Negative News Based Overreaction Sentiment Strategy

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Executive Summary

In this paper, the authors build a news-based sentiment trading strategy to identify buy-signals of stocks. The goal of this explanatory paper contains the following 3 parts: first, to introduce the current researches on investors' overreaction to news; second, to construct the overreaction sentiment factor; third, to testify the sentiment factor by back-testing and analyze individual companies as single-cases.

1 Literature Review

This trading strategy is based on momentum trading and negative news' overreaction signal. Previous researches are divided into following 4 aspects:

Topic	Literature Overview
Short-term momentum theory	Market efficient hypothesis fails to explain that stocks which have positive performance continued to outperform those with poor performance—Short-term momentum exists.
Over-reaction to news stories exists	Antweiler and Frank(2006) test 245,429 Wall Street Journal corporate news stories and found that typical response to a news story is a strong and prompt reaction followed by a gradual and lengthy reversal. In other words, overreaction to news is the typical pattern on the main American stock markets between 1973 and 2001.
People overreact to bad news	Veronesi(1999) found that Investors' willingness to hedge against changes in their own "uncertainty" makes stock prices overreact to bad news in good times.
Bad news is a better indicator to predict stock	Uhl(2014) tested 3.6 million Reuters news on its ability to forecast returns and found that negative Reuters sentiment has more predictive power than positive sentiment.

Table 1. literature overview

Table 2 shows that the typical response to news is first positive and then negative. This is a process of overreaction. (Antweiler and Frank, 2006)

Table 1 ASCARs and Median SCARs Conditioned on the Inclusion of Days Surrounding the Event Day, All Events

THE CONTRACTOR OF THE CONTRACT		ASC	ARs		Median SCARs			
Base Day	5d	10d	20d	40d	5d	10d	20d	40d
Third trading day before event	2.3^{c}	1.1 ^c	-0.0	-1.0^{c}	1.0^{c}	0.3	-0.1	-0.4
Second trading day before event	2.0^{c}	0.9^{c}	-0.1	-1.0^{c}	0.8^{c}	-0.0	-0.3	-0.8^{c}
First trading day before event	1.2^c	0.4	-0.5^{a}	-1.3^{c}	-0.1	-0.6^{b}	-0.7^{b}	-1.0^{c}
Event day	-0.6^{a}	-1.1^c	-1.4^{c}	-1.9^{c}	-2.6^{c}	-2.4^{c}	-2.0^{c}	-1.8^{c}
First trading day after event	-1.3^{c}	-1.8^{c}	-1.7^{c}	-2.3^{c}	-3.4^{c}	-3.3^{c}	-2.5^{c}	-2.1^{c}
Second trading day after event	-1.4^{c}	-1.9^{c}	-1.8^{c}	-2.3^{c}	-3.6^{c}	-2.9^{c}	-2.3^{c}	-2.2^{c}
Third trading day after event	-1.3^{c}	-1.8^{c}	-1.7^{c}	-2.2^{c}	-3.5^{c}	-2.9^{c}	-2.3^{c}	-2.3°

Average standardized cumulative abnormal returns (ASCARs) are scaled by 100 for easier readability. The columns identify the length of the event window of #d trading days, starting on and including the day stipulated in the column "Base Day." Statistical significance at the 95%, 99%, and 99.9% levels of confidence is indicated by the superscripts ^a, ^b, and ^c, respectively. The market model regressions are based on a 120 calendar-day pre-event window and the equal-weighted market index.

Table 2. Time range of overreaction from literature

Veronesi (1999) found that people especially overreact to bad news in good times. The author shows that investors' willingness to "hedge" against changes in their level of uncertainty makes them overreact to bad news in good times, making the price of the asset more sensitive to news in good times. Further he specifies the mechanism how investors overreact to bad news—Loss aversion. Since risk-averse investors want to be compensated for bearing more risk, they will require an additional return on the price of the asset. As a consequence, the price drops by more than it would in a present-value model. The author also shows by numerical examples that this increases with the investors' degree of risk aversion, thereby giving a precise role of risk aversion in determining asset price volatility.

