Pre-IPO Sentiment Analysis

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Abstract

We examine whether pre-IPO investor sentiment, particularly retail investor sentiment, as expressed through tweets on the social media platform Twitter has a correlation with the performance of IPOs. The ten largest IPOs in U.S. history that coincided with Twitter's existence were examined over various timescales to determine how well investor sentiment on Twitter would correlate over time, and two sentiment analysis models, VADER and FINBERT, were used to calculate sentiment for tweets in trying to understand which model would be more suitable for the nature of text on Twitter. It was found that sentiment readings calculated by the VADER model most strongly correlated with actual IPO performance and that the sentiments expressed on Twitter seemed to hold a correlation for up to 1 month.

1. Introduction

Sentiment analysis, along with other machine learning techniques, are today incorporated in the technical analysis of all manner of investors, from individuals to institutions, and all manner of investments. Historically, it has been a technique used to predict a stock's performance: news or social media, often in the form of tweets, are analyzed to determine whether a stock will increase in decrease or value. However, it is not always clear whether investor sentiment has led to a stock's price change or if the stock's price change has led to a change in investor sentiment. As the two variables are dependent on one another, it can at times be difficult to glean insights when examining stocks as a whole.(4)

However, one specific and less-explored use case is that of IPOs (an IPO is a company's first sale of stock to the public).(1) Whether it's a well-known company that's been historically private or a unicorn that's just taken off, many companies see IPOs as an opportunity to raise capital at scale to further fund growth efforts.(2)Every company whose stock is purchasable on a stock exchange, from technology giant Google to supermarket conglomerate Kroger, has performed an IPO.

Many investors, especially retail investors, may previously have seen IPOs as their opportunity to purchase shares of a company early on, to support a company they admire, or, for most, to make a profit. Most of the growth of a new company's earnings is estimated, but uncertainty is inherent to the nature of IPOs, and that has never daunted investors, even when they risk being deceived by hype and perceived opportunity.(6) However, today more than ever, IPOs are a risky investment. The percentage of unprofitable IPOs has risen from about 20% in the 1980s to around 80% today.(5) Notable IPOs that have been labeled failures include RobinHood, the investing platform offering zero-commission trading for all investors, and Uber, one of the world's most popular rideshare apps. Robinhood's shares fell 10% within minutes of going public and ended the day trading at \$29 billion, \$6 billion short of its expected \$35 billion valuation; Uber, similarly aimed to trade at \$45 per share at opening but closed at \$41.(7) And, according to the Financial Times, those who had bought IPO stocks would, over an extended period of time, have lost about 50% of their investment half the time and 75% of their investment 25% of the time.(3)

Increased risk associated with recent IPOs is discouraging; nevertheless, the potential for upside is huge, as successful IPOs may grow to multiply initial investments by orders of magnitude. Existing papers have attempted to clarify the relationship between investor sentiment and IPO performance. "Investor Sentiment and Pre-IPO Markets" by Francesca Cornelli, David Goldreich, and Alexander Ljungqvist, examines speculative European pre-IPO markets.(8) Jonas Krinitz and Dirk Neumann's "Decision Analytics for Initial Public Offerings: How Filing Sentiment Influences Stock Market Returns" performs sentiment (uncertainty) analysis on filings and news reports.(10) Bruno Guilherme's "Investing in Stock IPOs with Sentiment Analysis from Twitter optimized by Genetic Algorithms" seeks profits by selecting tweets representative of investor sentiment using genetic algorithms.(9) This paper, in contrast, seeks to examine tweets leading up to the biggest U.S. IPOs using VADER and FINBERT to make investing in IPOs less risky and more profitable than it has been recently, especially for the average investor. It will do so by clarifying the relationship between Twitter sentiment and performance as changes in stock price over various timescales. With further elaboration, research into the connection between sentiment and stock performance may eventually cause markets to price IPOs in a way that better reflects company value, reducing the losses that investors, most of all retail investors, experience.

2. Background and Related Work

2.1. Previous Work

Cornelli, Goldreich, Ljungqvist's "Investor Sentiment and Pre-IPO Markets" proposes a difference between rational investors, who are the reason markets are efficient, and irrational, "sentiment-motivated" investors. They seek to understand whether these irrational investors, often retail investors, have an effect on IPO prices, examining European IPOs specifically through grey markets. Grey markets are predominantly-retail-investor pre-IPO markets that allow investors to speculate on future stock prices. To understand the effect of these smaller investors, Cornelli, Goldreich, and Ljungqvist build a theoretical model for their behavior, concluding that grey market overoptimism inflates IPO prices, though pessimism does not negatively affect IPO prices. The price inflation generated by overoptimism is susceptible to exploitation by rational investors. Thus, positive sentiment plays a key role in IPO prices, though negative sentiment less so.(8)

Krinitz and Neumann examine sentiment of pre-IPO filings and prospecti, defining positive sentiment as certainty and negative sentiment as uncertainty. They examine 572 different IPOs and rely on the Loughran and McDonald Financial Sentiment Dictionary to gauge whether words are uncertain. After analysis of the aforementioned IPOs, they concluded that greater degrees of uncertainty in the prospectus led to worse performance over the first ten days; however, greater degrees of uncertainty in news sentiment led to strong first-day performances. This led Krinitz and Neumann to believe that uncertainty was a negative in the eyes of institutional investors and a positive in the eyes of retail investors.(10)

