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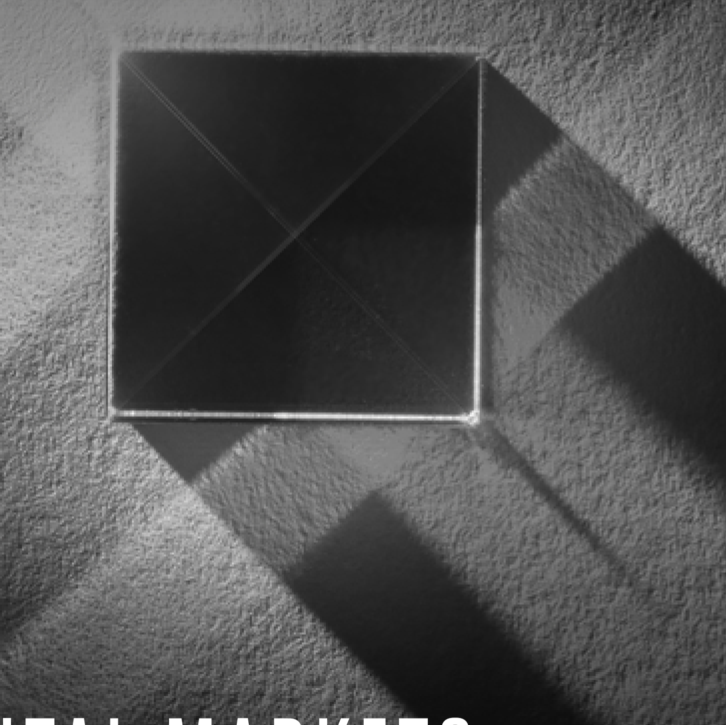

ALTERNATIVE MARKETS

Behavioral basis of cryptocurrencies markets: Examining effects of public sentiment, fear, and uncertainty on price formation

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ALTERNATIVE CAPITAL MARKETS

#49 APRIL 2019

THE CAPCO INSTITUTE

JOURNAL OF FINANCIAL TRANSFORMATION

RECIPIENT OF THE APEX AWARD FOR PUBLICATION EXCELLENCE

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Lance Levy, **Capco CEO**

BEHAVIORAL BASIS OF CRYPTOCURRENCIES MARKETS: EXAMINING EFFECTS OF PUBLIC SENTIMENT, FEAR, AND UNCERTAINTY ON PRICE FORMATION

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ABSTRACT

In recent years, cryptocurrencies have emerged as an exciting, innovative, and highly unorthodox asset class, primarily used for investment and trading purposes by globally-distributed investors. Although cryptocurrencies have attracted significant academic attention, there are currently no credible universally-accepted methodologies for determining their prices and returns. This study explores the use of sentiment analysis to model the effects of four different categories of sentiments towards the cryptocurrency markets to predict the direction of price: positivity/negativity (towards the underlying technology, development, and price of each cryptocurrency) and fear, uncertainty, and bullishness/bearishness in the financial markets. Investor sentiment is shown to successfully predict the price direction of cryptocurrencies, indicating that there is a potential for herding and anchoring biases among investors in crypto assets. Moreover, our analysis shows that cryptocurrencies can be used as a hedge against the stock market during times of market uncertainty, though not necessarily during times of investor fear.

1. INTRODUCTION

Since the second quarter of 2017, investors' interest in cryptocurrencies, and the blockchain technology underlying these new assets, has risen dramatically, stimulated by both the supply of the new crypto assets into the markets and surging cryptocurrency valuations. These developments coincided with the explosive growth in traditional and social media and search activities relating to coverage of the blockchain technologies and cryptocurrencies. Although Bitcoin remains the most well-known and important, in terms of market capitalization, cryptocurrency to-date, numerous sub-classes of crypto assets have emerged, including crypto coins (e.g., Bitcoin, Ethereum, Ripple, Litecoin, Iota, and Cardano), stable coins (cryptocurrencies targeting a pegged relationship to major currencies, namely the U.S. dollar, e.g., Tether and MakerDao), and crypto-tokens (cryptocurrencies backed to specific applications and initial coin offerings or ICOs, such as Tron, Byton, Vechain, and others). In addition, innovative technological applications were also grafted onto existent blockchains (e.g., Bitcoin Cash, Bitcoin Gold, and Bitcoin SV).

By mid-2018, more than 2,000 various cryptocurrencies had been listed on exchanges where billions of dollars' worth of trading volume occurs daily [CoinGecko.com (2018)]. These markets vary in terms of trading platform sophistication, security, regulatory coverage, liquidity, and the degree of anonymity and inter-connectedness within the crypto assets trading universe and with the traditional financial intermediaries.

As of mid-January 2019, total market capitalization of cryptocurrencies traded on specialist exchanges stood at just under U.S.$123.8 billion, with Bitcoin's market cap being U.S.$64.83 billion, followed by Ripple at U.S.$13.75 billion and Ethereum at U.S.$13.48 billion [Coinmarketcap (2018)]. Although Bitcoin's market cap had fallen from U.S.$229.12 billion to U.S.$67.1 billion during 2018, it was still significantly higher than what it was at the beginning of 2017, when its market cap was U.S.$16.05 billion. Aiding market liquidity and price discovery, in December 2017, the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME Group) both launched their own Bitcoin futures products.

The cryptocurrencies asset class has emerged as the new speculative investment vehicle, trading and buy-and-hold asset class for retail and sector-related (crypto assets mining and ICO-issuing) investors. However, despite a large volume of academic and investment (sell-side and buy-side) research into cryptocurrencies, there are no established and agreed methods, or credible tools, that investors can use to analyze and value these assets [Brown (2018)].

From the investment practitioner's perspective, Bitcoin generates no cash flows and investment returns are generated solely through increases in price, hence making them difficult to price. An added complication is that the after-tax returns of cryptocurrencies are subject to different tax regimes based on where the investor is domiciled. For example, under some tax regimes, investors in crypto assets accrue tax liabilities on capital gains arising from trading, not from closing of long positions, which further complicates the practical evaluation of returns of cryptocurrencies. The third issue relates to the poor quality of data reported by the exchanges, especially with regards trading volumes [Koetsier (2018), Sharma (2018)].

