ANALYSIS OF NEWS DATA DURING ASSET BUBBLES

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Contents

1. Summary

This analysis studies the nature of bearish news during the dot-com, cryptocurrency and FANMAG bubbles. For each episode, I use text-based news data to search for indications that market observers were concerned about asset overvaluation. I find that during all bubble episodes, relative overvaluation concerns rise as the underlying asset rallies. However, for the bubbles that have popped, these overvaluation levels remain quite steady in the months surrounding the actual market correction, suggesting that crashes are likely not caused by a sudden, increased awareness of an asset's overvaluation.

Although it is true that the level of relative concerns rise for all bubble episodes, the extent to which they do vary from bubble to bubble. I hypothesize that these levels depend on how familiar investors are with the underlying asset's fundamental value. To illustrate this, the relatively high levels of concerns seen during the dot-com and crypto bubbles may be a result of the poor understanding of the technologies—such uncertainty made it easy to argue against these assets, considering their prices shot to historic highs yet their fundamental value remained unknown. FANMAG companies on the other hand have long established themselves as companies with high fundamental value, thereby making it more difficult to justify a bearish take.

I also use sentiment analysis to confirm that articles mentioning overvaluation are indeed more bearish than their non-overvalued counterparts. As expected, I find that for both the dot-com and crypto bubbles, pre-crash overvalued scores were significantly lower.

Additionally, I find that overvalued sentiment in dot-com data does not seem to be significantly correlated with returns on the underlying security, whereas non-overvalued sentiment does. This suggests that overvalued news carried a fundamentally different message compared to the prevailing news of the time: whereas overvalued stories stuck with their original theses, non-overvalued stories were heavily swayed by the short-term performance of the underlying stocks. Although I was not able to replicate this finding with the crypto data, I hypothesize that these dynamics still hold here, and that the results did not materialize due to shortcomings with the sentiment algorithm itself (described in more detail later).

2. Overvaluation Concerns

2.1. **Data.** I compile summaries of articles published by several major newspapers via ProQuest and Twitter. I summarize the details of each dataset in Table 1.

The main difference between the datasets is that the summaries from dot-com articles are longer than those from crypto and FANMAG articles. This is because dot-com data was compiled via ProQuest, which happens to give a five-sentence abstract for each article. Crypto and FANMAG data on the other hand was compiled via Twitter where there is a 280-character tweet limit in place. As such, this pushes down the article summary to only about a sentence long each. Although the main ideas are adequately expressed, this does make sentiment analysis of Twitter data more difficult to execute well. Note that I discuss these shortcomings in more detail in Section 3.

Bubble	Dates	Sources	Platform	Filter	Total Articles
Dot-Com	Jul 1997- Dec 2001	WSJ Financial Times	ProQuest	Tech-stock news only	5767
Crypto	Jan 2016- Dec 2018	BBC Business MarketWatch Reuters Business WSJ Markets Bloomberg NYT Business	Twitter	Crypto news only	7915
FANMAG	May 2012- Aug 2020	Bloomberg Markets WSJ Markets MarketWatch	Twitter	All news (Markets) FANMAG (WSJ/MW)	68,888 (Markets) 15,987 (WSJ/MW)

Table 1. Summary of data used for each bubble.

2.2. **Measuring Overvaluation.** For each bubble episode, I create an "overvalued" subset that consists of articles whose summaries mention overvaluation of the underlying asset[1]. To visualize the extent that these concerns change through time, I determine the proportion of the amount of "overvalued" articles relative to the total number of articles. Specifically, I define this measure M_t at time t as

$$M_t = \frac{\text{\# of overvalued articles published on or before } t}{\text{\# of articles from total sample published on or before } t}.$$

I consider the relative article count rather than the raw count as I assume readers weight good and bad signals from the news. For instance, the reader will feel more bearish after a day with 20 overvalued articles and no non-overvalued articles than a day with 20 overvalued articles but 50 non-overvalued articles, despite the fact that the raw and relative counts are the same.

2.2.1. *Dot-Com.* I plot M_t using dot-com data in Figure 1. By the end of the sample, overvalued stories make up approximately 10% of all tech-stock related stories (560 articles out of 5767). Something immediately clear is that relative overvaluation concerns rise as tech stocks rally. The intuition behind this is simple: market rallies attract attention, and at least a small part of this will question the sustainability of such high prices. This was exactly the case in January 1999, where the sharp rise in share prices led both Alan Greenspan and Bill Gates to make public warnings against tech stocks, spurring even more scrutiny in the news.

