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Retail Investor Online Activity - Utilizing Wallstreetbets Data to Predict Returns

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Industrial Economics and Technology Management
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Preface

This thesis is submitted to fulfill the requirements for my degree in Industrial Economics and Technology Management (MSc) at the Norwegian University of Science and Technology. This thesis has allowed me to explore and investigate several data sources and broaden my insights and knowledge in finance.

I want to thank my Supervisor, Peter Molnár, for continuous support and guidance throughout this thesis. Associate Professor Molnár has not only given invaluable guidance on forming the scope of the thesis, but he has also given critical input on methodology.

Einar Romsaas
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Abstract

This study investigates whether sentiment- and activity levels based on posts and comments on Wallstreetbets can predict stock returns. The sentiment measure is formed using a supervised machine learning algorithm based on the corpus of posts and comments mentioning tickers, while the activity level is based on the mentioning of tickers in posts and comments on the forum.

The activity and sentiment variables are used to predict weekly abnormal stock returns. We find both sentiment and activity levels to provide predictive power on returns even after controlling for lagged metrics of abnormal returns, volatility, trading volumes, short interest, and bid-ask spreads.

Based on the results, we form trading strategies utilizing the weekly regression results to make weekly trades. The strategies are found to provide significant abnormal returns after transaction costs.

Sammendrag

Denne oppgaven undersøker hvorvidt aktivitet og sentiment på forumet Wallstreetbets har prediktiv evne på aksjers avkastning. Sentimentvariablenen som brukes tar utgangspunkt i en *supervised* maskinlæringsalgoritme som bruker tekst fra poster og kommentarer for å estimere sentiment, mens aktivitetsvariabelen baserer seg på hvor ofte tickere nevnes i poster og kommentarer.

Vi bruker aktivitets- og sentimentvariablene til å predikere ukentlige abnormal aksjeavkastning. Vi finner at både sentiment- og aktivitetsnivåer på Wallstreetbets har prediktiv evne på risikojustert avkastning utover hva som kan forklares av tidligere risikojustert avkastning, volatilitet, omsetning, omfang av shortsalg, samt bid-ask spreader.

Basert på resultatene presenterer vi flere handelsstrategier. Strategiene viser seg å gi signifikant positiv risikojustert avkastning over tradingperioden som undersøkes.

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1 Introduction

The predictability of stock returns has been an important topic in academic research for decades. While several studies bring evidence of market efficiency, i.e., market prices reflect all available, relevant information, others conclude that several market participants are irrational, so abnormal returns may be achieved over time for rational investors. This study's primary purpose is to examine the usefulness of posts and comments from the online social media forum Wallstreetbets on predicting stock returns. A detailed literature review is provided in the next section, while the introduction presents contributions, motivation for the studies performed, and a brief introduction to online social media forums and quantitative trading.

Wallstreetbets is a discussion forum on the social media platform Reddit, dedicated to investing, trading, and speculative bets. The forum was established in 2012 and has since grown to become the largest online community for retail investors. The forum has over 10 million registered followers, which allows posts on the forum to reach out to a big audience of investors. A significant proportion of the forum participants are young and inexperienced investors. The author hypothesizes that the forum primarily consists of noise traders, i.e., market participants being misinformed or not fully informed and consequently often trade irrationally. Since the thoughts and opinions of the presumed noise traders are freely available on Wallstreetbets, rational traders may take advantage of this information, potentially resulting in profitable trading opportunities.

Several forums and platforms online are dedicated to investing and trading. Examples include StockTwits, Seeking Alpha, and Wallstreetbets. Additionally, Wallstreetbets is just one out of many forums on Reddit dedicated to investing. As of May 18th, 2021, some of the largest forums dedicated to finance, investing, and speculation on Reddit was, with followers in parenthesis, r/Wallstreetbets (10 134 996), r/Investing (1 838 247), r/Pennystocks (1 540 780), r/StockMarket (1 463 005), r/Options (768 084), r/Robinhood (756 794) and r/Finance (487 740). The forums attract different types of investors. For example, to the author's impression, r/Pennystocks, and r/Wallstreetbets investors, on average, have a preference for highly risky trades. This study, however, considers Wallstreetbets only. First, the forum is the largest among the Reddit forums and the largest among all online investor forums as measured by followers. Second, existing literature largely considers retail investor social media activity on StockTwits and Twitter, with few studies having been published on Wallstreetbets. Lastly, the forum is highly relevant to examine as it has gained significant media attention recently, being the epicenter of a meme stock mania where retail investors have flocked to speculate in the shares of a small group of companies, leading to an abrupt surge in the stock price of these companies.

As opposed to traditional investing based on fundamental research, quantitative researchers utilize mathematical models, statistics, and data analysis to form algorithm-based trading strategies, often completely disregarding company fundamentals. More easily accessible data, more powerful computers, and better software have allowed for quantitative trading to play an increasingly important role in financial markets. Online social media forums are an ever-updating source of information potentially suitable for quantitative trading strategies. The online social media activity can be used to form company-specific activity indexes. Potentially even more interesting, the thoughts and opinions from the social media forums can be used to form company-specific sentiment measures, which may also be used in quantitative trading strategies.

Sentiment is given significant attention from market participants. For example, the monthly published U.S. consumer confidence index (CCI) is watched closely by investors worldwide. Academic research has also devoted a significant effort to test the predictive power of sentiment on market returns. Traditionally, company-specific investor sentiment has been hard to measure. However, the emergence of online social media forums dedicated to finance allows for market participants to read the thoughts and opinions of other investors. This study seeks to incorporate sentiment and activity measures from Wallstreetbets, combined with other non-fundamental measures from Wallstreetbets, to form quantitative trading strategies.

This study contributes to the literature from several perspectives. First and foremost, we examine the usefulness of posts and comments from the forum Wallstreetbets on predicting stock returns. Data from Wallstreetbets allow us to investigate both absolute levels of activity and sentiment, using our supervised learning algorithm to estimate stock-specific sentiment from posts and comments. Prior studies involving returns prediction based on search engine- and online social media information are, in general, focused on activity levels. To the author's knowledge, no studies have yet been published on returns-prediction based on data derived from Wallstreetbets. Second, few studies have presented trading strategies utilizing online social media sentiment in the returns prediction step. Most studies consider sentiment on a macro-scale versus market index returns, while this study focuses on company-specific sentiment versus company-specific returns. Third, our trading strategy results are significant in the sense that the strategies deliver significant abnormal return performance even after transaction costs. Hence, the study finds evidence in favor of behavioral finance theory. Fourth, we also provide data on the investment advice given on Wallstreetbets. The results indicate that Wallstreetbets investors indeed discuss stocks with on average poor future returns performance, providing evidence of the hypothesis that Wallstreetbets investors are uninformed traders on average. Fifth, we make two minor contributions in the field of sentiment analysis. We form an aggregated sentiment index based on the posts and comments on Wallstreetbets. We find the aggregated sentiment index to lag market index returns, with no evidence of bidirectional causality. Therefore, we conclude that the aggregated sentiment index is of little value in predicting market returns. We also provide data on the accuracy of the sentiment algorithm used in this study. To conclude, we find Wallstreetbets to be especially suitable for sentiment analyses due to the specialized jargon used on the forum.

This study bears similarities with several groups of financial research. Testing whether Wallstreetbets activity levels possess predictive power is similar to several studies on search engine volumes and Twitter data. Unlike studies utilizing search engine volumes, the data considered in this study stems solely from retail investors. Activity from professional investors and non-investors is less existent than for search engine data and Twitter approaches.

This study focuses on weekly return predictions, but daily and monthly predictions are also appended. The testing of predictive power can be divided into three parts. First, we present regression results from a fixed effects panel-data regression approach. Second, to ensure that the results are not due to overfitting and to check the tradeability of the results, we form a trading strategy based on the regression results. Third, we seek to verify the robustness of the trading strategy. Lastly, we verify the importance of the Wallstreetbets-derived variables in the trading strategies.

2 Literature Review

Several studies on Wallstreetbets have been performed concurrently as this study has been written. However, most of these studies are not peer-reviewed yet, and they are therefore not published in journals. Therefore, we do not consider these studies and instead focuses on other relevant studies not concerning Wallstreetbets.

2.1 Sentiment Analysis

Traditionally, studies concerning investor sentiment have measured sentiment through surveys or market positioning proxies such as the options put-call ratio. However, as online social media platforms have gained traction and retail investors to a greater extent than before use these forums to discuss financial instruments, a new source of measuring investor sentiment has emerged.

2.1.1 Traditional Measures of Investor Sentiment

Several studies have investigated traditional measures of market sentiment. The first group of sentiment research considers optimism and pessimism about the economy as a proxy of market sentiment. Fisher and Statman (2003)[1] investigate the consumer confidence measures of both the Conference Board and the University of Michigan to assess whether consumer confidence possess predictive power on stock market returns. Their main findings are that high stock returns boost consumer confidence and that there is a negative correlation between consumer confidence in one month and stock returns in the month to follow.

A second gauge on market sentiment is concerning optimism and pessimism about the stock market directly. These are primarily based on metrics derived from the stock market. Examples include the options put-call ratio (see, e.g., Dennis and Mayhew, 2002[2]; Wang, Keswani and Taylor, 2006[3]), the percentage share of cash held in mutual funds (see, e.g., Gup, 1973[4]; Branch, 1976[5]), mutual fund cash flows (Randall, Suk, and Tully, 2000[6]) and mutual funds net redemptions (Neal and Wheatley, 1998[7]). Other examples include Barron's Confidence index, defined as the yield spread between Aaa rated and Bbb rated bonds, as well as the TED spread (Lashgari, 2000[8]), known as the spread between the yield of T-bill futures and the yield of eurodollar futures (Lashgari, 2000[8]). Lastly, surveys directed towards market participants have been used to measure the stock market sentiment (see, for instance, Fisher and Statman, 2003[1]; Fisher and Statman, 2000[9]; Wang Keswani and Taylor, 2006[3]).

Wang, Keswani, and Taylor (2006)[3] find changes in the put-call ratio to be caused by returns. Their study also investigates the weekly surveys issued by the American Association for Individual Investors (AAII) and Investor Intelligence (II), which they also find to lag returns. Gup (1973)[4] finds the mutual funds' cash ratio to have predictive power on returns. Nevertheless, he also finds the indicator to be influenced by recent stock price movements. Thus, he concludes that the cash ratio may have a small and limited predictive power on returns. Lashgari (2000)[8] finds both Barron's Confidence index and the TED spread to explain variation in stock returns. The 2003-study by Fisher and Statman (2003)[1] uses surveys to investigate the sentiment of three groups of investors: individual investors, medium investors (newsletter writers), and Wall Street strategists. They find the correlation between newsletter writers and individual to be high, but the sentiment of Wall Street strategists to be uncorrelated with the others. Further, they find the sentiment of individual investors, newsletter writers, and Wall Street strategists to be negatively correlated with future S&P 500 returns, although not statistically significant for newsletter writers. The study finds investor sentiment generally to lag returns.

The third category of investor sentiment measures concerns the riskiness of the stock market. Baker and Wurgler (2006)[10] investigate several such measures. First, they consider an issuance metric, defined as the gross equity issuance divided by the sum of gross equity- and debt issuance. Second, they examine the RIPO, a metric based on the first-day performance of IPOs on the NYSE stock exchange. Third, they consider a metric based on detrended and logarithmic turnover on NYSE. Fourth, they examine a metric based on the closed-end fund discount, being the value-weighted discount on closed-end mutual funds.

The study by Baker and Wurgler finds that for periods of high sentiment, stocks that are attractive to speculators and optimists tend to perform poorly in the period to come. Typical characteristics of such stocks are that they have a short history, are small stocks, often unprofitable companies, are non-dividend paying, highly volatile, quickly growing, and being in a distressed financial state. The opposite is found to be true for periods of low sentiment. Their main finding is, however, that "several firm characteristics that display no unconditional predictive power actually hide strong conditional patterns that become visible only after conditioning on sentiment" [10]. Qiu and Welch (2004)[11] conclude that the closed-end fund discount (CEFD) is an inappropriate measure of investor sentiment by comparing results with direct sentiment data based on surveys from USB/Gallup. They do, however, conclude that the consumer confidence index works as a proxy for investor sentiment, again verified using sentiment data from UBS/Gallup surveys.

The last category of traditional sentiment gauges concerns risk aversion. Kumar and Persaud (2003)[12] investigates the Risk Appetite Index, defined as the Spearman's rank correlation of volatility versus excess returns. They conclude that return prediction models based on only fundamentals have less predictive power than models that also include some measure of risk appetite.

2.1.2 Investor Sentiment Derived from Online Social Media Platforms

Most prior studies on investor sentiment using social media platforms have investigated, to the author's knowledge, StockTwits and Twitter. StockTwits is a social media platform, in many ways similar to Twitter but directed towards investors and traders. As of 2014, StockTwits had more than 200 000 users. Unlike on Reddit, users on StockTwits can flag their messages as either "bullish" or "bearish," making the platform convenient for supervised learning on sentiment.

Olivera et al. (2014)[13] utilizes both Term Frequency-Inverse Document Frequency (TF-IDF), Information Gain, Class Percentage, and Weighted Class Probability with a bag-of-words approach on messages from StockTwits. Results show that the lexicons developed by their approach yield significantly better results than standard sentiment lexicons. Wang et al. (2015)[14] develops a sentiment analysis based on a supervised learning approach, analyzing articles on Seeking Alpha, a crowd-sourced content service for financial markets, and comments on StockTwits. They analyze sentiment using Naive Bayes, Support Vector Machine, and Decision Trees. Their highest accuracy is obtained with the Support Vector Machine, gaining an accuracy of 85.5% for SeekingAlpha articles and 76.2% for StockTwits comments, classifying articles and comments as either negative or positive. Using an n-gram based approach, Dickinson and Wu (2015)[15] investigates tweets from Twitter and obtains an accuracy of 68.5% and 63.4% when using a word2vec-based algorithm.

Sohangir et al. (2018)[16] investigate the performance of several deep learning models in their ability to classify StockTwits posts. They classify posts as either positive or negative (as opposed to positive, negative or neutral in this study). The highest accuracy is obtained with a convolutional neural network, obtaining an accuracy of 90.9%. Their model based on logistic regression obtained an accuracy of 70.9%, Doc2Vec obtained an accuracy of 67.2%, and LSTM obtained an accuracy of 69.2%.

Studies on social media platforms sentiment have not only tested the accuracy of algorithms but recently also tested the predictive power of sentiment on returns. Nofer and Hinz (2014)[17] investigate whether sentiment, as estimated from tweets, provides predictive power on index returns, as measured through the DAX index. They find a follower-weighted Twitter sentiment to provide predictive power on returns. However, they find that aggregated sentiment, i.e., when tweets are not weighted by the number of followers, provides no predictive power. They conclude that sentiment must be weighted by influence. This finding is at odds with Sul et al. (2017)[18], which predict returns of S&P 500 constituents using sentiment formed from Twitter posts. They find tweets from users with few followers to provide significant predictive power on returns, while tweets from users with many followers and heavily retweeted tweets had no predictive power. They hypothesize their findings to stem from that sentiment from users with few followers are diffused slowly and hence will slowly be incorporated into market prices. Uhl (2014)[19] finds sentiment, as estimated through Reuters articles, to predict returns, as measured by the Dow Jones Industrial Average index, better than macroeconomic factors. He finds negative Reuters sentiment to provide more predictive power than positive Reuters sentiment. Tan and Tas (2021)[20] investigate the predictive power of Twitter sentiment and activity. They find sentiment to possess predictive power but activity to be useless. Moreover, they find the sentiment to have more predictive power for small and emerging market firms. Using a holding period of one week, they find one of their trading strategies to obtain an annualized abnormal return of 22.15% before transaction costs for a portfolio with global stocks as their investment universe. For emerging market stocks, they obtain an annualized abnormal return of 36.84% before transaction costs. The strategies exhibit positive abnormal returns also when imposing round-trip transaction costs of 10 basis points.

2.1.3 Retail Investor Sentiment and Return Comovements

From an investing perspective, a correlation between returns and sentiment would have to exist for sentiment to be of interest. Hence, one would also expect a strong link between sentiment and trading behavior for sentiment to be interesting. This section covers prior studies done on retail investor behavior to motivate sentiment studies of Wallstreetbets, a forum of which generally consists of young and inexperienced traders and investors.

De Long et al. (1987)[21] discuss the concept of "noise traders," i.e., market participants that are misinformed or not fully informed. If such market participants exist, then one would require them to have little influence on asset prices in equilibrium for markets to be efficient. Suppose the view of the noise traders differs significantly from the "rational traders." In that case, they will buy high and sell low, which will make them lose money and eventually have negligible influence as market participants. However, they also conclude that some types of noise traders can flourish in the marketplace, even though rational speculators might take advantage of their mistakes. De Long et al. (1990)[22] spins further on the study from 1987, where they investigate the role and behavior of rational speculators. In the presence of positive feedback investors, i.e., investors who buy when prices increase and sell when prices decrease, they argue that it might be rational for speculators to rather follow the trend of the irrational positive feedback investors than actually bucking the trend. Soros (1987)[23] proposes a similar perspective, in which he describes strategies profiting on positive feedback investors. Kurov (2008)[24] shows that index futures traders are positive feedback traders. The study finds positive feedback trading to appear more frequently in periods of high investor sentiment, which makes the finding consistent with feedback trading being driven by the expectation of noise traders. Han (2008)[25] investigates whether investor sentiment prices S&P 500 options. He finds the option volatility smile to be steeper in periods of bearish sentiment. The study suggests that sentiment has incremental explanatory power compared to models not having sentiment as a parameter in predicting index option smile and risk-neutral skewness.

Burghardt (2010)[26] investigates retail investor herding behavior using a data set of submitted retail investor orders. He finds retail investors to have a substantial herding behavior, following overall market movements. Burghardt finds the same herding behavior to be high and substantial also for single equities. Kumar and Lee (2006)[27] examine the effect of retail trading patterns on co-movements in stock returns. Using trading data, they obtain a direct measure of investor sentiment and find that the sentiment measure has incremental explanatory power on returns for "small stocks, value stocks, stocks with low institutional ownership and stocks with lower prices." They find that as retail investors become positive (negative), their stocks deliver higher (lower) abnormal returns.

Most studies testing the predictive power of sentiment on volatility and returns are motivated by the idea that noise traders respond to changes in sentiment, which subsequently affects returns and volatility. Several studies bring evidence of the opposite (see, e.g., Brown and Cliff, 2004[28]; Solt and Statman, 1988[29]). Solt and Statman find the Bearish Sentiment Index, i.e., the ratio of the number of investment advisers who are bearish to the total number of investment advisers who are either bearish or bullish, to be useless in predicting stock price changes. The Granger causality is found to go from stock price returns to sentiment, not the opposite. Brown and Cliff (2004)[28] find a strong correlation between a series of different sentiment measures and conclude that they all have weak predictive power in predicting near-term stock returns.

2.2 The Predictive Power of Search Engine Data

Several studies have used publicly available online information to determine asset interest. Most such studies are focused on Google Trends, which grants the user access to both regional and global history of search interest for any search expression. Google Trends provides search volumes from the Google search engine.

Dietzel et al. (2014)[30], Beracha and Wintoki (2013)[31], and Wu and Brynjolfsson (2015)[32] all find evidence that Google Trends has predictive power in predicting property prices. Liu et al. investigate the stock price effects of the Malaysia Airlines plane that disappeared in 2014. They find that investor attention, measured by search engine interest, led stock price reactions for the

Malaysian Airlines stock. Vozlyublennaia (2014)[33] find that increased investor attention, as measured through search engine activity, diminishes return predictability and consequently improves market efficiency.

Preiss et al. analyze a set of search items supplemented by search items suggested by the Google Sets service. *Google Sets Service* is a tool that identifies semantically related words. They find that Google Trends data has "provided some insight into future trends in the behavior of economic actors." Preiss et al. have later been criticized for their methodology, e.g., by Challet and Ayed (2014)[34]. Challet and Ayed criticize mainly two matters. First, they argue that several of the search items used are backward-looking. For example, they include the search word *AIG* (American International Group Inc.), which before the 2008 crisis was hard to link with general investor sentiment, while AIG seems to be in retrospect a very relevant word among the thousands of potentially relevant words. However, their main criticism relates to an erroneous methodology with the Google Sets service, where related search words as from when their study was performed are used to predict returns back in time. Challet and Ayed (2014)[34] find no evidence of Google Trends data containing more information than stock price returns.

The study most similar in methodology to this study is likely by Bijl et al. (2016)[35]. They investigate search volumes for S&P 500 constituents in the period 2008 to 2013. Using weekly intervals, they find high Google search volumes to be associated with negative future excess returns. The study also examines a trading strategy based on the findings. The strategy yields positive abnormal returns before cost but negative abnormal returns after transaction costs.

3 Background

This section aims to provide information about Reddit and Wallstreetbets in order for the reader to more easily understand the data used in this study.

3.1 Reddit

Reddit is a social media platform where users interact in communities known as subreddits. The subreddits are dedicated to specific topics, e.g., programming, fashion, investing, and TV series. The users can interact with each other in the subreddits through posts, comments, and votes on posts and comments. As of January 2020, Reddit had approximately 52 million active users and over 100 000 forums. The largest of the subreddits dedicated to investing and trading, as measured by the number of users, is Wallstreetbets. [36]

3.2 Wallstreetbets

Wallstreetbets, also known as *r/wallstreetbets* and *WSB*, was started in 2012. Posts and comments from the forum are available from its inception, allowing for investigation of sentiment through text analysis and measuring activity levels from ticker- and company mentions in posts and comments.

The WallStreetBets community has a highly special jargon. The followers of the subreddit are referred to as *degenerates*, and not *members*, or *followers*, which would be more normal terms to use. Further, swearing and other forms of inappropriate language are a central part of the jargon used. The members often refer to each other as *fellow retards*, *apes*, and *autists*. Other forms of expression have also been developed within the community. For instance, *paper hands* refers to people having trouble staying away from the sell button. On the opposite side, *diamond hands* refer to people that do not sell their stocks, no matter how big the loss or gain is. Further, members are encouraged to boast about both their wins and losses. A completely wiped out portfolio is cherished as much as a portfolio with a stellar performance.