Guilherme seeks to understand how different genetic algorithms gather tweets and the differing sentiments that occur among these different sets of tweets. In order to optimize results, he uses a greedy algorithm to determine the proportion of effect that each of those eight algorithms should have in the final predictive model. Guilherme concludes that genetic algorithms can, indeed, successfully assist in determining whether an IPO will be successful and earn profit.(9)

2.2. Comparisons to Cornelli, Goldreich, and Ljungqvist

This project's methodology differs from that of Cornelli, Goldreich, and Ljungqvist with respect to means, geography, and their perspective on sentiment. The authors constructed a theoretical model that would generate the results they observed empirically. This project, on the other hand, makes observations about trends in financial performance and tweet sentiment; the underlying methodologies are fundamentally different. The authors also examine European grey markets. Though they claim that their conclusions can be extrapolated to the United States as well, this is not necessarily the case. Grey markets are a phenomenon that exist solely in Europe: it is extremely difficult for retail investors in the United States to purchase or speculate on shares of a company before its IPO. The two regions each have different ways of regulating and executing IPOs, too, which further separates the subject matters of this paper and theirs. Lastly, the authors frame sentiment in terms of overoptimism, which they gauge by how much higher grey market prices are than actual IPO prices. This financial metric for sentiment, which, again, depends on the European grey market, is different from the social media-based means that this experiment uses, even if both papers are targeting retail investors. Thus, Cornelli, Goldreich, and Ljungqvist do not provide sufficient insight into the way retail investors communicate their sentiment on social platforms, specifically Twitter, and the timescale over which these European investors have influence is unclear.

2.3. Comparisons to Krinitz and Neumann

Though Krinitz and Neumann do, indeed, use text-based sentiment analysis to attempt to evaluate the performance of IPOs, their methodology differs in terms of their sources for textual data, the number of and types of IPOs they examine, and their metrics for sentiment. They choose to examine pre-IPO filings and prospecti, which are longer-form legal documents meant to convey information to institutional investors. They thus reflect the sentiment not of investors but of those directly affiliated with the companies that are undergoing IPOs. They also choose to examine 572 different IPOs, performing a broader statistical analysis, but this makes it challenging to point out the effects that certain characteristics of companies that IPO may have that are affecting results, and the inclusion of significant amounts of smaller IPOs may skew their results. Lastly, their means of gauging positive and negative sentiment is different from that of this project. Rather than taking words as positive or negative, they choose to use high uncertainty as an indicator of negative sentiment and low uncertainty as an indicator of positive sentiment. And, rather than using existing machine learning models, they rely on the Loughran and McDonald Financial Sentiment Dictionary.

2.4. Comparisons to Guilherme

Guilherme's approach is focused specifically on generating returns and relies on genetic algorithms, which are evolution-inspired search heuristics that select the fittest individuals of every generation. Using 8 different genetic algorithms, he selects tweets from Twitter, calculates the sentiment of the tweets selected by each algorithm, and attempts to find a correlation between these sentiments and eventual stock performance. Though the methodology of using genetic algorithms may be reminiscent of the differing models used in this project, the fundamental difference lies in the fact that Guilherme selects different groups of tweets and calculates sentiment in the same way, whereas this project operates on the same set of tweets but calculates sentiment in different ways.

3. Approach

3.1. Novel Idea

This paper's distinguishing characteristics include analysis of timescales, usage of multiple models, and a focus on major IPOs in the United States. First, it builds off Krinitz and Neumann's principle that pre-IPO sentiment results in hype. Though they clarify that uncertainty in the news generates positive first-day returns and that uncertainty in the prospectus can generate negative returns over the first ten days, this paper seeks to understand whether the effects of sentiment can persist for longer. It also seeks to understand sentiment beyond hype; it is possible that investors are predictive, that their positive and negative sentiments correlate with the stock's longer-term success or failure. This examination of correlations between sentiment and stock price over extended periods of time has not been performed before.

Rather than using genetic algorithms to attain different sentiment readings as Guilherme does, the VADER and FINBERT models are used, with the former being trained on vast amounts of data for frequently-seen words and the latter being trained specifically for financial terms. Having two metrics for sentiment will also shed light on the efficacy of each model. More specifically, because tweets are a uniquely informal and short-form text, it is unclear whether the VADER model, more suited for short-form text, or the FINBERT model, suited for longer-form financial texts, will perform better.

This project's approach also places emphasis on the Top 10 IPOs in the United States specifically, making it more likely that there is a sufficient body of tweets to draw on: it makes sense that more is being tweeted about larger IPOs. This, in turn ensures that there are more distinct individuals posting to Twitter and that the sentiment is reflective of the public's opinion on the stock. And the companies' size makes it more likely for them to last for extended periods of time, allowing the effects of sentiment over both the short- and long-term to be seen in detail.

3.2. Merits of This Approach

By improving an understanding of the timescale over which Twitter sentiment analysis is useful for determining an IPO's performance, this project will allow investors, especially retail investors, to understand the relationship between what they may see on social media and how an IPO will perform. If social media is merely hype, then investors know to avoid (or at least to exercise caution) investing in stocks that people seem overly enthusiastic about. If it is actually a good means of predicting performance, then it would encourage investors to consider whether they want to make a longer-term investment or to pursue other investment options. The term "social media" is used because it is likely that short-form tweets map well onto platforms like Reddit. Twitter and Reddit users alike may find use in understanding the implications of sentiment before an IPO.

