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RESEARCH ARTICLE

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Bitcoin and sentiment

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Abstract
Baker and Wurgler identify high sentiment betas with small startup firms that have great growth potential. On the surface, cryptocurrencies share important features in common with high sentiment beta stocks. This paper investigates the degree to which, during the period July 18, 2010–February 26, 2018, the return to bitcoin displayed the characteristics of a high sentiment beta stock. Using a sentiment-dependent factor model, the analysis indicates that in large measure, bitcoin returns resembled returns to high sentiment beta stocks. Additionally, we show that bitcoin's expected returns are low when sentiment measured by Volatility Index is high while expected returns are high when sentiment is low.

KEYWORDS
behavioral finance, bitcoin, bubble, cryptocurrency

JEL CLASSIFICATION
E42; G10; G11; G12

1 | INTRODUCTION

This paper analyzes the degree to which returns to bitcoin reflect both fundamental factors and sentiment. Baker and Wurgler (2007) argue that some stocks are more vulnerable to being mispriced than others, stating: "Stocks of low capitalization, younger, unprofitable, high-volatility, non-dividend paying, growth companies … are likely to be disproportionately sensitive to broad waves of investor sentiment." This statement implies that when investors become excessively optimistic about stocks in general, they become even more optimistic about stocks of small firms that, while not currently profitable, are perceived as holding great potential for future profitability. Baker and Wurgler describe stocks that are disproportionately sensitive to investor sentiment as featuring "high sentiment beta." Because bitcoin is closely associated with blockchain technology, bitcoin should be priced like an equity investment in blockchain technology. Since the valuation of this blockchain technology is uncertain and there are limits to arbitrage, the behavior of bitcoin should resemble that of a high sentiment beta stock (following the logic of Baker & Wurgler, 2006, 2007). The main objective of this paper is to investigate the degree to which bitcoin resembles a "high sentiment beta" stock.

To investigate whether this intuition holds empirically, we analyze the history of bitcoin returns using a behavioral asset pricing model that features both sentiment and traditional factors relating to the standard Fama–French variables. In this respect, our model is a blend of three features. First is the use of factor structure, which is based on the pricing kernel approach described in Cochrane (2005) for the representative investor's marginal rate of substitution. Second is the pricing kernel approach, which is based on models of transaction technology equilibria (Starr, 2003). Third is the blend of sentiment and fundamentals, which is based on Baker and Wurgler (2006, 2007) and Shefrin (2008).

Bitcoin, the first decentralized cryptocurrency using blockchain technology, was first created in 2009. A recent literature has developed to study various aspects of blockchains, including the pricing of its associated cryptocurrencies.

The literature includes Athey, Parashkevov, Sarukkai, and Xia (2016), Catalini and Gans (2018), Cong, Li, and Wang (2018), Hu, Parlour, and Rajan (2018), Li and Mann (2018), and Pagnotta and Braschi (2018). Athey et al. (2016) note the difficulty with which traditional asset pricing models can explain the pricing of bitcoin tokens. Cong et al. (2018) develop a pricing model featuring a representative investor with rational expectations in which a surge in adoption rates produces increased volatility (sharp rise and decline). Hu et al. (2018) document the presence of a strong correlation effect between 222 other cryptocurrencies and bitcoin. Catalini and Gans (2018) present a framework for studying how the value of tokens is determined as part of the process for initial coin offerings (ICOs). Pagnotta and Braschi (2018) propose a theoretical model to examine the valuation of bitcoins and other blockchain tokens in a new type of production economy using a decentralized financial network (DN).

Li and Mann (2018) present a model that rationalizes the use of ICOs for launching peer-to-peer platforms. They note that some will view this growth as "valuable innovation in entrepreneurial finance" while others will view it as "irrational exuberance." Of course, the two views are not mutually exclusive, meaning that some ICOs might well represent valuable innovation while others stem from decisions that would not be described as rational.

Between the months of April and December 2017, the price of a bitcoin token increased from below $1,000 to $19,650, but then declined to $7,857 in March 2018. The material deleted should be simplified along the lines of: "Various authors in the popular press have noted the potential asset bubble characteristics of bitcoin (Krugman, 2018) as well as gender (Khalaf, 2018) and age biases (Nuryyev et al., 2020; Sovbetov, 2018) in cryptocurrency trading."

The comments in the popular press about bitcoin investing described above relate to key themes in the academic literature on sentiment. These themes include asset pricing bubbles (Shiller, 2005), the role of gender (Barber & Odean, 2001a, 2001b), the impact of retail investors on sentiment and small stocks (Barber, Odean, & Zhu, 2008), and the characterization of securities that are especially sensitive to sentiment (Baker & Wurgler, 2006, 2007).

The type of volatility exhibited by bitcoin in 2017 is reminiscent of volatility patterns that occurred during the dot.com bubble. As Baker and Wurgler (2007) state about high sentiment beta stocks: "[S]mall startup firms represented a majority of the excitement and subsequent carnage of the Internet bubble… Theoretically, it follows because 1) these categories of stocks tend to be harder to arbitrage (e.g., they have higher transaction costs) and 2) they are more difficult to value, making biases more insidious and valuation mistakes more likely."

Given the rapid growth of ICOs, investments in blockchain technology, and high volatility of cryptocurrency prices, intuition suggests strong similarities between cryptocurrencies and high sentiment beta stocks. Certainly, digital assets share some of the same features as the stocks of younger, small-cap firms that are not at present profitable, do not pay dividends, but do qualify as having the possibility of great growth potential.

The remainder of this paper is organized as follows. In Section 2, we present a theoretical transaction cost framework for analyzing the valuation of cryptocurrencies. In Section 3, we describe our data and research design. In Section 4, we present our empirical results based on standard asset pricing models and investor sentiment indices. In Section 5, we use vector autoregression (VAR) to focus directly on the dynamic relationship between sentiment and the return to bitcoin. In Section 6, we analyze the dynamic relationship between sentiment and bitcoin trading volume. In Section 7, we conclude.

2 | VALUATION OF BITCOIN AND OTHER CRYPTOCURRENCIES

The empirical approach we use to investigate the relationship of bitcoin pricing to sentiment involves a behavioral factor structure. This structure is based on several strands of the asset pricing literature, which we briefly describe below, with as little technical formality as possible.

The first strand of literature consists of general equilibrium-based transaction cost models developed by Foley (1970), Hahn (1971), Kurz (1974), Shefrin (1981), and Starr (2003). These models complement the cryptocurrency pricing literature mentioned above, and provide the foundation for the factor-based empirical approach employed below.

Transaction cost models are in the tradition of the Arrow–Debreu (1954) state price framework. In the Arrow–Debreu framework, commodities are identified not only with physical characteristics, but also with date–event pairs to capture time and uncertainty. In transaction cost models, additional attributes, besides physical traits, dates, and events, are used to define commodities. The most important attribute is whether a commodity is bought or sold. In these models, the difference in price between a bought commodity and sold commodity corresponds to the bid–ask price. Additional inclusion of ownership as an attribute of a commodity clarifies the value created by transaction technologies in a competitive environment involving competition among different exchanges for conducting transactions.

Cryptocurrencies are easily accommodated within traditional transaction cost models, as commodities which, as intermediate goods, provide the units of account for specific transaction technologies. As commodities, they can be produced and priced.[1] Recently, Easley, O'Hara, and Basu (2017) examine the role that transaction fees play in the bitcoin blockchain's evolution from a mining-based structure to a market-based ecology.

The second strand of literature is pricing kernel theory (Cochrane, 2005). Pricing kernel theory is set in a framework in which commodities share the same physical attributes, but differ in respect to date–event pairs. For the purpose of this discussion, a pricing kernel is a function that normalizes state prices by the probabilities of their associated date–event pairs. That is, the pricing kernel specifies the state price per unit probability associated with consumption in a given date–event pair. In the standard pricing kernel literature, state price per unit probability can be interpreted as the equilibrium marginal rate of substitution for a representative investor. As described in Cochrane (2005), in special cases, the marginal rate of substitution can feature a linear factor structure, such as the Fama–French factor model (Fama & French, 2015).

The third strand of literature is behavioral asset pricing which focuses on the degree to which market prices reflect sentiment (Baker & Wurgler, 2006, 2007; Shefrin, 2008). The work by Baker and Wurgler provides an index for measuring sentiment, a characterization of stocks that are sensitive to sentiment, and findings about how sentiment impacts return patterns associated with variables which underlie the Fama–French factors. Shefrin (2008) extends the standard pricing kernel theory to incorporate sentiment, and establishes that a behavioral pricing kernel can be expressed as the product of a sentiment index and a standard pricing kernel.