Posts on WallStreetBets are divided into 11 different categories: *DD*, *Discussion*, *YOLO*, *Daily Discussion*, *Earnings Thread*, *Loss*, *Gain*, *News*, *Mods*, *Weekend Discussion*, *Meme* and *Chart*. The category *DD* refers to *due dilligence*. Posts marked with the DD tag contains due dilligence on a specific stock or other tradeable instrument. The marks *Discussion*, *Daily Discussion* and *Weekend Discussion* refers to general discussion threads. The *YOLO*-mark refers to *You Only Live Once*, meaning that posts with this mark is about highly risky investments. The *Earnings Thread*-posts are designated posts involving discussions related to earnings announcements. In the *Loss*- and *Gain* categories, people publish their losses and their gains. Posts involving news are given the *News*-tag. Further posts with the *Mods*-tag are posts made by moderators of the subreddit. The *Meme*-tag refers to posts containing humorous images and videos. Lastly, the *Chart*-posts are posts containing various types of charts.

The Wallstreetbets forum has become highly regulated to avoid manipulative posts and comments from flooding the forum. Moderators regulate the forum, being regular community members that have gained the credibility to become moderators. They are permitted to delete posts and comments and cooperatively make forum rules. To avoid market manipulation, penny stocks, microcaps, OTC stocks, low-volume options, cryptocurrency, and any other security susceptible to manipulation, e.g., "pump and dumps" are prohibited from being discussed. Further, talk of special purpose acquisition companies ("SPAC's") has become prohibited. The forum has also put restrictions on encouraging other users to buy options due to fear of stock price reactions arising from delta-hedging from market makers.

Forum rules and guidelines are frequently updated. To the author's knowledge, the forum does not keep available records of historical changes in rules and guidelines. Posts and comments involving stocks with a market capitalization below one billion USD are automatically removed. The forum also removes all posts and comments about stocks with an average daily trading volume below an undisclosed threshold decided by the forum moderators. As of February 2021, the stocks listed in section G.1 were prohibited from being discussed on Wallstreetbets. [37]

The Wallstreetbets society has been given little attention for several years from the broader investor community. Nevertheless, the community's influence on financial instruments has occasionally been dramatic. In January and February 2021, the forum arranged a coordinated buying of stocks and call options on a selection of highly shorted stocks in order to cause short squeezes. The forum was suddenly given significant media attention, and according to Bloomberg, the Gamestop Corp. share peaked 1745% higher than what the stock was worth at the beginning of 2021. The stock of the movie theater chain AMC Entertainment gained 839%, while Blackberry and Nokia gained 279% and 69% in the same period [38]. Several other stocks were also included in the frenzy. The significant stock price reactions indicate that the forum, at least for some stocks, has influenced stock price movements.

4 Data

The data used in this study is obtained from two sources. First, the data constitutes all posts and comments on the Reddit forum Wallstreetbets from January 1st, 2016, to February 1st, 2021. Second, company data is retrieved from the Compustat - Capital IQ database through the Wharton Research Data Services (WRDS).

4.1 Data Cleaning of Reddit Posts and Comments

The Python-API Praw has been used to retrieve the posts and comments from Wallstreetbets. The date, time, and comment text have been retrieved for comments, and the date, time, title, and post-text have been retrieved for posts. An algorithm is used to search through all the posts and comments to look for words with the textual properties of a ticker. Specifically, the algorithm looks for capital-lettered alpha-numeric words consisting of one to six characters. The algorithm stores a list of all potential tickers found for every post and comment. For example, the list could be [GOOGL, AAPL, AAPL, AMZN, DOOR, BEAT, CHAD] for a given post or comment. A company mentioned x times will appear x times in the list. The list is subsequentially matched against a list of all stock tickers trading in North America from 2012 to 2021 to remove non-tickers. Thus, this study does not limit itself to large-cap index constituents but instead investigates all activity on Wallstreetbets, however, limited to North-American tickers. Nevertheless, the approach will be skewed towards larger companies since some small-caps are excluded due to missing Capital IQ data.

A problem with this approach emerges when comments and posts are written partly or solely in capital letters. Several tickers are also words frequently used in the English language. Examples of such tickers are LAND, LAKE, and KEY. These tickers are generally removed. However, some are kept in cases where the word is highly likely to refer to a ticker. For example, MRNA is kept, even though it may refer to both the ticker of Moderna Inc. and *Messenger RNA*. Tickers of major banks and investment banks are also removed since these tickers could be mentioned regarding their view on other tickers and macroeconomics in general. For example, CS (Credit Suisse) and JPM (JP Morgan) are excluded.

Furthermore, words and abbreviations used in the financial industry are removed. Examples are CIO (Chief Investment Officer), CF (cash flow), DCF (discounted cash flow), and FANG (abbr., "Facebook, Amazon, Netflix and Google"). Other potential misconceptions are also handled. For example, DOW (Dow Chemicals) is excluded due to potential misconceptions with the Dow Jones Industrial Average index. Lastly, tickers being equal to slang words specific to the Wallstreetbets community and other internet slang are removed. A complete list of excluded tickers is shown in appendix G.

The tickers remaining after the cleaning are given a weight decided by the ticker mentions in the post or comment. Every post and comment is given a total weight of one distributed on the tickers mentioned in the post or comment. The list [GOOGL, AAPL, AAPL] belonging to a specific post or comment would give GOOGL a weight of $1/3$ and AAPL a weight of $2/3$.

A problem with equal-weighting all posts and comments (with a weight of one) is that a post could gain significant attention without the comments associated with the post specifically mentioning the tickers mentioned in the post. In such a case, the methodology used in this study would underestimate the interest in the tickers mentioned in the specific post.

Ideally, the procedure should consider both tickers and company names when identifying interest in posts and comments since people sometimes may use tickers and other times company names. Further, the author assumes that people might use the company name for companies with simple and easily identifiable names. At the same time, they might tend to use tickers for companies with long and complex names. For example, people might write Disney instead of DIS, and BUD instead of Anheuser-Busch InBev. A problem of also considering company names is whether the official company name is equivalent to what the company is commonly known as. For example, the author believes most people would write *Disney* instead of *The Walt Disney Company.* The set of companies to look for could be pre-specified, and exceptions could be made for every single specific company, but at the cost of narrowing down the set of companies to look for. The author has therefore decided only to consider tickers.

The scraped posts and comments also have to be shifted in time. The closing time of the New York Stock Exchange represents a change of day, leading to all posts and comments written after market close being accounted for as being written the next day.

Once the above procedure is finished, the posts- and comments activity is arranged into a daily activity index for every specific ticker ever mentioned in the period considered.

4.2 Sentiment Classification Algorithm

The supervised learning algorithm used to estimate sentiment from the posts and comments on Wallstreetbets is based on term frequency-inverse document frequency (TF-IDF) and support vector machine (SVM), both of which are briefly explained in appendix A and B. The author has subjectively classified 4000 posts and 4000 comments as either positive, neutral, or negative to train the model. In order to evaluate the model, a 10-fold cross-validation procedure is performed, with a training set consisting of 6000 posts and comments and a test set of 2000 posts and comments. A positive classification corresponds to a score of *3*, a neutral score corresponds to *2* and a negative score corresponds to *1*. When estimating the sentiment of an out-of-sample post or comment, the algorithm assigns a probability of the post being positive, neutral, and negative. The post or comment will then be assigned a sentiment equal to

$$S = prob(Positive) \cdot 3 + prob(Neutral) \cdot 2 + prob(Negative) \cdot 1 \tag{1}$$

Thus, when the algorithm is used in an out-of-sample set of comments and posts, every post and comment will be assigned a score $S \in [1, 3]$. We set scores of 1, 2, and 3 instead of -1, 0, and 1 to avoid problems of dividing by zero and negative numbers when detrending the sentiment (see section 5.1).

The last step in the sentiment classification is to estimate the sentiment of all out-of-sample posts and comments. Once every post and comment is assigned a sentiment value, average sentiment values for every ticker are calculated daily. The result is a daily sentiment index for every specific ticker.

4.2.1 Pre-treatment of Posts and Comments

The comments and posts used in the sentiment prediction are pre-treated in several steps before being fed into the sentiment estimation algorithm. The pre-treatment is performed to increase the accuracy of the algorithm, with the ultimate goal being to reduce the number of words and signs that will later be associated with a sentiment score. The reduction is performed to increase the significance of each word and sign.

First, punctuation is removed to prevent punctuation from being linked with sentiment. However, tests indicate that including "!" and "?" yields an increased accuracy, which leaves "!" and "?" out of the punctuation removal. For instance, the reason for the increased accuracy may be that a post or comment containing "?" might be a post or comment with a weak degree of subjective opinion and is, therefore, more likely to be classified as neutral. All the text is also converted to lowercase characters. Further, stopwords, i.e., words that do not add much value to the opinion of the document, are removed. Examples of stopwords are "the", "is", "in", "for", "where", "when", "to" and "at". The third step in the pre-treatment is to remove non-ASCII characters.

Additionally, non-words are removed. Typically, these are HTML symbols and hyperlinks. The pre-treatment also involves removing frequently discussed brand words. These include "Siri" (Apple voice assistant), "Alexa" (Amazon voice assistant), and several products (such as "iPhone"). Further, the text is lemmatized in order to be able to consider inflected forms of a word as one single word. The algorithm also involves a step in which highly similar words are transformed into the same word. In principle, examples of such transformations is that "superb" and "excellent" could both be transformed into "awesome", while "dissatisfactory" and "unsatisfying" could be transformed into "dissatisfying." The last step in the pre-treatment is to remove tickers and company names from the text to avoid companies' names and tickers from being associated directly with a positive or negative sentiment.

4.3 General Description of the Reddit Data

Figure 1 displays the aggregate daily activity on the Wallstreetbets forum. The index counts the daily number of posts and comments that mention at least one ticker. As can be seen, the activity on the forum has increased significantly over the period considered, which is also why this study does not take the period 2012-2015 into consideration (the forum was founded in 2012), since the daily activity level is considered deficient.

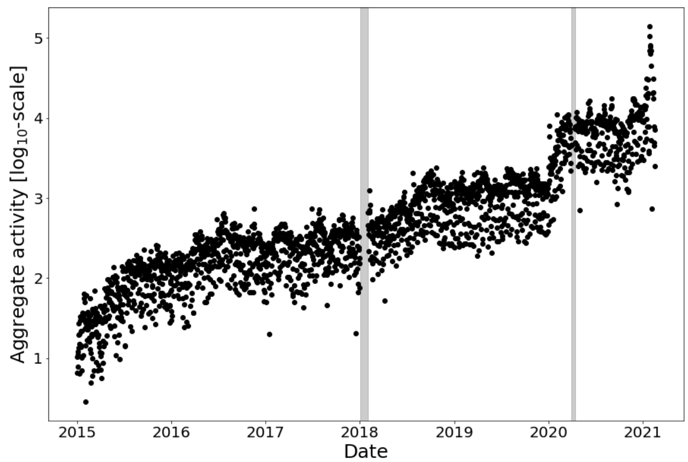

Figure 1: Aggregate activity on Wallstreetbets. The gray vertical lines displays periods of missing data.

The activity on Wallstreetbets varies significantly throughout the day and the week. Figure 2 shows the daily activity index on the forum, indexed to one on the busiest day of the week. As can be seen, the activity increases throughout the week until Thursday, before it drops significantly going into the weekend.

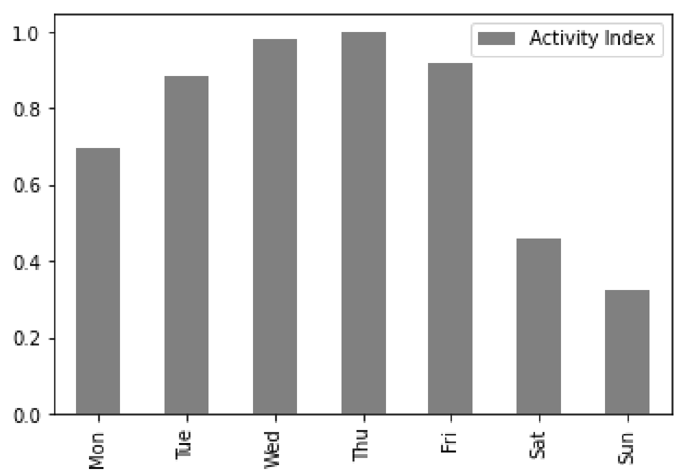

Figure 2: Activity by weekday on Wallstreetbets, indexed to 1 at Wednesdays.

The significant activity seasonality on Wallstreetbets throughout the week is problematic when predicting daily returns based on lagged activity values. The solution used to solve this problem for the daily regression, as appended in Appendix C, is to divide daily activity values by the activity index values presented in Figure 2.

For posts from the Wallstreetbets forum, the date ("DATE"), time ("TIME"), title ("TITLE"), text ("SELFTEXT"), and the number of comments associated with the post ("NOOFCOMMENTS) is extracted. Figure 3 shows an example of a typical Wallstreetbets post. In Figure 3, the line "COMPANIES" shows the tickers mentioned in the title and text combined.

```
------------------------------
DATE:2021-02-08
TIME:22:25:44
NOOFCOMMENTS: 201
TITLE: How to buy GME shares for 25% off:
The Most Retarded GME Play in the History Of The Universe
SELFTEXT: So, I am way to fond of my wife's boyfriend to do this...

But I am SO tempted to buy 1000 GME shares at $60,
 and then sell 10 covered calls for Feb 26th with a $60 strike price and $15 premium.

And then roll the fucking options premium back into more shares,
and then sell more covered calls.

Yes, this is a retarded play, don't do this, this is not advice.
It is just a commentary on how messed up the options are in GME right now.

Yes, I know this will result in the MM selling synthetic longs on the market,
thereby driving the price down...

Which is the craziest point! Because there are more shares now,
the calls go down in value!

So you buy them back, and do the whole thing again!
.....
Look, I know this is stupid, and I know it won't really work.
But I thought I would share some legit retarded idea,
that only exists because of monkey business in the market.
COMPANIES: GME;GME;GME;GME;

------------------------------
```

Figure 3: Example post from the Wallstreetbets forum.

Several posts that are submitted are removed. Posts could be removed for various reasons. Some are removed because they discuss micro-capitalization stocks being vulnerable to market manipulation actions. Others are removed simply due to lack of quality content or because they are manipulative or misleading. The removal of posts is done partly by scripts and partly by human moderators. As of February 2021, posts containing any of the tickers in appendix G.1 were automatically removed. Removed posts and comments are still stored in the database of posts and comments of which this study is based on. However, the number of comments ("NOOFCOMMENTS") is 0, and the text ("SELFTEXT") is changed to "[removed]." An example of such a post is shown in Figure 4.

```
------------------------------
DATE:2021-02-08
TIME:23:14:32
NOOFCOMMENTS: 0
TITLE: Reasons why $NIO "The TESLA of China" is on the rise!!
SELFTEXT: [removed]
COMPANIES: NIO;TESLA;;

------------------------------
```

Figure 4: Example post from the Wallstreetbets forum.

```
------------------------------
DATE:2016-10-19
TIME:23:39:34
BODY: Self-driving cars? Self-buying stock.
All in on TSLA just before the closing bell. Wish me luck.
COMPANIES: TSLA;

------------------------------
```

Figure 5: Example comment from the Wallstreetbets forum.

For comments, the same information as for posts is extracted, with the only difference being that comments do not have a title. Comments are generally shorter than posts, often limited to a few sentences. Figure 5 displays an example of a comment. Since comments are replies to other comments or posts, it can often be hard to understand the context of a given comment without knowing which post or comment it replies to. To avoid an intricate tree-structure of relations between posts and comments, we have considered two ways to handle this problem. The first option would be only to consider all posts and then use the number of comments associated with each post to measure the interest in what the posts concerns. A problem with this approach is that comments may be submitted days or weeks after the post is submitted. Consequently, when predicting future stock returns based on the posts, a strong bias may be introduced. If a post concerning a given stock starts to rise after the post is submitted, this increase in itself might attract more activity to the post. The second approach considered, which this study is based on, is to treat every single post and comment separately, giving them equal weights. Therefore, this approach only considers the posts and comments that directly mention tickers.

4.4 Data from Compustat - Capital IQ

The Capital IQ database is used to retrieve daily stock price data from the tickers mentioned on Wallstreetbets. The stock prices are adjusted for share splits, reverse share splits, stock dividends, and cash dividends to form total returns.

We also retrieve stock metrics data that may have predictive power on returns. Daily bid- and ask data are retrieved to calculate a daily bid-ask spread. Daily trading volumes, company market cap, and short interest are also retrieved from the Capital IQ database. The data from Capital IQ is combined with the activity- and sentiment indices to create prediction variables used to predict returns.

5 Methodology

5.1 Returns Prediction

We use a fixed effects panel data regression approach to investigate whether Wallstreetbets data has predictive power on abnormal returns. In order to predict returns, this study considers metrics based on prior returns, volumes traded, short interest, and the activity and sentiment measures based on the posts and comments on Wallstreetbets.

5.1.1 Returns

The dependent variable in the fixed effects panel data regression is abnormal returns. The daily stock returns retrieved from Compustat are adjusted for dividends and shares outstanding. The daily returns are adjusted using the Fama-French three-factor model to form abnormal returns. The Wilshire 5000 total return index is used as the market index. Consequently, abnormal daily returns can be written as:

$$R^{ab}_{d,t} = R_{d,t} - r_{f,d,t} - \beta_{MKT}(R_{MKT,t} - r_{f,d,t}) - \beta_{SMB}R_{SMB,t} - \beta_{HML}R_{HML,t} \tag{2}$$

where subscript MKT denotes *market*, SMB denotes *small minus big*, and HML denotes *high minus low book to market*. $r_{f,d,t}$ denotes the daily risk free rate at day t. All betas are 1-year rolling betas, with the betas being calculated based on returns data from research database of Kenneth French [39]. Superscript ab denotes *abnormal*. Weekly returns data are formed by compounding daily returns.

5.1.2 Wallstreetbets Activity

We consider the activity on Wallstreetbets forum as one of the prediction variables in the regression. The Wallstreetbets activity measure is included in two different variables. First, we include a detrended measure, where the activity is measured relative to prior activity. Second, we include a measure where the activity is measured relative to market cap. This measure aims to capture the relative influence of Wallstreetbets on a given stock.

5.1.3 Wallstreetbets Sentiment

As with Wallstreetbets activity, the Wallstreetbets sentiment is included as a detrended measure, where sentiment is measured relative to prior sentiment.

5.1.4 Trading Volume

The trading volume is included using a detrended measure similar to the Wallstreetbets sentiment and activity measures.

5.1.5 Volatility

Inspired by Granger and Poon (2003), which concludes that volatility estimates assuming the mean to be zero to be more precise, volatility over the past k days is calculated as

$$\sqrt{\sum_{i=1}^{k} L^i R_t^{d,2}} \tag{3}$$

The weekly regression uses 40 lags to calculate the volatility.

5.1.6 Bid-ask Spread

The bid-ask spread is calculated as

$$BAS_t = \frac{P_{ask,t} - P_{bid,t}}{(P_{ask,t} + P_{bid,t})/2}, \tag{4}$$

where the price close and the price bid is given at market closure. Weekly values of the bid-ask spread are calculated as the weekly mean of daily bid-ask spread values.

5.1.7 Short Ratio

The short ratio, denoted SR, is calculated as the number of shares short divided by the total number of outstanding shares.

$$SR_t = \frac{shares\ short_t}{shares\ outstanding_t}. \tag{5}$$

The weekly SR is calculated as the arithmetic mean of daily SR-values.

5.1.8 Variable Scaling

As explained, Wallstreetbets sentiment, Wallstreetbets activity, and trading volumes are included in the regression using detrended variables. For a parameter y (e.g., Wallstreetbets activity), the detrended value, x, is given as

$$x_t^w = \frac{y_t^w - \frac{1}{8}\sum_{i=1}^{8} y_{t-i}^w}{\frac{1}{8}\sum_{i=1}^{8} y_{t-i}^w},, \tag{6}$$

where superscript w denotes weekly variables.

The lag operator is denoted L. For example, $\sum_{i=1}^{5} L^i x_t^w$ denotes the sum of five lags of weekly increments from variable x. As will be obvious from the regression variables, several of them are included, with one term based on the most recent lag and one term based on several prior lags.

5.1.9 Prediction Based on Weekly Variables

The regression for weekly variables is shown in Equation 7. Abnormal returns, Wallstreetbets activity, Wallstreetbets sentiment, and trading volume are included in the regression using two variables. One variable considers the most recent lag of the given variable, while the other variable considers several prior lags.

$$
\begin{aligned}
R_t^{w,ab} = \alpha &+ (\beta_1 L^1) R_t^{w,ab} + \beta_2 L^2 \mathrm{CRET}_t^{4w} + (\gamma_1 L^1)(\text{Detrended Activity})_t^w \\
&+ \gamma_2 \frac{1}{4} \sum_{i=2}^{5} (L^i)(\text{Detrended Activity}_t^w) + (\zeta_1 L^1)(\text{Detrended Sentiment}_t^w) \\
&+ \zeta_2 \frac{1}{4} \sum_{i=2}^{5} (L^i)(\text{Detrended Sentiment}_t^w) + (\rho L^1)(\text{MCAP-scaled Activity}_t^w) \\
&+ (\kappa_1 L^1)(\text{Detrended Trading Volume}_t^w) + \kappa_2 \frac{1}{4} \sum_{i=2}^{5} (L^i)(\text{Detrended Trading Volume}_t^w) \\
&+ \epsilon_1 \sqrt{\sum_{i=1}^{40} (L^i) R_t^{d,ab,2}} + (\delta_1 L^1)(\text{Bid-Ask Spread}_t^w) + (\eta_1 L^1)(\text{Detrended Trading Volume}_t^w),
\end{aligned}
\tag{7}
$$

In Equation 7, all the Greeks are coefficients and CRET_t^{4w} being the four week cumulative abnormal return at time t, measured back in time.

