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ABSTRACT

Do behavioral factors mediate the relationship between industry returns and Bitcoin returns? We use four industry indices in technology, energy, clean energy, and banking, and the Sentiment index from Thomson Reuters Marketpsych Indices as a behavioral factor to investigate this question. We show that the sensitivities of technology and clean energy industry indices to Sentiment, positively and significantly, strengthen the relationship between sentiment and Bitcoin returns. By showing that behavioral factors mediate the association between the returns of industry indices and Bitcoin returns, we provide evidence that investors' Sentiment captures the association between Bitcoin and sectors related to cryptocurrencies. Our results, however, do not support prior studies' findings of a direct relationship between the industry indices and Bitcoin returns.

1. Introduction

There is an ongoing debate about what the value of Bitcoin should be. While the intrinsic value of Bitcoin remains enigmatic, empirical attempts to understand what factors might drive the behavior of its returns fall into two strands of literature. The first strand of literature addresses the issue based on the production costs of Bitcoin. For example, given the enormous computing and electricity power required in the mining and transaction processes (de Vries 2020), Symitsi and Chalvatzis (2018) find effects on Bitcoin returns stemming from Bitcoin-related industries such as the energy and technology sectors. The discussion of this relationship between Bitcoin and industries related to its production has also been joined by Borri (2019), Damianov and Elsayed (2020), and Selmi et al. (2018), among others. The second strand of literature seeks to understand Bitcoin value from its market characteristics, such as behavioral biases. For instance, Gurdgiev and O'Loughlin (2020) show that investor sentiment predicts the price direction of Bitcoin price movement, implying the direct impact of herding and anchoring biases in the market. Similarly, Kalyvas et al. (2020) show a weak correlation between Bitcoin price crash risk and behavioral factors, proxied by the Thomson Reuters Marketpsych Indices (TRMI). However, both strands of literature examine direct spillover effects between Bitcoin and behavioral factors or Bitcoin-related stocks, despite numerous studies documenting the significant impact of behavioral factors on the stock market. Therefore, in our paper, we attempt to connect these two groups of studies by exploring the possibility of an indirect effect from behavioral factors to Bitcoin through industries closely related to its production activities.

Bitcoin production involves solving complex algorithmic puzzles requiring expensive and energy-consuming IT equipment. As a result, the cost of Bitcoin might be closely related to industries that produce IT equipment and energy. For example, an increase in IT equipment and traditional energy prices might increase their stock values due to an enlarged profit margin and an increase in Bitcoin prices due to higher mining costs. In contrast,

a pro-environment policy in the green clean energy sector – e.g. tax reduction – might push up the value of relevant companies but lessen the value of Bitcoin because of the potential decrease in production costs.

Meanwhile, as a decentralized government-free currency, the value of Bitcoin is largely affected by traders' sentiment and behavioral biases (Bouri et al. 2018; Corbet, Lucey, and Yarovaya 2018a; de Gama Silva et al. 2019; Gurdgiev and O'Loughlin 2020). On the other hand, the effects of behavioral factors have also been extensively documented in the stock markets (Baker and Wurgler 2006; Kumar and Lee 2006; Sayim, Morris, and Rahman 2013; Tetlock 2007). Therefore, it is important to understand how behavioral factors may affect Bitcoin value through the channel of industries closely related to Bitcoin mining.

We commence our investigation by estimating the sensitivity of Bitcoin and related industry indices to the Sentiment index from the TRMI. Specifically, we adopt the methodology in Francis, Hasan, and Zhu (2014) and regress Bitcoin and industry indices' returns against the behavioral factor, Sentiment, approximated by the Sentiment index of the TRMI indices. By adopting a rolling window approach, we obtain a time-series estimate of the sensitivity of Bitcoin or related industry returns to the behavioral proxy, measured as the slope coefficients. Then we perform a preliminary examination of our conjecture. We show that Bitcoin returns' sensitivity to Sentiment displays a significant association with related industries' sensitivities to Sentiment. On the other hand, we do not observe a significant association between Bitcoin returns and the indices' returns of the related industries. These findings provide preliminary evidence that related industries' returns are associated with Bitcoin returns through behavioral factors such as investor sentiment.

Next, we study this mediating effect in more detail through a model with interaction terms. Particularly, we regress Bitcoin returns on Sentiment, industry sensitivities on Sentiment, and an interaction term of the two, while also controlling for factors that prior literature has identified as Bitcoin price determinants. We find that the interaction of Sentiment with the sensitivity of two industry indices (IT and clean energy) to Sentiment has a positive and significant association with Bitcoin returns. This result suggests that when the Sentiment is positively related to the returns of the IT and clean energy, this effect passes to the returns of Bitcoin, increasing its value, particularly when the Sentiment becomes stronger. Our findings confirm the importance of the technology and energy sectors for cryptocurrencies. Both these industries produce inputs for the development of cryptocurrencies. We show that if they display a positive sensitivity to Sentiment, we can observe a positive effect on Bitcoin returns mediated through Sentiment.