While most recent studies find that the markets are now dominated by the buy-and-hold investors [Gurdgiev and Corbet (2018), Wilson (2018), and Celeste et al. (2018)], given the chances of earning massive profits from buying cryptocurrencies, the herd mentality still remains prevalent within the market [Bishop (2017), Kharpal (2018)]. Consequently, from a purely behavioral perspective, an increasingly promising methodology for modeling demand for crypto assets is through capturing herding and other behavioral aspects of the investors' choices via sentiment analysis ("opinion mining"), which provides information on revealed preferences for an asset by actual and potential investors.

This study applies sentiment analysis to the cryptocurrency market. It is hypothesized that some of the sentiment factors that affect stock prices also affect cryptocurrency prices. We further hypothesize that since there is a lack of deep fundamentals pricing in cryptocurrencies markets, behavioral considerations of individual investors should dominate. As the result, we test whether the behavioral implications of sentiment have a greater impact on cryptocurrencies than on liquid assets such as equities. Given that the market is dominated by novice investors, cryptocurrencies should be more prone to irrational decision-making due to behavioral biases [Baker and Ricciardi (2014)].

In this article, we apply investor sentiment identification methods to the ten largest cryptocurrencies (based on their market capitalizations as of the end of May 2018 – the period that captures the markets with significant presence of retail and novice investors an precedes the sustained and large-scale sell-off in the markets that began in the second half of 2018). Our aim is to identify some of the behavioral factors that may affect the price of cryptocurrencies.

We consider the following behavioral factors:

- **Fear:** as measured by the market "fear index" (VIX).
- **Uncertainty:** as measured by the U.S. Equity Market Uncertainty index (EMUI).
- **Positivity/negativity:** as measured by using the opinions of the Bitcointalk.org forum participants.
- **Bullishness/bearishness:** in the overall financial markets, as measured by the CBOE put/call ratio.

Fear, uncertainty, and bullishness/bearishness are three behavioral or sentiment factors that directly impact the equity markets and indirectly other risky assets, including cryptocurrencies. In contrast, positivity/negativity sentiment is reflective of the investor sentiment specific to crypto assets.

We use a panel-data regression model based on the behavioral factors mentioned above. The sample used consists of daily observations from January 1, 2017 to May 9, 2018, excluding weekends and public holidays (i.e., 340 days). This time window allows us to analyze the dynamics of the cryptocurrency markets as characterized by significant change in holdings from the early crypto adopters/enthusiast investors to the increased interest from retail investors through the second half of 2017.

After addressing issues with stationarity and heteroscedasticity, a generalized least squares model with robust standard errors and log transformed variables is used to examine short-term price-sentiment relationships.

The study makes three contributions to the broader literature on the investment aspects of cryptocurrencies. Firstly, many of the published quantitative studies of cryptocurrencies specifically focus on Bitcoin, or the top three cryptocurrencies, including (usually) Bitcoin, Ehtereum, and Ripple. While cryptocurrencies are heavily correlated to the price of Bitcoin (see Table 2 in the data section below), adding more cryptocurrencies increases the robustness of the study. This study uses Bitcoin and nine other cryptocurrencies in a panel-data regression model that covers more than 90% of the entire value of the cryptocurrencies market. Secondly, behavioral finance and sentiment analysis are a growing field of research, with to-date minimal application to the crypto assets. Thirdly, use of behavioral indicators, such as sentiment factors, allows for a different view of the overall market framework, complementary to the Fractal Markets Hypothesis (FMH) but contrasting with the Efficient Markets Hypothesis (EMH). The former is increasingly being shown to be of descriptive value in the case of crypto assets as compared to the latter [Celeste et al. (2018), Gurdgiev and Harte (2018)].

2. REVIEW OF THEORETICAL AND EMPIRICAL LITERATURE

The cryptocurrency market has received a great deal of interest in recent years, and especially since the start of the bull markets in crypto assets around the end of the first half of 2017, followed by the large-scale bear market and crash that followed from the late January 2018.[1]

2.1 The FMH, EMH, and crypto assets

Much of the contemporary financial theory rests on the foundations of EMH, which states that current prices reflect available information [Fama (1970)]. The EMH forms the very basis of the rational models in financial analysis, models based on the underlying assumption that representative agents act as rational investors with some degree of foresight, precluding behavioral biases from systemically influencing market prices. What kind of information the prices reflect is determined by which version of EMH one subscribes to.[2] EMH allows one to treat market prices as random processes that do not convey any useful information about the future of the market.

If, however, price series are characterized by long-memory processes (processes that retain the effects of new information arrival over time during the price adjustment process), they are not independently distributed but follow patterns that could be detected and exploited [Cajueiro and Tabak (2004)], violating EMH fundamentals.

Given the long-memory consistent nature of financial markets, several alternatives to EMH have been produced over the years. The better-known alternative hypotheses include Adaptive Market Hypothesis (AMH) [Lo (2005)], which applies the principles of evolution of biological organisms to financial markets, and Fractal Market Hypothesis (FMH), postulating that markets have a self-similar structure that ensures their stability [Peters and Peters (1994)].

FMH is of particular importance when considering long-term effects of markets behavior or memory processes, and thus the more suitable framework for thinking about cryptocurrencies markets. FMH states that markets are fractal when there is sufficient liquidity provided by participating investors. Investors must have heterogeneous time horizons and investment expectations to provide liquidity. In other words, investors can be driven by behavioral biases, such as herding, anchoring, recency,

[1] At the start of January 2019, Bitcoin was down almost 80.2% on its peak, although still up 310.5% on the levels at the start of January 2017.

[2] Generally, the "strong" form of EMH states that all information, public and private, is reflected in stock prices, while the "weak" form states that markets reflect all past market information. "Semi-strong" levels of efficiency fall somewhere in between the two extremes, positing rapid adjustments to market as well as to fundamental, economic, and market-related information.

etc. Investors interpret market information differently, because they have different goals, which makes them differentially attentive to different type of news. Market bubbles and crashes are explainable under FMH: certain investment horizons become dominant, which creates an imbalance between buyers and sellers, impacting liquidity supplied to the markets, and sends asset prices exponentially higher, or plunging.

Since cryptocurrencies constitute a novel asset class, they simultaneously raise questions regarding informational efficiency, data quality, and behavioral biases that pivot on these considerations. They also present an exciting case regarding the choice of an appropriate theoretical framework that can aid our understanding of the price formation mechanisms.

