Does Dispersed Sentiment drive Returns, Turnover, and Volatility for Bitcoin?

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Abstract

We test the theoretical predictions of the differences-of-opinion literature by analyzing the extensive online discussion on Bitcoin to build a time-varying sentiment distribution, defining disagreement as dispersion in sentiment. High disagreement is associated with negative returns, high turnover growth, and high volatility, confirming the theory's predictions. However, we do not find that an increase in disagreement increases the price, which is seemingly at odds with the theoretical prediction of disagreement leading to overpricing. As the theory predicts, the disagreement effect weakens significantly after shorting instruments were introduced at the end of 2017. Our results are economically significant: at the monthly frequency, a one standard deviation increase in disagreement leads to a 9.2 percentage points lower cumulative return over the following eight months, and the adjusted R^2 of regressing contemporaneous returns on average sentiment and disagreement is 0.33.

Keywords: Speculative Bubble, Disagreement, Bitcoin, Sentiment Analysis, VADER

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1 Introduction

A large literature has studied the effect of investor disagreement on returns for different asset classes and periods and with ambiguous results. Generally, the literature discusses two possible opposing mechanisms: (i) in the presence of short-sale constraints, investor disagreement drives up prices, as optimists hold the assets, and returns will be low, and (ii) investor disagreement represents higher uncertainty and thus warrants a higher return for holding the asset.[1] The first mechanism, known as the differences-of-opinion channel, also predicts high turnover and price volatility when investor disagreement is high.

The differences-of-opinions literature is built on the key theoretical insight that if pessimists cannot participate in the market due to high short-selling costs, the asset price will be higher than the fundamental value, leading to subsequent low returns. Furthermore, as opinions fluctuate and trade becomes more likely, disagreement leads to high volatility and high turnover. These predictions have been derived from a long theoretical literature, starting from Miller (1977) and Harrison and Kreps (1978), later developed into behavioral agree-to-disagree models such as Hong and Stein (2003), Scheinkman and Xiong (2003), Hong, Scheinkman, and Xiong (2006), and more recently Simsek (2013).[2]

A crucial obstacle to testing the predictions of the difference-of-opinion literature has been that investor sentiment is not directly observable. Different proxies have been used, such as analyst opinions or newspaper articles (Sadka and Scherbina 2007). Nowadays, the availability of extensive online discussions about assets allows us to analyze statements and opinions issued by individuals who are potential investors. A seminal paper following this approach is Antweiler and Frank (2004), who analyzed online posts on Yahoo Finance and Raging Bull to predict market volatility and asset returns. Other papers analyzing asset characteristics using different dictionary-based algorithms are Tetlock (2007), Loughran and McDonald (2011), and Jegadeesh and Wu (2013).

In this paper, we exploit the magnitude of online discussion about a highly speculative asset on which opinions are widely divided (Bitcoin) to test a theory of investor disagreement and short-sell constraints. We scrape millions of online comments across a decade of discussion from a Bitcoin-focused online forum and extract sentiment using the lexicon- and rule-based sentiment algorithm called VADER (Hutto and Gilbert 2014), which is specifically trained for online data sets. Our contribution is to explore the joint time-series behavior of this sentiment measure, as well as its dispersion, on the one hand, and Bitcoin's return, turnover, and price volatility, on the other. Our approach allows us to test the predictions of the differences-of-opinion literature in a rich setting of textual data at daily, weekly, and monthly frequency. We argue that Bitcoin is the ideal asset to test these predictions, as it is complicated to judge its value (Bitcoin will never pay dividends). Therefore, opinions on Bitcoin's value differ widely. Moreover, institutionally and due to substantial price volatility, it is difficult to short Bitcoin.

We find that there is a significantly negative predictive relationship between disagreement and the return on holding Bitcoin. Disagreement forecasts negative returns into the future at the daily, weekly, and monthly frequencies. This empirical finding is consistent with the theoretical predictions of the

[1] For an extensive discussion, see Diether, Malloy, and Scherbina (2002).

[2] For a full overview of the differences-of-opinion literature, see Hong and Stein (2007) and Xiong (2013). Simsek (2021) provides an overview of the macroeconomic implications of investor disagreement.

differences-of-opinion literature. The effect is especially strong and predicts low returns several months into the future if sentiment and returns are measured at a monthly frequency, which we interpret as overpricing resolving slowly over time. The association between contemporaneous returns, average sentiment, and disagreement is economically significant as well: the adjusted R^2 is 0.33 at monthly frequency. A one standard deviation increase in disagreement leads to a negative return of about -9.2% over the following eight weeks. This is around 12% of the standard deviation of the eight-week returns for Bitcoin.

Although disagreement predicts low returns, which can be interpreted as a sign of overpricing, disagreement is not positively related to contemporaneous or past returns. This finding seems at odds with the usual understanding of the differences-of-opinion channel, predicting that an increase in disagreement first leads to positive returns and overpricing. However, the literature usually assumes that an asset's fundamental value is independent of investor beliefs or disagreement, but this might not be the case for a purely belief-driven asset such as Bitcoin. In this case, the emergence of disagreement could erode the coordination of beliefs among Bitcoin investors, which is key to the asset's value proposition. A slow adjustment of beliefs on the side of optimists can then lead to a situation in which disagreement predicts low returns in the medium term without initially increasing the price.

We study the consequences of the easing of short-sell constraints for Bitcoin starting in December 2017.[3]. We find that, as the literature would predict, the effect of disagreement on returns diminishes significantly towards the end of our sample. However, shorting Bitcoin remains expensive and risky, as margin requirements are high compared to other assets, and Bitcoin's price is extremely volatile.

Extending our analysis to volatility and turnover, we find that disagreement has a strong and significant effect on price volatility and turnover growth. Higher disagreement leads to persistently more trading at the same time as a short-lived increase in volatility. These findings generally are consistent with the predictions of the differences-of-opinion literature. Our findings are also economically significant in this case. In the regression, at a monthly frequency, the adjusted R^2 is 0.06 for turnover growth and 0.34 for volatility.

We contribute by extending the literature about disagreement to a speculative asset with a market capitalization that has increased to over a trillion US dollars since 2010.[4] This makes cryptocurrency assets worth serious scientific attention, despite their quirkiness and novelty. The determinants of their pricing and asset characteristics are interesting in their own right, even from a public policy perspective: a collapse of cryptocurrency prices (e.g., optimists could become disillusioned and leave the market) would destroy immense wealth.

The remainder of the paper is organized as follows. Section 2 explains the mechanism behind the results in the differences-of-opinion literature in a stylized model and contrasts it with other possible explanations, namely the idea that disagreement is just a symptom of underlying uncertainty and the that disagreement today is simply driven by low past returns. Section 3 details how we collected the data and conducted our sentiment analysis. Then, section 4 tests the derived relationships empirically and finds substantial support for the predictions of the theoretical literature. In section 5 we interpret our results. Section 6 concludes.

[3]The CME Group started offering futures contracts for Bitcoin only in December 2017 (CME Group 2017) and options on futures in January 2020 (CME Group 2019)

[4]As of April 2021. The whole market capitalization of all cryptocurrencies has pushed past 2 trillion.

2 Model

2.1 Disagreement in a Differences-of-Opinion Model

We present a simple discrete-time model of heterogeneous beliefs and limits to arbitrage[5] to motivate our empirical analysis. There are overlapping generations of risk-neutral traders indexed by i who each live for two periods and maximize end-of-life consumption.[6] The utility function of trader i is

$$U_{it} = \mathbb{E}_{it}\{C_{it+1}\}. \tag{1}$$

When young, traders either buy a long-lived asset from the old or invest in a risk-less bond with return $R > 1$. Traders are split into two groups - optimists and pessimists - who have diverging beliefs about the asset's value, in this case, Bitcoin. Traders have deep pockets, such that optimists have sufficient wealth to buy up the asset supply, and pessimists must stay out of the market due to short-sell constraints. Therefore, the equilibrium price will be determined by the optimists' beliefs only.

The features of the model's long-lived asset capture the essence of Bitcoin in reduced form. Bitcoin investors believe that a coordinated and permanent shift in beliefs will make Bitcoin valuable as a store of value and currency with some positive probability.[7] We denote this absorbing event as A_t if it takes place in period t. Because Bitcoin's protocol limits its supply, the value of one Bitcoin in this event can be derived according to a quantity theory of money type equation, which we denote as $\bar{P}$.[8] The probability of the collective shift is fixed over time to $\mathcal{P}(A_t) = \phi \in (0, 1)$. Once the event has taken place, all traders agree on Bitcoin's price being fixed to $\bar{P}$ for all future periods. As our focus is on explaining short- to medium-term fluctuations in the price of Bitcoin and not the long-term trend, we assume that ϕ is fixed over time.

However, traders believe that the probability ϕ is time-variant. In particular, they have heterogeneous beliefs about $\mathcal{P}(A_{t+1})$ but agree that the probability is fixed to ϕ from $t + 2$ onward. Within each group, beliefs are homogeneous.[9] The beliefs of group i are distributed as $\phi^i_s \overset{iid}{\sim} G(\phi^i_s)$, where $G(\cdot)$ is the continuous cumulative distribution function of ϕ^i_s over the interval $[0, 1]$.[10] We refer to the group that attributes a higher probability to A_{t+1} as *optimists* and the other group as *pessimists* ($\phi^o_{t+1} > \phi^p_{t+1}$).

Due to perfect competition between optimists, the price in period t is

$$P_t = \frac{1}{R}\left(\phi^o_{t+1}\mathbb{E}(P_{t+1}|A_{t+1}) + (1 - \phi^o_{t+1})\mathbb{E}(P_{t+1}|\neg A_{t+1})\right), \tag{2}$$

[5]For a comprehensive review of the theoretical differences-of-opinion literature, see Simsek (2021)

[6]Risk-neutrality is chosen to present the difference-of-opinion channel in the cleanest way. Risk-aversion is considered in section 2.2.

[7]For example, as of June 9th, 2021, Bitcoin became legal tender in El Salvador.

[8]We do not model the determinants of $\bar{P}$ explicitly, but instead focus on the relationship between disagreement and the price today, while taking $\bar{P}$ as given.

[9]The assumption of homogeneous in-group beliefs is not crucial and can be replaced with heterogeneous beliefs inside the group. Traders agree to disagree and do not learn from the price. This assumption can be relaxed by assuming that traders are overconfident.

[10]The *iid* assumption is made for simplicity to highlight that prices and beliefs are eventually mean-reverting, which would also hold if beliefs were somewhat persistent over time.

where $\mathbb{E}(P_{t+1}|A_{t+1}) = \bar{P}$. Optimists believe that with probability ϕ^o_{t+1} a belief shift will take place and they will sell the asset at a price $\bar{P}$ when old. Otherwise, they will sell the asset at a price P_{t+1} that depends on the beliefs of tomorrow's optimists. This leads us to the main prediction of the model.

Proposition 1. *Returns* $\frac{P_{t+1}-P_t}{P_t}$ *are* decreasing *in disagreement* $(\phi^o_{t+1} - \phi^p_{t+1})$ *holding the average belief* $(\phi^o_{t+1} + \phi^p_{t+1})/2$ *constant.*

The intuition for this result is that when disagreement is high, the overoptimism of optimists is more severe, which depresses returns going into the future. Naturally, such overoptimism increases the price initially, which leads to the following Corollary.

Corollary 1. *Past returns* $\frac{P_t-P_{t-1}}{P_{t-1}}$ *are* increasing *in disagreement* $(\phi^o_{t+1} - \phi^p_{t+1})$ *holding the average belief* $(\phi^o_{t+1} + \phi^p_{t+1})/2$ *constant.*

The model can also be extended to yield predictions for turnover when introducing convex costs for short-selling instead of assuming that such costs are infinite. For simplicity, assume that the costs are sufficiently high such that the marginal buyer remains an optimist.

Proposition 2. *With convex short-selling costs, turnover is* increasing *in disagreement* $(\phi^o_{t+1} - \phi^p_{t+1})$ *holding the average beliefs* $(\phi^o_{t+1} + \phi^p_{t+1})/2$ *constant.*

Convex short-selling costs are chosen for simplicity to relate disagreement and turnover. Generally, increased disagreement positively influences the perceived gains from trade, leading to additional traders entering the market, which can increase turnover even when the amount of short-selling is exogenously fixed per trader.

Volatility has a more ambiguous relationship with disagreement than returns or turnover. For example, if traders were long-lived and beliefs fully persistent, prices would be constant for any level of disagreement. As beliefs are short-lived in our stylized model, the relationship between volatility and disagreement is, in principle, non-linear. If today's optimists are pessimistic relative to the average optimists over time ($\phi^o_{t+1} < \mathbb{E}(\phi^o|\phi^o > \phi^p)$), then higher disagreement can move today's prices closer to the historical average while keeping the average belief constant, decreasing expected volatility.

Still, expected volatility can be positively related to today's disagreement when the distribution of beliefs $G(\phi^i_s)$ is subject to variance shocks. In this case, more disagreement today can indicate more volatile beliefs in the future, which increases expected price volatility. Therefore, we expect volatility to be positively related to disagreement.

Similarly, our predictions for returns and turnover can be extended dynamically if we think about an increase in disagreement stemming from such a mean-reverting variance shock to $G(\phi^i_s)$. Then, disagreement is persistent and overpricing due to disagreement does not resolve immediately, leading to protracted negative returns. Also turnover and volatility remain alleviated for several periods.

Before we turn to our empirical approach, note that the model is deliberately kept simple to provide intuition for the main mechanisms. Moreover, the model is stationary conditional on the base probability of adoption ϕ, whereas asset prices are usually non-stationary as returns follow random walks. Therefore, our simple model is best used to explain fluctuations that happen around the trend in Bitcoin's price. As the price and turnover clearly show non-stationary behavior in Figure 1, we will use returns, the growth rate of turnover and dispersion in hourly returns as LHS variables in our empirical analysis.[11]

Before moving to our empirical analysis, we present two alternative models through which the relationship between disagreement and returns can be interpreted.

2.2 Disagreement as Uncertainty

Large disagreement among traders can be a sign of fundamental uncertainty. When uncertainty increases, risk-averse traders require higher future returns to absorb the risk, which leads to a fall in the price today.

To capture this intuition, consider a model with overlapping generations of representative traders[12] with CARA-utility

$$U_t = 1 - \exp\left(-\gamma W_{t|t+1}\right). \tag{3}$$

where $\gamma \geq 0$ is the coefficient of absolute risk aversion and $W_{t|t+1}$ is end-of-period wealth of the representative trader born in period t, who is free to borrow or lend at interest rate $R > 1$. Without loss of generality, initial wealth is normalized to zero. Every period, the old trader sells a single risky asset to the young trader. Otherwise, the asset characteristics are unchanged.

As before, traders believe that the probability of the adoption event A_{t+1} is time variant. But this time, their beliefs are uncertain. At the beginning of the period, the representative trader draws a belief over ϕ_{t+1} with finite mean and positive variance. Beliefs are *iid* across generations.

