Bitcoin, speculative sentiments and crypto-assets valuation

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Abstract

What factors drive the valuation of Bitcoin and other crypto-assets? We use a novel measure and show that [1] Sentiments in Bitcoin drive the price action and have a material effect on returns [2] Sentiments in Bitcoin drive the valuation of other cryptocurrency assets [3] Sentiments in Bitcoin drive returns in other cryptocurrency assets. Our results show that optimistic sentiments in Bitcoin drive overvaluation in Bitcoin itself and other cryptocurrency assets. Our results support the notion that liquidity measures are salient factors in price discovery.

JEL Classifications: G30, G31, G32, G38

Keywords: Valuation, Cryptocurrencies, Bitcoin, Digital Assets, sentiments, speculation

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1 Introduction

A key result in the extant literature is that fundamentals drive valuation. Underlying this argument is the rationality of economic agents who use all available information to make investment decisions. Information could either be internally mandated disclosures (ex. quarterly reports, CEO's compensation, and sale of stocks) or external factors (ex. regulatory changes, pandemics, systemic shocks). As a result, valuation measures attempt to quantify the potential fair market price and account for much of the intrinsic worth of the specific asset under consideration.

However, valuation metrics might not be useful in some cases such as in the valuation of speculative assets. These assets tend to have a non-zero realized price, yet under valuation-based models, the expected value should be approximately zero. To this end, we attempt to address the following question: What drives the observed market values of Bitcoin and other crypto-assets?

We empirically show that sentiment drives valuations in Bitcoin and crypto-assets. Sentiment captures investors' biases and provides profitable opportunities due to the potential exploitation of these biases (Fisher and Statman 2000, Baker and Stein 2004, Brown and Cliff 2005). [1] Our working definition of sentiment is based on Lee, Shleifer, and Thaler (1991), that is the investors' expectations about the value of an asset and its returns that are not attributable to fundamentals. To measure sentiment in Bitcoin, and since sentiment is unobservable, we follow the prior literature and construct two asset-specific proxies for sentiment. Our first measure of sentiment is a ratio-based measure

[1] Given the nature of speculative assets, such profitable opportunities are consistent with rent-seeking behavior among economic agents.

of trading volume as higher trading volume turnover tends to be associated with higher sentiment (Chung, Kim, and Park 2017, Jiang and Li 2013). To bolster our measure, we also introduce a more innovative value-weighted measure of sentiments that takes into account the combined effect of marginal value per trade and short-term market frictions to document the price and returns dynamics of Bitcoin and other crypto-assets. We show that Bitcoin's sentiment is an important factor in both the prices and the returns of not only the asset itself but also other crypto assets.

In the extant literature, there is little consensus on the relationship between price and trading volume (Gagnon and Karolyi 2009, Hassan, Nassar, and Whitherspoon 2021). There is a documented positive relationship between trading volume and price momentum (Lee and Swaminathan 2000, Westerhoff 2006, Brown, Corcker and Foerster 2009). There is documented evidence of a short-term positive relationship in the context of initial public offerings (Chung, Kim, and Park 2017) while other works document a negative trade-off between mean and variance (Glosten et al. 1993, Lettau and Ludvigson 2003, MacKinlay and Park 2004, Nelson 1991). Anh and Hambusch (2024) attempt to reconcile these results by showing that optimistic sentiment periods are associated with negative excess returns and that periods of pessimistic sentiments are associated with positive but less volatile excess returns. We contribute to this line of work by introducing two novel measures of sentiment that focus on trading activities and the effect of the marginal dollar on Bitcoin and other crypto-assets valuations.

Specifically, we extend the literature on crypto-assets and valuation, which mainly focuses on the types and nature of blockchain, cryptocurrencies, and associated volatility (Hashemi, Nishikawa, and Dandapani (2019, 2021). related works such as Cheah and Fry 2015,O'

Dwyer and Malone 2014, Dowd and Hutchinson 2015, document that Bitcoin markets are susceptible to speculative swings and bubbles (Corbet, Lucey, and Yarovya 2018, Gkillas and Katsiampa, 2018, Beckmann, Geldner and Wüstenfeld, 2024). Some works investigate whether Bitcoin can serve as an effective medium of exchange (Dwyer 2014, Weber 2014) and its study of the hedging properties (Bouri, Moln´ar, Azzi, Roubaud, and Hagfors (2017). Akcora, Dey, Gel, and Kantarcioglu (2018) show that graph chainlets are useful in forecasting Bitcoin prices. Our work provides evidence and a novel measure of the main driver of Bitcoin and other crypto-assets valuation.

The key findings are as follows: [1] Sentiment in Bitcoin drives the price action and has a material effect on returns [2] Sentiment in Bitcoin drives the valuation of other cryptocurrencies [3] Sentiment in Bitcoin drives returns in other cryptocurrencies. Our results support the notion that optimistic sentiment in Bitcoin drives overvaluation in Bitcoin itself and other cryptocurrencies. Our results are consistent with the notion that sentiments are an important consideration in asset valuation (Shiller 2015)

The remainder of this paper is organized as follows. Section 2 discusses related literature and contextualizes our findings. Section 3 describes the data. Section 4 discusses empirical setup and results. Section 5 presents some robustness tests and section 6 concludes.

2 Related Literature

The literature on valuation and trading volume is mostly focused on tradable assets that issue dividends or have verifiable cash flows. The main focus in the extant literature is on volatility and serial correlations in returns (LeBaron 1992[a,b], Sentana and Wadhwani 1992).

Some works document positive autocorrelations on daily indices (Lo and MacKinlay 1988, Conrad and Kaul 1998, MacKinlay and Park 2004), while others document that higher trading volume dampens this effect (Campbell, Grossman, and Wang, 1993). Of note is the findings that the volume-return relationship is a function of investors underreacting to available information and noninformation trading, thus higher volume tends to be divorced from fundamentals (Asness et al. 2000, Doms and Morin 2004).