Uhl(2014) constructs Reuters news sentiment to predict stock price change. The author showed that both positive and negative Reuters sentiment are valid to predict stock returns in a monthly frequency setting, while negative Reuters sentiment adds more forecasting power than positive Reuters sentiment. Negative news sentiment strategy also outperforms the benchmark and strategy with positive new sentiment, with a highest Sharpe ratio of 2.54 and the highest success rate (shown in the table 3 below).

	Type of	Endogenous	Performance Stock Index Jan 2010 –	Performance Strategy Jan 2010 –	Outperformance Strategy / Stock Index Jan 2010 –	Sharpe Ratio** Jan 2010 –	Success Rate Jan 2010 -
_	Model	Lags*	Dec 2010	Dec 2010	Dec 2010	Dec 2010	Dec 2010
Endogenous Variables							
Dow Jones Industrials Stock Index			7.49%			0.48	
Dow Jones Industrials Stock Index, Dow Jones Industrials Stock Index Volume, the Conference Board Index, Positive and Negative Reuters Sentiment	VAR	3		37.43%	29.94%	2.67	75%
Dow Jones Industrials Stock Index, Negative Reuters Sentiment	VAR	4		35.73%	28.24%	2.54	75%
Dow Jones Industrials Stock Index, Positive Reuters Sentiment	VAR	6		17.21%	9.72%	1.02	50%
Dow Jones Industrials Stock Index, Dow Jones Industrials Stock Index Volume, and the Conference Board Index	VAR	2		25.61%	18.12%	1.63	67%
Dow Jones Industrials Stock Index, Positive and Negative Reuters Sentiment	VAR	4		41.54%	34.05%	3.28	83%

Table 3. Effect of negative news from literature

^{*}The endogenous lag length was selected according to the Akaike Information Criterion and Final Prediction Error Tests.

**For the calculation of the Sharpe Ratio, we use an average of the 1-month T-bill yield for the examined period (0.2% p.a.) as risk-free rate.

2 Test of Factor Effectiveness

2.1 Construction of factor

Tracing back to prospect theory in behavior finance, there is a systematic bias on investors' behavior when facing losses and gains. This strategy is rooted from that people might overreact to bad news, due to the aversion towards loss.

The factor is constructed on the basis of investors' overreaction on negative news. At the same time, whether the stock performs well in history before this news occurs is also taken into consideration. The factor to realize the strategy is a Boolean variable, where 1 means the stocks satisfies two conditions: first, a sudden negative news occurs, and second, the stock performs well in history. The two conditions are shown in detail separately:

Salient negative news: z-score of daily number of negative news > Z_{0.005}

To construct an agent to measure whether there is an amount jump of negative news, we first took a close look at daily number of negative news by Bloomberg. Figure 1 shows a typical historical pattern of this feature, which gives an intuition on how this number fluctuates along time: there are sudden increases in number of negative news. Salient negative news can be identified as a sharp increase in this feature.

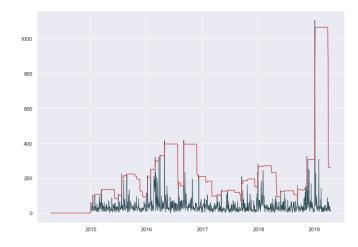


Figure 1. Number of negative news historical data. Daily number of negative news of AAPL is shown in the figure as an example of how selection on number of negative news works. Green line shows the number of negative news, and red line shows the number with a z-score of $Z_{0.005}$ calculated from historical data in the previous 60 days. Where green line exceeds red one is identified as a buy-in signal.

To better implement such identification among different stocks, historical z-score of this feature is calculated for all the 505 stocks in the S&P 500 pool to normalize number of news. Specifically, for each stock and each day in the previous one year, number of negative news is converted to the z-score of itself compared with historical numbers of negative news in the same stock before this day.

