[3] For example, once we omit the highest bins, the slope of the scatterplot flattens considerably and is statistically insignificant.

If *BTC sensitivity* represents a trade-based measure of demand for skewness, it might repackage lottery characteristics such as price level (Kumar, 2009; Han and Kumar, 2013), idiosyncratic volatility (Ang et al., 2006; Hou and Loh, 2016), distress risk (Campbell, Hilscher, and Szilagyi, 2008; Conrad, Kapedia, and Xing, 2014), MAX (Bali, Cakici, and Whitelaw, 2011), expected skewness (Boyer, Mitton, and Vorkink, 2010), and illiquidity (Amihud, 2002). We address this concern by performing bivariate dependent sorts, which first sort on the lottery or jackpot characteristic and then on *BTC sensitivity.* We also estimate monthly Fama-MacBeth (1973) regressions to control for characteristics as mentioned earlier. We further rule out risk-based explanations by estimating factor model regressions using the most prominent risk benchmarks. Across this range of asset pricing tests, we continue to observe a significant and negative *BTC sensitivity* premium.

To examine whether the low returns of high *BTC sensitivity* stocks are consistent with social transmission bias, we extract Google search trends of bitcoin following Liu and Tsyvinksi (2021). Search trends may reflect underlying social transmission of ideas from in-person or online discussions. We find that during periods of high social transmission, the negative *BTC sensitivity* premium is nearly twice as negative relative to low social transmission periods. In contrast, we find no significant differences in the negative *BTC sensitivity* premium across periods of high and low market-based investor sentiment (Baker and Wurgler, 2006). The latter result is important because it rules-out the possibility that equity market sentiment explains the negative *BTC sensitivity* premium and provides further evidence that *BTC sensitivity* is distinct

[3] Bin scatterplots display the expectation function between returns and *BTC sensitivity* conditional on characteristics that are known to predict returns. Specifically, we plot the time-series average residuals from *BTC sensitivity* against of the return residual for 25 bins.

from known lottery anomalies, which are affected by market sentiment (Stambaugh, Yu, and Yuan, 2012).

Our asset pricing tests alone do not provide definite conclusions about causality. One concern is that we cannot rule-out *all* possible risk factors because cryptocurrencies may have risks that have yet to be discovered. Another empirical hurdle is the lack of comprehensive individual account data to examine trading because crypto-exchanges and brokerages are independently operated. To assess causality, we design an instrumental variables analysis using the controversial Tether stablecoin. Griffin and Shams (2020) (henceforth GS) show that the authorization and flow of Tether tokens significantly predict future bitcoin returns in a way that is consistent with price manipulation. Using Tether to identify non-fundamental shocks to bitcoin returns, we find evidence indicative of a causal interpretation.

The remainder of the paper examines possible explanations for the negative *BTC sensitivity* premium. We identify two possible behavioral explanations. The first is cumulative prospect theory (Tversky and Kahneman, 1992; Barberis, Jin, and Wang, 2021). A key feature of prospect theory is the reference point, which investors use to evaluate gains and losses. Following Grinblatt and Han (2005), we use the capital gains overhang (CGO) measure to identify the investors' average stock-level reference point. Consistent with the use of the reference point, the negative *BTC sensitivity* premium concentrates in stocks with low CGO. The second feature is known as probability weighting, where investors overweight the likelihood of the tails of the expected return distribution (Barberis and Huang, 2008). We have argued that high *BTC sensitivity* stocks naturally fit this feature as speculators fixate on the salience (Bordalo, Gennaioli, and Shleifer, 2012) of these low probability high upside tail events. To verify this assumption, we compute the Tversky and Kahneman (TK) measure developed by Barberis, Mukherjee, and Wang (2016). We find that the speculative returns are significantly more negative among stocks with high TK. As a secondary test of expected skewness, we verify that high *BTC sensitivity* stocks have higher skewness of analyst earnings forecasts. As prospect theory is often applied alongside narrow framing, we perform tests of narrow framing using style category analysis (Barberis, Shleifer, and Wurgler, 2005; Chen, Singal, and Whitelaw, 2016) and daily retail order flow identified using the TAQ database (e.g., Boehmer, Jones, Zhang, and Zhang, 2021). The evidence is consistent with the use of narrow framing to evaluate high *BTC sensitivity* stocks.[4]

The other candidate explanation is over-extrapolation (Kahneman and Tversky, 1972; La Porta, Lakonishok, Shleifer, and Vishny, 1997), which proposes that investors fixate upon and over-extrapolate a salient past trend. This bias can also produce overvaluation and return reversal similar to the patterns we observe in the data. However, there is no obvious variable or pattern to extrapolate upon in our setting. While we cannot definitively ruled-out this interpretation, the lack of this key ingredient implies that over-extrapolation is unlikely to explain our results.

Additional robustness tests confirm that the main findings are not sensitive to our econometric choices. The negative *BTC sensitivity* premium remains statistically significant when *BTC sensitivity* is estimated using the aggregated cryptocurrency market return or the CoinMarketCap.com sub-sample. The results are also robust to (1) noise issues, (2) the inclusion of control for fundamental exposure to bitcoin, and (3) to the exclusion of all technology industry firms. We also perform an out-of-sample test using the China stock market and find that the negative *BTC sensitivity* premium also exists in Chinese equities.

By analyzing non-fundamental correlated trading with bitcoin, we hope to make three contributions. First, our evidence on the spread of speculative frenzy in bitcoin to equities complements the new stylized facts on cryptocurrency returns (Borri, 2019; Liu and Tsyvinksi, 2021; Liu, Tsyvinski, and Wu, 2021). Our new findings are important because they add to our understanding of the complex relation between cryptocurrencies and traditional finance. For example, cryptocurrencies are used to circumvent traditional financial intermediation (Foley, Karlsen, and Putnins, 2019; Yu and Zhang, 2020) but can also affect established financial markets

[4] Retail trading is highly correlated (Feng and Seasholes, 2004; Kumar and Lee, 2006; Barber, Odean, and Zhu, 2009) and sufficient to create price pressure (Dorn, Huberman, and Sengmueller, 2008; Liu, Wang, Yu, and Zhao, 2020).

such as currencies (Athey, Parashkevovz, Sarukkaix, and Xia, 2016; Makarov and Schoar, 2020). Second, our analysis of cryptocurrencies provides a unique setting to examine social transmission bias (Han, Hirshleifer, and Walden, 2021). The patterns in the data are generally consistent with the predictions of the theory: high *BTC sensitivity* stocks have high expected skewness and low future returns particularly during periods of high social transmission. Our findings imply that investors' biased beliefs can spread across markets, which is related to the association between gambling attitudes and the stock market (Kumar, 2009; Barber, Lee, Liu, and Odean, 2009; Gao and Lin, 2015).

Third, we contribute to the literature on prospect theory, narrow framing, and asset pricing. Grinblatt and Han (2005) and subsequent studies show that the reference point feature of prospect theory explains return anomalies such as momentum, idiosyncratic risk, and lottery-stock characteristics (e.g., An, Wang, Wang, and Yu, 2020; Liu, Wang, Yu, and Zhao, 2020). Barberis, Mukherjee, and Wang (2016) design and test a TK measure of the probability weighting feature of prospect theory. Related studies also document subsequent lower average returns on lottery stocks that are likely to have high expected skewness (e.g., Kumar, 2009; Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2013, Han and Kumar, 2013; Eraker and Ready, 2015;). Our analysis complements these studies by analyzing the role of prospect theory for a new test asset. On balance, our analysis suggests that prospect theory best explains the negative *BTC sensitivity* premium.

2. Data and construction of the *BTC sensitivity* measure

2.1. Data and the *BTC sensitivity* measure

We collect data from various sources. We obtain trading data for U.S. common share stocks (with share code equals 10 or 11) listed on the NYSE, AMEX, and NASDAQ from the Center of Research in Securities Prices (CRSP). We exclude financial firms (SIC 6000 to 6999) and utility firms (SIC 4900 to 4999) and drop the bottom fifth percentile by market capitalization in each month to avoid bid-ask bounce and issues arising from noise in returns. We also exclude all stocks that are associated with blockchain or Bitcoin in news articles (Factiva) or their regulatory

10K/10Q filings following Autore, Clarke, and Jiang (2020).[5] We treat delisting returns following Shumway (1997).[6]

We collect daily bitcoin prices from CoinMarketCap.com, which is a widely used website that tracks cryptocurrency prices. To ensure that the data are reliable, we crosscheck the accuracy of the price data with Coindesk.com. Since the bitcoin price data is available only after April 28, 2013 on CoinMarketCap.com, we gather earlier bitcoin price data from Mt. Gox. Our sample period covers 108 months starting in October 2010 and ending in September 2019. We align daily bitcoin returns to daily stock trading days by calculating the change in price over consecutive NYSE trading days. Our main analysis focuses on bitcoin because it is the most popular cryptocurrency, has the longest history, and represents nearly 50% of the total cryptocurrency market capitalization. We also create a top-ten cryptocurrency index and find similar results. The Internet Appendix provides additional descriptions of the bitcoin data.

To construct the *BTC sensitivity* measure, we obtain a parameter estimate $\theta_{i,t}^{B}$ using the following regression model:

$$\begin{aligned} R_{i,t-k} - R_{f,t-k} = \alpha_{i,t} + \theta_{i,t}^{B} BTC_{t-k} + \beta_{i,t}^{MKT} MKT_{t-k} + \beta_{i,t}^{SMB} SMB_{t-k} \\ + \beta_{i,t}^{HML} HML_{t-k} + \varepsilon_{i,t-k} \end{aligned} \tag{1}$$

where $R_{i,t-k}$ is firm i's stock daily return, and $R_{f,t-k}$ is the daily risk-free rate (30-day U.S. Treasury-bill yield) in the previous k months. BTC_{t-k} is the daily bitcoin return over the risk-free rate. MKT is the market factor (market return over the risk-free rate). SMB is the size factor, and HML is the value factor, as defined in Fama and French (1993).[7] Because bitcoin has a relatively short history, we set the estimation window k to three months. To ensure reliable estimates, we require at least 50 days of trading data in the three-month estimation window. We

[5] We obtain the sample of firms from the Internet Appendix of the published article.

[6] Our main findings are similar using the following stock screens: (1) using all stocks, (2) excluding stocks with price lower than $1 in the previous month, (3) excluding stocks with price lower than $5 in the previous month, (4) excluding stocks with market cap below the 20th percentile of NYSE stocks, and (5) using NYSE stocks only. These stock screening methods do not affect our main findings and the results are available upon request.

[7] We obtain these factors from Kenneth French's website.

include the Fama-French (FF) factors such that $\theta_{i,t}^{B}$ is orthogonal to priced risks that are known to explain expected stock returns.[8]

BTC sensitivity is defined as the absolute value of parameter estimate $|\theta_{i,t}^{B}|$ to capture non-fundamental return co-movement due to speculative trading. Daniel, Hirshleifer, and Sun (2019, p. 1681) state that "*In behavioral models, return comovement can result from commonality in stock mispricing (Barberis and Shleifer 2003), as well as commonality in investor errors in interpreting signals about fundamental factors (Daniel, Hirshleifer, and Subrahmanyam 2001).*" Positive estimates θ^{B+} can occur when investors trade bitcoin and stocks together in the same direction. Negative estimates θ^{B-} can arise when traders switch between bitcoin and stocks, perhaps to chase past performance. Excess comovement may also arise due to a popular strategy that harvests tax loss from cryptocurrencies to offset stock gains because bitcoin is treated as property under U.S. tax law and not subject to wash trading rules.[9]

We create firm characteristics for market capitalization (*Market cap*), book-to-market ratio (*B/M*), asset growth (*TAG*), operating profitability (*OP*), past one-year stock return from month t−12 to month t−2 (*MOM*), and past month t−1 return reversal (*STR*). We calculate institutional ownership (*IO%*) from the Thomson Reuters 13F database. We also construct the following measures that proxy for lottery-like features: idiosyncratic volatility (*IVOL*) (Ang, Hodrick, Xing, and Zhang, 2006), maximum daily return (*MAX*) (Bali, Cakici, and Whitelaw, 2011), and expected idiosyncratic skewness (*EIS*) (Boyer, Mitton, and Vorkink, 2010). We proxy for market frictions and illiquidity using daily *Turnover* and Amihud illiquidity (*ILLIQ*). We create a measure of retail trading activity (*Retail trading*) by identifying retail orders in the TAQ database as those orders that receive price improvement following Boehmer et al. (2021). Specifically, we identify retail trades as trades in the TAQ database with code "D" that clear at a fraction of a penny, but not

[8] Our results are robust to different estimation horizons (one month, six months, and a principal component analysis (PCA) factor that combines the one-, three-, and six-month estimates) and adjustments for estimation noise (Asparouhova, Bessembinder, and Kalcheva, 2010) and non-synchronous trading (Dimson, 1979).
[9] Wursthorn, M. (2021, Oct 4). Financial advisors pitch bitcoin to investors to offset portfolio losses. *The Wall Street Journal*

around the half penny (0.004, 0.005, 0.006). Using the IBES database, we calculate the number of analyst forecast (*No. of analysts*), the standard deviation of earnings per share (EPS) forecasts (*Dispersion*), and the skewness of the forecasts (*Forecast skewness*). Lastly, we construct two prospect theory related variables: capital gain overhang (CGO) and the Tversky and Kahneman (1992) prospect theory value (TK), developed in Grinblatt and Han (2005) and Barberis, Mukherjee, and Wang (2016), respectively. The construction of these measures is described in Section 4. We winsorize all continuous variables at the 1% and 99% levels to remove the influence of outliers. Table 1 provides variable construction details.

2.2. Characteristics of extreme *BTC sensitivity* stocks

To analyze the characteristics of high *BTC sensitivity* stocks, we sort stocks each month into ten groups based on *BTC sensitivity*. Table 1 reports the time-series averages of each stock characteristic across the ten groups. The final two columns separate the highest *BTC sensitivity* portfolio into θ^{B+} and θ^{B-}, respectively.

[Table 1 here]

Stocks in the highest *BTC sensitivity* decile can be characterized as unprofitable small-cap growth firms with low institutional ownership. While these stocks are relative losers over the past year, they experience relatively high returns in the most recent three months. They have low operating profitability and exhibit lottery-like features (Kumar, 2009) such as stock price level, expected idiosyncratic skewness, MAX, and idiosyncratic volatility. Hence, *BTC sensitivity* may represent a trade-based proxy for expect skewness, which is notoriously difficult to measure (Liu, Peng, Xiong, and Xiong, 2021) because expected skewness represents investors' beliefs on tail events that have yet to occur and are usually unobservable to the researcher. The extreme portfolios are illiquid, but also exhibit high average monthly turnover and high retail trading activity. From these simple sorts, we observe that stocks in the high *BTC sensitivity* decile experience negative unconditional future returns (*Return t*+1) on average. The last two columns confirm that extreme θ^{B+} and θ^{B-} stocks share similar characteristics. The similarity lends credence to our claim that θ^B captures correlated demand from non-fundamental trading. We provide further support for this argument in the next section.

Table 2 presents correlations of *BTC sensitivity* and stock characteristics. The overall patterns are similar to the previous sorts. *BTC sensitivity* exhibits the highest correlations with lottery-type characteristics including idiosyncratic volatility, maximum daily return, expected idiosyncratic volatility, price, and size.

[Table 2 here]

3. Return patterns of stocks with high *BTC sensitivity*

3.1. Univariate portfolio sorts on *BTC sensitivity*

We begin by conducting univariate portfolio sorts and examining the returns around the portfolio formation month. Next, we report the portfolio returns with risk adjustments. Finally, to account for estimation noise, we repeat our analysis using only stocks with significant *BTC sensitivity* estimates.

3.1.1. Return patterns around portfolio formation

We sort stocks each month into deciles based on *BTC sensitivity* and calculate realized returns of each portfolio in the following month. We create a long-short portfolio, which is zero-cost portfolio that buys stocks in the top *BTC sensitivity* decile and sells stocks in the bottom *BTC sensitivity* decile. We calculate the returns for the long-short portfolio three months before and six months after portfolio formation. As discussed earlier, Figure 1 shows the predicted time-series hump-shaped return pattern around the formation month. The long-short portfolio returns steadily rise in pre-formation months, peaking in the formation month, consistent with the high contemporaneous return of high *BTC sensitivity* stocks in Table 1. The abnormal returns are significantly negative in each of the six months after portfolio formation.

3.1.2. Portfolio sorts

Next, we report the average *BTC sensitivity*-sorted portfolio excess returns (raw return over the risk-free rate) and alphas based on the CAPM, Fama-French three-factor, and Carhart four-factor models using equal-weighted portfolios in the immediate month after portfolio formation. We calculate *t*-statistics based on Newey-West (1987) standard errors with up to 12 lags.

The results in Table 3 compliment Figure 1. We observe that high *BTC sensitivity* stocks suffer significantly low future returns. The first column in the left panel shows that the equal-weighted long-short portfolio generates an average monthly raw return of −1.32% (*t*-stat = −4.67) or more than −15% per year. The next column reports slightly larger abnormal returns using the CAPM.[10] The three- and four-factor models in columns 3 and 4 produce similar patterns with average monthly alphas of −1.54% (*t*-stat = −5.81) and −1.34% (*t*-stat = −5.38), respectively. A robust return pattern emerges across these specifications. The highest two *BTC sensitivity* deciles consistently exhibit significantly negative risk-adjusted average returns. In contrast, the lowest two *BTC sensitivity* deciles have insignificant risk-adjusted average returns. This suggests that the negative *BTC sensitivity* premium is due to the underperformance of high *BTC sensitivity* stocks and not due to the outperformance of low *BTC sensitivity* stocks. The return patterns are consistent with the view that high *BTC sensitivity* stocks are temporarily overvalued.

[Table 3 here]

Figure 2 shows that the economic magnitude of the mispricing is large. Each month, we calculate the dollar amount of mispricing for each stock in highest *BTC sensitivity* decile by subtracting the raw return from the DGTW benchmark return and then multiplying the difference by the market capitalization at the end of previous month. To obtain the total mispricing value for that month, we sum the mispricing value for all stocks in the high *BTC sensitivity* portfolio. We then accumulate the total over our sample period. For comparison, we

[10] It is worth noting that the CAPM alphas are negative in the second column. We provide a detailed explanation of this result in Section 3 in the online appendix.

also perform the same calculation for lottery-like anomalies such as MAX, idiosyncratic volatility, and expected skewness.

[Figure 2 here]

The total mispricing of stocks in the highest *BTC sensitivity* decile during the 72-month period is $99.7 billion, which averages to $923 million a month. In comparison, the total amounts for idiosyncratic volatility, MAX, and expected skewness were $23.5 billion, $26.1 billion, and $36.6 billion, respectively.

3.1.3. Portfolio sorts using only stocks with significant BTC sensitivity estimates

The OLS regression model (Equation 1) used to estimate *BTC sensitivity* is likely to incur estimation noise. Therefore, we repeat our portfolio analysis using only stocks that have *BTC sensitivity* estimates at the 10% significance level or better. The return patterns are much larger using this sample. The right panel of Table 3 reports a monthly four-factor alpha of −2.16% (*t*-stat = −4.32) for the long-short portfolio, which is more than 0.8% larger than the corresponding four-factor alphas using all stocks in the left panel.

The larger negative *BTC sensitivity* premium using more precise estimates indicates significant estimation noise in our *BTC sensitivity* measure. The implication is that our baseline tests are downward biased and understate the true magnitude of expected returns associated with high *BTC sensitivity* stocks.

3.2. Are the *BTC sensitivity* return patterns due to known characteristics or risks?

The evidence thus far further supports our claim that the speculative interest in bitcoin affects stock prices. However, if BTC sensitivity represents a trade-based measure of expected skewness, we might be re-documenting the return patterns of lottery-like characteristics in the existing literature. This section carefully examines this issue using (1) double portfolio sorts, (2) monthly cross-sectional Fama-MacBeth regressions, and (3) factor model tests.

3.2.1. Portfolio-level analysis: Dependent double sorts

We conduct bivariate 10×10 dependent sorts to examine whether the *BTC sensitivity* return patterns are orthogonal to the return patterns from lottery-like characteristics. We first sort stocks into deciles ranked on the lottery-like characteristic. Then within each decile group, we further sort stocks into decile portfolios based on *BTC sensitivity*. Decile 1 (10) contains stocks with the lowest *BTC sensitivity* (highest *BTC sensitivity*). The lottery-like characteristics we examine are size, price-level, MAX, idiosyncratic volatility, expected idiosyncratic skewness, turnover, illiquidity, and distress risk.