Celeste et al. (2018) provide a detailed summary of literature and empirical evidence, including own data analysis, to support the application of FMH to the cryptocurrencies, in contrast to EMH. From our point of view, the validity of the FMH framework in cryptocurrencies markets analysis lends additional robustness to the study of the impact of sentiment and behavioral factors on crypto assets valuations.

2.2 Sentiment analysis overview

Behavioral research has shown that both information and emotion play an important role in human decision-making [Dolan (2002), Kahneman and Tversky (1979)], and influencing investment choices [Nofsinger (2005)]. Using this knowledge, Bollen et al. (2011) used 9.8 million public tweets sent in 2008, creating a sentiment dataset, to investigated whether public mood is correlated to the Dow Jones Industrial Average or DJIA (as a proxy for the stock market). The results showed that the daily changes in the DJIA could be predicted by the public mood sentiment analysis with 86.7% accuracy. Guo et al. (2017) show that, while not always, investor sentiment can predict stock prices.

Cryptocurrency enthusiasts are very active on social networks, such as Twitter and Reddit, as well as on specialist forums, such as Bitcointalk.org, and their interactions, while reflective of the investor sentiment, can have both first and second order effects on the pricing of cryptocurrencies. The first order effects can relate to the immediate mood or sentiment status of the market's participants. A positive average sentiment across all investors can have the effect of reflecting the bullishness of the investors.

The second order effects are more varied. Firstly, there is a selection bias, similar to the effects of long-only investors in the CAPM setting with heterogeneous beliefs [He and Shi (2007)]. More bullish investors can dominate negative sentiment investors, skewing the demand and pricing observed in the markets towards the former. Secondly, indirect effects of current sentiment can be transmitted through sentiment anchoring (implying potentially autoregressive nature of sentiment and its effects on demand for and pricing of cryptocurrencies). Thirdly, to the extent that sentiment itself is anchored in investors cross-referencing each other through social media forums, there can be positive reinforcement of sentiment within these venues that can support complex pricing dynamics, including pump-and-dump schemes that have been previously detected in the crypto assets markets.

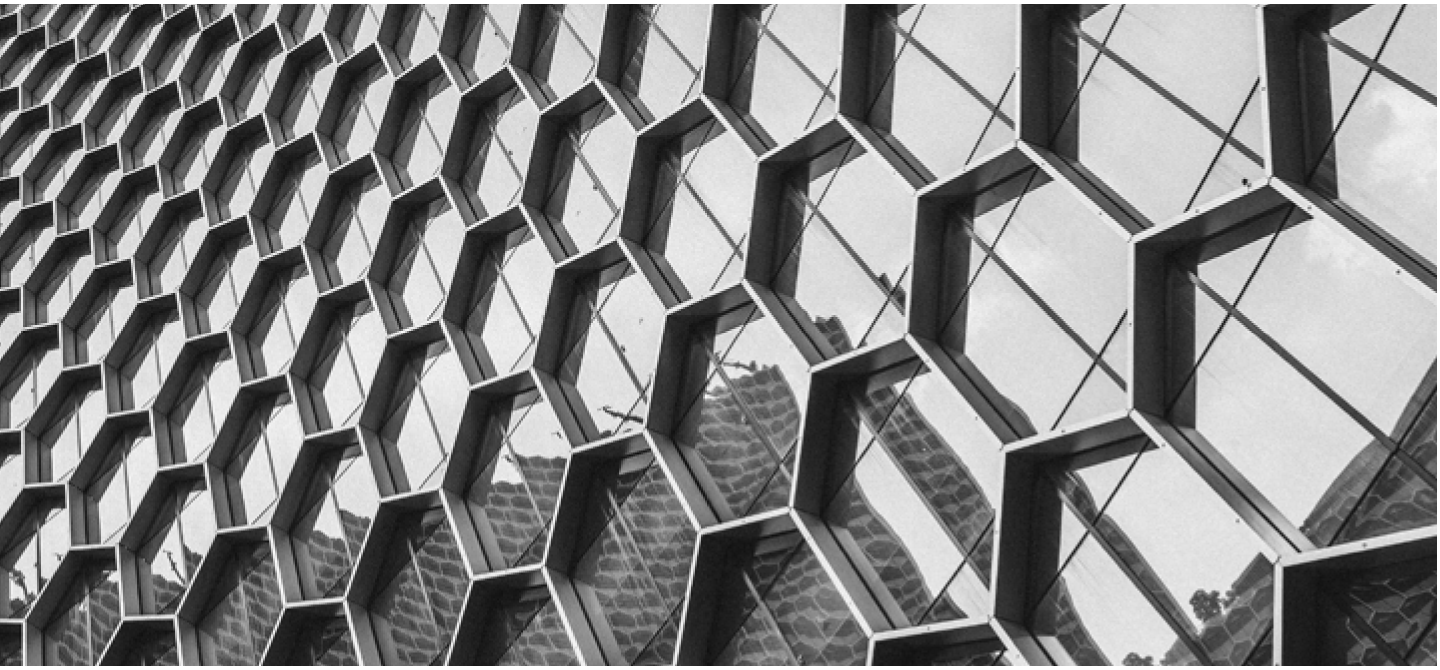
It could also be argued that the accuracy and quality of the information being communicated declines as information progresses through social media channels, where people's motives and interpretations differ, further influencing the decisions of readers. Baker and Wurgler (2007) studied the relevancy of investor sentiment and discovered that companies that were young, unprofitable, highly volatile, and had low market capitalization were very sensitive to investor sentiment. From a theoretical perspective this makes sense, since valuing these stocks is more difficult, which would make biases more "insidious" and increase the chances of valuation mistakes. This increases the value of information concerning these stocks to investors, but also increases the noise component in the information set. Cryptocurrencies are similarly young, unprofitable (profits mostly come from capital gains, similar to gold, but are harder to book due to lower liquidity and higher trading costs, and tax treatment of trading in cryptocurrencies), and highly volatile. In other words, cryptocurrencies have a similar disposition to sentiment as stocks with low liquidity.