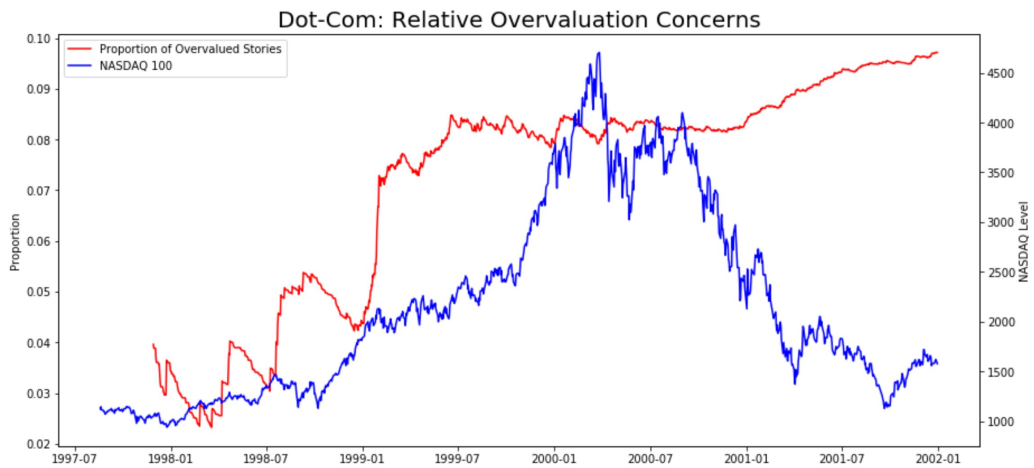

FIGURE 1. Dot-com bubble: Relative overvaluation concerns through time.

Another trend worth noting is that the relative amount of concerns remain steady in the months surrounding the crash. As such, it does not appear that the crash was linked to a sudden awareness among the public that tech stocks were overvalued.

[1]In particular, a story falls into this subset if its summary contains any one of the following words: *"bubble", "overvalue", "irrational", "too high", "mania", "tulip", "crash", "collapse", "speculative", "burst", "sky-high", "lost its senses", "strange", "bizarre", "psychology", "implode", "black hole", "high multiples" (and "dot-com", only for crypto and FANMAG).*

2.2.2. *Overvaluation Trends: Crypto.* I plot M_t using crypto data in Figure 2. By the end of the sample, overvalued stories make up approximately 8% of al crypto stories (556 tweets in total out of 7915). The pattern observed here is very similar to what is seen in Figure 1, with relative concerns rising with the CRIX, which is an aggregate measure of the price of cryptocurrencies (Trimborn & Haerdle, 2018).

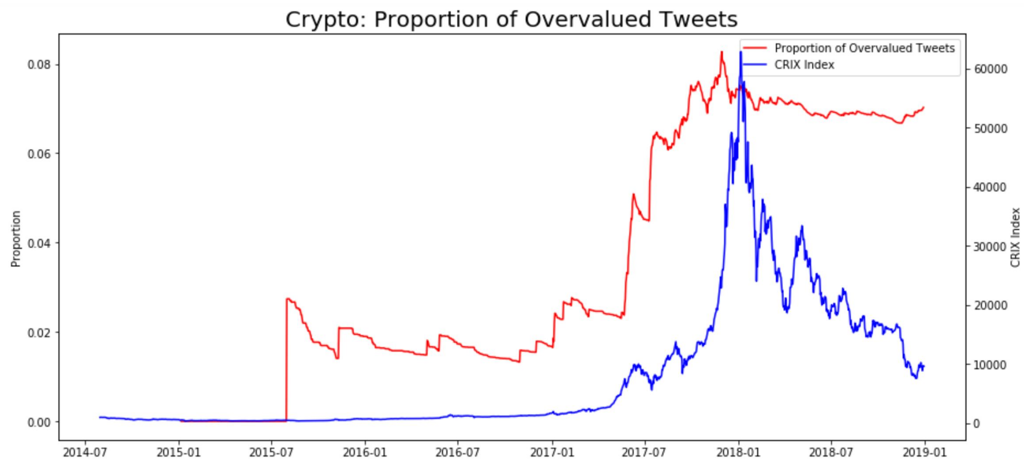

FIGURE 2. Crypto bubble: Relative overvaluation concerns through time.

Like that of dot-com, the crash of the crypto bubble does not seem to be linked to an increased awareness of the asset's overvaluation as relative overvaluation concerns remained quite steady in the months leading up to the crash. Unlike the dot-com episode however, there does appear to be a structural reason for its collapse. In particular, the price of Bitcoin reached its peak a mere few days after the introduction of Bitcoin futures market which was the first formally traded crypto derivative.

Taking these facts together, crypto pessimists may have been present all along yet they were only able to participate in the market after Bitcoin futures were introduced. Although it is true that futures should only affect the spot price of the underlying asset (Bitcoin), it should be noted that the returns of other crypto assets are heavily tied to that of Bitcoin—the correlation between Bitcoin and CRIX daily returns are about 0.7 in this period. As such, the collapse of the crypto bubble can be traced to the introduction of Bitcoin futures if these futures do in fact significantly affect Bitcoin's price.

To examine the extent to which people reacted to this new futures market, I search for tweets mentioning futures or derivatives. I then plot, like before, the proportion of the amount of these tweets relative to the total number of tweets. Shown in Figures 3 and 4, there was a considerable amount of attention about futures right before Bitcoin and CRIX peaked.