Since the introduction of Bitcoin, scholars have paid increasing attention to its price and return behavior (Bariviera 2017; Blau 2017; Chu, Chan, and Zhang 2020; Corbet et al. 2019; Gerritsen et al. 2020; Jain, McInish, and Miller 2019; Nadarajah and Chu 2017; Urquhart 2016; Zargar and Kumar 2019). However, it remains unclear how the value of Bitcoin should be determined. Theoretically, Pagnotta and Buraschi (2018) and Biais et al. (2020) provide models that explain Bitcoin value from the standpoint of its network effect. On the other hand, Cong and He (2019) and Sockin and Xiong (2020) model cryptocurrencies' value based on their production costs. Empirically, Wang et al. (2019) look into the spillover effects between Bitcoin and economic policy uncertainty indicators, while Gillaizeau et al. (2019) study the spillover effects between Bitcoin markets clarified by the fiat currency against which Bitcoin is traded. Gkillas et al. (2020) examine the spillover effect between Bitcoin, crude oil, and gold in the higher-order moments. Bouri et al. (2018) study the tail risks in cryptocurrencies. Our research contributes to this stream of literature by showing that behavioral factors affect the value of Bitcoin through industries related to its mining costs.

Our research also provides practical implications for investing in cryptocurrencies. We provide evidence on a hidden relation between Bitcoin and the indices of industries related to the Bitcoin mining process and operations through behavioral factors.

The remainder of this paper is structured as follows. In Section 2, we discuss our data and data sources, in Section 3, we describe our methodology, and in Section 4, we present and discuss our results. Section 5 concludes the paper.

2. Data and sample selection

This paper employs three data sources: (a) Bitcoin data, (b) industry stock market indices from Thomson DataStream, and (c) Marketpsych indices provided by Thomson Reuters. All our data are considered daily,

and combining them into a single dataset yields a total of 1908 observations spanning 1st October 2013 – 31st December 2018. Because some of our variables are available seven days a week and others available five days a week, the useful number of observations used to estimate the regression models is below 1908 and can vary, depending on the specification of the estimated model. Finally, all our variables are winsorized at 5% and 95% to remove outliers.

2.1. Bitcoin data

We employ tick-level data of Bitstamp[1] to generate daily Bitcoin prices and trading volume. We choose Bitstamp as it is one of the most popular and liquid Bitcoin exchanges (Shen, Urquhart, and Wang 2019). For our analysis, we transform Bitcoin prices to returns using the following equation.

$$\text{BTC Return} = \frac{\text{BTC Price}}{\text{Lagged BTC Price}} - 1 \tag{1}$$

2.2. Industry equity indices

We select four stock market indices that relate to information technology, banking and energy industries. Prior literature shows that these indices are associated with Bitcoin price returns (Symitsi and Chalvatzis 2018). The four indices are the S&P Global Clean Energy Index, MSCI World Energy Index, MSCI World Information Technology Index, and MSCI World Bank sourced from Thomson Datastream.

2.3. Thomson Reuters Marketpsych Indices

Finally, we employ the Thomson Reuters Marketpsych Indices (TRMI), which are available at the country level, daily, and seven days per week since January 1st, 1998. TRMI summarize the content and the quantity of economic, social, political, and other country-level news into meaningful daily indices, which gauge the overall Sentiment and several other market feelings that can be both positive (i.e. Optimism) and negative (i.e. Fear). These indices are generated by an algorithm developed by Thomson Reuters in collaboration with Marketpsych LLC, which identifies news stories from Thomson Reuters News Feed Direct, Factiva News, and other third-party news sources on a real-time basis and over a 24-hour rolling window.[2]

Next, we discuss some of the significant advantages of using the TRMI. First, the TRMI are available for many countries compared to more traditional sentiment measures (Baker and Wurgler 2006; Yu and Yuan 2011; Huang et al. 2015), allowing for a broader and more accurate analysis. Second, the TRMI are based on many news sources, suggesting that the indices are comprehensive, efficient, and reliable (Huang et al. 2018). Third, the TRMI are flexible as they are available for traditional news, social media, and combined news sources.[3]

This paper considers the Sentiment index that quantifies news stories' content on a continuous scale in the range −1 to +1, from the most negative to the most positive. We construct GDP-weighted averages of Sentiment by using the GDP data of the G20 economies that we source from the World Development Indicators of the World Bank.