5.2 Forming a Trading Strategy Based on the Weekly Returns Prediction

Even though a regression provides predictive power, trading strategies based on it may not be profitable due to transaction costs and compounding effects, i.e., even though the model predicts a positive average return, compounded returns may still be negative. Also, the data set used to obtain the R^2 may be too small, leading the R^2 to be high due to overfitting rather than predictive power. In the strategy, we allow for both buying stocks and selling stocks short. Further, we include transaction costs calculated as the bid-ask spread. The transaction cost is calculated as half the bid-ask spread at position opening plus half the bid-ask spread at position closing.

The trading strategy works as follows: We require a certain history for the fixed effects regression to calculate parameter estimates. We use a rolling regression window of 500 observations to calculate parameter estimates. From the parameter values, we predict the returns of all potential trading opportunities in the coming week. Based on the number of available potential investments (the ones with a full rank), the strategy buys the stocks that are predicted to yield a positive abnormal return after costs and short-selling the stocks predicted to yield a negative abnormal return after costs. The prediction is performed weekly, with the regression model being rolled to include the data from the prior week.

The transaction cost per trade is estimated as the full bid-ask spread. For trading opportunities arising in week t, we use the bid-ask spread of week $t-1$ to estimate the transaction cost of the position. Mathematically, the short- and long opportunities predicted by the model can be expressed as in Equation 8 and 9.

$$\begin{aligned} \text{Short Opportunities}_t &= \mathrm{R}^{ab}_{t,p} + \text{Bid-Ask Spread}_{t-1}, \\ & \mathrm{R}^{ab}_{t,p} + \text{Bid-Ask Spread}_{t-1} < 0, \end{aligned} \tag{8}$$

$$\begin{aligned} \text{Long Opportunities}_t &= \mathrm{R}^{ab}_{t,p} - \text{Bid-Ask Spread}_{t-1}, \\ & \mathrm{R}^{ab}_{t,p} - \text{Bid-Ask Spread}_{t-1} > 0, \end{aligned} \tag{9}$$

In the above equations, subscript p denotes prediction estimate. To obtain the actual returns obtained, the bid-ask spread estimates are swapped with the actual bid-ask spreads when the positions are opened and closed, while the predicted returns are swapped with the obtained returns.

In our base trading strategy, positions are sized as according to Equation 10 and 11.

$$\begin{aligned} \text{Short Position Weight}_t &= -\frac{1}{\text{Number of Short Opportunities}_t}, \\ & \text{Number of Short Opportunities}_t > 0 \end{aligned} \tag{10}$$

$$\begin{aligned} \text{Long Position Weight}_t &= -\frac{1}{\text{Number of Long Opportunities}_t}, \\ & \text{Number of Long Opportunities}_t > 0 \end{aligned} \tag{11}$$

If no short opportunities are found, the short position weight is set to 0. The same applies for long opportunities.

Since the activity on Wallstreetbets has increased steadily over the prediction period, more trading opportunities emerge in the latter part of the observation set than in the former part. A problem arising from this is that weeks with few available trading opportunities may experience position sizes larger than any investor would comfortably allow. The issue is particularly relevant for long positions, as the model by large predicts most stocks to yield negative abnormal returns. Therefore, we present results with a position size constraint of 0.05, meaning that any long position cannot exceed 5% of available funds, and any short position may not exceed -5% of available funds. Imposing position size limits will also limit the impact of volatile stocks, which may also give more credibility to the results since over- and underperformance are less likely to be attributable to a few positions. To make returns comparable with index performance, we allow the strategy to invest excess available funds into the market index. Thus, the strategy will always be 100% invested.

We also investigate how percentiles of the predictions perform. We divide the weekly long- and short opportunities into five quantiles based on the predicted returns. The quantile with the best-predicted performance will consist of the 20% best long-ideas and the 20% best short-ideas. Lastly, we test the importance of the Wallstreetbets-derived parameters. The importance of the variables is tested by running the trading strategies both with- and without the Wallstreetbets-derived variables in the returns-prediction regression.

5.3 Creating an Aggregated Retail Investor Sentiment Index

We also investigate the relation between index returns and Wallstreetbets sentiment. To form a sentiment index, we use the median of daily sentiment scores for individual tickers. The intuition behind the calculation of the sentiment index is simple. First, using the mean instead of the median will be more biased towards the euphoria sporadically covering some tickers. The forum is fundamentally skewed towards a positive market view, meaning that the effect of the sporadic euphoria may not be evened out by a negative view on other stocks. Second, using all posts and comments directly to calculate average daily sentiment would not be appropriate since this approach would be influenced towards the sentiment of highly discussed stocks. For example, the sentiment in February 2021 would largely reflect the sentiment of a small group of highly discussed stocks.

Based on the sentiment index, we perform a Granger causality test to test the direction of causality between Wallstreetbets retail investor sentiment and market index movements. We use daily index returns versus detrended sentiment to perfrom the Granger causaility test. Sentiment is detrended using 20 lags.

6 Results

6.1 Sentiment Analysis

The results from the analysis of the sentiment performance are shown in Table 1. The results presented in the table are based on a 10-fold sampling process, obtaining an accuracy of 0.7485. Further, note that the sample set is fundamentally undersampled in terms of negative posts and comments, with a support of only 270 out of the test-set sample of 2000. The low support is not due to a misrepresentative sampling process, but because most posts on the forum are considering long positions. The algorithm performs relatively bad when classifying negative posts and comments, which could imply that a larger sample set could significantly improve the overall accuracy.

Accuracy	0.7485			
Cohen's Kappa	0.5334			
	Precision	**Recall**	**F1-score**	**Support**
Negative	0.61	0.45	0.52	270
Neutral	0.80	0.85	0.82	1184
Positive	0.69	0.68	0.68	546
Macro average	0.70	0.66	0.67	2000
Weighted average	0.74	0.75	0.74	2000

Table 1: Sentiment performance using standard performance measures. *Support* denotes the number of observations. *Macro Average* denotes the equal-weighted average of Negative, Neutral and Positive scores, while the *weighted average* denotes the support-weighted average.

The sentiment algorithm provides results in line with prior research on sentiment accuracy on financial social media platforms. However, the algorithm provided in this study classifies posts and comments into three different labelings, as opposed to two for most other studies. Limiting the classification to only negatives and positives, i.e., to remove all neutral-labeled posts and comments from the training- and test set leads to improved accuracy, even though the size of the training set shrinks by almost 60%. Using the same procedure for predicting positives, neutrals, and negatives, we obtain an accuracy of 0.8253 and a Cohen's kappa of 0.5586, which outperforms prior studies even though the test set only contains just above 2000 posts and comments. Hence, one would expect to obtain accuracy above 0.8253 by increasing the test set.

Figure 6 shows the Wilshire 5000 Total Return Index development compared to daily sentiment levels on Wallstreetbets. The sentiment is visibly positively correlated with the market index performance. We find the median sentiment to be fundamentally positive, staying above the "neutral"-line of 2.0 over the whole period displayed in the figure.

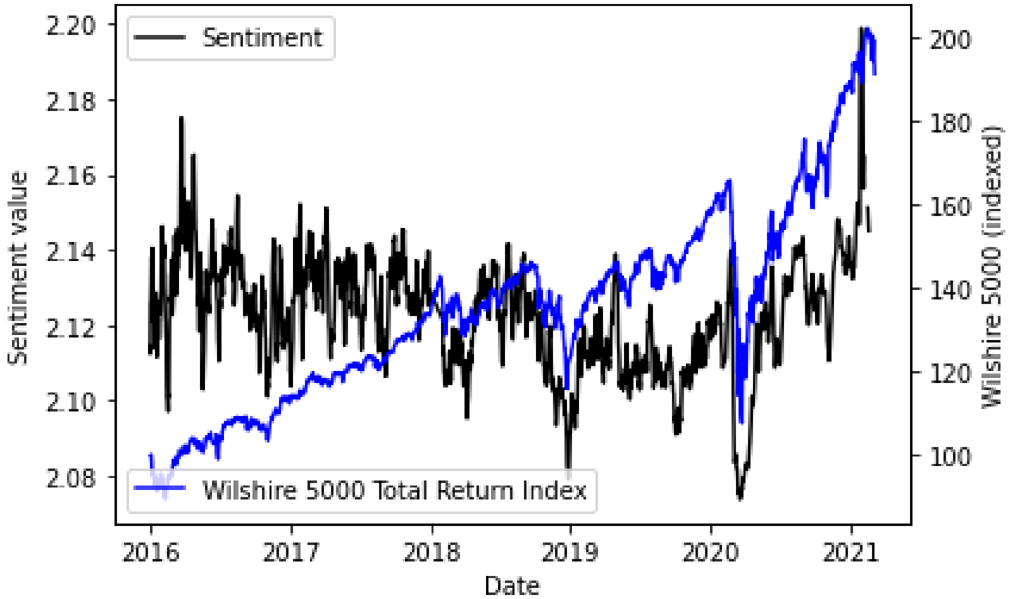

Figure 6: Median Wallstreetbets sentiment development versus Wilshire 5000 development.

Performing a Granger causality test as according to the methodology section (section 5.3), we find strong evidence of Granger causality from returns to sentiment. On the other hand, we find no statistically significant evidence of causality the other way around. The results are displayed in Table 2 and 3. The results indicate that prior returns strongly affect sentiment, giving sentiment on an aggregated market-level little value. Accordingly, the rest of the thesis considers company-specific sentiment.

Lag tested for	Granger Causality H_0: **index returns do not Granger-cause sentiment**
1 day	Rejected***
2 days	Rejected***
3 days	Rejected***
4 days	Rejected***
5 days	Rejected***
6 days	Rejected***
7 days	Rejected***
8 days	Rejected***
9 days	Rejected***
10 days	Rejected***

Table 2: Causality results, stock market returns versus detrended Wallstreetbets sentiment. *** Denotes significance at a 1% level.

Lag tested for	Granger Causality H_0: **sentiment does not Granger-cause index returns**
1 day	Not rejected
2 days	Not rejected
3 days	Not rejected
4 days	Not rejected
5 days	Not rejected
6 days	Not rejected
7 days	Not rejected
8 days	Not rejected
9 days	Not rejected
10 days	Not rejected

Table 3: Causality results, detrended Wallstreetbets sentiment versus stock market returns. *** Denotes significance at a 1% level.

6.2 Weekly Returns Prediction

This section presents the results for the prediction of the weekly returns. The Breusch-Pagan test and the Ljung-Box test were conducted to check for heteroskedasticity and autocorrelation. The tests indicate that both are present in the data set. Thus, the standard errors presented are robust standard errors. The heteroskedasticity autocorrelation covariance (HAC) method by Driscoll and Kraay (1998)[40] is used for this purpose, while the Hausman test has been used to decide on whether to use a random effects model or a fixed effects model, suggesting a fixed effects model. Results for the daily and monthly regressions are displayed in appendix C and D. Several variables are found to be statistically significant, including the sentiment index of the prior week, as well as the averaged sentiment index of the prior four weeks. The results are displayed in Table 4. The sentiment coefficients indicate that increases in sentiment are followed by a higher chance of negative abnormal returns. The detrended activity measure is found to provide no predictive power of significance. However, as measured by the Wallstreetbets activity divided by market cap, the relative activity is found to provide predictive power. The findings are based on 24 983 observations of full variable rank, of which an R^2 of 0.0469 is obtained. Note that not all variables are standardized, meaning the coefficients must be understood in relation to the model specification (see section 5.1).

The dependent variable in each regression is abnormal return. Each entry displays parameter values, and standard errors in parenthesis. *, ** and *** denote significance at a 10%, 5% and 1% level, respectively. The sample period is 01.01.2016 to 01.02.2020.

	Full Regression, Weekly	Insignificant Variables Removed, Weekly	Full Regression, Weekly, logged detrended variables	Insignificant Variables Removed, Weekly, logged detrended variables
Constant Term	-0.0014	-0.0028***	-0.0013*	-0.0030***
	(0.0018)	(0.0005)	(0.0021)	(0.0005)
R	0.0003		0.0003	
	(0.0006)		(0.0006)	
CRET	0.0030***	0.0032***	0.0030***	0.0032***
	(0.0003)	(1.254e-5)	(0.0003)	(1.234e-5)
Detrended Activity, ST	0.0001		-6.911e-9***	
	(0.0002)		(5.934e-8)	
Detrended Activity, LT	-0.0004		-1.312e-6	-1.343e-6***
	(0.0004)		(8.118e-8)	(5.017e-8)
Detrended Sentiment, ST	-5.675e-6***	-5.982e-6***	0.0159**	0.0177**
	(1.467e-6)	(1.523e-6)	(0.0071)	(0.0070)
Detrended Sentiment, LT	5.596e-6		0.0117	
	(3.913e-6)		(0.0131)	
MCAP-scaled Activity	-7471.5***	-9879.2***	-7386.1***	-9871.9***
	(1726.9)	(1947.3)	(1791.9)	(1935.0)
Detrended Trading Volume, ST	6.843e-5**		0.0167	
	(3.486e-5)		(0.0334)	
Detrended Trading Volume, LT	0.0007		-0.0124	
	(0.0005)		(0.0333)	
Volatility, ST	-0.0005		-0.0005	
	(0.0005)		(0.0005)	
Bid-Ask Spread	0.0875***	0.0711***	0.0767***	0.0715***
	(0.0287)	(0.0214)	(0.0259)	(0.0213)
Short-Ratio	0.0012		0.0010	
	(0.0101)		(0.0094)	
R^2	0.0492	0.0469	0.0486	0.0464
Observations	24983	24983	24983	24983
Companies	701	701	701	701

Table 4: Weekly fixed effects regression results.

6.3 Weekly Return Prediction Performance

This section presents the results from a set of trading strategies, as introduced in the methodology section. The strategies use a 5% investment size threshold. Some strategies presented are long-short, while others are long only. Regardless of the strategy, the parameters from the prediction will develop equally throughout the period considered, as long as the rolling window used to predict parameter values is of equal size. Figure 7 displays the development (scaled) of parameter values. The parameters generally have become more volatile in more recent years. The reason is likely that 500 observations cover a longer timespan in earlier periods. The rolling window used could also have been fixed to a specific number of days. However, the window would have to be relatively large since the activity in early periods is very low, in order to obtain a decent number of observations in the regression.

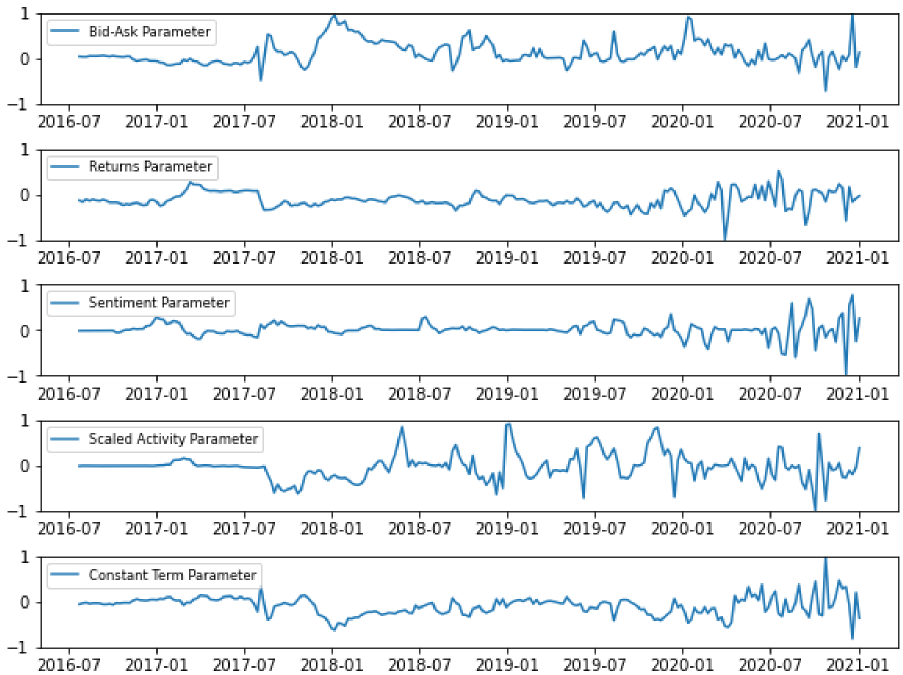

Figure 7: Parameter development using a rolling window of 500 observations. Scaled to the maximum observed absolute value.

The parameter estimates are strongly time-varying, with all parameters shifting between being positive and negative. A larger rolling window causes the parameters to be less volatile but is found to yield weaker performance, likely since large windows may fail to capture market shifts.

6.3.1 Strategy I: 5% Position Size Threshold, Go Long and Short the Best 10% Ideas

By going long the 10% best ideas, limiting any position size to 5% (-5% for short positions), the abnormal return performance is shown in Figure 8. We do not present results with no position size limit since the small number of available trades would yield significant single-stock risk. The strategy performs well at the beginning of the period before slightly underperforming until the 2020 stock market crash. Since the 2020 stock market crash, the strategy has exhibited significant abnormal returns. Please note the right-axis of the below plot (Figure 8), as it shows the total number of trading opportunities, both long and short, at any week. Using the 10% best ideas significantly limits the number of available trades.

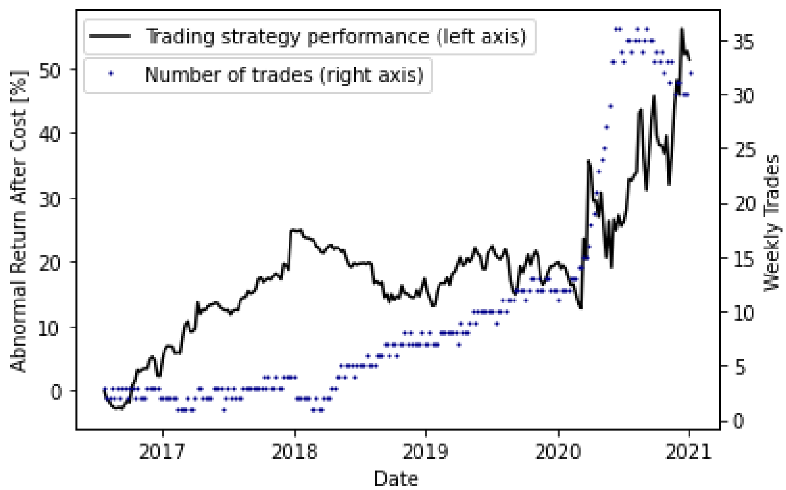

Figure 8: Abnormal return development, long-short strategy.

The return performance (unadjusted) of the strategy is shown in Figure 9. The strategy performs slightly better than the market index before strongly overperforming since the 2020 stock market crash. The strong post-crash performance coincides well with a strong increase in forum activity, as can be seen from the number of available trading opportunities.

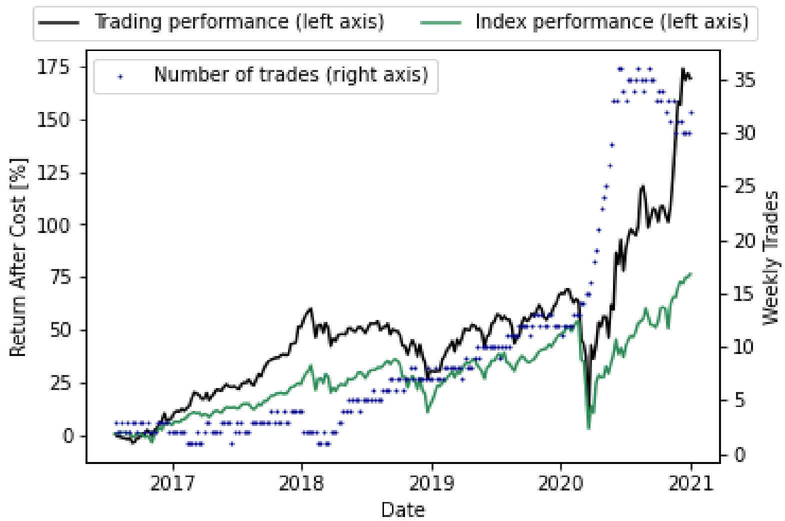

Figure 9: Return development, long-short strategy.

We also present the long exposure, the short exposure, and the net exposure before index-buying/index short-selling from the model, shown in Figure 10. The net exposure before index-repositioning is highly volatile, meaning that the strategy sometimes finds few long opportunities and other times find few short opportunities. The strategy is relatively similar to holding the index in early periods since the number of trading opportunities is limited.

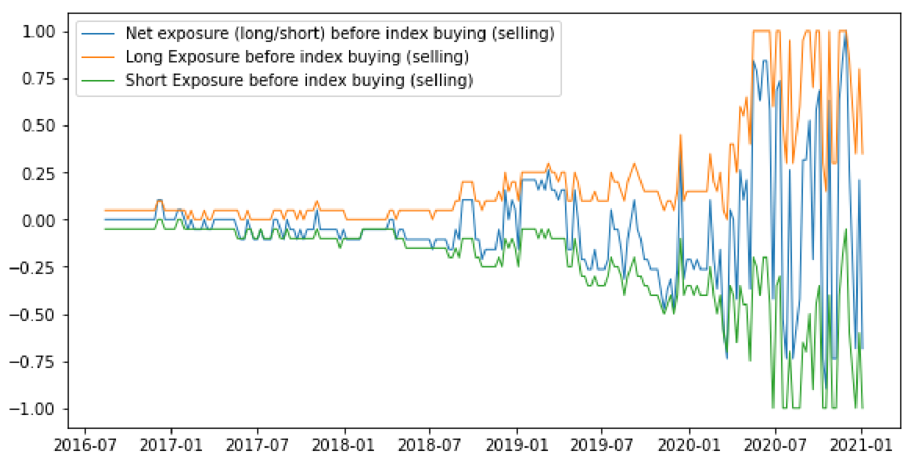

Figure 10: Exposure before index buying, long-short strategy.

6.3.2 Strategy II: 5% Position Size Threshold, Go Long the 10% Best Ideas, no Shorts Allowed

Since several stocks may not be easily available for shorting, we also present results for a long-only strategy, where the 10% best long-ideas every week are bought. Since the number of trades in the first years is limited, we keep the 5% position size threshold. The abnormal returns performance of this strategy is displayed in figure 11. The strategy performance is flat until right before the 2020 stock market crash, underperforming during the market crash, and overperforming in the rest of 2020.