Based on the normalized data, the condition for judging whether there is a jump can be set as $Z[N_{negnews}] > Z_{0.005}$, which means, if z score calculated above exceeds $Z_{0.005}$, then there is assumed to be salient increase in the number of negative news given the date and the stock.

Good previous performance: sum of daily returns in the previous 60 days > 5%

To find an agent for identifying a stock's good previous performance, the look-back period is set to 60 days. Sum of previous 60 daily returns is compared with a threshold, comparing results leads to judgement of good previous performance, which can be expressed as $\sum_{i=1}^{60} r_{t-i} > 0.05$. Combination of the two conditions: neg-news based overreaction sentiment factor

To summarize the discussion of news and performance agents, the trigger of buying-in is to meet the following two conditions simultaneously:

- 1) normalized daily negative news number exceeds $Z_{0.05}$
- 2) sum of previous 60 daily returns exceeds 5% Denoting buy signal as a 0-1 variable, such filtration can be expressed as:

$$\mathbf{1}_{\left\{Z\left[N_{negnews}\right]>Z_{0.05}\ and\ \sum_{i=1}^{n}r_{t-i}>5\%\right\}}$$

The daily specific identified buy-in companies can be found in Appendix B.

2.2 Statistical Test of Neg-news based Overreaction Sentiment Factor

To gauge the predictability of the factor on future returns, we compared multiple linear regression model containing both benchmark factor and neg-news based overreaction sentiment factor with simple linear regression model containing only the benchmark feature. ΔR^2 is reported in table 4 to illustrate how much additional variance can this factor explain compared with benchmark models. Table 4 shows that in either AR or market portfolio benchmark models, this factor leads to significant increase in R^2 (more than 1%), which shows an additional portion of variance of stock future returns can be explained by the factor.

BENCHMARK MODEL	SIGN OF COEFFICIENT	R_{BMK}^2	ΔR^2	P-VALUE
AR(3)	+	0.001	0.016	0.000
Mkt	+	0.003	0.016	0.000
AR(3), Mkt	+	0.004	0.015	0.000
AR(1)	+	0.000	0.015	0.000
AR(2)	+	0.000	0.015	0.000
AR(4)	+	0.001	0.015	0.000
AR(5)	+	0.001	0.015	0.000

Table 4. Over Reaction Sentiment Factor Statistics

Same method is implemented for returns in the next 1 $^{\sim}$ 10 days. Figure 2 shows a decreasing $\triangle R^2$ as time horizon goes longer.



Figure 2. ΔR^2 in predicting different horizons (percentage points). Factor predictability drops after 1 and 6 days.

3 Development of The Quantitative Trading Strategy

Buy-in signal shall be conducted at proper time. We backtested the buy-in time from t+0 to t+4 relative to factor value at time t and reported Sharpe Ratios in table 5. At t+1, the largest Sharpe Ratio is gained, implying that entering into the targeted positions at t+1 is the best option.

	Buy-in at t+0	Buy-in at t+1	Buy-in at t+2	Buy-in at t+3	Buy-in at t+4
Sharpe Ratio	0.806737	1.149077	0.687715	0.235509	0.074593

Table 5. sensitivity of "n" in strategy parameter "buy-in at t + n"

Time to hold securities also matters. If trading more frequently, the strategy is more exposed to the factor since it identifies signals every day, but this will lead to higher transaction cost and inadequate time to wait the price to recover from sudden negative news.

Table 6 showed that when fixing the transaction cost to $\left[\frac{2}{1000}*\text{total capital}\right]$ each transaction, the strategy gains best performance when rebalancing the portfolio every 10 days, and keeping the number of stocks to buy-in each time to 10 is enough for fully exposure to this factor.