Panel A of Table 4 reports results. To conserve space, we report the average portfolio returns across the ten control variable deciles to produce a set of *BTC sensitivity* portfolios with similar levels of the lottery characteristic, but different levels of *BTC sensitivity*. In the bottom two rows, we report the excess return and four-factor alpha of the long-short portfolio that is the difference between decile 10 and decile 1.

[Table 4 here]

Across all specifications, the long-short portfolios produce significantly negative four-factor alphas. In the first six columns, we report anomalies that have been associated with lottery preferences. The monthly four-factor alphas range from −0.25% (*t*-stat = −3.25) to −1.20% (*t*-stat = −5.55) per month, which are smaller than those reported in the univariate sorts but remain significant at the 1% level. The results in column (6) suggest that *BTC sensitivity* and *EIS* share a common component because *EIS* captures a large fraction of the negative *BTC sensitivity* premium. We interpret this finding to suggest that investors perceive that high *BTC sensitivity* stocks to have expected positive skewness and that the negative *BTC sensitivity* premium has a remaining component that is not fully captured by *EIS*.

The last two columns report dependent sorts based on *Turnover* and *ILLIQ*, which have average monthly four-factor alphas of −1.15% (*t*-stat = −5.71) and -1.27% (*t*-stat = −6.89), respectively. Collectively, the results suggest that while the negative *BTC sensitivity* premium shares a common component with lottery-like characteristics and market frictions, these characteristics cannot fully explain the pricing of high *BTC sensitivity* stocks. It is possible that our results could reflect attenuation in these anomaly returns in recent periods (McLean and Pontiff, 2016). However, we replicate these anomalies and find that they continue to generate significantly abnormal returns in our recent sample period. We present these results in the Internet Appendix, Table A2.

In sum, the analysis using conditional sorts provides two key takeaways. First, the results suggest that *BTC sensitivity* is not simply re-documenting the return patterns of lottery-like characteristics. Second, the negative *BTC sensitivity* premium continues to exist in double sorts.

3.2.2. Binned scatterplot graph and Fama-MacBeth cross-sectional regressions

The bivariate sorts show that our findings are not fully explained by existing lottery-like characteristics. However, other characteristics or a combination of characteristics (Fama and French, 2008) may explain our results. To investigate the marginal effect of *BTC sensitivity* on expected returns, we create a binned scatterplot (binscatter) from cross-sectional Fama-MacBeth regressions.

To create the binscatter graph, we implement a version of the Fama-MacBeth procedure as follows. Each month, we regress the stock return on a set of control variables (discussed below) but omit the *BTC sensitivity* measure. From this regression, we obtain the regression residuals (i.e., the return residuals). Next, we regress *BTC sensitivity* on the same set of control variables and obtain the *BTC sensitivity* residuals. Then, we divide the sample of stocks into 25 bins based on their *BTC sensitivity* residuals and calculate the average return residual and the average *BTC sensitivity* residual. Finally, we use the time-series average of the return residual and *BTC sensitivity* residual for each bin to plot the relation between *BTC sensitivity* and return.

[Figure 3 here]

Figure 3 reports the binscatter graph. The solid line represents the best fit line using all 25 bins. The slope of the line is significantly negative (-0.12, t-stat = -5.07) and equivalent to the parameter estimate on *BTC sensitivity* in the cross-sectional Fama-MacBeth regression. Visually, we can see that slope of the line is driven by the highest five *BTC sensitivity* bins (represented by star markers). To quantify this effect, we exclude the top 5 bins and refit an OLS line using the 20 lower bins. The slope of the line is less than half the magnitude and is statistically insignificant (-0.05, *t*-stat = -1.01). Consistent with patterns from the univariate sorts, the results suggest that the negative relation between *BTC sensitivity* and stock return is driven by the underperformance of extreme high *BTC sensitivity* stocks.

We also report the Fama-MacBeth regression results from the binscatter plots. The baseline regression includes controls for size, book-to-market, operating profitability, asset growth, momentum, and short-term reversals. To compare coefficient estimates across different specifications, we normalize all variables in each cross-section to have mean zero and standard deviation of one. We report the time-series averages of the coefficient estimates for the 108-month period between October 2010 and September 2019. The *t*-statistics are adjusted following Newey and West (1987) with up to 12 lags.

Panel B of Table 4 reports negative *BTC sensitivity* slopes across all specifications at the 1% significance level. The univariate regression in column (1) produces a coefficient estimate of −0.43 (*t*-stat = −5.25), which corresponds to the average monthly return spread of greater than 1% per month between the top and bottom decile *BTC sensitivity* portfolios. The economic magnitude of the associated effect is similar to that shown in Table 3 for the univariate sorts.[11] Column (2) includes characteristics known to explain the cross-section of stock returns: logarithm of market capitalization (*Ln*(*SIZE*)), logarithm of book-to-market ratio (*Ln(B/M)*), operating profitability (*OP*), asset growth (*TAG*), past return from month *t*-12 to *t*-2 (*MOM*), and past month return (*STR*). The *BTC sensitivity* slope remains significantly negative (coeff = −0.32; *t*-stat = −5.35) with the inclusion of these characteristics.

Columns (3) and (4) report significantly negative *BTC sensitivity* slope estimates with the inclusion of lottery-type stock characteristics (i.e., *IVOL*, *MAX*, and *EIS*). The slope estimate on *BTC sensitivity* also remains statistically significant (coeff = −0.12; *t*-stat = −3.33) after further

[11] The extreme decile *BTC sensitivity* cut-off point is about 1.28 standard deviation from the mean. Therefore, the corresponding long/short *BTC sensitivity* portfolio based on deciles are approximately 2.56 standard deviations apart. This translates to roughly -0.42%×2.56 = -1.08%.

controlling for illiquidity, market frictions, and distress risk in column (5). This slope estimate corresponds to the slope in the binscatter plot in Figure 3. The loadings on the control variables are consistent with the recent literature. McLean and Pontiff (2016) show that anomaly returns are significantly attenuated after initial academic publication. For example, in our recent sample period, the regression slopes on size, value, asset growth, and momentum are insignificant. However, operating profitability (Ball, Gerakos, Linnainmaa, and Nikolaev, 2015) remains significantly positive at the 1% level and *IVOL* has a significantly negative loading, consistent with Ang et al. (2006). Measures of illiquidity (*ILLIQ*) and market frictions (*Turnover*) are significant although short-term reversals are not.

Overall, the Fama-MacBeth regressions provide compelling evidence that the *BTC sensitivity* effect is priced in the cross-section. The negative *BTC sensitivity* premium cannot be fully explained by size, book-to-market, asset growth, profitability, momentum, short-term reversal, lottery-like features, and illiquidity. The evidence further supports our claim that the speculative frenzy in bitcoin spreads to the stock market.

3.2.3. Factor model analysis

We investigate whether recently proposed factor models can explain the negative *BTC sensitivity* premium because the traditional Fama-French three-factor model is unable to price small stocks with lottery-type features (Fama and French, 1993). We adjust the long-short portfolio returns using the following five factor models: (1) Fama-French five-factor model, (2) Fama-French five-factor model plus Carhart momentum factor, (3) the Frazzini and Pedersen (2014) Betting against Beta (BAB) factor with the four-factor model, (4) Stambaugh and Yuan (2017) four mispricing-factor model (M4), and (5) Bali et al. (2017) FMAX factor with the four-factor model.[12]

[12] We obtain the Fama French five-factors from Ken French's website, the M4 factors from Robert Stambaugh's website, the BAB factor from the AQR website, and the FMAX factor from Turan Bali's website. We thank the researchers for making their factors publically available. The Fama French five-factor model includes factors for profitability (RMW) and investment (CMA). The BAB model has a factor for the low beta anomaly. The M4 model has two mispricing factors that capture managerial decisions (MGMT) and firm performance (PERF). The FMAX factor has a factor for the MAX effect.

Panel C of Table 4 reports factor loadings and alpha estimates. The first row shows that the long-short portfolio has positive market exposure. The factor loadings from the three- (second row) and four-factor models (third row) show that high *BTC sensitivity* stocks have positive exposure to SMB and negative exposure to momentum. The five- and six-factor models show that high *BTC sensitivity* stocks have negative exposure to profitability.[13] These factor loadings imply that high *BTC sensitivity* stocks share systematic factors (i.e., recent losers and weakly profitable firms) that are known to have lower future returns. Row 6 shows that the long-short portfolio does not load on the BAB factor, which implies that leverage constraints are unlikely to explain the negative *BTC sensitivity* premium. Overall, these loadings are consistent with the stock characteristics shown in Table 1.

These models, however, are unable to fully explain the negative *BTC sensitivity* premium. The long-short portfolio continues to produce significant alphas of −1.39% (*t*-stat = −5.25) and −1.15% (*t*-stat = −5.08) from the five- and six-factor models, respectively. Because Fama and French (2016) show that the five-factor model captures much of the low returns associated with idiosyncratic volatility and high beta, the significant alphas imply that the *BTC sensitivity* effect is orthogonal to these known effects. The bottom two rows show that the portfolio loads significantly on the M4 and FMAX factors. Using the M4 model, the long-short portfolio loads negatively on both the MGMT and PERF factors, but the alpha estimate (coeff = −1.01%; *t*-stat = −3.57) is similar to the four-factor model baseline estimates. This result suggests that while the long-short portfolio has exposure to systematic mis-pricing factors, the negative *BTC sensitivity* premium is distinct from the common component of return anomalies captured by the M4 factors.

Among the factor models, the M4 and FMAX models are relatively successful in explaining the negative *BTC sensitivity* premium. The alpha estimates from the M4 and FMAX models are −1.01% (*t*-stat = −3.57) and −0.85% (*t*-stat = −4.17), respectively. These findings lend credence to

[13] Interestingly, once the momentum factor is included, the loading on HML becomes significantly negative (rows 3 and 5).

the view that *BTC sensitivity* is a trade-based proxy for expected skewness because these factors have a high correlation with lottery-like stocks (Bali et al., 2017; Liu, Stambaugh, and Yuan, 2018).[14]

3.3. Are the *BTC sensitivity* return patterns due to omitted risk factors?

We address the possibility that an omitted risk factor explains the negative *BTC sensitivity* premium using two approaches. First, we construct possible systematic factor associated with the fundamental value of bitcoin. We re-estimate our factor-model tests by including the following three bitcoin-related factors: (1) the monthly bitcoin excess return to provide a market-based valuation metric, (2) the change in bitcoin transactions on the network to capture the usage rate of bitcoin, and (3) the change in the hash rate of the bitcoin network. The hash rate measures the total processing power of the bitcoin network used to mine bitcoin. Our results are unchanged with the inclusion of these bitcoin fundamental risk factors (Table A5 in the Internet Appendix). Second, we conjecture that cryptocurrency-related risks not captured by our factors are most likely to concentrate among technology firms. As such, we repeat our main return analysis by omitting technology firms from the sample. As shown in Table A11 of the Internet Appendix, our results are similar using the non-technology sample.

3.4. Are the *BTC sensitivity* return patterns consistent with social transmission bias?

The spread of speculative frenzy from bitcoin to equities may occur due to biases that arise from the social transmission of ideas regarding cryptocurrencies. Social transmission bias (Han, Hirshleifer, and Walden, 2021) occurs when investor beliefs are distorted by observing convex and volatile returns. They may adopt these strategies and generate demand for similar securities with high expected skewness.

To measure social transmission, we follow Liu and Tsyvinski (2021) to extract the weekly search volume for the word "bitcoin" from Google Trends. We adjust the current week's search

[14] Asness et al. (2020) show that while the FMAX factor is related to lottery-demand, the BAB factor is related to lottery-demand only because high Beta stocks have high correlations with lottery-like stocks. Their decomposition shows that leverage constraints better explain the BAB factor.

interest by the average search interest in the previous 4 weeks and use the average of the adjusted weekly search interest in one month as the monthly measure of social transmission. We hypothesize that if the negative *BTC sensitivity* premium arises from social transmission bias, the premium will be more negative during high transmission periods. To test this prediction, we divide the entire period into high and low transmission periods, and conduct portfolio analysis separately to examine whether the negative *BTC sensitivity* premium is different across the two regimes.

[Table 5 here]

Table 5 reports the results. The findings in panel A indicate that the negative *BTC sensitivity* premium is significantly stronger following high social transmission periods. The excess return following high social transmission (exret = -1.78%, *t*-stat = -5.05) is more than twice as negative as that of the low social transmission periods (exret = -0.85%, *t*-stat = -2.58). We also find that the three lottery-type anomalies (MAX, idiosyncratic volatility, and idiosyncratic expected skewness) are also stronger following high social transmission, which suggests that these anomalies may also be affected by the speculation in the cryptocurrency market.

An alternative explanation for these patterns is that high social transmission periods are simply capturing stock market sentiment because market sentiment is associated with the mispricing of lottery-like stocks (Stambaugh, Yu, and Yuan, 2012). We examine this alternative explanation using the Baker and Wurgler (2006) sentiment index. Panel B reports the results. The first column shows that the long-short *BTC sensitivity* portfolio has similar returns following high (exret = -1.26%, *t*-stat = -2.94) or low periods of investor sentiment (exret = 1.19%, *t*-stat = -2.81). For the three lottery-type anomalies, the results are consistent with Stambaugh, Yu, and Yuan (2012) as the anomalies are stronger following high sentiment periods.

Overall, the results suggest that the negative *BTC sensitivity* premium is associated with social transmission but not stock market sentiment. The latter analysis is important because it rules-out the possibility that investor sentiment explains the negative *BTC sensitivity* premium and provides further evidence that *BTC sensitivity* is distinct from known lottery anomalies, which are affected by stock market sentiment (Stambaugh, Yu, and Yuan, 2012).

4. Tether flows as an exogenous shock to bitcoin returns

While the evidence strongly suggests that the speculative interest in bitcoin affects stock prices, some concerns linger. One issue is the possibility of an omitted risk factor because cryptocurrencies may have risks that have yet to be discovered. Another empirical hurdle is that the mechanism is probably untraceable because crypto-exchanges and brokerages are independently operated. To assess causality, an ideal experiment would be to use non-fundamental shocks to bitcoin returns to examine whether the pricing effects we document still exist.

We select the flow and authorization of Tether between different coin exchanges as a possible non-fundamental shock to bitcoin returns. Tether is a cryptocurrency with tokens issued by Tether Limited, whose ultimate owner is Bitfinex. Tether is the largest stable coin and pegged to the U.S. dollar (USD), i.e., each Tether token is claimed to be fully backed by USD reserves.[15] Tether provides a convenient "on-ramp" for many investors to enter and transact in the cryptocurrency market.

GS show that Tether authorizations and Tether flows between different exchanges predict future bitcoin price and other cryptocurrency prices. Bitcoin returns spike shortly after the authorization and flow of new Tether. The timing of these flows is suspicious and consistent with price manipulation. To use Tether flows as a valid instrument for bitcoin returns, it must satisfy the relevance condition and exclusion restriction. The relevance condition is met if Tether authorizations and flows significantly predict future bitcoin returns. To demonstrate relevance, we replicate the analysis in GS to assess the strength of the instrument. The exclusion restriction

[15] Tether coin was originally designed to always be worth $1.00, i.e., maintaining $1.00 in reserves for each Tether issued. But in a later investigation released on Feb 23, 2021 by New York Attorney General finds that "Tether's claims that its virtual currency was fully backed by U.S. dollars at all times was a lie." See the following report for more details: https://ag.ny.gov/press-release/2021/attorney-general-james-ends-virtual-currency-trading-platform-bitfinexs-illegal.

in satisfied if Tether authorization and Tether flow does not affect stock returns other than through *BTC sensitivity*. While the exclusion restriction is fundamentally untestable, we believe the restriction is likely satisfied for the following reason. Tether authorization and Tether flow are likely used to inflate bitcoin prices, not equity prices. Tether flows were not intended to affect stock prices because cryptocurrencies were traded on exchanges that were separate from equities during our sample period, Moreover, the Tether founders were likely holding large positions in bitcoin and would have strong incentives to manipulate or stabilize bitcoin prices rather than equity prices.

We obtain the Tether flow data from the Journal of Finance supplementary materials for the GS article. The dataset contains hourly data, including the hourly bitcoin returns, bitcoin return volatility, and the Tether authorizations and Tether flows, and other variables used in their analysis. Following GS, we conduct our first-stage regression at the hourly frequency as follows:

$$\begin{aligned}\frac{1}{3}\sum_{i=0}^{2} BTC_{t+i} = \ & \beta_1 Flow_{t-1} + \beta_2 Auth_{Post_{t-1}} + \beta_3 Flow_{t-1} \times Auth_{Post_{t-1}} \\ & + \beta_4 BTC_{t-1} + \beta_5 VoB_{t-1} + \beta_6 BTC_{t-1} \times VoB_{t-1} \\ & + \beta_7 MKT_{t-1} + \beta_8 SMB_{t-1} + \beta_9 HML_{t-1} + \varepsilon_t\end{aligned} \quad (2)$$

where BTC_t is the hourly bitcoin return of an equal-weighted price index that aggregates bitcoin prices on the following exchanges Bitfinex, Poloniex, Bittrex, Binance, HitBTC, Huobi, and OKEx. The dependent variable is the average hourly return in the next three hours. $Flow_t$ is the average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of bitcoin from Poloniex and Bittrex to Bitfinex. $Auth_{post}$ is an indicator variable that equals one if a Tether authorization occurred in the previous 72 hours, and zero otherwise. VoB_t is volatility calculated using hourly bitcoin returns over the previous 24 hours. MKT_t, SMB_t, and HML_t are the daily-level Fama-French three factors. We use the Fama-French three factors in the previous day to prevent a look-ahead bias but verify that our findings are similar using the same day Fama-French factors.

Table 6 reports the results from the first-stage regression (equation 2). The results support the view that the instruments satisfy the relevance condition. Consistent with GS, the loading on the interaction of Tether authorization and higher Tether flow is significantly positive with a *t*-statistic of 4.10, and the control variables also show the correct signs. The Cragg-Donald Wald F-statistic is 10.07 and is above the 10% level cutoff for weak instruments for standard two-stage least squares (2SLS) regression (Stock and Yogo, 2004). However, in our setting, this rule of thumb may not apply for two reasons. First, in 2SLS, the economic outcome of interest is the estimated local average treatment effect. In contrast, after we obtain the instrumented parameter estimate on predicted BTC return in the second stage, we compute the absolute value of that estimate to produce the *BTC sensitivity* measure. Then, our analysis has a third stage where we rank order the instrumented coefficients to examine the relation between *BTC sensitivity* and future stock returns. Second, the concern with weak instruments is that they produce too little variation in predicted outcomes, which causes inconsistent estimates. For our purposes however, the lack of variation due to weak instruments would create noise in the rank orderings and potentially biases against finding an association between *BTC sensitivity* and returns.

[Table 6 here]

To obtain the instrumented *BTC sensitivity* measure, we estimate Equation 3.

$$\begin{aligned} R_{i,t-k} - R_{f,t-k} = \alpha_{i,t} + \theta_{i,t}^{IB}\widehat{BTC}_{t-k} + \beta_{i,t}^{MKT}MKT_{t-k} + \beta_{i,t}^{SMB}SMB_{t-k} \\ +\beta_{i,t}^{HML}HML_{t-k} + \beta_{i,t5}BTC_{t-k-1} + \beta_{i,t6}VoB_{t-k-1} \\ + \beta_{i,t7}BTC_{t-k-1} \times VoB_{t-k-1} + \varepsilon_{i,t-k} \end{aligned} \tag{3}$$

where $R_{i,t-k}$ is firm i's stock daily return, and $R_{f,t-k}$ is the daily risk-free rate (30-day U.S. Treasury-bill yield) in the previous k months. $\widehat{BTC_{t-k}}$ is the instrumented daily bitcoin return over the risk-free rate, which we obtain by compounding the hourly predicted return to the daily level. We include the following control variables from Equation 2. BTC_{t-k-1} is the lagged realized daily bitcoin return over the risk-free rate. VoB_{t-k-1} is the lagged average hourly bitcoin return volatility in day (t-k-1). After obtaining the coefficient estimate $\theta_{i,t}^{IB}$, we compute the absolute value to produce the instrumented *BTC sensitivity* measure.