To further explore this, I plot the prices of the top cryptocurrencies by market cap around December 11, 2017, the first trading day that Bitcoin futures could be traded. Since Bitcoin futures do not directly affect the performance of the other currencies,

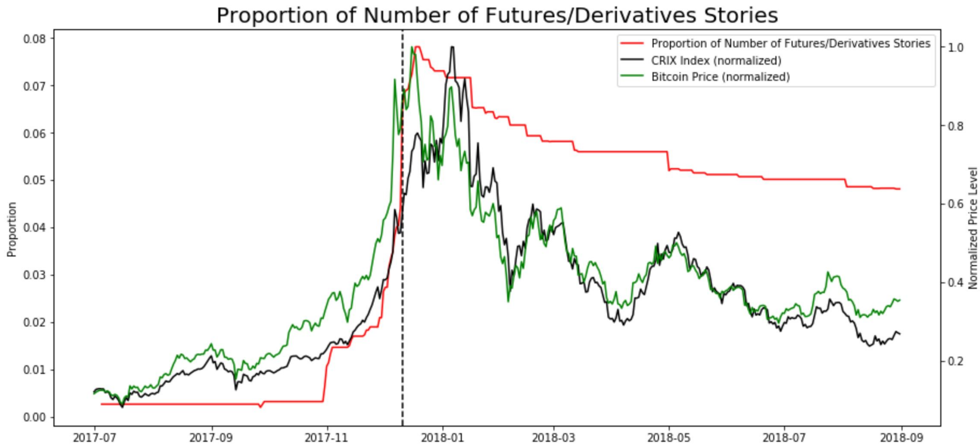

FIGURE 3. Proportion of the number of tweets about Bitcoin futures/derivatives to the overall number of crypto-related tweets. The dotted line denotes December 11, the first trading day Bitcoin futures could be traded.

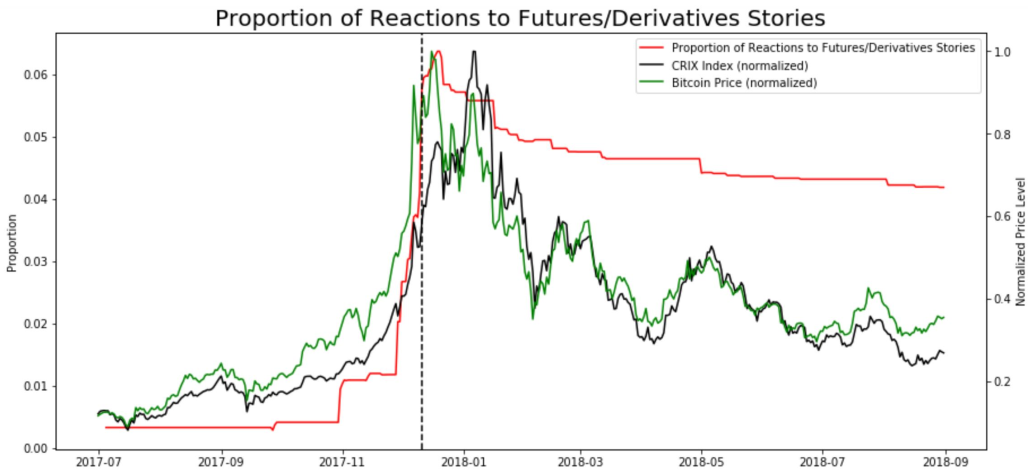

FIGURE 4. Proportion of the reactions to tweets about Bitcoin futures/derivatives to the overall number of crypto-related tweets. The dotted line denotes December 11, the first trading day Bitcoin futures could be traded.

Figure 5 shows an expected trend, with Bitcoin's price decreasing the most during this period of time.

To examine this further, I search online for papers relating the introduction of a Bitcoin futures market and the collapse of Bitcoin. I did find some evidence from other authors that formalize this link. In particular, Liu et al. (2020) find that upon applying a regression discontinuity framework with appropriate controls, there exists a significant and negative relationship between the introduction of Bitcoin futures and Bitcoin return, whereas the relationship is either positive or insignificant for other

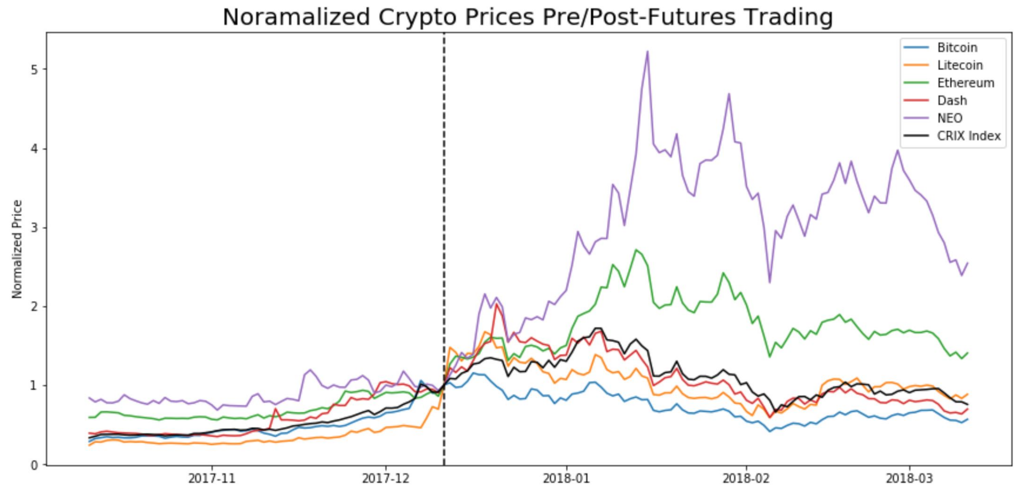

FIGURE 5. Price dynamics of the top cryptocurrencies before and after December 11, 2017, the first day that Bitcoin futures were traded. After this date, Bitcoin decreases the most in value out of the currencies considered.

non-Bitcoin cryptocurrencies. Additionally, Hale et al. (2018) hypothesize that the introduction of Bitcoin futures allowed pessimists to enter the market, which contributed to the reversal of the bitcoin price dynamics.