Using two models for sentiment analysis clarifies the best means of analyzing tweets: better results for VADER would indicate that tweets are not so different from ordinary text. If FINBERT performs better, it indicates that tweets, especially about financial matters, utilize a more specific set of vocabulary and require a more finely tuned model. One can extrapolate from this what models are best for more rigorous analyses of sentiment, perhaps ones used to actually predict exact stock performance, and also in general whether it's better to simply use VADER for tweets or to create and train a unique model tailored for the data being examined. And the focused nature of examining the 10 biggest U.S. IPOs ensures that much is being learned about the biggest investment opportunities and that the knowledge is applicable specifically within the realm of the U.S. stock market.

4. Implementation

4.1. System overview

The approach chosen had four primary steps: to gather tweets from the week before the IPO, to clean and prepare the data in a way that was optimized for sentiment analysis, to perform the sentiment analysis itself, and to draw connections between the results of sentiment analysis and stock performance. The relationships between these steps and the involved technologies are demonstrated in the below figure1:

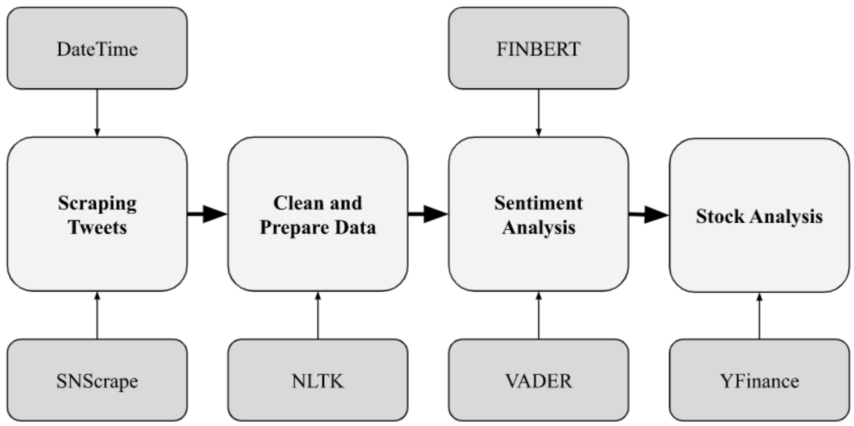

Figure 1: Flowchart depicting implementation process.

4.2. Steps Taken: Gathering Tweets

Gathering tweets required three key steps: deciding that tweets would be a reliable data source in the first place, choosing a library with which to scrape tweets, and, lastly, performing the actual scraping. Three initial data sources were considered: tweets, news articles, and a combination of both. Tweets would be favorable because of the abundance of data present. They would also accurately reflect the sentiment of retail investors, or, at the very least, retail investors who used Twitter as a means to communicate about their investing opinions. News articles would be favorable because their longer-form text would allow for a more accurate sentiment reading and the lack of noise in the data. Combining the data sources, of course, allowed for the potential of balancing the advantages and disadvantages of tweets and news articles on their own. However, performing research on the process of scraping news articles indicated that it would be both challenging and particularly time-consuming for the nature of this project's queries, specifically, the ten largest IPOs in U.S. history. Combining data sources would entail figuring out a favorable distribution of data – this would be another parameter to consider in addition to existing variables in language model and timescale – and the very nature of mixing data would make it unclear which data source was helpful or hurtful.

With regard to the library chosen for scraping tweets, two initial considerations were TweePy and Twint. The former offered scraping through Twitter's API, while the latter claimed to not require it. Both cases limited the number of tweets it was possible to scrape, with Twitter's API having limitations and Twitter having also implemented safeguards against scraping with Twint. As SNScrape had no such issues, it was the library chosen. The process of scraping tweets itself was challenging as well. Despite the sizes of the companies that IPOed, some companies were scarcely discussed on Twitter while others, like Facebook, were well-known and often posted about. This meant that tweets about such popular companies required more time to scrape; it was for this reason that, no matter the company, the number of tweets scraped per day was limited to 5,000. Even then, the scraping process took hours and was often repeated due to buggy code and challenges with using the SNScrape library. The lengthy nature of scraping meant that modular code needed to be written, and, to avoid wasting time, safeguards were written into scraping methods to ensure that the user was aware of when scraping for another day would commence and to prevent the user from scraping too soon and overwriting existing data. Complete datasets were exported as CSV files to be reusable and to remove the need to re-scrape.

4.3. Steps Taken: Cleaning and Preparing Tweets

Cleaning the tweets in a manner that was optimized for sentiment analysis required learning to use and actually utilizing the Natural Language Toolkit, ensuring that the manner in which data was processed would be good for sentiment analysis, and modularizing code to make it automated and more efficient. Learning to use the Natural Language Toolkit required research in the form of articles and videos that demonstrated how people used NLTK for a variety of purposes. NLTK and the Pandas library were used together in two primary ways. The first was modifying the underlying structure of the data and the Pandas DataFrame; the second was to modify data at the level of individual words.

With regard to the former, the data that had previously been stored in CSV files had to be imported as Pandas DataFrames; it was also important to tokenize the data so that it could be processed at the word level. Lastly, adding a column for the length of each sentence made it possible to remove empty tweets whose neutral sentiment would dilute positive or negative sentiment from other tweets. With regard to the latter, the data itself was processed by setmming, removing non-alphanumeric characters, making all characters lowercase, removing stopwords, removing non-English words, and removing URLs. Stemming was performed to reduce words to their roots – for example, "eaten" and "eat" would both become "eat" and would be consistently evaluated with the same sentiment. Non-alphanumeric characters, non-English words, and stopwords were removed to prevent unrecognized words from diluting sentiment. To clarify, stopwords, of which NLTK has 40, are common English words that contribute little to no semantic meaning; typical examples include articles like "the" or "an," as well as "is" and "are." Removing URLs served the same purpose, to prevent dilution of sentiment, though they were removed using native Python and not with NLTK – in hindsight, it would have been better to take full advantage of NumPy's vectorization functionality. And making all characters lowercase would standardize the data in the off chance that capital letters would be processed differently.