Figure 4 shows the portfolio performance around the portfolio formation date. We create a long-short portfolio that buys high *BTC sensitivity* (instrumented sensitivity) stocks and shorts low *BTC sensitivity* (instrumented sensitivity) stocks. Consistent with our baseline results illustrated in Figure 1, the portfolio experiences a price run-up during the initial three-month and a subsequent sharp reversal. The return pattern supports a causal interpretation between the stock's *BTC sensitivity* and further stock return.

[Figure 4 here]

The caveat to our analysis is that our sample period is short. The GS sample spans from March 01, 2017 to March 31, 2018, which limits our analysis to 11-month (June 2017 to April 2018). Hence, statistical analysis will lack power. Therefore, we interpret the patterns in Figure 3 as evidence consistent with a causal interpretation.

5. Does prospect theory explain the negative BTC sensitivity premium?

The negative *BTC sensitivity* premium could be explained by at least two behavioral theories. The first is cumulative prospect theory. Prospect theory predicts that if investors in high *BTC sensitivity* stocks overweight low probability, high upside outcomes, these securities will exhibit temporary overvaluation and reversal patterns. The second behavioral explanation is over-extrapolation. The key ingredient of this theory is that investors fixate upon a past trend and over-extrapolate it into the future. Over-extrapolation can also produce a return reversal, like the pattern we observe in the data. While we cannot definitively rule out over-extrapolation, it is not obvious which variables or patterns investors would over-extrapolate in our setting.

The remainder of this section assesses the prospect theory explanation in detail. We use various empirical analyses and introduce new tests to strengthen the overall evidence.

5.1. Reference point

We begin by analyzing the reference point feature in prospect theory. To estimate the reference point, we calculate the cost-based aggregate capital gain overhang (CGO) measure developed in Grinblatt and Han (2005) and used in Barberis, Jin, and Wang (2021). CGO is the aggregate turnover rate weighted average price of the stock in the previous year calculated as follows:[16]

$$R\_Price_t = \frac{1}{k}\sum_{n=1}^{52}\left(TO_{t-n}\prod_{\tau=1}^{n-1}(1 - TO_{t-n+\tau})\right)P_{t-n}$$

where k is a constant such that the weights on past prices sum to one; TO_{t-n} is the weekly turnover rate for week (t-n); P_{t-n} is the stock price at the end of week (t-n). To avoid the market microstructure impact, we lag the current stock price by one week (Grinblatt and Han, 2005). Thus, CGO is defined as $\frac{(P_{t-1} - R\_Price_t)}{P_{t-1}}$. To align with monthly rebalancing, we use the CGO calculated in the last week of each month (Barberis, Jin, and Wang, 2021). Negative CGO indicates that the reference point is higher than the current price and reflects that investors suffer losses on average. If investors evaluate negative CGO stocks relative to a reference point, they are risk seeking in these investments, which implies negative future returns. Therefore, we expect that the negative *BTC sensitivity* premium will be more pronounced for low CGO stocks.

Figure 5 reveals a striking pattern. The negative BTC sensitivity premium concentrates in stocks with low CGO. The figure plots the returns from dependent 5×5 bivariate sorts that first allocates stocks into quintiles of CGO, and then into quintiles of *BTC sensitivity*. The average return for stocks in the extreme *BTC sensitivity*/CGO quintile is −2.35%.

[Figure 5 here]

5.2. Probability weighting

[16] Grinblatt and Han (2005) use a 5-year period to estimate the reference points. We use a 1-year period because we expect speculators to have shorter holdings periods for high *BTC sensitivity* stocks. The results are similar if we use the 5-year period.

The probability weighting feature in cumulative prospect theory refers to investors' biased beliefs of the tail outcomes of the probability distribution. Because beliefs are typically unobservable, we infer the use of probability weighting by (1) employing the TK measure and (2) computing the skewness analyst earnings forecasts, which reflect the financial experts' expectation of the firm's future performance.

5.2.1. Probability weighting test: TK measure from Barberis, Mukherjee, and Wang (2016)

We calculate the TK measure developed in Barberis, Mukherjee, and Wang (2016) by using the monthly return in excess of the market return during the previous five years. First, we rank all the returns in ascending order from the most negative to the most positive. While the objective probability in the return distribution is 1/60, investors using prospect theory will overweight the extreme outcomes. For each return, we estimate the corresponding utility value assuming a power utility function using estimates from Tversky and Kahneman (1992) experimental data. Hence, the TK value represents a subjective probability weighted average utility. If investors use the TK value to form their subjective beliefs of the probability distribution, investors will buy stocks with a premium and to bet on the extreme future returns. We predict that high TK stocks are more speculative, which drives the low return of high BTC sensitivity stocks. [17]

[17] To calculate the TK value, we consider a gamble game with different outcomes with a corresponding probability. In the stock market, the outcomes will be the different stock returns. Thus, we first establish the gamble by specifying the return distribution. Following Barberis, Mukherjee, and Wang (2016), we extract the stock's monthly excess return over the market return in previous 5 years as the estimation sample. We further rank the returns in ascending order, starting from the most negative return to the most positive return. Each return will be associated with an equal objective probability of 1/60. The prospect theory states that investors will overweight the extreme outcomes when estimate the overall gamble utility, i.e., they assign a subjective probability to each outcomes. To match the prospect theory, we further estimate the subjective probability for each return using the following formula:

$$\pi_i = \begin{cases} w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) & for \quad 0 \le i \le n \\ w^-(p_{-m} + \cdots + p_i) - w^-(p_{-m} + \cdots + p_{i-1}) & for \quad -m \le i < 0 \end{cases}$$

with $w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}$, $w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{1/\delta}}$, $\gamma = 0.61$, $\delta = 0.69$, and $p_i = 1/60$. The parameter γ and δ are estimated in Tversky and Kahneman (1992) experimental data. After we get the subjective probability for each return, we calculate the utility for each return assuming a power utility function. Tversky and Kahneman (1992) propose the following utility function:

$$v_i = \begin{cases} {R_i}^\alpha & for \quad 0 \le i \le n \\ -\lambda * (-R_i)^\alpha & for \quad -m \le i < 0 \end{cases}$$

We test this prediction by conducting a dependent 5×5 bivariate sorts analysis that first allocates stocks into quintiles of TK, and then into quintiles of *BTC sensitivity*. Figure 6 shows that the low return of high *BTC sensitivity* stocks concentrates in stocks with high TK. The average return for stocks in the extreme *BTC sensitivity*/TK quintile is −1.90%.

[Figure 6 here]

5.2.2. Probability weighting test: Analyst forecast skewness

The summary statistics in Table 1 provide initial evidence that high *BTC sensitivity* stocks are associated with lower analyst followings, larger forecast dispersion, and higher forecast skewness. The high forecast skewness indicates that investors may overvalue high BTC sensitivity stocks. However, once the firm succeeds, it could provide extreme large returns.

We further examine the relation between *BTC sensitivity* and analyst forecast skewness formally using the Fama-MacBeth regressions. We regress the analyst forecast skewness of the future EPS forecasts on firm's *BTC sensitivity* each month and report the average coefficient in Table 7. Columns (1) to (3) report the results without any control variables, with controls of firm fundamentals, and with additional controls of analyst forecast factors, respectively. All the coefficients of *BTC sensitivity* are positive and significant at the 5%, suggesting that high *BTC sensitivity* stocks are associated with positively skewed earnings forecasts.

[Table 7 here]

5.3. Narrow framing

Investors with prospect theory preferences typically engage in narrow framing. This section examines the role of narrow framing using two tests.

5.3.1. Narrow framing test: Retail clientele

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with $\alpha = 0.88$, and $\lambda = 2.25$. The parameter α and λ are estimated in Tversky and Kahneman (1992) experimental data. Once we obtain the utility and the corresponding subjective probability for each return, the TK value is defined as the weighted average utility for all 60 returns, i.e., $\text{TK} = \sum_{i=-m}^{n} \pi_i * v_i$.

We expect retail investors to be more likely to exhibit narrow framing because they tend to hold undiversified portfolios. Teo and O'Connell (2003) find that institutional investors are less likely to have prospect theory utility. To identify retail order flow, we collect orders that receive price improvement following Boehmer et al. (2021).[18] We also use low institutional ownership as a second measure to identify retail trading (Kumar and Lee, 2006).

Figure 7 reveals a striking pattern that the low return of high *BTC sensitivity* stocks concentrates in stocks with high retail trading. The figure reports results from dependent 5×5 bivariate sorts that first allocates stocks into quintiles of retail trading, and then into quintiles of *BTC sensitivity*. The average return for stocks in the extreme *BTC sensitivity*/retail trading quintile is more than −2.35%. The return is -2.78% when sorting based on institutional ownership.

[Figure 7 here]

5.3.2. Narrow framing test: Trading habitat

Narrow framing is decision-making process that evaluates an investment separately from other investment risks. If investors use narrow framing to assess high *BTC sensitivity* stocks, their correlated flows can induce a common factor or co-movement in the returns of these securities (Lee, Shleifer, and Thaler, 1991; Barberis, Shleifer, and Wurgler, 2005), even if the cash flow fundamentals of the specific stocks are uncorrelated. To test this prediction, we estimate a set of univariate return regressions to detect excess co-movement following Chen, Singal, and Whitelaw (2016).

$$\begin{aligned} y_t &= \alpha + \beta_1 x_{1t} + \varepsilon_t, \\ y_t &= \alpha + \beta_2 x_{2t} + \varepsilon_t, \end{aligned} \tag{4}$$

where y_t represents the daily return of stocks that enter the highest decile *BTC sensitivity* portfolio at month *t*. We create two portfolios. x_{1t} represents the daily average portfolio return

[18] This analysis ends in December 2016 due to the data limitation in our TAQ database. Another useful proxy for retail orders is small-trade (trade size below $5,000) in the TAQ database. However, we cannot use this approach because in our recent time-period, institutional investors submit much smaller orders (Hu, Jo, Wang, and Xie, 2018).

of the stock's previous *BTC sensitivity* decile portfolio.[19] x_{2t} represents the daily average return of stocks in the highest *BTC sensitivity* decile portfolio but excludes the return of the focal stock. We then estimate each regression once before entering the highest *BTC sensitivity* portfolio and once afterwards. β_{-}^{*} represents the average estimated coefficient in the month preceding the stock addition, and $\overline{\beta}_{*}$ represents the average estimated coefficients in the month after the stock joins the portfolio. We also calculate the difference between β_{-}^{*} and $\overline{\beta}_{*}$ and cluster standard errors by month. We analyze three samples: top 100 *BTC sensitivity* stocks, top 500 *BTC sensitivity* stocks, and all *BTC sensitivity* stocks. The top 100 (top 500) include the 100 (500) stocks that most frequently appear in the portfolio during our sample period. All *BTC sensitivity* stocks are all stocks that have ever entered the highest decile *BTC sensitivity* portfolio.

Panel A of Table 8 reports the beta estimates from these regressions. The first two columns report the betas relative to the former *BTC sensitivity* decile portfolio before and after the stock enters the highest *BTC sensitivity* decile portfolio. The third column reports the change in these betas. The next three columns report the betas and the change in betas relative to the long-short portfolio. The last column contains the difference between the changes in the two beta coefficients (column 6 minus column 3).

[Table 8 here]

We observe that stocks begin to load more heavily (less heavily) on the highest *BTC sensitivity* decile portfolio (former *BTC sensitivity* decile portfolio) after they enter that portfolio. For the sample of the top 100 most frequently occurring high *BTC sensitivity* stocks, the coefficient with the highest *BTC sensitivity* decile portfolio increases significantly from 0.93 to 1.08, while the coefficient with the former *BTC sensitivity* decile portfolio decreases significantly from 1.25 to 1.08 (representing a 16% increase and 14% decrease, respectively). Consequently, the measure of total excess co-movement using the difference between these changes ((1.08-0.93) - (1.08-1.25) = 0.31) is large and statistically significant. The next two rows show similar results

[19] We find similar results when the non-high *BTC sensitivity* style portfolio is defined as the daily average returns all non-high *BTC sensitivity* stocks.

using the top 500 most frequently occurring high *BTC sensitivity* stocks or all stocks that have even entered the highest *BTC sensitivity* decile portfolio. In panel B, we repeat the above analysis for stocks that exit the *highest BTC sensitivity* decile portfolio. We observe that as the stock departs the highest *BTC sensitivity* decile portfolio, the coefficient with that portfolio decreases significantly.

Our findings are also similar in unreported analysis using bivariate regressions that include both x_{1t} and x_{2t}, as well as using value-weighted portfolios. Overall, the evidence is consistent with the view that investors are likely to use narrowly framing when evaluating these high *BTC sensitivity* stocks.

5.4. Verifying the results using Fama-MacBeth regressions

To ensure that the results from the prospect theory analysis are robust, we conduct portfolio analysis and Fama-MacBeth regressions, and report the results in the Internet Appendix, Table A3, Panel B. For the CGO analysis (column 1), we interact CGO × *BTC sensitivity* and observe a positive coefficient of the interaction term (coeff = 0.10, t-stat = 2.43), which suggests high CGO weaken the relationship between *BTC sensitivity* and future stock returns. We perform a similar analysis for the TK measure. The negative and significant coefficient of the interaction term between TK and *BTC sensitivity* (column 2) is also consistent with the portfolio analysis results. Finally, we interact retail order flow × *BTC sensitivity* and institutional ownership × *BTC sensitivity*. The results indicate that the negative BTC sensitivity premium is much larger in stocks with more retail trading and lower institutional ownership (Internet Appendix, Table A4).

6. Additional robustness tests

This section reports additional analysis to address concerns related to our sample, data selection, estimation issues, and noise-related concerns.

6.1. Using the CoinMarketCap.com sample

Our main analysis uses bitcoin data from both CoinMarketCap.com and Mt. Gox exchange. Using only data from CoinMarketCap.com (August 2013 to September 2019), we repeat the portfolio analysis in Table 3 and find similar patterns in the long-short portfolio returns. The results are available in the Internet Appendix, Table A6.[20]

6.2. Using the aggregated cryptocurrency market return

The cryptocurrency market has expanded beyond bitcoin in recent years. Although bitcoin remains the predominant security (Hu, Parlour, and Rajan, 2019), we verify that our results are robust by repeating the main analysis using a *BTC sensitivity* measure estimated with the aggregated cryptocurrency market return. Specifically, we construct a value-weighted cryptocurrency market return using the market capitalization weighted return of the top ten cryptocurrencies from CoinMarketcap.com (Table A1 in the Internet Appendix) based on their market capitalizations as of on March 31, 2018. Internet Appendix Table A7 shows that our inferences are unchanged using this approach.

6.3. Addressing noise in estimation and prices

We briefly discuss issues arising from estimation noise and noise in prices. Estimating the sensitivity of stock returns to bitcoin returns using OLS incurs estimation issues. One concern is that the sensitivities estimated over a three-month horizon could be too short or too long with respect to time-varying sensitivities. Second, non-synchronous trading issues can bias OLS estimates (Dimson, 1979). Third, because CRSP prices and returns contain non-negligible noise, particularly for the types of stock we analyze, our return estimates could be biased.

We perform the following tests to address these issues. First, we show that our main findings are similar when estimating sensitivities over a shorter one-month horizon or a longer six-month horizon. As an alternative approach, we extract a PCA factor from *BTC sensitivity* sensitivities estimated from the one-, three-, and six-month horizons and use the first component

[20] Since our results might be driven by the extremely volatile Bitcoin price during the 2017-2018 period, we conduct another robustness check by excluding this period. The results are in fact slightly stronger and are available upon request

as our measure of *BTC sensitivity*. Table A8 of the Internet Appendix reports that our conclusions are unchanged using these measures. Second, we estimate sensitivities using the Dimson approach by including a lead and a lag of the bitcoin return and summing together the sensitivity estimates. Table A9 in the Internet Appendix reports similar results using this approach. Third, we address concerns of noise in returns by weighting returns by the past month returns (Table A10 in the Internet Appendix), following the guidance of Asparouhova, Bessembinder, and Kalcheva (2010). Overall, the findings from these additional tests help to address concerns that noise issues may affect our main inferences.

6.4. Out-of-sample analysis: Financial firms and the China stock market

In our main analysis, we exclude financial stocks so that our test assets are comparable with existing literature. In Internet Appendix Table A12, we separately analyze financial stocks and continue to find a negative BTC sensitivity premium among financial firms. We also perform an out-of-sample test using the China stock market. As bitcoin and cryptocurrency are a global phenomenon, we expected the speculative frenzy to spread to international markets as well. We select China because it is second largest stock market in the world. Moreover, during our sample period, the majority of bitcoin was mined in China. Internet Appendix, Table A13 reports that negative BTC sensitivity premium also exists in the China stock market.

6.5. Positive *BTC sensitivity* versus negative *BTC sensitivity*

The *BTC sensitivity* measure contains both $\theta^{B+}$and θ^{B-}stocks. We examine the relative importance of each type by separately analyzing positive and negative *BTC sensitivity* sub-samples. Panel A of Table A14 in the Internet Appendix reports that the negative BTC sensitivity portfolio produces higher 4-factor alphas for θ^{B+}stocks (-1.76%, t-stat = -5.71) than for θ^{B-}stocks (-0.86%, t-stat = -3.34). Cross-sectional regression tests reported in panel B of Table A14 in the Internet Appendix provide similar inferences. While we do not have a definitive explanation for this result, one interpretation is that 'rotation' trading produces weaker pricing effects than 'flow' trading, perhaps due to the costs of moving capital from crypto exchanges to traditional brokerages.

7. Conclusion

We document that the speculative frenzy in bitcoin and cryptocurrencies spreads to equity markets and significantly affects stock prices. These new stylized facts add to our understanding of the relation between cryptocurrencies and traditional financial markets and institutions. Cryptocurrencies are used to circumvent traditional financial intermediation (Foley et al., 2018; Yu and Zhang, 2020) but can also affect established markets such as currencies (Athey et al., 2018; Makarov and Schoar, 2020). In future research, it would be interesting to examine whether cryptocurrencies affect money-related products such as lottery participation and casino activities or other markets such as venture capital or debt markets.

Our evidence also suggests that the social transmission of ideas (Hirshleifer, 2020; Han, Hirshleifer, and Walden, 2021) spreads rapidly. Our setting provides a natural environment to examine social transmission theory because the volatility and skewness of cryptocurrency returns are likely to grab the attention of investors and create biased beliefs. As cryptocurrencies mature and fall under the purview of regulators, we speculate that these price distortions could eventually diminish.

Finally, we find evidence to suggest that investors are likely to use prospect theory in conjunction with narrow framing to evaluate high *BTC sensitivity* stocks. We propose three empirical tests that add to the existing CGO and TK measures (Grinblatt and Han, 2005; Barberis, Mukherjee, and Wang, 2016). Our first test uses the skewness of analyst to assess the probability weighting feature. The second test assess narrow framing using retail order flow data (Boehmer et al., 2021). Third, we conduct excess comovement tests to show that high *BTC sensitivity* stocks form a trading habitat, which is consistent with narrow framing. Although we cannot definitively rule out other explanations such as extrapolative beliefs, on balance the set of results are most consistent with prospect theory.