The three strands of literature provide the basis for our empirical approach, which is to analyze the history of bitcoin returns using a behavioral factor approach. The transaction cost framework provides the basis for modeling bitcoin pricing in a state price structure, and therefore a pricing kernel structure. The standard pricing kernel framework provides the theoretical basis for associating a factor structure to the representative investor's marginal rate of substitution. We follow suit in this regard. The behavioral pricing kernel framework provides the theoretical basis for incorporating sentiment into a standard factor pricing model, to accommodate sentiment alongside fundamental variables.[2]

3 | DATA AND RESEARCH DESIGN

3.1 | Data

As Hu et al. (2018) find that secondary market returns of 222 other digital coins are strongly correlated with bitcoin returns while bitcoin is the world's largest and best-known cryptocurrency, we focus on bitcoin in this paper and obtain daily bitcoin price data from the Bitcoin.com (2018) webpage (https://charts.bitcoin.com/). The sample period covers July 18, 2010–February 26, 2018. We also obtain the following daily and monthly Fama–French market factors: For US markets ($R_M - R_f$), small minus big firm size premium (SMB), high minus low book-to-market ratios (HML), the momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA).[3] From Kenneth French's data library, we also obtained global market factors [$R_M - R_f$], global Fama–French three, global Carhart four, and global Fama–French five factors at daily and monthly frequencies.

We examine two sentiment indices, one survey based and the other market based. First is the weekly index released by the American Association of Individual Investors (AAII; 2018). Data for this index are obtained from the AAII webpage.[4] The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish,

[1]The class of general equilibrium models can easily be generalized to accommodate a variety of features associated with cryptocurrencies. Two such features are theft and cryptocurrency value in consumption. Theft and protection against theft are production activities involving externalities. Allowing cryptocurrencies to have consumption value enables some agents to derive psychological benefits simply from holding cryptocurrencies.

[2]Our approach involves estimating models in which the pricing kernel $\boldsymbol{m}$ is assumed to take one of several forms. These forms are function of $\boldsymbol{\Lambda}$, an index of sentiment, and $\boldsymbol{f}$, a set of pricing factors. We begin by estimating a traditional model based on $\boldsymbol{m} = \boldsymbol{\alpha} + \boldsymbol{\beta f}$, which we compare to estimates based on its behavioral counterpart $\boldsymbol{m} = \boldsymbol{\Lambda}(\boldsymbol{\alpha} + \boldsymbol{\beta f})$. Both models are nested in the general structure $\boldsymbol{m} = (1 + \boldsymbol{\Lambda})(\boldsymbol{\alpha} + \boldsymbol{\beta f})$.

[3]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[4]We focus on AAII as one of our two primary measures of sentiment because it relates directly to individual investors' relative bullishness, as the data suggest that bitcoin trading is dominated by individual investors. We interpret AAII as largely reflecting individual investors' expectations about future returns, rather than volatility. To capture the impact of volatility, we analyze the impact of Volatility Index (VIX; 2018). There are other measures of sentiment, such as Campbell and Shiller (1988, 1998) cyclically adjusted price–earnings and price-to-dividends, and Baker–Wurgler's principal component variable (BW), all of which reflect a wider set of variables. There are also sentiment variables based on key terms used in Twitter tweets. However, from the outset, we have chosen to focus on individual investor sentiment, and based on unreported tests of Twitter tweets we find that AAII is best suited for our purposes. The AAII webpage is https://www.quandl.com/data/AAII/AAII_SENTIMENT-AAII-Investor-Sentiment-Data.

bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a weekly basis. Only one vote per member is accepted in each weekly voting period.

As a second index of investor sentiment, we examine the VIX. VIX is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options. It is colloquially referred to as the fear index. *VIX* is calculated as the square root of the par variance swap rate for a 30-day term initiated today. We obtain monthly VIX index from the Chicago Board Options Exchange (CBOE).

3.2 | Research design

We proceed in two stages to identify the presence of nonzero abnormal returns associated with bitcoin, after first controlling for existing risk factors. In the first stage we conduct traditional time-series tests based on the capital asset pricing model (CAPM), Fama–French multifactor models, and a factor for momentum (Carhart, 1997).[5] In the second stage, we modify the framework to incorporate sentiment.

The first stage involves the estimation of a series of factor models, using time-series regressions on daily excess *Bitcoin returns*. We describe these models as CAPM, Fama–French three, Carhart four, and Fama–French five (Fama/French, 2018).[6] The regression specifications are

$$(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha_{\text{CAPM}} + \widehat{\beta_{\text{MKT}}}(R_{\text{m}t} - R_{\text{ft}}) + e_{it}, \tag{1}$$

$$(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha_{\text{FF3}} + \widehat{\beta_{\text{MKT}}}(R_{\text{m}t} - R_{\text{ft}}) + \widehat{\beta_{\text{SMB}}}\text{SMB}_t + \widehat{\beta_{\text{HML}}}\text{HML}_t + e_{it}, \tag{2}$$

$$(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha_{\text{FF4}} + \widehat{\beta_{\text{MKT}}}(R_{\text{m}t} - R_{\text{ft}}) + \widehat{\beta_{\text{SMB}}}\text{SMB}_t + \widehat{\beta_{\text{HML}}}\text{HML}_t + \widehat{\beta_{\text{UMD}}}\text{UMD}_t + e_{it}, \tag{3}$$

$$(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha_{\text{FF5}} + \widehat{\beta_{\text{MKT}}}(R_{\text{m}t} - R_{\text{ft}}) + \widehat{\beta_{\text{SMB}}}\text{SMB}_t + \widehat{\beta_{\text{HML}}}\text{HML}_t + \widehat{\beta_{\text{RMW}}}\text{RMW}_t + \widehat{\beta_{\text{CMA}}}\text{CMA}_t + e_{it}. \tag{4}$$

In these models, $R_{\text{Bitcoin},t}$ is computed as $\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right)$ and $R_{\text{m}t} - R_{\text{ft}}$ is the return on the value-weight market portfolio minus the US 1-month *T*-bill rate. SMB_t is the difference between the average return on the three small portfolios minus the average return on the three big portfolios. HML_t is the difference between the average return on the three high book-to-market stocks and one of the three low book-to-market portfolios. UMD_t is the difference between month *t* return on a value-weighted portfolio of high prior return portfolios and one of low prior return portfolios. RMW_t is the average return on the robust operating profitability portfolios minus the average return on the weak operating profitability portfolios, and CMA_t is the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios. All Fama–French factors, SMB_t, HML_t, UMD_t, RMW_t, and CMA_t, are obtained from Kenneth French's website. Additionally, we conduct time-series analysis using global CAPM, global Fama–French three, global Carhart four, and global Fama–French five factor models.[7]

To incorporate sentiment into the multifactor approach for Bitcoin Return, we estimate two general specifications involving the five Fama–French factors, and two proxies for sentiment. These specifications are structured to imbed both traditional and behavioral factors. Both specifications use first differences of sentiment, as it is changes in sentiment that most impact returns, rather than levels. The specifications are as follows:

$$\begin{aligned}(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha &+ \widehat{\beta_1}(R_{\text{m}t} - R_{\text{ft}}) + \widehat{\beta_2}\text{SMB}_t + \widehat{\beta_3}\text{HML}_t \\ &+ \widehat{\beta_4}\text{CMW}_t + \widehat{\beta_5}\text{RMA}_t + \widehat{\beta_6}(R_{\text{mt}} - R_{\text{ft}})_t \times \text{diff(Investor sentiment)}_t \\ &+ \widehat{\beta_7}\text{SMB}_t \times \text{diff(Investor sentiment)}_t + \widehat{\beta_8}\text{HML}_t \times \text{diff(Investor sentiment)}_t \\ &+ \widehat{\beta_9}\text{CMA}_t \times \text{diff(Investor sentiment)}_t + \widehat{\beta_{10}}\text{RMA}_t \\ &\times \text{diff(Investor sentiment or VIX)}_t + \widehat{\beta_{11}}\text{diff(Investor sentiment)}_t + e_{it},\end{aligned} \tag{5}$$

[5]The first stage builds the Fama–French three-factor model (FF3), we use an extended four-factor model (Carhart, 1997) that includes a momentum factor (UMD) suggested by Jegadeesh and Titman (1993; FF4) and a Fama–French five-factor model (Fama & French, 2015) that we extend to incorporate the impact of sentiment.

[6]We obtain the monthly Fama–French five factors, SMB, HML, UMD, RMW, and CMA a from Kenneth French's website.

[7]Global Fama–French factors are also available on Kenneth French's website.

$$(R_{\mathrm{Bitcoin},t} - R_{\mathrm{ft}}) = \alpha + \hat{\beta}_1(R_{\mathrm{m}t} - R_{\mathrm{ft}})_t \times \mathrm{diff}(\mathrm{Investor\,sentiment})_t + \hat{\beta}_2 \mathrm{SMB}_t \times \mathrm{diff}(\mathrm{Investor\,sentiment})_t. + \hat{\beta}_3 \mathrm{HML}_t \times \mathrm{diff}(\mathrm{Investor\,sentiment})_t + \hat{\beta}_4 \mathrm{CMA}_t \times \mathrm{diff}(\mathrm{Investor\,sentiment})_t + \hat{\beta}_5 \mathrm{RMA}_t \times \mathrm{diff}(\mathrm{Investor\,sentimentorVIX})_t + e_{it} \quad (6)$$

We compute diff(Investor sentiment) as $\mathrm{Spread(Bull - Bear)}_t - \mathrm{Spread(Bull - Bear)}_{t-1}$ using the AAII sentiment index. Diff(VIX) is calculated as $\mathrm{VIX}_t - \mathrm{VIX}_{t-1}$, where *VIX* is computed as $\ln\left(\frac{\mathrm{VIX\ Index}_t}{\mathrm{VIX\ Index}_{t-1}}\right)$.