The literature on sentiment focuses on how human behavior affects asset pricing. As a result, the literature focuses on the first moment (mean of returns) and second moments (variance) (Baker et al. 2012, Stambaugh et al. 2014, Anh and Hambusch 2024). Other studies show that on average the relationship between market beta and return is negative (Frazzini and Pedersen 2014, Antoniou et al. 2016). The general finding in this line of literature is that higher investor optimism is associated with negative returns for the overall market (Brown and Cliff 2005, Lemmon and Portniaguina 2006). Similar results have been observed in the international markets. For example, Schmeling (2009) and Chui et al. (2010) use consumer confidence measure and degree of individualism as proxies for sentiment. This literature documented negative effects of sentiments on returns are more pronounced in markets with less integrity with investors that exhibit herd-like behavior. Qiu and Welch (2005) document that changes in consumers' confidence are salient factors in the returns of small stocks. Chung, Kim, and Park (2017) document a short-term positive relationship between pre-market sentiments and excess returns during initial public offerings. We contribute to this literature by showing that sentiments in Bitcoin have a direct effect on the valuation of other crypto-assets, pointing to herding behavior in the cryptocurrency market.

Our paper also contributes to the literature on the intersection of behavioral finance and psychology literature on the role of emotions in decision-making. Sinclair and Mark (1995) document that mood matters in judgment and accuracy. In particular, happy individuals tend to be less accurate than sad individuals. They attributed this result to happy individuals using peripheral cues and heuristics in judgment therefore resulting in a less systematic approach. In contrast, some work shows that happiness is associated with higher productivity among workers (Oswald, Proto, and Sgroi, 2015) and is positively associated with risk-taking (Isen 1997, Mittel and Ross 1998, Yuen and Lee 2003). We contribute to this literature by showing that sentiment is an important driver of the valuation of speculative assets such as crypto-assets.

3 Data

The main data on cryptocurrencies is obtained from `https://Coincap.com` and Yahoo Finance for the period 12/21/2014 to 2/28/2022. We use daily data as it signals and captures the immediate short-term effects and fluctuations in both the specific asset under study and in the aggregate market. Table I presents the summary statistics of the main variable of interest. The average price of Bitcoin during the sample period is about $11,857.34, and the interquartile range is $11,179, with a value of $51,206 at the 95^{th} percentile, suggesting a significant fluctuation in the price of Bitcoin. The averages of the other cryptocurrencies are as follows: Ethereum $999.8, Litecoin $75.01, Solana $14.88, Binance (BNB) $38.74 and CCi30 $5686.17. We extracted the data on the cryptocurrency index from `https://cci30.com`. Sentiment has a mean of 0.33 with a standard deviation of 0.43, suggesting some fluctuations in sentiments around Bitcoin.

[INSERT TABLE I HERE]

Table II panel A reports price correlations and panel B reports volume correlations of all crypto-assets under consideration. Of note, the correlation between other cryptocurrencies price and volume to Bitcoin is noticeably high but there is some variation in the correlation amongst other cryptocurrencies. In particular, the correlations between Bitcoin and Ethereum price and trading volume are 0.92 and 0.85 respectively. However, the correlation between the trading volume of Solana and the trading volume of Bitcoin (Ethereum) is -0.028 (0.106), suggesting that there is some heterogeneity in trading volume across crypto-assets.

[INSERT TABLE II HERE]

4 Methodology and Results

4.1 Empirical Set-Up and Strategy

Our goal in this paper is to examine whether sentiments drive the value and returns of Bitcoin and other crypto-assets. Understanding the factor(s) that drive an asset's market value is important for both diversification and portfolio rebalancing decisions amongst heterogeneous market participants. Effectively, valuation is important for investors to assess the relative impact on their portfolio. Relative impact factor in the diversification role (positive correlation) of an asset and the hedging role of an asset (negative correlation) in the portfolio (Baur and Lucey 2010, Chan, Le, and Wu 2019).

Underlying our argument is the fact that Bitcoin and other crypto-assets neither issue dividends nor have any expected cash flows from potential future earnings. As such, the discounted value of Bitcoin and other assets is approximately zero. Similar to Taleb (2021), we assume that the value of any asset is equivalent to the sum of its discounted cash flows, any expected measurable service flows, and some speculative or heterogeneous beliefs amongst heterogeneous economic agents regarding the asset. The genesis of our hypothesis is that it is the heterogeneous beliefs amongst economic agents that drive the value of Bitcoin. We argue that heterogeneous beliefs can be modeled as a function of the immediate discernable expected value (EV) and short-term sentiments regarding the value of the asset. This argument is summarized as in equations [1] and [2] below:

$$\begin{aligned} Bitcoin\_Price = \{EV(Dividends/Cashflows) + EV(Serviceflows) + \\ +EV(Speculative/Heterogeneous\_Beliefs)\} = EV(Speculative/Heterogeneous\_Beliefs) \end{aligned} \tag{1}$$

$$EV(Speculative/Hetergeneous\_Beliefs) = f(Price_{t-1}, Short\_Term\_Sentiments) \tag{2}$$

While prior literature considered sentiments as simply noise (Black 1986), some more recent works (Baker and Wurgler 2007, Shiller 2015, Schmeling 2009) document that investors' sentiments have material effects on returns. Sentiments could be a result of exuberance demand or due to potential arbitrage opportunities on the asset. Effectively, sentiment reflects the differences in valuation between informed traders and uninformed traders (Brown and Cliff 2005, Lee, Shleifer, and Thaler 1991). Since sentiment is not directly observable, it is imperative to use some proxies, and the literature on liquidity management has documented that using some form of liquidity measure can serve as a proxy for sentiments (Baker and Stein 2004).

