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Herding and anchoring in cryptocurrency markets: Investor reaction to fear and uncertainty

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ABSTRACT

Cryptocurrencies have emerged as an innovative alternative investment asset class, traded in data-rich markets by globally distributed investors. Although significant attention has been devoted to their pricing properties, to-date, academic literature on behavioral drivers remains less developed. We explore the question of how price dynamics of cryptocurrencies are influenced by the interaction between behavioral factors behind investor decisions and publicly accessible data flows. We use sentiment analysis to model the effects of public sentiment toward investment markets in general, and cryptocurrencies in particular on crypto assets' valuations. Our results show that investor sentiment can predict the price direction of cryptocurrencies, indicating direct impact of herding and anchoring biases. We also discuss a new direction for analyzing behavioral drivers of the crypto assets based on the use of natural language AI to extract better quality data on investor sentiment.

1. Introduction

In recent years, a new asset class has captured the attention of the financial media, academia and investors. Launched on January 9, 2009 with the first iteration of the 0.1.0 Bitcoin protocol, investors' interest in cryptocurrencies, and blockchain technology underlying them, has risen dramatically, in line with both the supply of the new crypto assets, and their market values. An explosive growth in media reporting and search activities accompanied the evolution of this asset class, underpinning the sentiment-rich informational environment in which these assets evolve.

Although Bitcoin remains the dominant cryptocurrency to-date, hundreds of other cryptocurrencies and alt-coins have been developed. Sub-classes of crypto assets have emerged, including crypto coins (e.g. Bitcoin, Ethereum and Ripple, to name but a few), stable coins targeting a pegged relationship to major currencies (e.g. Tether and MakerDao), and tokens (cryptocurrencies backed by specific applications and initial coin offerings, e.g. Tron, and others). New innovative technological applications exploited existent blockchains (as exemplified by a range of Bitcoin hard forks, including Bitcoin Cash and Bitcoin Gold).

One of the key aspects of the cryptocurrency investment universe is the general lack of traditional quantifiable financial fundamentals that underpin crypto asset valuations (Hayes, 2017; Corbet et al., 2018; Brown, 2018; Berentsen and Schar, 2018). From 2017 on, the promise of technological innovation in payments and transactions facilitation originally serving as the key fundamental driver for cryptocurrencies demand, gave way to the speculative and investment interests in this asset class (Berentsen and Schar, 2018; Corbet and Gurdgiev, 2018). As cryptocurrencies generally offer no cash flow underlying their valuations, their investment returns arise through capital gains alone. Compared to the traditional investment instruments, such as equities and bonds, crypto assets are primarily speculative (Celeste et al., 2018; Corbet and Gurdgiev, 2018).

Another key aspect is that, from the behavioral perspective, cryptocurrencies generate significant flows of data that reflect the revealed preferences of investors. For example, at the peak of the crypto market valuations, back in late 2017–early 2018, widely-known media outlets were publishing numerous stories regarding

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the abnormal profits accumulated by early investors, spurring on large inflows of new investors and speculators (Bishop, 2017; Kharpal, 2018). As the market for crypto assets turned severely bearish in 1Q 2018, investor pools became dominated by the buy-and-hold miners (Corbet and Gurdgiev, 2018; Wilson, 2018; Celeste et al., 2018).

This lack of 'hard' financial fundamentals in valuation, coupled with active engagement by investors on social media make the crypto assets prime targets for sentiment analysis and behavioral factors identification (Corbet et al., 2018). This proposition is supported by the oretical developments in academic research. In general, there are three core frameworks for analyzing securities prices: the Efficient Markets Hypothesis (EMH, starting with Fama, 1970), the Fractal Markets Hypothesis (FMH, starting with (Peters and Peters, 1994), and the Adaptive Markets Hypothesis (AMH, starting with Lo, 2005). To-date, there are no conclusive studies that provide exhaustive evidence in favor of one or the other framework as being a preferred basis for valuation of crypto assets, although Celeste et al. (2018) shows substantial evidence that dynamic properties of major cryptocurrencies do in fact satisfy the conditions of the FMH, while violating the EMH.

In the above, the AMH relates crypto-asset valuations to market fundamentals, such as the behavioral aspects of investors' choices (Celeste et al., 2018), while the FMH offers indirect behavioral links between investors' preferences for liquidity supply and demand (which can be driven by sentiment) and the market pricing of the assets. From both of these points of view, sentiment analysis, or natural language-enabled 'opinion mining' using terminology of machine learning, presents a promising avenue for modeling prices of crypto assets, potentially allowing us to capture herding, anchoring and other behavioral aspects of the investors' choices. This approach provides information on revealed preferences for an asset by the actual and potential investors and involves an empirical evaluation of public opinions and emotions toward risky assets in general, and toward the crypto assets in particular, capturing their effects on price and returns dynamics.

With the rapid growth of the general social media interactions and specialist forums engagements, professional investors are increasingly using the opinions of the public in forming their investment strategies, liquidity preferences and even execution (Liu and Zhang, 2012). Fig. 1 below shows the interest in sentiment analysis increasing steadily since 2008, indicating an appetite amongst investors to deploy new ways to analyze financial assets complementary to the fundamentals-based models. Similarly, since 1Q 2017, public interest in crypto assets has grown substantially, albeit with a substantial volatility.