To ensure that the manner in which data was processed would be best for sentiment analysis, various combinations of the above means of cleaning the data were tested. Sentiment analysis was performed on some of this data to ensure that the results passed a sanity check and that the data cleaning approach had not significantly inhibited either language model. Code had to be modular and efficient, too: a single process() method was written to take a dataframe as input so that all the data for every stock could be cleaned at once; it also meant that modifying the data cleaning process simply meant modifying the process() method.

4.4. Steps Taken: Sentiment Analysis

Performing sentiment analysis required choosing models, writing additional Python code to standardize sentiment analysis, and modularizing code. Initially, only VADER was used; however, it became clear that, though VADER had an enormous vocabulary that was well-suited for most Twitter words, it struggled with more specific and esoteric terminology that had different meanings in financial contexts than in ordinary contexts – for example, “explode” or “bull” might be positive words in financial contexts but neutral or even negative in ordinary contexts. It was for this reason that FINBERT was incorporated. However, as it was unclear whether VADER’s vast vocabulary or FINBERT’s precision was better for the data, the average of their scores was incorporated as an additional metric. Standardizing sentiment analysis was required because VADER would return a score between -1 and 1 for a tweet, with -1 being the most negative and 1 being the most positive sentiment: this meant that scores of 0.523 or -0.1 were possible to indicate degrees of positive or negative sentiment. FINBERT, on the other hand, only returned whether inputted text was positive or negative. To make the data comparable, positive pieces of text were labeled with a 1, negative pieces of text with a -1, and neutral ones with a 0. This meant that taking the mean of both columns would result in values with the correct order of magnitude. Modularizing code was, of course, important for sentiment analysis as well, ensuring that it could be performed multiple times to fix bugs and allowing for sentiment analysis to be performed on all datasets consecutively.

4.5. Steps Taken: Stock Analysis

Gathering financial data and creating visualizations was done with YFinance and MatPlotLib. Though YFinance was the library of choice for gathering financial data in Python, one option that was considered was simply getting data from the Yahoo Finance website as well. Though this would allow for more granular data, as the YFinance library is limited to providing day-over-day data from early in a stock’s history, it was determined that manually recording data points or even scraping from the Yahoo Finance website would be too difficult. The former would be extremely time consuming, while the latter would require digging into the rather complex stock chart module Yahoo Finance had created in addition to building a Selenium script.

To plot data, MatPlotLib was chosen over PlotLy simply because of popularity and familiarity. There were significantly more resources available on how to use MatPlotLib and generate specific types of visualizations with it, especially with YFinance. MatPlotLib was also used in the past for other projects, establishing underlying experience that was helpful for this experiment. Though SeaBorn was considered to make visualizations more aesthetically pleasing, it was determined that the look of plots generated by MatPlotLib were better suited for this project and that SeaBorn visualizations would not be necessary.

5. Evaluation

5.1. Experiment design

The criteria for success would be to identify a model that performed both better than the other and also was more accurate than one would expect. More specifically, such a model would have to have more true positives and true negatives than expected. Though utilizing statistical significance as a lens for interpreting results was considered, it was determined that there were too few data points for this metric to be useful. It was hypothesized that FINBERT would outperform VADER, simply because FINBERT was better suited for dealing with financial vocabulary. And, given the volatile nature of stocks, it was also hypothesized that these sentiments as calculated by VADER and FINBERT would weaken in their correlations with stock prices (if such correlations did exist)

The expected accuracy rate if Twitter sentiment had no correlation to IPO performance would have been 50% over timescales of 2 weeks, 1 month, and 3 months. Though VADER seemed to have performed worse than expected prior to scaling, this decreased accuracy was attributed to data impurities and the fact that VADER was not perfectly equipped to analyze financial data; it is therefore likely that VADER was overly optimistic, interpreting neutral words in a positive light. It was also possible that people's seemingly positive statements were actually neutral or uncertain – for example, "This stock might do well." VADER post-scaling and FINBERT both performed better than expected, with accuracy rates well above 50%, making the experiment a success.14

5.2. Data: 2 Weeks

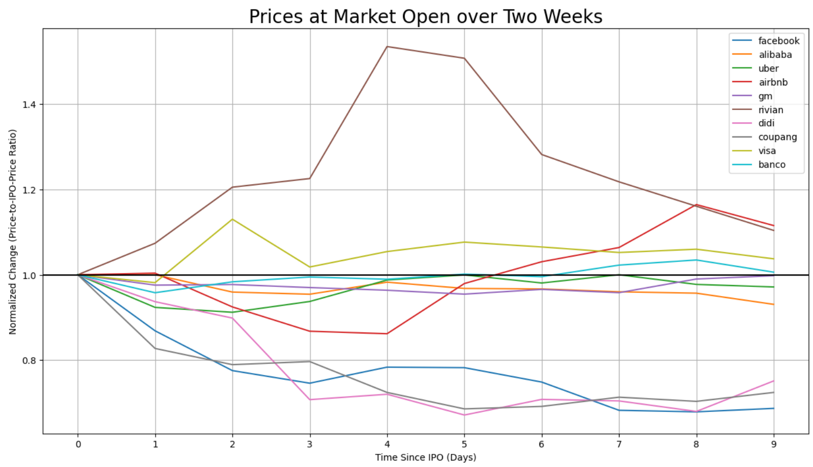

Figure 2: Opening prices of all stocks over 2 weeks.