Trading volume generally captures the liquidity of a specific stock. Stocks with high trading volumes are considered to be highly liquid while stocks with low trading volumes are considered to be illiquid (Chordia, Subrahmanyam, and Anshuman, 2001). As a result, trading volume can serve as a robust proxy for sentiments (Lee, Mucklow, and Ready 1993, Lee and Swaminathan 2000). This is because trading volume is an observable measure of heterogeneous beliefs amongst economic agents and thus accounts for the quality of private and public information regarding a specific asset or firm (Blume, Easley, and O'Hara 1994, Jones, Kaul, and Lipson 1994). Essentially, the trading volume takes into account informed trading and uninformed trading due to speculative beliefs (Koski and Michaely 2000, Harris and Raviv 1993). Thus, there is a positive relationship between trading volume and investors' sentiments. To account for short-term sentiment in Bitcoin, we construct the following measure:

$$Short\_Term\_Sentiments = \frac{Trading\_Volume_{t-1}}{\frac{1}{T}\sum\limits_{j=2} Trading\_Volume_{t-j}}, s.t, j = 2, 3, 4 \tag{3}$$

Observe that unlike alternative measures such as variance premium (PVAR) (Baker, Wurgler and Yuan, 2012), managerial motives in stock issues (NSI) (Daniel and Titman 2006, Pontiff and Woodgate 2008), and dividend premium (PDIV) measures (Baker and Wurgler 2004), our measure of sentiments is based solely on relative volume since Bitcoin neither issue dividends nor has any measurable cash flows. The fundamental thesis of this paper is that the valuation of Bitcoin, and by extension other cryptocurrencies, is entirely driven by speculative trading in the asset.

Underlying our argument is the notion that absent of any new information in the market, the trading volume at any given time *"t"* should be approximately equal to the average trading volume of the prior trading days. Averaging over the prior trading days controls for outlining effect due to either noise trading or any low-frequency variation in the series (Chordia and Swaminathan 2000, Campbell, Grossman, and Wang 1993, Jain and Joh 1988). Higher values of the proxy are associated with more positive sentiments in Bitcoin. And lower sentiments are associated with negative sentiments in Bitcoin. Because of herding in Bitcoin trading; that is noninformational and informational trade have highly correlated trading decisions. Our measure of sentiment accounts for unusual trading volume and therefore effectively captures short-term speculative behavior on Bitcoin.

4.2 Empirical Results

What drives the value of Bitcoin? This question is important as Bitcoin has no expected future cash flows, does not pay out dividends, has no expenses nor assets under management but has a non-zero observed historical trading price. Following Roll (1984), Goyenko et al. 2009, show that the value of any tradable asset evolves as follows:

$$V_t = \psi V_{t-1} + \mu_t, 0 \leq \psi \leq 1 \tag{4}$$

Where V_t is the unobservable fundamental value of the asset at time *"t"* and μ_t is an error with an expected value of zero. Note that the price is a robust proxy for the fundamental value of Bitcoin, and by extension other cryptocurrencies, since they neither generate any cash flows nor issue dividends (Taleb, 2021). Equation [4] can therefore be re-written as in equation [5] below where P_t is the price of any crypto-asset at time t :

$$P_t = \psi P_{t-1} + \eta_t + \epsilon_t, 0 \leq \psi \leq 1 \tag{5}$$

Where η is some potential salient factor such that $E[\eta_t] \neq 0$. We argue that the price of Bitcoin is mainly driven by heterogeneous beliefs or speculative sentiments, effectively implying that the expected value of the error term μ_t in equation [4] is non-zero and Bitcoin's price evolution can be modeled as in equation [5] above. This is also because Bitcoin can be seen as a speculative and highly risk-on asset due to its volatile nature as depicted in Figure [1]. Base on this argument, we formulate the following hypothesis:

Hypothesis 1: *Short-term sentiments drive Bitcoin's pricing and therefore valuation.*

To test the above hypothesis, we estimate the following equation:

$$Bitcoin\_Price_t = \beta_0 + \beta_1 Bitcoin\_Price_{t-1} + \beta_2 Sentiments + \epsilon_t \tag{6}$$

Table III presents our results from equation [6] above. We argue that economic agents' beliefs, which are a combination of the prior one-day price and short-term sentiments, drive the valuation and price action of Bitcoin. Observe that in column [1] the prior day's price of Bitcoin has a coefficient of 0.999 and is statistically significant at the 1% level. This suggests that the previous day's price is an important determinant of Bitcoin's valuation. This result is expected as under the efficient market hypothesis, the price of any asset tends to be highly correlated and the best predictor of today's price is generally yesterday's price. However, unlike most other assets that either generate some income or have measurable yield, Bitcoin is in a class of its own. our main argument is that the noise component in a typical martingale pricing model is more salient in the case of Bitcoin relative to other assets such as a dividend-paying stock.[2]

[INSERT FIGURE 1 HERE]

To this end, we present results with only the short-term sentiment measure as the main explanatory variable in model [2]. The coefficient of sentiment is statistically significant at the 1% level. Observe that R^2 is about 52%, indicating that sentiment explains a significant variation in the price of Bitcoin. In columns [4-5], we include the prior three days' prices as explanatory variables. The coefficients for these variables are not statistically significant. Overall, the results further validate our main finding that Bitcoin's price and subsequent valuation are mostly driven by the immediate short-term sentiment and the prior day's price. Our results support the notion that the price of Bitcoin can rise to astronomical values due to irrational exuberance. In particular, Bitcoin prices are mostly driven by continued price appreciation. The expectation of a continuous increase in prices divorced from any fundamental value can lead to irrational bubbles (Shiller 2015, Weber 2016). Our results are important because they provide a benchmark for the valuation of risk-on speculative assets and are consistent with the notion that noise traders' risk is a function of erroneous and unpredictable beliefs divorced of fundamental by uninformed traders (De Long et al. 1990, Anh and Hambusch 2024).

[INSERT TABLE III HERE]

[2] We are referring to a process in which conditional on available information today, the expected future value of an asset equals its value today.

4.3 Bitcoin, Sentiments and Crypto-Assets

Bitcoin currently has a market capitalization that accounts for more than 55% of the total cryptocurrency market capitalization.[3] The dominance of Bitcoin in an asset class without fundamentals suggests that sentiments around Bitcoin likely have a direct impact on the valuation of other crypto-assets. In general and all things considered, sentiments regarding a specific firm or asset should not be a significant driver of another asset's valuation. We therefore make the following conjecture:

Hypothesis 2: *Bitcoin's sentiment is a significant driver of crypto-assets prices and therefore valuations.*

To test this hypothesis, we selected the next four major cryptocurrencies by market capitalization. These are Ethereum, Litecoin, Solana, and Binance (BNB. To ensure that we also take into account the effect on the valuations of the other cryptocurrencies, we use a cryptocurrency market index. Specifically, we use the CCi30, which is an index launched in 2017 made up of the 30 largest cryptocurrencies by market capitalization. These 30 cryptocurrencies account for about 90% of the cryptocurrency market capitalization. Some cryptocurrencies were not included as they are very illiquid and are highly subjected to potential speculative attacks from a single trade which could result in a crash.[4] The index is rule-based and aims to effectively measure the movement and growth in the crypto market. An important feature of the index is its scope, providing a stable risk-adjusted

[3] `https://coinmarketcap.com/`

[4] See Rivin and Scevola (2018) on the stability of the index and the volatility of the illiquid cryptocurrencies.

performance of the crypto market (Rivin and Scevola, 2018).