Use of sentiment and opinion mining in financial analysis is supported by academic and professional studies, surveyed in numerous studies, including Brown and Cliff (2005), Bollen et al. (2011) and Schumaker et al. (2012). The general methodology for collecting sentiment data involves 'mining' social interactions from social media websites, computationally ranking the data in terms of the strength of signal (e.g. being either 'positive', 'negative' or 'neutral') and then relating this data to asset prices (Bollen et al., 2011). Other forms of sentiment data that can be used for direct analysis or robustness checks involves quoted indexes such as the CBOE Volatility Index (VIX, commonly known as the 'fear index') which tracks investors' expectations of S&P500 index volatility; and CNN Fear & Greed Index which attempts to capture the emotional direction of the market (CNN, 2018).

To extract behavioral information underpinning investors' valuations of the crypto assets, we apply investor sentiment identification methods across top ten cryptocurrencies (based on their market cap as of 1Q 2019, jointly covering more than 90 percent of the entire cryptocurrencies market capitalization). We test if sentiment can be used in price formation analysis to identify some of the behavioral factors that may affect the price of cryptocurrencies.

Focusing on the period of cryptocurrencies' maturation, from January 1, 2017 through April 2, 2019,[1] we consider the following behavioral factors:

- VIX 'Markets Fear Index' reflective of the general state of the investors' sentiment toward traditional risky assets, such as highly liquid equities,
- US Equity Market Uncertainty index, reflective of deeper sentiment of investor uncertainty concerning the traditional markets for risky assets,
- Investors' positivity/negativity sentiment toward cryptocurrencies, measured using the investors' opinions expressed by the Bitcointalk.org forum participants, and
- Bullishness/bearishness in the overall financial markets, measured by the CBOE Put/Call ratio (as reflective of the investor perceptions of liquidity conditions in the financial markets).

After addressing issues with stationarity and heteroscedasticity, as well as optimal model selection, a generalized least squares (GLS) panel model with robust standard errors is used to examine short-term price-sentiment relationships. Our selection of this model is guided by its applicability to the machine learning data analytic environment. We confirm our model robustness by also deploying the Generalized Method of Moments (GMM) estimation procedure in addition to the GLS.

We test our core hypotheses across the entire time series span, and across two different regimes in the history of cryptocurrencies: the period of sustained bull market from January 1, 2017 through December 18, 2018, and the period of bear market from December 19, 2018 through April 2, 2019. This enables us to discern the differences in behavioral investor sentiment effects on crypto assets prices across two distinct sentiment domains: the bull market hype and the bear market crash.

The study makes several contributions to the broader literature on the investment aspects of cryptocurrencies. Firstly, behavioral finance and sentiment analysis are a growing field of research, with minimal direct application on crypto assets to-date. Our results indicate that behavioral aspects of cryptocurrencies are statistically important factors in driving crypto-asset valuations, with cryptocurrencies' response to market-wide sentiment being sensitive as to whether the markets sentiment is dominated by uncertainty or fear. This suggests the existence of anchoring biases amongst cryptocurrency investors, with anchoring focused on general investment markets conditions. Beyond this, we show that general bullishness/bearishness (a proxy for liquidity conditions in the markets and risk-on/risk-off triggers) in the broader investment markets has no impact on cryptocurrency investors. These findings are consistent with the potential presence of recency biases amongst crypto asset investors, and non-linear effects of anchoring biases. We also find that cryptocurrencies are responsive to the crypto-specific sentiment amongst the specialist investors, signifying herding.

With this in mind, the paper is organized as follows. In the following section we review theoretical and empirical literature on sentiment and behavioral effects driving cryptocurrency markets. Section three describes methodologies of our data collection and analysis, while also defining tested hypotheses informed by the

[1] Our time window also allows us to study the dynamics in cryptocurrency markets characterized by significant change in holdings from specialist/crypto enthusiast investors in the earlier parts of 2017, to the period of increased interest in the assets from retail investors through the second half of 2017, into the start of the markets sell-off stage in 1Q 2018.

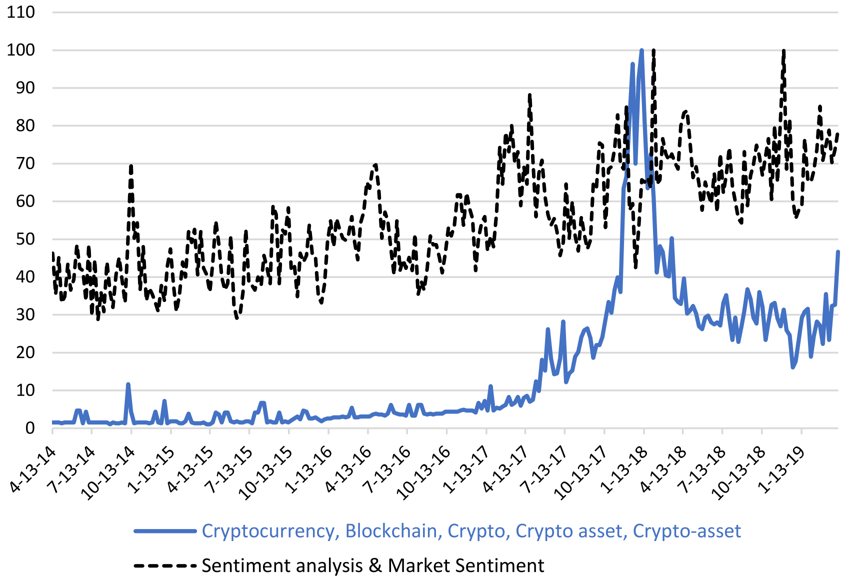

Fig. 1. Popularity of the combined search terms 'sentiment analysis', 'cryptocurrencies', 'blockchain' and 'crypto assets' on Google. January 2004–April 2019; Indices are set at historical period maximum value = 100.
Source: Google Search Trends, April 2019.

literature review. Section four discusses the main results of model estimation and limitations, suggesting the ways in which future expansion of machine learning tools can aid the process of price discovery in the crypto assets markets. Section five concludes.