2.2.3. *Overvaluation Trends: FANMAG.* Lastly, I consider the stocks of FANMAG (Facebook, Apple, Netflix, Microsoft, Amazon and Google) in the past decade. My dataset consists of all tweets (with no filter) by Bloomberg Markets, a subsidiary of Bloomberg Businessweek, that unlike its parent, posts exclusively about financial markets. I only consider tweets after May 2012, which is the earliest date where all FANMAG companies are public.

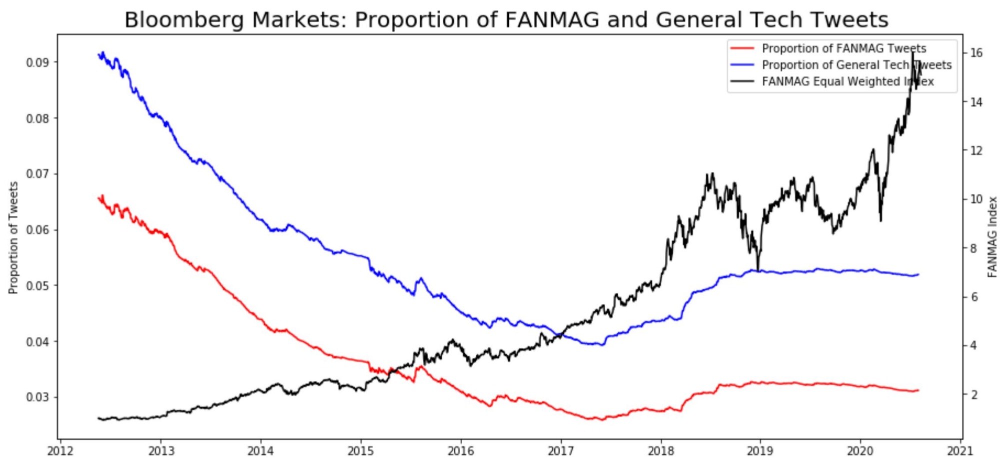

FIGURE 6. Bloomberg Markets: Proportion of the number of the number of tech tweets relative to all tweets published by Bloomberg Markets.

Before getting into the overvaluation trends, I first take a look at how much attention there was about the tech investments in general. As such, I plot the proportion of tweets about the tech industry to all tweets by Bloomberg Markets over time. As seen in Figure 6, the number of technology related tweets makes up about 5% of the total number of Bloomberg Markets tweets, where within tech tweets, more than half is coverage about FANMAG companies.

I now explore overvaluation concerns. I plot the proportion of overvalued FANMAG stories relative to all FANMAG stories in Figure 7.

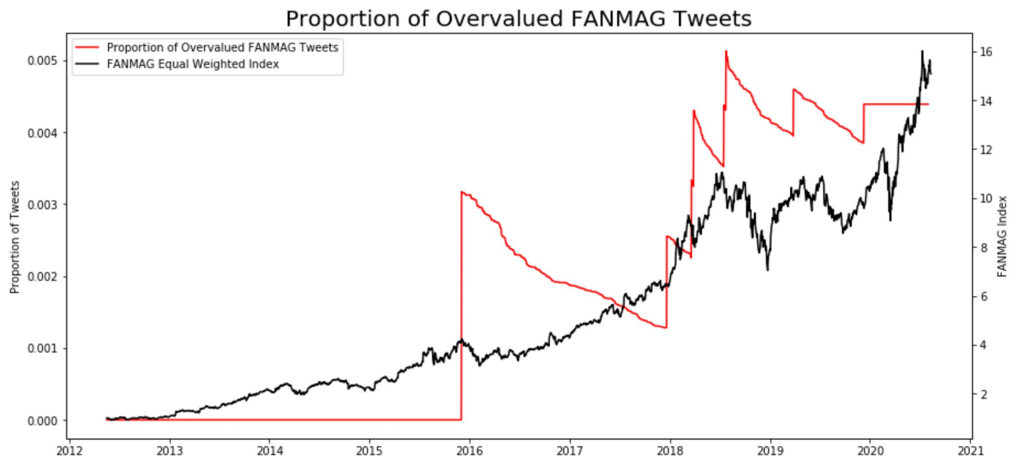

Figure 7. Proportion of the number of overvalued FANMAG stories to the total number of FANMAG stories published by Bloomberg Markets.

From these graphs, there appears to be very little concern about tech prices being too high. In particular, of the 2054 tweets about FANMAG, only 8 mentioned any signs of stock prices being too high (0.4%). For comparison, of the 1312 crypto-related tweets in this same dataset, 51 mentioned overvaluation (4%), about ten times the FANMAG amount.

However, despite the obvious magnitude differences between overvaluation concerns here and those from dot-com and bitcoin, the overall pattern traced by the graph here is quite similar. Specifically, relative overvaluation concerns do seem to rise with the prices of the underlying assets. As mentioned before, this makes sense as market rallies tend to attract media attention. With this, it is quite likely that at least a small part of this will question the sustainability of such high prices.