2.4. Uncertainty control factors

We employ two uncertainty factors in order to augment the regression models with additional controls. The first is the implied volatility index (VIX), a measure of uncertainty in the US equity market. The VIX index estimates the expectation of the near-term market volatility based on stock index option prices. We source this variable from the FRED database of the Federal Reserve Bank of St Louis. The VIX index is available daily, excluding non-trading days (e.g. weekends). The second uncertainty factor is the US economic policy uncertainty (EPU) index. This news-based index captures the overall level of uncertainty in terms of economic policy in the US and is available daily (seven days a week).[4] We use the natural logarithm of VIX and EPU to control for excess skewness and excess kurtosis in our estimations. We follow other studies in the finance and bitcoin literature (e.g.

Mueller, Stathopoulos, and Vedolin 2017; Wu et al. 2019) and use US-based measures of uncertainty because of the dominant economic role of the US in the global financial markets.

3. Methodology

3.1. Estimating sensitivities

We measure the daily sensitivity of the Bitcoin, information technology index, world energy sector, global clean energy sector, and the global banking sector to behavioral factors based on the global version of the 3-factor Fama and French model, motivated by Francis, Hasan, and Zhu (2014). We follow this approach because it enables us to estimate the sensitivities of microeconomic units, such as firms or sectors, to variables at the broader market level or the macroeconomic level. For example, Francis, Hasan, and Zhu (2014) employ this approach to estimate firm-specific sensitivities to economic policy uncertainty (EPU). The adoption of their approach is now common in the finance literature (Brogaard and Detzel 2015; Cui et al. 2020; Datta, Doan, and Iskandar-Datta 2019; Yang et al. 2019). The behavioral factor that we employ in this paper is at the broader market level. Hence, to estimate sector-specific sensitivities to this behavioral factor, the methodology of Francis, Hasan, and Zhu (2014) is appropriate. An ideal alternative would be to use behavioral factor data that are directly measured at the sector level. Alas, we do not have access to such data.

$$R_{i,t} = a + b_{1i}X_t + b_{2i}(R_{M,t} - r_{f,t}) + b_{3i}SMB_t + b_{4i}HML_t + \varepsilon_{it} \tag{2}$$

We also consider the global version of the 4-factor model, developed in Carhart (1997), an extension of the 3-factor model proposed in Fama and French (1993):

$$R_{i,t} = a + b_{1i}X_t + b_{2i}(R_{M,t} - r_{f,t}) + b_{3i}SMB_t + b_{4i}HML_t + b_5MOM_t + \varepsilon_{it} \tag{3}$$

Our analysis is also inclusive of the 5-factor model developed in Fama and French (2015), that is another extension of the 3-factor model in Fama and French (1993).

$$R_{i,t} = a + b_{1i}X_t + b_{2i}(R_{M,t} - r_{f,t}) + b_{3i}SMB_t + b_{4i}HML_t + b_5RMW_t + b_6CMA_t + \varepsilon_{it} \tag{4}$$

$R_{i,t}$ denotes the daily returns of the bitcoin, information technology index, world energy sector, global clean energy sector, and the global banking sector (discussed in Section 2.2), $R_{M,t} - r_{f,t}$ stands for the excess return on the world market, and SMB_t and HML_t stand for the size and value portfolios proposed in Fama and French (1993). MOM_t is the momentum factor proposed in Carhart (1997) controlling for the premium of winners minus losers. RMW_t and CMA_t represent, respectively, the profitability and investment portfolios proposed in Fama and French (2015). X_t is proxied by the *behavioral factors* from the Thomson Reuters Marketpsych Indices (discussed in Section 2.3). It should be noted that we use a one-year rolling window approach to estimate the models in order to obtain a time series of estimated coefficients. Finally, we use heteroscedasticity robust standard errors in all our models to address potential heteroscedasticity in the error terms.

3.2. Association of sensitivities

Once we run Equations (1) and (2), we obtain the estimates for the b_{1i} coefficients. These coefficients represent the sensitivity of Bitcoin returns and the returns of the industry indices on the Sentiment that we source from Thomson Reuters (i.e. the TRMI). Then, in the second stage, we run two models. The first model (Equation (5)) is provided below.

$$Btc\ Sens_t = a + b_1\ Industry\ Sens_t + \varepsilon_t \tag{5}$$

In this model, we investigate the association between the sensitivity of the returns of the industry indices to Sentiment (vector *Industry Sens*$_t$) with the sensitivity of Bitcoin returns to Sentiment (*Btc Sens*$_t$). Significant results following the estimation of Equation (5) would provide some preliminary evidence that the effect of Sentiment on Bitcoin returns would depend on the sensitivity of the industry indices' returns to the Sentiment.