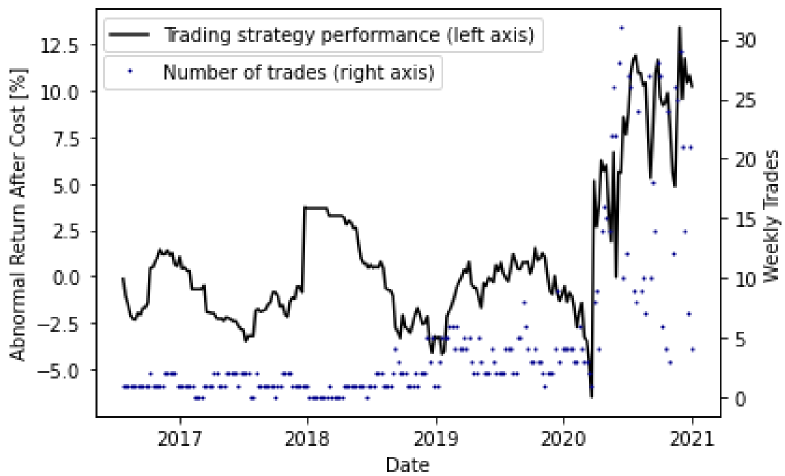

Figure 11: Abnormal return development, long-only strategy.

The return performance is shown in Figure 12. The strategy performs broadly in line with the market index from 2016 to 2020. The return performance since the stock market crash of 2020 has been strongly overperforming the index. However, the relatively weak abnormal return performance indicates that the strong return performance stems from taking very risky positions. A similar strategy, but only allowing shorting, yields an abnormal return of 38.02% over the period considered. The results indicate that the strategy achieves more success in predicting short candidates than long candidates. Also, over the trading strategy period, the trading strategy finds only 30.55% of trading opportunities to be long opportunities, leaving 69.45% of the set to be short opportunities.

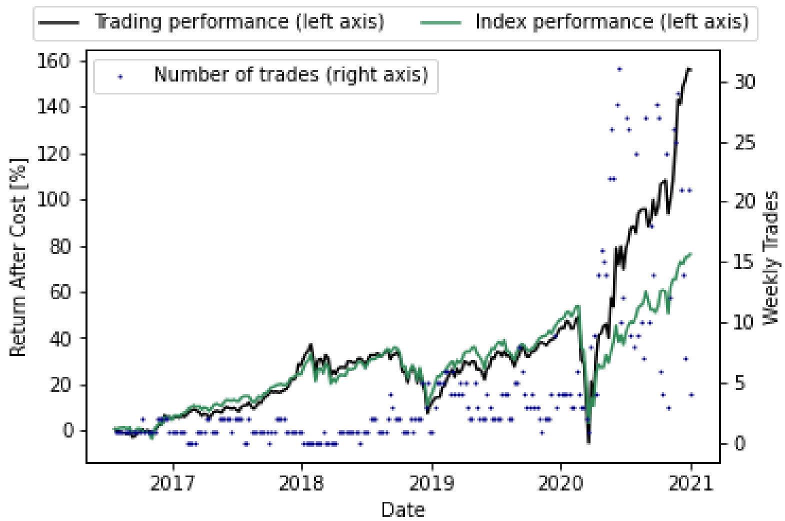

Figure 12: Return development, long-only strategy

6.3.3 Quantile Performance, 5% Position Size Threshold, Long and Short Allowed

We divide the suggested profitable trades into five quantiles based on the predicted abnormal returns. The first quantile is assigned the 20% predicted best long- and short opportunities, the second quantile is assigned the next 20% best predicted long- and short opportunities, etc. Hence, we would expect the first quantile to perform the best and the fifth quantile to perform the worst, yet still with positive predicted abnormal returns.

The quantile abnormal return performances are shown in Figure 13. As expected, the first quantile performs the best over the period. Unexpectedly, however, the predicted least profitable quantile yields an almost as good abnormal return performance while also being less volatile. Two of the quantiles also deliver negative abnormal returns over the trading period.

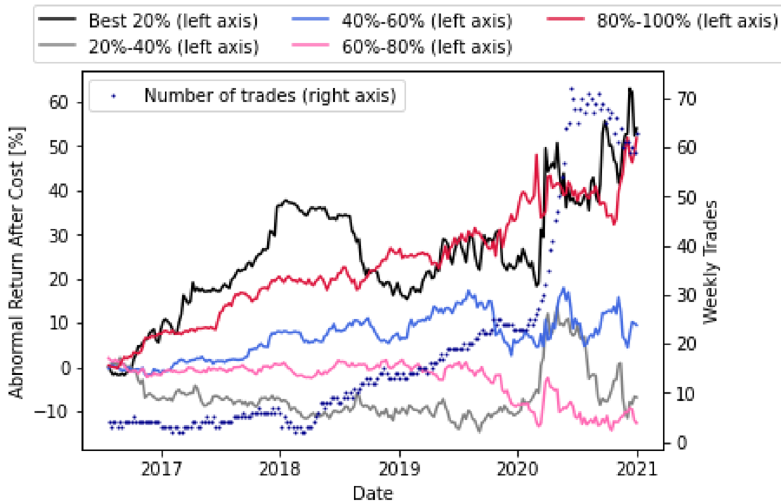

Figure 13: Abnormal return development, quantile strategies.

Investigating returns performance yields almost the same unexpected answers as for abnormal returns. The results are displayed in Figure 14. The 20% best-predicted trades yield the highest returns over the period, beating the market index with 73.68 percentage points over the trading period. The 20% least profitable trades also yield the second-highest return performance, while the market index beats all other quantiles.

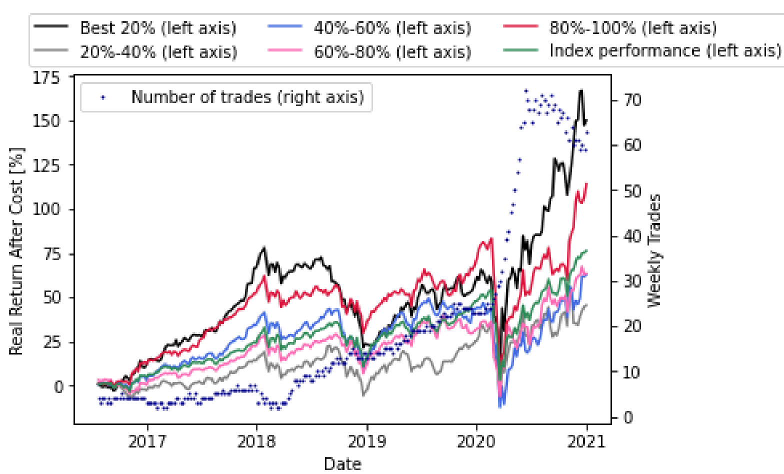

Figure 14: Return development, quantile strategies.

The exposure before index buying is shown in Figure 15. The number of trades for each quantile is higher than for the strategies involving only the 10% best trading ideas, giving the strategies less index-like performance in early periods of the trading strategies.

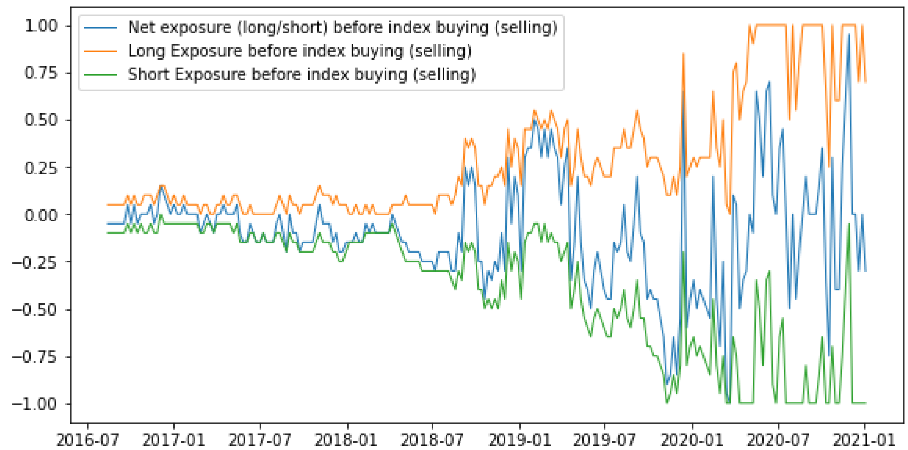

Figure 15: Exposure before index buying, quantile strategies.

The unexpected results in the quantile performance raise several concerns. First, the relatively strong performance of the expected least profitable trades is highly unexpected. Second, two of the quantiles obtain negative abnormal returns. Third, the abnormal return performance order appears to be relatively arbitrary, with the order being quantile [1, 5, 3, 2, 4] and not [1, 2, 3, 4, 5] as expected. However, we find that the average performance of the quantiles yields an abnormal return of 19.15% over the period and a return of 87.10%, versus a market index return of 76.27%.

The author has no clear answer for the unexpected quantile returns performance. However, since the number of daily trades per quantile ranges from just 2 (in 2017 and 2018) to 72 (in 2020), volatility may be expected in the former part of the trading period. The position size cap of 5% may still give single positions a significant influence on the returns outcome of a quantile, which may explain parts of the results obtained. However, the quantile with the lowest predicted abnormal return also appears to perform well in the latter part of the trading period, where the number of weekly trades is significantly higher and the position size constraint is inactive. Potentially, the number of trades performed in each trading quantile might be too low for results to be persistently stable.

Appendix E and F displays the ten most bought and shorted stocks over the trading period, which shows that large caps constitute a significant share of the trades. The expected least profitable quantile generally go long large cap companies, while the expected most profitable quantile generally go long smaller companies. The median market cap of the ten most actively long-traded companies for the expected most profitable quantile was as of May 2021 10.315 billion USD. For the expected least profitable quantile, the same number was 393.19 billion USD. It appears that large-cap tech stocks dominate the predicted least profitable trades.

For stocks that sometimes are frequently discussed and other times almost not discussed, changes in sentiment and activity may be significant, which leads to volatility in predicted returns. Larger companies that are more consistently actively discussed may not experience large shifts in sentiment and activity, and therefore they may always be predicted to yield abnormal returns close to 0. However, these large-cap tech companies have performed exceptionally well in recent years, which may have lead the least predicted trades to become highly profitable. These tech stocks may be considered boring, yet popular among retail investors, leaving, e.g., sentiment relatively stable.

The relatively low predictive power of the model implies that the prediction model often will be significantly wrong in its prediction and that relatively few predictions that completely misses may affect quantile performance significantly. The average absolute difference between predicted and actual abnormal returns is 6.22%, with a median of 3.80%. Also, as many as 1569 observations yields a deviation between predicted and actual abnormal returns of more than 10%. Hence, quantile returns performance must be expected to be significantly volatile, which may be evident from the quantiles trading strategy results.

6.3.4 Testing the Usefulness of the Wallstreetbets Parameters

We also provide data using a trading strategy based on a regression containing no prediction variables based on Wallstreetbets data. The abnormal returns results are shown in Figure 16. The strategy using no Wallstreetbets parameters also shows positive abnormal returns for the quantile with the best returns prediction, albeit somewhat lower than when Wallstreetbets-derived parameters are included. The average abnormal return across all the quantiles is 10.22%, also somewhat lower than the 19.15% achieved with the original strategy. Our results indicate that Wallstreetbets parameters contribute with predictive power in the regression. However, a significant share of the abnormal returns can be predicted with the remaining prediction variables (the bid-ask spread and prior abnormal returns). As can be seen from figure 16, the strategy based on the regression containing no prediction variables based on Wallstreetbets performs fewer trades than the original trading strategy.

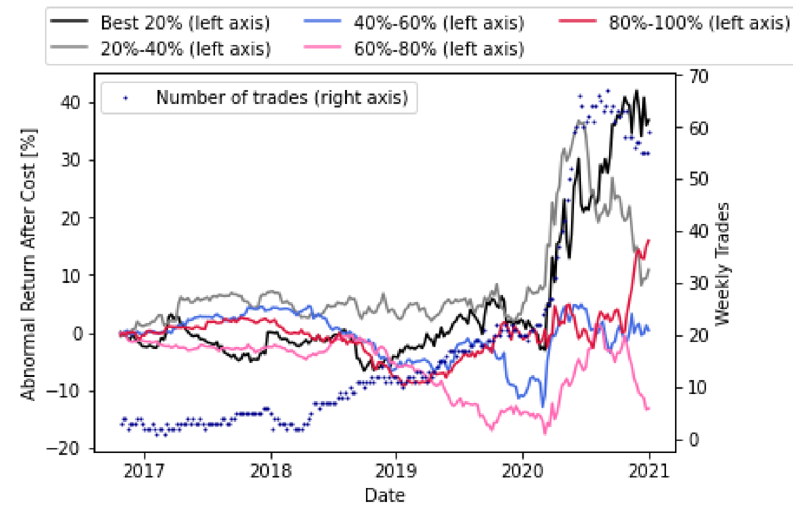

Figure 16: Abnormal return development, prediction using no Wallstreetbets-derived variables.

A strategy that continuously buys all stocks in the observation data set regardless of the predicted abnormal returns outcome is found to yield significant negative abnormal returns over the trading period. By buying all opportunities and non-opportunities, the abnormal returns performance is -26.53% over the trading period. In other words, Wallstreetbets investors appear to, on average, discuss stocks that underperform the market index.

7 Conclusion

The Wallstreetbets forum on Reddit contains the opinions and feelings of millions of retail investors. Based on historical data from Wallstreetbets, we find indications that sentiment and activity levels on Wallstreetbets predict stock returns, as opposed to Tan and Tas (2021), which only find sentiment to predict returns in their Twitter posts sample. In general, we find the performance of the trading strategies presented to perform exceptionally well since the 2020 stock market crash, with more moderate yet positive performance before that. Since the forum has become increasingly popular during the trading period, the forum may influence stock price performances in itself. However, a review of the stocks traded in the trading strategies reveals that large caps, where the potential influence of the forum may be negligible, accounts for the major share of the trades performed.

From the regression parameter values, we find positive sentiment to be followed by negative abnormal returns. This finding is similar to findings based on aggregated market sentiment, i.e., that positive sentiment is likely to be followed by negative returns (see, e.g., Fisher and Statman, 2003[1]). We also find a high relative activity on Wallstreetbets, as measured by the number of weekly mentions divided by market cap, to be followed by negative returns. However, we find the parameter values being strongly time-varying in the trading strategy. The presented strategies yield positive abnormal returns over the trading period, although being volatile.

We note that the number of available trading opportunities may be small compared to the relatively low predictive power of our model, introducing randomness in trading strategies' performances. Future research should aim to increase the number of trading opportunities to avoid this. This can be done in two ways. First, including company names and not only tickers in the data collection process would likely increase the number of trading opportunities. Second, studies similar to this study could be performed in the future, when the amount of data available from the forum has increased, with hopefully more daily trading opportunities. Lastly, the author also encourage to investigate other Reddit forums. This study was performed with the hypothesis that Wallstreetbets investors in general are noise traders, which based on average performance appears to be true. Other forums may consists of more sophisticated investors, and may therefore also be of interest to investigate.

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A TF-IDF

Term frequency-inverse document frequency (TF-IDF) is a statistical measure used to evaluate the relevance of a word to a document in a collection of documents. The measure is calculated by multiplying 1) the frequency (TF) of the word in a document with 2) the inverse document frequency (IDF) of the word across the corpus. Different weighting schemes for the TF and IDF can be employed. Mathematically, the model used in this study can be expressed as:

$$TF(t,d) = \frac{f(d,t)}{\sum_{t' \in d} f(d,t')}, \tag{12}$$

$$IDF(t) = log(\frac{1+n}{1+TF(d,t)}) + 1, \tag{13}$$

$$TF\text{-}IDF(d,t) = TF(d,t) \cdot IDF(t), \tag{14}$$

where f denotes frequency, n is the number of documents (in this study the sum of posts and comments), t refers a specific term (word), and d refers to a specific document (a specific post or comment). Consequently, TF is a matrix of shape $[D,T]$, and IDF is a vector of shape $[1,T]$, where T is the total number of unique words found in the corpus, and D is the number of documents in the corpus. The resulting matrix TF-IDF is of the shape $[D,T]$. To make the TF-IDF values comparable across documents (across rows), it is normal to normalize the TF-IDF matrix. Hence, element (d,t) in the TF-IDF matrix would be

$$TF\text{-}IDF_{normalized}(d,t) = \frac{TF\text{-}IDF(d,t)}{\sqrt{\sum_{t' \in T} (TF\text{-}IDF(d,t'))^2}} \tag{15}$$

With the set of documents all including a set of features $t' \in T$, all the documents are placed in the feature space. Since all the documents in the feature space is assigned a "positive", "neutral" or "negative" mark, we have, at least partially, mapped the feature space into "positive", "neutral" and "negative" areas. The results from TF-IDF can be used in order to predict the labeling of unlabeled documents. For this purpose, this study utilizes the support vector machine algorithm (see appendix B).

The TF-IDF methodology can briefly be divided into two parts: The TF-part and the IDF-part. When considering TF only, all terms (words) are considered equally important. Only the frequency of a given in a given document affects the TF-score. The IDF-term penalizes words that occur frequently across documents and favorizes words that occur rarely. Thus, words that occur frequently in document x but frequently across all documents will be strongly linked towards the classification of document x. For example, if post x is considered "positive", the words that occur frequently in x but rarely in other documents will likely be marked "positive".

B SVM

The support vector machine approach is also known as *the widest street approach*. The method produces a hyperplane boundary which is used to categorize new (unlabeled) points. Considering only two features, and two possible labelings, the situation is shown graphically in figure 17. In this study, every word is a feature. The documents are also labeled with three possible labelings, i.e., "positive", "neutral", and "negative". The method produces a hyperplane that seeks to maximise

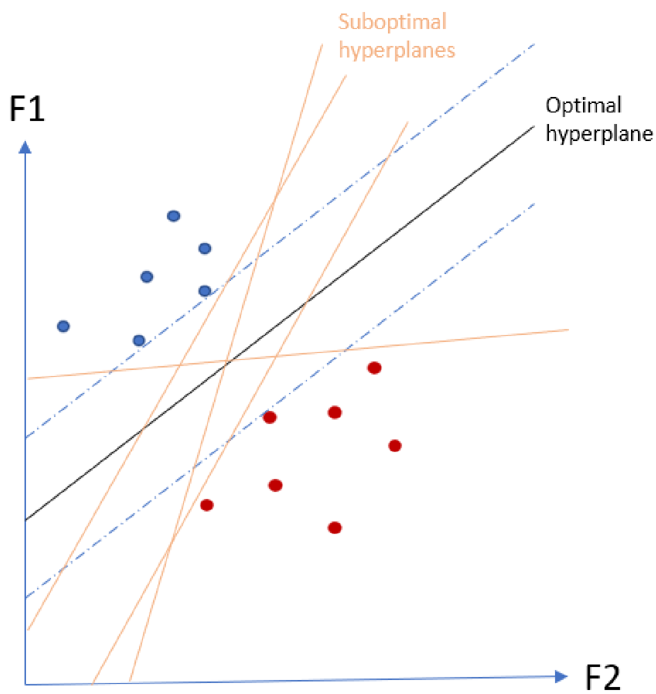

Figure 17: Support Vector Machine Examplified

the distance from nearby labeled points. The hyperplane is fitted to be equally far from the support vector points (i.e., the points in which lies closest to the hyperplane, and determines the optimal hyperplane) of each labeling. The support vector machine method can also be configured with a different kernel, which could allow for the plane to be nonlinear in shape. In this thesis, a radial basis function (rbf) kernel is used.

C Daily Return Prediction

C.1 Model Specification

When considering the prediction variables presented in section 5.1, the regression on daily abnormal returns can be expressed as

$$
\begin{aligned}
R_t^{d,ab} = \alpha &+ (\beta_1 L^1)R_t^{d,ab} + \beta_2 L^2 \text{CRET}_t^w + (\gamma_1 L^1)(\text{Detrended Activity})_t^d \\
&+ \gamma_2 \frac{1}{5}\sum_{i=2}^{6}(L^i)(\text{Detrended Activity}_t^d) + +(\zeta_1 L^1)(\text{Detrended Sentiment}_t^d) \\
&+ \zeta_2 \frac{1}{5}\sum_{i=2}^{6}(L^i)(\text{Detrended Sentiment}_t^d) + (\rho L^1)(\text{MCAP-scaled Activity}_t^d) \\
&+ (\kappa_1 L^1)(\text{Detrended Trading Volume}_t^d) + \kappa_2 \frac{1}{5}\sum_{i=2}^{6}(L^i)(\text{Detrended Trading Volume}_t^d) \\
&+ \epsilon_1 \sqrt{\sum_{i=1}^{5}(L^i)R_t^{d,ab,2}} + \epsilon_2 \sqrt{\sum_{i=1}^{20}(L^i)R_t^{d,ab,2}} + (\delta_1 L^1)(\text{Bid-Ask Spread}_t^d) \\
&+ (\eta_1 L^1)(\text{Detrended Trading Volume}_t^d),
\end{aligned}
\tag{16}
$$

To detrend the variables, being the same as with the weekly regression, we use the following specification:

$$
x_t^d = \frac{y_t^d - \frac{1}{20}\sum_{i=1}^{20} y_{t-i}^d}{\frac{1}{20}\sum_{i=1}^{20} y_{t-i}^d}, \tag{17}
$$

with all notation being equal to the notation in the methodology section.

C.2 Regression Results

The dependent variable in each regression is abnormal return. Each entry displays parameter values, and standard errors in parenthesis. *, ** and *** denote significance at a 10%, 5% and 1% level, respectively. The sample period is 01.01.2016 to 01.02.2020. Note the difference in sample size arising from more available observations of full rank when fewer variables are included.