Equations (5) and (6) can be regarded as versions of standard factor pricing models (1)–(4), but where factor loadings are functions of sentiment. In this regard, estimations of Equations (5) and (6) indicate how increases in sentiment impact the direction and magnitude of each factor on the return to bitcoin. The analysis enables us to answer questions, such as whether or not increases in sentiment make the return to bitcoin more apt to resemble the return to small stocks.

4 | EMPIRICAL RESULTS RELATING TO FACTOR STRUCTURE

4.1 | Application of standard asset pricing models to bitcoin returns

Figure 1 shows the time-series of Bitcoin Price and Bitcoin Return from July 18, 2010 to February 26, 2018. Panel A plots the time-series of Bitcoin Price and Panel B plots the time-series of Bitcoin Return. The bitcoin price decrease happened much more quickly during the two months of January to February of 2018 than the bitcoin price increase period of July 2010 to December 2017 (see Figure 1).

As displayed in Table 1 Panel A, during the initial sample period of July 18, 2010–December 29, 2017, the average price of bitcoin is \$739 with the minimum of \$0 and the maximum of \$19,194. During this time, the average (minimum and maximum) of bitcoin return is 0.0046 (−0.4102 and 0.4700). Panel B reports that the average (minimum and maximum) of weekly bitcoin returns during the period of July 22, 2010—February 26, 2018 is 0.0297 (−0.6193 and 1.1078). The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a weekly basis. The averages of bullish, bearish, and neutral individual investors are 36.60%, 30.29%, and 33.11%, respectively, suggesting that about 6.3% more individual investors view the market will be bullish than bearish.

The findings reported in Table 2 Panel A indicate no significant bivariate correlations between bitcoin returns and any factors associated with CAPM and Fama–French-based models. In addition, Panel B suggests that weekly bitcoin returns are not significantly correlated with investor sentiment measured by the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months.

Table 3 presents the coefficient estimates of CAPM, Fama–French three, Carhart four, and Fama–French five factor models for US daily excess returns on excess *Bitcoin Return*. We note that Jensen's alpha is significant and positive at the 0.1% significance level in all the above asset pricing models during our sample period. Notice too that all of the coefficients of CAPM and Fama–French market and other factors are insignificant, suggesting that bitcoin returns are largely nonsystematic, at least from the perspective of a traditional factor pricing model. Thus, it seems that bitcoin cannot be priced by traditional equity factors, consistent with Liu and Tsyvinski (2018).

Bitcoin is traded globally. For this reason, we repeat the procedure described above using global variables for the period July 18, 2010–May 31, 2017.[8] The results presented in Table 4 closely mirror Table 3 outcomes.

4.2 | Application of the behavioral asset pricing model to bitcoin returns

There are at least three different channels by which sentiment can impact bitcoin returns, which we study by estimating Equations (5) and (6). The first channel is bitcoin specific, which is reflected in bitcoin's Jensen's alpha. Given bitcoin's price history and the prior discussion, a reasonable prior expectation is for our estimates of Jensen's alpha for Equations

[8]The choice of sample period stems from the lack of availability of global CAPM, global Fama–French three, global Carhart four, and global Fama–French five factors.

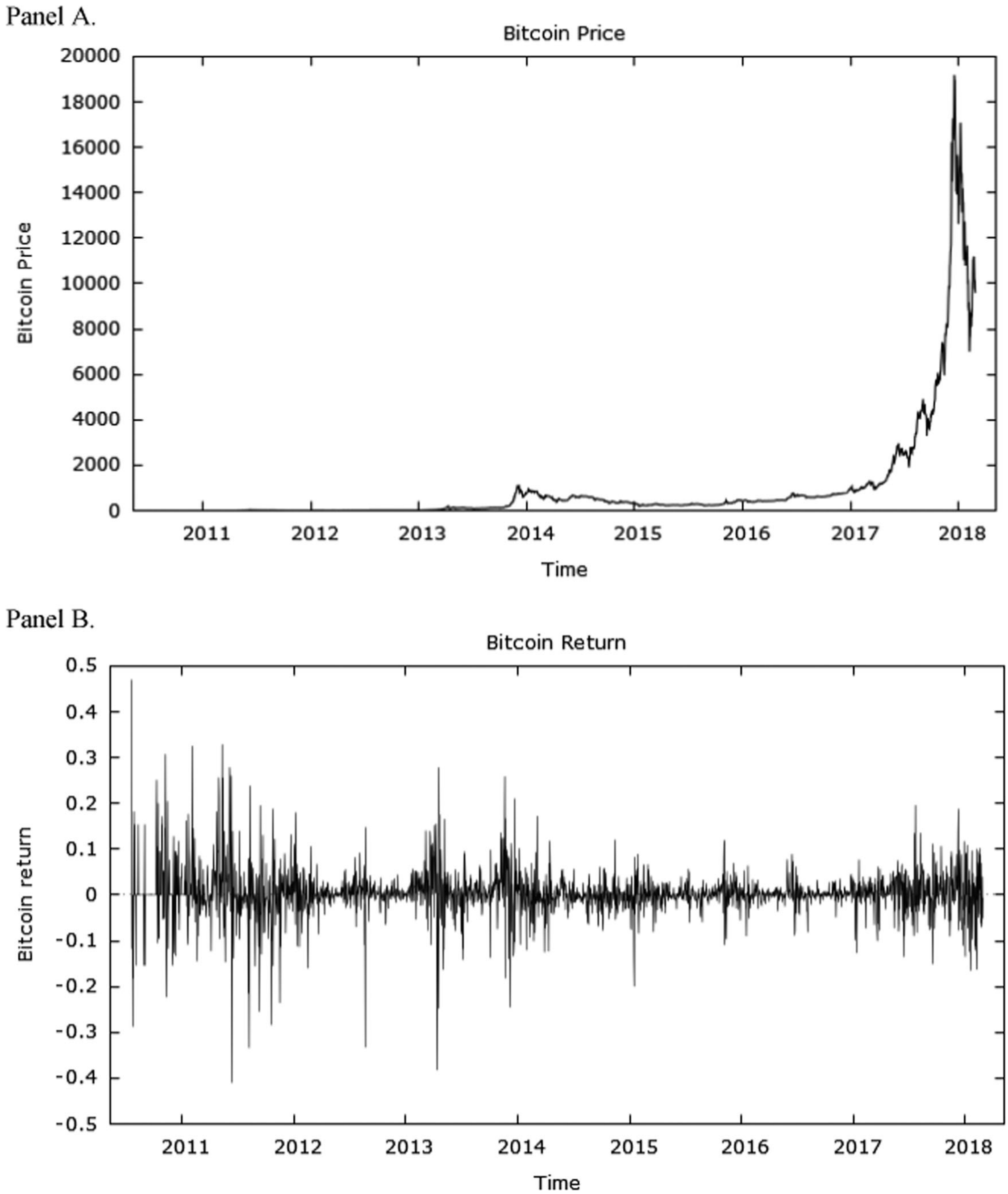

FIGURE 1 The time-series of *Bitcoin Price* and *Bitcoin Return*. This figure shows the time-series of *Bitcoin Price* and *Bitcoin Return* from July 18, 2010 to February 26, 2018. (a) The time-series of *Bitcoin Price* and (b) the time-series of *Bitcoin Return. Bitcoin Return* is computed by $\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right)$

(5) and (6) to be positive. The second channel involves the sensitivity of bitcoin's price to general market sentiment. Baker and Wurgler (2007) describe such sentiment as general optimism about stocks.

The third channel involves the manner in which sentiment mediates fundamental factor loadings, as noted by Baker and Wurgler (2006). Of special interest is the impact of sentiment on factor loadings associated with size (SMB) and profitability (RMW), because of the analogy between bitcoin and Baker and Wurgler's association of high sentiment beta to small startup firms that are not yet profitable but possess great growth potential. Because bitcoin is the cryptocurrency most closely associated with a blockchain technology, and blockchain activity is positively related to general economic activity, our prior expectation is that bitcoin returns will be statistically related to the market risk premium.