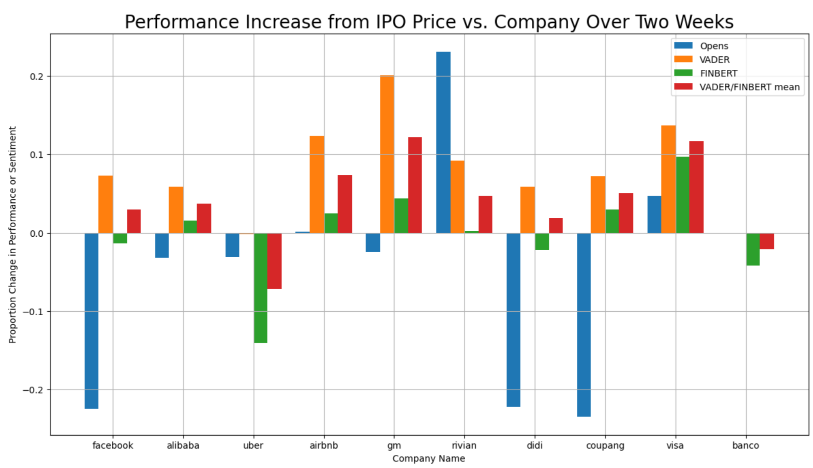

Figure 3: Bar graph depicting sentiment alongside stock performance.

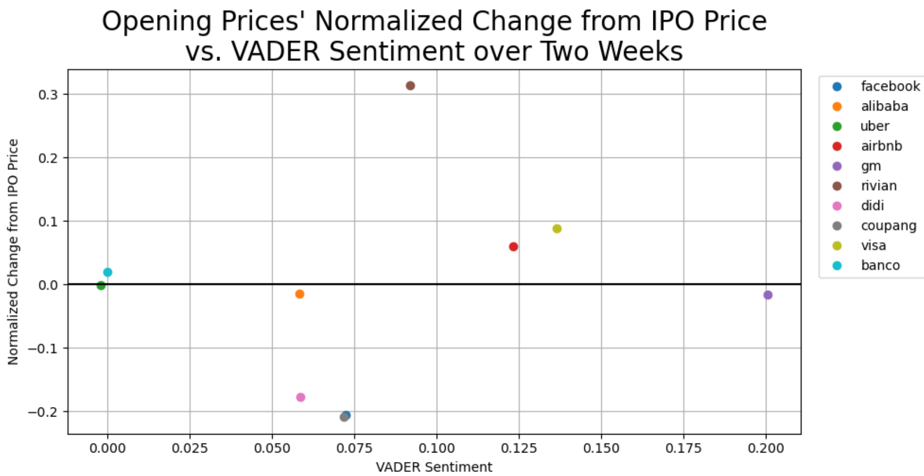

Figure 4: VADER sentiment on the x-axis versus stock deviation on the y-axis.

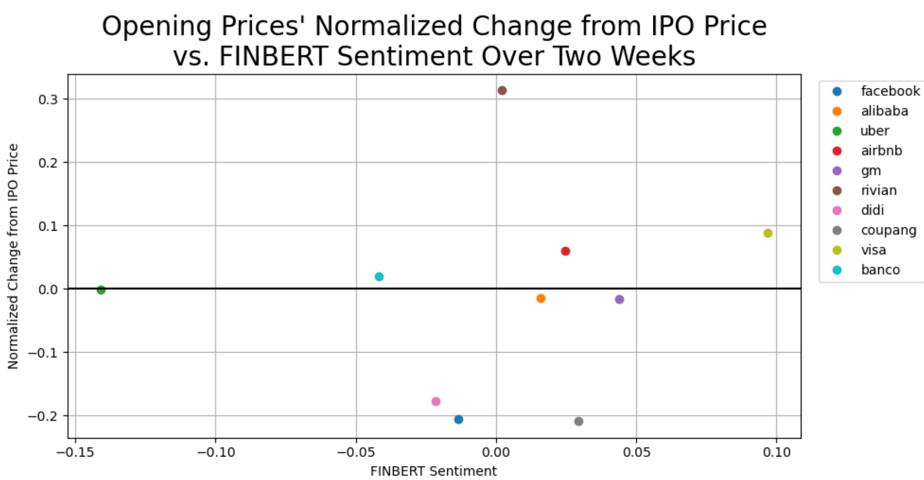

Figure 5: FINBERT sentiment on the x-axis versus stock deviation on the y-axis.