This would provide some initial evidence that Sentiment could affect Bitcoin returns through their effect in other industries. Hence, this would indicate that the transmission of the effect of Sentiment on Bitcoin returns is channeled through other industries.

3.3. Main model

This paper's main model, given in Equation (6), regresses the effect of Sentiment, industry sensitivity to Sentiment, and their interaction on Bitcoin returns. Out of all the explanatory variables, most of the interest falls on the coefficient of the interaction term (b_3). Significant values for this coefficient suggest that industry sensitivity to Sentiment facilitates the association between industry indices and Bitcoin returns.

$$BTC\ Return_t = \alpha + b_1 Sentiment_t + b_2 Industry\ Sens_t$$
$$+ b_3(Industry\ Sens_t * Sentiment_t) + b_4 Controls_t + \varepsilon_t \tag{6}$$

4. Results

In this section, we present our results in two parts. In the first part (Preliminary Analysis), we attempt to replicate the analysis from prior literature and contrast results. The second part (Main Analysis) estimates the models we develop in Section 3 (Methodology) and discusses our findings.

4.1. Preliminary analysis

Table 1 presents the estimated correlation coefficients of Bitcoin return and the returns of the four industry indices we discussed in Section 2 (Data). We observe that the estimated correlations between the return of Bitcoin and the four industry indices' returns are statistically insignificant.

Table 2 presents the results of regressing Bitcoin return on each of the industry returns individually while also controlling for factors that have been shown in prior literature to be associated with Bitcoin returns, Bitcoin Trading Volume (Volume), Volatility Index (VIX), and Political Uncertainty (EPU). The results suggest an insignificant association between the returns of Bitcoin and Industry indices.

Table 3 presents the estimates of regression Bitcoin return on Sentiment return by progressively adding control variables in the model (Volume, VIX, and EPU). In all cases, we find that the coefficient of sentiment return is insignificant.

4.1.1. Links to prior literature
Our preliminary results conform to the findings of Corbet et al. (2018b), who find cryptocurrency prices to be isolated from the stock market. The authors argue that in this relatively early stage of the cryptocurrency market development, structural conditions (e.g. the design, operations, and the clearing function of cryptocurrencies) are more important than the general financial conditions. However, our preliminary results are not entirely in line with another paper in the literature. Symitsi and Chalvatzis (2018) find significant associations between the price returns of Bitcoin and energy companies and, also, between the price returns of Bitcoin and technology

Table 1. Correlations of Bitcoin and Industry indices returns.

ρ	Bitcoin Return	MSCI Information Technology Return	MSCI World Energy Return	S&P Global Clean Energy Return	MSCI World Bank Return
Bitcoin Return	1				
MSCI Information Technology Return	0.0106	1			
MSCI World Energy Return	0.0291	0.510***	1		
S&P Global Clean Energy Return	0.0328	0.542***	0.524***	1	
MSCI World Bank Return	0.0237	0.592***	0.623***	0.560***	1

Standard errors in parentheses
*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2. Bitcoin return on Industry return regressions.

	(1) Bitcoin Return	(2) Bitcoin Return	(3) Bitcoin Return	(4) Bitcoin Return
Log Volume	0.00137***	0.00137***	0.00137***	0.00137***
	(0.000521)	(0.000522)	(0.000522)	(0.000522)
Log VIX	−0.0119***	−0.0116***	−0.0116***	−0.0115***
	(0.00432)	(0.00429)	(0.00429)	(0.00435)
Log EPU	0.00170	0.00164	0.00167	0.00164
	(0.00198)	(0.00197)	(0.00197)	(0.00197)
MSCI Information Technology Return	−0.00784			
	(0.120)			
MSCI World Energy Return		0.0416		
		(0.0935)		
S&P Global Clean Energy Return			0.0275	
			(0.102)	
MSCI World Bank Return				0.0438
				(0.116)
Constant	0.0307**	0.0301**	0.0303**	0.0300**
	(0.0144)	(0.0144)	(0.0144)	(0.0145)
Observations	1328	1328	1328	1328
Adj. R-Square	0.00880	0.00893	0.00885	0.00889

Standard errors in parentheses
*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Bitcoin return on Sentiment return regressions.