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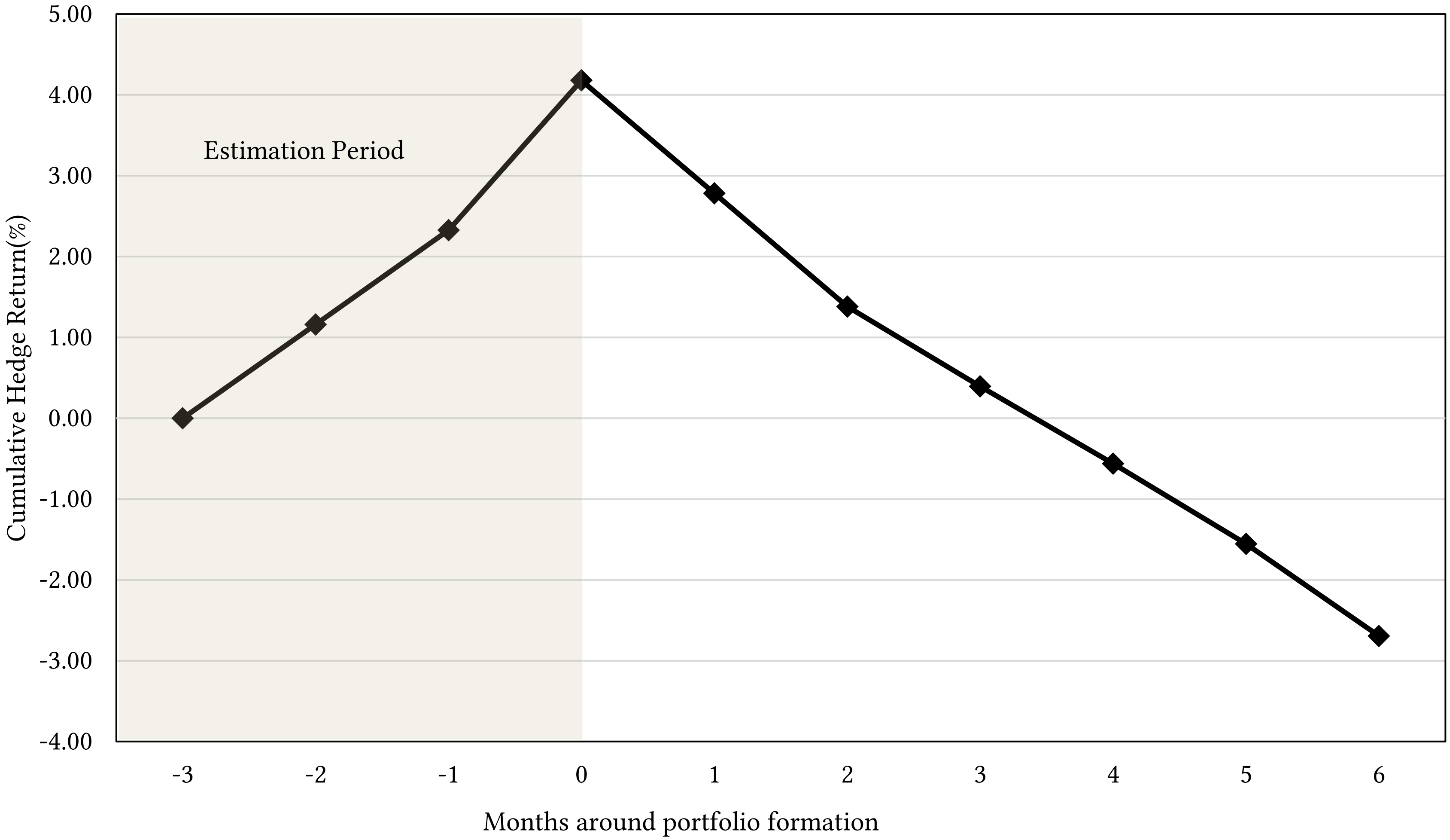


Figure 1. Cumulative long-short BTC sensitivity portfolio returns around formation month
This figure shows the cumulative long-short *BTC sensitivity* portfolio returns in the three months before and six months after portfolio formation. The long-short portfolio is a zero-cost portfolio that longs the highest *BTC sensitivity* decile stocks and shorts the lowest *BTC sensitivity* decile stocks. In the formation month (month *t*), all stocks are ranked and assigned to one of the ten decile portfolios based on their *BTC sensitivity* measure.

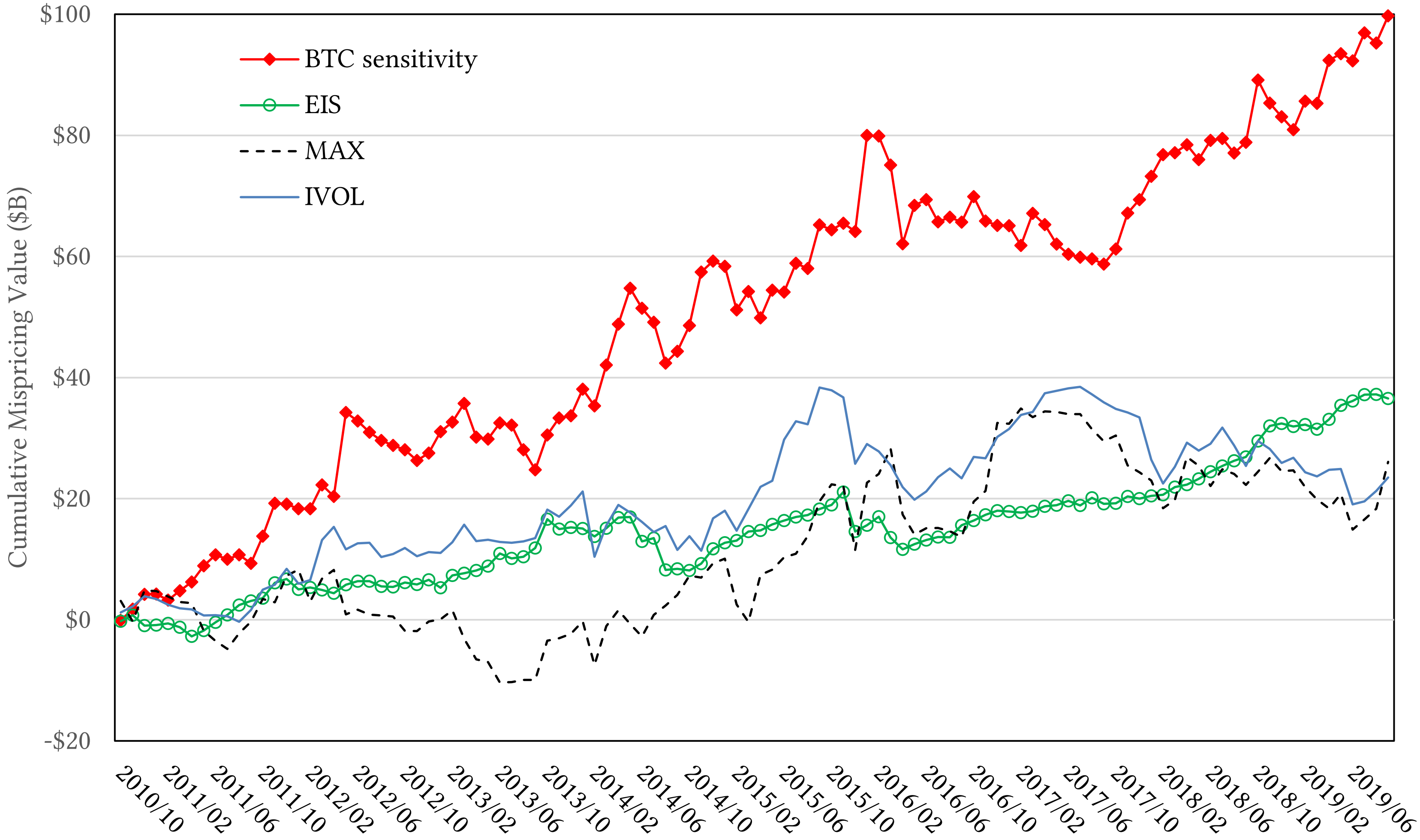


Figure 2. Cumulative characteristics-adjusted portfolio returns of high *BTC sensitivity* stocks compared to other anomalies
This figure shows the cumulative characteristics-adjusted portfolio return of high *BTC sensitivity* stocks. Specifically, each month we compute the long-short portfolio is a zero-cost portfolio that longs the highest *BTC sensitivity* decile stocks and shorts the lowest *BTC sensitivity* decile stocks. In the formation month (month *t*), all stocks are ranked and assigned to one of the ten decile portfolios based on their *BTC sensitivity* measure.

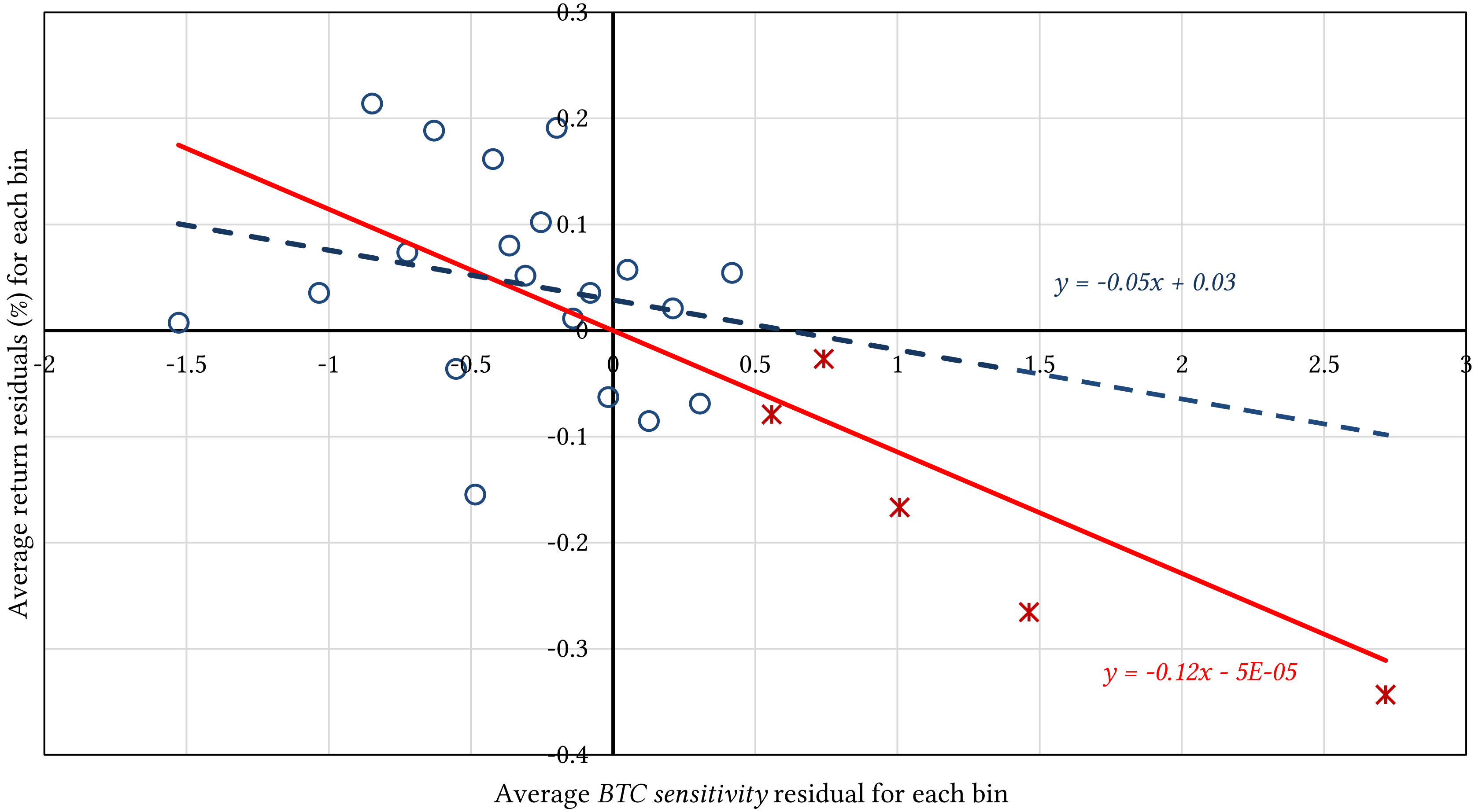


Figure 3. Binned scatterplots of portfolio return and stock *BTC Sensitivity*
This figure shows a binscatter plot of the relation between stock return and *BTC sensitivity*. Each month, we divide the entire sample into 25 bins based on their *BTC sensitivity* residuals and estimate the average return residual for each bin. Both return residuals and *BTC sensitivity* residuals are obtained by regressing the variable on all control variables. We compute the time-series average of the BTC residuals and return residuals for the 25 bins and plot the graph. The blue circles represent the first 20 bins, and the red stars represents the last 5 bins. The blue dash line is the OLS fitted line between *BTC sensitivity* residual and return residual using the first 20 bins, and the red line is the fitted line using all 25 bins. The corresponding regression coefficients are also reported along the two fitted lines.

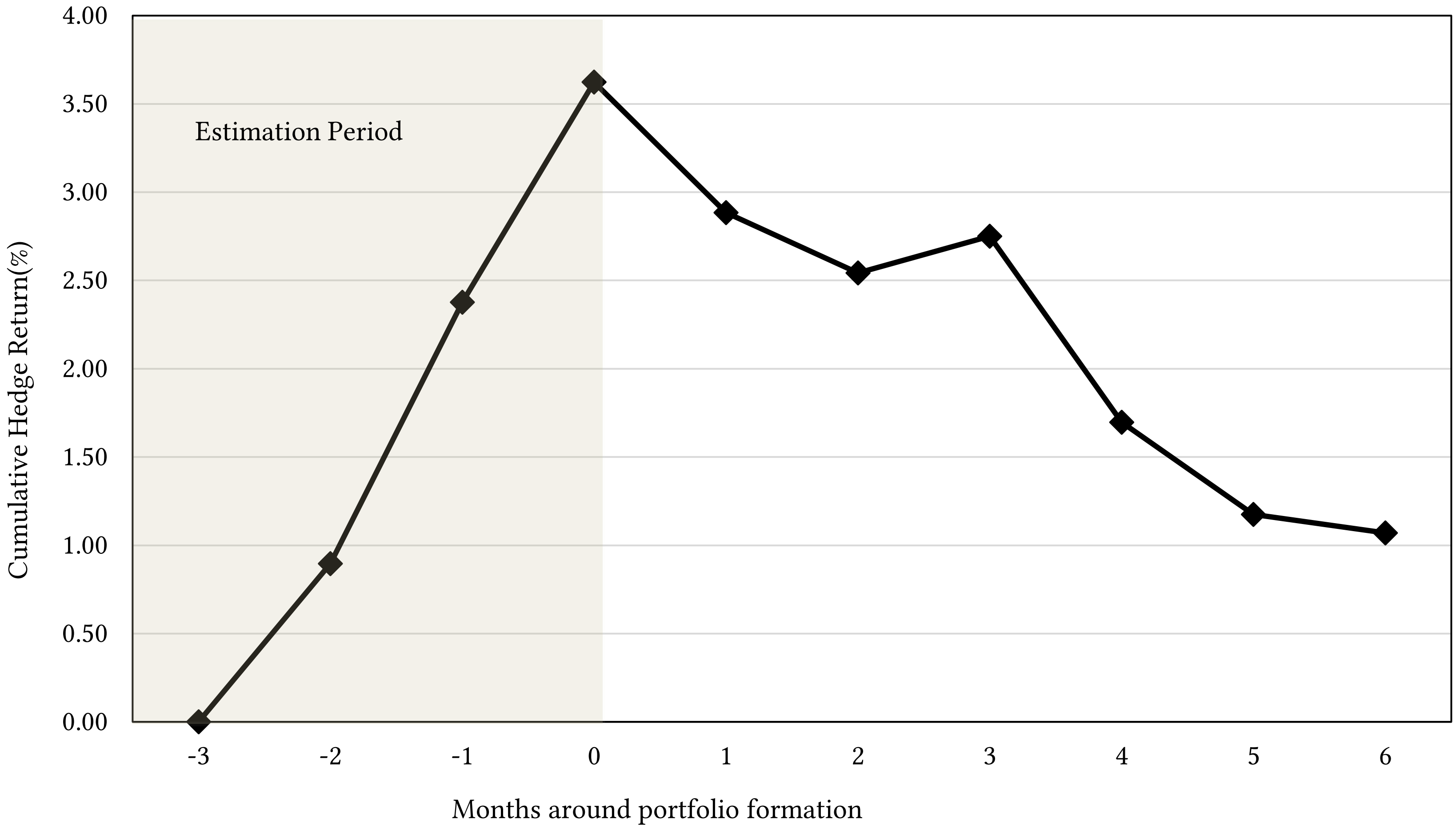


Figure 4. Cumulative long-short disruption portfolio return using the instrumented BTC Sensitivity
This figure shows the cumulative long-short disruption portfolio returns in the three months before and six months after portfolio formation. The long-short disruption portfolio is a zero-cost portfolio that longs the highest instrumented *BTC Sensitivity* decile stocks and shorts the lowest instrumented *BTC Sensitivity* decile stocks. In the formation month (month *t*), all stocks are ranked and assigned to one of the ten decile portfolios based on their instrumented *BTC Sensitivity* measure. The sample period is June 2017 to April 2018 due to constrain of the Tether data availability.

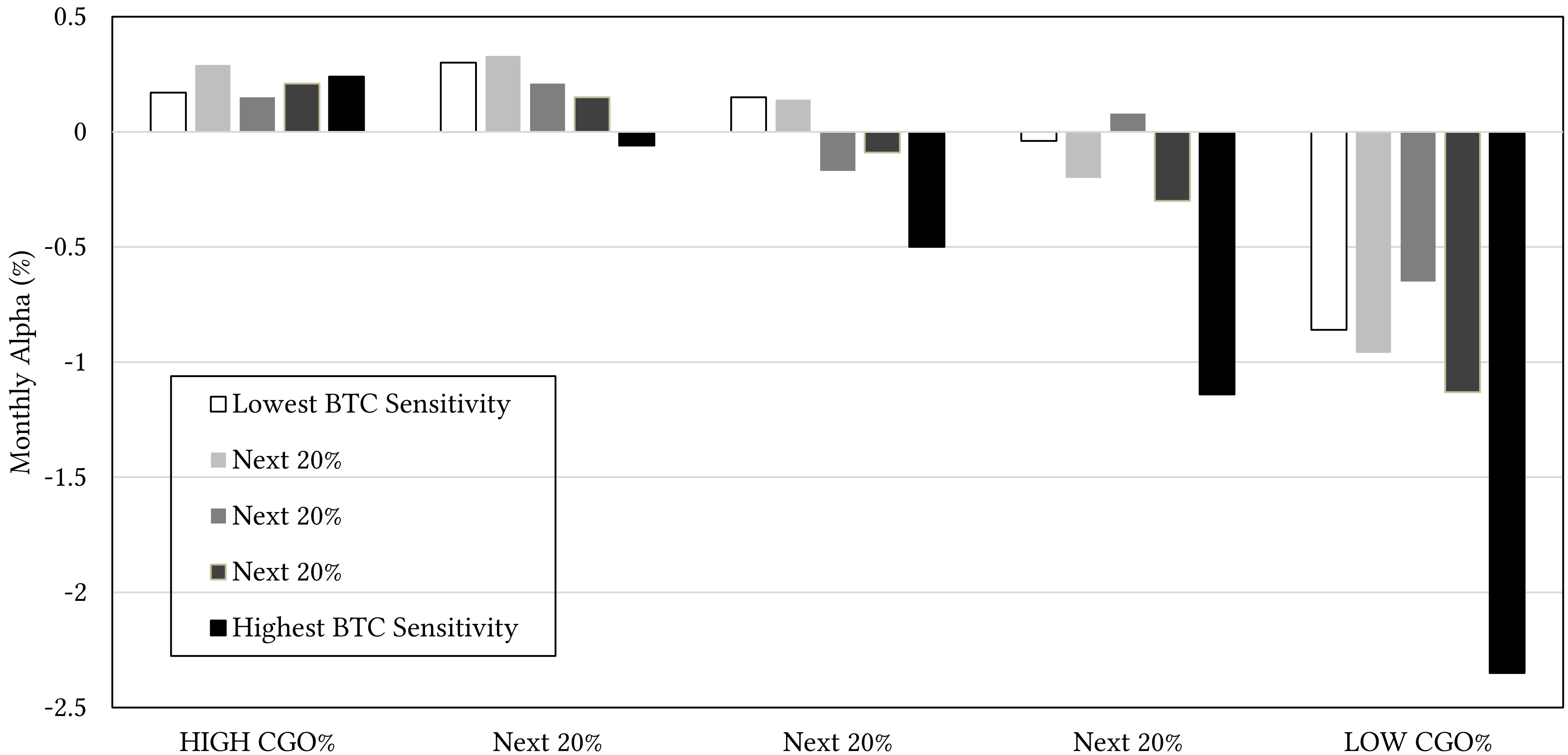


Figure 5. Double-sorted portfolio Carhart alphas by CGO and *BTC sensitivity*
This figure presents the average equal-weighted Carhart-adjusted alphas for the 5×5 portfolios formed by first sorting stocks into quintiles based on Capital Gain Overhang (CGO). Then, within each CGO quintile, stocks are further sorted into quintiles based on the BTC sensitivity.