TABLE 1 Descriptive statistics

Panel A: Summary statistics of bitcoin price, bitcoin return, and standard asset pricing factors										
Variable	***N***	**Mean**	**Stdev.**	**Skewness**	**Kurtosis**	**Quintile1**	**Median**	**Quintile3**	**Min.**	**Max.**
Bitcoin price	1,878	739	1,931	6	38	10	243	602	0	19,194
Bitcoin return	1,878	0.0046	0.0514	0.1368	12.7106	−0.0104	0.0015	0.0200	−0.4102	0.4700
MKTRF	1,878	0.0006	0.0092	−0.4211	4.9989	−0.0034	0.0007	0.0052	−0.0697	0.0497
SMB	1,878	0.0000	0.0052	0.2571	1.9365	−0.0033	0.0000	0.0033	−0.0192	0.0361
HML	1,878	0.0000	0.0047	0.3855	1.8495	−0.0029	−0.0002	0.0026	−0.0168	0.0237
UMD	1,878	0.0002	0.0069	−0.2560	2.0709	−0.0034	0.0005	0.0040	−0.0313	0.0365
CMA	1,878	0.0000	0.0029	0.3314	2.1559	−0.0018	0.0000	0.0016	−0.0132	0.0197
RMW	1,878	0.0001	0.0033	0.0421	1.9597	−0.0020	0.0000	0.0020	−0.0162	0.0164
Panel B: Summary statistics of weekly bitcoin returns and American Association of Individual Investors (AAII) sentiment index										
Variable	***N***	**Mean**	**Stdev.**	**Skewness**	**Kurtosis**	**Quintile1**	**Median**	**Quintile3**	**Min.**	**Max.**
Weekly bitcoin return	396	0.0297	0.1593	1.0071	7.8158	−0.0343	0.0104	0.0897	−0.6193	1.1078
Bullish	396	0.3660	0.0835	0.2662	−0.3721	0.3022	0.3595	0.4253	0.1775	0.6328
Neutral	396	0.3311	0.0655	0.3721	−0.1841	0.2825	0.3243	0.3767	0.1395	0.5286
Bearish	396	0.3029	0.0699	0.5976	0.2241	0.2519	0.2934	0.3429	0.1505	0.5448
Spread (bullish–bearish)	396	0.0631	0.1394	−0.0264	−0.1711	−0.0299	0.0635	0.1613	−0.3517	0.4688

Note: Panel A reports the summary statistics of the daily *Bitcoin Price*, *Bitcoin return*, and the standard asset pricing factors, $R_m - R_f$. The Fama and French (1993) three-factor model with the market (MKT), size (SMB), and book-to-market (HML) factors, momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) were obtained from Kenneth French's data library. *Bitcoin Return* is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right).$$

The sample period covers July 18, 2010–February 26, 2018. Panel B reports the summary statistics of the *weekly Bitcoin return* and American Association of Individual Investors sentiment index (AAII index). *Bitcoin Return* is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-7}}\right).$$

TABLE 2 Bivariate correlations

Panel A: Correlation matrix between daily bitcoin returns and standard asset pricing factors

	Bitcoin return	MKTRF	SMB	HML	UMD	CMA	RMW
Bitcoin return	1	0.0221 (0.3393)	−0.0092 (0.689)	−0.0102 (0.6603)	0.0081 (0.7271)	−0.0374 (0.1053)	0.0118 (0.6107)
MKTRF	0.0221 (0.3393)	1	0.3781 (<0.0001)	0.1334 (<0.0001)	−0.0909 (<0.0001)	−0.0982 (<0.0001)	−0.4921 (<0.0001)
SMB	−0.0092 (0.689)	0.3781 (<0.0001)	1	−0.0748 (0.0012)	−0.0583 (0.0115)	−0.0802 (0.0005)	−0.4242 (<0.0001)
HML	−0.0102 (0.6603)	0.1334 (<0.0001)	−0.0748 (0.0012)	1	−0.3994 (<0.0001)	0.5809 (<0.0001)	−0.2299 (<0.0001)
UMD	0.0081 (0.7271)	−0.0909 (<0.0001)	−0.0583 (0.0115)	−0.3994 (<0.0001)	1	−0.1507 (<0.0001)	0.0776 (0.0008)
CMA	−0.0374 (0.1053)	−0.0982 (<0.0001)	−0.0802 (0.0005)	0.5809 (<0.0001)	−0.1507 (<0.0001)	1	−0.0205 (0.375)
RMW	0.0118 (0.6107)	−0.4921 (<0.0001)	−0.4242 (<0.0001)	−0.2299 (<0.0001)	0.0776 (0.0008)	−0.0205 (0.375)	1

Panel B: Correlation matrix between weekly Bitcoin returns and AAII index

	Weekly bitcoin return	Bullish	Neutral	Bearish	Spread (bullish–bearish)
Weekly bitcoin return	1	0.04809 (0.3398)	−0.03456 (0.4929)	−0.02531 (0.6156)	0.04151 (0.41)
Bullish	0.04809 (0.3398)	1	−0.58307 (<0.0001)	−0.64869 (<0.0001)	0.92434 (<0.0001)
Neutral	−0.03456 (0.4929)	−0.58307 (<0.0001)	1	−0.24007 (<0.0001)	−0.22895 (<0.0001)
Bearish	−0.02531 (0.6156)	−0.64869 (<0.0001)	−0.24007 (<0.0001)	1	−0.89001 (<0.0001)
Spread (bullish–bearish)	0.04151 (0.41)	0.92434 (<0.0001)	−0.22895 (<0.0001)	−0.89001 (<0.0001)	1

Note: Panel A reports the correlation between daily *Bitcoin return* and the standard pricing factors, $R_M - R_f$ (MKTRF), SMB, HML, UMD, CMA, and RMW. Fama–French factors [$R_M - R_f$] (MKTRF), small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) are obtained from Kenneth French's website. Panel B reports the correlation between *weekly Bitcoin return* and American Association of Individual Investors sentiment index (AAII index). The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a weekly basis. Only one vote per member is accepted in each weekly voting period.

The estimates of Equations (5) and (6) are displayed in Tables 5 and 6. Notice that our estimates of Jensen's alpha are indeed significantly and positively different from zero. Equation (5) uses as a proxy for sentiment the first difference of the AAII index for the Bullish and Bearish spread.

The results displayed in Table 5 Panel A indicate the following. First, the returns to bitcoin are statistically related to the market risk premium. Moreover, the interaction term involving the market risk premium features a negative coefficient. Therefore, when sentiment declines, bitcoin returns become more sensitive to the market risk premium.

Factor loading estimates for two other interaction terms are statistically significant. The first pertains to size (SMB), with a negative sign, and the second pertains to investment (CMA), with a positive sign. The bitcoin size effect is that when sentiment declines, bitcoin returns share a common feature with the stocks of small firms. This finding has the same flavor as Baker and Wurgler's finding that the size effect only applies in connection with periods of negative sentiment. In particular, this finding is in line with the intuitive association of new cryptocurrencies to the stocks of small startups. The bitcoin investment effect is that when sentiment declines, bitcoin returns share a commonality with firms that invest

TABLE 3 Time-series tests of CAPM, Fama–French three, Carhart four, and Fama–French five factor models

Model	Factor sensitivities	Coefficient	*t* Stat	*p* Value
CAPM	Alpha	**0.00534*** **	**(3.82)**	**(0.0001)**
	MKTRF	0.12204	(0.91)	(0.3618)
	R^2	0.0005		
FF3	Alpha	**0.00530*** **	**(3.81)**	**(0.0001)**
	MKTRF	0.18191	(1.36)	(0.1740)
	SMB	−0.22699	(−1.00)	(0.3163)
	HML	−0.17866	(−0.66)	(0.5113)
	R^2	0.0011		
FF4	Alpha	**0.00529*** **	**(3.80)**	**(0.0001)**
	MKTRF	0.18199	(1.36)	(0.1747)
	SMB	−0.22364	(−0.97)	(0.3315)
	HML	−0.16140	(−0.57)	(0.5711)
	UMD	0.02879	(0.19)	(0.8529)
	R^2	0.0011		
FF5	Alpha	**0.00529*** **	**(3.82)**	**(0.0001)**
	MKTRF	0.18073	(1.27)	(0.2035)
	SMB	−0.11071	(−0.44)	(0.6617)
	HML	0.18913	(0.49)	(0.6248)
	CMA	−0.77678	(−1.34)	(0.1795)
	RMW	0.40246	(0.82)	(0.4124)
	R^2	0.0026		

Note: This table presents the coefficient estimates of CAPM, Fama–French three, Carhart four, and Fama–French five factor models for daily excess returns on *Bitcoin Return*. Fama–French factors $[R_M - R_f]$, small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), and momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) are obtained from Kenneth French's website. The daily *Bitcoin Return* is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right).$$

The sample period covers potential bubble period of July 18, 2010–December 29, 2017. Newey–West (1987) adjusted *t* statistics and associated *p* values are reported in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

aggressively rather than conservatively. In this respect, aggressive investment reduces firms' free cash flows and equity returns, whose effect on bitcoin is most pronounced during times in which investors generally become more bearish.

Table 5 Panel A indicates that bitcoin returns are statistically related to the coefficient on the Fama–French profitability factor RMW (β_5), and with a positive sign. Therefore, the return to holding bitcoin is generally positive during periods when the stocks of higher profitability firms outperform the stocks of lower profitability firms. At first glance, this finding appears to be at odds with bitcoin returns resembling the returns to the stocks of unprofitable firms. However, in interpreting this finding, it is important to keep in mind that the return to small growth stocks cannot be explained by the Fama–French three-factor model, as those stocks have historically earned low returns, not the high returns predicted by the model. Similarly, in the extended Fama–French factor model, profitability is related differently to small, growth stocks than to other stocks.