2. Literature on behavioral analysis of cryptocurrencies

Behavioral finance has generated direct evidence that investment choices are heavily guided by changes in investor sentiment (e.g. Nofsinger, 2005; Guo et al., 2017; Bollen et al., 2011). However, literature on behavioral aspects of demand for cryptocurrencies remains incomplete and is primarily dominated by the two strands of analysis. The first strand is related to modeling the dynamic properties of the cryptocurrencies, which only indirectly reveal a deeper link between crypto assets prices and the latent behavior of investors (Kristoufek, 2013; Alabi, 2017; Celeste et al., 2018; Shevchenko and Godwin, 2018; Corbet et al., 2018). The second strand focuses on modeling demand for this new asset class as a function of market fundamentals, again indirectly or latently indicating behavioral drivers underlying some of the key properties of cryptocurrencies price formation (Corbet et al., 2018). These studies provide an intuitive basis for using sentiment and behavioral analysis in determining prices of the crypto assets as they indicate the potential herding and anchoring behavior amongst investors (Kristoufek, 2013; Celeste et al., 2018).

Cryptocurrency enthusiasts are very active on social networks such as Twitter, Reddit, Quora and other platforms. However, views of cryptocurrency investor, as opposed to the views of a broader population of blockchain technology enthusiasts, are more efficiently captured by specialist forums, such as Bitcointalk.org which focus discussions within groups of active market participants. These social media interactions can have both first and second order effects on the pricing of cryptocurrencies, similar to those empirically found in other, more mature asset classes (Baker and Wurgler, 2007; Zouaoui et al., 2011).

The first order effects relate to the sentiment of the market participants, on average. Outside the cryptocurrencies market, Baker and Wurgler (2007) and Qian (2009) show that the relevancy of investor sentiment is higher for pricing equity in companies that were young, unprofitable, highly volatile and had low market capitalization. The logic behind this is that such companies are more difficult to value, which can make biases more 'insidious'. Similarly, Zouaoui et al. (2011) show that financial markets with little institutional investors participation are more susceptible to changes in investor sentiment. Cryptocurrency markets are young, less liquid and involve higher trading costs and lower institutional investors participation than mainstream asset classes (Celeste et al., 2018; Shevchenko and Godwin, 2018; Kharpal, 2017). This suggests that cryptocurrencies may exhibit stronger sensitivity to sentiment than more mature asset classes.

The second order effects of social and specialist media on asset prices can include a potential selection bias, in line with the effects of heterogeneous beliefs (He and Shi, 2007), where more bullish sentiment-driven investors can dominate rational or fundamentals-driven investors through their willingness to trade in the market. Additional effects of investor sentiment can also be transmitted through sentiment anchoring, generating autoregressive nature of sentiment effects on demand for and pricing of cryptocurrencies. Finally, to the extent that sentiment itself can be subject to herding, with investors cross-referencing each other through social media and specialist forums, there can be positive reinforcement of sentiment within these venues that can support complex pricing dynamics.

Considering these facts, investor sentiment could be a significant factor in the price movement of cryptocurrency prices.

2.1. Sentiment, social media and behavioral drivers of investment decisions

As mentioned earlier, investor sentiment analysis is a mainstream strand of the literature on asset valuations and market pricing (Heston and Sinha, 2017) and a broader methodological exposition of using text analysis to extract market sentiment data has been developed by Gao et al. (2013), Xu (2014), and others. In this study, we use Xu (2014) text analyzer methodology, while focusing on specialist cryptocurrency forums to derive investor sentiment data. We use both textual-processing data extraction techniques and sentiment-consistent indices creation to gauge investor optimism and pessimism toward the outlook for the crypto assets' performance.

Our paper also builds upon and improves two key studies that attempted to identify behavioral drivers of crypto assets valuations. The first study, by Bouoiyour and Selmi (2015), performed a quantitative analysis of Bitcoin price reactions to investors' sentiment with respect to the perceived attractiveness of the cryptocurrency, its exchange-trade ratio, a range of financial and technical instruments, and the Shanghai market index. The authors show that ∼20% of Bitcoin's price is driven by investor sentiment toward Bitcoin as instrumented by the volume of Google search queries. Qualitatively, the same was confirmed by Ciaian et al. (2016), which showed that the new investors' decisions to go long cryptocurrency might become altered by the influence of public attention (e.g. attention in the media), because such attention reduces search costs. This availability bias then triggers a high price response due to an increase in demand.

Use of very broad sources, such as Google Search data, for extraction of investor sentiment – a major drawback of the above studies – also informed Kristoufek (2015) paper. Kristoufek (2015) looked into the Google and Wikipedia search data for the term 'Bitcoin', showing that during the BTCUSD bubble which occurred in the first quarter of 2013, the price of Bitcoin was actually led by increased investor interest. Expanding the literature regarding social media effects on cryptocurrency prices, Martina et al. (2015) analyzed 1.9 million tweets mentioning Bitcoin showing that positive tweets may be used to predict changes in Bitcoin price 3–4 days in advance. However, the study only covers a 60-day period and the authors recognize that analysis over the longer time horizon may produce results of a higher quality.

One of the major limitations of the aforementioned studies is that type or nature of the investor sentiment remains undefined and largely unexplored in the literature. We explicitly control for this limitation by offering more granular indexation of sentiment data, in line with Kim et al. (2016). Another limitation is hinted upon by Bouoiyour and Selmi (2015) and relates to the use of general Google and Wikipedia search data as a signal of investor sentiment. These limitations arise because general audience search results involve both investors and non-investing public. We correct for this by extracting sentiment data from the more targeted sources, such as cryptocurrency-specific forums. In addition, we refine the measurement of the direction of sentiment in our textual processing, as discussed below, alleviating potential signal selection biases hinted at by Kim et al. (2016).