To double check that overvaluation concerns are indeed low for tech stocks, I compile a new dataset of tweets about FANMAG and tech companies in general from the WSJ Markets and MarketWatch Twitter accounts. Similar to the low numbers found in the previous dataset, only 61 tweets mentioned overvaluation, representing about 0.3% of all tweets in the sample. After plotting how these tweets materialized through time below in Figure 8, the pattern is slightly different from what was observed in the Bloomberg Businessweek dataset—it makes sense that these patterns do not line up exactly, as there was no clear event that would have made overvaluation concerns between different sources sync up. However, it can be argued that the rapid FANMAG rally in late 2017 should have elicited a larger response in this WSJ/MarketWatch data.

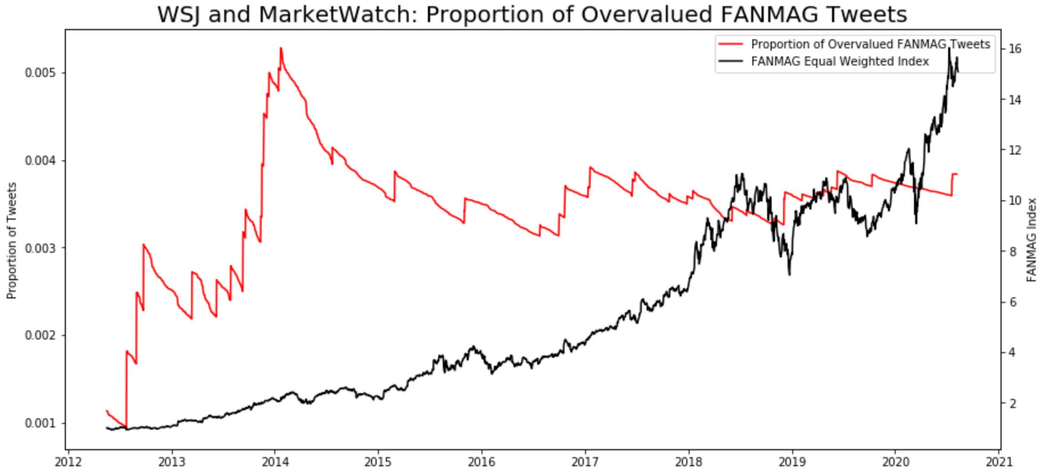

FIGURE 8. WSJ and MarketWatch Data: Proportion of the number of overvalued FANMAG articles relative to to all FANMAG articles in this sample.

2.2.4. *Discussion.* As such, although it is true that the level of relative concerns rise for all bubble episodes, the extent to which they do vary from bubble to bubble. I hypothesize that these levels depend on how familiar investors are with the underlying asset's fundamental value.

The relatively high levels of concerns seen during the dot-com and crypto bubbles may be a result of the poor understanding of the underlying technologies. The uncertainty of what these assets were actually worth made it easy to argue against them, considering their prices shot to historic highs while their fundamental values remained unknown. FANMAG companies on the other hand have long established themselves as companies with high fundamental value—their products are household names and their company reputations are sky high. As such, a bearish take must be quite nuanced in order to make sense, which makes is difficult for many people to fully understand.

3. SENTIMENT ANALYSIS

3.1. **Sentiment Divergence.** To quantify the difference in opinion from overvalued and non-overvalued articles, I perform sentiment analysis on the text data. Doing so verifies that overvalued articles are indeed more bearish than their non-overvalued counterparts during the bubble's run-up.

I use both the Loughran-McDonald and Harvard IV-4 sentiment dictionaries, where I take a $2:1$ weighted average. I give more weight to the Loughran-McDonald score, as it is specifically built for analyzing financial documents. As such, each article is assigned a value between -1 and 1, with 1 being the most "positive" score possible.

As mentioned earlier, sentiment analysis using Twitter data alone may not provide the most accurate results. Tweets are generally only a sentence long. As well, news accounts also tend to stray away from emotive language. This means that there is not too much room for the algorithm to perform at its best.

As such, the focus of this section should be on the dot-com data, which is on average, about five to six times longer. The sentiment algorithm therefore works better in this setting.

3.1.1. *Dot-Com.* In Figure 9, I compare the 60-day backwards rolling average of sentiment scores for overvalued articles with that for non-overvalued stories. It is clear that the overvalued sentiment is markedly lower than non-overvalued sentiment during the bubble's run up.