Table 5 Panel B displays similar results when the VIX is used in place of the AAII sentiment series. One difference between the two specifications is that the coefficient on the sentiment variable (β_{11}) is also statistically significant. Because an increase in the VIX corresponds to a decline in bullishness, we expect the coefficient signs in Table 5 Panel B to be opposite from the coefficient signs in Table 10 Panel A. See, for instance, the opposite signs of β_6 and β_7.

For the sake of completeness, we include the counterpart to Table 6 when the factor structure is taken to have only sentiment-interaction terms instead of the more general specifications (5). For the AAII sentiment results reported in Table 6 Panel A, the general findings are similar, with two differences to note. First, it is the book-to-market interaction variable

TABLE 4 Time-series tests of global CAPM, global Fama–French three, global Carhart four, and global Fama–French five factor models

Model	Factor sensitivities	Coefficient	*t* Stat	*p* Value
CAPM	Alpha	**0.00495*** **	**(3.46)**	**(0.0006)**
	MKTRF	0.09134	(0.60)	(0.5501)
	R^2	0.0002		
FF3	Alpha	**0.00493*** **	**(3.44)**	**(0.0006)**
	MKTRF	0.12554	(0.74)	(0.4569)
	SMB	0.18759	(0.48)	(0.6337)
	HML	−0.07863	(−0.20)	(0.8420)
	R^2	0.0004		
FF4	Alpha	**0.00498*** **	**(3.48)**	**(0.0005)**
	MKTRF	0.09977	(0.57)	(0.5719)
	SMB	0.19710	(0.50)	(0.6170)
	HML	−0.25731	(−0.63)	(0.5297)
	UMD	−0.25069	(−0.99)	(0.3238)
	R^2	0.0008		
FF5	Alpha	**0.00498*** **	**(3.50)**	**(0.0005)**
	MKTRF	0.10588	(0.53)	(0.5971)
	SMB	0.11492	(0.28)	(0.7792)
	HML	0.76160	(1.24)	(0.2144)
	CMA	−1.73411	(−1.65)	(0.0999)
	RMW	0.65545	(1.03)	(0.3025)
	R^2	0.0034		

Note: This table presents the coefficient estimates of global CAPM, global Fama–French three, Carhart four, and Fama–French five factor models for daily excess returns on *Bitcoin Return*. Global Fama–French factors [$R_M - R_f$], small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) are obtained from Kenneth French's website. The daily *Bitcoin Return* is computed by $\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right)$. The sample period covers potential bubble period of July 18, 2010–May 31, 2017 due to data availability of global market factors. Newey–West (1987) adjusted *t* statistics and associated *p* values are reported in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

rather than the size interaction variable that is statistically significant. Second, the market risk premium interaction variable is weakly significant at the 10% level. For the VIX results reported in Table 6 Panel B, the market risk premium interaction variable is statistically significant, as is the profitability interaction variable, but not the size interaction, book-to-market interaction, and investment interaction variables. In combination, our results from the interaction effects of both traditional and behavioral factors on bitcoin returns are largely supportive of Baker and Wurgler's (2007) assertion that “[T]hey are more difficult to value, making biases more insidious and valuation mistakes more likely.”

5 | EMPIRICAL RESULTS RELATING TO COEVOLUTION OF SENTIMENT AND BITCOIN RETURNS

One of the main implications of the regression analysis above is that sentiment impacts bitcoin returns indirectly through traditional factors, but with no direct discernable direct effect. This leaves open the question of how bitcoin returns and sentiment have coevolved over time. To investigate this issue, we employ VAR models that focus on the dynamic relationship between *Investor sentiment index* and *Bitcoin Return*. The VAR model is a natural extension of the univariate autoregressive model to a dynamic multivariate time-series and is a tool to observe predictable relationships among variables. In the VAR model, all variables are treated as endogenous, indicating that one equation exists for each variable as a dependent variable, and each equation has lagged values of all of the included variables as independent variables, including the dependent variable itself. The VAR model also captures the linear interdependencies among multiple time-series because they incorporate the joint generation mechanisms of the variables involved.

TABLE 5 Impact of traditional and behavioral factors and their interactions on bitcoin return

	Panel A: Diff(Investor sentiment)			Panel B: Diff(VIX)		
Parameter	**Coefficient**	***t* Stat**	***p* Value**	**Coefficient**	***t* Stat**	***p* Value**
α	0.1145**	(2.49)	(0.0149)	0.1123***	(2.75)	(0.0074)
$\hat{\beta}_1$	4.5310***	(2.81)	(0.0062)	5.1213***	(3.98)	(0.0001)
$\hat{\beta}_2$	1.3467	(0.61)	(0.5410)	−0.4867	(−0.33)	(0.7452)
$\hat{\beta}_3$	−0.9011	(−0.64)	(0.5238)	−2.2668	(−1.44)	(0.1530)
$\hat{\beta}_4$	1.2305	(0.43)	(0.6664)	1.9969	(0.66)	(0.5089)
$\hat{\beta}_5$	6.2448*	(1.97)	(0.0519)	4.1206**	(2.20)	(0.0307)
$\hat{\beta}_6$	−11.9103**	(−2.34)	(0.0217)	6.4395***	(2.96)	(0.0040)
$\hat{\beta}_7$	−12.5525**	(−2.03)	(0.0454)	8.7505***	(3.33)	(0.0013)
$\hat{\beta}_8$	−7.6435	(−1.15)	(0.2549)	−4.7171	(−0.70)	(0.4868)
$\hat{\beta}_9$	44.3330**	(2.55)	(0.0128)	−7.4278	(−0.62)	(0.5398)
$\hat{\beta}_{10}$	14.4749	(1.44)	(0.1525)	7.5326	(1.52)	(0.1317)
$\hat{\beta}_{11}$	−0.4008	(−1.23)	(0.2235)	0.2934**	(2.59)	(0.0114)
R^2	0.2186			R^2	0.209	

Note: This table presents the coefficient estimates of the following regression using Fama–French five factors and investor sentiment index on monthly *Bitcoin Excess Return* as follows:

$$\begin{aligned}\left(R_{\text{Bitcoin},t} - R_{\text{ft}}\right) = \alpha + \hat{\beta}_1\left(R_{\text{m}t} - R_{\text{ft}}\right) + \hat{\beta}_2\text{SMB}_t + \hat{\beta}_3\text{HML}_t + \hat{\beta}_4\text{CMW}_t + \hat{\beta}_5\text{RMA}_t \\ + \hat{\beta}_6\left(R_{\text{m}t} - R_{\text{ft}}\right)_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_7\text{SMB}_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_8\text{HML}_t \times \text{diff(Investor sentiment)}_t \,. \\ + \hat{\beta}_9\text{CMA}_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_{10}\text{RMW}_t \times \text{diff(Investor sentimentorVIX)}_t + \hat{\beta}_{11}\text{diff(Investor sentiment)}_t + e_{it}\end{aligned}$$

The monthly Fama–French five factors, $[R_{\text{M}} - R_{\text{f}}]$, small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) are obtained from Kenneth French's website. To compute monthly bitcoin return and monthly sentiment index, we select the observations at the end of each month. Monthly *Bitcoin Return* (R_{Bitcoin}) is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right).$$

We compute diff(Investor sentiment) by $\text{Spread(Bull−Bear)}_t - \text{Spread(Bull−Bear)}_{t-1}$ using AAII sentiment index. Diff(VIX) is calculated by $\text{VIX}_t - \text{VIX}_{t-1}$, where *VIX* is computed by

$$\ln\left(\frac{\text{VIX Index}_t}{\text{VIX Index}_{t-1}}\right).$$

The sample period covers July 30, 2010–February 26, 2018. Newey–West (1987) adjusted *t* statistics and associated *p* values are reported in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A *p*th-order VAR model can be represented as follows:

$$Y_t = \alpha + B(L)Y_t + e_t, \tag{7}$$

where $Y_t = (Y_{1,t}, ..., Y_{K,t})$ is a vector time-series of variables, α a k vector of intercepts, and $B(L)$ a polynomial in the lag operator L. e_t presents the error terms assumed to follow an i.i.d. normal distribution with zero vector expectation and a variance matrix, $e_t \sim \text{iid}(0, \Sigma)$.