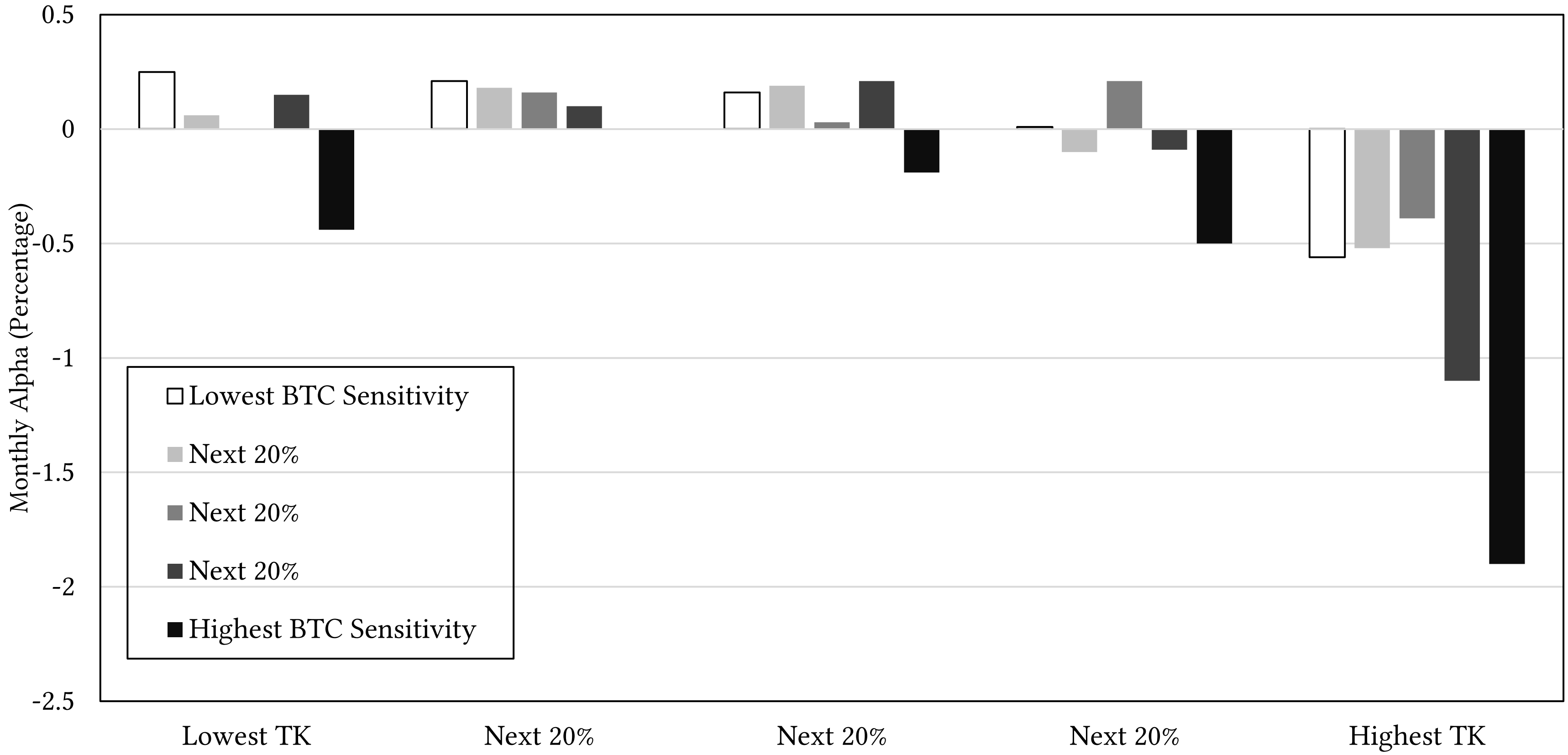
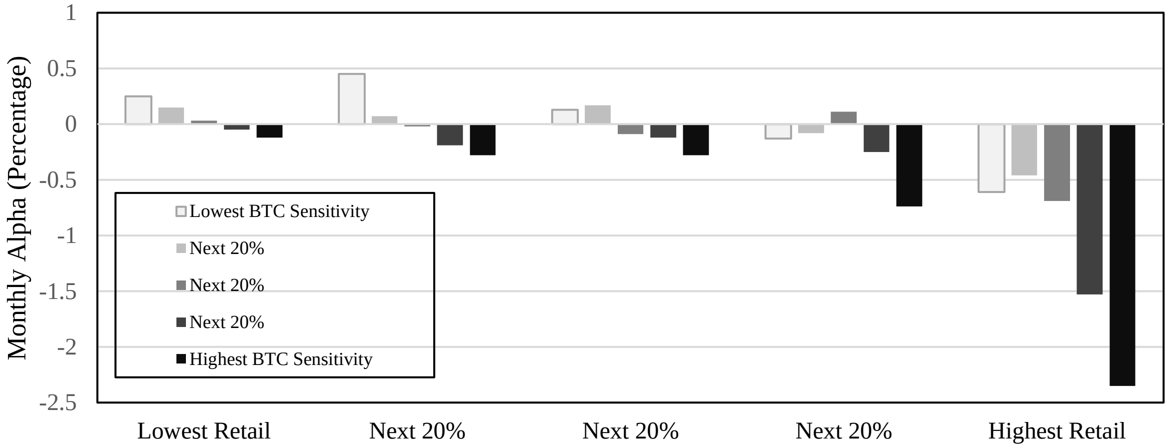


Figure 6. Double-sorted portfolio Carhart alphas by TK measure and *BTC sensitivity*
This figure presents the average equal-weighted Carhart-adjusted alphas for the 5×5 portfolios formed by first sorting stocks into quintiles based on the Kahneman and Tversky (1979) prospect theory value. Then, within each retail trading quintile, stocks are further sorted into quintiles based on *BTC sensitivity.*

Panel A: Monthly Carhart alphas of portfolios double-sorted by retail trading volume and BTC sensitivity



Panel B: Monthly Carhart alphas of portfolios double-sorted by institutional ownership (IO%) and BTC sensitivity

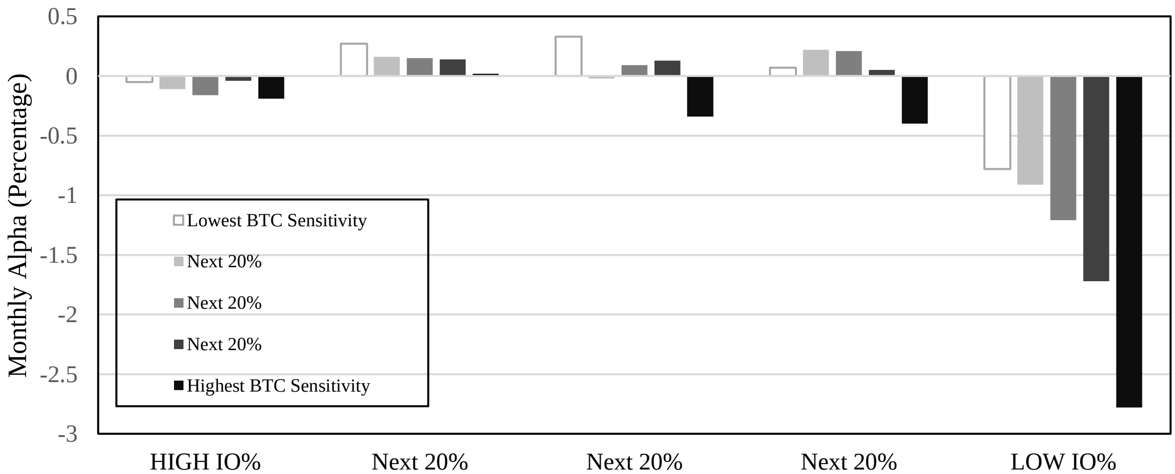


Figure 7. Double-sorted portfolio Carhart alphas by retail trading and *BTC sensitivity*
This figure presents the average equal-weighted Carhart-adjusted alphas for the 5×5 portfolios formed by first sorting stocks into quintiles based on the following proxies for retail trading: retail trading volume (Panel A) and institutional ownership (Panel B). Then, within each retail trading quintile, stocks are further sorted into quintiles based on the *BTC sensitivity*.

Table 1. Average stock characteristics for portfolios of stocks sorted by θ^B

This table shows the time-series average of the mean values of stock characteristics on 10 portfolios sorted by *BTC sensitivity*. We also report the stock characteristics for the extreme positive raw BTC sensitivity stocks (top 5%) and extreme negative BTC sensitivity stocks (bottom 5%) in the last two columns. BTC sensitivity is estimated using Equation (1). Bitcoin returns used Equation (1) are calculated using the stock market trading day buy-and-hold returns to match the stock returns in the CRSP. Coefficient θ^B is the individual stocks' raw sensitivity based on 3-month estimating period. *BTC sensitivity* $|\theta^B|$ is the absolute value of θ^B. *BTC sensitivity (%Sig.)* is defined as the percentage of stocks with significant *BTC sensitivity* estimate at the 10% level. *No. of stocks* is the average number of stocks in month *t*+1 for each portfolio. *Return t*+1 is the equal-weighted average return (in percentage) for each portfolio in month *t*+1. *Mkt cap* is the average of individual stocks' market capitalization (in $billions) in month *t*. *IO%* is the shares held by institutional investors in quarter *t*-2. *MOM* is the cumulative stock return in previous one year except the last one month. *STR* is the short term reversal, defined as the previous month's stock return. *B/M* is the book value of equity to market value of equity ratio in fiscal year *t*-1. *OP* is the annually operating profitability in fiscal year *t*-1, adjusted with R&D expense following Ball et al (2015). *TO* (%) is the average monthly turnover ratio of the individual stocks during the previous 3-month. *Retail trading* (%) is defined as the total retail trading volume scaled by the total trading volume in month *t*. We adjust the CRSP reported trading volume for NASDAQ stocks following Anderson and Dyl (2005). *ILLIQ* is the Amihud (2002) illiquidity measure in month *t*. *Price* is the average of individual stocks' price in month *t*. *IVOL* is the idiosyncratic volatility, defined as the standard deviation of the residuals from the regression of daily stock returns to Fama French three factors in month *t*. *Max* is the maximum daily stock return in month *t*. *EIS* is the future expected idiosyncratic skewness estimated in month *t*, as in Boyer, Mitton and Vorkink (2010). *Distress* is the estimated distress risk following Campbell, Hilscher, and Szilagyi (2008). *No. of analysts* is the number of analysts following the stock in month t-1. *Dispersion* is the standard deviation of the analysts' forecasts on firm's future annual EPS. *Forecast Skewness* is the skewness of the EPS forecast. CGO is the capital gain overhang measure developed in Grinblatt and Han (2005). TK is the Tversky and Kahneman (1992) prospect theory value developed in Barberis, Mukherjee, and Wang (2016). The sample period is from October 2010 to September 2019.

Table 1 continued

	Low	2	3	4	5	6	7	8	9	High	H – L	$+\theta^{B+}$	$-\theta^{B-}$
BTC sensitivity	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.08	0.11	0.24	0.24	0.24	0.23
BTC sensitivity (% sig)	0.01	0.17	0.21	0.19	1.14	3.93	8.54	15.31	25.59	48.11	48.10	48.31	47.19
θ^B	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.24	-0.23
No. of stocks	243	244	244	244	244	244	244	244	244	244	-	128	116
Return t+1 (%)	1.03	0.99	0.95	1.00	0.86	1.02	0.75	0.69	0.28	-0.29	1.32	-0.54	0.00
Mkt cap ($B)	2.79	2.74	2.68	2.48	2.27	1.99	1.72	1.33	0.97	0.54	-2.25	0.52	0.56
IO%	65.86	65.86	65.37	64.90	63.48	62.04	60.11	56.31	50.47	39.33	-26.39	38.75	39.93
MOM (%)	13.61	13.60	13.23	12.92	12.88	11.97	11.16	9.60	7.44	2.65	-10.96	4.07	2.09
STR (%)	1.03	1.14	0.97	0.90	0.97	0.95	0.96	0.86	0.66	1.36	0.33	1.80	1.23
B/M	0.55	0.55	0.56	0.56	0.57	0.59	0.59	0.61	0.63	0.67	0.12	0.66	0.67
OP	0.13	0.13	0.13	0.13	0.12	0.11	0.10	0.09	0.06	-0.01	-0.14	-0.01	0.00
TO (%)	13.49	13.56	13.67	13.69	13.95	14.41	14.87	15.12	16.23	20.54	7.05	20.73	19.99
Retail trading (%)	7.57	7.62	7.86	7.99	8.46	9.00	9.54	10.77	12.50	16.08	8.51	16.30	15.84
ILLIQ (10^{-5})	0.58	0.55	0.56	0.57	0.65	0.67	0.71	0.84	1.05	1.48	0.90	1.45	1.55
Price ($)	38.03	37.62	36.59	35.20	32.51	29.50	26.59	21.88	16.96	11.34	-26.69	11.21	11.70
IVOL (%)	1.64	1.69	1.74	1.80	1.90	2.04	2.20	2.45	2.86	3.97	2.33	4.00	3.94
Max (%)	4.63	4.78	4.86	5.02	5.28	5.63	6.03	6.63	7.73	10.87	6.24	11.05	10.74
EIS	0.52	0.52	0.55	0.58	0.64	0.71	0.79	0.93	1.13	1.48	0.96	1.48	1.46
Distress	-8.27	-8.26	-8.21	-8.19	-8.13	-8.07	-7.97	-7.78	-7.55	-6.97	1.30	-6.99	-6.98
No. of analysts	8.72	8.65	8.57	8.31	8.09	7.78	7.41	6.86	6.21	5.09	-3.63	4.97	5.11
Dispersion	0.13	0.14	0.14	0.14	0.16	0.17	0.19	0.21	0.25	0.29	0.16	0.29	0.28
Forecast Skewness	0.10	0.09	0.08	0.10	0.09	0.13	0.15	0.16	0.16	0.19	0.09	0.17	0.19
CGO	-0.01	-0.01	-0.01	-0.01	-0.02	-0.03	-0.04	-0.06	-0.10	-0.17	-0.16	-0.17	-0.16
TK	-0.09	-0.08	-0.07	-0.07	-0.06	-0.06	-0.06	-0.06	-0.05	-0.05	0.04	-0.05	-0.05

Table 2. Time-series average of cross-sectional correlations

This table presents the time-series average of cross-sectional correlations between *BTC sensitivity* and stock characteristics in Table 1. Variable definitions are available in Table 1. *Ln*(*Price*) is the logarithm of stock price in month *t*. *Ln*(*Size*) is the natural logarithm of the market value in month *t*. Spearman correlations are shown above the diagonal; Pearson correlations are shown below the diagonal. The sample period is from October 2010 to September 2019.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
BTC sensitivity	(1)		0.41	0.32	0.35	-0.32	0.03	0.26	-0.29	0.03	-0.03	-0.13
IVOL	(2)	0.46		0.58	0.83	-0.58	0.02	0.48	-0.53	0.05	-0.04	-0.24
EIS	(3)	0.36	0.54		0.44	-0.74	-0.27	0.72	-0.77	0.21	-0.13	-0.37
MAX	(4)	0.38	0.85	0.38		-0.45	0.04	0.38	-0.40	0.03	0.23	-0.20
Ln(Price)	(5)	-0.35	-0.52	-0.76	-0.38		0.27	-0.74	0.80	-0.24	0.14	0.37
TO	(6)	0.15	0.18	-0.07	0.17	0.11		-0.67	0.49	-0.17	0.01	0.03
ILLIQ	(7)	0.07	0.12	0.22	0.08	-0.17	-0.17		-0.95	0.27	-0.07	-0.24
Ln(Size)	(8)	-0.31	-0.46	-0.75	-0.33	0.78	0.27	-0.28		-0.29	0.11	0.28
Ln(B/M)	(9)	0.01	0.01	0.13	0.00	-0.19	-0.07	0.10	-0.25		-0.01	-0.07
STR	(10)	0.01	0.08	-0.10	0.36	0.11	0.00	-0.01	0.07	0.00		0.03
MOM	(11)	-0.09	-0.15	-0.32	-0.13	0.31	0.02	-0.06	0.21	-0.06	0.01	

Table 3. Portfolio sorts: Excess returns and alphas on portfolios of stocks sorted by BTC sensitivity

This table reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced decile portfolios sorted by their BTC sensitivity measure. The left-side 4 columns present result using all stocks with a *BTC sensitivity* estimate, and the right-side 4 columns report the result using subsample which constraints the sample to those stocks with a significant regression coefficient at the 10% level. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. Long-short return or Alpha is the return or alpha of a zero-cost portfolio that buys the top *BTC sensitivity* decile portfolio and shorts the bottom *BTC sensitivity* decile portfolio (i.e., H – L). The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	BTC sensitivity estimate				Significant *BTC sensitivity* estimate			
	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	1.03	-0.27	0.02	0.05	1.29	0.25	0.39	0.35
	(3.06)	(-1.95)	(0.21)	(0.48)	(4.62)	(1.67)	(2.98)	(2.67)
2	0.99	-0.27	-0.04	-0.03	1.00	-0.21	-0.00	-0.04
	(2.79)	(-1.67)	(-0.31)	(-0.23)	(2.68)	(-0.97)	(-0.01)	(-0.22)
3	0.95	-0.40	-0.12	-0.07	0.98	-0.25	0.03	0.06
	(2.73)	(-2.90)	(-1.70)	(-0.98)	(2.65)	(-1.32)	(0.12)	(0.26)
4	1.00	-0.38	-0.10	-0.04	1.15	-0.19	0.17	0.20
	(2.55)	(-2.16)	(-1.02)	(-0.43)	(2.80)	(-0.96)	(0.87)	(0.91)
5	0.86	-0.54	-0.25	-0.21	0.84	-0.43	-0.08	0.01
	(2.07)	(-3.04)	(-2.81)	(-2.07)	(1.94)	(-1.52)	(-0.27)	(0.04)
6	1.02	-0.38	-0.06	0.00	0.44	-0.88	-0.50	-0.36
	(2.59)	(-2.43)	(-0.69)	(0.02)	(0.93)	(-2.90)	(-2.10)	(-1.61)
7	0.75	-0.64	-0.31	-0.24	0.24	-1.28	-0.90	-0.85
	(1.94)	(-3.59)	(-2.80)	(-2.00)	(0.36)	(-3.14)	(-2.70)	(-2.47)
8	0.69	-0.70	-0.39	-0.28	0.13	-1.63	-1.32	-1.22
	(1.64)	(-2.95)	(-2.59)	(-1.70)	(0.22)	(-4.17)	(-3.88)	(-3.50)
9	0.28	-1.26	-0.86	-0.71	-0.28	-1.83	-1.43	-1.27
	(0.59)	(-5.35)	(-4.94)	(-4.34)	(-0.38)	(-3.00)	(-2.33)	(-1.97)
10 (High)	-0.29	-1.94	-1.52	-1.29	-0.77	-2.59	-2.12	-1.81
	(-0.53)	(-6.40)	(-5.65)	(-4.59)	(-0.99)	(-4.73)	(-3.80)	(-3.38)
H – L	-1.32***	-1.68***	-1.54***	-1.34***	-2.05***	-2.84***	-2.51***	-2.16***
(*t*-stat)	(-4.67)	(-6.67)	(-5.81)	(-5.38)	(-3.36)	(-5.54)	(-4.51)	(-4.32)

Table 4. Additional asset pricing tests

In each month, we first sort the stocks into deciles based on a stock characteristic including *Size, Price, MAX, IVOL*, distress risk (*Distress*), expected idiosyncratic skewness (*EIS*), average daily turnover ratio over the previous three-month (*Turnover*), and Amihud illiquidity (*ILLIQ*); and then within each decile, we further sort stocks into deciles based on *BTC sensitivity*. Panel A of this table reports four-factor alphas of portfolios. The bottom row presents the long-short portfolio return and the four-factor alpha of a zero-cost portfolio that buys the top BTC sensitivity decile portfolio and shorts the bottom BTC sensitivity decile portfolio.