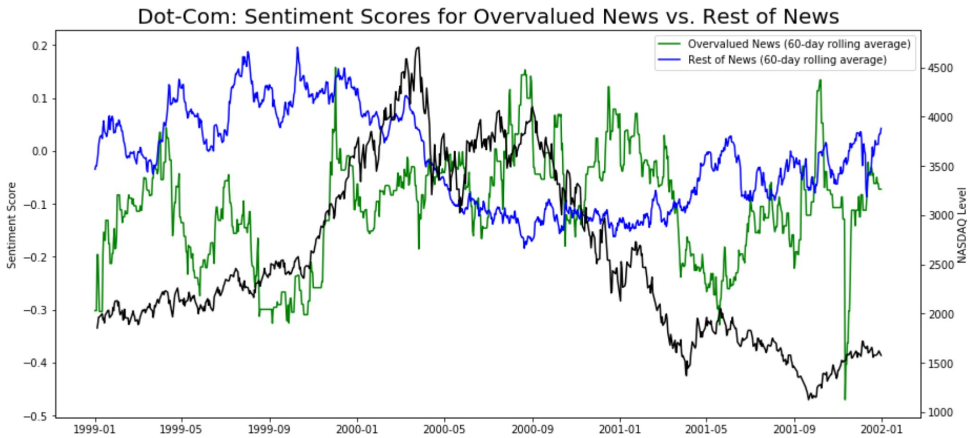

FIGURE 9. Dot-com: 60-day backwards rolling average of sentiment scores for stories that do and do not fall into the "overvalued" subset.

To verify that this difference is indeed significant, I perform a one-sided Welch t-test with the alternate hypothesis that mean overvalued scores are lower than mean non-overvalued scores prior to the peak. The test gives a t-statistic of 4.64, thereby suggesting that the average difference is significant at the 1% level. The average overvalued score in this period is -0.13, whereas the average non-overvalued score is 0.07.

3.1.2. *Crypto.* Despite the shortcomings of using raw Twitter data, I present some results here. In particular, I use the same procedure above to examine the divergence in sentiment scores. In Figure 10, I plot the 45-day backwards rolling average of sentiment scores for each category.

The most striking feature is that non-overvalued scores are actually in negative territory for much of the pre-crash period, and is at times, even lower than overvalued scores. I attribute this to two things:

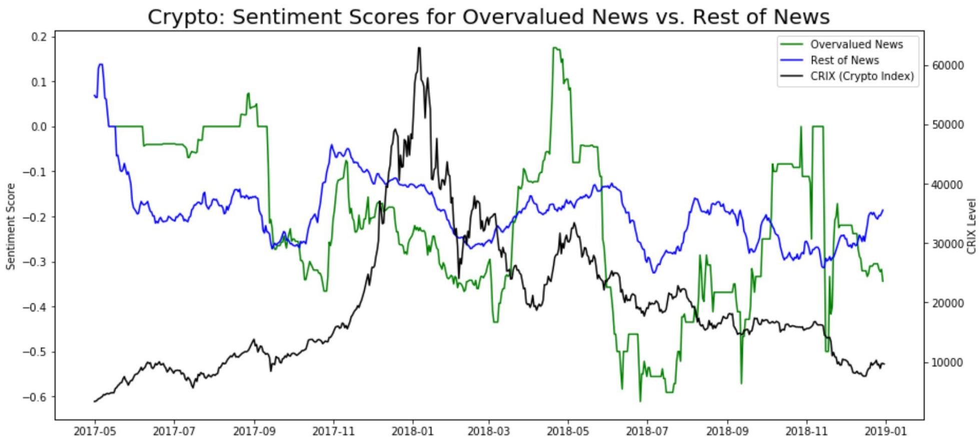

FIGURE 10. Crypto: 45-day backwards rolling average of sentiment scores for stories that do and do not fall into the "overvalued" subset.

For one, several high-profile events such as security flaws in cyprto exchanges and the illegal use of the currency in drug purchases caused a portion of non-overvalued scores to be quite negative. These stories should actually be classified as overvalued since they realistically negatively affect the asset's fundamental value. However, as these tweets are very short, this argument was not explicitly stated, and was thus too implicit for the algorithm to notice. Additionally, non-overvalued tweets that should have been quite positive may not have been given high enough of a positive score due to inaccuracies caused by the shortness of the tweets.

Despite this though, overvalued sentiment still remained quite a bit lower than non-overvalued news between late 2017 and the bubble's peak. To determine if this pre-crash difference is statistically significant, I perform a one-sided Welch t-test with the alternate hypothesis that mean overvalued scores are lower than mean non-overvalued scores. The test gives a t-statistic of 2.46. The average overvalued score in this period is -0.24, whereas the average non-overvalued score is -0.12.

3.1.3. *FANMAG.* Since only about 30 FANMAG articles were classified as overvalued in this dataset, graphing a backwards rolling average here produces a very discontinuous graph, so I do not show it here. Performing a one-sided Welch t-test on sentiment scores with the alternate hypothesis that mean overvalued scores are lower than mean non-overvalued scores yields a t-statistic of 0.506. Overvalued articles are therefore not only low in count, but are not significantly lower in sentiment either.

3.2. **What Drives Sentiment Scores?** In this section, I examine whether sentiment scores are driven by the performance of the underlying asset. If overvalued articles are truly bearish and loyal to their view, there should be little to no correlation between overvalued sentiment and asset returns.

3.2.1. *Dot-Com.* I preform two time series regressions: first, I regress the weekly average sentiment of overvalued news on the weekly performance of tech stocks, and second, I perform the same regression except using non-overvalued news instead. I report these results in Table 2. As expected, I find that overvalued scores are not positively correlated with weekly returns on the NASDAQ, whereas non-overvalued scores are to the 1% level. As well, the coefficient for non-overvalued stories is also more than ten times that for overvalued stories. Taken together, these findings suggest that overvalued news carried a fundamentally different message from the prevailing news of the time: whereas overvalued stories remained consistent to their thesis, non-overvalued stories were heavily swayed by the short-term performance of the underlying stocks.