Perhaps the most advanced sources of cryptocurrencies pricing analysis based on investor sentiment are Phillips and Gorse (2018) and Mai et al. (2018). These studies partially address some of the limitations in the broader literature on crypto assets valuations mentioned above. Phillips and Gorse (2018) considered four cryptocurrencies (Bitcoin, Ethereum, Litecoin and Monero) and used the Reddit forum which has a large cryptocurrency user base, although the forum is not crypto assets specific. The authors linked the number of posts per day, subscriber growth and the number of new authors joining per day to cryptocurrencies' prices to show that in the short term, increases in forum activity led to a decrease in price. However, in the medium and the long term, online activity is positively correlated with changes in price (e.g. Gruhl et al., 2005. Phillips and Gorse (2018) also confirmed that the data from Reddit offers a better predictive indicator than more general audience-based Google search and Wikipedia. Li et al. (2018) provide a similar analysis of the smaller cryptocurrency, ZCurrency, using Twitter data. Meanwhile, Mai et al. (2018) tested the predictability of Bitcoin price by analyzing the sentiment in posts regarding Bitcoin on Twitter and the Bitcointalk.org using the Natural Language Toolkit. The results suggest that improved sentiment in cryptocurrency investment community leads increases in underlying crypto assets prices by one day.

Methodologically, however, the Natural Language Toolkit may not be the best application in studying sentiment of cryptocurrencies due to the specific vocabulary and acronyms associated with cryptocurrencies markets (Mai et al., 2018). The methods used in our study address this problem by manually building a lexicon that includes crypto-specific words and applying this to the same specialist forum used in the Mai et al. (2018) study, Bitcointalk.org. In addition, we cover a larger set of cryptocurrencies and study both the bull market period and the bear market period.

2.2. *Fear and uncertainty in the markets*

Fear and uncertainty impact market participants via risk aversion (rational economics models) and loss aversion (behavioral economics models) channels. These channels, in an investment setting, relate to hedging and safe haven properties of the underlying risky assets, as defined in Ciner et al. (2013). In this context, it is important to consider the existent literature on risk hedging properties of crypto assets; a literature more extensive than that on direct evidence of behavioral biases in investor decisions relating to this new asset class.

Ciaian et al. (2016), referenced earlier, as well as Dyhrberg (2016), explored the hedging capabilities of Bitcoin, showing that BTC can act as a short-term safe haven against equities and the dollar. Bouri et al. (2016) also found that bitcoin had a hedging-type relationship with the VIX index prior to the 2013 BTCUSD crash. Baur et al. (2015) established evidence of Bitcoin having hedging properties vis-à-vis equities, precious metals, currencies, energy instruments and bonds.

Overall, much of the literature to-date lends support to the view that, based on methodology developed in Ciner et al. (2013), Bitcoin could potentially act as a safe haven and/or a hedge against adverse price shocks impacting traditional financial assets, linking the investor sentiment of fear to the cryptocurrencies pricing behavior vis-a-vis other asset classes. In line with the prior findings, therefore, we include CBOE's VIX index as our markets-revealed measure of fear sentiment amongst the investors.

In contrast to other studies, however, Kristoufek (2015) found only weak signs that Bitcoin can act as a safe haven asset with respect to the Financial Stress Index (FSI) and the price of gold in Swiss francs. The former is a frequently used gauge of financial uncertainty; the latter is considered a classic safe haven. According to Kristoufek (2015), when uncertainty increases, the price of Bitcoin also increases. However, there are few long-term intervals that show this relationship to be statistically significant. The instability of hedging relations is a feature commonly linked to higher measures of uncertainty (as opposed to volatility) in markets environments. Chulia et al. (2017) used the Equity Market Uncertainty index (Baker et al., 2013) to see how uncertainty affects emerging and mature markets, while Bouri et al. (2017) used standardized volatility indices for a number of countries to determine if Bitcoin pricing is influenced by market uncertainty. Bandopadhyaya and Jones (2008) investigated the use of the CBOE Put/Call ratio (PCR) in analyzing equity investor sentiment. The PCR is a contrarian indicator where an increase in the PCR relates to an increase in pessimism in the market. As a measure of S&P 500 investor sentiment, it was concluded that the PCR approximates non-economic factors that may impact equity price changes more than the VIX. From the point of view of the aforementioned studies, it is worth looking at the US Equity Uncertainty Index and PCR, in addition to VIX, to see if a different indicators or measures of uncertainty may produce different results.

3. Data collection, descriptive statistics and methodology

The data used in this paper are sourced from CoinGecko, CBOE, Bitcointalk.org and FRED database. The data covers the period from January 1, 2017, the first month with significant forum participation on Bitcointalk.org, through April 2, 2019. The frequency of the data is daily.

To expand the research on behavioral drivers of cryptocurrencies valuations to the crypto market as a whole, the dependent variable chosen was the price of ten of the largest cryptocurrencies based on market capitalization at May 9, 2018. The cryptocurrencies used in the study were: Bitcoin, Ethereum, Ripple, Litecoin, NEM, Dash, Monero, Lisk, Verge and Stratis. The cryptocurrency prices follow a highly skewed and leptokurtic distribution, warranting a log transformation of the raw data.

The independent variables used in this study are defined as follows.