Many of the studies find that investor sentiment is significant in predicting prices. However, it is important to note that much of the literature on the subject focuses on one country or region, which reduces their application to cryptocurrencies, as they are traded and held globally. Controlling for the single country bias, Zouaoui et al. (2011) find that countries with lower institutional investors' involvement are more susceptible to stock price movements occurring due to changes in the investor sentiment. With regards to cryptocurrencies, while some hedge funds are introducing cryptocurrencies to their portfolios, the majority of traditional institutional investors have hardly made a material impact on the cryptocurrency market [Kharpal (2017)]. Considering these facts, investor sentiment could be a significant factor in the price movement of cryptocurrencies, to a far greater extent than their impact on other, more liquid, more geographically isolated, and more established asset classes, such as equities.

In applying sentiment data to predicting stock prices, Heston and Sinha (2017) explored textual processing and its usefulness in predicting stock returns. The study concluded that news on a daily basis can predict stock returns for one to two days. However, news taken on a weekly basis can predict stock returns for one quarter. If the news stories are positive, then a quick increase in price is expected, but the study also found that prices have a long-delayed reaction after the release of bad news. For this study, textual processing similar to the kind used in Heston and Sinha (2017) is applied to comments made on cryptocurrency forums rather than in general news forums/venues. For robustness, we pair this with indices that measure broader markets sentiment.

2.3 Social media positivity in the markets

In discovering whether increased attention towards, and popularity of, cryptocurrencies is a driver of prices, Bouoiyour and Selmi (2015) looked at Bitcoin's association with investors' attractiveness to Bitcoin, its exchange-trade ratio, its monetary velocity, its estimated output volume, the hash rate, the price of gold, and the Shanghai market index. Their study is interesting since it presents several factors that may influence prices. Their study showed that around 20% of Bitcoin's price is driven by investors' attractiveness to Bitcoin, as determined by the volume of Google search queries. The other variables in the study have an insignificant impact on price except for the Shanghai market index, which accounts for approximately 10% in Bitcoin price variation. While the results indicate that positive sentiment (conveyed through the variable: "attractiveness to Bitcoin") affects Bitcoin's price, the authors showed that the remaining 70% of Bitcoin's price movements is explained by "its own innovative shocks," which is an ambiguous explanation, effectively relying on using the residual as the signal of systemic unexplained component of price formation.



Kristoufek (2015) looked into the Google Search data and Wikipedia searches for the term "Bitcoin." The study showed that both search engines provide similar information. During the price bubble that took place in the first quarter of 2013, the price of Bitcoin was actually led by increased interest. A similar dynamic appeared for the second bubble that started in October 2013, although those findings were not statistically reliable. When the crash of the first 2013 bubble occurred, an increase in interest still correlated to the price of Bitcoin, however, it interestingly converted to being negatively correlated. Ciaian et al. (2016) mention several studies that suggest new investors' decisions to go long cryptocurrency might become altered by the influence of public attention (e.g., attention in forums). New investors favor those investments that are under the influence of public attention because such attention reduces search costs. This availability bias then triggers a high price response due to an increase in demand. The study furthers the argument that cryptocurrency prices may be influenced by comments on popular specialist social forums, such as bitcointalk.org.

> "...cryptocurrencies can be used as a hedge against the stock market during times of uncertainty, although not during times of fear."

Adding to the literature regarding social media and how it affects cryptocurrency prices, Martina et al. (2015) analyzed 1.9 million tweets mentioning Bitcoin and spanning 60 days to see if the sentiment analysis of the tweets was associated with Bitcoin's prices. The results affirmed that positive tweets may be used to predict changes in Bitcoin prices three to four 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. Li et al. (2018) also examined tweets as a medium for investor sentiment to predict the price movement of one small-cap cryptocurrency called ZClassic. 130,000 tweets were gathered, analyzed, and then assigned a value of either positive, negative, or neutral. They found that using sentiment analysis of tweets proved successful in predicting the price movements of ZClassic. The range of data only spanned 3.5 weeks.

Kim et al. (2016) showed that through the sentiment analysis of cryptocurrency forums, investors can predict, in part, price changes for Bitcoin, Ethereum, and Ripple. The fluctuation in the price of Bitcoin was significantly correlated with the amount of topics, positive comments, and replies made on the Bitcointalk.org forum. This result was stronger (with an accuracy of 79.6%) when a lag of six days was applied to sentiment variables. Ethereum and Ripple also showed significant results. However, the forums used for analyzing the sentiment, forum.ethereum.org and xrpchat.com, are exclusive to these two cryptocurrencies. This may create a bias in the data because these forums will only contain the opinions and comments of registered users, who likely signed up because they are interested in that particular cryptocurrency. A forum that invites discussion regarding all cryptocurrencies might be more suited to this type of sentiment analysis, since it will likely invite more discussion from people with negative sentiment towards the respective cryptocurrencies.

Phillips and Gorse (2018) considered four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Monero) and used the discussion forum Reddit (which has a large cryptocurrency user base) to investigate if the amount of posts per day, subscriber growth, and amount of new authors per day is correlated with price. Their study also included Google search volume and Wikipedia view data. By using wavelet coherence analysis, they found that in the short term, increases in online activity led to a decrease in price. In the medium term, online activity is positively correlated with changes in price. It also found that Wikipedia views lacked consistency and that the data from Reddit proved to be a better predictive indicator in the long term.

Mai et al. (2018) tested the predictability of Bitcoin price by analyzing the sentiment in posts regarding Bitcoin on Twitter and the Bitcointalk.org forum using a python script and the Natural Language Toolkit 3.0. The results proved that days with more positive posts preceded days with increases in Bitcoin price. One additional positive forum post was associated with a rise of 3.53 basis points in the price of Bitcoin the following day.

The Natural Language Toolkit 3.0, while proven effective in analyzing sentiment, may not be the best application in studying sentiment of cryptocurrencies. This is due to the specific vocabulary, slang, and acronyms associated with cryptocurrencies. The methods used in our study, in contrast to Mai et al. (2018), address this problem by manually building a lexicon that includes crypto-specific words and applying this to the same forum used in the Mai et al. (2018) study, Bitcointalk.org. In addition, we cover a larger set of cryptocurrencies. Similar to some of the studies mentioned above, applying a positive, negative, and neutral value to each comment appears to be an appropriate way of measuring investor sentiment found in the cryptocurrency forums.