	(1) Bitcoin Return	(2) Bitcoin Return	(3) Bitcoin Return	(4) Bitcoin Return
Sentiment RTN	−0.00352	−0.00365	−0.00350	−0.00323
	(0.00266)	(0.00266)	(0.00310)	(0.00314)
Log Volume		0.000870**	0.00149***	0.00151***
		(0.000423)	(0.000525)	(0.000527)
Log VIX			−0.0123***	−0.0123***
			(0.00432)	(0.00432)
Log EPU				0.00154
				(0.00203)
Constant	0.00297***	0.00503***	0.0393***	0.0328**
	(0.000758)	(0.00127)	(0.0118)	(0.0148)
Observations	1907	1904	1313	1313
Adj. R-Square	0.000444	0.00252	0.0114	0.0111

Standard errors in parentheses
*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

companies. In our analysis, we find no such significant associations (Table 2) [5], yet the correlation coefficients we estimate (Table 1) yield similar results as in Symitsi and Chalvatzis (2018). However, the findings of Symitsi and Chalvatzis (2018) support the view that industries that are more related to the structural conditions of the cryptocurrency markets are more likely to be associated with the performance of cryptocurrencies.

Our main analysis in the following section attempts to reconcile the contrasting evidence in the prior literature. Although Corbet et al. (2018b) provide limited evidence regarding the association between the stock market and cryptocurrencies, they argue that structural conditions are important for the performance of cryptocurrencies. Sectors related to the production and operation of Bitcoin (energy and technology sectors) and the competition that Bitcoin faces (banking sector) represent important components of the structural conditions of the cryptocurrency market. Hence, investigating if behavioral factors mediate the association between industry indices and Bitcoin returns becomes a valuable exercise.

Table 4. Bitcoin and Industry sensitivity on Sentiment regressions (Fama and French 1993).

	(1) Bitcoin Sensitivity on Sentiment
MSCI IT Sensitivity on Sentiment	−0.000162** (0.0000650)
MSCI World Energy Sensitivity on Sentiment	−0.000342*** (0.0000459)
S&P Global Clean Energy Sensitivity on Sentiment	2.055*** (0.120)
MSCI World Bank Sensitivity on Sentiment	−7.950*** (0.305)
Constant	−0.00794*** (0.000334)
Observations	1105
Adj. R-Square	0.732

Standard errors in parentheses
*$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2. Main analysis

From estimating Equation (5), the first stream of main results is available in Table 4. We observe that the sensitivity of Bitcoin to Sentiment has a significant association with the sensitivities of four industry indices to Sentiment. More specifically, our results indicate a negative association between the IT industry's sensitivity (proxied by the MSCI IT index) to Sentiment and the sensitivity of Bitcoin to Sentiment. Besides, we find negative, positive, and negative associations, respectively, between the sensitivities of energy (proxied by MSCI World Energy), clean energy (proxied by S&P Global Clean Energy), and the banking industry (proxied by MSCI World Bank) and the sensitivity of Bitcoin to Sentiment. These significant associations demonstrate that the sensitivity of Bitcoin returns to Sentiment and that the sensitivity of industry indices to Sentiment are interdependent. Hence, this could facilitate the transmission of the effects of behavioral factors from the industry indices to Bitcoin.

We examine if this is the case with Equation (6). The results from the specifications of Equation (6) are available in Table 5. Table 5 contains four different estimates of Equation (6), progressively adding industry sensitivities to Sentiment and their interactions with the Bitcoin return. We find that the interactions of Sentiment with two industry sensitivities to Bitcoin (IT and clean energy) significantly impact Bitcoin return. This means that when Sentiment affects the IT and clean energy sectors' returns favorably, then this effect passes to the returns of Bitcoin by increasing its value, particularly when Sentiment becomes stronger. This confirms the importance of the technology and energy sectors for cryptocurrencies. Both these industries produce inputs for the development of cryptocurrencies. Hence, if they display a positive sensitivity to Sentiment, this could positively affect Bitcoin returns through Sentiment. We further observe that the interaction of Sentiment with the energy industry's sensitivity to Sentiment is negative with relatively small economic significance.

These findings reveal the increasing importance of clean energy in the process of Bitcoin mining. Forbes reports that Bitcoin mining exhibits an intensive use of sustainable energy (around 56%).[6] This percentage renders Bitcoin mining one of the most sustainable industries in the world. Furthermore, the location choice process for Bitcoin mining strongly considers the availability of renewable energy sources in each candidate area.[7]

Finally, the interaction of Sentiment and the sensitivity of the banking industry to Sentiment is statistically insignificant. There is a wider push towards greater adoption of cryptocurrencies in mainstream finance transactions. However, cryptocurrencies still have some disadvantages in comparison with fiat money. Thakor (2020) discusses, analytically, these disadvantages of cryptocurrencies. The *first* is that the use of cryptocurrencies as the medium of exchange remains limited because it represents a tiny fraction of overall payments. The *second* is that many cryptocurrency transactions between companies and consumers still involve intermediaries that convert cryptocurrencies to fiat currency. The *third* is that, to date, cryptocurrencies have not yet achieved the status of a stable source of value because they display large price fluctuations. Hence, investors might view the banking sector as immune to the rise of cryptocurrencies in the short term.