The price P_t is derived from the representative trader being indifferent between holding the asset or lending out P_t at interest rate R,

$$1 - \mathbb{E}_t \left\{\exp\left(-\gamma P_{t+1}\right)\right\} = 1 - \exp\left(-\gamma R P_t\right), \tag{4}$$

leading to

$$P_t = \frac{-\log \mathbb{E}_t \left\{\exp\left(-\gamma P_{t+1}\right)\right\}}{\gamma R}. \tag{5}$$

The price P_t depends on the the representative trader's expectations about the probability of adoption ϕ_{t+1}. Due to risk-aversion, a mean-preserving increase in uncertainty about ϕ_{t+1} must lead to a lower price P_t, which is captured in the following Proposition.

Proposition 3. *Returns* $\frac{P_{t+1}-P_t}{P_t}$ *are* increasing *in the representative trader's variance of beliefs on the probability of the adoption event* ϕ_{t+1}.

As before, a fall in today's price due to higher uncertainty must also mean that past returns were negative, which leads to the following corollary.

[11] Although beliefs almost solely drive price movements and trading in Bitcoin, our approach of extracting sentiment from text is not well-suited to explain the long-term price movements in Bitcoin. Sentiment analysis is more appropriate to measure how prevalent relatively positive or negative sentiment is in a given moment in time, which can be an important determinant for short- to medium-run price movements.

[12] The same result would also hold when considering a model with a mass of heterogeneously informed traders as in Grossman and Stiglitz (1980). In that case, an increase in fundamental risk leads to higher disagreement and posterior uncertainty. A decrease in the precision of private signals can have similar effects as shown in CHAPTER 2.

Corollary 2. *Past returns* $\frac{P_t - P_{t-1}}{P_{t-1}}$ *are* decreasing *in the representative trader's variance of beliefs on the probability of the adoption event* ϕ_{t+1}.

It follows that viewing disagreement as a proxy of uncertainty leads to exactly opposite predictions on the relationship between disagreement and returns compared to the differences-of-opinion model. When traders are risk-averse, they require a higher return when absorbing greater risks, leading to falling prices. In contrast, in the presence of overconfidence and short-sell constraints, higher disagreement means that price-setting optimists are increasingly over-optimistic, inflating the price today and leading to low future returns.

2.3 Disagreement as a Side-Show

As we set out to derive a proxy for sentiment and disagreement from posts in an online forum, reverse causality is a plausible concern. Such posts may merely react to price movements but not reveal any information that could be useful to predict future returns. In the following, we suppose that sentiment is a function of lagged returns.

$$\text{Sent}_{it} = \alpha_i + \sum_{s=0}^{S} \gamma_{is} \left(\frac{P_{t-s} - P_{t-1-s}}{P_{t-1-s}} \right) + \varepsilon_{it} \tag{6}$$

where $S < \infty$ and $\varepsilon_{it} \overset{iid}{\sim} \mathcal{N}(0, \sigma_\varepsilon^2)$. Finally, we use in our analysis average sentiment and the dispersion in sentiments as disagreement, formally

$$\text{Sent}_t = \sum_i \text{Sent}_{it}. \tag{7}$$

$$\text{Dis}_t = \sqrt{Var(Sent_{it})} \tag{8}$$

Naturally, sentiment should react positively to current, and past returns ($\forall s : \gamma_{is} > 0$) as investors profit from positive returns.[13] Less clear is the relationship between disagreement and past returns. One possible explanation draws on *confirmation bias*. Following this idea, investors in Bitcoin may be likely to disregard information that does not match their prior.

Suppose that investors are split into two groups. The first group consists of dogmatically optimistic traders (high α_o), who do not revise their beliefs in the face of new information ($\gamma_{os} \approx 0$).[14] The second group is composed of less optimistic traders ($\alpha_p < \alpha_o$) with more flexible beliefs ($\gamma_{ps} > 0$). As a result, both groups hold more similar beliefs when returns are positive and disagree more intensely when returns are negative. Therefore, we would expect to see a negative relationship between past returns and disagreement.

To derive predictions about the predictability of returns using sentiment and disagreement, we consider two returns processes. First, prices may follow a random walk and returns are, therefore,

[13] A positive relationship may also be plausible when interpreting sentiments as expectations about future returns. Greenwood and Shleifer (2014) show that investors increase their expectations of future returns after positive past returns.

[14] It is also possible to assume that there are dogmatic pessimists, but attributing dogmatism to optimists is in line with anecdotal evidence of a fraction of Bitcoin investors who buy Bitcoin and hold it for extended periods irrespective of news. Moreover, dogmatic pessimists should eventually leave the market.

white noise. In this case, sentiment or disagreement cannot forecast returns as they are not correlated with the innovations to the price. Second, returns may be autocorrelated, which can lead to sentiment and disagreement predicting future returns.[15] Nonetheless, sentiment and disagreement should lose their predictive power when controlling for lagged returns.

3 Data

We use publicly available data from the *Kraken.com* exchange for the opening and closing price of Bitcoin and an aggregated measure of turnover across all major exchanges from *coinmarketcap.com*. We compute daily returns by dividing the difference between closing and opening prices by the opening price and turnover as the daily dollar volume divided by Bitcoin's total market capitalization.[16] We compute a volatility measure as the standard deviation of hourly returns in a given day, week, or month.

We relate Bitcoin's market characteristics to sentiment changes among Bitcoin investors. For this purpose, we scrape the Bitcoin-related online-forum *bitcointalk.org* using the python package *Scrapy*. In particular, we scrape all threads and comments from the *Speculation* subforum, which most closely covers discussions on Bitcoin's price movements and expectations about future price developments. We gathered 1,482,589 comments that were posted between 18 October 2010 and 21 April 2021.

We gathered comments from 54,173 unique accounts, of which 7,183 accounts opened discussion topics. Posting activity follows a power law, as the top ten percent of most active accounts (more than 32 posts) produce more than 84% of all content. In contrast, the median number of posts per account is three. At the same time, no single account dominates the discussion, as the most active account wrote 1.3% of all posts (19758 in total or five posts per day). Overall concentration is low with a Herfindahl index of 0.0011.[17] According to *bitcointalk.org*,[18] there are in total over three million registered users, and more than a million page views a day. With this reach, *bitcointalk.org* is an important medium in discussions related to cryptocurrencies.[19]

We use all comments with non-zero valence in our analysis, as the Speculation subforum is already focused on Bitcoin's price movements. The forum allows users to quote other comments in their posts. We filter out such repetitions as quotes and keep only the new part of each post.[20] We run our main specification starting 1 January 2014, as the number of posts per day reaches a higher and more stable level from 2014 on. Figure C.2 provides a word cloud with the most commonly used words of a random

[15] Positive autocorrelation may arise when new information is only gradually incorporated (McQueen, Pinegar, and Thorley 1996), whereas negative autocorrelation may stem from overreaction to new information (Lo and MacKinlay 1990).

[16] Since crypto exchanges are open 24/7, the opening and closing prices are the earliest and latest price available in a specific period according to UTC.

[17] We show the time series of the number of active users in Figure C.1a, which is positively correlated to the overall number of posts. In Figure C.1b, we show that the Herfindahl Index is stable over time and decreased during the surge in activity in 2018.

[18] See `https://bitcointalk.org/index.php?action=stats`.

[19] For example, today's second-largest cryptocurrency *Ether* and its Initial Coin Offering were first announced on *bitcointalk.org* in January 2014: `https://bitcointalk.org/index.php?topic=428589.0`.

[20] We do not attempt to weigh posts according to importance (e.g., through their number of views or quotes), but instead attribute the same weight to every post. Although an abundance of quotes potentially reflects the greater importance of the quoted post, we find that filtering out quotes increases the explanatory power of our sentiment and disagreement measure in all regressions.

sample of 10,000 comments.

Figure 1 summarizes the time series of the main variables at a weekly frequency: the price level, turnover, price volatility measured as the standard deviation of hourly returns, average sentiment, and dispersion in sentiments. Additionally, the right upper panel displays the number of posts on the Speculation subforum of *bitcointalk.org*. As both the price and turnover display a clear trend, we will use their growth rates. All time series have substantial time variation, which we exploit in our empirical analysis. Bitcoin's price follows a distinct boom and bust cycle. Turnover and volatility increase when Bitcoin's price increases or decreases rapidly (e.g., the boom leading up to December 2017 or the short-term bust in 2019.). Posts per week are also cyclical and peak at around 7000 posts per week at the beginning of 2018. Finally, although average sentiment and the standard deviation of sentiment is relatively noisy week-to-week, both time series show persistence at lower frequencies.

Table 1 provides summary statistics (mean, standard deviation, the first and ninth decile cut-offs, as well as the median) for our main variables of interest: sentiment, disagreement, returns, turnover growth, volatility. All statistics are shown daily, weekly, and monthly frequency. Strikingly, mean returns for bitcoin are quite high, with 7.6% monthly. Volatility is also high, with an average standard deviation of hourly returns of around 0.9 percentage point.

	Frequency	Mean	SD	Q10	Median	Q90
Sentiment	daily	0.097	0.042	0.044	0.096	0.15
	weekly	0.096	0.034	0.054	0.095	0.14
	monthly	0.096	0.031	0.056	0.094	0.136
Disagreement	daily	0.099	0.019	0.076	0.099	0.122
	weekly	0.1	0.014	0.081	0.1	0.118
	monthly	0.1	0.013	0.08	0.101	0.116
Return	daily	0.3%	4 %	-3.9 %	0.2%	4.4 %
	weekly	1.6%	10.7%	-12.4%	1.1%	15.6%
	monthly	7.6%	23.2%	-18.9%	6.2%	37.4%
Turnover Growth	daily	7 %	49 %	-31.5%	-1.3%	45.2%
	weekly	5.5 %	35.8%	-29.3%	-1.5%	46.5%
	monthly	9.3 %	40.6%	-28.7%	0 %	64.1%
Volatility	daily	0.8 %	0.77%	0.22 %	0.58%	1.57%
	weekly	0.91%	0.68%	0.34 %	0.72%	1.68%
	monthly	0.99%	0.64%	0.42 %	0.78%	1.84%

Table 1: Summary statics of sentiment, disagreement, returns, turnover growth, and volatility of Bitcoin.

Notes: Mean, standard deviation, first decile, median and ninth decile of the main variables. Statistics for returns, volatility, and turnover growth are in percentage points.

3.1 Sentiment Analysis using Vader

We use a lexicon and rule-based algorithm called VADER (**V**alence **A**ware **D**ictionary and s**E**ntiment **R**easoner) for the sentiment analysis.[21] The underlying lexicon and algorithm are specialized for the

[21] A detailed description of VADER can be found on Github: `https://github.com/cjhutto/vaderSentiment`

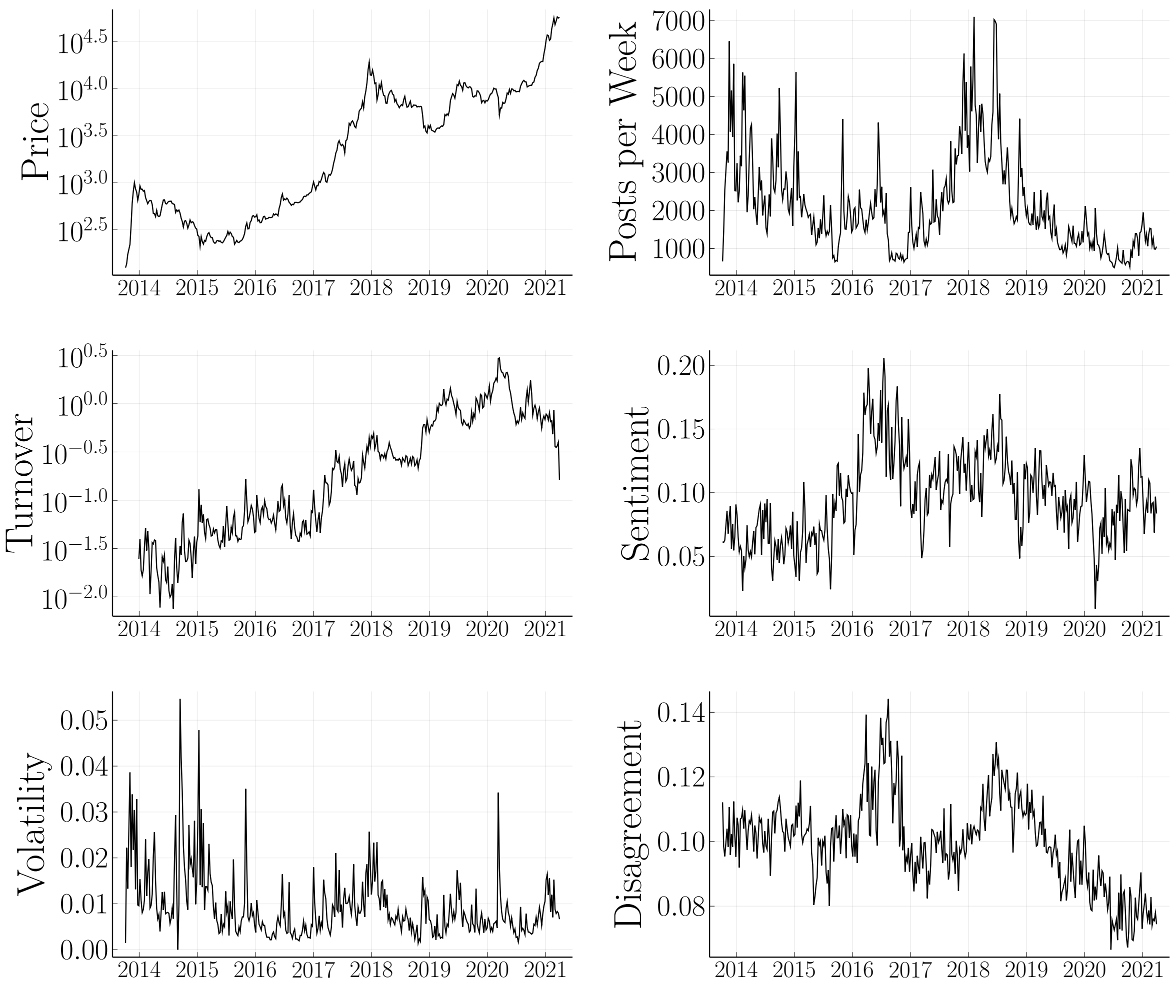


Figure 1: Overview over the main variables at weekly frequency.

Notes: On the left: returns (difference between closing and opening price divided by opening price), turnover (volume divided by market capitalization) and volatility (standard deviation of hourly returns). On the right: number of posts, sentiment (the mean of the comment sentiment distribution) and disagreement (the standard deviation of the comment sentiment distribution).

analysis of social media posts (see Hutto and Gilbert 2014, for a comparison with other lexica).[22]

A sentiment lexicon is a mapping from "tokens" (words, stems of words, abbreviations, etc.) to a numerical indicator of sentiment. Each token carries a certain valence (negative, neutral, or positive sentiment) irrespective of context. These valence intensities were generated by letting ten independent human raters rate tokens. The final valence is the average of the individual ratings (Wisdom of the Crowd approach). All human raters had been pre-screened, trained, and quality checked. Following this approach, over 9000 tokens were rated on a scale from "[-4] Extremely Negative" to "[4] Extremely Positive" with an option to rate the token as "[0] Neutral." Already existing established lexicons inspired the list of tokens (e.g., LIWC, ANEW, and GI) to which Western-style emoticons (e.g., ":-)"), sentiment-related acronyms and initialism (e.g. "LOL", "ROFL") and commonly used slang (e.g., "nah," "meh") were added. After dropping tokens that ended up with a neutral mean-sentiment rating or a standard deviation of individual ratings higher than 2.5, about 7500 tokens were left and rated on the -4 to $+4$ scale.