2.4 Fear and uncertainty in the markets

Ciaian et al. (2016) also incorporated macroeconomic and financial developments in their study. The authors rely on Dimitrova (2005), which explores how a decrease in the price of stocks causes foreign investors to sell financial assets that they hold. In turn, this creates a depreciation of the respective currency. However, according to Ciaian et al. (2016), this may stimulate the price of Bitcoin if investors exchange their stock investments with investments in Bitcoin if it is viewed as a safe haven or a hedge for currencies. Consequently, stock market indices have an expectation to be negatively correlated with the price of Bitcoin. Bouri et al. (2016) found that Bitcoin had an inverse relationship with the U.S. VIX, but that its hedging capabilities existed only until the Bitcoin crash of 2013. Based on methodology developed in Ciner et al. (2013), Bitcoin could have potentially acted as a safe haven for VIX prior to the crash of 2013.

Contrary to the belief that Bitcoin cannot be used as a hedge, Dyhrberg (2016) explored the its hedging capabilities by using a GARCH (or Generalized Autoregressive Conditional Heteroscedasticity) model. The results show that Bitcoin does have safe-haven properties when used against the FTSE index as well as the U.S. dollar in the short-term. Baur et al. (2015) found that Bitcoin can act as a hedge against traditional assets such as equities, precious metals, currencies, energy instruments, and bonds. Bouoiyour and Selmi (2015) suggest that while Bitcoin can be used as a hedge in the short-term, it is far from being a safe-haven asset. Notably, these studies pre-date Bitcoin and crypto assets' explosive dynamics over 2017-2018 period.

In light of the aforementioned findings, it seems appropriate to look at the hedging potential for cryptocurrencies against market fear proxies. We do so below by integrating the CBOE's VIX index into our analysis.

Kristoufek (2015) also found no evidence of Bitcoin being a safe haven asset after observing its relationship with the Financial Stress Index (FSI) and price of gold in Swiss francs – the former being a proxy for financial uncertainty and the latter being considered a safe-haven in itself. According to the study, when uncertainty increases, the price of Bitcoin also increases. However, there are few long-term intervals that produce statistically significant results, and this undermines the overall result. The instability of hedging relationships is a feature commonly linked to higher measures of uncertainty (as opposed to volatility) in market environments. From this point of view, it may also be interesting to look at the U.S. Equity Uncertainty Index, in addition to volatility index or VIX, which tracks financial uncertainty, to see if a different indicator of uncertainty may generate statistically significant results.

Following Kristoufek's (2015) study on the sentiment of uncertainty, Chulia et al. (2017) used the U.S. EMUI to see how uncertainty affects emerging and mature markets. Using daily data from 1998 to 2016, they found that spikes in uncertainty reduce stock market returns. Bouri et al. (2017) used Bitcoin price data and a global volatility index data to determine how it is impacted by uncertainty. They found that, similar to the equity market, Bitcoin does act as a hedge against uncertainty. Again, it would be interesting to see if the EMUI has a symmetric effect on a broader universe of crypto assets.

In summary, it appears that the price of cryptocurrencies could be influenced by uncertainty. To explore this, uncertainty is introduced in this study using the U.S. Equity Market Uncertainty index, as it provides daily data and its correlation with cryptocurrencies has as yet not been investigated.

2.5 Bullishness/bearishness in the markets

Mao et al. (2015) studied the effect of online bullishness on international financial markets, finding that both Twitter and Google bullishness not only have a positive correlation to investor sentiment, but also have a lead on established investor sentiment surveys. It was also shown that high levels of bullishness on Twitter can be used to predict stock return increases.

Bandopadhyaya and Jones (2008) investigated the use of the CBOE put/call ratio (PCR) in analyzing 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 investor sentiment, it was concluded that the PCR approximates non-economic factors that may drive price changes better than the VIX, and thus act as a better measure of market sentiment. Our study focuses on the PCR's correlation with the cryptocurrency market.

3. DATA COLLECTION AND PRELIMINARY ANALYSIS

The data used in this paper are sourced from CoinGecko, CBOE, Bitcointalk.org, and FRED. The data is collected from January 1, 2017 to May 9, 2018. The reason for this timeframe is because there is little or no forum participation before 1st January 2017. The frequency of the data is daily. The cryptocurrencies used in the study were: Bitcoin, Ethereum, Ripple, Litecoin, NEM, Dash, Monero, Lisk, Verge, and Stratis. Some cryptocurrencies have been omitted from the actual top ten digital currencies, as per their market capitalizations, because they either did not exist in January 2017, or the cryptocurrency represented a "fork" or a spin-off of the original (e.g., Ethereum Classic).[3]

3.1 Explanatory variables

The U.S. Equity Uncertainty Index is used as a measure of uncertainty in the U.S. equity markets [Baker et al. (2013)]. Data for Cryptocurrency Forum Sentiment was extracted from the comments on the popular cryptocurrency forum Bitcointalk.org, using web-crawler platform Import.io as follows: for each comment made it received a score of +1, -1 or 0 depending on whether it was positive, negative, or neutral toward cryptocurrency price dynamics. When extracting the forum data, quotes were removed to avoid double-counts of the same comment. Once all the comments were collected, they were analyzed for whether they were positive, negative, or neutral comments. We addressed the issues raised in Loughran and McDonald (2011), who show that using general sentiment analysis on topics in accounting and finance leads to high rates of misclassification, by using a lexicon-based sentiment analyzer specifically created for the purpose of this study, using the Loughran-McDonald master dictionary. We also manually tested the sentiment analyzer to confirm its accuracy in detecting the general mood of comments in the discussion threads. The CBOE PCR was used as a bullish/bearish sentiment indicator: when the ratio is rising, it suggests that investors believe the market is declining [Qian (2009)]. Lastly, the VIX or the "market fear gauge," an index quoted by the CBOE, was used as a benchmark measure of expected short-term (30 days forward) volatility [Whaley (2009)].