The US Equity Uncertainty Index (Baker et al., 2013) is used as a measure of uncertainty in the US equity markets, as sourced from the Federal Reserve Bank of St. Louis (FRED) database.

The Cryptocurrency Forum Sentiment reflects the sentiment toward cryptocurrencies based on comments on the largest English language cryptocurrency forum 'Bitcointalk.org'. The data was collected as follows: for each comment made, the comment received a score of either +1, -1 or 0 depending on whether it expressed a positive, negative or neutral outlook on the cryptocurrency's valuation. The data was then converted into a positive set of values via rescaling to allow log transformation. In capturing this data, the forum had to be scraped using web-crawler software, for every comment made between January 1, 2017 and April 2, 2019 covering all of the ten cryptocurrencies in this study. For Bitcoin, the 'Bitcoin Speculation' sub-forum was used. For the rest of the cryptocurrencies, their respective announcements threads were used. When extracting the forum data, quotes were removed to avoid double-counts of the same comment. Once all the comments were collected, they had to be analyzed for whether they were consistent with positive, negative or neutral sentiment signals. To do this, we relied on Loughran and McDonald (2011) methodology for constructing a lexicon-based sentiment analyzer, manually refining a custom master dictionary to increase its accuracy.[2]

The Chicago Board Options Exchange (CBOE) put/call ratio is the total amount of trading volume in puts (which includes index options and options on individual stocks on the NASDAQ, NYSE and AMEX) divided by the total trading volume in calls (Lamont and Stein, 2004). The put/call ratio is a bearish (bullish) sentiment indicator: when the ratio is rising (falling), it suggests that investors expect the markets to decline (rise) (Qian, 2009).

The CBOE VIX is a benchmark index reflecting investors' expectations for 30-days forward volatility in the S&P 500 equity index. For the purpose of this study and its association to sentiment, the index is commonly referred to as the 'investor fear gauge' (Whaley, 2000). The data used in this study was the daily closing value.

Whilst cryptocurrencies provide daily price data through the weekends, equities and other investments are only quoted on trading days.[3] As such, the CBOE Put/Call ratio and VIX index data cover only trading days and excludes weekends and public holidays across the total sample. For this study, the cryptocurrency prices on weekends and public holidays were omitted, so that cryptocurrency price changes over the weekends and holidays are absorbed into weekday changes consistent with the data for other variables.

To test the variables for stationarity, unit root tests were conducted including the Augmented Dickey–Fuller test (Dickey et al., 1984) and the Phillips–Perron test (Phillips and Perron, 1988). The results (available from the authors upon a request, spanning full period of data, the bull market sub-period and the bear market sub-period) indicate the presence of a unit root in the LnPrice variable but not in any of the other variables. We first-difference the *lnprice* variable in line with Engle and Granger (1987).

3.1. Descriptive statistics

The descriptive statistics and correlation matrix for the variables are presented in Tables 1 and 2 below.

All ten cryptocurrency variables show high volatility — with standard deviations lying close to the mean. Skewness and kurtosis statistics support using log transformation of the variables and subsequent use of robust econometric methodologies for testing the data (GMM). The correlation matrix between the ten cryptocurrencies shows a high degree of positive correlation between them all, adding to the robustness of the study in terms of choosing a panel data model, and the GLS and the GMM methodologies.

3.2. Research hypotheses

The primary objective of this research is to explore the significance of investor sentiment on the price movements of major cryptocurrencies using four independent variables outlined above.

The variables used in the study are representative of particular market-level sentiment that investors may be feeling, including: positivity or negativity, high or low uncertainty, sentiment of high or low fear, and bullishness or bearishness. To alleviate any confusion positivity/negativity sentiment refers to the sentiment an investor has specifically regarding the respective cryptocurrency, its underlying technology and/or price he/she is researching. Bullishness/bearishness refers to the sentiment experienced overall in the broader financial markets.

The following sub-hypotheses suggest the likely directions of the relationships between the prices of cryptocurrencies and the independent variables.

It is expected that, on average over time, the price of cryptocurrencies should be positively correlated with higher market uncertainty (Kristoufek, 2015; Bouri et al., 2017; Sarwar, 2017), implying that cryptocurrencies can act as a hedge against the stock market uncertainty as measured by the Equity Uncertainty Index.

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[2] Once all the comments were collected, they had to be analyzed for whether they were consistent with positive, negative or neutral signals. To do this, we first used a number of sentiment analysis programs. However, in our manual checks, all of the sentiment analyzers we tested proved to be inaccurate in detecting the mood of forum participants. The reason for this is because these programs are not designed to read market- and cryptocurrency-related jargon (such as 'bullish', 'bearish', 'buy', 'sell', 'HODL', etc.). To address this, a lexicon-based sentiment analyzer was specifically created for the purpose of this study, using the Loughran and McDonald (2011) master dictionary which targets financial words and classifies them as either positive or negative. To further improve upon the lexicon-based sentiment analyzer, every thread on the Bitcoin Speculation sub-forum and random samples of Ethereum and other cryptocurrencies-related comments were manually inspected for more words that indicated positive or negative sentiment toward cryptocurrencies, not captured by the analyzer. All new terms detected by the manual checks were subsequently added to the lexicon-based sentiment analyzer master dictionary. Final tests confirmed the robustness of our lexicon-based automated analyzer tool.

[3] OTC trading, dark pools and trading during off-exchange hours still occur on the weekends. However, these data are not available to the public and are integrated into the publicly quoted prices with lags.

Table 1
Descriptive statistics.