[INSERT TABLE IV HERE]

Our results are presented in Table IV. Columns [1] present the results for Ethereum. The coefficient of the prior day's Ethereum price is statistically significant at the one percent level, suggesting that the prior day's price is an important determinant of Ethereum's price and subsequent valuation. The coefficient of sentiment is positively and statistically significant at the 1% level, suggesting that Bitcoin has a salient effect on Ethereum pricing. Economically, one standard deviation in Bitcoin's sentiment has about a 5.3 percentage points increase in the price of Ethereum. Column [2] presents estimates for Litecoin's price. The previous day's price of Litecoin is statistically significant at the 1% level and is an important determinant of Litecoin's today's price and subsequent valuation. Bitcoin's sentiment measure is also statistically significant at the 1% level. Economically, one standard deviation in Bitcoin's sentiment is associated with a 6% percentage point increase in the price of Litecoin. Column [3] reports the estimates for Solana. While we find that the previous day's price is salient, we do not find any statistical evidence to support the notion that sentiment in Bitcoin has a material effect on Solana. [5] Column [4] presents estimates of BNB. We can observe that the coefficient of the prior day's price is positive and statistically significant at the 1% level, suggesting that yesterday's price is an important determinant of today's price. The coefficient of Bitcoin's sentiment is statistically significant at the 1% level. Economically, one standard deviation in Bitcoin's sentiment is associated with a 2.4 percent increase in the price of BNB. Column [5] presents results in which the dependent variable is the price of the index (CCi30). The coefficient estimates for the prior day's price is statistically significant at the 1% level.

[5]Potentially due to limited data on Solana, which is only available for 2 years.

The coefficient of sentiment is statistically significant at the 1% level. Economically, one standard deviation in Bitcoin's sentiment has about an 8% percent increase in the value of the index. Overall, the results indicate that Bitcoin's sentiment is a salient factor in the valuation of other cryptocurrencies.

4.4 Crypto-Assets: Risks and Returns

Hypothesis 3a: *Sentiments drive excess returns in Bitcoin.*

Hypothesis 3b: *Sentiments in Bitcoin drive returns of other cryptocurrencies*

The extant literature has documented that stocks with higher trading volume tend to have lower expected returns in the cross-section. However, in the case of crypto-assets, price appreciation is an important determinant of valuation and drives interest in the assets. An increase in trading volume might suggest a lower return per unit of trading volume but an increase in volume can lead to further appreciation in the price, which could mean higher returns. As a result, the effect(s) of sentiments on returns is not ex-ante obvious. In this section, we examine whether sentiments in Bitcoin predict the time series or cross-section of a crypto-asset's returns. To test the first part of the above hypothesis on whether sentiments affect Bitcoin's return. We estimate the following augmented market model:

$$[R_{b,t} - R_{f,t}] = \alpha + \beta_1 RMCF_t + \beta_2 Sentiments_t + \epsilon_t \tag{7}$$

Where $\{R_{b,t} - R_{f,t}\}$ is the excess returns of Bitcoin on day t, which is the average daily return minus the risk-free rate proxied by the 10-year Treasury bill daily rate. We assume that any rational risk-seeking market participant would expect, on average, returns above the risk-free rate. $RMCF_t$ is the daily crypto-market risk premium. We use the cryptocurrency market index (Rivin and Scevola, 2018) as the proxy for the crypto market since it accounts for 90% of the crypto-market capitalization. $Sentiments_t$ refers to our short-term sentiments in equation [3] above.

[INSERT TABLE V HERE]

Our results are presented in Table V. Columns [1] suggest that sentiments partially explain excess returns in Bitcoin. In columns [2-4], we include crypto-market premium and equity market premium as additional control variables. This is because changes in the aggregate market affect all market participants. The combined results suggest that market premium is a stronger factor that explains return.

We next test whether sentiments in Bitcoin explain the returns of crypto-assets. We focus on the main four alternative crypto-assets and the cryptocurrency market index. We then estimate the following equation.

$$R_{i,t} = \alpha + \beta_1 Sentiment_t + \beta_2 Control_{i,t-1} + \epsilon_t \tag{8}$$

Where $R_{i,t}$ is the crypto-asset raw cumulative return and the additional $Control_{i,t}$ is the one-day prior return of the crypto-assets, $R_{i,t-1}$,under consideration. Given the lack of fundamental factors in crypto-assets on which investment decisions might be based; prior returns are likely to be an important consideration.

Table VI presents the results to test hypothesis 3b above. We find that Bitcoin's sentiments drive the returns in the crypto-market. However, similar to the results reported in Table IV, we do not find any evidence that sentiments drive returns in Solana. Our results are consistent with the notion that hubris and speculative sentiments matter in asset returns (Baker and Stein 2004).