Table 1: Descriptive statistics of the variables

VARIABLE	N	MEAN	STANDARD DEVIATION	SKEWNESS	KURTOSIS	MIN	MAX
BITCOIN	340	5537.432	4533.999	0.9951446	3.223341	784.28	19188.05
ETHEREUM	340	366.0573	314.8953	0.9253896	3.139247	9.6268	1361.44
DASH	340	336.4864	304.2355	1.35203	4.583646	11.2054	1493.591
LISK	340	7.197206	8.062563	1.265486	3.65157	0.101672	32.74986
LITECOIN	340	81.97478	80.38994	1.172157	3.604904	3.734	360.662
MONERO	340	126.7323	120.109	0.9846647	2.912851	11.198	542.3255
NEM	340	0.2838645	0.3171296	2.336845	9.328439	0.0032964	1.794839
RIPPLE	340	0.4171065	0.5135199	2.386356	10.41572	0.005376	3.22005
STRATIS	340	5.057671	4.348135	1.12152	4.552691	0.048092	22.76509
VERGE	340	0.0253526	0.0421381	2.130654	7.452737	0.0000104	0.2071443
UNCERTAINTY	340	26.59985	52.6277	7.418349	68.87616	4.94	591.21
FORUMSENT	340	-0.1205882	1.686364	-0.7488451	5.491211	-8	5
PUTCALL	340	0.9270294	0.1288307	0.6000725	4.301916	0.64	1.54
VIX	340	12.738	4.061839	2.415084	10.46591	9.14	37.32

[3] The cryptocurrency prices are skewed and have a high kurtosis, warranting a log transformation of the raw data.

Table 2: Correlations between cryptocurrencies

	BITCOIN	ETHEREUM	DASH	LISK	LITECOIN	MONERO	NEM	RIPPLE	STRATIS	VERGE
BITCOIN	1.0000									
ETHEREUM	0.8695	1.0000								
DASH	0.9560	0.8795	1.0000							
LISK	0.8479	0.9562	0.8803	1.0000						
LITECOIN	0.9402	0.9037	0.9256	0.8960	1.0000					
MONERO	0.9528	0.9378	0.9452	0.9336	0.9614	1.0000				
NEM	0.8162	0.8755	0.8852	0.8591	0.8247	0.8604	1.0000			
RIPPLE	0.7777	0.8779	0.8197	0.8844	0.8267	0.8627	0.9374	1.0000		
STRATIS	0.7882	0.8735	0.8468	0.8034	0.7896	0.8131	0.9126	0.8314	1.0000	
VERGE	0.7621	0.8185	0.8107	0.8606	0.8177	0.8554	0.8837	0.9143	0.7657	1.0000

3.2 Transforming the data

A log transformation of each variable was taken. The motivation behind this was to:

1. Narrow the scale of data to lessen any non-linearity (creating more reliable results).

2. Neutralize the mostly-positive skewness and lower the high kurtosis as seen in Table 1 above.

To test the variables for stationarity, two-unit root tests were conducted including the Augmented Dickey-Fuller test and the Phillips-Perron test. The results of the unit root tests indicated presence of a unit root in the LnPrice variable but not in any of the other variables. In solving the non-stationary LnPrice variable, we first-difference the variable [Engle and Granger (1987)], making the LnPrice variable stationary.

3.3 Descriptive statistics

The descriptive statistics and correlation matrices for the variables are presented in Table 1. Table 2 shows the correlation matrix between the ten different cryptocurrencies chosen for this study.

As expected, all ten cryptocurrency variables show high volatility – with standard deviations lying close to the mean and large dispersions between the minimum and maximum observations present. The correlation matrix between the ten cryptocurrencies shows a high correlation between them all. This implies that when one cryptocurrency rises, other cryptocurrencies tend to rise at the same time, and adds to the robustness of the study in terms of choosing a panel data model.

4. MAIN RESEARCH HYPOTHESIS AND RESULTS

The primary objective of this research is to create an econometric model and conduct a panel data regression analysis that explores the significance of investor sentiment on the price movement of cryptocurrencies using four independent variables.

Hypothesis 1: Investor sentiment has predictive power over the price of cryptocurrencies. Under conditions of rising market uncertainty, we expect that the price of cryptocurrencies should rise [Kristoufek (2015), Bouri et al. (2017), Sarwar (2017)]. This hypothesis implies that cryptocurrencies can act as a short-term hedge or a flight-to-safety asset against the stock market during the times of elevated market uncertainty.

Hypothesis 2: Cryptocurrencies are a hedge against the stock market in times of uncertainty. The positive and negative sentiment of the cryptocurrency market in this study is conveyed using the sentiment captured from the cryptocurrency forum Bitcointalk.org. Using this as the proxy for overall market sentiment, it is hypothesized that when the sentiment of the market is positive, the price of cryptocurrencies should increase. Our forum sentiment hypothesis adapts the theory of the herding behavioral biases, which owes its roots to Keynes (1930), and the general herding literature in finance.

Table 3: Random-effects model regression results

DEPENDENT VARIABLE:	d_*ln*price		
INDEPENDENT VARIABLES:	COEFFICIENT	Z-SCORE	P-VALUE
*ln*uncertainty	0.006125	2.34	0.019[b]
*ln*forumsentiment	0.048116	4.74	0.000[a]
*ln*putcall	0.007496	0.65	0.515
*ln*VIX	-0.039498	-9.16	0.000[a]
Constant	-0.078847	-2.00	0.046[b]
Random effects GLS	Number of observations	3390	
	Number of groups	10	
R-Sq	Within	0.0119	
	Between	0.0587	
a, b, c are significant levels at 1%, 5%, and 10%, respectively			

Hypothesis 3: Cryptocurrencies experience an increase in price when sentiment towards its underlying technology, development, and price is positive. It is hypothesized that an increase in bullishness in the financial markets (a decrease in the CBOE PCR) will result in an increase in the price of cryptocurrencies [Mao et al. (2015), Bandopadhyaya and Jones (2008), Li and Wang (2017)].

Hypothesis 4: When investors are mostly bullish/bearish in the financial markets, cryptocurrencies will experience an increase/decrease in price. In following the literature, it can be assumed that, similar to stocks, a rise in the VIX will result in a fall in price of cryptocurrencies [Ciaian et al. (2016)]. This is because fear can be assumed to be a more serious and negative emotion than uncertainty, and when investors are in fear with respect to the direction of the stock market prices, they will be apprehensive in investing their money in any risky asset, including cryptocurrencies.

Hypothesis 5: Cryptocurrencies are not a hedge against the stock market during times of fear.[4] From a methodological point of view, we specify a panel data model that will allow us to test the hypotheses stated above.[5]

The following is the formal representation of the model:

$$\Delta ln\text{price}_{it} = \beta_1 + \beta_2\, ln\text{uncertainty}_{it} + \beta_3\, ln\text{forumsentiment}_{it} + \beta_4\, ln\text{putcall}_{it} + \beta_5\, ln\text{VIX}_{it} + \omega_{it} \quad (1)$$

where:

$$\omega_{it} = \varepsilon_{it} + u_{it} \quad (2)$$

The composite error term 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.