	(1)	(2)
VARIABLES	Non-Overvalued Stories	Overvalued Stories
Weekly NASDAQ Returns	0.0143***	0.00194
	(0.00379)	(0.00918)
Constant	0.0107	−0.241***
	(0.0192)	(0.0453)
Observations	136	78
R-squared	0.063	0.000

Table 2. Dot-com: Regressions of non-overvalued and overvalued sentiment on weekly NASDAQ returns. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

3.2.2. *Crypto.* I perform the same analysis as the last section. Surprisingly, not only is weekly CRIX returns significantly correlated with overvalued stories, the magnitude to which it is is about two times that of non-overvalued stories. The only logical explanation for this is that the overvalued tweets are not long enough for the algorithm to detect the correct sentiment. My hypothesis is that upon optimizing the algorithm or using another more complete dataset, the same effect as in the dot-com data would appear.

	(1)	(2)
VARIABLES	Non-Overvalued Stories	Overvalued Stories
Weekly CRIX Returns	0.00475**	0.00817**
	(0.00222)	(0.00326)
Constant	-0.0999***	-0.3429***
	(0.0307)	(0.0789)
Observations	138	44
R-squared	0.016	0.053

Table 3. Crypto: regressions of non-overvalued and overvalued sentiment on weekly CRIX returns. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

3.2.3. *FANMAG.* Due to the low overvaluation count in the FANMAG dataset, I do not perform this analysis.

4. Sentiment Analysis From Renault (2017)

Here, I repeat the sentiment analysis of the previous section but with a better tuned sentiment algorithm. In particular, I use the lexicon specified in Renault (2017) that is built specifically to detect bullish/bearish sentiment from messages posted on social media (StockTwits, in particular). This is an improvement over the Loughran-McDonald dictionary, as the Loughran-McDonald approach was originally intended to be used on accounting documents. Since the data I use is largely from newspapers and Twitter, the Renault lexicon is clearly a better choice.

As in the previous section, I establish two facts about each bubble episode: 1) overvalued articles have significantly lower sentiment scores than non-overvalued articles, and 2) overvalued scores are not positively correlated with weekly returns of the underlying asset, while non-overvalued scores are.

The Renault lexicon dramatically improves results. Whereas the Loughran-McDonald lexicon can only verify the two facts for the dot-com bubble, the Renault lexicon is able to do so for both the dot-com and crypto bubbles.

4.1. **Sentiment Divergence Using the Renault Lexicon.** Here, I establish that overvalued articles have significantly lower sentiment scores than non-overvalued articles during both the dot-com and crypto bubbles.

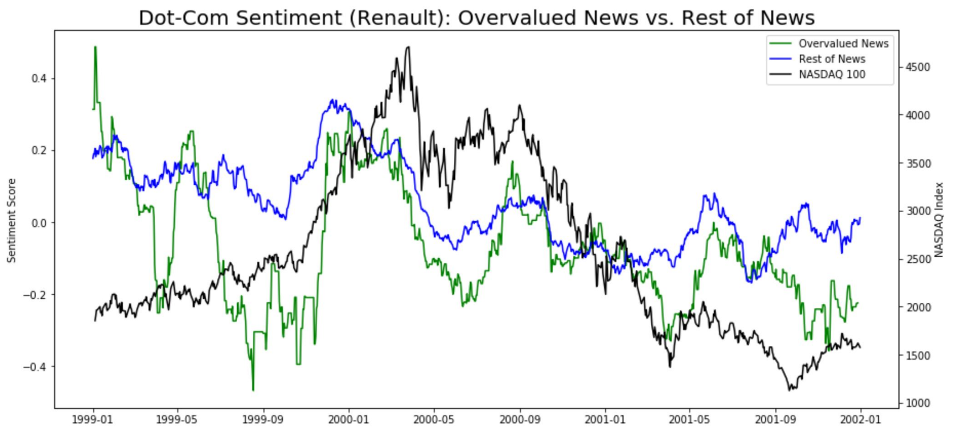

Figure 11. Dot-com (Renault): 60-day backwards rolling average of sentiment scores for stories that do and do not fall into the "overvalued" subset.

4.1.1. *Dot-Com (Renault).* Using the dot-com data, I compare the 60-day backwards rolling average of overvalued sentiment with that of non-overvalued sentiment. As observed in Figure 11, mean overvalued sentiment remains markedly lower than mean non-overvalued sentiment throughout the entire period. This contrasts with what is observed when the Loughran-McDonald is used, where overvalued sentiment fluctuates above and below non-overvalued sentiment as soon as the bubble's peak is reached.

I next perform a one-sided Welch t-test with the alternate hypothesis that mean overvalued scores are lower than mean non-overvalued scores. A t-statistic of 2.71 is observed for stories published before the bubble's peak, and a t-statistic of 3.96 is observed for stories published throughout the entire period. Like what is seen when Loughran-Mcdonald is used, these t-statistics are significant at the 1% level, implying that overvalued stories are significantly more bearish than the other news in these periods.