5.3. Data: 1 Month

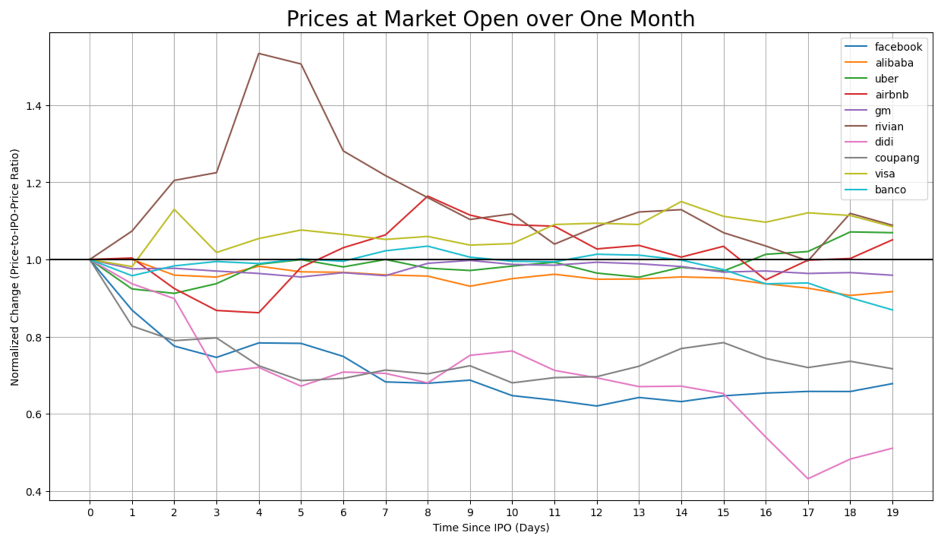

Figure 6: Opening prices of all stocks over 1 month.

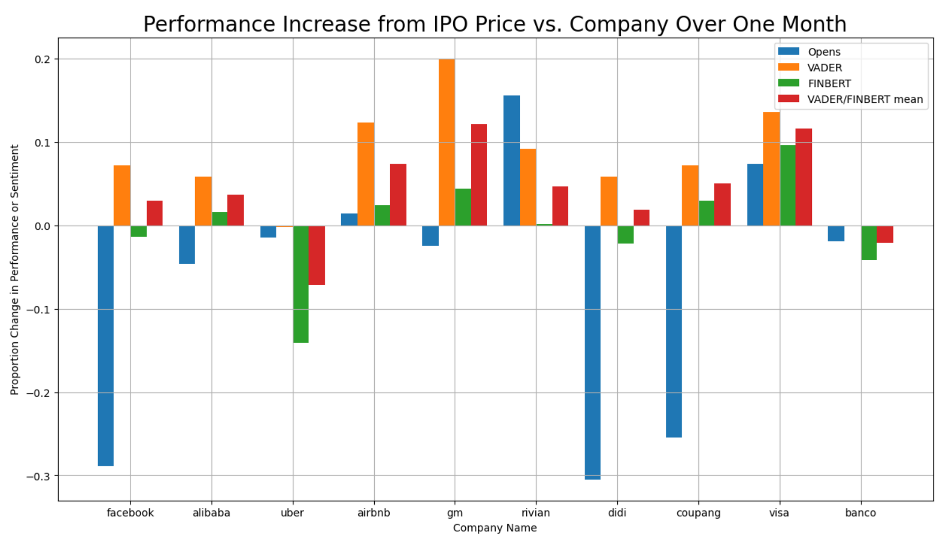

Figure 7: Bar graph depicting sentiment alongside stock performance.

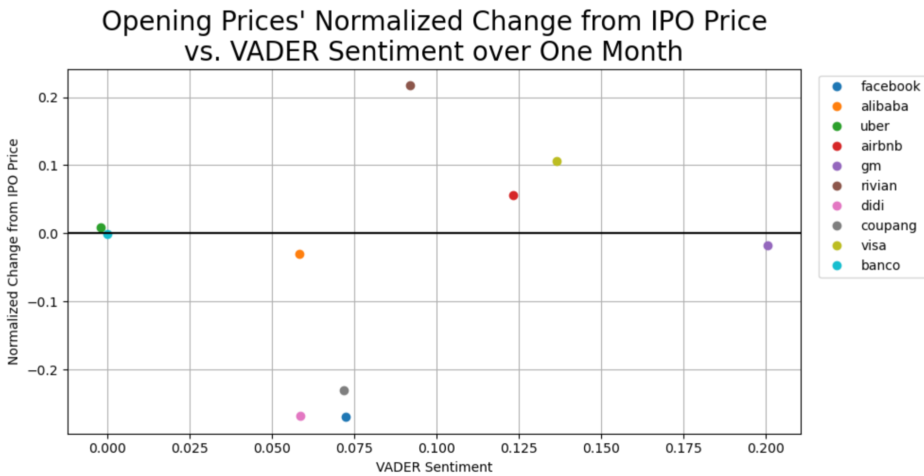

Figure 8: VADER sentiment on the x-axis versus stock deviation on the y-axis.

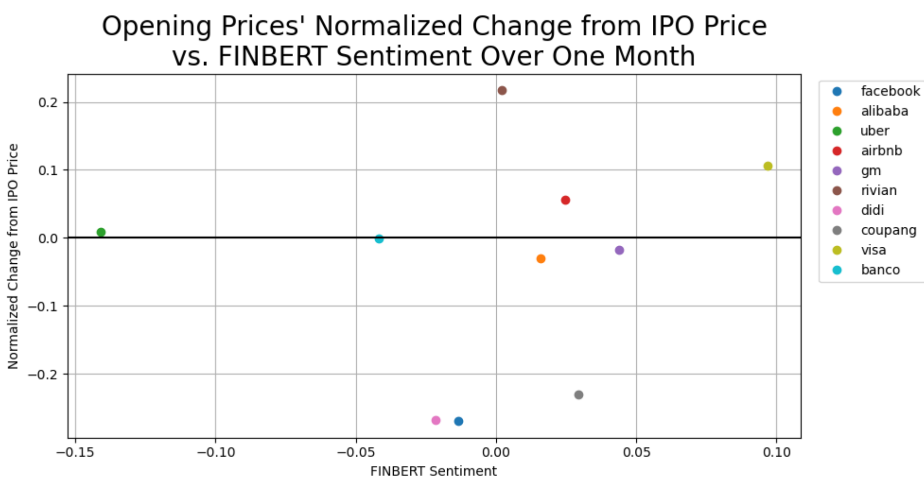

Figure 9: FINBERT sentiment on the x-axis versus stock deviation on the y-axis.