Table 5. Bitcoin return on Sentiment return regressions (Fama and French 1993).

	(1) Bitcoin Return	(2) Bitcoin Return	(3) Bitcoin Return	(4) Bitcoin Return
Log Volume	0.00139**	0.00138**	0.00131**	0.00150**
	(0.000554)	(0.000569)	(0.000568)	(0.000584)
Log VIX	−0.0109**	−0.0109**	−0.00947**	−0.00840*
	(0.00451)	(0.00471)	(0.00474)	(0.00478)
Log EPU	0.00148	0.00147	0.00133	0.00111
	(0.00219)	(0.00229)	(0.00230)	(0.00229)
Sentiment RTN	−0.00282	−0.000928	0.00278	0.00233
	(0.00355)	(0.00487)	(0.00516)	(0.00877)
MSCI IT Sensitivity on Sentiment	−0.000356	−0.000361	−0.0000473	0.000143
	(0.000515)	(0.000576)	(0.000708)	(0.000725)
Sentiment RTN * MSCI IT Sensitivity on Sentiment	0.00148	0.00225	0.00524*	0.00531**
	(0.00227)	(0.00238)	(0.00267)	(0.00269)
MSCI World Energy Sensitivity on Sentiment		−0.0000134	−0.000119	0.000116
		(0.000404)	(0.000446)	(0.000432)
Sentiment RTN * MSCI World Energy Sensitivity on Sentiment		−0.00107	−0.00261*	−0.00264*
		(0.00131)	(0.00145)	(0.00138)
S&P Global Clean Energy Sensitivity on Sentiment			0.760	0.488
			(0.818)	(0.820)
Sentiment RTN * S&P Global Clean Energy Sensitivity on Sentiment			8.371***	8.716***
			(3.044)	(3.003)
MSCI World Bank Sensitivity on Sentiment				−5.499**
				(2.647)
Sentiment RTN * MSCI World Bank Sensitivity on Sentiment				−0.708
				(9.814)
Constant	0.0290*	0.0290*	0.0260*	0.0191
	(0.0160)	(0.0161)	(0.0158)	(0.0160)
Observations	1063	1063	1063	1063
Adj. R-Square	0.00847	0.00706	0.0108	0.0135

Standard errors in parentheses
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Our findings also show that the direct effect of our behavioral factor (Sentiment RTN) on Bitcoin returns is not significantly different from zero. This is consistent with the findings of Kalyvas et al. (2020), who show that behavioral factors display a weak direct association with the crash risk of Bitcoin's price. In contrast, Gurdgiev and O'Loughlin (2020) show that investor sentiment has a positive and significant relationship with the returns of cryptocurrencies. However, the measure of investor sentiment they use is specific to the cryptocurrency market, while our sentiment measure is market-wide. Our interaction terms analysis provides evidence that the general investor sentiment is still able to associate with Bitcoin prices indirectly through the sensitivity that industries related to cryptocurrencies display towards such Sentiment.

4.3. Additional analysis

To test the validity of our results and inference, we repeat the analysis by estimating Equations (5) and (6), using the sensitivity estimates from Equations (3) and (4) instead of Equation (2). The results are illustrated in Tables 6 and 7, respectively, and are qualitatively similar to the results of our main analysis (Table 5), suggesting that the inference remains unchanged.

Overall, our findings indeed show that sensitivities of the industries, closely related with cryptocurrencies, to Sentiment, facilitate the effect of Sentiment on Bitcoin returns.

4.4. An example

In this Section we discuss an example illustrating some implications of our findings for investors. To implement this example, we perform the following steps. First, we calculate the median of the full sample on the Sentiment, information technology and clean energy sensitivities to Sentiment. Based on the median values we find, we split

Table 6. Bitcoin return on Sentiment return regressions (Carhart 1997).