[INSERT TABLE VI HERE]

4.5 Alternative measure of sentiments

To further validate our findings, we construct a dollar-weighted measure of sentiment that takes into account the ratio of the daily average dollar value of trading volume; effectively capturing the daily price response associated with a marginal dollar of trading. Our model is consistent with the extant literature and liquidity models framework in Amihud (2002), Berkman and Eleswarapu (1998), Cooper, Groth, and Avera (1985), Amihud, Mendelson, and Lauterback (1997). The measure is constructed as follows for any asset "i":

$$Dollar\_Weighted\_Sentiment_i = \left(\frac{\theta}{1-\theta}\right)\left(\frac{Volume_{i,t-1}}{Price_{i,t-1}}\right)\left(\frac{Volume_{i,t}}{Price_{i,t}}\right)^{-1} \tag{9}$$

Where θ accounts for short-term market fluctuations in particular the buy-sell trading activities implied in bid-ask spread. Effectively, θ reflects the velocity in trading activities due to new information flows induced by general market frictions. The dollar-weighted sentiment measure (DWS) measure is more robust to large fluctuations in short-term trading since it effectively measures the dollar gain per trading volume. Put differently, DWS proxies the dollar volume required to effect a percentage change in the price of the asset under consideration. As we are using daily data, it is reasonable to assume that θ equals 0.5, implying that there is no substantial difference in price trading action in the immediate short-run. This assumption is consistent with extant literature on measuring effective spread using transaction prices (Lipson and Mortal 2009, Roll 1984, Acharya and Pedersen 2005).

Figure [2] illustrates the distribution of the DWS measure. We can observe that relative to the pure volume measure of sentiment, the DWS is more stable but the density distribution has a long right tail. This suggests that sentiments in crypto-assets are persistent and tend to have a long duration. Our result supports the findings that market correction occurs either because of the presence of arbitrageurs or due to changes in heuristic beliefs (Baker and Wurgler 2007, Baker et al., 2012, Ahn and Hambusch 2024, Yu and Yuan 2011)

[INSERT FIGURE 2 HERE]

We re-examined our main hypothesis using the DWS measure in equation [9] above. Our results are reported in Table VII. The coefficient of DWS across all crypto-assets is positive and statistically significant at the 1% level, which supports our main hypothesis that sentiment in Bitcoin significantly drives crypto-asset valuation.

[INSERT TABLE VII HERE]

5 Robustness Tests

5.1 Is the price Dynamic Driven by Momentum Trading?

There is a potential concern that our measure of sentiment might simply be picking up general momentum in the market. To address this concern, we use the ishares MSCI momentum factor ETF (MTUM) as a proxy for general momentum trading in the equity market. The index is based on documented factors that drive short-term risk and return by buying winners and selling losers (Jegadeesh and Titman 2002, Clarke, Silva, and Thorley 2006). The index is comprised of firms that exhibit highly significant price momentum. We add the index as an additional control and test our main hypothesis.

The key idea is that if our sentiment measure is merely picking up general market momentum, then we should not expect to observe any material effect as the momentum index will dominate the sentiment measure. The results are documented in Table VIII. Columns [1,2] show that momentum has a positive loading and is statistically significant at the 1% level but this disappears once we control for the prior day's prices. Momentum is generally correlated with fund flows, which leads investors to seek alpha in other sectors of the market including the crypto-market. However, observe that the loading on our sentiment measure is still positive and statistically significant, indicating that sentiment is an important driver of Bitcoin's price and subsequently returns. Our results are consistent with the notion that retail and contrarian investors' sentiments tend to have an upward pressure on valuations (Da et al. 2011).

[INSERT TABLE VIII HERE]

5.2 Accounting for COVID-19 pandemic

Previous research shows that the COVID-19 pandemic had a direct effect on the crypto market. We examine whether the documented effect is mostly driven by short-term sentiments and not by the general macroeconomic uncertainty during the COVID-19 pandemic. To estimate the effects of the COVID-19 pandemic, we created a dummy "COVID" equal to 1 if the timeline is from March 2020 to February 2022 and zero if otherwise. We end our period in February 2022 since the vaccine became available and the government introduced policies to alleviate the impact of COVID-19 on the economy.

Table [IX] reports our results. Column [1] indicates that the COVID dummy is positive and statistically significant at the 1% level. However, once we control for short-term sentiments; that is the combination of the prior day's price and our sentiment measure, the effects of COVID disappear. Observe that both our sentiments measure and prior day price are statistically significant which is consistent with our first hypothesis. Additionally, we control for the interaction term between sentiment and COVID-19 since an argument could be made that both are jointly determined given the construction of our sentiment measure. The interaction term then captures Bitcoin's sentiment during the COVID-19 pandemic. The results are reported in column [4], we can observe that the interaction term is dominated by the combination of prior price and sentiment; which are our proxy for short-term sentiments.

[INSERT TABLE IX HERE]

5.3 Timeline Analysis and Returns Dynamic

A case could be made that the duration under consideration matters since Bitcoin was initially viewed as an obscure asset whose sentiment was dominated by a few enthusiasts and software developers. To this end, we categorized the sample period into three major stages [1] the Early period [2] the post-10 K period [3] the stay-at-home period. Enthusiasts dominated the Early period and the general money flows were mostly from this group. The post-10 K period reflects the timeline during which Bitcoin surpassed 10,000 USD. This period is important as more market participants started paying close attention to cryptocurrencies. The stay-at-home period refers to the COVID-19 pandemic period during which a large fraction of the general public became familiar with Bitcoin and other cryptocurrencies.

We present our results in Table [X]. Observe that our variable of interest, sentiment, is salient and statistically significant at the 1% level. Our analysis underscores the significant impact of sentiments on Bitcoin's valuation. Overall, the result supports our main thesis that sentiments matter and drive valuation in cryptocurrencies.

[INSERT TABLE X HERE]

6 Conclusion

What factor(s) drive the valuation of Bitcoin and other crypto-assets? This is an important question as cryptocurrencies neither have expected future cash flows nor issue dividends. In this paper, we show that sentiments are a significant determinant of valuations in Bitcoin and other crypto-assets. We show that sentiments in Bitcoin are an important factor in the valuation of other crypto-assets. Our results support the notion that liquidity measures accounting for trading volume are salient factors in price discovery.