Although relying on a lexicon for sentiment analysis, VADER is not a bag-of-words algorithm that neglects the syntax and order of words. Instead, VADER employs five simple rules to improve its sentiment ratings for whole sentences. First, punctuation is included by using the exclamation point (!) as an intensifier. Secondly, capitalization increases the sentiment intensity. Thirdly, modifiers are used to adjust the intensity. With the corresponding valence between -1 (very negative) and 1 (very positive) computed by VADER, "Bitcoin has a bright future" (0.44) is less intense than "Bitcoin has a very bright future" (0.49) and more intense than "Bitcoin has a somewhat bright future" (0.38). Fourthly, the conjunction "but" is used to signal a reversal of semantic orientation. For example, "Bitcoin had a great year, but has a lot of problems" (-0.25) conveys negative sentiment, although the initial statement is positive. Lastly, the three words before a sentiment-laden token are included in the sentiment rating to check for words that flip the semantic orientation. For example, "Bitcoin does not have a great future" (-0.34) conveys negative sentiment, although "great" carries positive sentiment.

To sum up, VADER is an appropriate sentiment analysis tool for the domain of our investigation. We use the "compound" measure, a weighted average of sentiment normalized to values between -1 (extremely negative) and 1 (extremely positive). As suggested by the package authors, we compute the sentiment index for each comment on the sentence level and use the mean to compute comment-level sentiment. Finally, we aggregate the sentiment data at different frequencies and use the mean to measure the level of daily, weekly, and monthly sentiment. We use the standard deviation of variance as a proxy for disagreement among investors.

4 Empirics

Our empirical approach is to extract a sentiment measure from comments on *bitcointalk.org* and use this measure as a proxy for beliefs about the success of Bitcoin (ϕ^i_{t+1} in the model). In particular, we think of our sentiment measure as being relative to some time-variant base level of expectations (e.g., a time-variant ϕ). In that way, high sentiment can be interpreted as expectations of positive returns

[22] The authors show that VADER can produce valence ratings with high correlation to human mean-sentiment ratings. In particular, run on a corpus of over 4000 Tweets, sentiment, as calculated by VADER, had the largest correlation (0.88) and R^2 (0.77) to the human mean-sentiment rating.

at any point in time. Henceforth, we refer to the valence measure as computed by VADER from each comment simply as sentiment.

Whereas we capture an average stance of sentiment through the first moment the sentiment distribution, we define disagreement as the dispersion in sentiment. If comments with positive and negative sentiment are posted during the same period, we interpret such dispersion as a sign of high disagreement. We use these measures to analyze the effect of disagreement, conditional on average sentiment, on the return, turnover growth, and volatility of Bitcoin.

All our regressions are summarized by the following equation,

$$X^j_{t+s} = \alpha^j_s + \sum_{l=0}^{L} (\beta^{j,l}_{\mu,s}\text{Sentiment}_{t-l} + \beta^{j,l}_{\sigma,s}\text{Disagreement}_{t-l}) + \varepsilon_{t+s}. \tag{9}$$

We use returns, turnover growth, and the dispersion in hourly returns (volatility) as the LHS variable X^j_{t+s} where j stands for each different variable. We run the regression at different leads s and for lags in case of returns. Moreover, we also use long-horizon returns with overlapping observations as the LHS variable, in which case X^j_{t+s} stands for the return between the beginning of period $t+1$ and the end of period $t+s$. We include up to L lags of sentiment and disagreement and estimate (9) for each variable at daily, weekly, and monthly frequency. Throughout, we apply HAC-robust standard errors following Newey and West (1987). To address concerns due to the persistence of our regressors, we repeat our forecasting regressions with confidence intervals computed according to Campbell and Yogo (2006).[23] Additionally, for the regression with long-horizon returns, we adjust our confidence intervals according to Hjalmarsson (2011), which additionally increases the bandwidth as our forecasting horizon lengthens.

4.1 Return Regressions

We set out to predict returns of Bitcoin through sentiment and disagreement. As a first step, we present evidence that the price of Bitcoin is indeed predictable while not taking a stance on the specific predictor. For this purpose, we use the variance ratio test of Lo and MacKinlay (1988). The idea of the test is that if prices move randomly, the variance of returns should increase linearly in the horizon. If this assumption is violated, returns are not random and can potentially be predicted.

	2 Lags	3 Lags	4 Lags	5 Lags	6 Lags	10 Lags
Daily	-0.58	-0.43	-0.30	-0.22	-0.03	0.45
Weekly	0.83	1.28	1.55	1.41	1.36	1.55
Monthly	1.81*	1.74*	1.96*	1.93*	1.82*	1.54

Table 2: Lo and MacKinlay (1988) Variance Ratio Test for Return Predictability.

Notes: We find that Bitcoin's returns are predictable at lower frequencies. Critical values are as for the two-sided t-test. *: p <0:10, **: p <0:05, ***: p <0:01

As shown in Table 2, we find evidence that Bitcoin's returns are indeed predictable at monthly frequencies, which we confirm in our regression analysis. Before turning to our regression results, we

[23] We provide ACFs of our variables in Section C.1.

recap the predictions for the relationship between disagreement and returns for each model in Table 3.

	Past Returns	Future Returns
Difference-of-Opinion	>0	<0
Uncertainty	<0	>0
Side-Show	>0	0

Table 3: Predictions for the Relationship between Disagreement and Returns.

The presented models of differences-of-opinion in the presence of short-sell constraints and disagreement as uncertainty yield exactly opposite predictions regarding the relationship of returns and disagreement. If optimists price the asset as in the differences-of-opinion model, an increase in disagreement, while holding average sentiment constant, leads to an increase in overpricing. Such overpricing then is predictive of lower returns in the future due to the mean-reversion of overoptimism. In contrast, an increase in disagreement can be viewed as a sign of uncertainty, which leads to risk-averse traders requiring higher returns, thus lowering the price today. Finally, in the model in which sentiment is simply a reflection of past returns, disagreement should have no predictive power when controlling for past returns.

4.1.1 Regressions

As a first step, we estimate the relationship between sentiment and disagreement in period t, and returns in $t-1$, t, and $t+1$ to distinguish between the different models.

	Returns t-1 daily	Returns t daily	Returns t+1 daily	Returns t-1 weekly	Returns t weekly	Returns t+1 weekly	Returns t-1 monthly	Returns t monthly	Returns t+1 monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sentiment	0.73***	0.70***	0.09	3.11***	4.59***	1.04*	8.84***	13.38***	4.84**
	(0.08)	(0.09)	(0.08)	(0.48)	(0.55)	(0.61)	(2.18)	(2.02)	(2.22)
Disagreement	−0.45***	−0.42***	−0.08	−2.86***	−3.52***	−1.14**	−9.56***	−12.21***	−7.69***
	(0.07)	(0.07)	(0.07)	(0.49)	(0.47)	(0.56)	(2.16)	(1.92)	(2.41)
Constant	0.93***	0.85***	0.48	13.26***	13.74***	6.88**	52.85***	59.67***	51.59***
	(0.32)	(0.32)	(0.37)	(3.18)	(2.97)	(3.41)	(14.41)	(13.77)	(16.51)
N	2,635	2,634	2,633	378	377	376	88	87	86
R^2	0.03	0.03	0.001	0.09	0.18	0.01	0.17	0.34	0.09
Adjusted R^2	0.03	0.03	−0.0001	0.09	0.18	0.01	0.15	0.33	0.06

Notes: Returns are the growth rate between the opening and closing price in percentage points. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 4: Sentiment, disagreement, and returns.

Notes: Sentiment is positively related with returns, whereas disagreement is negatively related to returns. All relationships are stronger at lower frequencies.

Our results are not strictly in line with the proposed models. As seen in Table 4, the contemporaneous effect of disagreement on the return is negative, as is the effect one period ahead. For example, a one standard deviation increase in disagreement in month t decreases the return in the subsequent month by 7.7 percentage points. The negative contemporaneous relationship is what we would have expected from the model with risk-averse traders, while the negative predictive effect is in line with the differences-of-opinion model. Therefore, neither model explains the empirical results exactly.

To test whether sentiment and disagreement contain information beyond what is reflected by past returns, we report in Table 5 the one-period-ahead predictive regression while controlling for lagged returns. If the "disagreement as a side-show" model was true, we would expect that sentiment and disagreement do not predict returns and that past returns significantly forecast future returns. However, this turns out to be incorrect: past returns have little explanatory power for future returns and the coefficients for sentiment and disagreement remain close to what they where in the regression without lags in Table 4. Thus, all in all, none of the three most suggestive models really seem to provide a comprehensive explanation for our empirical results.

	Returns t+1								
	daily	daily	daily	weekly	weekly	weekly	monthly	monthly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sentiment	0.10	0.09	0.08	0.94	0.71	0.68	3.98	4.08	4.10
	(0.08)	(0.09)	(0.09)	(0.59)	(0.59)	(0.62)	(2.61)	(2.58)	(2.71)
Disagreement	−0.08	−0.08	−0.07	−1.07*	−0.87	−0.84	−6.91**	−7.01**	−7.16**
	(0.07)	(0.07)	(0.07)	(0.57)	(0.61)	(0.65)	(2.95)	(2.99)	(3.14)
Return t	−0.02	−0.03	−0.03	0.02	0.02	0.02	0.06	0.06	0.07
	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)	(0.11)	(0.10)	(0.11)
Return t-1		0.003	0.002		0.05	0.05		−0.01	−0.02
		(0.03)	(0.03)		(0.07)	(0.07)		(0.10)	(0.11)
Return t-2			0.01			0.03			−0.03
			(0.02)			(0.06)			(0.04)
Constant	0.48	0.47	0.45	6.62*	5.83	5.55	47.79**	48.32**	49.83**
	(0.36)	(0.37)	(0.37)	(3.49)	(3.75)	(3.92)	(18.80)	(18.79)	(20.16)
N	2,624	2,616	2,608	375	374	373	86	86	86
R^2	0.001	0.001	0.001	0.01	0.01	0.02	0.09	0.09	0.10
Adjusted R^2	−0.0000	−0.0004	−0.001	0.004	0.003	0.002	0.06	0.04	0.04

Notes: Returns are the growth rate between the opening and closing price in percentage points. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 5: Sentiment, disagreement and future returns controlling for lags.

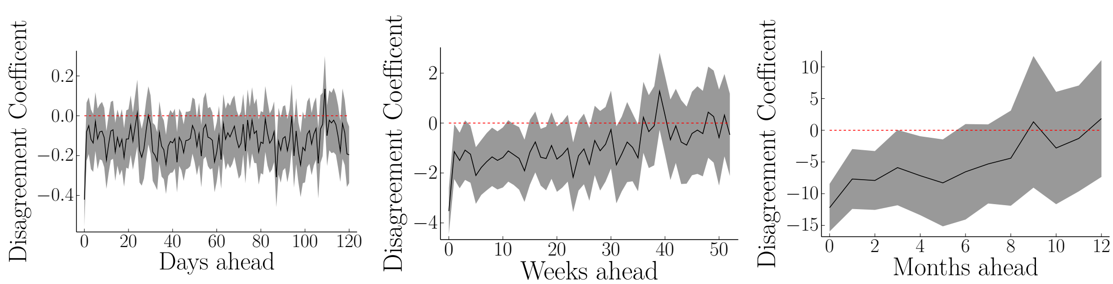
Notes: The coefficients on all lagged returns are insignificant and including lags reduces the adjusted R^2. The sign on sentiment's and disagreement's coefficient remains stable, but including lags marginally decreases the size and increases the standard errors, leading to a decrease in significance.

An additional testable prediction whether sentiment and disagreement predict returns further into the future. Indeed, if beliefs and, therefore, disagreement are persistent, overpricing as in the differences-of-opinion model might resolve only slowly. As a result, disagreement should predict negative returns for multiple periods ahead.

To this end, we estimate (9) for many periods ahead and present the results in Figure 2. We find that disagreement has a strongly persistent negative effect on future returns, which is more pronounced at lower frequencies, cancelling out higher-frequency noise. At monthly frequency, disagreement has a significantly negative effect on returns at 95% confidence up to five months into the future. The plots at the daily and weekly frequency show that this effect is not driven by outliers, but that returns are consistently negative. Thus, disagreement predicts lower returns for up to half a year ahead, which, through the lens of the differences-of-opinion model, suggests that prices take a long time to revert back from overoptimistic levels.[24]

As seen in Figure 1, sentiment and disagreement are relatively persistent and may feature stochastic trends. Indeed, Augmented Dickey-Fuller tests on disagreement rejects the null of the series featuring a unit root at the daily frequency, however does not reject the null at the weekly and monthly frequency, highlighting persistent low-frequency movements. As is well known, very persistent regressors can lead to t-statistics that are too large. Therefore, we provide estimates of confidence intervals that take into account the persistence of regressors.

To address these concerns, we employ the methodology in Campbell and Yogo (2006) to compute confidence intervals that are robust to the presence of persistent regressors and show the results in Figure 3, where the black line shows the central value of the confidence interval. Different to before, we use univariate local projections of returns on disagreement, as Campbell and Yogo (2006) is only applicable to univariate predictive regressions. We find that our results hold at the 90% confidence level.[25]



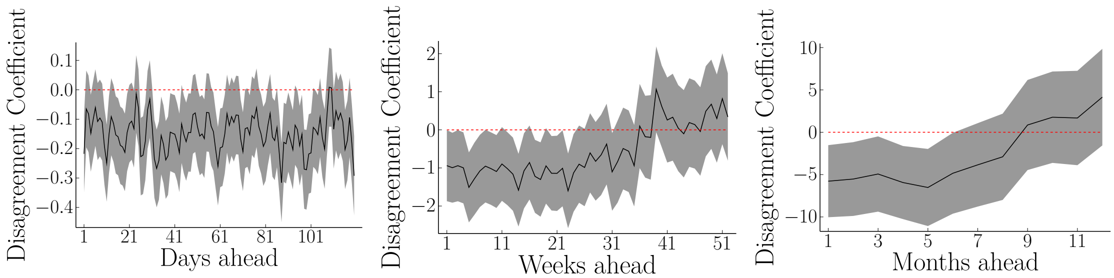
(a) Daily Returns. (b) Weekly Returns. (c) Monthly Returns.

Figure 2: Local Projections of Returns on Disagreement controlling for Sentiment with HAC-robust Standard Errors.

Notes: The shown estimates are the coefficients on disagreement when estimating (9) for leads of returns. Error bands are at 95% confidence and standard errors are HAC-robust according to Newey and West (1987).

[24]This long-lasting effect is also found for other markets. Disagreement in the stock market may forecast lower returns for up to a year (Diether, Malloy, and Scherbina 2002).

[25]We also run our regressions in first differences and show the results in Figures B.1 and B.2. Although significance suffers due to the introduction of additional noise through differencing, the basic results continue to hold. However, we focus on the regression in levels due to its straightforward interpretation.