"Δ*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*uncertainty," which is the log of the U.S. Equity Uncertainty Index. "*ln*forumsentiment" represents the log transformation of the Bitcointalk.org forum's sentiment results and also includes the constant as mentioned in section 3.3 above; "*ln*putcall" is the log transformation of the CBOE PCR data and "*ln*VIX" is the log transformation of the VIX index.

Based on implementation of the GLS model for random effects panel data estimation, we obtain the results presented in Table 3.

The "*ln*uncertainty" variable shows a statistically significant result with a p-value of 0.019. This implies that an increase in the U.S. EMUI results in a small increase in the cryptocurrencies prices. This supports the hypothesis that cryptocurrencies are a potential hedge or a flight-to-safety/safe haven against the stock market during times of uncertainty.

The "*ln*forumsentiment" variable is also highly statistically significant with p-value 0, implying that positive investor sentiment has a positive effect on the price of cryptocurrencies.

The "*ln*putcall" variable p-value of 0.515 fails to produce statistically significant results, providing no support for the hypothesis that "when investors are mostly bullish in the financial markets, cryptocurrencies will experience an increase in price." An explanation for this may be because the CBOE PCR only accounts for puts and calls on its own exchange and does not account for those traded on other exchanges and geographical markets, where high cryptocurrency purchasing participation is taking place, such as Asia and Europe.

[4] In dealing with hedging or flight-to-safety/safe haven hypotheses, we refer to Ciner et al. (2013) methodology.

[5] Tests used in deriving the optimal specification for the model are available from the authors upon request.

The "*ln*VIX" variable was statistically significant with a p-value of 0. The result supports the hypothesis and current literature that cryptocurrencies are negatively correlated to the VIX and that they are not a hedge against the stock market during times of fear. Because of cryptocurrencies' negative correlation to the VIX and similar relationship to equities in instances of fear, this would imply that it is important for cryptocurrency investors to conduct global macro analysis when making investment decisions.

5. CONCLUSION

Dynamic attributes of cryptocurrencies, such as volatility and uncertainty, are important issues that impede this new asset's growth because they increase risks, reduce stability and resilience of hedging properties, and drive behavioral biases into investment and trading strategies and actions of investors. Today, cryptocurrencies and broader crypto assets reflect the adverse effects of an investment environment that is characterized by volatility, uncertainty, complexity, and ambiguity (VUCA). Consequently, it is almost impossible to identify stable (over time and across markets conditions) macro- and microeconomic determinants of cryptocurrencies prices.

This research has sought to quantify the relationship between investor sentiment and the monetary value of cryptocurrencies. The hypotheses addressed span behaviorally rich areas of investors' sentiments and the perceptions of market uncertainty. Based on the existing literature on behavioral finance, four emotions of investor sentiment were identified: fear (across all financial markets, as proxied by the CBOE VIX index), uncertainty (across the U.S. equity markets, as measured by the U.S. EMUI), positivity/negativity sentiment toward cryptocurrencies (based on specialist fora comments relating to crypto assets), and bullishness/bearishness across the broader financial markets (as measured by the CBOE's Total PCR).

From examining the results, investor sentiment can be used to predict the price direction of cryptocurrencies. Moreover, the results indicated that cryptocurrencies can be used as a hedge against the stock market during times of uncertainty, although not during times of fear. When there is an overall positivity in the cryptocurrency marketplace amongst investors and cryptocurrency enthusiasts, a rise in cryptocurrency prices is expected. Likewise, when sentiment turns sour, prices do tend to fall. This suggests that there is a strong presence of herding biases in the behavior of cryptocurrency investors. Finally, it was shown that the overall bullishness/bearishness of the financial markets does not have an impact on the price of cryptocurrencies, suggesting that anchoring and recency biases, if present, are non-linear and potentially environment-specific.

The findings presented in this study have implications for investors, cryptocurrency adopters, and academics. From an investor's point of view, the results from this under-researched branch of investment analysis can be used to build on the information already presented in previous studies of the subject and improve the accuracy with which the price direction of cryptocurrencies is predicted. This information is also useful to cryptocurrency adopters, in that it helps them understand the different forms of sentiment and their relationships with cryptocurrencies.

REFERENCES

Baker, K. H., and V. Ricciardi, 2014, "How biases affect investor behavior," European Financial Review February-March, 7-10

Baker, M., and J. Wurgler, 2007, "Investor sentiment in the stock market," Journal of economic perspectives, 21:2, 129-152

Baker, S. R., N. Bloom, and S. J. Davis, 2013, "U.S. equity market uncertainty index," Economic Policy Uncertainty, https://bit.ly/2nX0d9l

Bandopadhyaya, A., and A. L. Jones, 2008, "Measures of investor sentiment: a comparative analysis put-call ratio vs volatility index," Journal of Business and Economics Research 6:8, 27-34

Baur, D. G., Hong, K. J., and A. D. Lee, 2015, "Bitcoin – currency or asset?" Melbourne Business School, 2016 Financial Institutions, Regulation & Corporate Governance (FIRCG) Conference, https://bit.ly/2TpMMgl

Bishop, J., 2017, "Meet the man traveling the world on $25 million of bitcoin profits," Forbes, July 7, https://bit.ly/2WDqPg3

Bollen, J., H. Mao, and X. Zeng, 2011, "Twitter mood predicts the stock market," Journal of Computational Science 2:1, 1-8

Bouoiyour, J., and R. Selmi, 2015, "What does bitcoin look like?" Annals of Economics & Finance 16:2, 449–492

Bouri, E., G. Azzi, and A. H. Dyhrberg, 2016, "On the return-volatility relationship in the Bitcoin market around the price crash of 2013," Economics Discussion Papers no. 2016-41, Kiel Institute for the World Economy (IfW), Kiel, https://bit.ly/2DOq2RS

Bouri, E., R. Gupta, A. K. Tiwari, and D. Roubaud, 2017, "Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions," Finance Research Letters 23, 87-95

Brown, A., 2018, "How to make sense of cryptocurrency valuations," Bloomberg, April 17, https://bloom.bg/2TrTAdB