Transaction cost = 0.002

Sharpe Ratio	holding period (days) = 5	10	15
Number of stocks to buy-in = 2	0.568	0.929	0.184
5	0.492	1.291	0.438
10	0.458	1.149	0.401
15	0.456	1.148	0.388
20	0.465	1.148	0.388

Number of stocks to buy-in = 10

Sharpe Ratio	holding period (days) = 5	10	15
Transaction cost = 0.001	0.727	1.276	0.479
0.002	0.458	1.149	0.401
0.003	0.189	1.022	0.322
0.004	-0.076	0.895	0.244
0.005	-0.339	0.768	0.165

Table 6. Sharpe ratios for different choices of parameters

The strategy buys targeted stocks 1 day later than the occurrence of negative news signal, and holds them for 10 days, with an illustration in figure 3. Besides, settings of Single factor backtesting are shown in table 7.

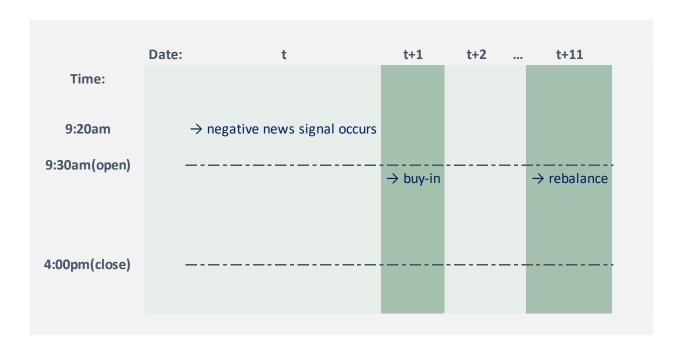


Figure 3. illustration of buy and sell time points. Assuming the news sentiment signal identified by the previous factor occurs at time t, it triggers a buy-in at opening of t+1 and book profit at t+11.

	Settings
Backtest period	2015.4.14 ~ 2019.4.12
Investment universe	S&P 500 stocks
Number of stocks to buy-in each time	5
Weighting method	equally weighting
Frequency of re-balancing	every 10 trading days
Transaction cost	$\frac{2}{1000}$
Initial capital	\$1
Benchmark	S&P 500 Index

Table 7. settings of backtesting parameters

Backtesting Results

Table 8 showed some main results of the strategy, and figure 4 presented the P&L curve. The strategy's Sharpe Ratio in the past 4 years is 1.291, outperforming the S&P 500.

	S&P 500 index	Neg-news sentiment factor
Daily Average Return	0.0012	0.0004
CAGR	0.500	1.479
Sharpe Ratio	0.469	1.291
Max Drawdown	0.190	0.170
Downside Std Dev	0.009	0.012
Downside Std Dev (5%)	0.024	0.031
Sortino Ratio	0.444	0.990
Sortino Ratio 5	0.169	0.379

Table 8. Factor Backtesting Performance Measurements

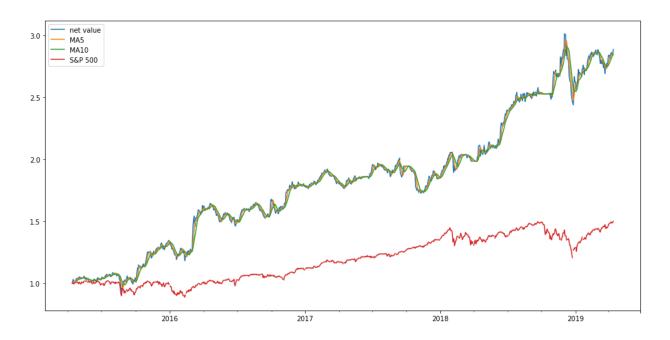
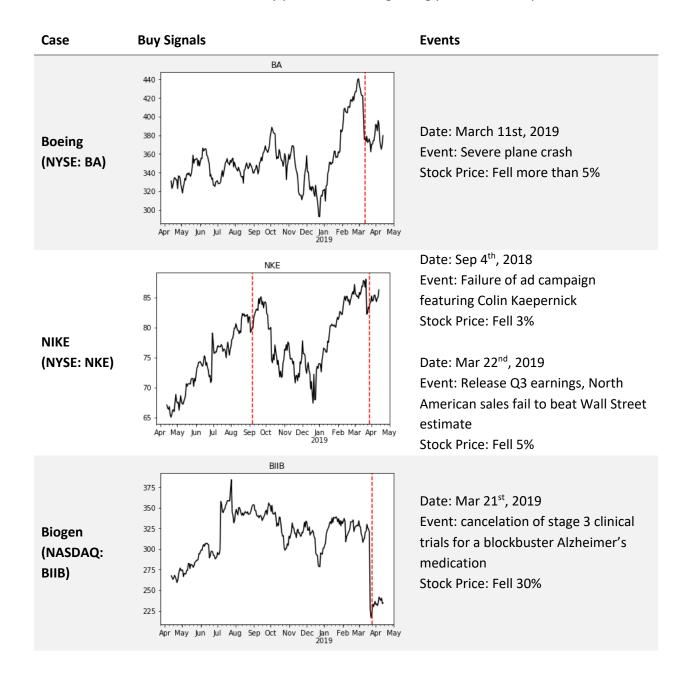