	Full Regression, Daily	Insignificant Variables Removed, Daily	Full Regression, Daily, logged detrended variables	Insignificant Variables Removed, Daily, logged detrended variables
Constant Term	-0.0002		-0.1134	
	(0.0009)		(0.0010)	
R	0.1414***	0.2788***	0.0610***	0.2787***
	(0.0405)	(0.1066)	(0.0177)	(0.1066)
CRET	-16.823	-17.193***	-18.515	-17.193***
	(0.6254)	(1.1121)	(0.6257)	(1.1213)
Detrended Activity, ST	-0.0004		0.0060	
	(0.0009)		(0.0038)	
Detrended Activity, LT	-0.0006		0.0011	
	(0.0016)		(0.0033)	
Detrended Sentiment, ST	-1.9e-7		-0.0044	
	(2.748e-7)		(0.0128)	
Detrended Sentiment, LT	6.318e-6	2.983e-06***	0.0189*	0.0204**
	(1.117e-6)	(1.314e-06)	(0.0105)	(0.0098)
MCAP-scaled Activity	-1.2553		-1.301e-5	
	(1.7726)		(1.6009)	
Detrended Trading Volume, ST	0.0008		0.2731	
	(0.0030)		(0.2022)	
Detrended Trading Volume, LT	-0.0026		-0.6151	
	(0.0028)		(0.3819)	
Volatility, ST	7.887e-06		0.0021	
	(0.0002)		(0.0084)	
Bid-Ask Spread	4.7569		-0.1134	
	(4.3362)		(4.7195)	
Short-Ratio	-0.0018		0.0065	
	(0.0037)		(0.0142)	
R^2	0.0119	0.0115	0.0119	0.0113
Observations	20656	35224	20656	35224
Companies	346	393	346	393

Table 5: Daily fixed effects regression results

D Monthly Return Prediction

D.1 Model Specification

For the monthly regression, the prior lag (month) is considered for the Wallstreetbets sentiment and activity, as well as the prior quarter prior to that. The regression can be expressed as

$$
\begin{aligned}
R_t^{m,ab} = {} & \alpha + (\beta_1 L^1) R_t^{m,ab} + \beta_2 L^2 \mathrm{CRET}_t^{3m} + (\gamma_1 L^1)(\text{Detrended Activity})_t^m \\
& + \gamma_2 \frac{1}{3} \sum_{i=2}^{4} (L^i)(\text{Detrended Activity}_t^m) + +(\zeta_1 L^1)(\text{Detrended Sentiment}_t^m) \\
& + \zeta_2 \frac{1}{3} \sum_{i=2}^{4} (L^i)(\text{Detrended Sentiment}_t^m) + (\rho L^1)(\text{MCAP-scaled Activity}_t^m) \\
& + (\kappa_1 L^1)(\text{Detrended Trading Volume}_t^m) + \kappa_2 \frac{1}{3} \sum_{i=2}^{4} (L^i)(\text{Detrended Trading Volume}_t^m) \\
& + \epsilon_1 \sqrt{\sum_{i=1}^{40} (L^i) R_t^{d,ab,2}} + (\delta_1 L^1)(\text{Bid-Ask Spread}_t^m) + (\eta_1 L^1)(\text{Detrended Trading Volume}_t^m),
\end{aligned}
\tag{18}
$$

To detrend the variables, being the same as with the weekly regression, we use the following specification:

$$
x_t^m = \frac{y_t^m - \frac{1}{8} \sum_{i=1}^{8} y_{t-i}^m}{\frac{1}{8} \sum_{i=1}^{8} y_{t-i}^m}, \tag{19}
$$

with m denoting monthly variables, and all other notation being equal to the notation used in the methodology section.

D.2 Regression Results

The dependent variable in each regression is abnormal return. Each entry displays parameter values, and standard errors in parenthesis. *, ** and *** denote significance at a 10%, 5% and 1% level, respectively. The sample period is 01.01.2016 to 01.02.2020.

	Full Regression, Monthly	Insignificant Variables Removed, Monthly	Full Regression, Monthly, logged detrended variables	Insignificant Variables Removed, Monthly, logged detrended variables
Constant Term	0.1180		-0.3896**	-0.5197***
	(0.1119)		(0.1734)	(0.1321)
R	-0.0218		-0.0299	
	(0.0655)		(0.0528)	
CRET	-0.0104**	-0.0095**	-0.0082	
	0.0052	(0.0043)	(0.0075)	
Detrended Activity, ST	-0.2708		-0.0199	
	(0.2905)		(0.0612)	
Detrended Activity, LT	0.2487		0.0216	
	(0.1700)		(0.0339)	
Detrended Sentiment, ST	0.0801		0.0495	
	(0.1739)		(0.7112)	
Detrended Sentiment, LT	0.0938		0.0999	
	(0.1734)		(0.0339)	
MCAP-scaled Activity	0.0994**	0.0111**	0.0884***	0.0952***
	(0.0505)	(0.0054)	(0.493)	(0.0469)
Detrended Trading Volume, ST	-0.0103*		-0.3929***	-0.4288***
	(0.0055)		(0.1268)	(0.2046)
Detrended Trading Volume, LT	0.0084		-0.0038	
	(0.0060)		(0.0417)	
Volatility, ST	0.0393		-0.0175	
	(0.0379)		(0.0369)	
Bid-Ask Spread	0.0173		0.0146	
	(0.0369)		(0.0346)	
Short-Ratio	0.1042**	0.1046**	0.0749*	
	(0.0422)	(0.0420)	(0.0433)	
R^2	0.0196	0.0162	0.0158	0.0121
Observations	11531	11531	11531	11531
Companies	895	895	895	895

Table 6: Monthly fixed effects regression results

E Top 10 Shorted Stocks per Quantile

Top shorted stocks per quantile (number of short trades in parenthesis)

	Quantile				
	Best 20%	**20%-40%**	**40%-60%**	**60%-80%**	**80%-100%**
1	AAPL (44)	FB (42)	AAPL (41)	AMZN (43)	GOOGL (45)
2	TSLA (42)	INTC (40)	FB (38)	GOOGL (35)	TSLA (39)
3	AMD (35)	MSFT (37)	AMZN (36)	AAPL (30)	AMZN (37)
4	MU (35)	WMT (34)	WMT (32)	MSFT (29)	AAPL (33)
5	GME (30)	ES (32)	MSFT (30)	ATVI (28)	ATVI (33)
6	TWTR (27)	NFLX (28)	NFLX (29)	MU (28)	JD (31)
7	NFLX (27)	BABA (28)	INTC (29)	FB (27)	MU (30)
8	ROKU (27)	MCD (28)	ES (28)	INTC (27)	OI (30)
9	BABA (26)	SQ (27)	ATVI (27)	ES (26)	FB (29)
10	AC (26)	AMZN (26)	MCD (27)	NFLX (26)	NFLX (29)

Table 7: Top 10 shorted stocks, quantile strategy

F Top 10 Bought Stocks per Quantile

Top bought stocks per quantile (number of long trades in parenthesis)

	Quantile				
	Best 20%	**20%-40%**	**40%-60%**	**60%-80%**	**80%-100%**
1	AC (33)	CRON (32)	SNAP (27)	AMZN (27)	GE (29)
2	TLRY (29)	BB (30)	AMD (23)	GE (25)	ES (27)
3	ACB (28)	AMD (25)	TSLA (20)	TSLA (23)	TWTR (25)
4	GME (26)	JD (21)	TWTR (20)	TWTR (21)	GOOGL (25)
5	NC (18)	TLRY (20)	AMZN (20)	SNAP (18)	AMZN (23)
6	NVAX (18)	NFLX (18)	GE (20)	MCD (17)	AAPL (23)
7	TSLA (17)	GE (18)	FB (19)	ES (16)	BABA (21)
8	BABA (17)	CGC (18)	SA (17)	NFLX (16)	AMD (21)
9	ROKU (17)	FB (16)	ADBE (17)	AMD (16)	NFLX (20)
10	NOK (17)	SQ (16)	GOOGL (16)	FB (16)	FB (20)

Table 8: Top 10 bought stocks, quantile strategy

G Excluded Tickers

This section presents all tickers being excluded from trading. Tickers are excluded because they could refer to something else than a stock ticker. The list contains tickers that also can refer to common words, proper names, abbreviations, slang, Wallstreetbets jargon, financial jargon, and also likely misspellings of common words.

ALOT; ABLE; ACES; ADAM; ADD; ADHD; ADIL; ADS; AERO; AF; AFTER; AG; AGAIN;

AGE; AGRO; AH; AHEAD; AIM; AINT; AIR; AKA; ALERT; ALEX; ALFA; ALLY; ALONE; ALOT; ALSO; ALT; ALU; AMEN; AMID; AMIT; AN; ANIME; ANY; AOL; APE; APES; API; APP; APPS; APRIL; AQUA; AR; ARCH; ARENT; ARK; ARKF; ARKG; ARKK; ARR; ART; AS; ASA; ASAP; ASF; ASH; ASIA; ASK; ASKED; ASS; ATE; ATL; ATOM; AU; AUD; AUTO; AWAY; AWE; AWS; AXE; AYE; BACK; BACON; BAE; BAG; BALLS; BAM; BAN; BANG; BANK; BAR; BARE; BASE; BAT; BATS; BAY; BBC; BBQ; BBY; BC; BEAM; BEAN; BEAR; BEARS; BEAT; BED; BEE; BEER; BEES; BEG; BEING; BELLY; BELOW; BEN; BEST; BET; BETS; BF; BID; BILL; BIN; BINGO; BIRD; BIT; BITE; BITS; BJ; BK; BLM; BLOOD; BLOW; BLUE; BMI; BMO; BNP; BNY; BOB; BODY; BOE; BOIL; BOLD; BOMBS; BOND; BOOKS; BOOM; BOOST; BOOT; BOOTY; BORED; BORN; BOSS; BOT; BOTH; BOTOX; BOUT; BOY; BRAG; BRAIN; BREAD; BREW; BRO; BROKE; BS; BT; BTC; BTW; BUDDY; BUG; BUGS; BUILT; BULL; BURN; BUS; BUT; BUYS; BY; CA; CAD; CAFÉ; CAGR; CAKE; CALF; CALI; CALL; CALLS; CALM; CAME; CAMP; CAMS; CANT; CAPE; CAR; CARE; CARS; CART; CASE; CASH; CAT; CATO; CATS; CBOE; CC; CCO; CCP; CD; CE; CELL; CENT; CERN; CF; CFA; CGI; CHAD; CHART; CHAT; CHEAP; CHECK; CHEST; CHILL; CHINA; CHIP; CHIPS; CHOSE; CIA; CIK; CIO; CITI; CITY; CLICK; CLIFF; CLOCK; CLUB; CMO; CN; CNET; CNG; CNY; CO; COD; CODE; COHN; COIN; COINS; COKE; COL; COLD; COM; COME; CONE; COO; COPS; CORE; CORN; CORP; COST; COULD; COUP; COW; COWS; CPA; CPI; CPU; CR; CRACK; CRASH; CRIES; CRM; CROP; CRY; CRYO; CS; CTRL; CUB; CUBA; CUBE; CUBS; CUCKS; CUP; CURE; CUS; CUT; CUZ; CV; CVC; DAD; DADDY; DAILY; DAMN; DAN; DANG; DARE; DARK; DATA; DATE; DATED; DAU; DAWN; DAX; DAY; DAYS; DB; DC; DCF; DDR; DEA; DEAD; DEAL; DEAR; DEBT; DEC; DECK; DEF; DEMO; DENT; DEO; DIAL; DICE; DICK; DIDNT; DIET; DIG; DINE; DIP; DIRT; DIRTY; DISC; DJI; DKK; DLC; DNA; DOC; DOES; DOESN; DOG; DOGE; DOGGY; DOGS; DOGZ; DON; DOOR; DORM; DOT; DOW; DPS; DR; DRINK; DRIP; DROP; DUAL; DUDE; DUDES; DUDG; DULL; DUMB; DUMP; DUO; DUST; DVD; EACH; EAR; EARN; EARS; EARTH; EAST; EATS; EBT; ECHO; ECON; ED; EDD; EDGE; EG; EGGS; EGO; EH; EKG; ELF; EMMA; EMO; EMP; EN; ENACT; END; ENDS; ENJOY; ENTER; EOD; EOM; EOS; EOY; EP; EPIC; EQ; ERC; ERIC; ERM; ERP; ESG; EST; ET; ETC; ETH; ETN; EVA; EVAN; EVE; EVEN; EVER; EVERY; EVIL; EVP; EX; EXAM; EXIT; EXPO; EXTRA; EY; EYE; EYES; EZ; FA; FACE; FACT; FAG; FAITH; FAKE; FAME; FAN; FANG; FAR; FARE; FARM; FASB; FAT; FATE; FAULT; FAX; FBI; FCA; FCF; FCKING; FEAR; FEB; FELL; FICO; FID; FILL; FILM; FINAL; FIND; FINE; FINRA; FINS; FIRE; FIRM; FISH; FIST; FIT; FITS; FIVE; FIX; FKING; FLAG; FLAT; FLESH; FLEX; FLIP; FLOAT; FLOW; FM; FML; FOIL; FOLD; FOOD; FORCE; FOREX; FORM; FORT; FORUM; FOUND; FOUR; FOX; FRAME; FRAMES; FREE; FRI; FRIES; FROG; FROM; FRONT; FTSE; FTW; FUCKN; FUEL; FUK; FUN; FUND; FUNNY; FURY; FV; FX; FYI; GAF; GAHD; GAIN; GAINZ; GAME; GAP; GAS; GAY; GBP; GDP; GEM; GEMS; GENE; GEO; GERM; GETS; GF; GG; GIG; GIGA; GIRL; GIVEN; GIVES; GL; GLAD; GLOBE; GLORY; GMO; GMT; GOAL; GOAT; GOD; GOLD; GOLF; GONE; GONNA; GOOD; GOVT; GPS; GPU; GRANT; GRAY; GREAT; GRID; GRIN; GROSS; GROUP; GROW; GROWTH; GS; GSM; GTA; GTAIV; GTFO; GUESS; GUH; GUI; GULF; GUM; GUN; GURU; GUT; GUTS; GUY; HACK; HAD; HAH; HAHA; HAHAH; HAIL; HAIR; HALF; HALO; HAND; HAPPY; HARD; HAS; HAT; HAWK; HAY; HD; HE; HEAD; HEAT; HEAVY; HELD; HELL; HEMP; HER; HERB; HERD; HERES; HERO; HERS; HES; HEY; HFT; HI; HIHI; HIHO; HILL; HIPS; HIS; HITS; HK; HMU; HOG; HOGS; HOLY; HOME; HOOK; HOP; HOPE; HORSE; HOST; HOT; HOURS; HOUSE; HR; HS; HSA; HSBC; HTD; HTML; HUB; HUG; HUMAN; HUNT; HYG; HYPE; IB; ICE; ID; IDEA; IDEAS; IDIOT; IE; IEA; IF; IG; II; III;

IIII; IIIV; IMAC; IMF; IMO; INC; INDEX; INFO; ING; INN; IOT; IPOD; IQ; IR; IRA; IRL; IRON; IS; ISNT; ISO; ITS; IVE; IVWM; JACK; JACKS; JAN; JESUS; JET; JETS; JFK; JK; JOB; JOE; JOIN; JOKE; JONES; JP; JPM; JPY; JULY; JUMP; JUNE; JV; KATE; KEEP; KEN; KENT; KEY; KHAN; KICK; KIDS; KIDZ; KILO; KIM; KING; KIRK; KITE; KKR; KNOW; KNOWS; LA; LADS; LAKE; LAND; LAST; LATE; LAW; LAZY; LEAD; LEAF; LEAP; LEARN; LEAST; LEFT; LEGIT; LEND; LEO; LESS; LET; LICK; LID; LIDAR; LIFE; LIFT; LIME; LINK; LION; LIT; LIVE; LLC; LLP; LMK; LNG; LOAN; LOANS; LOI; LONE; LONG; LOOK; LOOP; LORD; LOSE; LOST; LOT; LOTZ; LOUD; LOVE; LOW; LOWER; LP; LSD; LSE; LTD; LTE; LTM; LUCK; LUCY; LULLZ; LULZ; LUNG; LVL; LYFE; LYING; MA; MAC; MACAU; MACE; MAE; MAGA; MAGIC; MAH; MAIN; MAJOR; MAKIN; MAMA; MAN; MANU; MAP; MARIA; MARK; MASS; MATH; MAX; MAY; MAYBE; MBA; MBS; MC; MCAP; MCB; MD; MDB; MEAN; MEDIA; MEET; MEGA; MELT; MEME; MEN; MENU; MET; MFS; MID; MIGHT; MILE; MILL; MIN; MIND; MINE; MINI; MINS; MINT; MISS; MIT; MITT; MJ; MKT; ML; MM; MOAT; MOD; MODS; MOM; MONTH; MOOD; MOON; MOST; MOVES; MOVIE; MOVIES; MP; MPH; MR; MS; MSCI; MTH; MULTI; MUST; MUTE; MVP; NAH; NAIL; NAKED; NAME; NANO; NAP; NAV; NBA; NEAR; NEED; NEO; NERD; NERDS; NET; NEW; NEWLY; NEWS; NGL; NI; NICE; NINE; NJ; NK; NLP; NO; NOAH; NONE; NOOB; NORTH; NOTE; NP; NSA; NUT; NUTS; NY; NYC; NZ; OCT; ODIN; OFC; OG; OH; OIL; OKAY; OLD; OLED; OMER; OMFG; OMG; ONCE; ONTO; OOO; OP; OR; ORE; OREO; OSB; OTHER; OUR; OWN; OX; PA; PACE; PACK; PAIN; PALM; PAN; PANEL; PAPER; PART; PASS; PATH; PAVE; PAW; PAWZ; PAX; PAY; PAYS; PB; PC; PCB; PDF; PDT; PE; PEAK; PEDOS; PEEL; PEN; PENN; PENNY; PEPSI; PER; PERU; PETS; PHAT; PHD; PHONE; PHP; PIA; PICK; PIE; PIECE; PIGS; PILL; PIN; PINE; PINS; PIPE; PLAN; PLAY; PLAYS; PLC; PLEAS; PLOW; PLS; PLUS; PLZ; PM; PMI; PNG; POINT; POOL; POPE; PORN; POSH; POST; POTUS; POW; POWER; PP; PPE; PPL; PPT; PR; PRE; PRICE; PRINT; PRO; PROOF; PROS; PROUD; PS; PST; PT; PUNK; PUSSY; PUT; PUTS; PW; QE; QR; QUAD; QUICK; QUIET; QUOTE; RACE; RAIL; RALLY; RAM; RAMP; RARE; RASP; RATE; RAVE; RAY; RAYS; RE; READ; REAL; RED; REIT; REITS; RENT; REPO; RESET; REST; RF; RICE; RICK; RIG; RING; RIP; RISE; RISK; RISKY; RL; RMB; RN; RNA; ROAD; ROAM; ROCK; ROE; ROFL; ROI; ROIC; ROLL; ROME; ROOF; ROOM; ROOT; ROSE; ROW; RPM; RT; RUG; RULE; RUM; RUN; RUSH; RUT; SAAS; SAFE; SAID; SAIL; SALE; SALES; SALT; SAME; SAND; SAVE; SAVED; SAY; SAYS; SBE; SCAM; SCENE; SDOW; SEE; SEED; SEEK; SELF; SELL; SEMI; SEND; SENT; SEP; SET; SEX; SHAG; SHALL; SHARE; SHARES; SHAW; SHINE; SHIP; SHIPS; SHOES; SHOP; SHOW; SICK; SIDE; SIGN; SIGNS; SILO; SIMP; SIN; SING; SINO; SIR; SIRI; SIX; SIZE; SKILL; SKY; SLAB; SLACK; SLEEP; SLIM; SLOT; SLOW; SLVV; SMA; SMALL; SMART; SMH; SMOKE; SNORT; SOAP; SOCK; SOFT; SOHO; SOIL; SOLD; SOLID; SOLO; SOME; SON; SONG; SORRY; SOS; SOUL; SOUTH; SP; SPAC; SPACE; SPEC; SPEND; SPIKE; SPIN; SPOT; SPX; SPY; SSD; STAR; START; STEAK; STEEL; STEP; STFU; STICK; STILL; STOCK; STOCKS; STONK; STORM; STORY; STRAP; STRONG; SUB; SUE; SUIT; SUITS; SUN; SUPER; SUS; SVP; SWEET; SWING; SYNC; SYRIA; TA; TACO; TAIL; TAKE; TAKES; TAP; TARD; TAXES; TBH; TC; TD; TDA; TEA; TEACH; TEAM; TEAR; TECH; TELL; TEN; TERM; TESLA; TEST; TF; TFSA; TGIF; THAN; THANK; THANKS; THATS; THEIR; THEN; THETA; THING; THO; THOR; THOSE; THREE; THX; TICK; TIER; TIGHT; TIME; TIMES; TINY; TIP; TIRED; TITLE; TL; TLDR; TMRW; TODAY; TOLD; TON; TONS; TOO; TOP; TOPPY; TOPS; TOUR; TOWN; TP; TRACK; TRADE; TRAIN; TRASH; TREE; TREND; TRIAL; TRIP; TRUMP; TRUST; TRY; TTM; TUBE; TUFF; TURN; TV; TWO; TY; TYPE; UAE; UBS; UGLY; UI; UN; UNBAN; UNITE; UNTIL; UPON; UPS; USA; USBC;

USER; USING; USO; USS; UTC; UTF; UTZ; VALUE; VC; VEGA; VEIN; VERB; VET; VHS; VICE; VIP; VIRAL; VIX; VOTE; VPN; VR; VS; VTI; WA; WACC; WAGE; WAIT; WAKE; WALL; WANNA; WAR; WARM; WAS; WASD; WASH; WAT; WATT; WAVE; WAY; WAYS; WC; WEEK; WELL; WENT; WERE; WFH; WHATS; WHEN; WHERE; WHICH; WHILE; WHOLE; WHOS; WHY; WILD; WILLS; WING; WINS; WIRE; WISH; WOLF; WOLVES; WOMEN; WON; WONT; WOOD; WORK; WORLD; WORTH; WOUND; WOW; WRAP; WRLD; WTI; WWE; WWW; XBOX; XD; XL; XMAS; XRAY; YA; YALL; YANG; YEA; YEAH; YEAR; YELL; YES; YET; YO; YOLO; YOLOO; YOLOOO; YORK; YOULL; YOURE; YRS; YT; YTD; ZONE; TRUE;