	(1) Bitcoin Return	(2) Bitcoin Return	(3) Bitcoin Return	(4) Bitcoin Return
Log Volume	0.00138**	0.00138**	0.00132**	0.00150**
	(0.000554)	(0.000567)	(0.000566)	(0.000584)
Log VIX	−0.0109**	−0.0109**	−0.00966**	−0.00848*
	(0.00451)	(0.00468)	(0.00471)	(0.00476)
Log EPU	0.00145	0.00148	0.00136	0.00111
	(0.00219)	(0.00228)	(0.00229)	(0.00228)
Sentiment RTN	−0.00295	−0.00137	0.00105	0.000475
	(0.00358)	(0.00470)	(0.00490)	(0.00780)
MSCI IT Sensitivity on Sentiment	−0.000337	−0.000362	−0.0000765	−0.0000147
	(0.000526)	(0.000587)	(0.000703)	(0.000706)
Sentiment RTN * MSCI IT Sensitivity on Sentiment	0.00156	0.00230	0.00491*	0.00494*
	(0.00232)	(0.00243)	(0.00268)	(0.00265)
MSCI World Energy Sensitivity on Sentiment		0.0000145	−0.0000649	0.000113
		(0.000384)	(0.000415)	(0.000398)
Sentiment RTN * MSCI World Energy Sensitivity on Sentiment		−0.000986	−0.00221	−0.00222*
		(0.00126)	(0.00138)	(0.00128)
S&P Global Clean Energy Sensitivity on Sentiment			0.697	0.289
			(0.796)	(0.807)
Sentiment RTN * S&P Global Clean Energy Sensitivity on Sentiment			7.394**	7.656***
			(2.982)	(2.932)
MSCI World Bank Sensitivity on Sentiment				−5.165**
				(2.535)
Sentiment RTN * MSCI World Bank Sensitivity on Sentiment				−0.860
				(9.552)
Constant	0.0291*	0.0290*	0.0263*	0.0199
	(0.0160)	(0.0161)	(0.0158)	(0.0160)
Observations	1063	1063	1063	1063
Adj. R-Square	0.00841	0.00694	0.00975	0.0122

Standard errors in parentheses
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

the full sample into two subsamples.[8] Next, we compare the Sharpe ratios of Bitcoin, information technology and global clean energy indices and find that, in periods with high Sentiment and when the two industries display a high positive sensitivity to Sentiment, the Sharpe ratio of Bitcoin is greater than the Sharpe ratio of the two industries. For instance, in periods with high Sentiment, and when the information technology index exhibits a high positive sensitivity to Sentiment, the Bitcoin achieves an annualized Sharpe ratio of 1.50, higher, compared to the Sharpe ratio of information technology (−2.13) and global clean energy (−4.07). The results are qualitatively similar when we use the global clean energy sensitivity instead of the information technology sensitivity on Sentiment. On the other hand, in periods with low Sentiment, and when the two industries display a lower sensitivity to Sentiment, we document opposite results – i.e. the Sharpe ratios of information technology and global clean energy indices are greater than Bitcoin's.[9]

5. Conclusions

This paper explores the potential mediation effect of behavioral factors on the relationship between industry indices on Bitcoin returns. We employ four industry indices in technology, energy, clean energy, and banking, and the Sentiment index from Thomson Reuters Marketpsych Indices as a proxy for investor behavior for the purposes of our analysis. Our results provide evidence of a significant positive association between the sensitivities of technology and clean energy industry indices and the returns of Bitcoin when the Sentiment becomes stronger, with the latter result exhibiting high economic significance. We further observe that the interaction of Sentiment with the energy industry's sensitivity to Sentiment is negative with relatively small economic significance. Finally, the interaction of Sentiment and the sensitivity of the banking industry to Sentiment is statistically

Table 7. Bitcoin return on Sentiment return regressions (Fama and French 2015).