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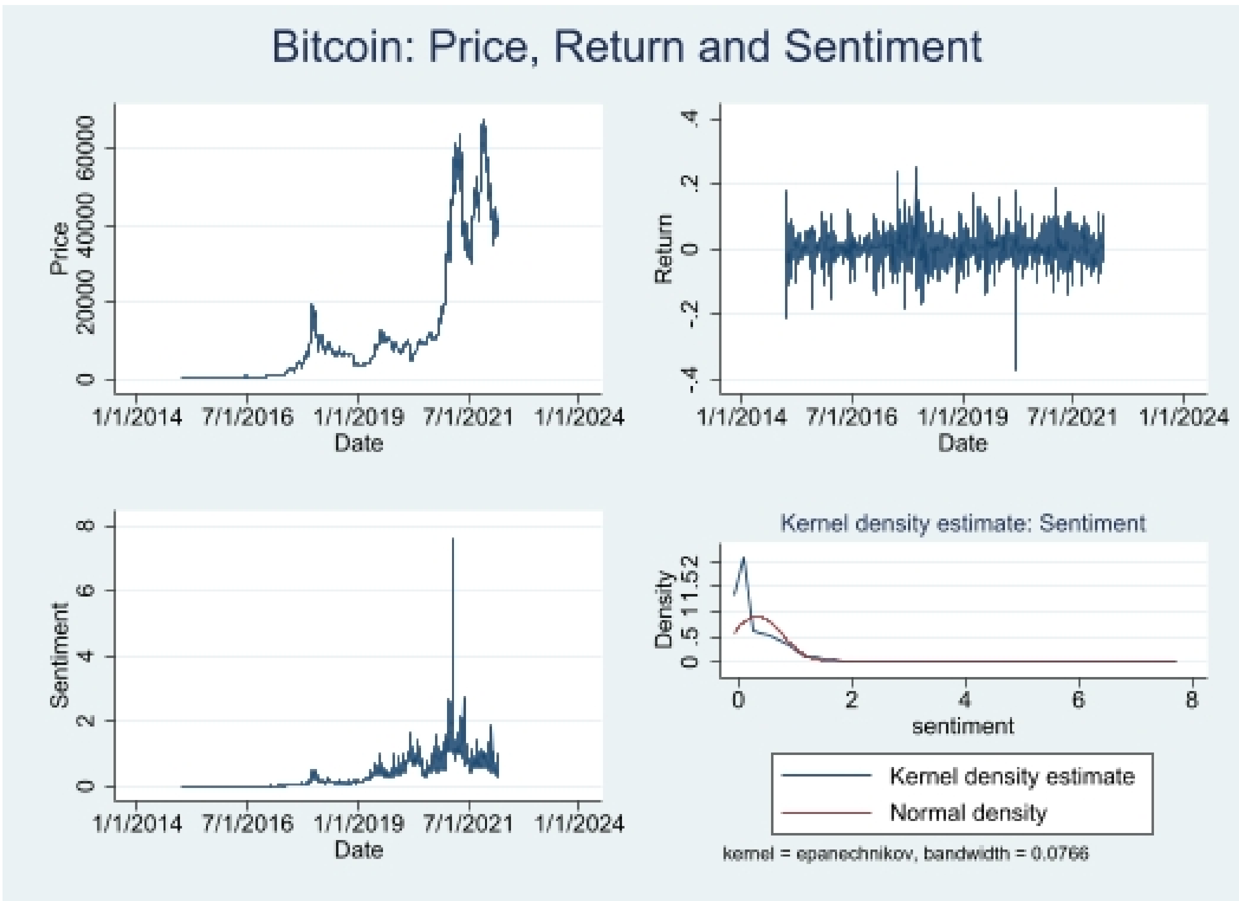

Figure 1:

Presents the price, returns, kernel density and sentiment measure of Bitcoin.

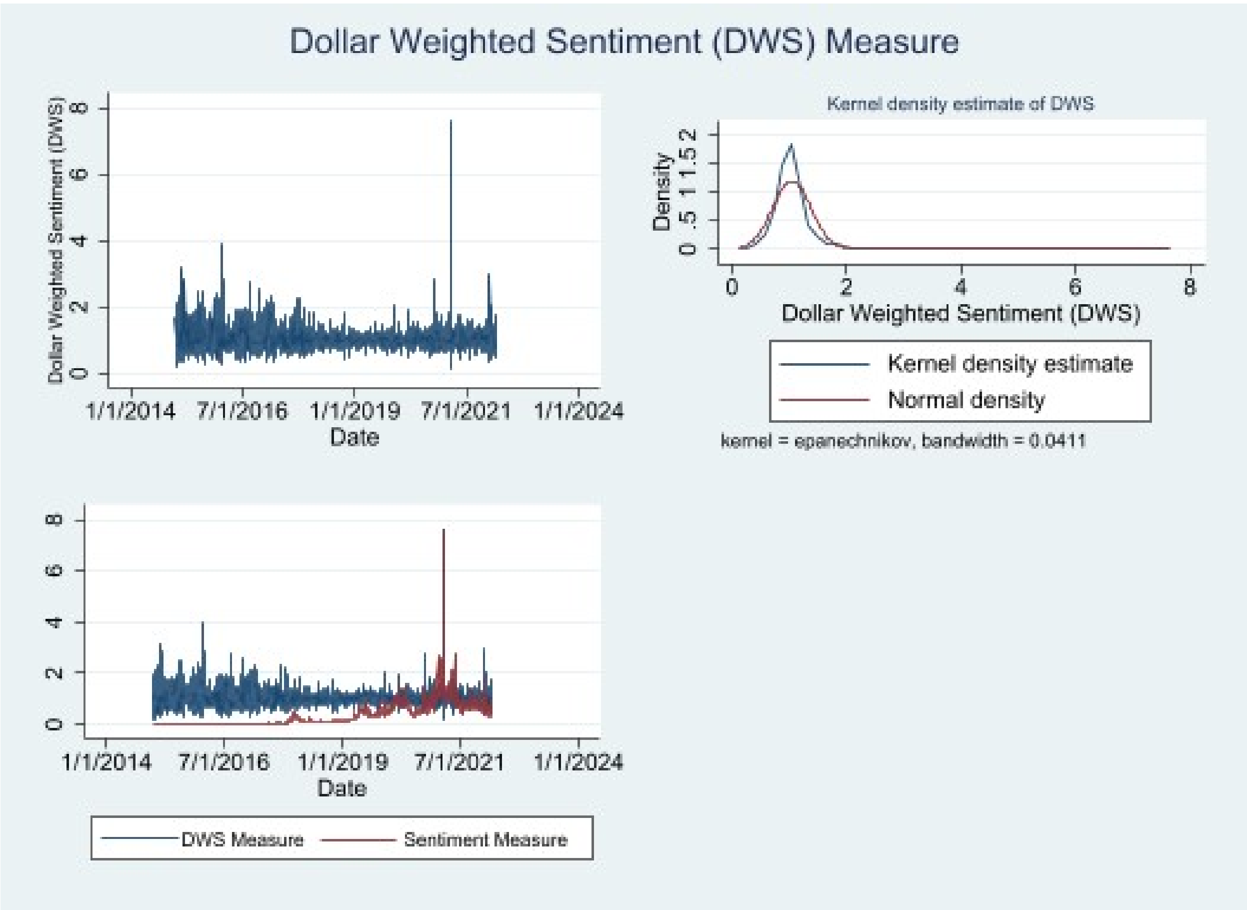

Figure 2:

Presents dollar-weighted sentiment, kernel density, and sentiment measure.