In this study, we implement a bivariate VAR model using *Bitcoin Return* and *Investor sentiment*, that is, $Y_t = (\text{Bitcoin Return}_t, \text{Investor Sentiment}_t)$, to capture their dynamics. A *p*th-order bivariate VAR for our study can be written as follows:

TABLE 6 Impact of the interactions of traditional and behavioral factors on bitcoin return

	Panel A: Diff(Investor sentiment)			**Panel B: Diff(VIX)**		
Parameter	**Coefficient**	***t* Stat**	***p* Value**	**Coefficient**	***t* Stat**	***p* Value**
α	0.1723***	(2.72)	(0.0080)	0.1769***	(3.42)	(0.0010)
$\hat{\beta}_1$	−10.1005*	(−1.75)	(0.0833)	5.8665***	(2.97)	(0.0039)
$\hat{\beta}_2$	−9.7776	(−1.49)	(0.1389)	5.232376	(1.52)	(0.1326)
$\hat{\beta}_3$	−18.4811**	(−2.58)	(0.0116)	−0.93292	(−0.16)	(0.8720)
$\hat{\beta}_4$	55.2107***	(4.16)	(0.0001)	−13.1146	(−1.26)	(0.2115)
$\hat{\beta}_5$	8.4440	(0.84)	(0.4059)	9.9038*	(1.80)	(0.0758)
R^2	0.1115			R^2 0.0888		

Note: This table presents the coefficient estimates of the following regression using Fama–French five factors and investor sentiment index on monthly *Bitcoin Excess Return* as follows:

$$(R_{\text{Bitcoin},t} - R_{\text{ft}}) = \alpha + \hat{\beta}_1 (R_{\text{mt}} - R_{\text{ft}})_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_2 \text{SMB}_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_3 \text{HML}_t \times \text{diff(Investor sentiment)}_t.$$
$$+ \hat{\beta}_4 \text{CMA}_t \times \text{diff(Investor sentiment)}_t + \hat{\beta}_5 \text{RMW}_t \times \text{diff(Investor sentimentorVIX)}_t + e_{it}$$

The monthly Fama–French five factors, $[R_M - R_f]$, small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), momentum factor (UMD), robust minus weak factor (RMW), and conservative minus aggressive factor (CMA) are obtained from Kenneth French's website. To compute monthly bitcoin return and monthly sentiment index, we select the observations at the end of each month. Monthly *Bitcoin Return* (R_{Bitcoin}) is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-1}}\right).$$

We compute diff(Investor sentiment) by $\text{Spread(Bull−Bear)}_t - \text{Spread(Bull−Bear)}_{t-1}$ using AAII sentiment index. Diff(VIX) is calculated by $\text{VIX}_t - \text{VIX}_{t-1}$, where *VIX* is computed by

$$\ln\left(\frac{\text{VIX Index}_t}{\text{VIX Index}_{t-1}}\right).$$

The sample period covers July 30, 2010–February 26, 2018. Newey–West (1987) adjusted *t* statistics and associated *p* values are reported in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

$$\begin{bmatrix} \text{Bitcoin Return}_t \\ \text{Investor Sentiment}_t \end{bmatrix} = \begin{bmatrix} \alpha_{\text{Bitcoin Return}} \\ \alpha_{\text{Investor Sentiment}} \end{bmatrix} + \begin{bmatrix} b_{11}(L) & b_{12}(L) \\ b_{21}(L) & b_{22}(L) \end{bmatrix} \begin{bmatrix} \text{Bitcoin Return}_{t-1} \\ \text{Investor Sentiment}_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\text{Bitcoin Return}} \\ e_t^{\text{Investor Sentiment}} \end{bmatrix}, \tag{8}$$

where α_k are the intercepts and $b(L)$ the polynomials in the lag operator L. $e_t^{\text{Bitcoin Return}}$ and $e_t^{\text{Investor Sentiment}}$ are the error terms that are assumed to follow an i.i.d. normal distribution with the zero vector expectation and the variance matrix, $e_t \sim \text{iid}(0, \Sigma)$,

$$\Sigma = \begin{bmatrix} \sigma^2_{\text{Bitcoin Return}} & \rho\sigma_{\text{Bitcoin Return}}\sigma_{\text{Investor Sentiment}} \\ \rho\sigma_{\text{Investor Sentiment}}\sigma_{\text{Bitcoin Return}} & \sigma^2_{\text{Investor Sentiment}} \end{bmatrix}.$$

In Equation (8), the diagonal coefficients $b_{11}(L)$ and $b_{22}(L)$ denote the conditional momentum in *Bitcoin Return* and *Investor sentiment*. The off-diagonal coefficients, $b_{12}(L)$, denote the impact of the lagged *Investor sentiment* on *Bitcoin Return* while the coefficients on $b_{21}(L)$ representing the impact of the lagged *Bitcoin return* on the *Investor sentiment*.

We first apply unit-root tests using the augmented Dickey–Fuller (ADF; 1979) test and the Phillips and Perron (PP; 1988) test to determine whether a variable has a unit root or the time-series is nonstationary. The results presented in Table 7 Panel A suggest that *p* values of all weekly bitcoin returns, bullish, bearish, neutral investor percentage, and the spread between bullish and bearish investor sentiment are all <5%, suggesting that no time-series variables have unit roots, and that the time-series are stationary.

TABLE 7 Unit-root tests for AAII investor sentiment index and Volatility Index (*VIX*)

Panel A: Unit-root tests for AAII investor sentiment index

Variables		ADF Intercept	ADF Trend and intercept	PP Intercept	PP Trend and intercept
Weekly bitcoin return	*t* Stat	−17.3922	−17.4530	−18.0295	−18.0340
	p Value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Lag length/band width	0	0	10	9
Bullish	*t* Stat	−5.9460	−6.1072	−6.9677	−7.2186
	p Value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Lag length/band width	1	1	2	2
Bearish	*t* Stat	−9.3763	−9.4903	−9.4336	−9.5368
	p Value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Lag length/band width	0	0	6	5
Neutral	*t* Stat	−3.2286	−3.6202	−6.9831	−8.4348
	p Value	(0.0191)	(0.0294)	(0.0000)	(0.0000)
	Lag length/band width	3	3	10	11
Spread (bull–bear)	*t* Stat	−8.4777	−8.4891	−8.3402	−8.3537
	p Value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Lag length/band width	0	0	3	3

Panel B: Unit-root tests for VIX

Variables		ADF Intercept	ADF Trend and intercept	PP Intercept	PP Trend and intercept
Monthly bitcoin return	*t* Stat	−6.9105	−6.9902	−6.9208	−6.9589
	p Value	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Lag length/band width	0	0	2	3
VIX	*t* Stat	−13.4245	−13.3737	−15.1088	−15.0419
	p Value	(0.0001)	(0.0000)	(0.0001)	(0.0000)
	Lag length/band width	0	0	6	6

Note: Panel A reports the unit-root test results for each variable. The weekly *Bitcoin Return* is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-7}}\right).$$

The American Association of Individual Investors (AAII) sentiment index measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a weekly basis. Only one vote per member is accepted in each weekly voting period. *Investor Sentiment* is computed by

$$\ln\left(\frac{\text{AAII Investor Sentiment Index}_t}{\text{AAII Investor Sentiment Index}_{t-7}}\right).$$

We use the augmented Dickey–Fuller (ADF; 1979) test and the Phillips and Perron (PP; 1988) test to determine whether a variable has a unit root. *p* Values are MacKinnon (1996) one-sided *p* values. Bandwidths are selected by Newey–West using Bartlett kernel. Panel B reports the unit-root test results for each variable. The monthly *Bitcoin Return* is computed by

$$\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-30}}\right).$$

The *VIX* is calculated as the square root of the par variance swap rate for a 30-day term initiated today. We obtain monthly VIX index from the Chicago Board Options Exchange (CBOE). *VIX* is computed by

$$\ln\left(\frac{\text{VIX Index}_t}{\text{VIX Index}_{t-30}}\right).$$

The sample period covers July 30, 2010–February 26, 2018.

Consider the VIX. In Panel B, we test for the existence of unit root in the VIX series and find that it is also stationary. This suggests that the mean, variance, and autocorrelations do not change over time, and standard statistical inference is reliable. Because all variables follow a stationary process, we can conduct the VAR model without considering a co-integration test or the Vector Error Correction Model (VECM).

Table 8 Panel A presents the coefficients on *Bitcoin Return* equations in bivariate VAR regressions and Panel B reports the coefficients on Investor Sentiment equations in bivariate VAR. The optimal lag length p is chosen by the Hannan–Quinn information criterion (HQC; 1979). The results suggest that while *Bitcoin Returns* do not Granger-cause Investor Sentiment Index for the Investor Sentiment equations (Panel B), Investor Sentiment Index does Granger-cause *Bitcoin Returns* for the ratio of the *Bitcoin Return*s equation (Panel A). In particular, bullish (bearish) investor sentiment significantly drives *Bitcoin Returns* positively (negatively). It is noteworthy that although the time period of the bitcoin price decrease (i.e., January–February, 2018) is much shorter, and the percentage of bearish investor sentiment is somewhat lower, the negative impact of bearish investor sentiment on *Bitcoin Returns* seems to be a bit larger than the positive impact of bullish investor sentiment on *Bitcoin Returns*.