Panel B reports the time-series monthly averages of the estimated coefficients from Fama-MacBeth cross-sectional regressions. All stock characteristics are standardized (N~(0,1)) to make the results comparable. The dependent variable is a firm's monthly return (in percentage). The explanatory variable of interest is BTC sensitivity. The control variables include: the logarithm firm of market capitalization (*Ln*(*SIZE*)), the logarithm of book-to-market equity (*Ln*(*B/M*)), annually operating profitability (*OP*), total asset growth (*TAG*), momentum (*MOM*), Short-term reversal (*STR*), idiosyncratic volatility (*IVOL*), maximum daily return (*MAX*), expected idiosyncratic skewness (*EIS*), Amihud illiquidity (*ILLIQ*), average daily turnover ratio (*Turnover*), the logarithm of stock price (*Ln*(*Price*)), and distress risk (*Distress*).

Panel C presents risk-adjusted returns (alpha) in percentage and the respective factor loadings of the long-short decile portfolio based on *BTC sensitivity* based eight factor models: (1) the CAPM, (2) the Fama-French three-factor model, (3) the FF+Carhart four-factor model, (4) the Fama-French five factor model, (5) the FF+Carhart six-factor model, (6) the Frazzini and Pedersen (2014) betting against beta factor (BAB) + Carhart four-factor model, (7) the Stambaugh and Yuan (2017) four-factor mispricing (M4) model, and (8) the Bali et al. (2017) Max factor (FMAX) + Carhart four-factor model.

The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019. For the M4 mispricing pricing model, the sample period ends in December 2016 due to data availability. For the FMAX factor, the data period ends in December 2018 due to data availability.

Panel A. Bi-variate portfolio sorts: Four-factor alphas of portfolios sorted on lottery/liquidity characteristics and BTC sensitivity

	(1) Size	(2) Price	(3) MAX	(4) IVOL	(5) Distress	(6) EIS	(7) TO	(8) ILLIQ
1 (Low)	1.00	0.92	0.93	0.87	1.18	0.96	1.09	1.01
2	0.86	0.90	0.84	0.75	1.12	1.00	0.95	0.84
3	0.83	0.79	0.85	0.78	1.01	0.84	0.85	1.07
4	0.93	0.95	0.94	0.95	1.13	1.02	0.96	0.82
5	0.98	1.05	0.88	0.89	1.14	1.04	0.91	1.02
6	0.95	0.89	0.88	0.78	1.02	0.96	0.97	0.90
7	0.64	0.56	0.64	0.79	0.94	0.83	0.79	0.71
8	0.66	0.58	0.77	0.82	0.93	0.81	0.68	0.65
9	0.44	0.56	0.54	0.44	0.88	0.75	0.45	0.34
10 (High)	-0.03	0.06	-0.01	0.22	0.55	0.68	-0.08	-0.11
H – L	-1.03***	-0.86***	-0.94***	-0.65***	-0.63***	-0.28***	-1.17***	-1.11***
(*t*-stat)	(-4.03)	(-3.84)	(-5.12)	(-4.93)	(-2.80)	(-3.33)	(-4.81)	(-5.12)
Alpha	-1.20***	-0.98***	-0.99***	-0.69***	-0.62***	-0.25***	-1.15***	-1.27***
(*t*-stat)	(-5.55)	(-4.38)	(-5.67)	(-5.12)	(-2.99)	(-3.25)	(-5.71)	(-6.89)

Table 4. Continued.

Panel B. Firm-level Fama-MacBeth cross-sectional return regressions

	(1)	(2)	(3)	(4)	(5)
BTC sensitivity	-0.43***	-0.32***	-0.17***	-0.16***	-0.12***
	(-5.25)	(-5.35)	(-4.02)	(-3.75)	(-3.33)
Ln(SIZE)		0.06	-0.11**	-0.30***	-0.15
		(0.93)	(-2.03)	(-3.23)	(-1.41)
Ln(B/M)		-0.00	-0.04	-0.05	-0.08
		(-0.05)	(-0.38)	(-0.49)	(-0.84)
OP		0.38***	0.32***	0.30***	0.31***
		(4.67)	(3.96)	(3.97)	(4.29)
TAG		-0.13	-0.11	-0.12	-0.11
		(-1.60)	(-1.37)	(-1.53)	(-1.42)
MOM		0.28***	0.26***	0.23**	0.27***
		(3.28)	(2.94)	(2.51)	(3.05)
STR		-0.06	-0.00	-0.05	-0.05
		(-0.96)	(-0.05)	(-0.61)	(-0.69)
IVOL			-0.49***	-0.57***	-0.52***
			(-5.12)	(-4.35)	(-4.32)
MAX				0.13	0.15
				(1.30)	(1.59)
EIS				-0.40**	-0.39***
				(-2.60)	(-2.80)
ILLIQ					-0.04
					(-1.16)
Turnover					-0.31***
					(-3.93)
Ln(Price)					-0.03
					(-0.32)
Distress					0.23***
					(4.27)
Intercept	0.73*	0.73*	0.73*	0.73*	0.73*
	(1.84)	(1.84)	(1.84)	(1.84)	(1.84)

Table 4. Continued.

Panel C. Factor risk-adjusted returns for the long-short BTC sensitivity portfolio

		Alpha	MKT	SMB	HML	UMD	RMW	CMA	BAB	MGMT	PERF	FMAX
(1)	CAPM model	-1.68***	0.33***									
		(-6.67)	(3.59)									
(2)	3-Factor model	-1.54***	0.24***	0.46***	-0.09							
		(-5.81)	(2.63)	(2.59)	(-0.76)							
(3)	4-Factor model	-1.34***	0.14*	0.47***	-0.37***	-0.42***						
		(-5.38)	(1.90)	(3.07)	(-3.03)	(-4.51)						
(4)	5-Factor model	-1.39***	0.18	0.24	-0.13		-0.02	-0.80***				
		(-5.25)	(1.47)	(1.39)	(-0.87)		(-0.07)	(-4.40)				
(5)	6-Factor model	-1.15***	0.06	0.23	-0.46***	-0.47***	0.01	-0.91***				
		(-5.08)	(0.66)	(1.61)	(-3.02)	(-4.77)	(0.03)	(-5.57)				
(6)	BAB model	-1.08***	0.12*	0.43***	-0.37***	-0.34***			-0.31			
		(-3.52)	(1.67)	(2.64)	(-3.17)	(-3.35)			(-1.13)			
(7)	M4 model	-1.01***	-0.00	-0.17						-0.53***	-0.52***	
		(-3.57)	(-0.02)	(-0.87)						(-4.13)	(-5.95)	
(8)	FMAX model	-0.85***	-0.08	0.09	-0.17	-0.32***						0.63***
		(-4.17)	(-0.93)	(0.54)	(-1.45)	(-4.00)						(3.62)

Table 5. Social transmission bias and the negative BTC sensitivity premium

This table reports the excess returns (in percentage) and the corresponding *t*-statistics of monthly rebalanced decile portfolios under high- and low-social transmission periods in Panel A and high- and low-stock market sentiment periods in Panel B. "H – L" is the difference between the hedge portfolio's excess return under high sentiment period and low sentiment period. We report the excess portfolio returns based on BTC sensitivity and other three typical lottery-type stock characteristics: MAX(%), IVOL, and EIS. The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Panel A: Long-short hedge portfolio returns under high/low social transmission periods

	BTC Sensitivity	MAX(%)	IVOL	EIS
Excess return of high sentiment period	-1.78***	-1.96***	-2.17***	-2.80***
	(-5.05)	(-4.15)	(-5.81)	(-5.38)
Excess return of low sentiment period	-0.85**	-1.11**	-1.26**	-1.08**
	(-2.58)	(-2.56)	(-2.52)	(-2.25)
H – L	-0.93**	-0.84	-0.91*	-1.71***
(*t*-stat)	(-2.26)	(-1.63)	(-1.78)	(-4.74)

Panel B: Long-short hedge portfolio returns under high/low stock market sentiment

	BTC Sensitivity	MAX(%)	IVOL	EIS
Excess return of high sentiment period	-1.26***	-1.67***	-2.01***	-2.06***
	(-2.94)	(-3.02)	(-3.26)	(-3.26)
Excess return of low sentiment period	-1.19***	-1.10*	-1.16*	-1.46**
	(-2.81)	(-1.94)	(-1.95)	(-2.18)
H – L	-0.06	-0.57	-0.84**	-0.61
(*t*-stat)	(-0.27)	(-1.57)	(-2.08)	(-1.49)

Table 6. Instrumental variables analysis: First-stage regression of bitcoin return and Tether flow

This table reports the first-stage estimates of the relation between bitcoin return and Tether authorization and Tether flow. The dependent variable is the average three-hour bitcoin returns. Flow(t-1) is the lagged average net hourly flow of Tether from Bitfinex to Poloniex and Bittrex and of bitcoin from Poloniex and Bittrex to Bitfinex. Auth_Post(t-1) is an indicator variable that equals one if a Tether authorization occurred in the previous 72 hours, and zero otherwise. BTC(t-1) is the lagged realized bitcoin return. VoB(t-1) is volatility calculated using hourly bitcoin returns over the previous 24 hours. MKT, SMB, and HML are the daily Fama-French three factors, lagged by 1 day. The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from March 01, 2017 to March 31, 2018, 396 days, 9504 hours.

Dependent variable	{Bitcoin Return(t)+ Bitcoin Return(t+1)+ Bitcoin Return(t+2)}/3
Flow(t-1)	-0.386
	(-0.62)
Auth_Post(t-1)	-6.513***
	(-3.68)
Flow(t-1) × Auth_Post(t-1)	4.205***
	(4.10)
BTC(t-1)	-0.009
	(-0.64)
VoB(t-1)	103.596***
	(4.10)
BTC(t-1) × VoB(t-1)	-0.313**
	(-2.29)
MKT(t-1)	185.14**
	(1.96)
SMB(t-1)	-98.46
	(-0.61)
HML(t-1)	58.64
	(0.37)
Constant	-1.74
	(-1.17)
Nobs	9,504
R^2_adj	0.009
F-stat	10.07

Table 7. Probability weighting: BTC sensitivity and analyst forecast skewness

This table reports the time-series monthly averages of the estimated coefficients from Fama-MacBeth cross-sectional regressions. The dependent variable is the analyst forecast skewness of the future EPS forecasts. The explanatory variable of interest is BTC sensitivity. All other stock characteristics are standardized (N~(0,1)) to make the results comparable. The control variables include: the logarithm firm of market capitalization (*Ln*(*SIZE*)), the logarithm of book-to-market equity (*Ln*(*B/M*)), annually operating profitability (*OP*), total asset growth (*TAG*), momentum (*MOM*), the number of analyst forecast (*No. of analysts*), and the standard deviation of the analyst forecast (*Dispersion*). The *t*-statistics are shown in parentheses using the Newey and West (1987) corrected standard errors with up to twelve lags. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	(1)	(2)	(3)
BTC sensitivity	0.03***	0.02***	0.02**
	(3.19)	(3.32)	(2.36)
Ln(SIZE)		0.02	-0.03
		(0.61)	(-1.62)
Ln(B/M)		0.00	0.00
		(0.15)	(0.02)
OP		-0.00	-0.00
		(-0.41)	(-0.42)
TAG		0.01	0.01
		(1.19)	(1.13)
MOM		-0.15***	-0.13***
		(-15.31)	(-24.35)
No. of analysts			0.07**
			(2.43)
Dispersion			0.03***
			(4.04)
Intercept	0.12***	0.12***	0.12***
	(3.65)	(3.65)	(3.65)

Table 8. Narrow framing: Co-movement of individual high *BTC sensitivity* stocks and BTC sensitivity decile portfolios

This table presents co-movement regressions of individual high *BTC sensitivity* stocks on the highest *BTC sensitivity* portfolio. Following Chen, Singal, and Whitelaw (2016), we estimate the following univariate regressions:

$$y_t = \alpha + \beta_1 x_{1t} + \varepsilon_t,$$
$$y_t = \alpha + \beta_2 x_{2t} + \varepsilon_t,$$

where y_t is the daily return for a sample of stocks that enter the portfolio. x_{1t} is the daily average portfolio return of the former *BTC sensitivity* decile portfolio that the focal stock exits. x_{2t} is the daily average portfolio return of the highest *BTC sensitivity* decile portfolio. $\underline{\beta}_*$ is the average estimated coefficients in the month preceding the stock addition. $\overline{\beta_*}$ is the average estimated coefficients in the first month after the stock is added into the highest *BTC sensitivity* decile portfolio. Panel A reports estimates from a sample of stocks that enter the highest *BTC sensitivity* decile portfolio. Panel B reports estimates from a sample of stocks that exit the highest *BTC sensitivity* decile portfolio. We report results using (1) the top 100 high *BTC sensitivity* stocks based on the number of months that the stock is included in the highest *BTC sensitivity* decile portfolio, (2) top 500 high *BTC sensitivity* stocks, and (3) all stocks that have entered the portfolio. The *t*-statistics (shown in parentheses) are computed based on standard errors clustered by month. The sample period is from October 2010 to September 2019.

Panel A: Entering into the highest BTC sensitivity decile portfolio

	Former *BTC sensitivity* decile portfolio return (focal stock exits)			Highest *BTC sensitivity* portfolio return			Difference
	$\underline{\beta}^1$	$\overline{\beta_1}$	$\Delta\beta_1$	$\underline{\beta}^2$	$\overline{\beta_2}$	$\Delta\beta_2$	$\Delta\beta_2 - \Delta\beta_1$
Top 100	1.25	1.08	-0.17	0.93	1.08	0.15	0.31
	(28.85)	(27.43)	(-3.16)	(25.22)	(31.55)	(3.14)	(9.21)
Top 500	1.29	1.11	-0.19	0.98	1.05	0.08	0.26
	(57.93)	(60.17)	(-7.14)	(53.63)	(65.82)	(3.50)	(16.02)
All stocks	1.20	1.05	-0.15	0.92	0.97	0.05	0.20
	(95.78)	(104.65)	(-10.39)	(88.02)	(110.82)	(4.16)	(22.50)

Panel B: Exiting from the highest BTC sensitivity decile portfolio

	Former *BTC sensitivity* decile portfolio return (focal stock exits)			Highest *BTC sensitivity* portfolio return			Difference
	$\underline{\beta}^{1b}$	$\overline{\beta_{1b}}$	$\Delta\beta_{1b}$	$\underline{\beta}^{2b}$	$\overline{\beta_{2b}}$	$\Delta\beta_{2b}$	$\Delta\beta_{2b} - \Delta\beta_{1b}$
Top 100	1.06	1.16	0.10	1.04	0.91	-0.13	-0.23
	(29.66)	(30.58)	(2.17)	(32.07)	(29.55)	(-3.19)	(-7.43)
Top 500	1.11	1.20	0.10	1.04	0.94	-0.10	-0.20
	(62.65)	(66.09)	(4.30)	(68.02)	(62.97)	(-5.23)	(-14.33)
All stocks	1.04	1.12	0.08	0.95	0.89	-0.07	-0.15
	(106.74)	(114.15)	(6.43)	(113.16)	(106.67)	(-6.43)	(-19.97)

Internet Appendix for

Does the speculative frenzy in bitcoin spread to the stock market?

This is the Internet Appendix for *Does the speculative frenzy in bitcoin spread to the stock market?* Section 1 describes our data sources and construction of the cryptocurrency market return. Section 2 reports additional results discussed in the main text. Section 3 discusses the baseline results in Table 3.

Section 1. Data description

Figure A1 shows a summary of the entire cryptocurrency market from a screenshot of the CoinMarketCap.com home page on July 6, 2018. There are 1,615 cryptocurrencies with an estimated market capitalization of US$266 billion. Table A1 lists the detailed top ten coins used for the construction of the entire cryptocurrency market. The market capitalization is based on information on March 31, 2018.

Bitcoin is the largest cryptocurrency currently, followed by Ethereum, Ripple, Bitcoin Cash, and Litecoin. As reported in CoinMarketCap.com, bitcoin accounts for 43.92% market share of the total cryptocurrency market as of March 31, 2018, while the total market share of the second to tenth coin is 35.98%, which is less than the market share of bitcoin. Overall, the top-ten coins capture nearly 80% of the cryptocurrency market. Bitcoin and Litecoin have the oldest data availability; both are active since the first record date in CoinMarketCap.com, followed by Ripple and Stellar. Other cryptocurrencies, such as IOTA, EOS, Bitcoin Cash, and Cardona, have a relative short period of price data.

For the top ten coins based on the market capitalization on March 31th, 2018, we extract data on history prices, available supply volume, trading volume over last 24 hours, and market capitalization. After calculating the corresponding stock-trading day's returns for all ten coins, we calculate the market capitalization weighted daily return as the market return of the entire cryptocurrency market.

Section 2. Tables for additional test results

Table A1. Top 10 Cryptocurrencies

Section 3. Additional explanation of the baseline results as in Table 3

We note that all the decile portfolio's CAPM alphas are negative in Table 3, suggesting that all the decile portfolios underperform the CAPM benchmark. We propose two explanations for this unusual pattern.

First, during our sample period, financial stocks outperform the other stocks. While, in our sample selection, we follow the common criterion to exclude the financial stocks (sic between 6000 and 6999). Thus, our sample will relatively underperform the market, which consists all stocks. In the online appendix table A12, we show an out-of-sample test using the financial stocks, and we find 9 out of the 10 decile portfolios are associated with positive CAPM alpha, which support that financial stocks outperform the market portfolio. In Figure A2, we also plot the cumulative portfolio returns for the market portfolio and financial stock portfolio. The equal-weighted (value-weighted) cumulative return for financial stocks is about 211% (167%) during our sample period, while the equal-weighted (value-weighted) cumulative return for all stocks is about 97% (175%). The results clearly suggest that financial stocks perform better during our sample period.

Second, large-cap stocks outperform the small-cap stocks during our sample period. Table 3 reports the equal-weighted decile portfolio returns, but the CAPM benchmark is estimated as the value-weighted market return, the weighting scheme will lead to negative alphas. As shown in Figure A2, the equal-weighted cumulative market return is only 97% during our sample period, but the value-weighted cumulative market return is 175%. We also repeat out baseline portfolio analysis using value-weighted weighting scheme, and report the results in Table A15. When using the non-financial stocks, the second portfolio shows positive CAPM alpha, and the first and fifth portfolio show near-zero CAPM alphas. When we pool the financial stocks and non-financial stocks together, the top 2 decile portfolios are associated with positive alphas.

Overall, although the negative CAPM alphas in Table 3 are relatively unusual, the short sample period and the unique market feature in this period explain the negative CAPM alphas. Large stocks outperform small stocks and financial stocks outperform non-financial stocks together explain the negative alphas in Table 3. Besides, the results in Table A15 also suggest that the pricing effect of BTC sensitivity still exist when using value-weighted weight scheme. Although the excess return using value-weighted method becomes smaller (1.01% VS 1.32%), the magnitude is still significant and larger than 1% per month.

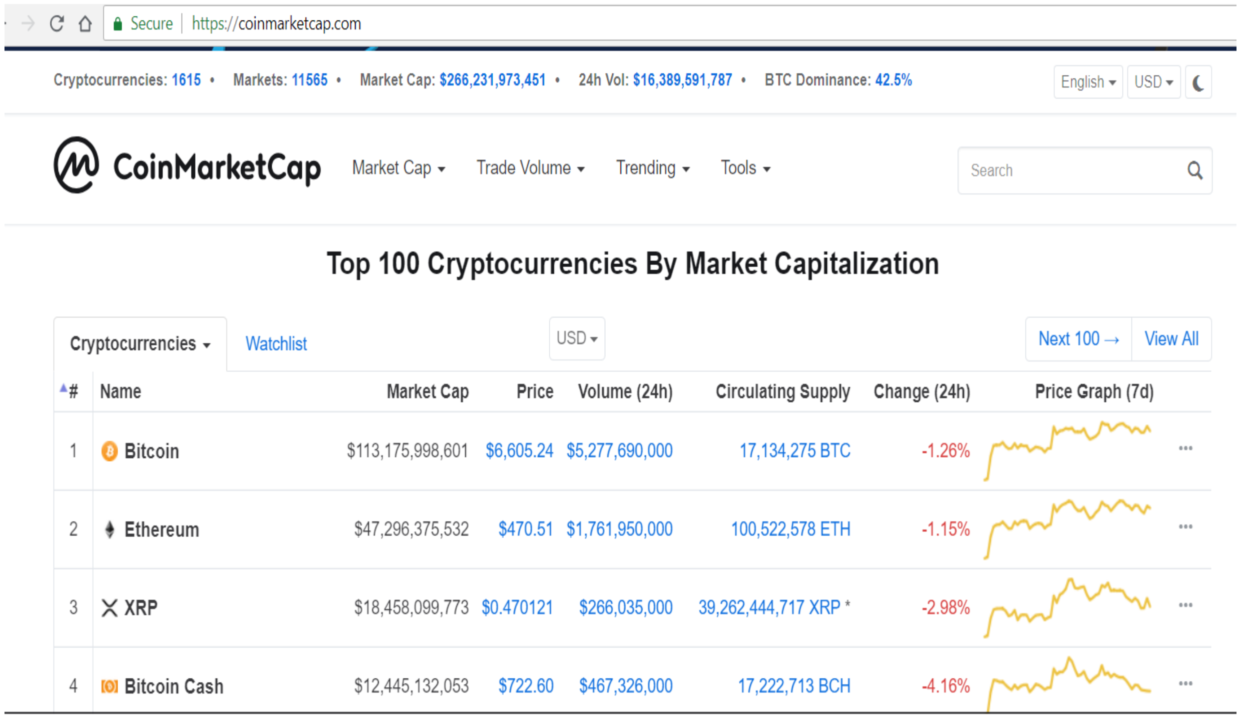


Figure A1: Screenshot of the homepage of CoinMarketCap.com
This screenshot is taken from coinmarketcap.com at about 23:00 pm on July 6, 2018. It shows the homepage of the website.