TABLE I: Summary Statistics

This table presents summary statistics for the cryptocurrencies used in this paper. CCi30 is a basket of cryptocurrencies that accounts for 90% of the crypto-market. Sentiment is captures sentiments in Bitcoin.

	Obs	Mean	Std. Dev	25^{th}	75^{th}	95^{th}
Bitcoin	2617	11857.34	16325.5	678.30	11857.3	51,206
Ethereum	1573	999.8	1220.9	194.49	1391.61	3847.46
Litecoin	2399	75.01	5.59	71.12	118.41	213.22
Solana	690	14.88	70.29	1.97	92.24	200.18
Binance Coin (BNB)	2304	38.74	173.563	15.71	305.07	490.07
CCi30	2616	5686.17	7256.67	270.90	6084.01	23047.7
Sentiment	2616	0.33	0.43	0.01	0.54	1.16

TABLE II: Correlations Table

This table presents correlations across crypto-assets used in this paper. Panel A reports price correlations and Panel B reports volume correlations.

	Bitcoin	Ethererеum	Litecoin	Solana	BNB	CCi30
Price/Value:		**Panel**	**A**			
Bitcoin	1.0000					
Ethereum	0.9232	1.0000				
Litecoin	0.8011	0.7010	1.0000			
Solana	0.6673	0.8760	0.4793	1.0000		
BNB	0.9185	0.9620	0.6435	0.7997	1.0000	
CCI30	0.9503	0.9454	0.8964	0.7055	0.91937	1.0000
Volume:		**Panel**	**B**			
Bitcoin	1.0000					
Ethereum	0.8589	1.0000				
Litecoin	0.8346	0.7209	1.0000			
Solana	-0.0282	0.1066	-0.1825	1.0000		
BNB	0.5964	0.6952	0.4034	0.2420	1.0000	
CCI30	0.9206	0.9442	0.8478	0.0954	0.7100	1.0000

TABLE III: Bitcoin: Price Determinants and Valuation

This table presents estimates of determinants of Bitcoin's price. Sentiment captures sentiments in Bitcoin. The other controls are lagged realized prices of Bitcoin.

	(1)	(2)	(3)	(4)	(5)
	Price	Price	Price	Price	Price
Price_{t-1}	0.999***		0.997***	0.974***	0.974***
	(1050.28)		(726.88)	(49.56)	(49.52)
Sentiment		26842.8***	110.3**	106.6**	
		(53.27)	(2.16)	(2.08)	
Price_{t-2}				0.0221	0.0221
				(0.80)	(0.80)
Price_{t-3}				0.0160	0.0185
				(0.58)	(0.67)
Price_{t-4}				-0.0152	-0.0153
				(-0.77)	(-0.78)
Constant	23.40	2914.6***	11.96	12.34	23.40
	(1.22)	(10.50)	(0.60)	(0.62)	(1.22)
N	2616	2616	2616	2613	2613
R^2	0.998	0.520	0.998	0.998	0.998

NOTE: t-statistics in parentheses * p:0.10, ** p:0.05, *** p:0.01

TABLE IV: Bitcoin: Price Determinants and Valuation

This table presents estimates of determinants of crypto-assets prices. Sentiment captures sentiments in Bitcoin. The other controls are lagged prices of other crypto-assets.

	(1)	(2)	(3)	(4)	(5)
	Ether	LTC	Sol	BNB	CCi30
Sentiment	12.42***	1.080***	0.437	2.131***	110.1***
	(2.59)	(2.64)	(1.02)	(2.72)	(4.03)
$Ether_{t-1}$	0.997***				
	(561.74)				
LTC_{t-1}		0.991***			
		(385.22)			
Sol_{t-1}			0.998***		
			(350.89)		
BNB_{t-1}				0.996***	
				(514.46)	
$CCi30_{t-1}$					0.994***
					(600.65)
Constant	-1.957	0.353	-0.105	-0.455	3.930
	(-0.61)	(1.62)	(-0.23)	(-0.90)	(0.32)
N	1572	2398	689	1572	2615
R^2	0.996	0.990	0.995	0.995	0.996

Note: t-statistics in parentheses: * p: 0.10, ** p: 0.05, *** p:0.01

TABLE V: Crypto-Assets: Sentiments and Returns

Excess returns are Bitcoin returns above the risk-free rate. Cryptomarket risk premium is the difference between Cryptoindex returns and risk-free rate and the equity market risk premium is the difference between equity market risk return and risk-free rate.

	(1)	(2)	(3)	(4)
	Excess Returns	Excess Returns	Excess Returns	Excess Returns
Sentiment	1.049***	0.0578		0.396
	(4.41)	(0.46)		(1.46)
Crypto_Market Risk Premium		0.785***		
		(68.12)		
Equity Market Risk Premium			0.811***	0.767***
			(9.38)	(8.39)
Constant	-1.989***	-0.370***	80.89***	76.28***
	(-15.51)	(-5.14)	(9.19)	(8.16)
N	1800	1800	1411	1411
R^2	0.011	0.724	0.059	0.060

Note: t-statistics in parentheses: * p:0.10, ** p:0.05, *** p:0.01

TABLE VI: Crypto-Assets: Sentiments and Returns

The dependent variable is the return of each crypto asset under consideration. The sentiment captures the general sentiment on Bitcoin. The lagged price of each crypto-asset is included as an additional control.