G.1 Tickers Automatically Deleted by Wallstreetbets

WBAI; AHC; ATEN; AGD; AWP; ACP; JEQ; AOD; ACEL; ACCO; ATV; PEO; AGRO; ASIX; AVK; AENZ; MITT; AFB; AWF; AIO; CBH; NCV; NCZ; ACV; NIE; PINE; ALTG; AMBC; AMC; AXL; AFGC; ARL; ARA; AVD; AMRX; AP; AXR; FINS; ANH; AFT; AIF; ARC; ARCH; ASC; ACRE; ARDC; AGX; AAIC; ARLO; AHH; ARR; AFI; ASA; AHT; ASPN; AC; ATTO; AT; BW; BGH; BCSF; BANC; BBAR; BLX; BBDC; MCI; MPV; BNED; BZH; BRBR; BHE; BHLB; BGSF; BH; BGIO; BFZ; CII; BHK; DSU; BGR; EGF; FRA; BFO; BGT; BOE; BME; BAF; BKT; BGY; BKN; BTA; BZM; MHE; BIT; MUI; MUA; BKK; BBK; BBF; BYM; BFK; BLE; MEN; MUC; MUH; MHD; MFL; MUJ; MHN; MUE; MUS; MVT; MYC; MCA; MYD; MYF; MFT; MIY; MYJ; MYN; MPA; MQT; MYI; MQY; BNY; BSE; BFY; BCX; BSD; BUI; BHV; BGB; BGX; BSL; APRN; BXG; BVH; BXC; DCF; DHF; DMB; DSM; LEO; BCEI; BQ; BORR; BPT; BHR; BWG; LND; MNRL; BEDU; VTOL; BKD; RA; BRT; BBW; BY; CAI; CAL; CPE; CSU; CMO; CSV; CARS; CSPR; CSLT; CTT; CATO; IGR; CDR; CEL; CPAC; CEN; CEPU; ECOM; CHRA; CLDT; CMCM; CHMI; CHS; DL; CHN; CGA; COE; CYD; CBB; CINR; CIR; BLW; CIA; CIO; CVEO; CCO; EMO; CEM; CTR; CLW; CLPR; CNF; FOF; LDP; MIE; PSF; RFI; CXE; CIF; CXH; CMU; CLNC; STK; CCM; CCR; CEIX; TCS; CTRA; CPS; CTK; CXW; CORR; CPLG; CAAP; CMRE; CPF; CRT; CAPL; CRY; CULP; CURO; SRV; SZC; CUBI; UAN; CELP; DAC; DEX; DDF; DBI; DESP; DHX; DHT; DSSI; DSX; DBD; DMS; DFIN; LPG; DBL; PLOW; DVD; DRD; DS; DCO; DSE; DTF; DUC; DPG; DLNG; DX; ECC; ESTE; KODK; EOI; EFT; EFL; EFF; EHT; ETX; EOT; EVN; ETJ; EFR; EVF; EVG; ETO; ETB; EXD; ELVT; EFC; EARN; EEX; EIG; EDN; EXK; ERF; EBF; ENVA; ETM; EVC; ENZ; EQS; ESGC; ETH; EEA; XAN; EXPR; EXTN; SFUN; FPI; AGM; FMN; FMO; FINV; FSLF; FFA; FMY; FDEU; FIF; FSD; FEI; FPL; FIV; FCT; FGB; FEO; FAM; FPH; DFP; PFD; PFO; FLC; FLNG; FTK; FLY; FOR; FET; FBM; FEDU; FC; FT; FI; RESI; FF; GCV; GGZ; GGT; GUT; GBL; GNT; GCI; GLOG; GLOP; GATO; GNK; GAM; GCO; GEL; GEN; GNE; GPRK; GLT; CO; GMRE; GLP; GSL; GER; GRC; GPX; GHM; GPMT; AJX; GHL; SUPV; GTT; GGM; GPM; GOF; GBAB; GHLD; HBB; HNGR; HVT; HCHC; HCI; HLX; HRTG; HT; HESM; HEXO; PCF; HGLB; HFRO; HPR; HIL; HMLP; HZN; HOV; HMI; HCFT; HY; IDT; IMAX; ICD; IHC; IFN; INSI; INSW; IPI; IVC; VBF; VCV; VTA; IHIT; IHTA; VLT; IVR; OIA; VMO; VKQ; VPV; IQI; VVR; VTN; VGM; IIM; IRET; IO; IRS; IVH; JAX; JILL; JOF; JT; JMP; BTO; HEQ; JHS; JHI; HPF; HPI; HPS; PDT; HTD; HTY; JP; JE; LRN; KYN; KMF; KRP; KFS; KIO; KNL; KNOP; KOP; KF; KOS; KRA; SCX; LAIX; LCI; LPI; LGI; LEAF; LEE; LEJU; LC; ASG; LITB; SCD; LOMA; LXU; LUB; LL; LXFR; LDL; MFD; MGU; MCN; MX; MMD; MTW; MN; MCS; MPX; HZO; MLP; MEC; MBI; MUX; MTL; MCC; MDLY; MDP; MTR; MSB; MCB; MXE; MXF; MCR; MGF; MIN; MMT; MFM; MFV; AMPY; MLR; HIE; MG; MIXT; MOD; MOGU; MEG; CAF; MSD; EDD; IIF; MOV; MRC; MVF; MZA; MVO; MVC; MYE; NBR; NC; NTP; NPK; NGS; NGVC; NRP; NTZ; NLS; NVGS; NNA; NM;

NMM; NP; NPTN; NSCO; NTST; HYB; GF; NWHM; IRL; SNR; NYC; NR; NREF; NHF; NEX; NGL; NINE; NL; NAT; NOA; NRT; DNOW; NUW; NAZ; NKX; NCB; NCA; JCE; JHAA; JHB; JCO; JQC; JDD; DIAX; JEMD; NEV; JFR; JRO; NKG; JGH; NXC; NXN; NID; NMY; NMT; NUM; NMS; NOM; JLS; JMM; NHA; NMI; NJV; NXJ; NYV; NNY; NAN; NUO; NPN; NQP; JPC; JPT; JPI; JRI; JRS; SPXX; NIM; NXP; NXQ; NXR; NSL; JSD; NBB; JTD; JTA; NPV; NIQ; OII; OCN; OFG; OIS; ODC; OLP; ONE; OOMA; OPY; ORC; OEC; ORN; OSG; PAM; PARR; PKE; PRTY; PBF; PBFX; BTU; PEI; PBT; PVL; PRT; GHY; ISD; FENG; DNK; PHX; PCQ; PCK; PZC; PCM; PCN; NRGX; PGP; PHK; PKO; PFL; PFN; PMF; PML; PMX; PNF; PNI; PYN; RCS; PHD; PHT; MAV; MHI; AGS; PLYM; PSTL; PDS; APTS; PGZ; PRA; AAN; PUMP; PROS; PRS; PMM; PIM; PMO; PPT; NEW; PZN; QEP; QUAD; NX; QD; QUOT; RRD; RMED; RFL; RNGR; PACK; RYAM; RC; RLH; RM; RGS; SOL; RENN; RFP; RVI; REVG; REV; REX; RMM; RMI; RIV; RSF; OPP; RGT; RMT; RES; RPT; RYB; RYI; SBR; SB; SFE; SMM; SJT; SD; SAR; BFS; SALT; STNG; KTF; KSM; SRL; SCU; CKH; SMHI; WTTR; SQNS; SFL; SBOW; SI; SM; SOI; SOS; SOR; SPE; SRLP; SII; SQZ; SXI; SGU; SRT; SPLP; SCM; EDF; EDI; STON; SRI; SPH; SMLP; SXC; STG; SUP; SWZ; TWN; TALO; TSI; TISI; TK; TNK; TRC; HQH; THQ; HQL; THW; TDF; EMF; TEI; GIM; TEN; TTI; TGH; CEE; GRX; GDL; THR; TPRE; TDW; TLYS; TMST; TWI; NDP; TYG; TEAF; NTG; TTP; TPZ; TSQ; TRTX; TCI; TGS; TREC; TG; TPVG; GTS; TGI; TBI; TNP; TUFN; TPB; TPC; SLCA; USX; UMH; UFI; UTL; UHT; UVE; UTI; UBA; UBP; USDP; EGY; VHI; VAPO; VEC; VEL; VNTR; VRTV; VET; VRS; VCIF; VIAO; VVI; VNCE; VHC; VGI; ZTR; VPG; VIST; VOC; IAE; IHD; IGA; IGD; IDE; IID; IRR; PPR; WTI; WNC; HCC; WPG; WEI; EOD; WEA; EMD; GDO; EHI; HIX; HIO; HYI; SBI; IGI; PAI; MMU; WMC; DMO; MTT; MHF; MNP; WIW; WIA; WLKP; WHG; WSR; WLL; WOW; XYF; XFLT; XIN; YRD; YI; PIH; TURN; ATNF; BCOW; FCCY; KRKR; ETNB; NMTR; JFU; ABEO; AXAS; ABST; ACIU; ACTG; ACST; AXDX; ARAY; ACRX; ACER; ACHV; ACRS; ACNB; ACOR; AFIB; ADMS; ADMP; ADAP; ADXN; AEY; ADIL; ACET; ADTX; ADMA; ADTN; ADES; ADXS; AEGN; AGLE; AEHR; AMTX; AERI; ARPO; AIH; AEZS; AEMD; AFMD; AGEN; AGRX; AGYS; AGMH; AGFS; AIKI; ALRN; AIRT; AIRG; ANTE; AKTX; AKBA; KERN; AKRO; AKER; AKUS; AKTS; AKU; ALSK; ALBO; ALDX; ALRS; ALCO; ALGS; ALIM; ALYA; ALJJ; ABTX; ALNA; ARLP; AESE; AHPI; AMOT; ALLT; AOSL; ATEC; ALPN; ALTA; ATHE; ALT; ASPS; ALTM; AMAL; AMRK; AMBC; AMTB; AMTBB; AMRH; ATAX; AFIN; AMNB; AOUT; APEI; AREC; AMRB; AMSWA; AMSC; AVCT; CRMT; ASRV; ATLO; AMST; POWW; AMPH; AMYT; ASYS; AMRS; ANAB; AVXL; ANCN; ANGO; ANIP; ANIK; ANIX; ANNX; ANPC; ATRS; AEHL; ATEX; APOG; APEN; AINV; AMEH; APDN; AGTC; AAOI; APLT; AUVI; APRE; APVO; APTX; APM; APTO; APYX; AQMS; AQB; AQST; ARAV; ABUS; ABIO; RKDA; FUV; ARDX; ARDS; ARKR; AROW; ARTL; ARTNA; ARTW; APWC; ASLN; ASPU; AWH; ASMB; ASRT; ATRO; ALOT; ASTC; ASUR; AACG; ATHX; ATHA; ATIF; AAME; ACBI; ATLC; ATCX; ATNI; ATOM; ATOS; BCEL; LIFE; AUBN; AUDC; AEYE; EARS; JG; AUTL; AUTO; AVDL; AVCO; ATXI; AVEO; AVNW; CDMO; AVID; AVGR; RCEL; AVRO; AWRE; ACLS; AXLA; AXGN; AXTI; AYLA; AYRO; AYTU; AZYO; AZRX; RILY; BOSC; BFC; BOCH; BMRC; BKSC; BOTJ; BSVN; BFIN; BWFG; DFVL; DFVS; TAPR; BBSI; BSET; BXRX; BCML; BBQ; BCBP; BEEM; BBGI; BELFA; BELFB; BLPH; BLCM; BLU; BNFT; BNTC; BRY; XAIR; BYSI; BCYC; BGFV; BASI; BCDA; BIOC; BDSI; BDSX; BFRA; BHTG; BKYI; BIOL; BLRX; BMRA; BNGO; BVXV; BPTH; BSGM; BIVI; BTBT; BJRI; BKCC; TCPC; BLNK; BCOR; BLBD; BHAT; BLCT; BKEP; BSBK; WIFI; BNSO; BIMI; BRQS; BOMN; BPFH; BOXL; BCLI; BWAY; BBI; BDGE; BLIN; BWB; BRID; BCOV; BYFC; BWEN; BROG; BPYU; BRKL; BMTC; BSQR; BTAQU; BFST; CFFI; CABA; CDZI; CSTE; CLBS; CHI; CCD; CHW; CGO; CAMP; CALB; CALA; CALT; CLMT;

CLXT; CMBM; CATC; CAC; CAMT; CAN; CGIX; CPHC; CBNK; CCBG; CPLP; CSWC; CPTA; CAPR; CSTR; CPST; CARA; CRDF; PRTS; TAST; CARE; CARV; CASA; CASI; CASS; SAVA; CTRM; CATB; CBIO; CPRX; CBFV; CBAT; CBMB; CBTX; CECE; CELC; CLDX; APOP; CLRB; CBMG; CLSN; CYAD; CETX; CDEV; CNTG; CVCY; CNBKA; CNTY; CRNT; CERC; CERE; CEVA; CFBK; CSBR; CTHR; CHEK; CMPI; CKPT; CEMI; CHMG; CHFS; CHMA; CSSE; PLCE; CMRX; CAAS; CCRC; JRJC; HGSH; CIH; CJJD; CLEU; CHNR; CREG; SXTC; CXDC; PLIN; KDNY; IMOS; COFS; CDXC; CHUY; CDTX; CMCT; CNNB; CIDM; CTRN; CTXR; CZNC; CZWI; CIZN; CIVB; CLAR; CLNE; CLSK; CLFD; CLRO; CLPT; CLSD; CLIR; CBLI; CLVS; CLPS; CCNE; CNSP; CCB; COCP; CODA; CODX; CDAK; CVLY; JVA; COGT; CWBR; CLCT; COLL; CLGN; CBAN; CSCW; CMCO; CVGI; JCS; ESXB; CFBI; CTBI; CWBC; CGEN; CPSI; CTG; SCOR; CHCI; CMTL; CNCE; BBCP; CDOR; CFMS; CNFR; CNOB; CONN; CNSL; CWCO; CPSS; CFRX; CRBP; CLDB; KOR; CRVS; CPAH; ICBK; CVLG; COWN; CPSH; CRAI; CRTD; CREX; CCAP; CRESY; CXDO; CRNX; CCRN; CFB; CRWS; CCLP; CSPI; CTIC; CUE; CPIX; CMLS; CURI; CRIS; CUTR; CVV; CYAN; CYBE; CYCC; CYCN; CBAY; CYRN; CTMX; CTSO; DJCO; DAKT; DARE; DRIO; DSKE; DAIO; DTSS; DTEA; DWSN; DBVT; TACO; DCTH; DENN; DMTK; DXLG; DSWL; DMAC; DHIL; DFFN; DGII; DMRC; EQOS; DRAD; DGLY; DCOM; DRTT; DLHC; BOOM; DOGZ; DLPN; DGICA; DGICB; DMLP; LYL; DSPG; DLTH; DUOT; DRRX; DXPE; DYAI; DYNT; DVAX; DYN; DZSI; EBMT; EGLE; EGRX; EML; EAST; EBON; ECHO; MOHO; EDAP; EDSA; EDUC; EGAN; EIGR; EKSO; LOCO; SOLO; ECOR; ELSE; ESBK; ELOX; ELTK; ELYS; EMCF; EMKR; ENTA; NDRA; WATT; EFOI; ERII; ENG; ENLV; ENOB; ETTX; ENTX; EBTC; EOSE; EPSN; EQ; EQBK; ERYP; ESCA; ESPR; GMBL; ESQ; ESSA; EPIX; ESTA; VBND; VUSE; ETON; CLWT; EDRY; ESEA; EVLO; EVK; EVER; MRAM; EVFM; EVGN; EVOK; EOLS; EVOL; XGN; ROBO; XELA; EXFO; XCUR; EXTR; EYEG; EYEN; EYPT; EZPW; FLMN; DUO; FANH; FARM; FMAO; FMNB; FAMI; FAT; FTHM; FBSS; FNHC; FENC; GSM; FFBW; FDBC; FDUS; FRGI; FISI; FBNC; FNLC; FRBA; FBIZ; FCAP; FCBP; FCBC; FCCO; FCRD; THFF; FFNW; FFWM; FGBI; INBK; FMBH; FXNC; FNWB; FSFG; FSEA; FUNC; FUSB; MYFW; SVVC; FPRX; FVE; FLXN; ESG; ESGG; LKOR; QLC; FPAY; FLXS; FLNT; FLDM; FFIC; FLUX; FNCB; FHTX; FONR; FRSX; FORR; FBRX; FBIO; FORD; FWP; FOSL; FRAN; FRAF; FRLN; RAIL; FEIM; FRPH; FSBW; HUGE; FSTX; FTEK; FULC; FLL; FNKO; FUSN; FTFT; FFHL; FVCB; WILC; GTHX; GAIA; GALT; GLTO; GRTX; GLMD; GMDA; GAN; GNSS; GENC; GFN; GENE; GNFT; GNUS; GNMK; GNCA; GNPX; GEOS; GOVX; GABC; GERN; GEVO; GIGM; GILT; GLAD; GOOD; GAIN; LAND; GLBZ; GBLI; SELF; GWRS; CHIC; GLBS; GLYC; GLNG; GMLP; GDEN; GOGL; GTIM; GOSS; GRAY; GECC; GEC; GLDD; GSBC; GPP; GPRE; GCBC; GTEC; GNLN; GLRE; GP; GRNQ; GSKY; GDYN; GSUM; GRIF; GRIN; GRTS; GRPN; GVP; GSIT; GTYH; GNTY; GFED; GHSI; GIFI; GURE; GWGH; GYRO; HOFV; HNRG; HALL; HJLI; HAFC; HAPP; HCDI; HONE; HLIT; HARP; HROW; HBIO; HCAP; HA; HWKN; HWBK; HAYN; HBT; HSTM; HTBX; HSII; HSDT; HMTV; HNNA; HEPA; HTBK; HFWA; HGBL; HCCI; HX; HFEN; HFFG; HIBB; HPK; HIHO; HIFS; HQI; HSTO; HMNF; HOLI; HBCP; HFBL; HMST; HTBI; FIXX; HOFT; HOOK; HBNC; HRZN; HOTH; HMHC; HWCC; HBMD; HTGM; HUSN; HSON; HDSN; HUIZ; HGEN; HURC; HBP; HVBC; HYMC; HYRE; IIIV; IBEX; ICAD; ICCH; ICHR; ICLK; ICON; IPWR; IDEX; IDYA; INVE; IDRA; IEC; IESC; IROQ; IFMK; IHRT; IKNX; IMAC; ISNS; IMRA; IMBI; IMTX; IMMR; ICCC; IMUX; IMNM; IMRN; IMMP; PI; IMV; IBCP; INFI; IFRX; III; IEA; IMKTA; INM; INMB; IPHA; INOD; ISSC; INGN; INZY; INPX; ISIG; INSE; IIIN; NTEC; IMTE; IDN; TILE; IGIC; IMXI; IDXG; XENT; IVAC; IIN; INTZ; IVA; ISTR; ICMB; ITIC; NVIV; INVO; IRMD; IRIX; IRCP; ITMR; ITI; ITRM; ITRN; ISEE; IZEA; MAYS; JAGX; JAKK; JAN; JRSH; JCTCF;