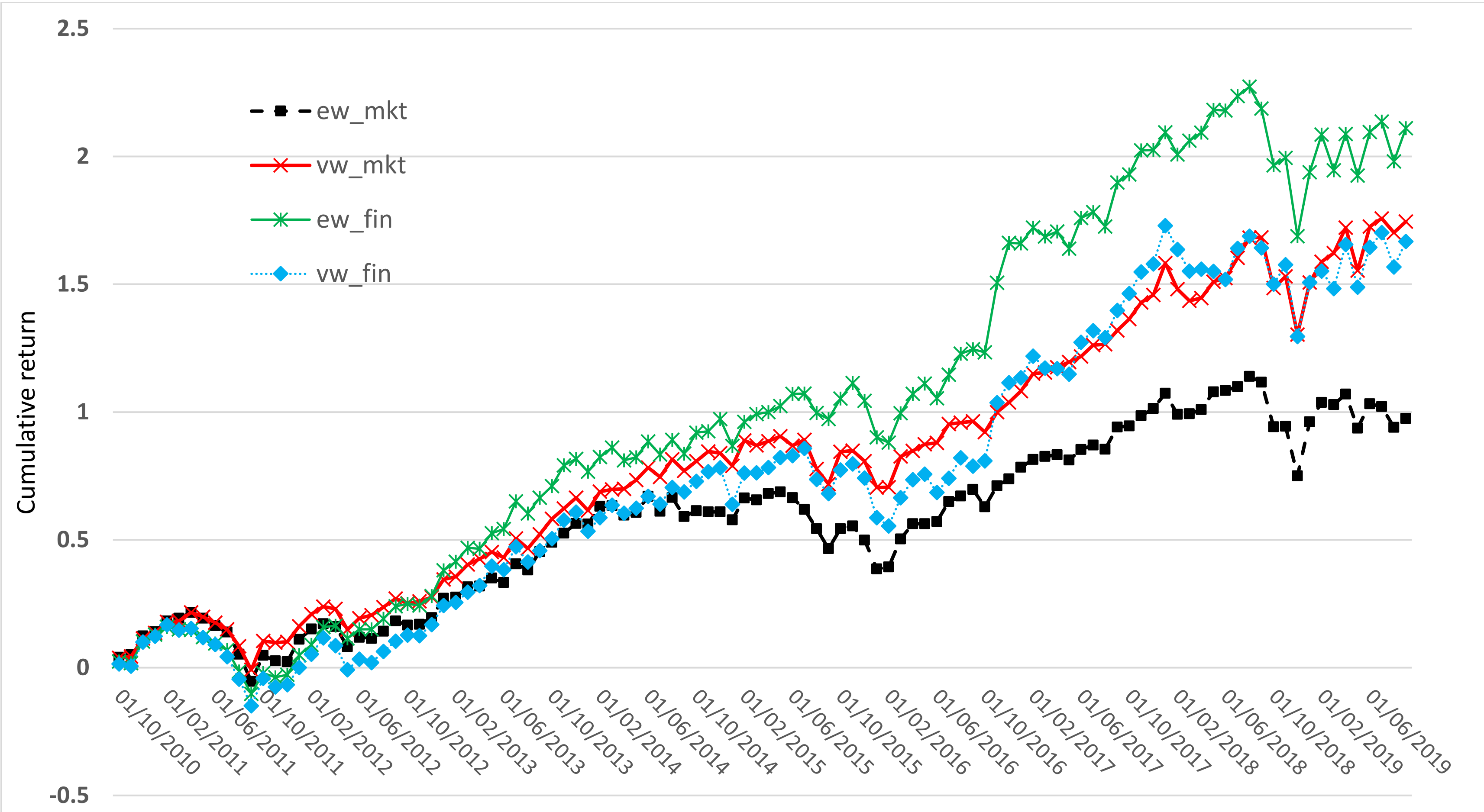


Figure A2: Cumulative portfolio return of different portfolios
This figure presents the cumulative returns to a $1 dollar investment in different portfolios using different weighting schemes. We report 4 different portfolio combinations: the equal-weighted market portfolio, the value-weighted market portfolio, the equal-weighted financial stocks portfolio, and the value-weighted financial stock portfolio. The sample period starts from October 2010, and end in September 2019.

Table A1. Top 10 Cryptocurrencies

This table shows the list of the 10 largest cryptocurrencies by market capitalization and their market share. Data are from CoinMarketCap.com as of March 31, 2018

Rank	Coin name	Trading symbol	Data starting month	Market cap ($bil)	Market share
1	Bitcoin	BTC	201305	116.82	43.92%
2	Ethereum	ETH	201508	38.91	14.63%
3	Ripple	XRP	201308	19.96	7.50%
4	Bitcoin Cash	BCH	201708	11.89	4.47%
5	Litecoin	LTC	201305	6.63	2.49%
6	EOS	EOS	201707	4.65	1.75%
7	Cardona	ADA	201710	3.81	1.43%
8	Stellar	XLM	201408	3.51	1.32%
9	NEO	NEO	201609	3.27	1.23%
10	IOTA	MIOTA	201706	3.09	1.16%

Table A2. Returns of lottery and liquidity related anomalies during the recent sample period

This table shows the average Long/Short (L/S) returns and risk-adjusted returns (in percentage) of the BTC sensitivity (BTC) return pattern and other lottery/liquidity related anomalies. L/S return or risk-adjusted alpha is the return or alpha of a zero-cost portfolio that longs the top undervalued decile portfolio and shorts the bottom overvalued decile portfolio. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart four-factor model. The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Name of anomaly	L/S Return	CAPM Alpha	3-Factor Return	4-Factor Alpha
1	*BTC*	-1.32***	-1.68***	-1.54***	-1.34***
		(-4.67)	(-6.67)	(-5.81)	(-5.38)
2	Sig *BTC*	-2.05***	-2.84***	-2.51***	-2.16***
		(-3.36)	(-5.54)	(-4.51)	(-4.32)
3	SIZE	1.30***	1.36***	1.18***	0.99***
		(4.66)	(4.56)	(3.97)	(3.27)
4	Price	1.35***	1.85***	1.60***	1.26***
		(3.16)	(4.99)	(4.13)	(3.21)
5	MAX	-1.53***	-2.20***	-1.95***	-1.75***
		(-4.08)	(-7.05)	(-6.56)	(-6.28)
6	IVOL	-1.72***	-2.37***	-2.08***	-1.83***
		(-4.46)	(-7.01)	(-6.11)	(-5.43)
7	EIS	-1.94***	-2.61***	-2.40***	-2.07***
		(-4.49)	(-6.93)	(-6.61)	(-5.54)
8	TO	-0.81**	-1.77***	-1.53***	-1.33***
		(-2.42)	(-5.09)	(-4.32)	(-4.18)
9	ILLIQ	-0.74***	-0.50**	-0.42	-0.36
		(-3.61)	(-1.99)	(-1.56)	(-1.30)
10	Distress	-0.16	-0.69***	-0.34	-0.06
		(-0.47)	(-2.67)	(-1.65)	(-0.39)

Table A3. Reference point, probability weighting, and high BTC sensitivity stocks

This table examines the impact of reference point and probability weighting on the performance of high BTC sensitivity stocks. Panel A reports the portfolio analysis results, and Panel B shows the cross-sectional Fama-MacBeth regression results. In Panel A, we divide the whole sample into high/low CGO/KT subsamples, and conduct the portfolio sorting analysis for each subsample separately. In Panel B, we include the interaction terms between BTC sensitivity and CGO/TK in the Fama-MacBeth regression. All stock characteristics are standardized (N~(0,1)) to make the results comparable. The dependent variable is the firm's monthly return (in percentage). CGO, short for capital gain overhang, reflect the overall reference point, following Grinblatt and Han (2005), but we use a 1-year estimation period. TK is the prospect theory value in Tversky and Kahneman (1992) and Barberis, Mukherjee, Wang (2016). The t-statistics are shown in parentheses using the Newey and West (1987) corrected standard errors with up to twelve lags. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

Panel A: portfolio sorting results

	(1) Low CGO (below median)	(2) High CGO (above median)	(3) Low TK (below median)	(4) High TK (above median)
1 (Low)	0.90	1.21	1.31	0.85
2	0.71	1.12	1.18	0.84
3	0.74	1.20	1.10	0.89
4	0.59	1.34	1.16	0.68
5	0.69	1.17	1.26	0.98
6	0.70	1.20	1.05	1.01
7	0.38	1.26	1.23	0.73
8	0.36	1.05	0.94	0.33
9	-0.32	1.08	0.89	0.17
10 (High)	-0.94	0.82	0.64	-0.47
H – L	-1.84***	-0.39	-0.67***	-1.33***
(*t*-stat)	(-5.42)	(-1.19)	(-3.46)	(-3.37)
Alpha	-1.85***	-0.35	-0.64***	-1.40***
(*t*-stat)	(-5.25)	(-1.21)	(-2.84)	(-3.36)

Panel B: Fama-MacBeth regressions

	(1)	(2)
BTC sensitivity	-0.08**	-0.09***
	(-2.26)	(-2.73)
BTC sensitivity × CGO	0.10**	
	(2.43)	
BTC sensitivity × TK		-0.11**
		(-2.59)
Control variables	Yes	Yes

Table A4. Retail investor trading activity and high BTC sensitivity stocks

This table examines the impact of retail investor trading activity on the performance of high BTC sensitivity stocks. Panel A reports the portfolio analysis results, and Panel B shows the cross-sectional Fama-MacBeth regression results. In Panel A, we divide the whole sample into high/low retail trading subsamples, and conduct the portfolio sorting analysis for each subsample separately. In Panel B, we include the interaction terms between BTC sensitivity and retail trading activities in the Fama-MacBeth regression. All stock characteristics are standardized (N~(0,1)) to make the results comparable. The dependent variable is the firm's monthly return (in percentage). Retail trading is measure of retail trading volume defined as the fraction of transactions that experienced price-improvements in the TAQ database following Boehmer et al. (2021). The *t*-statistics are shown in parentheses using the Newey and West (1987) corrected standard errors with up to twelve lags. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019. For the retail trading data, the sample period ends December 2016 due to data availability.

Panel A: portfolio sorting results

	(1) Low retail trading (below median)	(2) High retail trading (above median)	(3) Low IO% (below median)	(4) High IO% (above median)
1 (Low)	1.24	0.73	0.80	1.24
2	1.24	0.63	0.73	1.08
3	1.20	0.87	0.98	1.07
4	1.25	0.71	0.57	1.13
5	1.13	0.94	0.86	1.01
6	1.16	0.76	0.57	1.12
7	1.08	0.74	0.53	1.16
8	1.11	0.41	0.29	1.04
9	0.98	-0.07	-0.37	0.81
10 (High)	0.91	-0.67	-0.95	0.91
H – L	-0.33	-1.41***	-1.75***	-0.34
(*t*-stat)	(-1.43)	(-4.34)	(-5.03)	(-1.19)
Alpha	-0.45*	-1.90***	-2.31***	-0.62**
(*t*-stat)	(-1.73)	(-6.14)	(-8.26)	(-2.13)

Panel B: Fama-MacBeth regressions

	(1)	(2)
BTC sensitivity	-0.06	0.02
	(-1.62)	(0.42)
BTC sensitivity × Retail trading	-0.13***	
	(-3.43)	
BTC sensitivity × IO%		0.21***
		(4.21)
All control variables as in Table 5	Yes	Yes

Table A5. Bitcoin factor risk-adjusted returns

This table presents alpha estimates and factor loadings of the long-short *BTC sensitivity* portfolio. In each month, all stocks are sorted by the absolute value of Bitcoin sensitivity into decile portfolios. We form a zero-cost portfolio that longs the bottom decile portfolio and shorts the top decile portfolio. Alpha is the intercept from the regression of the zero-cost portfolio on the respective model's risk factors. The factors include the Carhart four-factor model plus one of the three factors extracted from the Bitcoin market: (1) the monthly Bitcoin excess return (BTC return), (2) the monthly change in the hash rate (ΔBTC hash rate), and (3) the monthly change in the number of Bitcoin transactions (ΔBTC transactions). The *t*-statistics shown in parentheses are based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	(1)	(2)	(3)	(4)
Alpha	-1.31***	-1.53***	-1.22***	-1.51***
	(-5.25)	(-5.75)	(-4.66)	(-5.26)
BTC return	-0.00			-0.00
	(-0.75)			(-1.30)
Δ BTC hash rate		0.01		0.02***
		(0.95)		(2.61)
Δ BTC transaction			-0.02***	-0.02***
			(-4.76)	(-4.40)
MKT	0.14*	0.13*	0.12	0.12
	(1.90)	(1.90)	(1.53)	(1.53)
SMB	0.47***	0.46***	0.50***	0.48***
	(3.03)	(3.00)	(3.25)	(3.15)
HML	-0.37***	-0.37***	-0.38***	-0.39***
	(-3.13)	(-2.95)	(-3.33)	(-3.34)
UMD	-0.41***	-0.42***	-0.40***	-0.41***
	(-4.42)	(-4.67)	(-4.35)	(-4.57)

Table A6. Portfolio sorts: Using CoinMarketCap.com sample

This table reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced decile portfolios sorted by BTC sensitivity. Bitcoin return is calculated using the stock market trading day buy-and-hold returns to match the returns in CRSP. The calculation of the Bitcoin returns matches the identical trading dates used to compute the daily stock returns. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and a four-factor model that includes Fama-French three factors and Carhart momentum factor. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top *BTC sensitivity* decile portfolio and shorts the bottom *BTC sensitivity* decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is August 2013 to September 2019, covering a total 74 months.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	0.78	-0.29	0.04	0.07
	(2.35)	(-1.85)	(0.28)	(0.49)
2	0.64	-0.40	-0.16	-0.14
	(2.04)	(-2.32)	(-1.10)	(-0.96)
3	0.64	-0.48	-0.16	-0.13
	(1.91)	(-3.00)	(-2.19)	(-1.64)
4	0.78	-0.38	-0.05	-0.01
	(1.80)	(-1.60)	(-0.42)	(-0.05)
5	0.55	-0.58	-0.25	-0.22
	(1.24)	(-2.50)	(-1.92)	(-1.54)
6	0.74	-0.44	-0.06	-0.02
	(1.75)	(-2.18)	(-0.56)	(-0.15)
7	0.44	-0.72	-0.34	-0.28
	(1.10)	(-3.33)	(-2.29)	(-1.99)
8	0.39	-0.78	-0.42	-0.32
	(0.86)	(-2.51)	(-2.15)	(-1.50)
9	-0.06	-1.34	-0.85	-0.73
	(-0.11)	(-4.23)	(-3.48)	(-3.36)
10 (High)	-0.62	-2.05	-1.56	-1.37
	(-1.10)	(-5.77)	(-4.61)	(-4.21)
H − L	-1.41***	-1.76***	-1.59***	-1.44***
(*t*-stat)	(-4.27)	(-5.66)	(-4.89)	(-5.10)

Table A7. Portfolio sorts: Using prominent digital currency market daily returns

This table reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced decile portfolios sorted by their absolute return sensitivity to the whole digital currency market daily returns. The digital currency market return is calculated using the value-weighted daily returns of the top 10 digital currencies. We calculate the daily return for each coin using the stock market trading day buy-and-hold return. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top BTC sensitivity decile portfolio and shorts the bottom BTC sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period starts in Aug 2013 until September 2019, covering total 74 months.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	0.81	-0.19	0.02	0.04
	(2.31)	(-1.04)	(0.15)	(0.28)
2	0.74	-0.31	-0.12	-0.10
	(1.90)	(-1.79)	(-0.70)	(-0.56)
3	0.75	-0.34	-0.15	-0.13
	(2.02)	(-2.64)	(-1.82)	(-1.73)
4	0.93	-0.17	0.02	0.05
	(2.25)	(-1.21)	(0.19)	(0.49)
5	0.73	-0.31	-0.10	-0.04
	(1.93)	(-1.58)	(-0.82)	(-0.37)
6	0.64	-0.52	-0.27	-0.20
	(1.34)	(-2.51)	(-1.72)	(-1.54)
7	0.53	-0.49	-0.24	-0.18
	(1.30)	(-2.61)	(-1.58)	(-1.28)
8	0.62	-0.56	-0.32	-0.24
	(1.25)	(-2.24)	(-1.83)	(-1.49)
9	0.15	-1.07	-0.78	-0.69
	(0.25)	(-2.80)	(-2.19)	(-2.19)
10 (High)	-0.55	-1.85	-1.52	-1.34
	(-0.89)	(-4.46)	(-3.82)	(-3.79)
H − L	-1.36***	-1.65***	-1.54***	-1.38***
(*t*-stat)	(-3.60)	(-3.94)	(-3.50)	(-3.68)

Table A8. Portfolio sorts: Using 1-month, 6-month, and PCA based BTC sensitivity

This table reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced decile portfolios sorted by their BTC sensitivity. Bitcoin return is calculated using the stock market trading day buy-and-hold returns to match the returns in CRSP. The calculation of the Bitcoin returns matches the identical trading dates used to compute the daily stock returns. Alternative BTC sensitivity measure is estimated either using previous 1 month, 6 months, or the PCA measure based on 1-month, 3-month, and 6-month *BTC sensitivity*. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top *BTC sensitivity* decile portfolio and shorts the bottom *BTC sensitivity* decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. To get the 6-month BTC sensitivity will reduce the sample period, and the sample period in this table starts in October 2010 until September 2019.