	(1)	(2)	(3)	(4)	(5)
	Ether_Return	BNB_Return	LTC_Return	Sol_Return	CCi30_Return
Sentiment	12.39***	2.131***	1.080***	0.437	110.1***
	(2.58)	(2.72)	(2.63)	(1.02)	(4.02)
$Ether\_Return_{t-1}$	0.997***				
	(561.56)				
BNB_Return_{t-1}		0.996***			
		(514.29)			
LTC_Return_{t-1}			0.991***		
			(385.11)		
Sol_Return_{t-1}				0.998***	
				(350.50)	
$CCi30\_Return_{t-1}$					0.994***
					(600.52)
Constant	-1.934	-0.463	0.335	-0.109	3.920
	(-0.60)	(-0.91)	(1.55)	(-0.24)	(0.32)
N	1571	1571	2397	688	2614
R^2	0.996	0.995	0.990	0.995	0.996

Note: t-statistics in parentheses: p:0.10, ** p:0.05, *** p:0.01

TABLE VII: Alternative Measure of Sentiments

The dependent variable is each crypto-asset's return under consideration. The dollar-weighted measure captures general sentiments in Bitcoin. The lagged price of each crypto-asset is included as an additional control.

	(1)	(2)	(3)	(4)	(5)	(6)
	Bit_Ret	Ether_Ret	BNB_Ret	LTC_Ret	Sol_Ret	CCi30_Ret
Dollar Weighted Sentiment	192.0***	48.07***	7.710***	2.270***	1.725***	176.4***
	(4.13)	(6.71)	(6.67)	(4.94)	(3.13)	(6.33)
$BitcoinReturn_{t-1}$	0.999***					
	(1053.15)					
$EtherReturn_{t-1}$		0.998***				
		(619.33)				
$BNBReturn_{t-1}$			0.998***			
			(573.91)			
$LTCReturn_{t-1}$				0.995***		
				(480.16)		
$SolanaReturn_{t-1}$					0.997***	
					(355.84)	
$CCi30Return_{t-1}$						0.998***
						(779.03)
Constant	-177.4***	-46.00***	-7.423***	-1.949***	-1.512**	-168.3***
	(-3.40)	(-5.95)	(-5.99)	(-3.70)	(-2.42)	(-5.34)
N	2615	1571	1571	2397	688	2614
R^2	0.998	0.996	0.995	0.990	0.995	0.996

Note: t-statistics in parentheses: * p: 0.10, ** p:0.05, *** p:0.01

TABLE VIII: Momentum Trading

This table presents estimates of determinants of Bitcoin's price. Sentiment captures sentiments in Bitcoin. The other controls are lagged prices of Bitcoin. Momentum (MTUM index) capture is the general momentum in the equity market.

	(1)	(2)	(3)
	Price	Price	Price
Momentum	29814.9***	138.4	142.1
	(28.63)	(1.13)	(1.16)
Sentiment	10197.0***	217.3***	213.8**
	(12.33)	(2.59)	(2.54)
$Price_{t-1}$		0.992***	0.959***
		(432.72)	(37.88)
$Price_{t-2}$			0.0410
			(1.13)
$Price_{t-3}$			0.00413
			(0.11)
$Price_{t-4}$			-0.0123
			(-0.45)
Constant	12852.44***	598.6	614.2
	(28.12)	(1.12)	(1.15)
N	1802	1802	1801
R^2	0.698	0.997	0.997

Note: t-statistics in parentheses: * p: 0.10, ** p: 0.05, *** p: 0.01

TABLE IX: Bitcoin: COVID-19 Pandemic

This table presents estimates of determinants of Bitcoin's price. Sentiment captures sentiments in Bitcoin. The other controls are lagged prices of Bitcoin. COVID is a dummy variable that equals to "1" during COVID-19 years and zero if otherwise.

	(1)	(2)	(3)	(4)	(5)
	Price	Price	Price	Price	Price
COVID	23914.0***	11196.8***	9155.0***	90.45	41.32
	(40.43)	(18.13)	(7.59)	(1.00)	(0.85)
Sentiment		20319.7***	19740.2***	111.1*	93.56*
		(34.10)	(29.72)	(1.94)	(1.75)
COVIDxSentiment			2958.8**	73.29	
			(1.97)	(0.66)	
$Price_{t-1}$				0.997***	0.974***
				(684.23)	(49.50)
$Price_{t-2}$					0.0222
					(0.81)
$Price_{t-3}$					0.0163
					(0.59)
$Price_{t-4}$					-0.0154
					(-0.78)
Constant	6264.9***	2469.4***	2577.8***	8.754	11.90
	(21.90)	(9.39)	(9.60)	(0.43)	(0.60)
N	2617	2616	2616	2616	2613
R^2	0.385	0.574	0.575	0.998	0.998

Note: t-statistics in parentheses: p:0.10, ** p:0.05, *** p:0.01

TABLE X: Bitcoin: Timeline

The dependent variable is each Bitcoin's return. The Sentiment is the proxy of general sentiments in Bitcoin. Crypto-market risk premium is the difference between the crypto-assets return and risk-free rate .

	(1)	(2)	(3)	(4)	(5)	(6)
	Return	Return	Return	Excess Return	Excess Return	Excess Return
Timeline	2014-2016	2017-2019	2020-2022	2014-2016	2017-2019	2020-2022
Crypto_Market Risk Premium	0.0166	-0.0417	0.0294	0.0319*	-0.0654	0.0628***
	(0.91)	(-0.71)	(1.40)	(1.76)	(-1.10)	(2.98)
Sentiment	0.0286	0.0196**	0.0261***	0.303	1.972**	2.669***
	(0.77)	(2.24)	(3.31)	(0.82)	(2.23)	(3.38)
Constant	-0.00301	-0.0140	-0.0179**	-2.522***	-3.922***	-2.635***
	(-0.63)	(-1.50)	(-2.09)	(-5.27)	(-4.16)	(-3.06)
N	502	502	544	502	502	544
R^2	0.3	0.11	0.24	0.08	0.12	0.38

Note: t-statistics in parentheses:* p: 0.10, ** p: 0.05, *** p: 0.01