Variable	N	Mean	Standard Deviation	Skewness	Kurtosis
bitcoinprice	565	5571.127	3658.825	1.114	4.547
ethereumprice	565	327.821	271.587	1.207	4.136
dashprice	565	268.388	256.559	1.971	7.293
liskprice	565	5.733	6.707	1.853	6.023
litecoinprice	565	73.849	65.639	1.624	5.638
moneroprice	565	114.089	98.341	1.396	4.582
nemprice	565	0.216	0.264	3.075	14.601
rippleprice	565	0.417	0.405	2.931	16.160
stratisprice	565	3.777	3.816	1.712	6.557
vergeprice	565	0.022	0.034	2.758	11.768
uncertainty	565	37.627	59.109	4.643	33.057
forumsent	565	39.004	1.580	−0.635	5.862
putcall	565	0.946	0.139	0.999	6.063
vix	565	14.145	4.536	1.630	6.186

Table 2
Correlation matrix.

	bitcoinprice	ethereumprice	dashprice	liskprice	litecoinprice	moneroprice	nemprice	rippleprice	stratisprice
ethereumprice	0.8415								
dashprice	0.8957	0.8679							
liskprice	0.8129	0.9422	0.8941						
litecoinprice	0.9162	0.9032	0.9147	0.8977					
moneroprice	0.939	0.9286	0.9348	0.9304	0.9572				
nemprice	0.7673	0.8572	0.8991	0.8732	0.8235	0.8551			
rippleprice	0.7717	0.8352	0.7753	0.8476	0.8124	0.8466	0.8873		
stratisprice	0.7111	0.8496	0.8685	0.8246	0.783	0.8008	0.9202	0.7572	
vergeprice	0.7555	0.8215	0.8103	0.8636	0.8293	0.8615	0.8756	0.9027	0.7573

Hypothesis 1. Cryptocurrencies are a hedge against the stock market in times of uncertainty, supporting the proposition that crypto assets can be viewed as an available alternative to traditional risk management assets, such as equities, by investors (availability bias)

When the market participants are generally positive regarding cryptocurrencies, we can assume that the cryptocurrency market itself will experience increases in prices. In researching cryptocurrencies, investors post and exchange comments on cryptocurrency of interest on specialist forums. Higher positivity expressed by investment forums participants (the peers) regarding their potential investment target should be associated with higher propensity by an individual investor to buy it or to continue holding it, in line with the theory of herding biases (Kumar and Goyal, 2015).

Hypothesis 2. Cryptocurrencies experience an increase in price when sentiment toward its underlying technology, development and price is positive in line with crypto assets' specific herding effects

The CBOE Put/Call Ratio (PCR) is an indicator of bullishness/bearishness in the overall financial markets. It is hypothesized that an increase in bullishness in the financial markets (a decrease in the PCR) will result in an increase in the price of cryptocurrencies (Mao et al., 2015; Bandopadhyaya and Jones, 2008; Li and Wang, 2017).

Hypothesis 3. When investors are bullish in the financial markets in general, cryptocurrencies will experience an increase in price, in line with the general financial markets herding effects

VIX is commonly used as a measure of 'fear' in the equity market and a rise in its value is often associated with a fall in the stock market. In following the literature, we assume that a rise in the VIX will be associated with decreases in the prices of cryptocurrencies (Ciaian et al., 2016). The reasoning behind this hypothesis is that fear can negatively dominate uncertainty (Kahneman and Tversky, 1979): investors experiencing fear are apprehensive in going long any risky asset, including cryptocurrencies.

Hypothesis 4. Cryptocurrencies are not a hedge against the stock market during times of fear, in line with prospect theory.

3.3. Methodology

From a methodological point of view, we want to specify a panel data model that will allow us to test the hypotheses stated above.

We first test our data for multicollinearity using a VIF test. The results of our estimation, available upon the request, show that the variance inflation factors are very low (with the highest VIF statistic estimated at 1.23 and the lowest at 1.00), indicating that our model does not contain a multicollinearity problem.

When heteroscedasticity is present, significance tests are generally inappropriate and using them may lead to wrong inferences (Long and Ervin, 2000). In testing to see if there was evidence of heteroscedasticity in this study, both the Breusch–Pagan test (Breusch and Pagan, 1979) and a likelihood-ratio test (Harvey, 1976) were conducted. Both produced significant p-values indicating that heteroscedasticity is present (the results of both tests are available upon the request). To remedy this, the Huber–White Sandwich estimator method was used which uses robust standard errors in the regression (Freedman, 2006).

Ramsey's RESET test was conducted for omitted variables. According to the results from the test, there are no signs of omitted variables in the regression. Finally, a Wooldridge test was carried out to detect serial correlation as this causes results to be less efficient (Drukker, 2003). The results showed that there was no evidence of serial correlation in the model. Both test results are available upon request.

In light of the above test, an OLS regression was deemed to be inapplicable. Instead, GLS model offered the most efficient and unbiased estimation procedure for the data. In deciding between a Fixed-effects model or Random-effects model, a Hausman test (Hausman, 1978), was conducted which revealed that a random-effects model is more appropriate for the data (Laird and Ware, 1982). We tested our findings from the GLS model by using GMM to further address the presence of non-normality. As

GMM estimators qualitatively confirm the conclusions of the GLS estimation, our GMM results are available upon the request.

The following is the formal representation of the model:

$$\Delta \ln \text{price}_{it} = \beta_1 + \beta_2 \ln \text{uncertainity}_{it} + \beta_3 \ln \text{forumsentiment}_{it} + \beta_4 \ln \text{putcall}_{it} + \beta_5 \ln \text{VIX}_{it} + \omega_{it} \tag{5.1}$$

where:

$$\omega_{it} = \varepsilon_i + u_{it} \tag{5.2}$$

The composite error term defined in (5.2) has two components: ε_i which is the cross-section or individual-specific error component and u_{it}, which is the combined time series and cross-section component.