We further conduct VAR analysis with alternative measure of investor sentiment, VIX for robustness, and present the results in Table 9. The optimal lag length p is chosen by the HQC (1979). In *Bitcoin Return* equation, the coefficient on VIX (lagged 1) is significantly negative, which implies that a change in VIX index from days $t-30$ to t negatively affects bitcoin return. This negative impact of VIX on *Bitcoin Returns* can be interpreted to mean that investors' fear about the future market tends to induce a decrease in the price of bitcoin. Intuitively, when the VIX increases, investors grow afraid of increased volatility, and sell bitcoin, lowering the bitcoin price. Expressed differently, if the VIX decreases, then the market is less volatile, and investors become willing to take risks to earn above average returns by buying bitcoin, thereby driving up its price. We consider this finding to be consistent with Baker and Wurgler's (2006) premise that bitcoin resembles a high sentiment beta stock, and imply that expected returns are low when sentiment is high while expected returns are high when sentiment is low. More specifically, Baker and Wurgler (2006) suggest that the impact of investor sentiment will be most noticeable for speculative assets and hypothesize that the returns associated with speculative assets will be low (high) after high (low) measures of investor sentiment. Thus, the negative influence of VIX on bitcoin returns is consistent with the perspective of Baker and Wurgler (2006). In addition, in the VIX equation, the coefficient on *Bitcoin returns* 2 months prior, positively affects VIX. If a rapidly rising bitcoin price is viewed as evidence of a speculative bubble, then our findings suggest an increase in the fear of future market volatility.

We consider the above findings of a potential speculative bubble and an inverse association between investor sentiment (through VIX) and bitcoin returns to be in direct contrast with Fama (2014) who questions whether there is evidence for the existence of bubbles.

6 | EMPIRICAL RESULTS RELATING TO COEVOLUTION OF VIX AND BITCOIN TRADING VOLUME

To round out our analysis, we investigate the relationship between bitcoin trading volume and sentiment. To do so, we conduct bivariate VAR using monthly bitcoin trading volume and investor sentiment (AAII index or VIX). The variable *Bitcoin Volume* is computed as the log-difference $\ln\left(\frac{\text{Bitcoin Trading Volume}_t}{\text{Bitcoin Trading Volume}_{t-30}}\right)$.

Before conducting VAR analysis, we checked whether monthly *Bitcoin Volume* and investor sentiment (AAII, respectively, VIX) follow stationary processes, by conducting unit-root tests using the ADF (1979) and the PP (1988) test. The results show that *Bitcoin Volume* and investor sentiment (AAII, respectively, VIX) do not have unit roots, and therefore, are stationary.

Table 10 presents the coefficients bivariate from a VAR analysis on *Bitcoin Volume* and investor sentiment (AAII, respectively, VIX). The optimal lag terms (p) are selected by the HQC. The results suggest that investor sentiment (AAII, respectively, VIX) does Granger-cause *Bitcoin Volume*, whereas *Bitcoin Volume* does not Granger-cause investor sentiment (AAII, respectively, VIX).

In the *Bitcoin Volume* equation, the coefficient on AAII (lagged 1) is significantly positive (negative), implying that a lag 1 change in AAII positively (negatively) impacts *Bitcoin Volume*. When using VIX, we found that VIX (lagged 1) negatively impacts *Bitcoin Volume*. This negative impact of VIX on *Bitcoin Volume* suggests that investors' fear about the future market tends to induce a decrease in *Bitcoin Volume*.

TABLE 8 Bivariate autoregression (VAR) models of AAII index

Panel A: Bitcoin return	**Bitcoin return**			
	Bullish	**Neutral**	**Bearish**	**Spread**
Constant	−0.00114	0.04245	0.03541	0.02024
	[−0.03]	[0.98]	[0.91]	[2.27]
Bitcoin return (-1)	0.11487	0.11449	0.11760	0.11630
	[2.29]	[2.28]	[2.35]	[2.33]
Bitcoin return (-2)	0.15575	0.15149	0.15843	0.15787
	[3.13]	[3.03]	[3.1]	[3.17]
Investor sentiment (-1)	**0.29070****	0.04339	**−0.30864****	**0.17368****
	[2.00]	[0.21]	**[−2.09]**	**[2.22]**
Investor sentiment (-2)	−0.22594	−0.10288	0.26550	−0.13912
	[−1.55]	[−0.51]	[1.79]	[−1.77]
Adj. R^2	0.0412	0.0322	0.0429	0.0436
Panel B: Investor sentiment index	**Investor sentiment**			
	Bullish	**Neutral**	**Bearish**	**Spread**
Constant	0.07553	0.05246	0.09848	0.01943
	[5.82]	[4.95]	[7.43]	[3.38]
Bitcoin return (-1)	−0.01847	−0.00586	0.02235	−0.03939
	[−1.06]	[−0.47]	[1.30]	[−1.22]
Bitcoin return (-2)	0.00543	−0.01027	0.00597	0.00089
	[0.31]	[−0.83]	[0.35]	[0.02]
Investor sentiment (-1)	0.66812	0.60948	0.59677	0.63937
	[13.33]	[12.37]	[11.82]	[12.69]
Investor sentiment (-2)	0.12758	0.23388	0.07365	0.08421
	[2.53]	[4.75]	[1.45]	[1.66]
Adj. R^2	0.5857	0.6540	0.4138	0.4839

Note: This table presents the results from the bivariate vector autoregression (VAR) using weekly *Bitcoin returns* and American Association of Individual Investors (AAII) Investors Sentiment index are as follows:
$\begin{bmatrix} \text{Bitcoin Return}_t \\ \text{Investor Sentiment}_t \end{bmatrix} = \begin{bmatrix} \alpha_{\text{Bitcoin Return}} \\ \alpha_{\text{Investor Sentiment}} \end{bmatrix} + \begin{bmatrix} b_{11}(L) & b_{12}(L) \\ b_{21}(L) & b_{22}(L) \end{bmatrix} \begin{bmatrix} \text{Bitcoin Return}_{t-1} \\ \text{Investor Sentiment}_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\text{Bitcoin Return}} \\ e_t^{\text{Investor Sentiment}} \end{bmatrix}$. *Bitcoin Return* is computed by $\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-7}}\right)$. The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a weekly basis. Only one vote per member is accepted in each weekly voting period. *Investor Sentiment* is computed by $\ln\left(\frac{\text{AAII Investor Sentiment Index}_t}{\text{AAII Investor Sentiment Index}_{t-7}}\right)$. α_k are the intercepts and $b(L)$ is a polynomial in the lag operator L. $e_t^{\text{Bitcoin Return}}$ and $e_t^{\text{Investor Sentiment}}$ are the error terms that are assumed to follow an i.i.d. normal distribution with the zero vector expectation and the variance matrix $e_t \sim \text{iid}(0, \Sigma)$, $\Sigma = \begin{bmatrix} \sigma^2_{\text{Bitcoin Return}} & \rho\sigma_{\text{Bitcoin Return}}\sigma_{\text{Investor Sentiment}} \\ \rho\sigma_{\text{Investor Sentiment}}\sigma_{\text{Bitcoin Return}} & \sigma^2_{\text{Investor Sentiment}} \end{bmatrix}$.

Panel A reports the coefficients of *Bitcoin Return* equations in bivariate VAR and Panel B reports the coefficients of Investor Sentiment equations in bivariate VAR. The optimal lag length p is chosen by the Hannan–Quinn information criterion (HQC). ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers July 30, 2010–February 26, 2018.

TABLE 9 Bivariate autoregression (VAR) models of VIX

	Bitcoin return	VIX
Constant	0.101601	−0.02609
	[2.45]	[−1.13]
Bitcoin return (-1)	0.22757	−0.0411
	[2.00]	[−0.65]
Bitcoin return (-2)	−0.017008	**0.166608*** **
	[−0.15]	**[2.74]**
VIX (-1)	**−0.394973** **	−0.43109
	[−1.99]	[−3.91]
VIX (-2)	−0.24936	−0.11033
	[−1.25]	[−1.00]
Adj. R^2	0.0907	0.1654

Note: This table presents the results from the bivariate vector autoregression (VAR) using monthly *Bitcoin returns* and Volatility Index (VIX), as follows: $\begin{bmatrix}\text{Bitcoin Return}_t\\ \text{VIX}_t\end{bmatrix}=\begin{bmatrix}\alpha_{\text{Bitcoin Return}}\\ \alpha_{\text{VIX}}\end{bmatrix}+\begin{bmatrix}b_{11}(L) & b_{12}(L)\\ b_{21}(L) & b_{22}(L)\end{bmatrix}\begin{bmatrix}\text{Bitcoin Return}_{t-1}\\ \text{VIX}_{t-1}\end{bmatrix}+\begin{bmatrix}e_t^{\text{Bitcoin Return}}\\ e_t^{\text{VIX}}\end{bmatrix}$. The monthly *Bitcoin Return* is computed by $\ln\left(\frac{\text{Bitcoin price}_t}{\text{Bitcoin price}_{t-30}}\right)$. The *VIX* is calculated as the square root of the par variance swap rate for a 30-day term initiated today. We obtain monthly VIX index from the Chicago Board Options Exchange (CBOE). *VIX* is computed by$\ln\left(\frac{\text{VIX Index}_t}{\text{VIX Index}_{t-30}}\right)$.
α_k are the intercepts and $b(L)$ is a polynomial in the lag operator L. $e_t^{\text{Bitcoin Return}}$ and e_t^{VIX} are the error terms that are assumed to follow an i.i.d. normal distribution with the zero vector expectation and the variance matrix e_t~iid$(0, \Sigma)$, $\Sigma=\begin{bmatrix}\sigma^2_{\text{Bitcoin Return}} & \rho\sigma_{\text{Bitcoin Return}}\sigma_{\text{VIX}}\\ \rho\sigma_{\text{VIX}}\sigma_{\text{Bitcoin Return}} & \sigma^2_{\text{VIX}}\end{bmatrix}$.
The optimal lag length p is chosen by the Hannan–Quinn information criterion (HQC). ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers July 30, 2010–February 26, 2018.