Figure 4. Factor PnL In Backtesting. This plot shows the value of the portfolio, both portfolio constructed and rebalanced based on our factor, and the S&P 500 index portfolio, given initial capital equals \$1. Moving average of the factor portfolio value is also plotted.

4 Case Analysis

In this part, some examples of identifying buy-in signals for certain companies by the negative news sentiment strategy will be given to explain how this strategy works in a much clearer way. The return of this strategy comes from properly identifying buy-in points after salient negative news when other investors are overly pessimistic and gaining profit as stock price recovers.



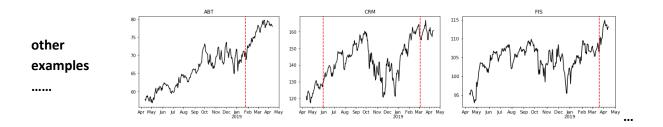


Table 9. buy signals identified by neg-news sentiment factor based strategy

Summary

Recent empirical studies show that investors tend to overreact to news stories, especially negative news. To put it the other way, price fluctuates more in short-term when negative news of stock occurs. Presumably, psychological loss aversion cause investors to overreact to bad news of stocks that has previous excellent performance. Based on this mechanism, we focus on stocks that have good previous performance yet with negative news and seek to build a news-based sentiment factor to catch the signal to buy stock when bad news occurs. Following back-testing and single company stock analysis show that this news-based sentiment factor worked well in identifying and capturing buy-in signal and that this trading strategy significantly outperforms the S&P 500 index in multiple key ratios such as net value, Sharpe ratio, Sortino ratio.

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Appendix

A. Test of other Bloomberg sentiment data

Despite number of negative news used in this research, there are also other sentiment indicators available in use. We tested some of them by reporting the R² increase compared with AR(3) model in linear regressions to examine the fit on future returns. Chart below shows the factor used in this research is the one that can explain the most additional variance compared with benchmark.

	Sign of coefficient	P-value	△R ² (in percentage points)
NEWS_PUBLICATION_COUNT	-	0.000	0.017
NEWS_NEG_SENTIMENT_COUNT [= n]	-	0.000	0.888
NEWS_POS_SENTIMENT_COUNT [= m]	+	0.000	0.058
NEWS_DISPERSION [= $\frac{mn}{(m+n)^2}$]	-	0.000	0.225
NEWS_HEAT_READ_DAVG	-	0.000	0.034
NEWS_HEAT_READ_DMAX	-	0.000	0.012

B. Buy-in signals before market open

Following buy-in signals are identified by neg-news sentiment factor, available before market open.