		Excess Return	CAPM Alpha	3-Factor Return	4-Factor Alpha
	Low	0.87	-0.37	-0.12	-0.09
		(2.45)	(-2.82)	(-1.27)	(-0.94)
1-m *BTC*	High	-0.38	-1.84	-1.34	-1.13
Sensitivity		(-0.68)	(-5.89)	(-5.42)	(-4.21)
	H – L	-1.24***	-1.47***	-1.22***	-1.04***
	(*t*-stat)	(-4.36)	(-5.73)	(-4.88)	(-4.05)
	Low	1.06	-0.17	0.12	0.14
		(3.35)	(-1.45)	(1.37)	(1.70)
6-m *BTC*	High	-0.28	-1.81	-1.38	-1.18
Sensitivity		(-0.48)	(-5.46)	(-5.08)	(-4.26)
	H – L	-1.34***	-1.64***	-1.50***	-1.32***
	(*t*-stat)	(-4.07)	(-5.43)	(-5.08)	(-4.57)
	Low	1.09	-0.02	0.20	0.20
		(3.73)	(-0.20)	(2.35)	(2.59)
PCA based	High	-0.57	-2.06	-1.61	-1.38
BTC		(-0.99)	(-6.39)	(-5.60)	(-4.79)
Sensitivity	H – L	-1.66***	-2.04***	-1.81***	-1.58***
	(*t*-stat)	(-4.69)	(-6.71)	(-5.99)	(-5.39)

Table A9. Portfolio sorts: Using Dimson adjustment

This table reports the average returns or alphas and the corresponding *t*-statistics of monthly rebalanced on decile portfolios sorted by their *BTC sensitivity*. Bitcoin return is calculated using the stock market trading day buy-and-hold returns to match the returns in CRSP. The calculation of the Bitcoin returns matches the identical trading dates used to compute the daily stock returns. Following Dimson (1979), we also control for the lead-and-lag bitcoin return into our baseline regression, and use the absolute value of the summation of the three coefficients of the lead-lag bitcoin returns as the *BTC sensitivity* measure. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top sensitivity decile portfolio and shorts the bottom sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	1.07	-0.16	0.12	0.17
	(2.99)	(-1.06)	(1.36)	(1.85)
2	0.94	-0.36	-0.09	-0.05
	(2.82)	(-2.73)	(-1.25)	(-0.70)
3	0.90	-0.42	-0.14	-0.11
	(2.36)	(-2.72)	(-1.29)	(-1.17)
4	0.87	-0.49	-0.21	-0.16
	(2.43)	(-3.33)	(-2.23)	(-1.78)
5	0.96	-0.42	-0.11	-0.05
	(2.52)	(-2.50)	(-1.17)	(-0.44)
6	0.88	-0.52	-0.20	-0.15
	(2.30)	(-3.09)	(-2.32)	(-1.52)
7	0.85	-0.58	-0.28	-0.19
	(2.09)	(-3.48)	(-2.65)	(-1.75)
8	0.74	-0.72	-0.36	-0.26
	(1.70)	(-3.39)	(-2.50)	(-1.70)
9	0.20	-1.37	-1.02	-0.89
	(0.41)	(-5.84)	(-7.01)	(-5.72)
10 (High)	-0.14	-1.74	-1.33	-1.12
	(-0.27)	(-6.29)	(-7.00)	(-5.36)
H − L	-1.20***	-1.58***	-1.45***	-1.28***
(*t*-stat)	(-6.04)	(-8.58)	(-8.69)	(-7.16)

Table A10. Portfolio sorts: Using previous month return as portfolio weighting scheme

This table reports the average returns or alphas and the corresponding *t*-statistics of monthly rebalanced on decile portfolios sorted by their *BTC sensitivity*. Bitcoin return is calculated using the stock market trading day buy-and-hold returns to match the returns in CRSP. The calculation of the Bitcoin returns matches the identical trading dates used to compute the daily stock returns. To address the noise concern in the portfolio return estimation, following Asparouhova, Bessembinder, and Kalcheva (2010), we use the stock's past one month raw return as the stock's weight in the portfolio. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top sensitivity decile portfolio and shorts the bottom sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	1.02	-0.25	0.03	0.05
	(3.02)	(-1.83)	(0.29)	(0.52)
2	0.98	-0.28	-0.05	-0.05
	(2.71)	(-1.67)	(-0.38)	(-0.35)
3	0.95	-0.38	-0.10	-0.06
	(2.74)	(-2.69)	(-1.37)	(-0.76)
4	0.98	-0.39	-0.11	-0.06
	(2.49)	(-2.12)	(-1.06)	(-0.54)
5	0.84	-0.53	-0.24	-0.21
	(2.02)	(-2.87)	(-2.53)	(-1.94)
6	1.01	-0.39	-0.06	-0.01
	(2.53)	(-2.39)	(-0.72)	(-0.14)
7	0.72	-0.65	-0.33	-0.26
	(1.83)	(-3.67)	(-2.92)	(-2.18)
8	0.65	-0.73	-0.42	-0.33
	(1.50)	(-2.95)	(-2.67)	(-1.89)
9	0.29	-1.23	-0.82	-0.69
	(0.61)	(-5.04)	(-4.44)	(-3.90)
10 (High)	-0.36	-1.99	-1.58	-1.36
	(-0.63)	(-6.11)	(-5.26)	(-4.54)
H − L	-1.38***	-1.74***	-1.61***	-1.41***
(*t*-stat)	(-4.47)	(-6.11)	(-5.38)	(-5.16)

Table A11. Portfolio sorts: Excluding high-tech firms

This table reports the average returns or alphas in percentage and the corresponding t-statistics of monthly rebalanced decile portfolios sorted by their BTC sensitivity. We exclude the high-tech firms from the sample. High-tech firms are defined as the industry 32, 34, 35 and 36 in the Fama and French 48 industry classification. Industry 32 is the telecommunication industry; the industry 34 is the business services industry; the industry 35 is the computer industry; and the industry 36 is the electronic equipment (chips) industry. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top BTC sensitivity decile portfolio and shorts the bottom BTC sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	1.08	-0.24	0.06	0.08
	(3.22)	(-1.76)	(0.56)	(0.76)
2	0.94	-0.33	-0.07	-0.07
	(2.50)	(-1.71)	(-0.41)	(-0.45)
3	0.82	-0.55	-0.24	-0.19
	(2.33)	(-3.28)	(-3.28)	(-2.54)
4	1.02	-0.34	-0.04	0.02
	(2.46)	(-1.82)	(-0.37)	(0.19)
5	0.89	-0.53	-0.22	-0.19
	(2.07)	(-2.94)	(-2.29)	(-1.87)
6	0.95	-0.47	-0.12	-0.05
	(2.43)	(-2.86)	(-1.28)	(-0.53)
7	0.74	-0.68	-0.34	-0.28
	(1.79)	(-3.51)	(-3.06)	(-2.37)
8	0.71	-0.72	-0.38	-0.26
	(1.61)	(-2.77)	(-2.05)	(-1.32)
9	0.25	-1.36	-0.89	-0.72
	(0.52)	(-5.09)	(-4.57)	(-4.08)
10 (High)	-0.25	-1.97	-1.55	-1.32
	(-0.45)	(-6.10)	(-5.23)	(-4.38)
H − L	-1.33***	-1.74***	-1.60***	-1.40***
(*t*-stat)	(-4.28)	(-6.12)	(-5.19)	(-4.83)

Table A12. Portfolio sorts: Out-of-sample test using financial stocks

This table reports the average returns or alphas in percentage and the corresponding t-statistics of monthly rebalanced equal-weighted stock returns on decile portfolios sorted by their *BTC sensitivity*. The sample contains financial firms only. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top sensitivity decile portfolio and shorts the bottom sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Excess Return	CAPM Alpha	3-factor Return	4-factor Alpha
1 (Low)	1.40	0.40	0.73	0.67
	(4.61)	(2.35)	(5.22)	(4.40)
2	1.23	0.23	0.56	0.48
	(4.19)	(1.12)	(4.47)	(4.28)
3	1.32	0.27	0.64	0.58
	(4.43)	(1.27)	(4.75)	(4.82)
4	1.16	0.10	0.45	0.41
	(3.80)	(0.49)	(3.00)	(2.81)
5	1.34	0.26	0.64	0.61
	(4.02)	(1.04)	(4.42)	(4.51)
6	1.21	0.15	0.53	0.51
	(3.38)	(0.58)	(3.33)	(3.40)
7	1.35	0.31	0.67	0.59
	(3.69)	(1.27)	(4.19)	(4.04)
8	1.15	0.11	0.44	0.40
	(3.38)	(0.45)	(2.49)	(2.50)
9	1.14	0.07	0.39	0.34
	(2.66)	(0.22)	(2.02)	(1.95)
10 (High)	0.54	-0.53	-0.28	-0.23
	(1.15)	(-1.46)	(-0.83)	(-0.71)
H − L	-0.85**	-0.94***	-1.01***	-0.90**
(*t*-stat)	(-2.38)	(-2.87)	(-2.67)	(-2.33)

Table A13. Portfolio sorts: Out-of-sample test using Chinese market stocks

This table reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced decile portfolios sorted by their BTC Sensitivity measure. We repeat our baseline analysis using Chinese stock market data extracted from CSMAR. Following Liu, Stambaugh, Yu (2019), we exclude the shell stocks and use the Ch4 factor model to adjust the risk factor in China. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include the CAPM, the Liu, Stambaugh, and Yu CH3 factor model, and CH4 factor model. Long-short return or Alpha is the return or alpha of a zero-cost portfolio that buys the top *BTC Sensitivity* decile portfolio and shorts the bottom *BTC Sensitivity* decile portfolio (i.e., H − L). The *t*-statistics shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from April 2014 to June 2019, totally 63 months.

	Full sample of stocks with a BTC sensitivity				Subsample of stocks with significant BTC sensitivity only			
	Excess Return	CAPM Alpha	CH3 Alpha	CH4 Alpha	Excess Return	CAPM Alpha	CH3 Alpha	CH4 Alpha
1 (Low)	1.53	0.43	0.74	0.55	1.77	0.89	0.99	0.57
	(1.27)	(1.18)	(2.31)	(1.90)	(1.66)	(2.47)	(1.74)	(1.53)
2	1.50	0.39	0.64	0.40	1.34	0.36	0.47	0.04
	(1.29)	(0.92)	(2.21)	(1.65)	(1.22)	(1.13)	(1.29)	(0.13)
3	1.41	0.27	0.48	0.37	0.80	-0.24	-0.05	-0.25
	(1.17)	(0.74)	(3.03)	(2.40)	(0.81)	(-0.94)	(-0.16)	(-0.88)
4	1.34	0.21	0.50	0.35	1.24	0.18	0.65	0.53
	(1.13)	(0.58)	(2.26)	(1.99)	(1.22)	(0.62)	(3.10)	(3.26)
5	1.16	0.03	0.40	0.20	0.67	-0.40	0.18	-0.02
	(0.97)	(0.08)	(2.35)	(1.26)	(0.64)	(-1.81)	(0.62)	(-0.11)
6	0.95	-0.19	0.34	0.15	0.44	-0.64	0.19	-0.01
	(0.82)	(-0.65)	(1.53)	(0.85)	(0.36)	(-2.06)	(0.53)	(-0.03)
7	0.88	-0.27	0.21	0.16	0.51	-0.65	0.10	0.08
	(0.71)	(-0.63)	(1.72)	(1.91)	(0.42)	(-2.00)	(0.38)	(0.30)
8	0.69	-0.50	0.13	0.10	0.34	-0.81	0.01	-0.04
	(0.53)	(-1.21)	(0.80)	(0.85)	(0.27)	(-1.52)	(0.02)	(-0.13)
9	0.14	-1.02	-0.20	-0.15	-0.30	-1.48	-0.20	-0.23
	(0.11)	(-1.88)	(-1.13)	(-0.90)	(-0.22)	(-2.83)	(-0.66)	(-0.75)
10 (High)	-0.58	-1.79	-0.46	-0.32	-1.19	-2.37	-0.98	-0.84
	(-0.41)	(-2.73)	(-2.36)	(-1.46)	(-0.81)	(-3.47)	(-3.31)	(-2.87)
H – L	-2.11***	-2.22***	-1.21***	-0.87***	-2.96***	-3.27***	-1.97***	-1.40***
(*t*-stat)	(-5.59)	(-6.26)	(-4.26)	(-3.01)	(-5.06)	(-6.25)	(-3.89)	(-3.58)

Table A14. Positive and negative BTC sensitivity

This table separately analyzes the returns for positive and negative BTC sensitivity stocks. Panel A reports the average returns or alphas in percentage and the corresponding *t*-statistics of monthly rebalanced portfolio returns sorted by their BTC sensitivity. In each month, we divide all the stocks into either positive sensitivity group or negative sensitivity group, and conduct the portfolio analysis for each sub-group. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top sensitivity decile portfolio and shorts the bottom sensitivity decile portfolio. Panel B reports the results from Fama-MacBeth return regressions. All stock characteristics are standardized to make the results comparable. The dependent variable is a firm's monthly return (in percentage). The explanatory variable of interest is either the positive BTC sensitivity or negative BTC sensitivity. The control variables include: idiosyncratic volatility (*IVOL*), the logarithm firm of market cap (Ln(*SIZE*)), the logarithm of book-to-market equity (Ln(B/M)), annually operating profitability (OP), total asset growth (*TAG*), momentum (*MOM*), maximum daily return (*MAX*), expected idiosyncratic skewness (*EIS*), Short-term reversal (*STR*), Amihud illiquidity (*ILLIQ*), average daily turnover (*Turnover*), the logarithm of stock price (Ln(*Price*)), and the distress risk (*Distress*). The table reports the time-series monthly averages of the estimated coefficients. The *t*-statistics are shown in parentheses using the Newey and West (1987) corrected standard errors with up to twelve lags. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

Panel A: Portfolio analysis

	positive BTC sensitivity stocks				negative BTC sensitivity stocks			
	Excess Return	CAPM Alpha	3-Factor Return	4-Factor Alpha	Excess Return	CAPM Alpha	3-Factor Return	4-Factor Alpha
Low	1.05	-0.23	0.07	0.11	1.03	-0.28	-0.02	0.01
	(2.87)	(-1.44)	(0.64)	(0.93)	(3.26)	(-2.16)	(-0.14)	(0.08)
2	1.06	-0.28	-0.03	-0.02	0.93	-0.26	-0.02	-0.02
	(2.67)	(-1.51)	(-0.24)	(-0.12)	(2.86)	(-1.37)	(-0.14)	(-0.12)
3	0.90	-0.51	-0.22	-0.17	0.98	-0.34	-0.06	-0.01
	(2.49)	(-3.03)	(-1.92)	(-1.47)	(2.82)	(-2.26)	(-0.56)	(-0.13)
4	0.95	-0.40	-0.10	-0.04	0.92	-0.47	-0.18	-0.12
	(2.45)	(-2.29)	(-1.07)	(-0.35)	(2.16)	(-2.28)	(-1.18)	(-0.79)
5	1.04	-0.37	-0.10	-0.05	0.73	-0.65	-0.35	-0.35
	(2.50)	(-2.11)	(-0.93)	(-0.46)	(1.62)	(-2.60)	(-2.12)	(-1.87)
6	0.84	-0.55	-0.24	-0.19	1.02	-0.41	-0.09	-0.04
	(2.22)	(-3.16)	(-2.22)	(-1.82)	(2.40)	(-2.14)	(-0.68)	(-0.27)
7	0.69	-0.68	-0.33	-0.29	1.00	-0.41	-0.09	0.02
	(1.79)	(-3.43)	(-2.66)	(-2.28)	(2.49)	(-2.15)	(-0.66)	(0.14)
8	0.48	-0.96	-0.65	-0.57	0.75	-0.64	-0.31	-0.17
	(1.04)	(-3.51)	(-3.50)	(-3.29)	(1.91)	(-3.15)	(-1.75)	(-0.90)
9	0.31	-1.27	-0.85	-0.69	0.43	-1.07	-0.68	-0.52
	(0.58)	(-3.58)	(-2.93)	(-2.39)	(0.95)	(-4.44)	(-3.88)	(-2.93)
High	-0.54	-2.24	-1.79	-1.65	0.04	-1.53	-1.14	-0.86
	(-0.85)	(-6.38)	(-6.18)	(-5.59)	(0.07)	(-5.19)	(-3.88)	(-2.69)
H − L	-1.58***	-2.01***	-1.86***	-1.76***	-1.00***	-1.25***	-1.13***	-0.86***
(*t*-stat)	(-4.54)	(-6.58)	(-5.93)	(-5.71)	(-3.65)	(-5.05)	(-4.13)	(-3.34)

Table A14 (cont'd)

Panel B: Fama-MacBeth regression results

	(1)	(2)	(3)
Positive BTC sensitivity	-0.17***		-0.18***
	(-2.71)		(-2.89)
Negative BTC sensitivity		-0.02	-0.05
		(-0.40)	(-0.85)
Ln(SIZE)	-0.15	-0.14	-0.15
	(-1.37)	(-1.32)	(-1.41)
Ln(B/M)	-0.08	-0.07	-0.08
	(-0.85)	(-0.81)	(-0.86)
OP	0.31***	0.32***	0.31***
	(4.33)	(4.34)	(4.31)
TAG	-0.11	-0.11	-0.11
	(-1.45)	(-1.42)	(-1.45)
MOM	0.27***	0.27***	0.27***
	(3.02)	(3.04)	(3.04)
IVOL	-0.05	-0.05	-0.05
	(-0.72)	(-0.76)	(-0.73)
MAX	-0.53***	-0.56***	-0.53***
	(-4.66)	(-4.70)	(-4.36)
EIS	0.15	0.16	0.16
	(1.63)	(1.64)	(1.62)
STR	-0.39***	-0.39***	-0.39***
	(-2.81)	(-2.81)	(-2.80)
ILLIQ	-0.04	-0.04	-0.04
	(-1.21)	(-1.18)	(-1.16)
Turnover	-0.31***	-0.32***	-0.31***
	(-3.90)	(-4.03)	(-3.88)
Ln(Price)	-0.03	-0.02	-0.03
	(-0.32)	(-0.22)	(-0.34)
Distress	0.23***	0.23***	0.23***
	(4.22)	(4.18)	(4.20)
Intercept	0.73*	0.73*	0.73*
	(1.84)	(1.84)	(1.84)

Table A15. Portfolio sorts: Using value-weighted weighting scheme

This table report the portfolio sorting analysis as in Table 3. But we use the value-weighted weighting scheme to estimate the decile portfolio returns. We also report the results for non-financial stocks and all stocks separately. At the end of each month, we sort non-financial stocks or all stock into decile portfolio by their *BTC sensitivity,* and estimate the value-weighted portfolio returns. Excess return is the average returns in excess of the risk-free rate. Alpha is the intercept from the regression of monthly excess returns on risk factors specified by an asset pricing model. The factor models include: the CAPM, the Fama-French three-factor model, and the Carhart our-factor model. H − L return or Alpha is the return or alpha of a zero-cost portfolio that longs the top sensitivity decile portfolio and shorts the bottom sensitivity decile portfolio. The *t*-statistics are shown in parentheses are computed based on standard errors with Newey-West corrections. ***, **, and, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests. The sample period is from October 2010 to September 2019.

	Non-financial stocks with a BTC sensitivity				All stocks with a BTC sensitivity			
	Excess Return	CAPM Alpha	3-Factor Return	4-Factor Alpha	Excess Return	CAPM Alpha	3-Factor Return	4-Factor Alpha
Low	1.15	-0.01	0.02	0.04	1.20	0.06	0.11	0.11
	(3.93)	(-0.07)	(0.13)	(0.24)	(4.36)	(0.43)	(0.76)	(0.79)
2	1.36	0.25	0.23	0.22	1.27	0.13	0.17	0.16
	(5.47)	(3.08)	(2.87)	(2.92)	(4.44)	(1.14)	(1.47)	(1.54)
3	0.99	-0.19	-0.17	-0.15	1.05	-0.10	-0.06	-0.07
	(3.01)	(-1.07)	(-0.97)	(-0.84)	(3.63)	(-0.66)	(-0.43)	(-0.52)
4	1.01	-0.29	-0.23	-0.23	1.03	-0.20	-0.12	-0.11
	(3.61)	(-2.53)	(-1.96)	(-1.75)	(3.67)	(-2.43)	(-1.22)	(-0.97)
5	1.21	-0.00	0.01	0.05	1.15	-0.08	-0.01	0.00
	(4.08)	(-0.01)	(0.07)	(0.28)	(4.12)	(-0.58)	(-0.10)	(0.03)
6	1.10	-0.24	-0.14	-0.08	1.01	-0.26	-0.17	-0.16
	(3.51)	(-2.02)	(-1.29)	(-0.84)	(3.20)	(-2.17)	(-1.29)	(-1.15)
7	0.77	-0.55	-0.38	-0.33	0.95	-0.37	-0.25	-0.19
	(2.11)	(-3.30)	(-2.21)	(-1.99)	(2.84)	(-2.73)	(-1.76)	(-1.44)
8	0.82	-0.59	-0.42	-0.35	0.76	-0.61	-0.42	-0.36
	(2.18)	(-3.30)	(-3.34)	(-2.64)	(2.05)	(-3.50)	(-2.68)	(-2.32)
9	0.76	-0.68	-0.46	-0.32	0.90	-0.57	-0.36	-0.25
	(1.65)	(-2.69)	(-1.96)	(-1.42)	(2.18)	(-2.88)	(-2.36)	(-1.62)
High	0.14	-1.51	-1.21	-0.99	0.15	-1.43	-1.11	-0.87
	(0.29)	(-5.83)	(-5.05)	(-4.98)	(0.33)	(-6.06)	(-4.80)	(-5.10)
H − L	-1.01***	-1.49***	-1.24***	-1.03***	-1.05***	-1.49***	-1.22***	-0.99***
(*t*-stat)	(-3.49)	(-4.68)	(-3.85)	(-4.01)	(-3.85)	(-5.17)	(-4.20)	(-4.64)