(a) Daily Returns. (b) Weekly Returns. (c) Monthly Returns.

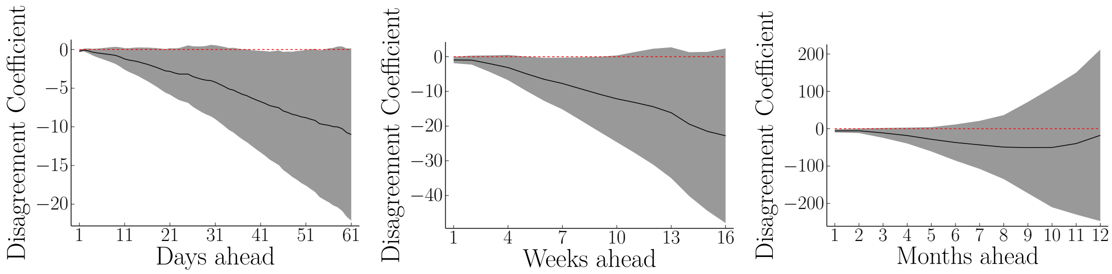
Figure 3: Univariate Robust Local Projection of Returns on Disagreement.

Notes: In a univariate regression, we find that disagreement predicts negative returns for several periods at all frequencies. 90% confidence intervals according to Campbell and Yogo (2006).

Another way to express our findings on the persistence of disagreement shocks is to focus on the cumulative returns over multiple months. Similar to Figure 3, in Figure 4 we run univariate predictive regressions with disagreement in period t as the predictor for the cumulative returns between the opening price in $t+1$ and the closing price in $t+s$. We compute first the confidence intervals as in Campbell and Yogo (2006) and additionally widen them by a factor $\sqrt{s}$ as suggested by Hjalmarsson (2011). Without this adjustment, the implied confidence intervals would be too narrow for long-horizon regression with overlapping observations.

We find that disagreement's effect on cumulative returns is close to being significant at the 90% confidence level for most horizons and significant at the 90% level for some horizons (e.g., five to nine weeks ahead). This loss in significance compared to Figure 3 is somewhat puzzling, but we attribute it to the conservative computation of the confidence intervals. Note also that these are univariate regressions. Given that disagreement and sentiment are positively correlated, and that sentiment is positively related to returns, we would expect that disagreement's effect on returns is *biased towards zero* when not controlling for sentiment.

For the estimates that are significant at 90% confidence, we find that a one standard deviation shock on disagreement leads to a eight-week return that is about 9.2 percentage points lower, which corresponds to about 13% of the standard deviation of eight-week returns for Bitcoin. Furthermore, though insignificant, we find that disagreement's effect on cumulative returns only reverts after more than twelve months.



(a) Daily Cumulative Returns. (b) Weekly Cumulative Returns. (c) Monthly Cumulative Returns.

Figure 4: Long-Horizon Regression of Cumulative Returns on Disagreement.

Notes: We find that a positive one standard deviation shock to disagreement has long-lasting negative effects on returns. Confidence intervals are at 90% according to Hjalmarsson (2011).

Finally, since we hypothesize that the predictive power of disagreement is due to disagreement (and thus overoptimistic beliefs) being persistent, we test whether disagreement remains predictive when controlling for contemporaneous disagreement. In Table B.3, which is shown in the appendix, we run our regression on contemporaneous returns while including contemporaneous sentiment and disagreement, as well as three lags at each frequency. We find that lagged disagreement is insignificant at daily and monthly frequencies yet significantly positive at weekly frequency. At the same time, contemporaneous disagreement's coefficient remains significantly negative at all frequencies.

Again, this finding does not fit well in any of the suggested theories. Whereas the difference-in-opinion model predicts that lagged disagreement inflates yesterday's price with a negative effect on today's return, viewing disagreement as a sign of increasing uncertainty should depress yesterday's price with a positive effect on today's return. We do not find strong evidence for either story.

4.2 Turnover and Volatility Regressions

We present our results for the contemporaneous effect of sentiment and disagreement on turnover growth and price volatility in Table 6. We find that sentiment is significantly associated with contemporaneous turnover growth and volatility of Bitcoin at all frequencies. Moreover, our results grow in magnitude and explanatory power when looking at lower frequencies, i.e., longer-lasting increases in sentiment or disagreement have greater effects.

Our results are in line with the theoretical predictions of the difference-in-opinion model: disagreement increases trading activity and drives up price volatility. This last finding suggests that increases in disagreement indicate more underlying volatility of beliefs.

	Turnover Growth t			Volatiliy t		
	daily	weekly	monthly	daily	weekly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment	-6.59^{***}	-7.20^{***}	-12.23^{***}	-0.22^{***}	-0.36^{***}	-0.42^{***}
	(1.09)	(2.48)	(4.58)	(0.03)	(0.07)	(0.12)
Disagreement	5.11^{***}	4.91^{***}	9.19^{**}	0.10^{***}	0.21^{***}	0.23^{**}
	(0.92)	(1.77)	(4.23)	(0.03)	(0.07)	(0.11)
Constant	-4.68	-9.06	-23.09	0.80^{***}	0.47	0.50
	(3.53)	(8.78)	(27.85)	(0.11)	(0.34)	(0.55)
N	2,644	378	86	2,616	378	87
R^2	0.02	0.04	0.08	0.08	0.25	0.36
Adjusted R^2	0.02	0.03	0.06	0.08	0.24	0.34

Notes: Turnover is total dollar volume across all major exchanges divided by the market capitalization of Bitcoin. Turnover Growth is computed as the growth rate between past period's turnover and current turnover in percentage points. Volatility is the standard deviation of hourly returns over a day, week, or month. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 6: Contemporaneous Regressions of Turnover Growth and Volatility on Sentiment and Disagreement

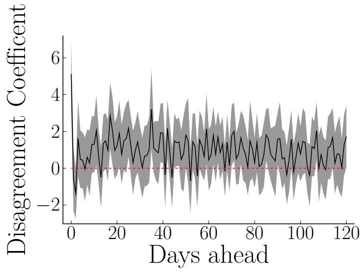
On the other hand, we find that sentiment and disagreement do not have much predictive power in explaining turnover growth and volatility one period ahead, as shown in Table 7. Disagreement predicts volatility only at the daily and weekly frequency and does not predict turnover growth at all. Note that the lack of mean-reversion in turnover growth means that the effect of disagreement on turnover is relatively persistent. This finding is also confirmed at longer horizons in the local projections in Figure 5 when focusing on the effect of disagreement. We provide univariate local projects with confidence intervals according to Campbell and Yogo (2006) in Figure C.3. Analogously to the return regressions in first differences, Tables B.1 and B.2 in the appendix show the contemporaneous and one-period-ahead regressing and volatility.

	Turnover Growth t+1			Volatiliy t+1		
	daily	weekly	monthly	daily	weekly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment	-0.09	2.02	2.88	-0.20^{***}	-0.25^{***}	-0.25^{*}
	(0.99)	(1.79)	(4.16)	(0.03)	(0.07)	(0.14)
Disagreement	-0.62	-2.41	-3.03	0.08^{***}	0.10^{*}	0.09
	(0.86)	(1.68)	(5.22)	(0.03)	(0.06)	(0.11)
Constant	10.48^{**}	16.78^{*}	23.61	0.81^{***}	0.88^{***}	1.03^{*}
	(4.20)	(10.17)	(35.02)	(0.11)	(0.32)	(0.57)
N	2,643	377	86	2,615	377	86
R^2	0.0002	0.005	0.01	0.06	0.11	0.12
Adjusted R^2	-0.001	-0.001	-0.02	0.06	0.11	0.10

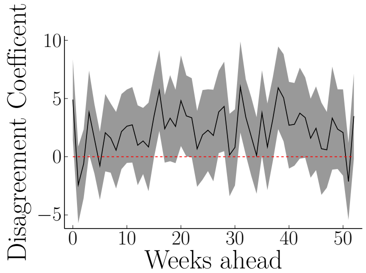
Notes: Turnover is total dollar volume across all major exchanges divided by the market capitalization of Bitcoin. Turnover Growth is computed as the growth rate between past period's turnover and current turnover in percentage points. Volatility is the standard deviation of hourly returns over a day, week, or month. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 7: Predictive Regressions of Turnover Growth and Volatility on Sentiment and Disagreement.

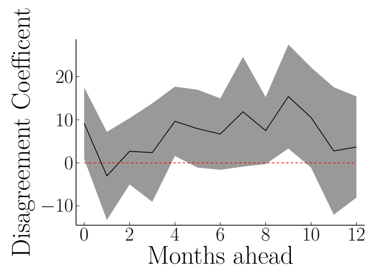
Notes: Disagreement predicts lower returns at weekly and monthly frequency. Turnover remains alleviated after an increase in disagreement, whereas the effect of disagreement on volatility disappears after a week.



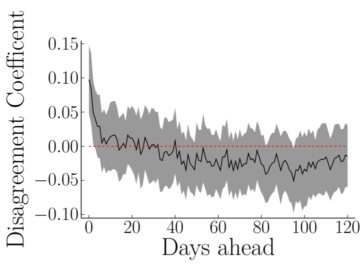
(a) Daily Turnover.



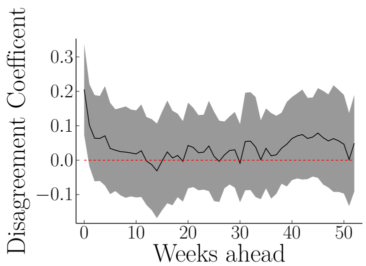
(b) Weekly Turnover.



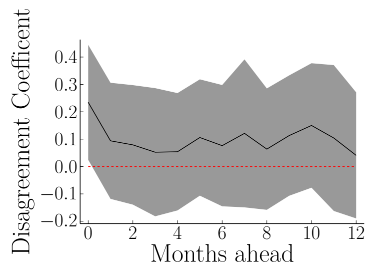
(c) Monthly Turnover.



(d) Daily Volatility.



(e) Weekly Volatility.



(f) Monthly Volatility.

Figure 5: Local Projections of Turnover Growth and Volatility on Disagreement with HAC-robust Standard Errors.

Notes: The shown estimates are the coefficients on disagreement when estimating (9) for leads of turnover growth and volatility. Error bands are at 95% confidence and standard errors are HAC-robust according to Newey and West (1987).

Although the main focus of our analysis is on the effect of disagreement on returns, turnover growth, volatility, we provide for completeness the corresponding local projections focusing on the effect of sentiment in Figure C.4 with HAC-robust standard errors. Figure C.5 shows the results for the univariate regressions with sentiment as the predictor with confidence intervals computed according to Campbell and Yogo (2006).

4.3 Introduction of CME Futures at the end of 2017

The presented framework analyzed the effect of disagreement in the presence of short-sell constraints. A major event in this context is the introduction of futures trading contract at the Chicago Mercantile Exchange on 18 December 2017 (CME Group 2017) and options on futures contract started on 12 January 2020 (CME Group 2019). The introduction of futures contracts and options does not only make markets more complete but should also substantially alleviate short-sell constraints.

The difference-in-opinion model predicts that an easing of short-sell constraints through the introduction of futures and options can eliminate the effect of disagreement, as pessimists can voice their opinion through short-selling. To study this prediction, we estimate (9) contemporaneously and year-by-year. We focus on the contemporaneous specification, as the regression with lagged sentiment and disagreement in Table B.3 suggests that disagreement's negative effect on future returns stems contemporaneous disagreement We show the coefficient on disagreement with 95% error bands in Figure 6. We also report the monthly specification for completeness, although twelve observations per year are arguably too little to draw solid inference.

We find that the coefficient and its error bands on disagreement change over time. In particular, the negative effect of disagreement on returns is particularly large in 2017 and 2018 at the daily and weekly frequencies, whereas no effect can be measured in 2015. Potentially, this result can be related to insufficient variance in disagreement and returns in 2015, such that some episodes can be characterized as more or less speculative.

Starting from 2017, the estimate of disagreement's coefficient for returns tends toward zero. Moreover, the estimate for 2020 is insignificantly different from zero at all frequencies, and the difference between the coefficients in 2016 and 2020 is statistically significant as shown in Table B.4. This finding can be interpreted as short-sell constraints having sufficiently eased since 2018 such that disagreement does not lead to overpricing anymore.[26]

We also study the role of sentiment more generally over time by showing the R^2 of estimating (9) year-by-year in Figure 7. Generally, we find that sentiment and disagreement play a larger role at lower frequencies as demonstrated by higher R^2s. We also see here that the importance of sentiment changes over time. Although the coefficient on disagreement tends towards zero at the end of the sample, the explanatory power of sentiment and disagreement combined remains high. This is not surprising, as Bitcoin remains a speculative asset also when short-selling is permitted.

5 Discussion

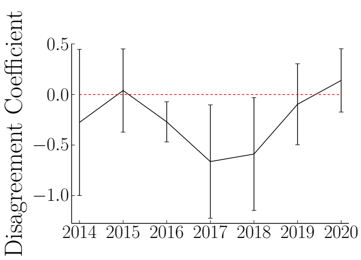
We can summarize our main results as follows: disagreement does predict lower subsequent returns for up to five months into the future and the explained variation is not small (but also not suspiciously large) with an adjusted R^2 of around 6% for the one-month-ahead regression [27], high disagreement does also come with a negative contemporaneous effect on returns. Robustness checks, such as correcting for regressor persistence and controlling for lagged regressors and returns, respectively, do not alter this result. Furthermore, high disagreement comes with contemporaneously higher price volatility and turnover growth, however, for these variables we do not see a strong predictive effect.

5.1 Disagreement and Overpricing

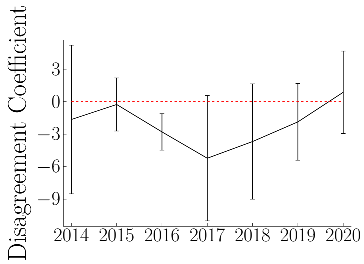
Our main result that returns can be predicted by disagreement is in line with the differences-of-opinion argument that we characterize in 2.1: we find that high dispersion in our sentiment measure (i.e., disagreement is high) forecasts long-lasting negative returns at daily, weekly, and monthly frequencies. Through the lens of the differences-of-opinion literature, we would interpret this result as buyers' overoptimism decaying slowly, which could only occur if pessimists' ability or willingness to short-sell

[26] We conduct a similar analysis for sentiment in Figure C.6. Similarly, we find that the effect of sentiment changes over time, but does not go to zero towards the end of our sample.

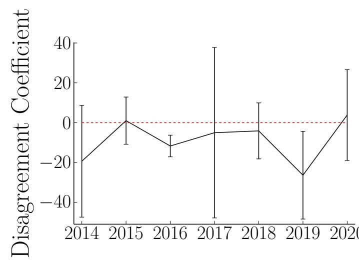
[27] The analysis at higher frequencies picks up more noise, which leads to our R^2 being generally largest at monthly frequency.



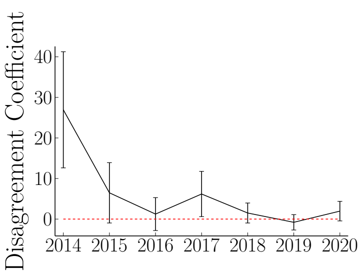
(a) Daily Returns.