2015-01-07	DATE	ID	ENTIFIED E	BUY-IN TAR	GET STOCKS	S	DATE	IDE	NTIFIED BU	Y-IN TARGET STOCKS
2015-01-09	2015-01-07	'CXO'	'MS'	'PYPL'	'URI'					
2015-01-12 'DLTR' 'KO'	2015-01-08	'ADP'	'EA'	'GD'			2019-01-16	'C'	'NEM'	
2015-01-13	2015-01-09	'BEN'	'ES'	'HP'			2019-01-17	'ALB'	'BLK'	'SHW'
2015-01-14 'ABC' 'CME' 'MET' 'TIF' 2019-01-22 2015-01-15 'JPM' 'LEG' 'XLNX' 2019-01-23 2015-01-16 'ADBE' 'BAC' 'BWA' 'C' 2019-01-24 'SWK' 2015-01-19 'BBY' 'LEN' 'SLB' 'STI' 2019-01-25 'HRL' 'TXN' 2015-01-20 2019-01-28 'MKC' 'WDC' 'XRAY' 2015-01-21 'BLL' 'HPQ' 'JKHY' 'MS' 2019-01-29 2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-12	'DLTR'	'KO'				2019-01-18	'FISV'	'MS'	'MTD'
2015-01-15 'JPM' 'LEG' 'XLNX' 2019-01-23 2015-01-16 'ADBE' 'BAC' 'BWA' 'C' 2019-01-24 'SWK' 2015-01-19 'BBY' 'LEN' 'SLB' 'STI' 2019-01-25 'HRL' 'TXN' 2015-01-20 2019-01-28 'MKC' 'WDC' 'XRAY' 2015-01-21 'BLL' 'HPQ' 'JKHY' 'MS' 2019-01-29 2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-13						2019-01-21	'NFLX'	'PPG'	
2015-01-16 'ADBE' 'BAC' 'BWA' 'C' 2019-01-24 'SWK' 2015-01-19 'BBY' 'LEN' 'SLB' 'STI' 2019-01-25 'HRL' 'TXN' 2015-01-20 2019-01-28 'MKC' 'WDC' 'XRAY' 2015-01-21 'BLL' 'HPQ' 'JKHY' 'MS' 2019-01-29 2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-14	'ABC'	'CME'	'MET'	'TIF'	•••	2019-01-22			
2015-01-19 'BBY' 'LEN' 'SLB' 'STI' 2019-01-25 'HRL' 'TXN' 2015-01-20 'Z019-01-28 'MKC' 'WDC' 'XRAY' 2015-01-21 'BLL' 'HPQ' 'JKHY' 'MS' 2019-01-29 2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-15	'JPM'	'LEG'	'XLNX'			2019-01-23			
2015-01-20	2015-01-16	'ADBE'	'BAC'	'BWA'	'C'		2019-01-24	'SWK'		
2015-01-21 'BLL' 'HPQ' 'JKHY' 'MS' 2019-01-29 2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-19	'BBY'	'LEN'	'SLB'	'STI'		2019-01-25	'HRL'	'TXN'	
2015-01-22 'AMD' 'FITB' 'IBM' 'JEF' 2019-01-30 'CAT' 'NVDA' 2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-20						2019-01-28	'MKC'	'WDC'	'XRAY'
2015-01-23 'AXP' 'DFS' 'EBAY' 'EMR' 2019-01-31 'AGN' 'TRIP'	2015-01-21	'BLL'	'HPQ'	'JKHY'	'MS'		2019-01-29			
	2015-01-22	'AMD'	'FITB'	'IBM'	'JEF'	•••	2019-01-30	'CAT'	'NVDA'	
2015-01-26 'COF' 'DG' 'DLTR' 'ISRG' 2019-02-01 'TSN' 'XEL'	2015-01-23	'AXP'	'DFS'	'EBAY'	'EMR'		2019-01-31	'AGN'	'TRIP'	
	2015-01-26	'COF'	'DG'	'DLTR'	'ISRG'	•••	2019-02-01	'TSN'	'XEL'	