5.4. Data: 3 Months

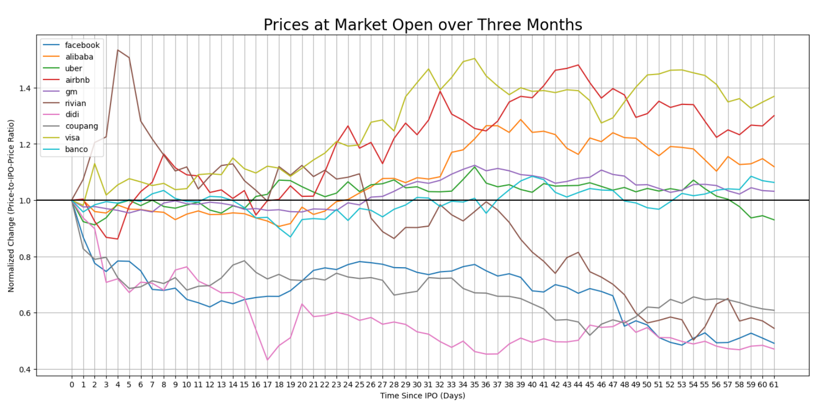

Figure 10: Opening prices of all stocks over 3 months.

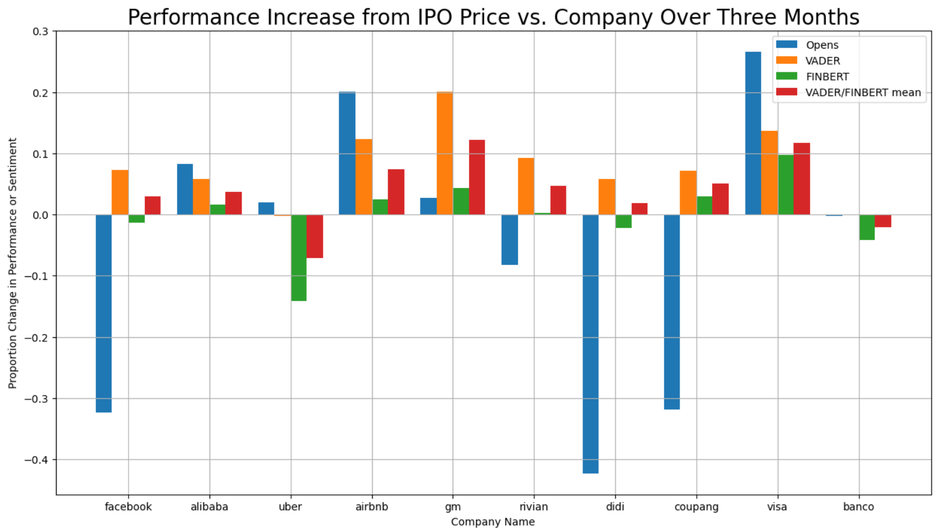

Figure 11: Bar graph depicting sentiment alongside stock performance.

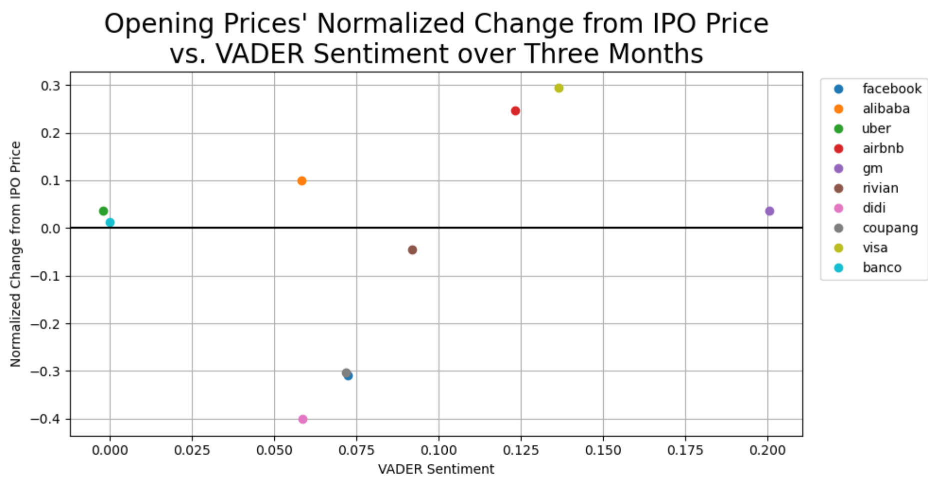

Figure 12: VADER sentiment on the x-axis versus stock deviation on the y-axis.