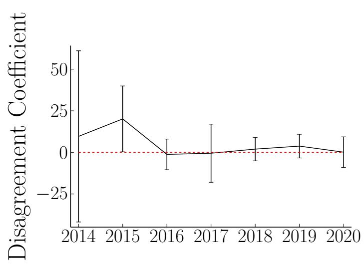
(b) Weekly Returns.



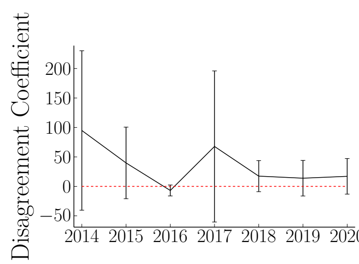
(c) Monthly Returns.



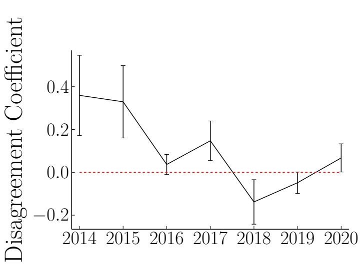
(d) Daily Turnover.



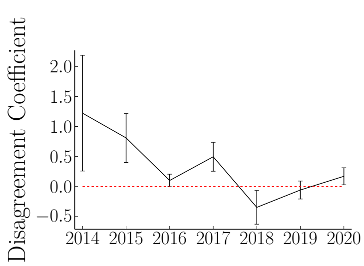
(e) Weekly Turnover.



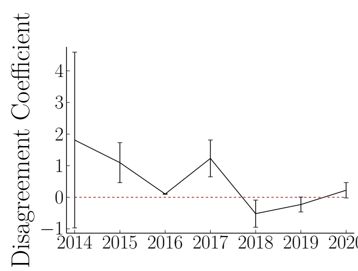
(f) Monthly Turnover.



(g) Daily Volatility.



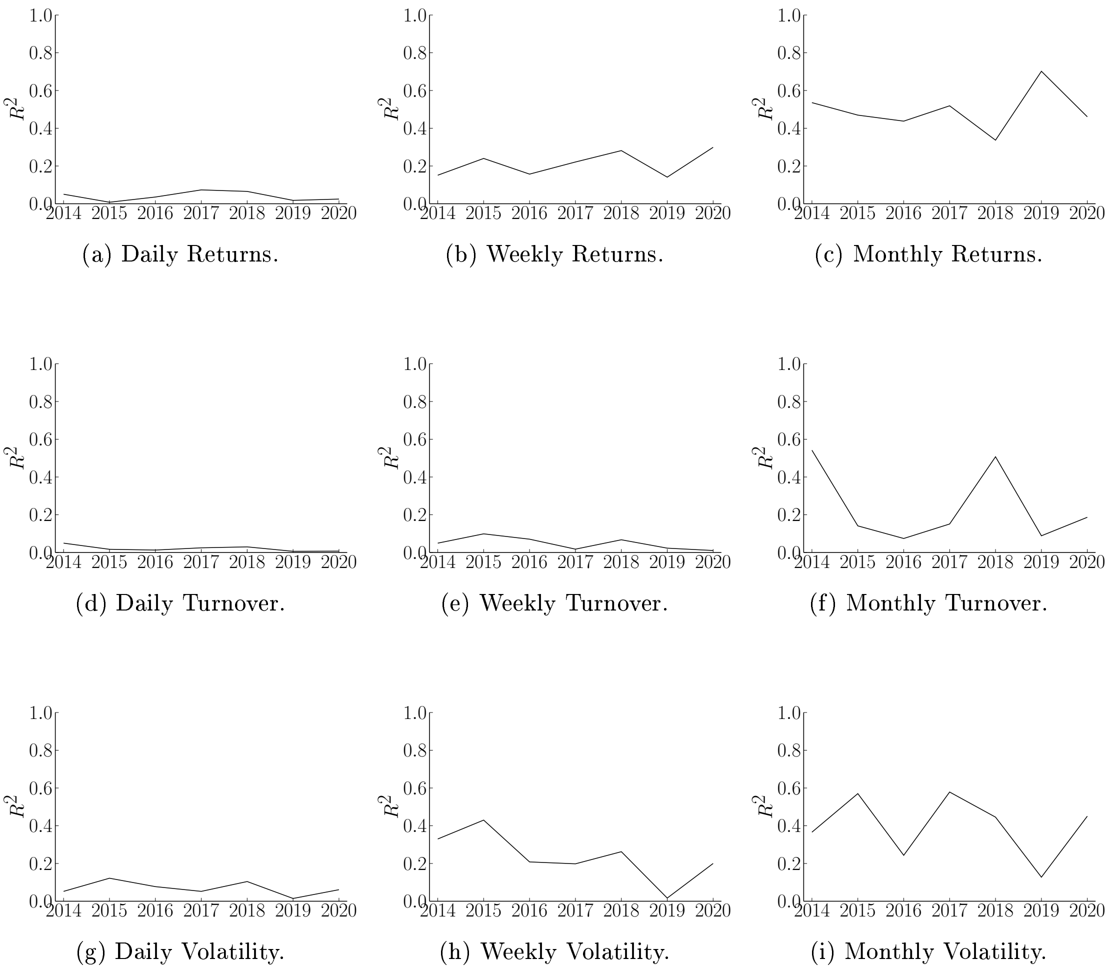
(h) Weekly Volatility.



(i) Monthly Volatility.

Figure 6: Disagreement's coefficient when estimating (9) contemporaneously and year-by-year.

Notes: We find that that the contemporaneous effect of disagreement is relatively stable over time. Towards the end of the sample, the negative correlation between disagreement and returns vanishes. Error bands are at 95% confidence and standard errors are HAC-robust according to Newey and West (1987).



(a) Daily Returns. (b) Weekly Returns. (c) Monthly Returns.

(d) Daily Turnover. (e) Weekly Turnover. (f) Monthly Turnover.

(g) Daily Volatility. (h) Weekly Volatility. (i) Monthly Volatility.

Figure 7: R^2 when estimating (9) contemporaneously and year-by-year.

is limited. Moreover, we also find positive effects of high disagreement on turnover and volatility, which can be interpreted as market participants trading more often when their opinions are more dispersed.

However, our findings also differ from the standard differences-in-opinion story as portrayed in 2.1. Following a standard interpretation of the channel, the fundamental value of the asset is orthogonal to investors' beliefs. Therefore, an increase in overoptimism as reflected by high disagreement leads to overpricing. Thus, from the viewpoint of the differences-of-opinion literature, we would have hypothesized that the contemporaneous effect of disagreement on returns is positive. However, we find that it is significantly negative. This result would be expected if disagreement was just a symptom of underlying uncertainty, as we show in 2.2, or if disagreement was caused by negative past and contemporaneous returns, as we discuss in 2.3. However, with these two explanations we should not see that disagreement predict negative returns. If the subsequent negative returns are interpreted as a correction of overpricing caused by mean-preserving disagreement, why do we not see a price increase of equal magnitude leading to this overpricing?[28]

Our empirical results suggest that there has to some mechanism that goes beyond these straightforward stories that previous literature has discussed. [29] In the case of an asset entirely supported by beliefs, such as Bitcoin, disagreement could be associated with an erosion of the coordination that makes the asset valuable in the first place. This view reconciles our finding that disagreement is a sign of overpricing with the fact that we do not observe a price increase in the first place. A rise in disagreement lowers the "fair" or "objective" value of the asset while also keeping the price from falling immediately, leading to overpricing.

At the same time, we find that disagreement increases exactly when the price is already falling, for example, as shown in Figure 8 during the 2018 bust. Therefore, negative returns could themselves increase disagreement. A possible explanation is that traders filter negative news, which coincides with negative returns, heterogeneously. Consider as an extreme example that traders can be split into two groups: dogmatic believers and skeptics. Traders who believe dogmatically in Bitcoin might not correct their beliefs in the face of negative news. In contrast, other, less convinced traders quickly correct their beliefs downward and sell when the price starts falling. The loss of potential buyers and users of Bitcoin leads to a fall in Bitcoin's medium-term value.

This narrative is in sharp contrast to a view of an asset's fundamental value being unaffected by beliefs or disagreement. In general, asset prices may influence a firm's fundamentals in the presence of financial frictions, such that overvaluation due to the optimism of buyers can fix another inefficiency. In our case, the force behind said overvaluation - disagreement - is possibly detrimental to the asset's fundamentals, which leads to further negative returns.

5.2 Easing of Short-Sell Constraints

According to the literature on differences-of-opinion, disagreement leads to overpricing in the presence of short-sell constraints. Being able to short allows pessimists to trade on their belief, which reduces asset prices and offsets the influence of optimists. For Bitcoin, short-selling was difficult for two reasons: (i) the lack of financial instruments, especially through established exchanges accessible to institutional

[28]We only find a positive relationship between past disagreement and contemporaneous returns at weekly returns in Table B.3. Still, the effect is much smaller than the subsequent predicted negative returns as in Figure 2 and 3.

[29]See Diether, Malloy, and Scherbina (2002) for an overview of the proposed channels.

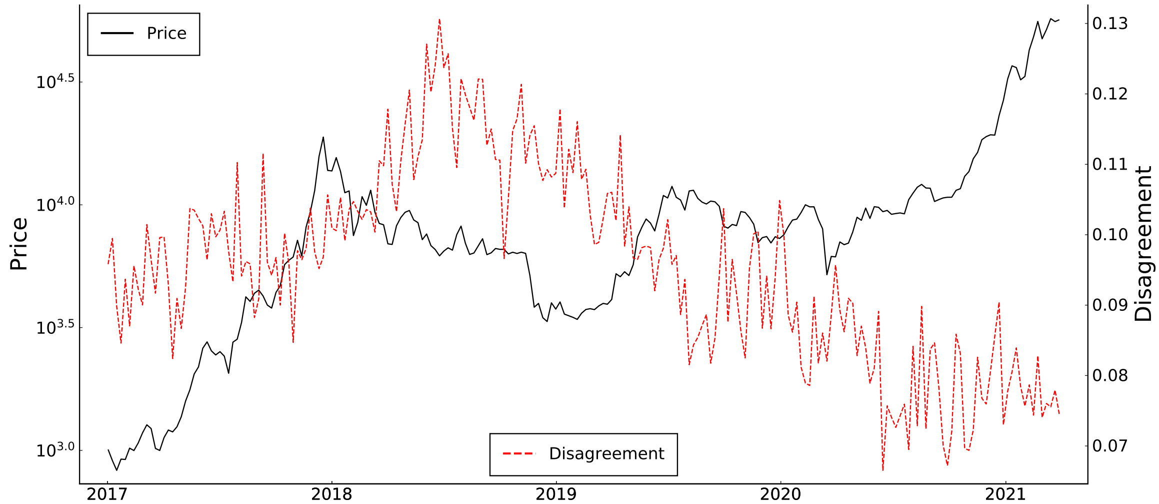


Figure 8: Disagreement peaked after returns turned already negative in 2018.

investors, and (ii) the extremely high volatility and explosive price behavior. Since the end of 2017, we have seen the gradual introduction of shorting instruments for Bitcoin, which addresses the first point. It is now possible to borrow Bitcoin on large exchanges[30], the Chicago Mercantile Exchange introduced future contracts for Bitcoin in December 2017 (CME Group 2017) and options on futures contracts in January 2020 (CME Group 2019), which enabled especially institutional investors to bet on a falling price of Bitcoin.

The introduction of CME's futures contracts coincided with a steep fall in the price of Bitcoin, which supports the narrative that over-optimistic buyers inflated Bitcoin's price, and the introduction of futures contracts eased short-sell constraints considerably. This easing should also diminish the effect of disagreement that we find in our analysis. Indeed, if we compare the coefficient of disagreement in the regression on contemporaneous returns in the years 2016 and 2020, we find that the effect is significantly reduced as in Table B.4. However, we find that the effect of disagreement on returns is also small in 2014 or 2015, well before short-sell constraints were eased. These small coefficients can potentially be understood as a sign that our disagreement channel is not strong at all times, as our disagreement measure appears to be noisy without a clear trend in 2014 and 2015.

In Figure 9 we repeat the local projection from Figure 3 to see whether the effect of disagreement on future returns changes after the introduction of futures contracts. In this analysis, we test whether weekly disagreement observed in 2019 predicts returns that stretch until the end of 2020. Indeed, we find that in this time-frame in which futures contract were already well-established, disagreement predicts initially positive returns, which is more in line with the model with risk-averse traders. In reality, aspects of both models are likely to be relevant, and, therefore, the shift of return predictions from negative to positive suggests that relaxed short-sell constraints led to the difference-of-opinion channel being less important.

[30] The annualized interest rates are between around 12% as of April 2021 on *Kraken.com* while requiring 20% collateral in the form of cash or cryptocurrencies.

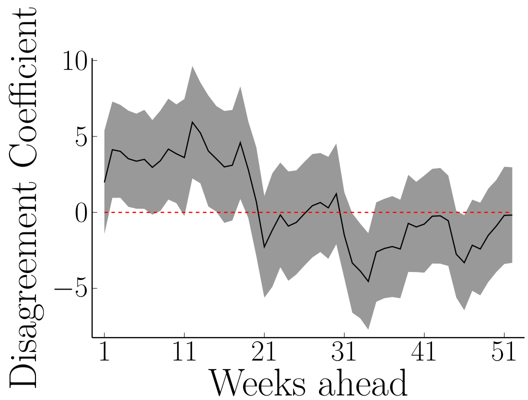


Figure 9: Univariate Robust Local Projection of Returns on Disagreement from 2019.

Notes: We find that in contrast to our earlier results, disagreement predicts initially positive returns. 90% confidence intervals according to Campbell and Yogo (2006).

Although our analysis suggests that short-sell constraints loosened, shorting Bitcoin remains costly due to limits-to-arbitrage: the maintenance volatility scan exemplifies this for the CME future contract, which as of April 2021 stands around 60%, much higher than on future contracts for other assets.[31] Relatedly, as of April 2021, the CME requires a maintenance amount for a futures contract over five Bitcoin that corresponds to 36% to 40% of the current spot price, which is much larger than the respective 5% for S&P 500 futures at CME. In other words, investors need to lock up larger amounts of capital to bet on price movements of Bitcoin than for other assets, which limits the ability of investors to take on larger positions.

5.3 Limitations

Our analysis has several limitations. First, we base our measurement of sentiment on the VADER algorithm. This algorithm is trained on online comments but has not been tested on a cryptocurrency domain. Our sentiment measure is positively correlated with returns, suggesting that the algorithm performs reasonably well for our purposes. Moreover, we use this sentiment measure as a proxy for disagreement around a time-variant level of beliefs. Ideally, we would observe beliefs and disagreement directly, which is impossible without detailed surveys.

Secondly, we are observing only a subset of potential Bitcoin investors. The online forum that we analyzed does not contain institutional investors, nor can we be certain that it represents a balanced sample of all bitcoin investors. Investors who visit an online forum and post many comments about Bitcoin might differ from those who trade quietly. Still, relevant for our purposes is only that users of *bitcointalk.org* representatively reflect the sentiments present in the general population of potential bitcoin investors.