JFIN; JBSS; JOUT; JNCE; JUPW; KDMN; KXIN; KALA; KLDO; KALV; KMDA; KNDI; KSPN; KZIA; KBSF; KRNY; KELYA; KELYB; KFFB; KEQU; KTCC; KZR; KFRC; KE; KBAL; KIN; KINS; KTRA; KIRK; KRBP; KTOV; KLXE; KOPN; KOSS; KWEB; KBNT; KRUS; KVHI; FSTR; LJPC; LSBK; LBAI; LAKE; LNDC; LARK; LMRK; LE; LTRN; LNTH; LTRX; LRMR; LAWS; LAZY; LCNB; LPTX; LEGH; LMAT; LNSR; LEVL; LXRX; LLIT; LTRPA; LCUT; LFVN; LWAY; LTBR; LPTH; LMB; LLNW; LMST; LMNL; LMNR; LINC; LIND; LGHL; LPCN; LIQT; YVR; LQDA; LQDT; LIVE; LIVX; LXEH; LIXT; LIZI; LMFA; LMPX; LOGC; LOOP; LORL; LYTS; LUMO; LUNA; LKCO; LBC; LYRA; MCBC; MFNC; MAGS; MGTA; MGIC; MGYR; MHLD; MNSB; MLVF; TUSK; LOAN; MNTX; MTEX; MNKD; MARA; MCHX; MRIN; MARPS; MRNS; MRKR; MRLN; MBII; MMLP; MCFT; MTRX; MATW; MAXN; MDCA; MDJH; MDRR; MFIN; MDVL; MDIA; MDNA; MNOV; MDGS; MDWD; MEIP; MGTX; MTSL; MBWM; MERC; MBIN; MFH; MREO; EBSB; VIVO; MRBK; MACK; MRUS; MESA; MTCR; METX; MCBS; MGPI; MBOT; MVIS; MICT; MPB; MTP; MCEP; MBCN; MSBI; MSVB; MOFG; MIST; MLND; MDXG; MNDO; MIND; NERV; YGMZ; MGEN; MIRM; MSON; AVO; MITK; MMAC; MTC; MOGO; MWK; MKD; MTEM; MBRX; MKGI; MCRI; MGI; MNPR; MRCC; MORF; MOSY; MPAA; MOTS; MOXC; MTBC; MTSC; GRIL; MBIO; MVBF; MYSZ; MYRG; NBRV; NAKD; NNDM; NAOV; NH; NSSC; NATH; NKSH; NCMI; NESR; NHLD; NSEC; NWLI; NAII; NHTC; NATR; NTUS; NMCI; NCSM; NMRD; NGMS; NLTX; NEON; NEOS; NVCN; NEPH; NEPT; UEPS; NETE; NTWK; NBSE; NRBO; NURO; STIM; NBEV; NEWA; NEWT; NXTC; NEXT; NODK; NICK; NCBS; NISN; NNBR; NBLX; NDLS; NSYS; NBN; NTIC; NFBK; NRIM; NWPX; NWFL; NVFY; NOVN; NVUS; NCNA; NUZE; NVEE; NVEC; NXTD; NYMX; OIIM; OVLY; OCSL; OCSI; OMP; OAS; OBLN; OBSV; OBCI; OPTT; OFED; OCGN; OCUP; ODT; OMEX; OFS; OCCI; OVBC; OPOF; OSBC; ZEUS; OMER; ONCY; ONTX; ONCR; ONCS; ONCT; OSS; OSPN; OSW; ONEW; OTRK; OPBK; OPGN; OPNT; OPRT; OPT; OBAS; OCC; OPRX; OPHC; OPTN; ORMP; OSUR; ORBC; OEG; ORTX; OGI; ORGO; ONVO; ORGS; SEED; OBNK; OESX; ORPH; ORRF; OFIX; KIDS; OSMT; OSN; OTEL; OTIC; OTLK; OVID; OXBR; OXFD; OXLC; OXSQ; OYST; PFIN; PTSI; PEIX; PMBC; PAE; PRFX; PBLA; PAND; PANL; PRTK; PCYG; PKBK; PKOH; PTNR; PTRS; PBHC; PNBK; PATI; PAVM; PAYS; PCB; PCSB; PCTI; PDFS; PDLI; PDLB; PDSB; PGC; PVAC; PFLT; PNNT; PWOD; PEBO; PEBK; PFIS; PRCP; PRDO; PSHG; PFMT; PERI; PESI; PPIH; PETQ; PETS; PTPI; PFSW; PHAS; PAHC; PHIO; PLAB; PHUN; PICO; PLL; PIRS; PME; PT; PBFS; PPSI; PXLW; PLYA; PLRX; PLBC; PSTI; PSTV; PLXP; PCOM; POLA; PTE; PYPD; PTMN; PSTX; PBPB; POWL; PBTS; PWFL; PRPO; DTIL; POAI; PFBC; PLPC; PFBI; PFC; SQFT; PBIO; PRVL; PRGX; PNRG; PRTH; PCSA; PDEX; IPDN; PFHD; PFIE; PROF; PROG; PRPH; PRQR; PTGX; TARA; PTVCA; PTVCB; PTI; PRTA; PRVB; PVBC; PROV; PBIP; PMD; PHCF; PULM; PLSE; PBYI; PCYO; PUYI; PXS; QK; QADB; QCRH; QIWI; QLGN; QMCO; QRHC; QH; QUIK; QUMU; QTNT; QTT; RRD; RADA; RDCM; RADI; RDUS; RDNT; METC; RAND; RNDB; RAPT; RAVE; RBB; RICK; RCMT; RDI; RDIB; RNWK; RCON; REPH; RRBI; RRGB; RDVT; RDHL; REED; RGLS; REKR; RBNC; RELV; RLMD; MARK; RNLX; KRMD; RBCAA; FRBK; REFR; RSSS; RESN; RGP; RETO; RWLK; RZLT; RFIL; RGCO; RBKB; RIBT; RELL; RMBI; RIGL; RNET; RMNI; RIOT; REDU; RVSB; RIVE; RMRM; RMTI; RCKY; RMCF; RBCN; RUBY; RUHN; RMBL; RUTH; STBA; SANW; SFET; SGA; SLRX; SALM; SAL; STSA; SVRA; SBFG; SCSC; SMIT; SCHN; SCHL; SJ; SCPL; SCPH; WORX; SCYX; SEAC; SHIP; SPNE; EYES; SECO; SNFCA; SEEL; SLCT; SIC; SELB; SLS; LEDS; SNCA; SENEA; SENEB; SNES; AIHS; SRTS; SQBG; SREV; SESN; SVBI; SGBX; SGOC; SMED; SHSP; SFT; PIXY; TYHT; SCVL; SHBI; SSTI; SIBN; SIEB; SIEN; BSRR; SRRA; SWIR; SIFY; SIGA; SGTX; SGLB; SGMA; SLN; SILC; SBTX; SAMG; SSNT; SINO; SVA; SINT;

SIOX; SYTA; EDTK; SGH; SND; SMBK; SWBI; SMSI; SMID; SMTX; TLMD; SCKT; SOHU; SLRC; SUNS; SLNO; SLGL; SLDB; SNGX; SOLY; SONM; SONN; SNOA; SOHO; SFBC; SMMCU; SPFI; SFST; SMBC; SONA; SP; SGRP; SPKE; SPTN; SPPI; SPRO; ANY; SPI; STXB; SPOK; SPWH; FUND; SPRB; SRAX; STAF; STND; SBLK; STFC; MITO; GASS; STCN; STEP; SBT; STRL; SYBT; BANX; SSKN; SSYS; STRT; STRS; STRM; SBBP; SUMR; SMMF; SSBI; SMMT; WISA; SNDE; SNDL; SNSS; STKL; SUNW; SLGG; SPCB; GIK; SGC; SPRT; SURF; SRGA; SRDX; SSSS; STRO; SWKH; SYNC; SYNL; SNCR; SNDX; SYBX; SYPR; SYRS; TTOO; TRHC; TCMD; TAIT; TLC; TANH; TAOP; TEDU; TH; TARS; TATT; TTCF; TAYD; TSHA; CGBD; GLG; PETZ; TCCO; TGLS; TELA; TNAV; TLGT; TELL; TENX; TBNK; TESS; TFFP; WTER; ANDE; TBBK; BPRN; CHEF; TCFC; DXYN; XONE; FBMS; FLIC; HCKT; CUBA; INTG; JYNT; LOVE; OLB; STKS; PECK; SHYF; YORW; NCTY; TXMD; THTX; THMO; THRY; TSBK; TIPT; TITN; TMDI; TTNP; TVTY; TLSA; TOMZ; TNXP; TOPS; TRCH; TRMD; TBLT; TCON; TACT; TRNS; TGA; TMDX; TA; TZOO; TIG; TRMT; TRVN; TRVI; TPCO; TCDA; TRIB; TSC; TSCAP; TRVG; TRUE; TRST; MEDS; TSRI; TC; TCX; TOUR; HEAR; TWIN; TYME; USCR; USEG; GROW; USAU; USWS; UCL; UK; UFPT; ULBI; UNAM; UNB; UBCP; UBOH; UFCS; UIHC; UBFO; USLM; UG; UNTY; UBX; UEIC; ULH; USAP; UVSP; TIGR; UONE; UONEK; MYT; URGN; UROV; USAT; USAK; USIO; UTMD; UTSI; UXIN; VCNX; VALU; VNDA; VREX; VBLT; VXRT; VBIV; VECO; VERO; VRA; VSTM; VERB; VERY; VRME; VERI; VRNA; VRCA; VTNR; VERU; VMD; VRAY; VKTX; VBFC; VFF; VLGEA; BBIG; VIOT; VIRC; VTSI; BBC; BBP; VMAR; VISL; VTGN; VTRU; VIVE; VVPR; VJET; VOXX; VYGR; VSEC; VTVT; VUZI; VYNE; WAFU; WTRH; WSG; WASH; WSBF; WTRE; WVE; WSTG; WTBA; WNEB; WPRT; WWR; WEYS; WHLR; WHF; FREE; WHLM; WVVI; WLDN; WLFC; WIMI; WINT; WINA; WETF; WKEY; WRLD; WRAP; WVFC; XFOR; XBIT; XELB; XBIO; XENE; XERS; XOMA; XSPA; XTLB; XNET; YTRA; YTEN; YRCW; CTIB; YJ; ZAGG; ZCMD; ZIOP; ZIXI; ZKIN; ZSAN; ZVO; ZUMZ; CNET; ZYNE; ZYXI; GOED; XXII; IAF; AEF; FCO; ACU; ATNM; AE; ACY; UAVS; AGE; AIRI; AXU; AAU; APT; AAMC; AMBO; DIT; AMS; USAS; AMPE; ANVS; ARMP; AINC; AWX; ASM; BTN; BCV; BHB; BRN; BATL; BIOX; PHGE; BGI; BKTI; BDR; BRBS; BRG; DMF; CMCL; CEI; CANF; YCBD; CVM; CET; LEU; CVR; CPHI; CKX; GLV; GLQ; GLO; COHN; CIX; LODE; CDOR; MCF; CMT; CRMD; CRF; CLM; CVU; CIK; DHY; CRHM; CTO; CTEK; DXR; VCF; VFL; VMM; DLA; DNN; DSS; DPW; DXF; GRF; EVM; CEV; EIM; ENX; EVY; ELMD; ELLO; ECF; EMAN; MSN; EMX; UUUU; ENSV; ELA; ESP; EVBN; EVI; EPM; EXN; FEN; BDL; FSI; FTF; FSP; FRD; FTSI; FURY; GAU; GGN; JOB; GSAT; GORO; GSV; AUMN; GSS; GV; GLDG; GDP; GTE; GPL; AIM; HMG; HUSA; IBIO; IMH; IOR; IGC; INDO; INFU; IHT; NSPR; ITRG; INS; THM; INTT; INUV; VKI; ISR; ISDR; ITP; KLR; KIQ; LSF; LGL; LCTX; MHH; MTNB; MMX; MTA; MXC; MLSS; MYO; NNVC; NAVB; NTIP; NBW; NHS; NML; NBH; NBO; NRO; GBR; NEN; NXE; NAK; NOG; NBY; NTN; NES; OBLG; OCX; OGEN; PTN; PZG; PED; HNW; PLAG; PLG; PLM; PW; PLX; RLGT; RHE; RCG; RVP; REI; SACH; SNMP; SENS; SVT; SMTS; SIF; XPL; LOV; STXS; SSY; SDPI; SYN; TKAT; TRX; TGB; TGC; GLU; GGO; TMBR; TAT; TRXC; TMQ; TPHS; TRT; UFAB; UAMY; UUU; URG; UEC; VGZ; VNRX; VOLT; EAD; ERC; ERH; WRN; WYY; WTT; XTNT; ZDGE; ZOM;

WBAI; AHC; AGD; AWP; ACP; JEQ; AOD; ACEL; ACCO; PEO; AGRO; ASIX; AVK; AENZ; AWF; AIO; CBH; NCV; NCZ; ACV; NIE; ALTG; AMBC; AXL; AFGC; ARL; AVD; AMRX; AXR; ANH; AIF; ASC; ARDC; AGX; AAIC; AHH; AFI; AHT; ASPN; ATTO; BW; BGH; BCSF; BBAR; BLX; BBDC; MPV; BNED; BZH; BRBR; BHE; BHLB; BGSF; BH; BGIO; BFZ; CII; BHK; DSU; BGR; EGF; BFO; BGT; BOE; BME; BAF; BKT; BGY; BKN; BTA; BZM; MHE; MUI; MUA; BKK; BBK; BBF; BYM; BFK; BLE; MUC; MUH; MFL; MUJ; MHN; MUE; MVT;

MYC; MCA; MYD; MYF; MFT; MIY; MYJ; MYN; MPA; MQT; MYI; MQY; BNY; BSE; BFY; BCX; BUI; BHV; BGB; BGX; BSL; APRN; BXG; BVH; BXC; DCF; DHF; DMB; DSM; BCEI; BQ; BORR; BPT; BHR; BWG; LND; MNRL; BEDU; BKD; BRT; BBW; CPE; CSU; CMO; CSLT; CTT; IGR; CEL; CPAC; CEPU; ECOM; CHRA; CLDT; CMCM; CHMI; DL; CHN; CGA; COE; CYD; CBB; CINR; BLW; CVEO; CCO; CEM; CLW; CLPR; CNF; FOF; LDP; MIE; RFI; CXE; CIF; CXH; CMU; CLNC; STK; CCM; CCR; CEIX; TCS; CTRA; CTK; CXW; CPLG; CAAP; CMRE; CPF; CAPL; CULP; CURO; SRV; SZC; CUBI; UAN; CELP; DAC; DEX; DDF; DBI; DESP; DHX; DHT; DSSI; DSX; DBD; DFIN; DRD; DS; DCO; DSE; DTF; DUC; DPG; DLNG; ECC; EOI; EHT; ETX; EOT; EVN; ETJ; EFR; EVF; EVG; ETO; ETB; EXD; ELVT; EFC; EEX; EIG; EDN; EXK; ERF; EBF; ENVA; ETM; EVC; ENZ; EQS; ESGC; EEA; XAN; EXPR; EXTN; SFUN; FPI; AGM; FMN; FMO; FINV; FSLF; FFA; FMY; FDEU; FIF; FSD; FEI; FPL; FIV; FCT; FGB; FEO; FPH; DFP; PFD; PFO; FLC; FLNG; FTK; FET; FBM; FEDU; FC; FI; RESI; GCV; GGZ; GGT; GBL; GNT; GCI; GLOG; GATO; GNK; GCO; GNE; GPRK; GMRE; GLP; GSL; GRC; GPX; GHM; GPMT; AJX; GHL; SUPV; GTT; GGM; GPM; GOF; GBAB; GHLD; HBB; HNGR; HVT; HCHC; HCI; HLX; HRTG; HESM; HEXO; PCF; HGLB; HFRO; HPR; HIL; HMLP; HZN; HMI; HCFT; HY; IDT; IMAX; ICD; IHC; IFN; INSI; INSW; IPI; IVC; VBF; VCV; VTA; IHIT; IHTA; VLT; IVR; OIA; VMO; VKQ; VPV; IQI; VVR; VTN; VGM; IIM; IRET; IVH; JAX; JOF; JT; JMP; BTO; HEQ; JHS; JHI; HPF; HPI; HPS; HTD; HTY; JE; LRN; KYN; KMF; KFS; KIO; KNL; KF; SCX; LAIX; LCI; LPI; LGI; LEJU; ASG; LITB; SCD; LOMA; LXU; LUB; LXFR; MGU; MCN; MX; MMD; MTW; MCS; MPX; HZO; MLP; MEC; MBI; MUX; MTL; MCC; MDLY; MDP; MTR; MSB; MCB; MXE; MXF; MCR; MGF; MMT; MFM; MFV; AMPY; MLR; MIXT; MOGU; CAF; MSD; EDD; IIF; MOV; MRC; MVF; MZA; MVO; MVC; MYE; NBR; NTP; NPK; NGS; NGVC; NRP; NTZ; NLS; NVGS; NNA; NMM; NPTN; NSCO; NTST; HYB; NWHM; SNR; NREF; NHF; NEX; NOA; NRT; DNOW; NUW; NAZ; NKX; NCB; NCA; JCE; JHAA; JHB; JCO; JQC; JDD; DIAX; JEMD; JFR; JRO; NKG; JGH; NXC; NXN; NID; NMY; NMT; NUM; NMS; JLS; JMM; NHA; NMI; NJV; NXJ; NYV; NNY; NUO; NPN; NQP; JPC; JPT; JPI; JRI; JRS; SPXX; NXP; NXQ; NXR; NSL; JSD; NBB; JTD; JTA; NIQ; OII; OCN; OFG; OIS; ODC; OLP; OOMA; OPY; OEC; ORN; OSG; PKE; PRTY; PBF; PBFX; PBT; PVL; PRT; GHY; ISD; FENG; DNK; PHX; PCQ; PCK; PZC; PCM; PCN; NRGX; PHK; PKO; PFL; PFN; PMF; PML; PMX; PNF; PNI; PYN; RCS; PHT; MAV; MHI; AGS; PLYM; PSTL; PDS; APTS; PGZ; PRA; AAN; PMM; PIM; PMO; PZN; QEP; NX; QD; RRD; RMED; RFL; RNGR; RYAM; RLH; RGS; RENN; RFP; RVI; REVG; RMM; RMI; RSF; RGT; RMT; RYB; RYI; SBR; SFE; SMM; SJT; SAR; BFS; STNG; KTF; KSM; SRL; SCU; CKH; SMHI; WTTR; SQNS; SFL; SBOW; SOI; SOR; SPE; SRLP; SII; SQZ; SXI; SGU; SRT; SPLP; SCM; EDF; EDI; STON; SPH; SMLP; SXC; SWZ; TWN; TALO; TSI; TISI; TK; TNK; TRC; HQH; THQ; HQL; THW; TDF; TEI; GIM; TTI; TGH; CEE; GRX; GDL; THR; TPRE; TDW; TLYS; TMST; NDP; TEAF; NTG; TTP; TPZ; TSQ; TRTX; TCI; TGS; TREC; TG; TPVG; GTS; TGI; TBI; TNP; TUFN; TPB; TPC; SLCA; USX; UMH; UFI; UTL; UHT; UVE; UTI; UBA; UBP; USDP; EGY; VHI; VAPO; VEC; VNTR; VRTV; VRS; VCIF; VIAO; VVI; VNCE; VHC; VGI; ZTR; VPG; VIST; IAE; IHD; IGA; IGD; IID; IRR; WTI; WNC; HCC; WPG; WEA; EMD; GDO; EHI; HIX; HIO; HYI; SBI; IGI; PAI; MMU; WMC; DMO; MTT; MHF; MNP; WIW; WIA; WLKP; WHG; WSR; WLL; XYF; XFLT; XIN; YRD; YI; PIH; ATNF; BCOW; FCCY; KRKR; ETNB; NMTR; JFU; ABEO; AXAS; ABST; ACIU; ACST; AXDX; ARAY; ACRX; ACHV; ACRS; ACNB; ACOR; AFIB; ADMS; ADMP; ADAP; ADXN; AEY; ADIL; ACET; ADTX; ADMA; ADTN; ADES; ADXS; AEGN; AGLE; AEHR; AMTX; AERI; ARPO; AIH; AEZS; AEMD; AFMD; AGEN; AGRX; AGYS; AGMH; AGFS; AIKI; ALRN; AIRG; AKTX; AKBA; AKRO; AKER; AKUS; AKTS; AKU; ALSK;

ALBO; ALDX; ALRS; ALCO; ALGS; ALIM; ALYA; ALJJ; ABTX; ALNA; ARLP; AESE; AHPI; AMOT; ALLT; AOSL; ATEC; ALPN; ATHE; ALTM; AMAL; AMRK; AMBC; AMTB; AMTBB; AMRH; ATAX; AFIN; AMNB; AOUT; APEI; AREC; AMRB; AMSWA; AMSC; AVCT; CRMT; ASRV; ATLO; AMST; POWW; AMPH; AMYT; ASYS; AMRS; ANAB; AVXL; ANCN; ANGO; ANIP; ANIK; ANIX; ANNX; ANPC; ATRS; AEHL; ATEX; APOG; APEN; AINV; AMEH; APDN; AGTC; AAOI; APLT; AUVI; APRE; APVO; APTX; APM; APTO; APYX; AQMS; AQB; AQST; ARAV; ABUS; ABIO; RKDA; FUV; ARDX; ARKR; AROW; ARTL; ARTNA; ARTW; APWC; ASLN; ASPU; AWH; ASMB; ASRT; ATRO; ASTC; AACG; ATHX; ATHA; ATIF; AAME; ACBI; ATLC; ATCX; ATNI; ATOS; BCEL; AUBN; AUDC; AEYE; AUTL; AVDL; AVCO; ATXI; AVEO; AVNW; CDMO; AVGR; RCEL; AVRO; AWRE; ACLS; AXLA; AXGN; AXTI; AYLA; AYRO; AYTU; AZYO; AZRX; RILY; BOSC; BFC; BOCH; BMRC; BKSC; BOTJ; BSVN; BFIN; BWFG; DFVL; DFVS; TAPR; BBSI; BSET; BXRX; BCML; BCBP; BEEM; BBGI; BELFA; BELFB; BLPH; BLCM; BNFT; BNTC; BRY; XAIR; BYSI; BCYC; BGFV; BASI; BCDA; BIOC; BDSI; BDSX; BFRA; BHTG; BKYI; BLRX; BMRA; BNGO; BVXV; BPTH; BSGM; BIVI; BTBT; BJRI; BKCC; TCPC; BLNK; BCOR; BLBD; BHAT; BLCT; BKEP; BSBK; BNSO; BIMI; BRQS; BOMN; BPFH; BOXL; BCLI; BWAY; BBI; BDGE; BLIN; BWB; BRID; BCOV; BYFC; BWEN; BROG; BPYU; BRKL; BMTC; BSQR; BTAQU; BFST; CFFI; CABA; CDZI; CSTE; CLBS; CHW; CGO; CALB; CALA; CALT; CLMT; CLXT; CMBM; CATC; CAC; CAMT; CGIX; CPHC; CBNK; CCBG; CPLP; CSWC; CPTA; CAPR; CSTR; CPST; CRDF; PRTS; TAST; CARV; CASI; CASS; CTRM; CATB; CBIO; CPRX; CBFV; CBAT; CBMB; CBTX; CECE; CELC; CLDX; APOP; CLRB; CBMG; CLSN; CYAD; CETX; CDEV; CNTG; CVCY; CNBKA; CNTY; CRNT; CERC; CEVA; CFBK; CSBR; CTHR; CHEK; CMPI; CKPT; CEMI; CHMG; CHFS; CHMA; CSSE; PLCE; CMRX; CAAS; CCRC; JRJC; HGSH; CIH; CJJD; CLEU; CHNR; CREG; SXTC; CXDC; PLIN; KDNY; IMOS; COFS; CDXC; CHUY; CDTX; CMCT; CNNB; CIDM; CTRN; CTXR; CZNC; CZWI; CIZN; CIVB; CLAR; CLNE; CLSK; CLFD; CLRO; CLPT; CLSD; CLIR; CBLI; CLVS; CLPS; CCNE; CNSP; CCB; COCP; CODX; CDAK; CVLY; JVA; COGT; CWBR; CLCT; CLGN; CBAN; CSCW; CMCO; CVGI; ESXB; CFBI; CTBI; CWBC; CGEN; CPSI; CTG; SCOR; CHCI; CMTL; CNCE; BBCP; CDOR; CFMS; CNFR; CNOB; CNSL; CWCO; CPSS; CFRX; CRBP; CLDB; CRVS; CPAH; ICBK; CVLG; COWN; CPSH; CRAI; CRTD; CREX; CCAP; CRESY; CXDO; CRNX; CCRN; CFB; CRWS; CCLP; CSPI; CTIC; CPIX; CMLS; CURI; CRIS; CUTR; CVV; CYBE; CYCC; CYCN; CBAY; CYRN; CTMX; CTSO; DJCO; DAKT; DRIO; DSKE; DAIO; DTSS; DTEA; DWSN; DBVT; DCTH; DENN; DMTK; DXLG; DSWL; DMAC; DHIL; DFFN; DGII; DMRC; EQOS; DRAD; DGLY; DCOM; DRTT; DLHC; DOGZ; DLPN; DGICA; DGICB; DMLP; LYL; DSPG; DLTH; DUOT; DRRX; DXPE; DYAI; DYNT; DVAX; DYN; DZSI; EBMT; EGLE; EGRX; EML; EDAP; EDSA; EGAN; EIGR; EKSO; ECOR; ESBK; ELOX; ELTK; ELYS; EMCF; EMKR; ENTA; NDRA; EFOI; ERII; ENLV; ENOB; ETTX; ENTX; EBTC; EOSE; EPSN; EQBK; ERYP; ESCA; ESPR; GMBL; ESSA; EPIX; ESTA; VBND; VUSE; CLWT; EDRY; ESEA; EVLO; EVK; MRAM; EVFM; EVGN; EVOK; EOLS; EVOL; XGN; XELA; EXFO; XCUR; EXTR; EYEG; EYEN; EYPT; EZPW; FLMN; FANH; FMAO; FMNB; FAMI; FTHM; FBSS; FNHC; FENC; GSM; FFBW; FDBC; FDUS; FRGI; FISI; FBNC; FNLC; FRBA; FBIZ; FCAP; FCBP; FCBC; FCCO; FCRD; THFF; FFNW; FFWM; FGBI; INBK; FMBH; FXNC; FNWB; FSFG; FSEA; FUNC; FUSB; MYFW; SVVC; FPRX; FVE; FLXN; ESGG; LKOR; QLC; FPAY; FLXS; FLNT; FLDM; FFIC; FNCB; FHTX; FONR; FRSX; FORR; FBRX; FBIO; FWP; FOSL; FRAF; FRLN; FEIM; FRPH; FSBW; FSTX; FTEK; FULC; FLL; FNKO; FUSN; FTFT; FFHL; FVCB; WILC; GTHX; GALT; GLTO; GRTX; GLMD; GMDA; GNSS; GENC; GFN; GNFT; GNMK; GNCA; GNPX; GEOS; GOVX; GABC; GERN; GEVO; GIGM; GLBZ; GBLI; GWRS; GLBS;