4.1.2. *Crypto (Renault).* As discussed in the previous section, the Loughran-McDonald lexicon is not particularly kind to the crypto data. For instance, the algorithm suggests that overvalued crypto scores are higher than non-overvalued scores for at least half a year, which is a rather difficult fact to reconcile. Additionally, the Welch t-test applied here shows only a difference significant to the 5% percent level.

I now apply the Renault lexicon to the crypto data. In particular, I compare the 45-day backwards rolling average of overvalued scores with that of non-overvalued scores. As seen in Figure 12, overvalued scores are markedly lower than that of other news throughout the entire sample. Unlike the dot-com bubble, there is a clear divergence in scores between overvalued and non-overvalued stories at the bubble's peak.

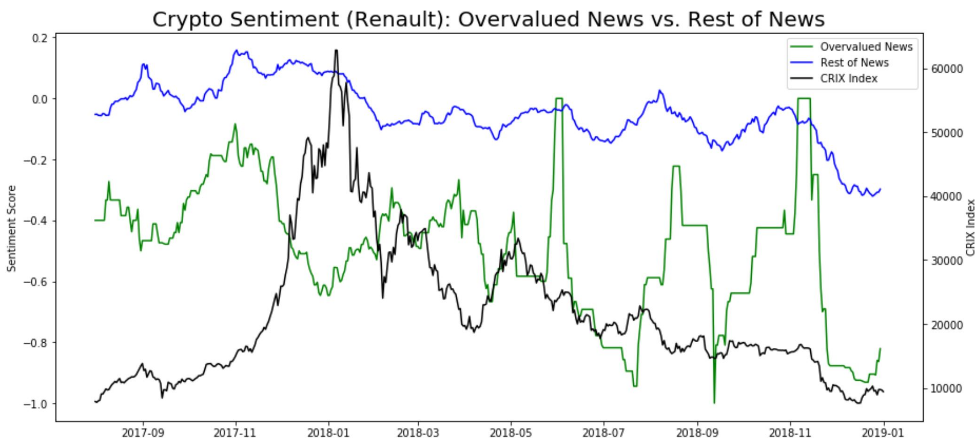

Figure 12. Crypto (Renault): 45-day backwards rolling average of sentiment scores for stories that do and do not fall into the "overvalued" subset.

I next perform a one-sided Welch t-test with the alternate hypothesis that mean overvalued scores are lower than mean non-overvalued scores. A t-statistic of 11.27 is observed for stories published prior to the bubble's peak, and a t-statistic of 14.51 is observed for stories throughout the entire sample. The level of statistical significance is much greater than 1% level−a dramatic improvement over the Loughran-McDonald result.

4.2. **Drivers Behind Sentiment Scores Using the Renault Lexicon.** In this section, I examine whether sentiment scores are driven by the performance of the underlying asset. If overvalued articles are truly bearish, there should be little to no correlation between overvalued sentiment and asset returns.

The Renault lexicon improves results here as well. The Loughran-McDonald lexicon is only able to verify this for the dot-com bubble, whereas the Renault lexicon is able do so for both bubble episodes.

4.2.1. *Dot-Com Bubble (Renault).* Like the setup used previously, I preform two time series regressions. I first regress the weekly average sentiment of overvalued news on the weekly performance of tech stocks, and then perform the same regression using non-overvalued news instead. I report these results in Table 4.

Results here are similar to what is observed when using the Loughran-McDonald lexicon. In particular, overvalued scores are not positively correlated with weekly returns on the NASDAQ, whereas non-overvalued scores are significantly correlated at the 1% level. Note that the coefficient for non-overvalued stories is more than ten times that for overvalued stories.

	(1)	(2)
VARIABLES	Non-Overvalued Stories	Overvalued Stories
Weekly NASDAQ Returns	0.01997***	0.00189
	(0.00517)	(0.0120)
Constant	0.0526**	−0.0442
	(0.0220)	(0.0571)
Observations	136	78
R-squared	0.0949	0.0003

Table 4. Dot-com: Regressions of non-overvalued and overvalued sentiment on weekly NASDAQ returns. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.2.2. *Crypto Bubble (Renault).* The results here follow a similar pattern to the dot-com episode. As seen in Table 5 overvalued scores are not significantly correlated with weekly returns of the CRIX, whereas non-overvalued scores are significantly correlated at the 1% level.

As such, these findings suggest that overvalued stories carry a fundamentally different message from the prevailing news—whereas overvalued stories remain consistently bearish, non-overvalued stories are heavily swayed by the short-term performance of underlying assets.

5. Works Cited

(1) Brunnermeier, M., Nagel, S. "Hedge funds and the technology bubble." *The Journal of Finance* 59.5 (2004): 2013-2040.

VARIABLES	(1) Non-Overvalued Stories	(2) Overvalued Stories
Weekly CRIX Returns	0.00938***	0.00775
	(0.00358)	(0.00585)
Constant	−0.0238**	−0.60228***
	(0.0318)	(0.0783)
Observations	138	44
R-squared	0.0600	0.0543

Table 5. Dot-com: Regressions of non-overvalued and overvalued sentiment on weekly CRIX returns. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

(2) Hale, G., Krishnamurthy, A., Kudlyak, M., & Shultz, P. (2018). How futures trading changed bitcoin prices. *FRBSF Economic Letter,* 12, 1-5.

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