In Eq. (5.1), $\Delta \ln$ price is the dependent variable which is the first difference of the natural logarithm of each of the ten cryptocurrencies included in this study. The independent variables include ln uncertainity which is the log of the US Equity Uncertainty Index. ln forumsentiment represents the log transformation of the Bitcointalk.org forum's sentiment; ln putcall is the log transformation of the CBOE Put/Call ratio data and ln VIX is the log transformation of the VIX index.

As discussed earlier, we estimate the model across three time horizons. The first period, from January 1, 2017 through December 18, 2018, was a period of explosive growth in cryptocurrencies valuations. The second period, from December 19, 2018 through April 2, 2019, was characterized by a major bear market trend in cryptocurrencies. Finally, we also estimate the model across the entire data sample.

4. Results and analysis

Based on implementation of the GLS model for random effects panel data estimation with robust standard errors, we obtain the following results, summarized in Table 3.

4.1. US equity market uncertainty index

The ln uncertainty relating to the equity markets has a statistically significant positive effect on cryptocurrencies valuations in overall data sample, and during the bull market period. The coefficient is only weakly (p-value of 0.065) significant during the bear market period. As mentioned earlier, a rise in the index implies a rise in uncertainty. Thus, our results indicate that in times of uncertainty in the equity market, cryptocurrencies valuations tend to increase during the bull market periods, but show a statistically weaker reaction to uncertainty in the bear markets. This supports our prior Hypothesis 1 that cryptocurrencies can serve as a hedge against the stock market during times of uncertainty, but only in the case of the bull market conditions.

The coefficients estimated magnitudes are small, however, especially during the periods when the coefficient is statistically significant at 95% or better. The US Equity Uncertainty index is extremely volatile with movements of at least 100% occurring monthly and the largest spike reaching approximately 3000% in growth. Equally important, severe volatility spikes took place in the index during the period of the Trump Administration, most notably in December 2016, May–June 2016, June–August 2017, December 2017, and November 2018–January 2019. Because of this, even small changes in market uncertainty can be associated with noticeable changes in asset prices.

4.2. Bitcoin forum sentiment

The ln forumsent variable is also highly statistically significant and positive across both the entire time period under consideration and the two sub-periods relating to the bull and the bear markets. The effect is stronger in magnitude in the bear markets. These results strengthen the theory that a positive sentiment in the cryptocurrencies markets has a positive effect on the price of cryptocurrencies, as postulated in Hypothesis 2. Thus, cryptocurrencies experience an increase in price when sentiments toward their underlying technology, development and price dynamics are positive, and this effect is consistent across both the bull and the bear markets environments. In so far as, as we argued above in Section 3, these results indicate presence of herding effects specific to cryptocurrencies markets, differences in the magnitude of the estimated coefficients suggest that herding is more prevalent in bear markets environments. This is broadly consistent with the traditional view of the four domains of risk aversion as defined in Kahneman and Tversky (1992).

4.3. CBOE Put/Call ratio

The ln putcall variable fails to produce statistically significant results during the bull market run period, providing no support to Hypothesis 3 that 'when investors are mostly bullish in the financial markets, cryptocurrencies will experience an increase in price'. However, the coefficient is statistically positive for the overall sample period and for the bear market sub-period. Thus, herding effects from the general markets to crypto assets appear to be directional and conditional on a bearish sentiment prevailing in the cryptocurrencies. Since the CBOE Put/Call ratio only accounts for puts and calls listed on CBOE exchange, the ln putcall does not fully account for the puts and calls traded in other markets, especially those, where high cryptocurrency investment activity was taking place during the sustained bull market run of 2017–2018, such as Asia and Eastern Europe.

4.4. VIX index

The ln VIX variable was statistically significant. This means that an increase in the VIX index, results in a decrease in the price of cryptocurrencies. The result supports our Hypothesis 4 that cryptocurrencies are negatively correlated with the VIX and that cryptocurrencies are not a hedge against the stock market during times of fear in general. These conclusions hold both across the bull and bear markets. Because of cryptocurrencies' negative correlation to the VIX and similar relationship to equities in instances of market fear, our results imply that it is important for cryptocurrency investors to conduct macro analysis when making investment decisions, even though there is currently no consensus in the academic literature concerning the relationship between macroeconomic fundamentals and crypto assets valuations.

4.5. Robustness

It is important to note some of the potential limitations of our study. Firstly, some of the data we used may have been incomplete in capturing the range of global factors determining the demand for and the supply of cryptocurrencies. Cryptocurrencies are traded internationally with large volumes of trading originating in the United States, South Korea, China, India and Eastern Europe. Considering this, the Bitcointalk.org forum uses primarily English in all its threads. Mapping the comments from this website the sentiment of the overall cryptocurrency market may fail to capture the opinions and sentiments of some

Table 3
Random-effects GLS model results.