TABLE 10 Bivariate autoregression (VAR) models using *bitcoin trading volume and investors sentiment* (*VIX) index*

Panel A: Bitcoin trading volume					
	AAII index				
	Bullish	**Neutral**	**Bearish**	**Spread**	**VIX**
Constant	−0.4005	0.6701	0.0545	0.0257	0.0559
	[−0.81]	[1.23]	[0.11]	[0.24]	[0.61]
Bitcoin trading volume (-1)	−0.4094	−0.4150	−0.3745	−0.3908	−0.3930
	[−3.97]	[−3.94]	[−3.65]	[−3.80]	[−3.75]
Bitcoin trading volume (-2)	−0.2978	−0.3394	−0.2932	−0.2898	−0.3189
	[−2.87]	[−3.23]	[−2.85]	[−2.81]	[−3.11]
Investor sentiment (VIX) (-1)	**2.8612*** **	−1.4039	**−2.2910***	**1.5084** **	**−0.7995***
	[2.32]	[−0.75]	**[−1.64]**	**[2.14]**	**[−1.76]**
Investor sentiment (VIX) (-2)	−1.6004	−0.3971	2.2943	−1.0364	0.1843
	[−1.30]	[−0.21]	[1.71]	[−1.50]	[0.39]
Adj. R^2	0.1984	0.1587	0.1868	0.1968	0.1883
Panel B: Investor sentiment index (VIX)					
	AAII index				
	Bullish	**Neutral**	**Bearish**	**Spread**	**VIX**
Constant	0.1715	0.1066	0.1732	0.0403	−0.0136
	[3.90]	[3.27]	[4.55]	[2.49]	[−0.61]

TABLE 10 (Continued)

Panel B: Investor sentiment index (VIX)					
	AAII index				
	Bullish	Neutral	Bearish	Spread	VIX
Bitcoin trading volume (-1)	−0.0041	0.0029	0.0032	−0.0058	−0.0095
	[−0.44]	[0.45]	[0.39]	[−0.35]	[−0.37]
Bitcoin trading volume (-2)	0.0091	0.0048	−0.0124	0.0221	−0.0029
	[0.98]	[0.76]	[−1.54]	[1.37]	[−0.11]
Investor sentiment (VIX) (-1)	0.3940	0.5694	0.2899	0.3062	−0.4100
	[3.57]	[5.11]	[2.66]	[2.78]	[−3.72]
Investor sentiment (VIX) (-2)	0.1392	0.1138	0.1255	0.1227	−0.1468
	[1.26]	[1.02]	[1.19]	[1.14]	[−1.30]
Adj. R^2	0.1877	0.3833	0.1085	0.1121	0.1029

Note: This table presents the results from the bivariate vector autoregression (VAR) using monthly *Bitcoin Trading Volume* and Investors Sentiment (or Volatility Index, VIX), as follows:
$\begin{bmatrix} \text{Bitcoin Return}_t \\ \text{Investor Sentiment(VIX)}_t \end{bmatrix} = \begin{bmatrix} \alpha_{\text{Bitcoin Return}} \\ \alpha_{\text{Investor Sentiment(VIX)}} \end{bmatrix} + \begin{bmatrix} b_{11}(L) & b_{12}(L) \\ b_{21}(L) & b_{22}(L) \end{bmatrix} \begin{bmatrix} \text{Bitcoin Return}_{t-1} \\ \text{Investor Sentiment(VIX)}_{t-1} \end{bmatrix} + \begin{bmatrix} e_t^{\text{Bitcoin Return}} \\ e_t^{\text{Investor Sentiment(VIX)}} \end{bmatrix}$. *Bitcoin Trading Volume* is computed by $\ln\left(\frac{\text{Bitcoin Trading Volume}_t}{\text{Bitcoin Trading Volume}_{t-30}}\right)$. The AAII Investor Sentiment Survey measures the percentage of individual investors who are bullish, bearish, and neutral on the stock market for the next 6 months; individuals are polled from the ranks of the AAII membership on a monthly basis. Only one vote per member is accepted in each monthly voting period. *Investor Sentiment* is computed by$\ln\left(\frac{\text{AAII Investor Sentiment Index}_t}{\text{AAII Investor Sentiment Index}_{t-30}}\right)$. The *VIX* is calculated as the square root of the par variance swap rate for a 30-day term initiated today. We obtain monthly VIX index from the Chicago Board Options Exchange (CBOE). *VIX* is computed by $\ln\left(\frac{\text{VIX Index}_t}{\text{VIX Index}_{t-30}}\right)$.
α_k are the intercepts and $b(L)$ is a polynomial in the lag operator L. $e_t^{\text{Bitcoin Trading Volume}}$ and $e_t^{\text{Investor Sentiment(VIX)}}$ are the error terms that are assumed to follow an i.i.d. normal distribution with the zero vector expectation and the variance matrix
$e_t \sim \text{iid}(0, \Sigma),\ \Sigma = \begin{bmatrix} \sigma^2_{\text{Bitcoin Trading Volume}} & \rho\sigma_{\text{Bitcoin Trading Volume}}\sigma_{\text{Investor Sentiment(VIX)}} \\ \rho\sigma_{\text{Investor Sentiment(VIX)}}\sigma_{\text{Bitcoin Trading Volume}} & \sigma^2_{\text{Investor Sentiment(VIX)}} \end{bmatrix}$.
Panel A reports the coefficients of *Bitcoin Trading Volume* equations in bivariate VAR and Panel B reports the coefficients of Investor sentiment (VIX) equations in bivariate VAR. The optimal lag length p is chosen by the Hannan–Quinn information criterion (HQC). ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period covers July 30, 2010–February 26, 2018.

7 | CONCLUSION

Blockchain technologies have the potential to revolutionize finance; and the behavioral perspective focuses on the impact of sentiment as well as fundamentals. The fundamentals associated with cryptocurrencies involve the benefits that blockchain technologies bring to reducing both costs and the potential for fraud.

Financial history is replete with examples in which rapidly changing fundamentals give rise to nonzero sentiment. As occurred during the "dot-com period," rapid technological advances can lead to improved fundamentals, which in turn get unrealistically extrapolated by investors to produce an asset pricing bubble. Given the surge in popularity of cryptocurrencies and the lack of widely accepted models for computing the intrinsic values of these assets, the behavioral approach suggests focusing on the role of sentiment in these markets.

The main issue analyzed in this paper is the degree to which bitcoin's return trajectory shares the features of high sentiment beta stocks, as these stocks are most vulnerable to asset pricing bubbles during times that overall sentiment is rising. Baker and Wurgler note that high sentiment beta stocks correspond to small startups that are currently unprofitable but hold great potential for future profitability.

Our main empirical finding is that bitcoin returns featured a complex sentiment component, consistent with bitcoin resembling a high sentiment beta stock that has experienced a speculative bubble. Although VAR analysis identifies a dynamic relationship between bitcoin returns and sentiment, we find that sentiment mostly operated on bitcoin returns indirectly by modulating the magnitudes of traditional factor loadings, rather than operating directly. Notably, the character of the interaction effects we find is broadly consistent with sentiment-interaction effects reported by Baker and Wurgler (2006).

Specific findings for the sample period we study are that when sentiment declined, bitcoin returns exhibited a larger size effect, a larger market beta (factor loading), and more closely resembled the returns to firms that invested aggressively.[9] In addition, bitcoin returns are positively related to the equity returns to profitable firms, a finding which is difficult to interpret because of the well-established anomalous return patterns associated with small growth stocks and low profitability. We also find that expected returns of bitcoin are low when sentiment measured by VIX is high while expected returns are high when sentiment by VIX is low, supporting the general characterization in Baker and Wurgler (2006, 2007).

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DATA AVAILABILITY STATEMENT

We obtain daily Bitcoin price and Bitcoin Volume data from the Bitcoin.com webpage (https://charts.bitcoin.com/). Fama–French asset pricing factors are obtained from Kenneth French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). American Association of Individual Investors (AAII) index data are obtained from the AAII webpage (https://www.quandl.com/data/AAII/AAII_SENTIMENT-AAII-Investor-Sentiment-Data). We obtain monthly VIX index from the Chicago Board Options Exchange (CBOE).

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