2015-01-27	'NSC'				
2015-01-28	'CAT'	'DHI'	'DOV'	'FB'	•••
2015-01-29	'AOS'	'FCX'	'HES'	'MDT'	•••
2015-01-30	'CL'	'QCOM'	'TEL'	'VRTX'	
2015-02-02	'CB'	'COP'	'CVX'	'DGX'	
2015-02-03					
2015-02-04	'APC'	'NOV'			
2015-02-05					
2015-02-06	'ADP'	'ANTM'	'CDNS'	'FMC'	
2015-02-09	'HRS'	'PM'	'PRU'		
2015-02-10					
2015-02-11	'MAS'	'MCD'			
2015-02-12	'HAL'	'OMC'	'PXD'		
2015-02-13	'FTI'	'INTU'	'NFLX'	'NTAP'	
2015-02-16	'AIG'	'APA'	'AXP'	'CAG'	•••
2015-02-17					
2015-02-18	'CSX'	'HIG'			
2015-02-19	'BSX'	'NOC'	'XEC'		
2015-02-20	'DUK'	'EOG'	'MRO'	'XOM'	
2015-02-23	'BLL'	'COG'	'DE'	'SYY'	
2015-02-24					
2015-02-25	'NBL'	'OKE'			
2015-02-26	'ANTM'	'HPQ'			
2015-02-27	'MO'	'ROST'			
2015-03-02					
2015-03-03					
2015-03-04					
2015-03-05					
2015-03-06	'HRB'				
2015-03-09	'ABBV'	'STT'	'ZION'		
2015-03-10	'MCD'				
2015-03-11					
2015-03-12	'DUK'	'FTI'	'VRSK'		
2015-03-13	'MSI'				
2015-03-16	'INTC'				
2015-03-17					
2015-03-18					
2015-03-19	'FLIR'	'KHC'			
2015-03-20	'ADBE'				
2015-03-23	'BK'	'NUE'	'TGT'		

2019-02-04	'COG'	'DWDP'			
2019-02-05					
2019-02-06	'ABMD'				
2019-02-07	'ADM'	'EA'			
2019-02-08	'ATVI'	'STI'			
2019-02-11	'AMZN'	'BBT'	'HAS'	'MKC'	
2019-02-12					
2019-02-13					
2019-02-14	'TAP'				
2019-02-15	'CTL'	'DHI'	'F'		
2019-02-18	'KO'	'NVDA'	'XRAY'		
2019-02-19					
2019-02-20	'ABMD'				
2019-02-21					
2019-02-22	'CVS'				
2019-02-25	'KHC'	'MCO'	'NKE'		
2019-02-26	'BRK/B'				
2019-02-27	'DHR'	'HD'			
2019-02-28	'ABBV'	'WYNN'			
2019-03-01	'BKNG'				
2019-03-04					
2019-03-05					
2019-03-06	'LLY'	'NEM'			
2019-03-07	'AON'				
2019-03-08	'SWK'				
2019-03-11	'KR'				
2019-03-12	'BA'				
2019-03-13					
2019-03-14					
2019-03-15	'DOW'	'FB'	'XEL'		
2019-03-18	'DG'				
2019-03-19					
2019-03-20	'FIS'	'FLIR'			
2019-03-21	'FDX'	'FOXA'			
2019-03-22	'BIIB'	'MCO'	'MU'		
2019-03-25	'TSN'				
2019-03-26					
2019-03-27	'NKE'				
2019-03-28	'CCL'	'WCG'			
2019-03-29	'CNC'				

2015-03-24	'IPGP'	'KSU'			
2015-03-25	'FCX'	'VRTX'			
2015-03-26	'VRSN'				
2015-03-27	'CAG'	'PVH'	'SLB'	'UPS'	
2015-03-30	'AMP'				
2015-03-31	'XLNX'				
2015-04-01					
2015-04-02	'CHTR'	'FBHS'	'HPQ'	'UHS'	•••
2015-04-03	'MDLZ'				
2015-04-06	'MDT'				
2015-04-07	'EMR'				

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2019-04-01	'CAG'	'JEF'		
2019-04-02				
2019-04-03	'FLIR'	'WBA'		
2019-04-04	'WYNN'			
2019-04-05	'STZ'			
2019-04-08				
2019-04-09				
2019-04-10				
2019-04-11	'LMT'	'PNR'		
2019-04-12	'RSG'			
2019-04-15				

2019-04-16