	Full data sample			Bull Market period			Bear Market period		
	01/01/2017–02/04/2019			01/01/2017–18/12/2018			19/12/2018–02/04/2019		
	Coefficient	Z test	P-value	Coefficient	Z test	P-value	Coefficient	Z test	P-value
ln uncertainty	0.00396***	3.19	0.001	0.00636**	2.02	0.043	0.0176*	1.84	0.065
ln forumsent	0.0389***	5.21	0.000	0.0381***	3.87	0.000	0.0686***	5.49	0.000
ln putcall	0.0136**	2.13	0.034	−0.0133	−0.60	0.548	0.0153***	2.57	0.010
ln VIX	−0.0458***	−6.19	0.000	−0.0342**	−1.98	0.045	−0.0178***	−3.66	0.000
constant	−0.0287	−1.06	0.288	−0.0562	−0.89	0.371	−0.214***	−4.64	0.000
R-sq:									
- within	0.135			0.057			0.118		
- between	0.194			0.251			0.082		
Overall	0.134			0.064			0.116		

*Denote coefficients that are statistically significant at 10% significance level.
**Denote coefficients that are statistically significant at 5% significance level.
***Denote coefficients that are statistically significant at 1% significance level.

investors. The extent of this bias, however, is ameliorated by the fact that trading in cryptocurrencies involves sufficient familiarity with the trading platforms and financial markets that primarily operate in English. By their nature, cryptocurrencies are also attracting younger and more educated investors. English language is, therefore, less likely to present a meaningful barrier to crypto assets investors in Korea, China and Russia.

Nonetheless, one key area for future research in determining the links between markets and investors sentiment and crypto assets valuations, therefore, should focus on using natural language-based data extraction software to:

1. Better detect sentiment signals in languages other than English,
2. Better identify semiotic and linguistic/cultural markers for sentiment, including those in languages other than English, and
3. Deploying new AI techniques to broaden the sentiment identification process to include non-language signifiers, such as emojis, gifs, and images.

In reference to the positivity and negativity of the comments in the forum sentiment variable, each comment is assigned a value of either +1, −1 or 0 to indicate sentiment. This may not fully reflect the intensity of investors reactions to these comments, even if it captures accurately the general direction of the reaction. Behavioral studies show that negative information can have a greater impact on a person's mood than positive information does. Adding to the aforementioned potential for deploying AI systems to improve sentiment recovery, future research should focus on data extraction systems for:

4. Identifying more granular systemic rankings for sentiment direction and intensity; and
5. Linking this identification to various linguistic, semiotic and cultural environments.

Behavioral finance shows evidence that the strength of sentiment impact on investors can be anchored to the state of the markets, generating asymmetric and unstable reactions, depending on the general markets environment in which the comments are received (Baumeister et al., 2001). Our study confirms some of this evidence by focusing on two very broadly defined market regimes, the bull market and the bear market in crypto assets. Looking forward, it may be more reasonable to explore more sophisticated, and better technologically enabled analytical platforms that AI advances in pattern recognition and automated data analysis support. One productive future avenue can be assessing if and how an assignment of asymmetric values to negative, as opposed to positive, comments and sentiment signifiers and using higher frequency sentiment data extraction can improve our ability to detect market sentiment changes. In part, such innovations can help us assign variable value to negative comments during the periods of small market price declines as opposed to larger market declines, moving this analysis away from focusing on very broadly defined and long run bull/bear markets environments.

5. Conclusions

Dynamic attributes of cryptocurrencies, including the linkages between investor sentiment, investor behavior and crypto assets valuations, are an important issue that impedes this new asset's price discovery in the markets. These aspects of cryptocurrencies increase risks, reduce stability and resilience of hedging properties of this asset class, and drive behavioral biases into investment and trading strategies of investors. More broadly, cryptocurrencies reflect the adverse effects of the early stage (in terms of development and evolution) investment environment that is characterized by volatility, uncertainty, complexity and ambiguity (VUCA) forces in their price dynamics. This makes it harder for investors to identify stable (over time and across markets conditions) macro- and micro-economic determinants of cryptocurrencies prices. These considerations inform the importance of behavioral factors in driving all asset classes valuations.

This research has sought to quantify the relationship between investor sentiment, investors' general perceptions of financial and crypto assets markets uncertainty, and the market value of cryptocurrencies. By consulting existing literature, four emotions of investor sentiment were identified and used in the study. These included fear, uncertainty, positivity/negativity and bullishness/bearishness. In quantifying fear, the CBOE VIX index was used as a proxy for this emotion. Uncertainty was quantified using the US Equity Market Uncertainty Index. Comments made on the forum Bitcointalk.org were aggregated and analyzed for sentiment and then used as the proxy for positivity and negativity in the cryptocurrency market. For bullishness/bearishness in the overall financial markets, the CBOE's Total Put/Call ratio was used.

We show that investor sentiment has an important link to the price direction of cryptocurrencies, and that cryptocurrencies can be used as a hedge against the stock market during times of uncertainty. However, during times of fear, cryptocurrencies do not act as a suitable safe haven against equities. When there is overall positivity amongst cryptocurrency investors, cryptocurrency prices tend to rise, indicating a presence of herding biases amongst crypto assets investors. The overall bullishness/bearishness of the financial markets has an asymmetric impact on the price of cryptocurrencies, suggesting that anchoring and recency biases, if present, are non-linear and environment-specific.

The findings have implications for investors, cryptocurrency adopters and academics. Behavioral finance, sentiment analysis and cryptocurrencies are growing fields that are still developing evidence in support of larger, more fundamentally anchored theoretical frameworks, such as the Fractal Markets Hypothesis (FMH) and the Adaptive Markets Hypothesis (AMH). This study adds to the existing literature, supporting – based on behavioral signals and fundamentals – the key tents of the FMH and AMH. Our analysis also allows us to expand the view as to how artificial intelligence-aided pattern recognition, language-based processing of data and better instrumentation of higher frequency analysis can further investors' understanding of the price formation mechanisms at play in the markets for crypto assets.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Constantin Gurdgiev: Methodology, Validation, Formal analysis, Writing - original draft, Supervision, Conceptualization. **Daniel O'Loughlin:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft.

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