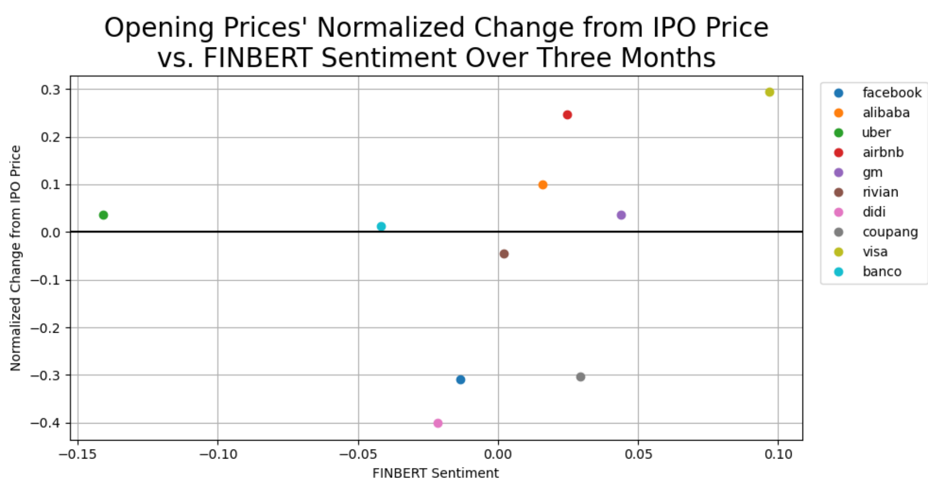

Figure 13: FINBERT sentiment on the x-axis versus stock deviation on the y-axis.

5.5. Data: Summary

Expected					
Time Frame	**TP**	**TN**	**FP**	**FN**	**Accuracy**
2W	2	3	2	3	50%
1M	2	3	2	3	50%
3M	3	2	3	2	50%

VADER					
Time Frame	**TP**	**TN**	**FP**	**FN**	**Accuracy**
2W	4	1	5	0	50%
1M	3	1	5	1	40%
3M	4	0	4	2	40%

VADER (Scaled)					
Time Frame	**TP**	**TN**	**FP**	**FN**	**Accuracy**
2W	3	5	1	1	80%
1M	3	5	1	1	80%
3M	2	3	2	3	50%

FINBERT					
Time Frame	**TP**	**TN**	**FP**	**FN**	**Accuracy**
2W	3	3	1	3	60%
1M	3	3	1	3	60%
3M	2	4	2	2	60%

Figure 14: FINBERT sentiment on the x-axis versus stock deviation on the y-axis.

6. Summary

6.1. Conclusions

Results indicate that, though a VADER with no adjustment performs extremely poorly, adjusting for the fact that the VADER model may be excessively optimistic actually causes it to perform better than FINBERT. Both VADER models performed more poorly over time, while the FINBERT model was consistently better than randomly guessing over a timescale of three months.

All these results, of course, must be taken with a grain of salt due to the limited number of IPOs chosen. It is possible that VADER merely appeared to get worse over time when it was simply coincidence and that FINBERT merely appeared to remain consistent over time when, in fact, the market was moving randomly. The length of time elapsed between tweets chosen and results examined would suggest that how well models perform at the 3-month mark is random.

A preliminary conclusion that can be drawn is that VADER, due to mapping positive or negative sentiment to individual words, was able to better handle the stripped down nature of post-processing tweets. FINBERT, on the other hand, is a more fine-tuned version of BERT (Bidirectional Encoder Representations from Transformers). Testing FINBERT on test phrases such as “Bullish on NVIDIA” and “Exploding growth” yielded mostly neutral results, but the phrase “Despite the fact that NVIDIA struggled, it has nonetheless rallied in the past few months” was overwhelmingly positive. This indicates that FinBERT, perhaps because it was trained on articles and longer-form text, is better suited to finding the sentiment given more words, whereas VADER is more suited to identifying the sentiment of shorter-form text.

6.2. Limitations

One limitation on the project was time. Given a few more months, it would likely have been possible to do a larger-scale analysis of various IPOs beyond just the ten biggest IPOs in history, allowing results to be more certain. Another challenge was the fact that certain libraries, notably

YFinance, had limitations on the granularity of older data. Despite attempts to see hour-by-hour data from the first days of the IPO, YFinance could only offer day-by-day data. It would have been helpful to examine trends within hours of IPO, as it is possible that Twitter sentiment had particularly strong correlations with IPO performance at the level of hours or even minutes after IPO. Computing resources were a challenge as well. Despite using Microsoft Azure, scraping and sentiment analysis would still take hours – notably, the FinBERT model took extremely long to run due to its convoluted nature. With more computing resources, it would have been possible to get and analyze more data with more complexity, more quickly.

6.3. Future work

In the future, it would be interesting to perform a more rigorous analysis of the unique characteristics of certain IPOs. For example, Alibaba, Didi, Coupang, and Banco Santander Brasil were all non-U.S. companies that IPOd in the U.S. One possible path to go down would be to see whether there was a greater disparity between the initial sentiment around companies from overseas and their eventual performance. It is also possible that macroeconomic circumstances had an effect on IPO performance, so it might have been interesting to account for such disparities by focusing on IPOs from a specific week or month.

It would also be interesting to observe whether the same trends observed for the ten IPOs selected for this project hold on a larger scale, for other IPOs. It would of course be important to consider the fact that the size of an IPO is a contributing factor to its performance; nevertheless, examining trends across more IPOs would make conclusions drawn more statistically sound. Following in the footsteps of Cornelli, Goldreich, and Ljungqvist, it could be interesting to examine European markets and even to compare sentiment as observed in their grey markets with sentiment as expressed on Twitter.

Taking inspiration from Guilherme, it would be interesting to explore genetic algorithms as a means of analyzing sentiment differently – rather than having different systems for evaluating sentiment result in different sentiment results, using genetic algorithms would change the initial datasets and, by extension, the calculated sentiment. It could also be helpful to explore sentiment analysis models beyond VADER and FINBERT, perhaps even to create a new model based on tweets on financial content.

7. Bibliography

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Tools used:

SNScrape

DateTime Module

NLTK

VADER

FINBERT: https://huggingface.co/ProsusAI/finbert

YFinance

MatPlotLib