Cajueiro, D. O., and B. M. Tabak, 2004, "The Hurst exponent over time: testing the assertion that emerging markets are becoming more efficient," Physica A: Statistical Mechanics and its Applications 336, 521–537

Celeste, V., S. Corbet, and C. Gurdgiev, 2018, "Fractal dynamics and wavelet analysis: deep volatility properties of bitcoin, ethereum and ripple," working paper, https://ssrn.com/abstract=3232913

Chulia, H., R. Gupta, J. M. Uribe, and M. E. Wohar, 2017, "Impact of U.S. uncertainties on emerging and mature markets: evidence from a quantile vector autoregressive approach," Journal of International Financial Markets, Institutions & Money 48, 178-191

Ciaian, P., M. Rajcaniova, and D. Kancs, 2016, "The economics of bitcoin price formation," Applied Economics 48:19, 1799-1815

Ciner, C., C. Gurdgiev, and B. Lucey, 2013, "Hedges and safe haves: an examination of stocks, bonds, gold, oil and exchange Rates. International Review of Financial Analysis 29:C, 202-211

CoinGecko.com, 2018, CoinGecko, https://www.coingecko.com/en

Coinmarketcap, 2018, https://coinmarketcap.com/

Dimitrova, D., 2005, "The relationship between exchange rates and stock prices: Studied in a multivariate model," Issues in Political Economy 14(1), 3-9

Dolan, R., 2002, "Neuroscience and psychology: Emotion, cognition, and behavior," Science 298:5596, 1191-1194

Dyhrberg, A. H., 2016, "Hedging capabilities of bitcoin. Is it the virtual gold?" Finance Research Letters 16, 139-144

Engle, R. F., and C. Granger, 1987, "Co-integration and error correction: representation, estimation, and testing," Econometrica 55:2, 251-276

Fama, E. F., 1970, "Efficient capital markets: a review of theory and empirical work," Journal of Finance 25, 383-417

Freedman, D. A., 2006, 'On the so-called 'Huber sandwich estimator' and 'obust standard errors,' The American Statistician 60:4, 299-302

Guo, K., Y. Sun, and X. Qian, 2017, "Can investor sentiment be used to predict the stock price? Dynamic analysis based on China stock market," Physica A: Statistical Mechanics and its Applications 469, 390-396

Gurdgiev, C., and S. Corbet, 2018, "Ripples in the crypto world: systemic risks in cryptocurrency markets," International Banker, June, https://bit.ly/2WFteXl

Hayes, A. S., 2017, "Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing bitcoin," Telematics and Informatics 34:7, 1308-1321

He, X., and L. Shi, 2007, "Zero-beta CAPM with heterogeneous beliefs," 20th Australasian Finance & Banking Conference 2007 Paper, https://bit.ly/2G7wrdm

Heston, S. L., and N. R. Sinha, 2017, "News versus sentiment: predicting stock returns from news stories," Financial Analysts Journal 73:3, 67-83

Kahneman, D., and A. Tversky, 1979, "Prospect theory: an analysis of decision under risk," Econometrica, 47:2, 263-291

Keynes, J. M., 1930, A treatise on money, in two volumes. s.l.: Macmillan & Company

Kharpal, A., 2017, "Central banks could hold bitcoin and ether for the first time in 2018, cryptocurrency CEO says," December 18, https://cnb.cx/2AVY6rC

Kharpal, A., 2018, "Bitcoin headed to $100,000 in 2018, says analyst who predicted last year's price rise," January 16, https://cnb.cx/2Dc6MLz

Kim, Y. B., J. G. Kim, W. Kim, J. H. Im, T. H. Kim, S. J. Kang, and C. H. Kim, 2016, "Predicting fluctuations in cryptocurrency transactions based on user comments and replies," PLOS One, 11(8), p. e0161197, https://bit.ly/2G6HEuC

Koetsier, J., 2018, "Report: top crypto exchange bithumb faking up to 94% of trading volume; bithumb denies allegations," Forbes, December 19, https://bit.ly/2HOrLea

Kristoufek, L., 2015, "What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis," PLOS One 10:4, p. e0123923, https://bit.ly/2D4Dol9

Li, X., and C. A. Wang, 2017, "The technology and economic determinants of cryptocurrency exchange rates: the case of bitcoin," Decision Support Systems 95, 49-60

Lo, A. W., 2005, "Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis," Journal of Investment Consulting 7:2, 21-44

Loughran, T., and B. McDonald, 2011, "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks," Journal of Finance 66:1, 35-65

Mai, F., S. Zhe, B. Qing, X. Wang, and R. H. L. Chiang, 2018, "How does social media impact bitcoin value? A test of the silent majority hypothesis," Journal of Management Information Systems 35:1, 19-52

Mao, H., S. Counts, and J. Bollen, 2015, "Quantifying the effects of online bullishness on international financial markets," ECB Statistics Paper, vol. 9

Martina, M., I. Lunesu, and M. Marchesi, 2015, "Bitcoin spread prediction using social and web search media," UMAP Workshops, https://bit.ly/2DPTCGO

Nofsinger, J., 2005, "Social mood and financial economics," Journal of Behaviour Finance 6:3, 144-160

Peters, E. E., and D. Peters, 1994, Fractal market analysis: applying chaos theory to investment and economics, John Wiley & Sons

Phillips, R. C., and D. Gorse, 2018, "Cryptocurrency price drivers: wavelet coherence analysis revisited," PLOS One 13:4, p. e0195200, https://bit.ly/2D4n1LK

Qian, H., 2009, "Time variation in analyst optimism: an investor sentiment explanation," Journal of Behavioural Finance 14, 182-193

Sarwar, G., 2017, "Examining the flight-to-safety with the implied volatilities," Finance Research Letters 20, 118-124

Sharma, M., 2018, "Report suggests 87% of the trading volumes at top 25 cryptocurrency exchanges could be fake," Crypto News Review, December 17, https://bit.ly/2MKOJ4B

Whaley, R. E., 2009, "Understanding the VIX," Journal of Portfolio Management 35:3, 98-105

Wilson, T., 2018, "As bitcoin trading shift shape, big money stays away," The Globe and Mail, December 7, https://tgam.ca/2RCBunD

Zouaoui, M., G. Nouyrigat, and F. Beer, 2011, "How does investor sentiment affect stock market crises? Evidence from panel data," Financial Review 46:4, 723-747

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