	(1) Bitcoin Return	(2) Bitcoin Return	(3) Bitcoin Return	(4) Bitcoin Return
Log Volume	0.00137**	0.00135**	0.00129**	0.00127**
	(0.000555)	(0.000569)	(0.000568)	(0.000567)
Log VIX	−0.0108**	−0.0110**	−0.00945**	−0.00922*
	(0.00451)	(0.00459)	(0.00468)	(0.00470)
Log EPU	0.00147	0.00159	0.00140	0.00157
	(0.00219)	(0.00227)	(0.00230)	(0.00232)
Sentiment RTN	−0.00268	−0.00143	0.00383	−0.00291
	(0.00353)	(0.00446)	(0.00522)	(0.00745)
MSCI IT Sensitivity on Sentiment	−0.000285	−0.000360	0.000000727	0.000238
	(0.000536)	(0.000612)	(0.000761)	(0.000862)
Sentiment RTN * MSCI IT Sensitivity on Sentiment	0.00151	0.00223	0.00557**	0.00650**
	(0.00234)	(0.00249)	(0.00278)	(0.00307)
MSCI World Energy Sensitivity on Sentiment		0.0000869	−0.0000619	−0.000106
		(0.000462)	(0.000530)	(0.000537)
Sentiment RTN * MSCI World Energy Sensitivity on Sentiment		−0.000984	−0.00289*	−0.00299*
		(0.00148)	(0.00170)	(0.00170)
S&P Global Clean Energy Sensitivity on Sentiment			0.775	1.009
			(0.827)	(0.897)
Sentiment RTN * S&P Global Clean Energy Sensitivity on Sentiment			8.337***	9.775***
			(3.127)	(3.569)
MSCI World Bank Sensitivity on Sentiment				−1.605
				(1.825)
Sentiment RTN * MSCI World Bank Sensitivity on Sentiment				−7.540
				(6.957)
Constant	0.0288*	0.0286*	0.0256	0.0227
	(0.0160)	(0.0161)	(0.0158)	(0.0163)
Observations	1063	1063	1063	1063
Adj. R-Square	0.00819	0.00667	0.0105	0.0100

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

insignificant. Overall, our results suggest that when the indices of highly related industries react strongly and positively to increased Sentiment, then this is reflected in the price of Bitcoin. Furthermore, these findings underline the importance of the technology and clean energy sectors for the production and operation of cryptocurrencies.

We conduct several robustness tests as a means of testing the correctness of our results. Notably, we employ three different models to estimate industry sensitivities to Bitcoin, controlling for the Fama and French (1993) market, size and value portfolios, controlling for the Carhart (1997) momentum portfolio, and also controlling for the Fama and French (2015) profitability and investment portfolios. While our base case is developed around the model controlling for Fama and French (1993) factors, all three methodologies generate qualitatively similar results.

Our inference is similar to the findings from prior literature but via a different route. Symitsi and Chalvatzis (2018) find a direct link between Bitcoin and technology and energy indices. Our analysis does not provide sufficient evidence that such a link exists. We attribute this to the very volatile nature of Bitcoin and the use of control variables in our models. However, we do identify a link via changes in Sentiment in conjunction with changes in the sensitivities of those industries to Sentiment.

Our results also have significant implications for cryptocurrency investors, whom we advise paying close attention to TRMI Sentiment and the sensitivity of the technology and clean energy industries since, per our findings, these are significant determinants of Bitcoin returns. For example, an individual who invests in Bitcoin can incur significant gains in periods when Sentiment is high while information technology and global clean energy industries display strong positive sensitivity to Sentiment.[10]

Possible future extensions to this research include expanding the analysis to incorporate additional cryptocurrencies (e.g. Etherium and Ripple), alternative proxies for behavioral factors, and a more recent sample of data.[11]

Notes

1. Sourced from www.bitcoincharts.com.
2. For further information on the TRMI indices visit https://www.marketpsych.com.
3. Our results are based on the combined dataset. Results for the other two datasets can be provided upon request.
4. We source the EPU index from www.policyuncertainty.com.
5. We attribute the absence of statistical significance in our results to the use of control variables that prior literature identifies as relevant to Bitcoin. Such factors include the US Implied Volatility Index (VIX), the Bitcoin trading volume (Volume) and the US Economic Policy Uncertainty Index (EPU). For more information see Kalyvas et al. 2020; Mueller, Stathopoulos, and Vedolin 2017 and Wu et al. 2019, among others.
6. https://www.forbes.com/sites/greatspeculations/2021/07/06/bitcoin-mining-uses-a-higher-mix-of-sustainable-energy-than-any-major-country-or-industry/?sh = 3630b17b4cc9.
7. https://www.economist.com/china/2021/07/10/deep-in-rural-china-bitcoin-miners-are-packing-up.
8. For each of Sentiment, information technology and clean energy sensitivities we split the sample in two subsamples based on the respective estimated median value. In the case of Sentiment, the two subsamples depict periods of low and high Sentiment. In the case of information technology and clean energy sensitivities, the two subsamples depict periods of low and high sensitivity of those industries to Sentiment.
9. We test the hypothesis that the Sharpe ratios of the Bitcoin and the two industries are equal, using the methodology of Ledoit and Wolf (2008) with 5000 bootstrap resamples and a block size equal to $b = 5$. We find that the differences in the Sharpe ratios of the Bitcoin and the two industries are statistically significant at 5%.
10. For more information refer to Section 4.4.
11. Our sample of data spans 1st October 2013 – 31st December 2018 due to a limitation of our TRMI data that end on 31 of December 2018.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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