Finally, we did not control for who posted the comments in our regressions: were there some participants who posted many more comments than others and how did the make-up and breadth of

[31] The maintenance volatility scan is the highest level of change that is "most likely" to occur with the underlying volatility affecting each future option's price. If the volatility of an asset is high, the margin requirement will be high as well. For comparison, S&P 500 Futures with a duration of seven months have a volatility scan of 25%

the discussion participants change over the years? We only tested that the concentration of comments across individuals at any given time is not too high to introduce an obvious bias to our results (as we report in Figures C.1a and C.1b). Our empirical analysis does not exploit additional information on commenters' identities. However, they represent an interesting topic for future research.

6 Conclusion

We performed sentiment analysis on posts from the online forum *bitcointalk.org* to obtain a measure of investors' sentiment regarding the prospects of Bitcoin. We used the dispersion of these sentiment data points as a proxy for disagreement to explore the empirical predictions of the differences-of-opinion literature. We find that disagreement indeed predicts lower returns while being related to higher turnover and volatility, confirming the theoretical predictions of our model. The most striking result is that disagreement predicts negative returns for up to seven months into the future, pointing towards a slow correction of large overvaluations. Moreover, sentiment and disagreement play a large role in explaining returns, with an adjusted R^2 of 0.33 in the regression on contemporaneous returns.

We study the change in effects of disagreement after CME introduced futures contracts in December 2017 (CME Group 2017). We find that the effect of disagreement significantly diminishes in the years after the introduction, in line with the view that a combination of disagreement and short-sell constraints is necessary to generate overpricing and subsequent predictable lower returns. An important departure from the previous empirical literature is that we find no strong evidence of a positive effect of disagreement on the contemporaneous or past return of Bitcoin. We hypothesize that disagreement may erode the coordination, which is the foundation of Bitcoin's value proposition, leading to a price decrease.

Future research could seek to understand better the effects of changes in beliefs at the investor level. Also, the network structure of online discussions can be exploited to understand better belief formation and the impact of different kinds of discussions on the price of Bitcoin. One could explore, for example, the narratives that generate disagreement between participants through topical analysis. A better understanding of the determinants of investor disagreement can help refine asset pricing theory.

A Proofs

Proof of Proposition 1. Since the price tomorrow is independent of disagreement or the average belief today given that ϕ is constant over time and beliefs are *iid* across group of traders and time, it is sufficient to show that the optimists' belief ϕ^o_{t+1} and, therefore, P_t are increasing in disagreement $\phi^o_{t+1} - \phi^p_{t+1}$ when holding the average belief $\frac{\phi^o_{t+1}+\phi^p_{t+1}}{2}$ constant. The optimists' belief can be written as

$$\phi^o_{t+1} = \underbrace{\frac{\phi^o_{t+1} + \phi^p_{t+1}}{2}}_{\text{Average Belief}} + \frac{1}{2}\underbrace{(\phi^o_{t+1} - \phi^p_{t+1})}_{\text{Disagreement}}. \tag{10}$$

Indeed, if the RHS increases due to an increase in disagreement and the average belief stays constant, the LHS must increase. The increase in optimists' belief ϕ^o_{t+1} leads to higher price P_t as follows from (2) and $\bar{P} > \mathbb{E}(P_{t+1}|\neg A_{t+1})$, which lowers future returns. □

Proof of Corollary 1. Follows from the Proof of Proposition 1, except that disagreement increases today's price and, therefore, increases past returns $\frac{P_t - P_{t-1}}{P_{t-1}}$. □

Proof of Proposition 2. Since the price is set by optimists with $\phi^o_{t+1} > \phi^p_{t+1}$ and $\bar{P} > \mathbb{E}(P_{t+1}|\neg A_{t+1})$, it must be that the pessimists' valuation is below the current price P_t, i.e.,

$$V^p_t = \frac{1}{R}\left(\phi^p_{t+1}\bar{P} + (1 - \phi^p_{t+1})\mathbb{E}(P_{t+1}|\neg A_{t+1})\right) < P_t, \tag{11}$$

Therefore, the maximization problem of pessimists is

$$\max_{d_t \le 0} \quad d_t(P_t - V^p_t) - c(d_t) \tag{12}$$

with the solution $d^*_t : c'(d^*_t) = P_t - V^p_t$. It follows that pessimists short the asset more if V^p_t is lower due to more pessimistic beliefs ϕ^p_{t+1}, which decreases in disagreement as apparent in:

$$\phi^p_{t+1} = \underbrace{\frac{\phi^o_{t+1} + \phi^p_{t+1}}{2}}_{\text{Average Belief}} - \frac{1}{2}\underbrace{(\phi^o_{t+1} - \phi^p_{t+1})}_{\text{Disagreement}}. \tag{13}$$

Therefore, an increase in disagreement while holding the average belief constant means that pessimists are even more pessimistic, which lowers V^p_t and increases the short positions d^*_t and turnover. □

Proof of Proposition 3. Tomorrow's price is independent of the belief of the young representative trader given that ϕ is constant over time and beliefs are *iid*. It remains to show that the price today is decreasing in the uncertainty of the young representative trader when the average belief is held constant.

The young representative trader views ϕ_{t+1} as a random variable X where $|\mathbb{E}(X)| < \infty$ and $Var(X) \in (0, \infty)$. Denote alternative beliefs that are more uncertain than X but have the same mean as $Z = X + Y$ where $\mathbb{E}(Y) = 0$ and $Var(Y) \in (0, \infty)$ and Y is independent of X. It is sufficient to show that a representative trader with more uncertain beliefs has a lower utility holding the asset than a more certain trader with the same mean belief. Given that the utility function (3) is concave in ϕ,

$$\mathbb{E}\left(U_t(Z)\right) = \mathbb{E}\left(U_t(X+Y)\right) \tag{14}$$

$$\overset{\text{L.I.E.}}{=} \mathbb{E}\left(\mathbb{E}\left(U_t(X+Y)|X\right)\right) \tag{15}$$

$$\overset{\text{Jensen's}}{<} \mathbb{E}\left(U_t\left(\mathbb{E}\left(X+Y|X\right)\right)\right) \tag{16}$$

$$= \mathbb{E}\left(U_t\left(X\right)\right), \tag{17}$$

where the utility function U_t is written as a function of ϕ. Since a trader with more uncertain beliefs is worse off compared to a trader with more certain beliefs but the same mean, it follows that the price P_t must fall to restore the indifference as in (4). As a result, future returns increase in uncertainty. □

Proof of Corollary 2. Follows from the Proof of Proposition 3, except that disagreement decreases today's price and, therefore, decreases past returns $\frac{P_t - P_{t-1}}{P_{t-1}}$. □

B Tables

	Return Diff t			Turnover Growth t			Volatiliy Diff t		
	daily	weekly	monthly	daily	weekly	monthly	daily	weekly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sentiment Diff	0.59***	5.97***	15.68***	−6.06***	−10.16***	−15.26***	−0.07***	−0.21***	−0.28***
	(0.12)	(0.88)	(2.56)	(0.98)	(2.27)	(4.11)	(0.01)	(0.04)	(0.05)
Disagreement Diff	−0.20*	−2.32***	−4.31*	4.65***	7.16***	11.83***	0.02*	0.15***	0.14***
	(0.10)	(0.68)	(2.59)	(0.98)	(2.12)	(4.27)	(0.01)	(0.04)	(0.04)
Constant	0.005	0.02	0.28	7.04***	5.52***	10.03***	−0.0004	0.0000	−0.01
	(0.03)	(0.25)	(2.53)	(0.76)	(1.38)	(3.78)	(0.01)	(0.01)	(0.05)
N	2,623	376	87	2,642	378	86	2,595	378	87
R^2	0.01	0.18	0.29	0.02	0.11	0.21	0.01	0.16	0.25
Adjusted R^2	0.01	0.17	0.27	0.02	0.11	0.19	0.01	0.15	0.23

Notes: Returns are the growth rate between the opening and closing price in percentage points. Turnover is total dollar volume across all major exchanges divided by the market capitalization of Bitcoin. Turnover Growth is computed as the growth rate between past period's turnover and current turnover in percentage points. Volatility is the standard deviation of hourly returns over a day, week, or month. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Changes in sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. We compute the difference in a variable as today's value minus yesterday's value. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table B.1: Estimating (9) contemporaneously in First Differences.

Notes: An alternative to providing robust standard errors is differencing variables until both independent and dependent variables are stationary. We find that the results remain generally unchanged, as changes in disagreement are negatively related to returns and positively related to turnover growth and changes to volatility.

	Return Diff t+1			Turnover Growth t+1			Volatiliy Diff t+1		
	daily	weekly	monthly	daily	weekly	monthly	daily	weekly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sentiment Diff	-0.62^{***}	-4.11^{***}	-11.54^{***}	1.13	2.51^{*}	9.94^{**}	-0.01	0.06^{**}	0.17^{***}
	(0.12)	(0.88)	(2.66)	(0.97)	(1.44)	(4.08)	(0.01)	(0.03)	(0.06)
Disagreement Diff	0.20^{*}	2.47^{***}	2.38	0.97	-1.83	-4.23	0.02	-0.08^{**}	-0.13^{**}
	(0.12)	(0.74)	(2.51)	(0.96)	(1.57)	(3.47)	(0.01)	(0.03)	(0.06)
Constant	-0.003	0.10	0.56	7.01^{***}	5.33^{***}	8.87^{**}	-0.001	-0.003	-0.01
	(0.03)	(0.38)	(2.69)	(0.75)	(1.58)	(4.02)	(0.01)	(0.02)	(0.05)
N	2,622	375	86	2,641	377	86	2,594	377	86
R^2	0.01	0.10	0.16	0.001	0.01	0.07	0.001	0.02	0.12
Adjusted R^2	0.01	0.09	0.14	0.0002	0.002	0.05	-0.0000	0.02	0.10

Notes: Returns are the growth rate between the opening and closing price in percentage points. Turnover is total dollar volume across all major exchanges divided by the market capitalization of Bitcoin. Turnover Growth is computed as the growth rate between past period's turnover and current turnover in percentage points. Volatility is the standard deviation of hourly returns over a day, week, or month. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Changes in sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. We compute the difference in a variable as today's value minus yesterday's value. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table B.2: Estimating (9) one-period-ahead in First Differences.

Notes: We find that the effects of sentiment and disagreement revert in comparison to Table B.1. Note that disagreement's effect of the change in returns one-period-ahead is insignificant and smaller in magnitude than the contemporaneous effect, pointing to a protracted negative effect of disagreement on returns.

		Returns t			Turnover Growth t			Volatiliy t	
	daily	weekly	monthly	daily	weekly	monthly	daily	weekly	monthly
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sentiment t	1.08^{***}	8.32^{***}	20.29^{***}	-8.74^{***}	-15.87^{***}	-22.62^{***}	-0.16^{***}	-0.38^{***}	-0.49^{***}
	(0.10)	(0.79)	(3.18)	(1.33)	(3.83)	(6.92)	(0.02)	(0.06)	(0.10)
Sentiment t-1	-0.30^{***}	-4.19^{***}	-8.00^{**}	4.49^{***}	16.24^{***}	21.84^{***}	-0.09^{***}	0.02	0.06
	(0.10)	(0.95)	(3.41)	(1.39)	(3.49)	(8.02)	(0.02)	(0.03)	(0.09)
Sentiment t-2	-0.13	1.00	0.15	1.27	-0.79	-10.48	-0.02	0.004	0.08
	(0.10)	(0.97)	(3.68)	(1.36)	(3.36)	(7.18)	(0.02)	(0.05)	(0.07)
Sentiment t-3	-0.24^{**}	-2.32^{***}	-2.10	-1.46	-3.88	5.44	-0.02	0.01	-0.04
	(0.11)	(0.74)	(3.27)	(1.23)	(3.18)	(8.66)	(0.02)	(0.05)	(0.08)
Disagreement t	-0.39^{***}	-4.89^{***}	-11.60^{***}	6.75^{***}	12.34^{***}	23.06^{**}	0.08^{***}	0.29^{***}	0.45^{***}
	(0.08)	(0.87)	(3.93)	(1.19)	(3.84)	(9.91)	(0.02)	(0.07)	(0.12)
Disagreement t-1	0.09	2.30^{**}	-2.26	-2.65^{**}	-11.44^{***}	-20.20^{**}	0.05^{***}	-0.02	-0.11
	(0.09)	(1.02)	(4.67)	(1.20)	(4.31)	(8.29)	(0.02)	(0.05)	(0.11)
Disagreement t-2	0.05	-0.49	0.36	-3.34^{***}	-7.93^{**}	-7.09	0.01	-0.07	-0.07
	(0.09)	(1.00)	(3.94)	(1.22)	(3.14)	(10.61)	(0.01)	(0.06)	(0.10)
Disagreement t-3	-0.09	0.41	3.22	1.90	10.07^{***}	8.43	0.004	-0.02	-0.12
	(0.09)	(0.77)	(3.56)	(1.36)	(3.52)	(8.70)	(0.01)	(0.04)	(0.08)
Constant	1.13^{***}	12.65^{***}	54.00^{***}	3.23	-4.02	-4.46	0.71^{***}	0.65^{*}	1.02^{*}
	(0.42)	(3.42)	(15.92)	(4.07)	(8.52)	(32.69)	(0.16)	(0.39)	(0.61)
N	2,628	377	87	2,638	378	86	2,610	378	87
R^2	0.04	0.27	0.41	0.03	0.14	0.25	0.09	0.26	0.40
Adjusted R^2	0.04	0.26	0.35	0.03	0.12	0.18	0.09	0.24	0.34

Notes: Returns are the growth rate between the opening and closing price in percentage points. Turnover is total dollar volume across all major exchanges divided by the market capitalization of Bitcoin. Turnover Growth is computed as the growth rate between past period's turnover and current turnover in percentage points. Volatility is the standard deviation of hourly returns over a day, week, or month. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table B.3: Estimating (9) contemporaneously and with three lags of sentiment and disagreement

Notes: The coefficients on lags of sentiment and disagreement are broadly consistent with mean-reversion. Whereas sentiment in period t is positively related to returns in period t, sentiment in period $t-1$ has a *negative* effect on returns in t, albeit the coefficient is at most half as large as the contemporaneous effect. The effect of disagreement on returns only exhibits mean-reversion of at weekly frequency.