GLYC; GLNG; GMLP; GDEN; GOGL; GTIM; GOSS; GECC; GEC; GLDD; GSBC; GPP; GPRE; GCBC; GTEC; GNLN; GLRE; GRNQ; GSKY; GDYN; GSUM; GRIF; GRTS; GRPN; GVP; GSIT; GTYH; GNTY; GFED; GHSI; GIFI; GURE; GWGH; HOFV; HNRG; HJLI; HAFC; HAPP; HCDI; HLIT; HROW; HBIO; HCAP; HWKN; HWBK; HAYN; HBT; HSTM; HTBX; HSII; HSDT; HMTV; HNNA; HEPA; HTBK; HFWA; HGBL; HCCI; HX; HFEN; HFFG; HIBB; HPK; HIHO; HIFS; HQI; HSTO; HMNF; HOLI; HBCP; HFBL; HMST; HTBI; FIXX; HOFT; HBNC; HRZN; HOTH; HMHC; HWCC; HBMD; HTGM; HUSN; HSON; HDSN; HUIZ; HGEN; HURC; HBP; HVBC; HYMC; HYRE; IIIV; ICAD; ICCH; ICHR; ICLK; IPWR; IDEX; IDYA; INVE; IDRA; IEC; IESC; IROQ; IFMK; IHRT; IKNX; IMAC; ISNS; IMRA; IMBI; IMTX; IMMR; ICCC; IMUX; IMNM; IMRN; IMMP; IMV; IBCP; INFI; IFRX; IEA; IMKTA; INM; INMB; IPHA; INOD; ISSC; INGN; INZY; INPX; ISIG; INSE; IIIN; NTEC; IMTE; IDN; IGIC; IMXI; IDXG; XENT; IVAC; IIN; INTZ; ISTR; ICMB; ITIC; NVIV; INVO; IRMD; IRIX; IRCP; ITMR; ITI; ITRM; ITRN; ISEE; IZEA; JAGX; JAKK; JRSH; JCTCF; JFIN; JBSS; JOUT; JNCE; JUPW; KDMN; KXIN; KALA; KLDO; KALV; KMDA; KNDI; KSPN; KZIA; KBSF; KRNY; KELYA; KELYB; KFFB; KEQU; KTCC; KZR; KFRC; KE; KBAL; KINS; KTRA; KRBP; KTOV; KLXE; KOPN; KOSS; KWEB; KBNT; KRUS; KVHI; FSTR; LJPC; LSBK; LBAI; LNDC; LMRK; LTRN; LNTH; LTRX; LRMR; LCNB; LPTX; LEGH; LMAT; LNSR; LEVL; LXRX; LLIT; LTRPA; LCUT; LFVN; LWAY; LTBR; LPTH; LMB; LLNW; LMST; LMNL; LMNR; LINC; LGHL; LPCN; LIQT; YVR; LQDA; LQDT; LIVX; LXEH; LIXT; LIZI; LMFA; LMPX; LOGC; LORL; LYTS; LUMO; LKCO; LBC; MCBC; MFNC; MGTA; MGIC; MGYR; MHLD; MNSB; MLVF; MNTX; MTEX; MNKD; MCHX; MRIN; MARPS; MRNS; MRKR; MRLN; MBII; MMLP; MCFT; MTRX; MATW; MAXN; MDCA; MDJH; MDRR; MFIN; MDVL; MDIA; MDNA; MNOV; MDGS; MDWD; MEIP; MGTX; MTSL; MBWM; MERC; MBIN; MFH; MREO; EBSB; VIVO; MRBK; MRUS; MTCR; METX; MCBS; MGPI; MBOT; MVIS; MICT; MPB; MTP; MCEP; MBCN; MSBI; MSVB; MOFG; MLND; MDXG; MNDO; NERV; YGMZ; MGEN; MIRM; MSON; MITK; MMAC; MTC; MOGO; MWK; MKD; MTEM; MBRX; MKGI; MCRI; MGI; MNPR; MRCC; MORF; MOSY; MPAA; MOXC; MTBC; MTSC; GRIL; MBIO; MVBF; MYSZ; MYRG; NBRV; NAKD; NNDM; NAOV; NSSC; NATH; NKSH; NCMI; NESR; NHLD; NSEC; NWLI; NAII; NHTC; NATR; NTUS; NMCI; NCSM; NMRD; NGMS; NLTX; NEOS; NVCN; NEPH; NEPT; UEPS; NETE; NTWK; NBSE; NRBO; NURO; NBEV; NEWA; NXTC; NODK; NCBS; NISN; NNBR; NBLX; NDLS; NSYS; NBN; NTIC; NFBK; NRIM; NWPX; NWFL; NVFY; NOVN; NVUS; NCNA; NUZE; NVEE; NVEC; NXTD; NYMX; OIIM; OVLY; OCSL; OCSI; OMP; OBLN; OBSV; OBCI; OPTT; OFED; OCGN; OCUP; ODT; OMEX; OFS; OCCI; OVBC; OPOF; OSBC; ONCY; ONTX; ONCR; ONCS; ONCT; OSS; OSPN; OSW; ONEW; OTRK; OPBK; OPGN; OPNT; OPRT; OBAS; OCC; OPRX; OPHC; OPTN; ORMP; OSUR; ORBC; OEG; ORTX; OGI; ORGO; ONVO; ORGS; OBNK; OESX; ORPH; ORRF; OFIX; OSMT; OSN; OTEL; OTLK; OXBR; OXFD; OXLC; OXSQ; OYST; PFIN; PTSI; PEIX; PMBC; PAE; PRFX; PBLA; PAND; PANL; PRTK; PCYG; PKBK; PKOH; PTNR; PTRS; PBHC; PNBK; PATI; PAVM; PCSB; PCTI; PDLI; PDLB; PDSB; PGC; PVAC; PFLT; PNNT; PWOD; PEBO; PEBK; PFIS; PRCP; PRDO; PSHG; PFMT; PESI; PPIH; PETQ; PTPI; PFSW; PHAS; PAHC; PHIO; PLAB; PHUN; PICO; PLL; PIRS; PME; PBFS; PPSI; PXLW; PLYA; PLRX; PLBC; PSTI; PSTV; PLXP; PCOM; PTE; PYPD; PTMN; PSTX; PBPB; POWL; PBTS; PWFL; PRPO; DTIL; POAI; PFBC; PLPC; PFBI; SQFT; PBIO; PRVL; PRGX; PNRG; PRTH; PCSA; PDEX; IPDN; PFHD; PFIE; PRPH; PRQR; PTGX; PTVCA; PTVCB; PTI; PRTA; PRVB; PVBC; PBIP; PMD; PHCF; PULM; PLSE; PBYI; PCYO; PUYI; PXS; QK; QADB; QCRH; QIWI; QLGN; QMCO; QRHC; QH; QUIK; QUMU; QTNT; QTT; RRD; RADA; RDCM; RADI; RDUS; RDNT; METC; RNDB; RBB; RCMT; RDI; RDIB; RNWK; RCON; REPH; RRBI; RRGB; RDVT; RDHL;

RGLS; REKR; RBNC; RELV; RLMD; RNLX; KRMD; RBCAA; FRBK; REFR; RSSS; RESN; RGP; RETO; RWLK; RZLT; RFIL; RGCO; RBKB; RIBT; RELL; RMBI; RIGL; RNET; RMNI; REDU; RVSB; RMRM; RMTI; RCKY; RMCF; RBCN; RUHN; RMBL; STBA; SANW; SFET; SGA; SLRX; SALM; STSA; SVRA; SBFG; SCSC; SMIT; SCHN; SCHL; SCPL; SCPH; WORX; SCYX; SEAC; SPNE; SECO; SNFCA; SLCT; SELB; SLS; LEDS; SNCA; SENEA; SENEB; SNES; AIHS; SRTS; SQBG; SREV; SESN; SVBI; SGBX; SGOC; SMED; SHSP; SFT; PIXY; TYHT; SCVL; SHBI; SSTI; SIBN; SIEB; SIEN; BSRR; SRRA; SWIR; SIFY; SIGA; SGTX; SGLB; SGMA; SLN; SILC; SBTX; SAMG; SSNT; SINO; SVA; SINT; SIOX; SYTA; EDTK; SGH; SND; SMBK; SWBI; SMSI; SMID; SMTX; TLMD; SCKT; SOHU; SLRC; SLNO; SLGL; SLDB; SNGX; SOLY; SONM; SONN; SNOA; SFBC; SMMCU; SPFI; SFST; SMBC; SONA; SGRP; SPKE; SPTN; SPPI; SPRO; SPI; STXB; SPOK; SPWH; SPRB; SRAX; STAF; STND; SBLK; STFC; MITO; GASS; STCN; SBT; STRL; SYBT; BANX; SSKN; SSYS; STRT; STRS; STRM; SBBP; SUMR; SMMF; SSBI; SMMT; WISA; SNDE; SNDL; SNSS; STKL; SUNW; SLGG; SPCB; SGC; SPRT; SRGA; SRDX; SSSS; STRO; SWKH; SYNL; SNCR; SNDX; SYBX; SYPR; SYRS; TTOO; TRHC; TCMD; TAIT; TAOP; TEDU; TATT; TTCF; TAYD; TSHA; CGBD; GLG; PETZ; TCCO; TGLS; TELA; TNAV; TLGT; TENX; TBNK; TFFP; WTER; ANDE; TBBK; BPRN; TCFC; DXYN; XONE; FBMS; FLIC; HCKT; INTG; JYNT; OLB; STKS; SHYF; YORW; NCTY; TXMD; THTX; THMO; THRY; TSBK; TIPT; TITN; TMDI; TTNP; TVTY; TLSA; TOMZ; TNXP; TRCH; TRMD; TBLT; TCON; TRNS; TGA; TMDX; TZOO; TIG; TRMT; TRVN; TRVI; TPCO; TCDA; TRIB; TSC; TSCAP; TRVG; TRST; TSRI; TCX; TYME; USCR; USEG; USAU; USWS; UCL; UFPT; ULBI; UNAM; UNB; UBCP; UBOH; UFCS; UIHC; UBFO; USLM; UG; UNTY; UBX; UEIC; ULH; USAP; UVSP; TIGR; UONE; UONEK; MYT; URGN; UROV; USAT; USAK; USIO; UTMD; UTSI; UXIN; VCNX; VALU; VNDA; VREX; VBLT; VXRT; VBIV; VECO; VERO; VRA; VSTM; VRME; VERI; VRNA; VRCA; VTNR; VERU; VMD; VRAY; VKTX; VBFC; VFF; VLGEA; BBIG; VIOT; VIRC; VTSI; BBP; VMAR; VISL; VTGN; VTRU; VVPR; VJET; VOXX; VYGR; VSEC; VTVT; VUZI; VYNE; WAFU; WTRH; WSG; WSBF; WTRE; WVE; WSTG; WTBA; WNEB; WPRT; WWR; WEYS; WHLR; WHLM; WVVI; WLDN; WLFC; WIMI; WINT; WINA; WETF; WKEY; WRLD; WVFC; XFOR; XBIT; XELB; XBIO; XENE; XERS; XOMA; XSPA; XTLB; XNET; YTRA; YTEN; YRCW; CTIB; YJ; ZAGG; ZCMD; ZIOP; ZIXI; ZKIN; ZSAN; ZVO; ZUMZ; CNET; ZYNE; ZYXI; GOED; IAF; AEF; FCO; ACU; ATNM; ACY; UAVS; AIRI; AXU; AAU; AAMC; AMS; USAS; AMPE; ANVS; ARMP; AINC; AWX; ASM; BTN; BCV; BHB; BRN; BATL; BIOX; PHGE; BGI; BKTI; BDR; BRBS; BRG; DMF; CMCL; CEI; CANF; YCBD; CVM; CET; CVR; CPHI; CKX; GLV; GLQ; GLO; COHN; CIX; CDOR; MCF; CMT; CRMD; CRF; CLM; CVU; CIK; DHY; CRHM; CTO; CTEK; DXR; VCF; VFL; VMM; DLA; DNN; DSS; DPW; DXF; GRF; EVM; CEV; EIM; ENX; EVY; ELMD; ELLO; ECF; EMAN; MSN; EMX; UUUU; ENSV; ELA; EVBN; EVI; EPM; EXN; FSI; FTF; FSP; FRD; FTSI; GAU; GGN; GSAT; GORO; GSV; AUMN; GSS; GV; GLDG; GPL; HMG; HUSA; IBIO; IMH; IOR; IGC; INDO; INFU; IHT; NSPR; ITRG; THM; INTT; INUV; VKI; ISR; ISDR; ITP; KLR; KIQ; LSF; LGL; LCTX; MHH; MTNB; MMX; MTA; MXC; MLSS; MYO; NNVC; NAVB; NTIP; NBW; NHS; NML; NBH; NBO; NRO; GBR; NEN; NXE; NAK; NBY; NTN; NES; OBLG; OCX; OGEN; PTN; PZG; HNW; PLAG; PLG; PLM; PLX; RLGT; RHE; RCG; RVP; REI; SACH; SNMP; SVT; SMTS; SIF; XPL; LOV; STXS; SSY; SDPI; TKAT; TRX; TGB; TGC; GLU; GGO; TMBR; TRXC; TMQ; TPHS; TRT; UFAB; UAMY; UUU; URG; UEC; VGZ; VNRX; EAD; ERC; ERH; WRN; WYY; WTT; XTNT; ZDGE; ZOM RX.TO; TTR.TO; SFD.TO; SCR.TO; PTG.TO; USO.TO; DAN.TO; TGM.TO; ACS.TO; M.PR.A; CKG.TO; APH.TO; ENW.TO; MJS.TO; SY.TO; NMX.TO; EYC.TO; MT.TO; PHO.TO; TIC.TO; SOG.TO; QHR.TO; AFM.TO; CUU.TO; POE.TO; FCD.UN; BBI.TO; MPH.TO; M.TO; GRC.TO;

PRV.UN; MQL.TO; BCM.TO; NTS.TO; CGT.TO; ED.UN; GCU.TO; AUG.TO; CXV.TO; DAP.U; BLN.TO; WZR.TO; BOE.TO; CSO.TO; BGM.TO; RPC.TO; RFC.TO; SGC.TO; RD.TO; OPS.TO; TGX.TO; ZEN.TO; JNX.TO; SAT.TO; BTI.TO; UCU.TO; NVO.TO; TII.TO; ATU.TO; EMX.TO; OGI.TO; MCR.TO; SPN.TO; DMYD; DMYD; CWC.TO; IKM.TO; RBX.TO; PM.TO; ASM.TO; DMI.TO; ATC.TO; LGO.TO; IEI.TO; VIT.TO; DMG.H; BRI.TO; MCW.TO; CAC.TO; EOX.TO; EHT.TO; NOX.TO; ANK.TO; ATY.TO; HUD.TO; IGX.TO; ODN.TO; SGW.TO; BPE.TO; CMI.TO; VDLR; VDLR; BUS.TO; AII.TO; LVL.TO; PRO.TO; EBM.TO; AGB.TO; VGO.TO; COT.TO; LLG.TO; FF.TO; IOU.TO; COB.U; HEM.TO; ZMS.TO; GOK.TO; FLY.TO; TVL.TO; APO.TO; SVA.TO; AM.H; PRN.TO; MRZ.TO; LND.TO; MD.TO; SEB.TO; AAP.TO; OYL.TO; OVT.TO; KZD.TO; NEL.UN; VPY.TO; PML.TO; MMY.TO; CLI.TO; LA.TO; AVE.TO; SKX.TO; TLT.TO; MIR.TO; SV.TO; PFM.TO; ONE.TO; UNI.TO; PEA.TO; SLG.TO; GPV.TO; FPC.TO; NCE.TO; ERG.TO; CST.TO; LSI.TO; CRE.TO; MLN.TO; ANF.TO; ASN.TO; GTP.TO; NXT.TO; ES.TO; PSH.TO; LAB.TO; RZZ.TO; VVA.TO; MTE.TO; TZR.TO; HMT.TO; SBM.TO; TOO.TO; ROE.TO; MIN.TO; EGD.TO; PE.TO; TSD.TO; DSY.TO; TLK.TO; CEB.TO; CFL.TO; HEO.TO; TEP.UN; KXM.TO; SLC.TO; CPM.TO; MAP.P; EV.TO; SQD.TO; GRM.TO; SMD.TO; PMI.TO; ALV.TO; XOP.TO; BKM.TO; TK.TO; NCA.TO; FAN.TO; DVG.TO; MYA.TO; GXS.TO; CCB.TO; SPI.TO; DUG.TO; TXR.TO; ENA.TO; SPS.A; CZX.TO; NAN.TO; Q.A; PYR.TO; JFI.TO; AT.TO; VCI.TO; SDX.TO; CSX.TO; PDP.TO; JAG.TO; YFI.TO; JTR.TO; BCT.TO; HI.TO; GMN.TO; GBL.TO; GGG.TO; RML.TO; MEI.TO; EPO.TO; TSM.TO; XX.TO; LMD.TO; IMA.TO; AFY.TO; CZO.TO; NWX.TO; CCE.TO; GQC.TO; SEI.TO; MXI.TO; LIO.TO; IFX.TO; KTN.TO; AQS.TO; ALP.TO; BEE.TO; OML.TO; NTQ.TO; RYU.TO; AGD.TO; AOS.TO; REK.TO; PYD.TO; NEE.TO; TIL.TO; SNS.TO; FFF.TO; ART.TO; NSP.TO; SKE.TO; QST.TO; KIV.TO; LPS.TO; GWA.TO; ACE.H; EIL.TO; EGT.TO; ILA.TO; RPM.TO; SDZ.TO; MJN.TO; TLA.TO; CNH.TO; SUF.A; IMM.TO; AN.TO; CNY.TO; WAF.TO; JDL.TO; PPX.TO; ZAO.TO; EBN.TO; RVV.TO; ORG.TO; QIC.U; GPH.TO; VML.TO; JCO.TO; LM.TO; APV.TO; NQ.TO; KMT.TO; MKT.TO; AGM.TO; RTH.TO; NPH.TO; IDW.TO; ROI.TO; FCF.TO; CFY.TO; MVC.H; GAZ.UN; QIS.TO; YO.TO; RP.TO; CXB.TO; MSD.TO; TAU.TO; SME.TO; HLM.TO; GRB.TO; FA.TO; HTL.TO; ADI.TO; UG.TO; MTZ.TO; SMB.TO; SSP.TO; TSG.TO; NZN.TO; CBX.TO; EUO.TO; OEE.TO; WKM.TO; PNG.TO; TCO.TO; QTA.TO; EOG.TO; PNG.V; PNG.V; DVN.TO; ACH.TO; SMI.TO; AFE.TO; YAK.TO; RK.TO; NAA.TO; GLW.TO; REX.TO; AME.TO; ISD.TO; PSP.TO; IBH.TO; BCF.TO; EL.TO; PCQ.TO; AWI.TO; NUG.TO; LMS.TO; TXX.TO; SIO.TO; MVP.TO; ZUM.TO; EMH.TO; DE.TO; SIM.TO; PKT.TO; WHY.TO; SCZ.TO; OCN.TO; IPC.TO; PRB.TO; DJI.TO; ATE.TO; KAR.TO; CBJ.TO; FBI.TO; ARS.TO; NGE.TO; MTO.TO; NAR.TO; DSF.TO; GBB.TO; RAB.TO; GRG.TO; BCC.TO; FMS.TO; OEG.TO; MGZ.H; MNP.TO; PLU.TO; PGM.TO; SDS.TO; VMS.TO; CDN.TO; STT.TO; TEN.TO; LPC.TO; GZZ.TO; OOO.TO; ERA.TO; AHR.TO; CX.TO; DVO.U; RHC.TO; REG.TO; AGG.TO; CKB.TO; FCV.TO; ESU.TO; CNX.TO; GKX.TO; CNS.TO; IDI.TO; CHK.P; IWG.TO; UFC.TO; IMU.TO; MGW.TO; VIV.TO; WEE.TO; MNM.TO; CWV.TO; FUU.TO; HME.TO; AUN.TO; GQ.TO; GRR.TO; RDS.TO; AGE.TO; SHRM; NUMI; WUHN;LCA; SUNW; “SNDL”; HEXO; NUMI; GBTC