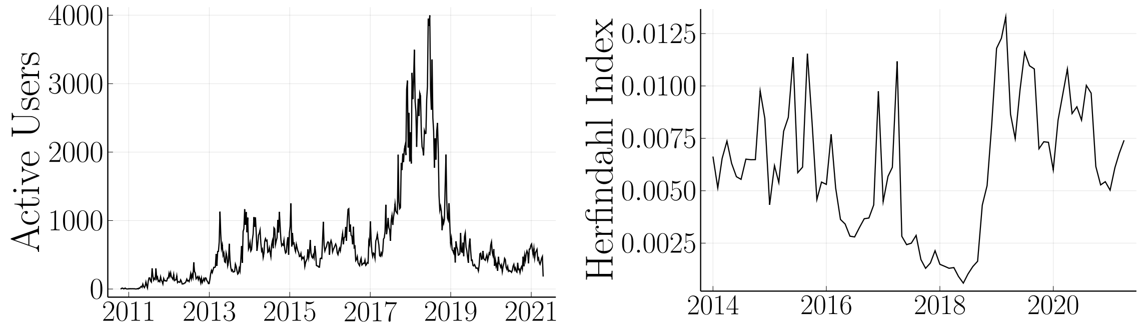
	Returns t		
	daily	weekly	monthly
	(1)	(2)	(3)
Sentiment	0.93***	6.78***	20.75***
	(0.11)	(0.90)	(3.29)
Disagreement	−0.42***	−4.90***	−17.46***
	(0.10)	(0.90)	(3.05)
Year 2017	1.60	2.87	−91.41
	(1.45)	(21.14)	(146.18)
Year 2018	0.59	−13.11	−98.69
	(1.80)	(20.73)	(73.90)
Year 2019	−0.91	−19.83	−119.45**
	(1.22)	(12.87)	(59.61)
Year 2020	−1.47*	−31.84**	−132.51**
	(0.83)	(12.98)	(58.94)
Year 2021	2.20	179.96***	108.93
	(3.03)	(44.45)	(79.60)
Disagreement x Year 2017	−0.12	0.35	15.04
	(0.28)	(3.17)	(19.50)
Disagreement x Year 2018	−0.10	1.71	11.17
	(0.30)	(2.59)	(8.53)
Disagreement x Year 2019	0.29	3.20*	16.71**
	(0.23)	(1.81)	(8.17)
Disagreement x Year 2020	0.52***	5.77***	21.37**
	(0.18)	(2.19)	(9.38)
Disagreement x Year 2021	−0.31	−32.35***	−18.16
	(0.77)	(8.07)	(13.48)
Constant	−0.33	13.78**	67.32***
	(0.54)	(6.12)	(20.81)
N	1,917	274	63
R^2	0.05	0.27	0.54
Adjusted R^2	0.04	0.23	0.43

Notes: Returns are the growth rate between the opening and closing price in percentage points. Sentiment is the mean of the comment sentiment distribution computed by VADER, and disagreement is the standard deviation of the same distribution. Sentiment and disagreement are normalized by their respective 2014-2021 standard deviation. We generate all variables at daily, weekly, and monthly frequency. Values in parenthesis are HAC-robust standard errors following Newey and West (1987).
*: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table B.4: Estimating the (9) including Year-FEs.

Notes: The effect of disagreement on contemporaneous returns is significantly different in 2020 compared to 2016. The sign on the coefficient is positive taking together the base effect and interaction term. However, disagreement has again a more negative effect in 2021.

C Figures



(a) Number of active users in each week.

(b) Concentration of authorship in each month.

Figure C.1: Activity and concentration graphs for *bitcointalk.org*.

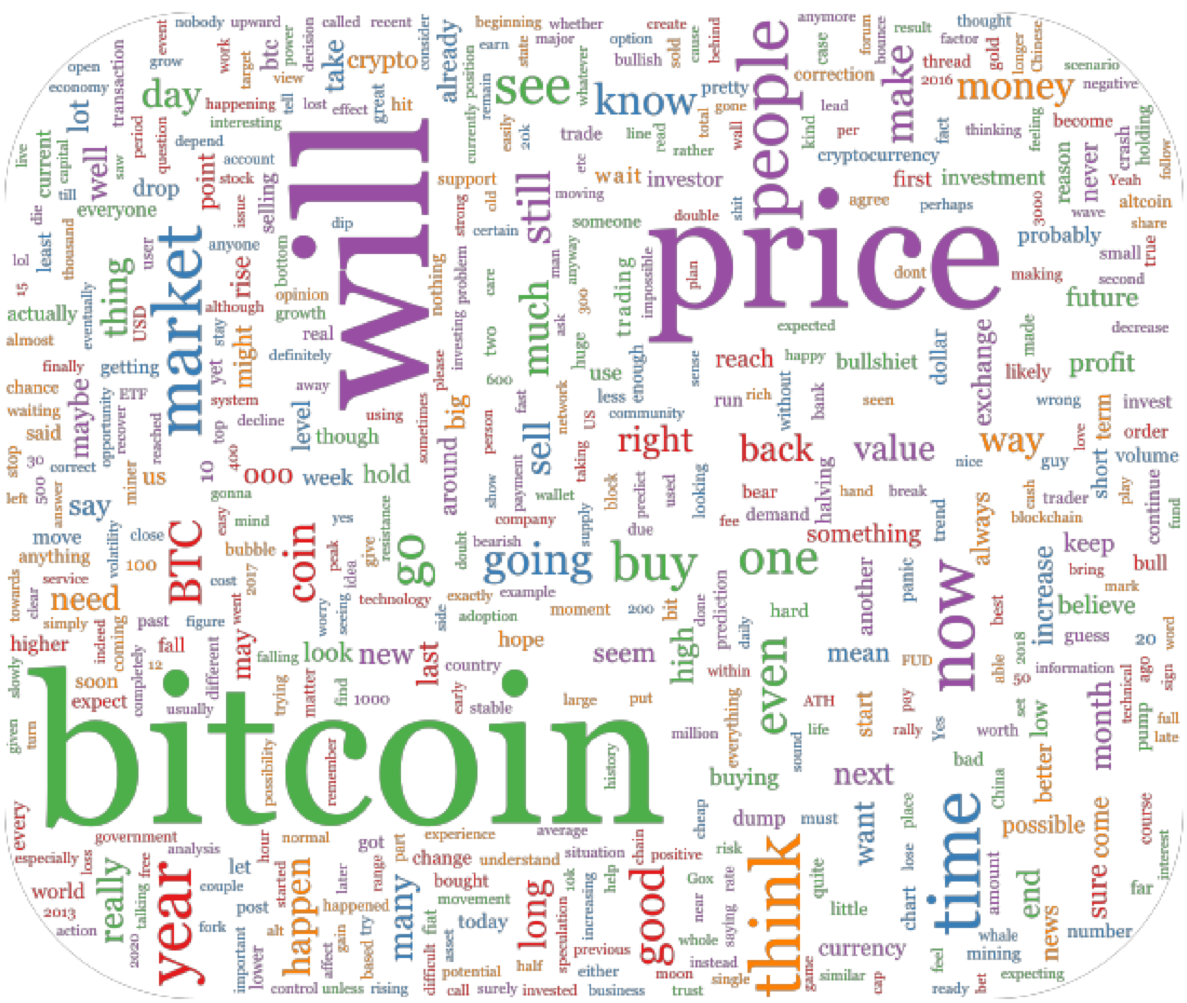
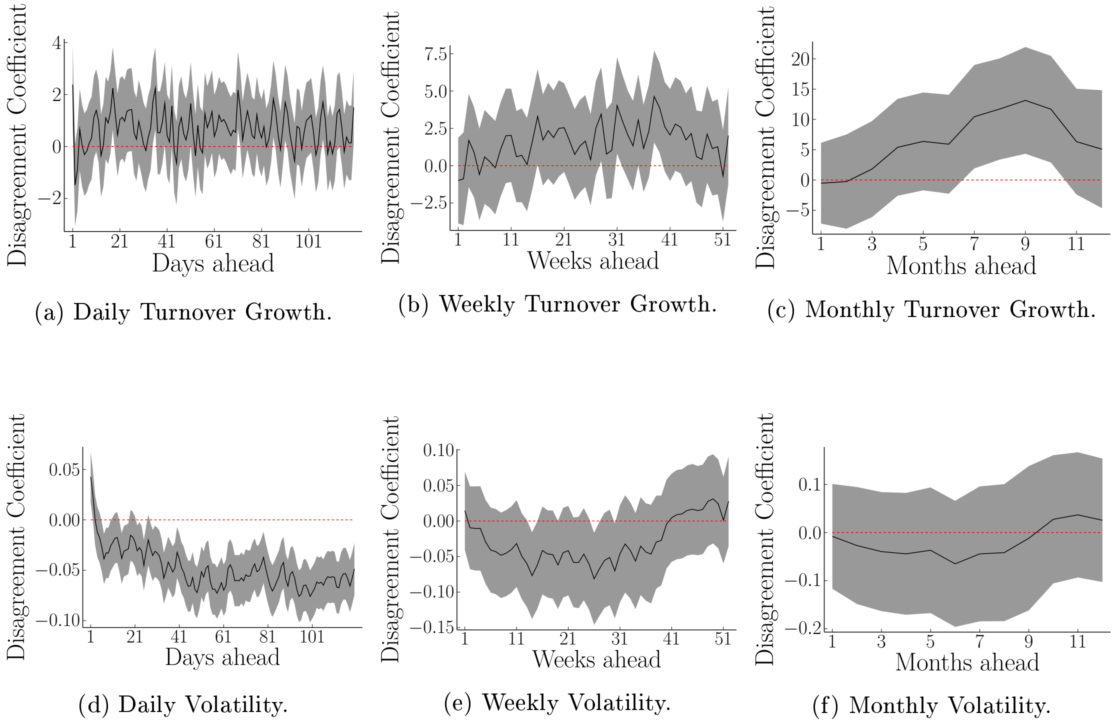


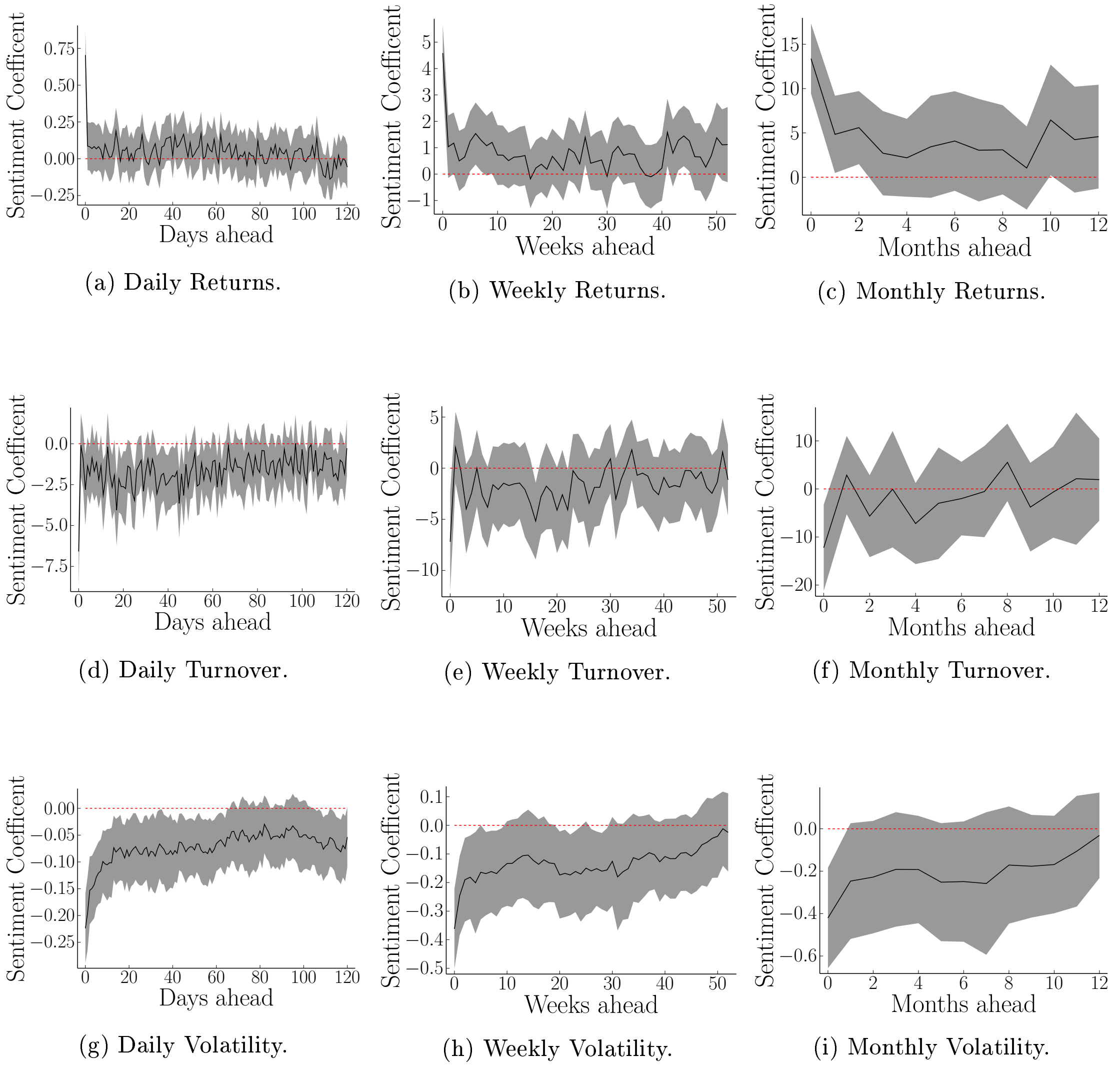
Figure C.2: Most commonly used words out of a random sample of 10,000 comments.



(a) Daily Turnover Growth. (b) Weekly Turnover Growth. (c) Monthly Turnover Growth.

(d) Daily Volatility. (e) Weekly Volatility. (f) Monthly Volatility.

Figure C.3: 10% Campbell Yogo Standard Error Bands.



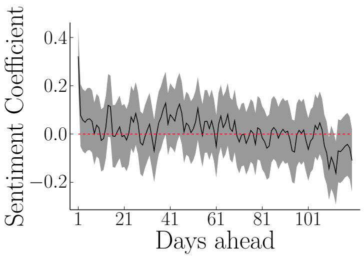
(a) Daily Returns. (b) Weekly Returns. (c) Monthly Returns.

(d) Daily Turnover. (e) Weekly Turnover. (f) Monthly Turnover.

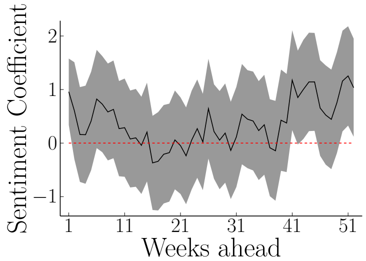
(g) Daily Volatility. (h) Weekly Volatility. (i) Monthly Volatility.

Figure C.4: Local Projections of Returns on Sentiment controlling for Disagreement with HAC-robust Standard Errors.

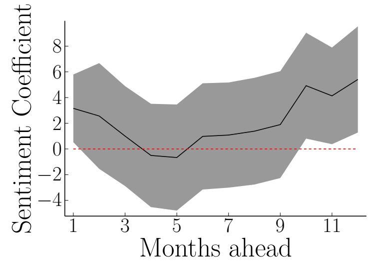
Notes: The shown estimates are the coefficients on sentiment when estimating (9) for leads of returns, turnover growth, and volatility. Error bands are at 95% confidence and standard errors are HAC-robust according to Newey and West (1987).



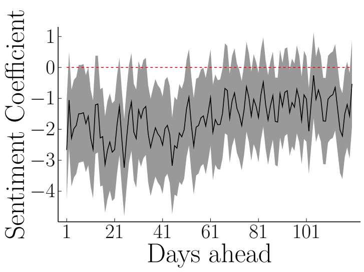
(a) Daily Returns.



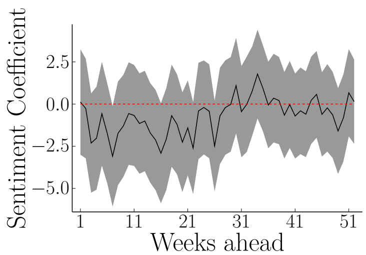
(b) Weekly Returns.



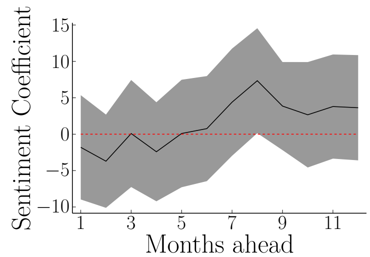
(c) Monthly Returns.



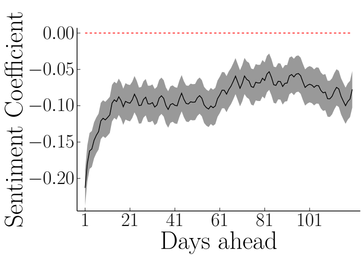
(d) Daily Turnover.



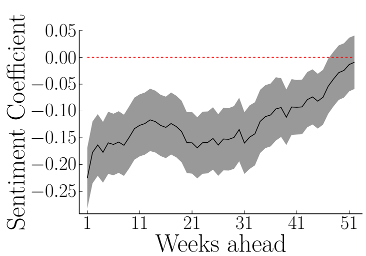
(e) Weekly Turnover.



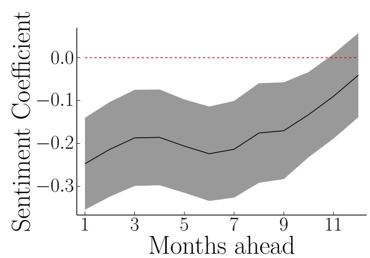
(f) Monthly Turnover.



(g) Daily Volatility.



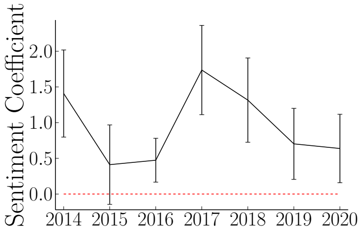
(h) Weekly Volatility.



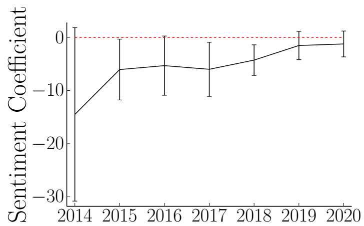
(i) Monthly Volatility.

Figure C.5: Univariate Robust Local Projection of Returns, Turnover Growth, and Volatility on Sentiment.

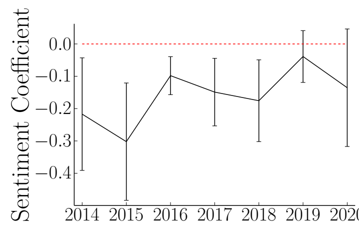
Notes: In a univariate regression, we find that disagreement predicts negative returns for several periods at all frequencies. 90% confidence intervals according to Campbell and Yogo (2006).



(a) Daily Returns.

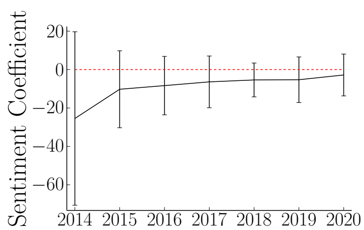


(b) Daily Turnover.

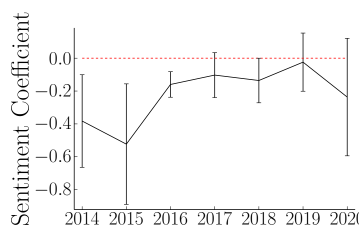


(c) Daily Volatility.

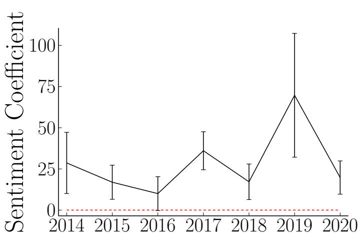
(d) Weekly Returns.



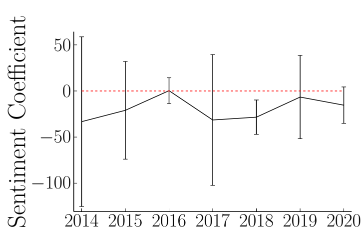
(e) Weekly Turnover.



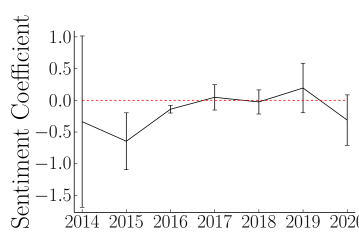
(f) Weekly Volatility.



(g) Monthly Returns.



(h) Monthly Turnover.



(i) Monthly Volatility.

Figure C.6: Sentiment's coefficient when estimating (9) contemporaneously and year-by-year.

Notes: We find that that the contemporaneous effect of sentiment is relatively stable over time. Error bands are at 95% confidence and standard errors are HAC-robust according to Newey and West (1987).

C.1 Autocorrelation Plots

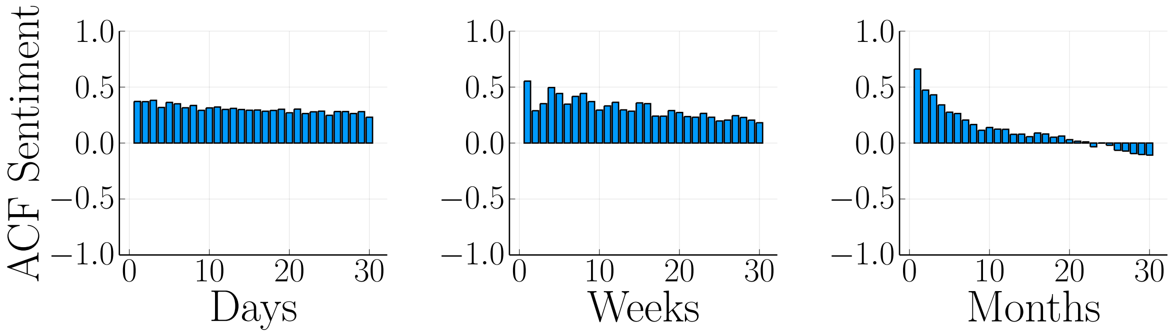


Figure C.7: ACF Sentiment.

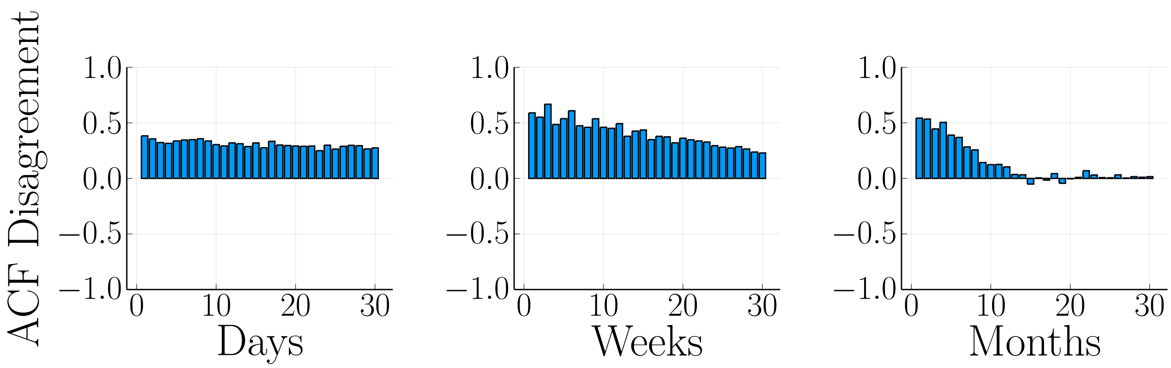


Figure C.8: ACF Disagreement.

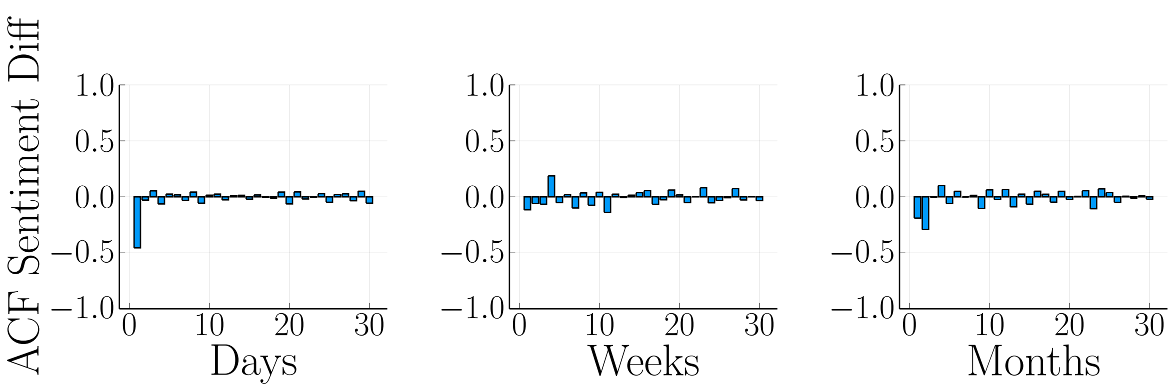


Figure C.9: ACF Changes in Sentiment.

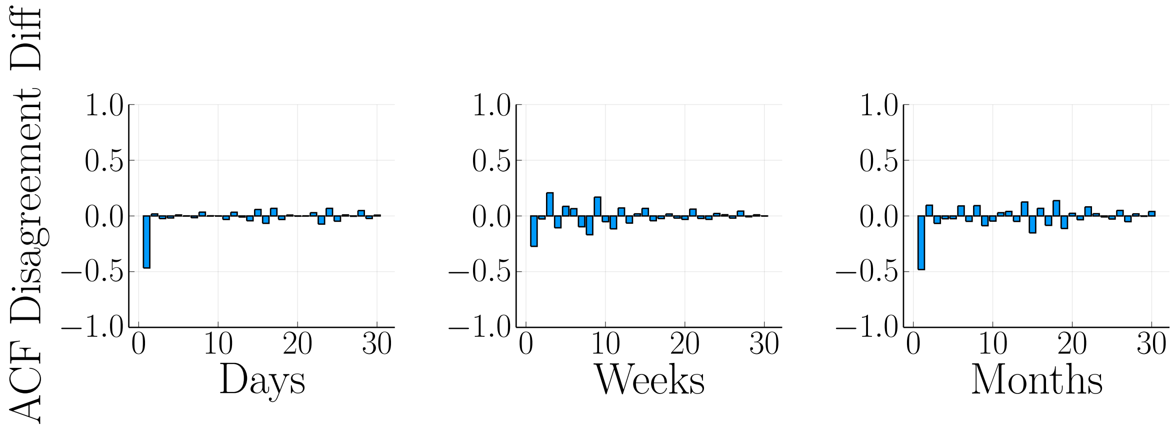


Figure C.10: ACF Changes in Disagreement.

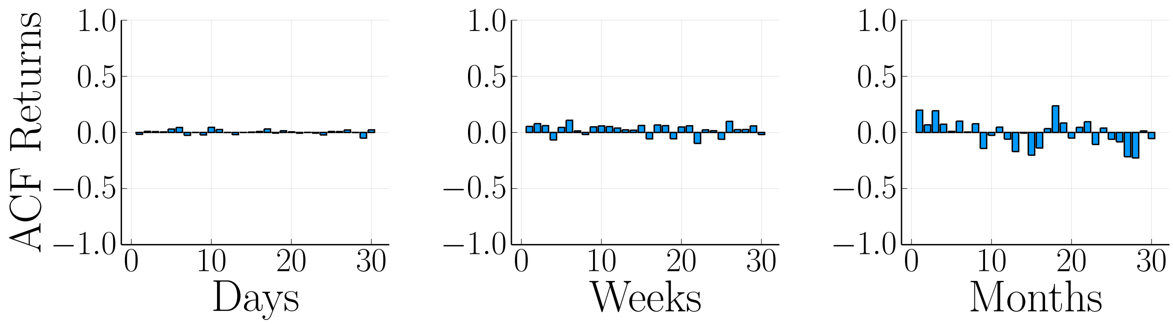


Figure C.11: ACF Returns.

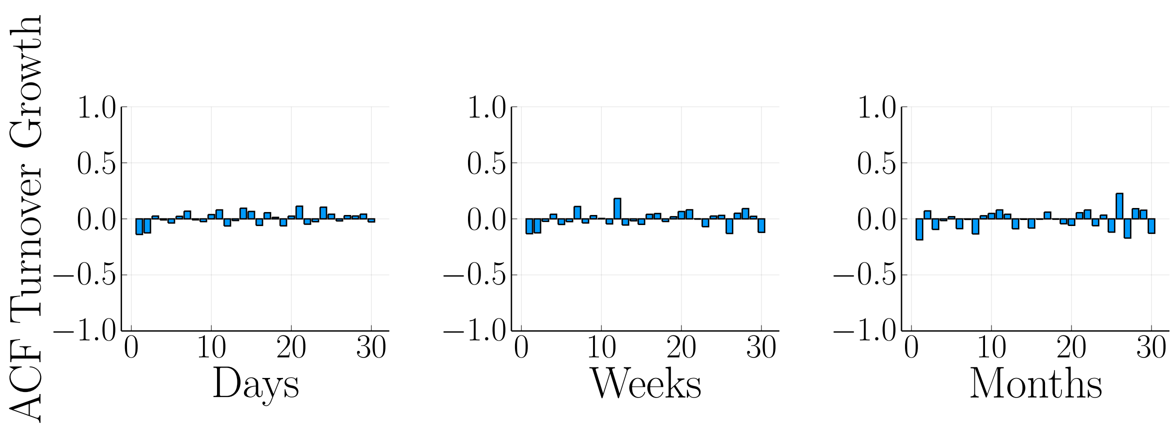


Figure C.12: ACF Turnover Growth.

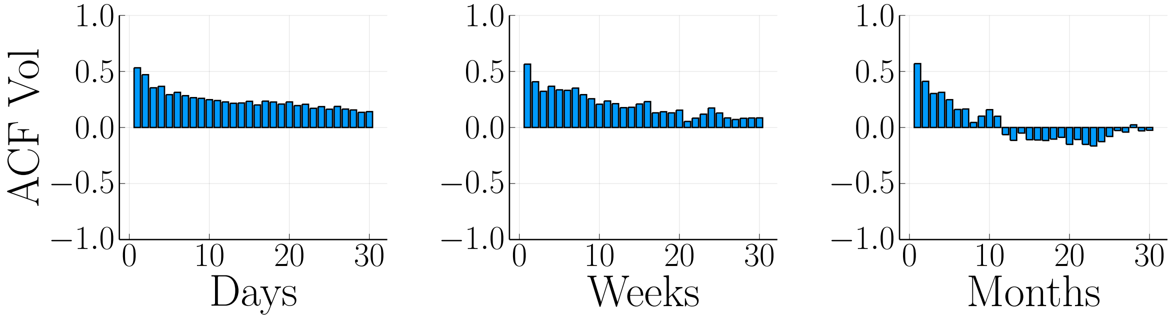


Figure C.13: ACF Volatiliy.

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