Mean Reversion and the Stock Price Overreaction Effect On Top Daily % Losers

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Abstract:

Prior literature from Atkins and Dyl (1990) has shown evidence of reversals in stocks following significant one day losses. However, in their paper the authors concluded that the large bid-ask spread associated with significant one day losers supports a weak form of efficient market theory, making it impossible to exploit the reversion for profit. In this paper, we plan to build on Atkins and Dyl's work by using more recent data, limiting our focus to higher volume stocks with historically tighter bid-ask spreads, using date specific bid-ask spreads, and testing specific strategies (i.e. buying a top day percentage loser at the opening price of the next day and holding for certain amounts of time) in order to refute Atkins and Dyl's claim that no profitable strategy exists from exploiting losers.

The Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) asserts that stock prices reflect all available information about companies, making it impossible to beat the market on a risk-adjusted basis. There are three forms of the EMH, each of which operates off its own set of varying assumptions. The weak-form EMH suggests stock price reflects all historical information. Therefore, basing investment decisions on historical movement and other technical analysis is useless. The semi-strong form EMH suggests prices reflect all currently publicly known information. Therefore, both fundamental analysis and technical analysis would be of little to no use in informing investment decisions. Lastly, strong-form EMH suggests prices reflect all current public information and private information. Under the assumptions of strong form EMH, no investment strategy can consistently beat the market.

The Overreaction Hypothesis

Since EMH was first presented, there have been many theories and hypotheses challenging it, one of which being the overreaction hypothesis. The Contrarian/Overreaction Hypothesis (DeBondt and Thaler 1985, 1987) asserts that buying previous losers and selling short previous winners results in abnormal short-term returns. This is based on the hypothesis that previous big losers are left undervalued as a result of overreaction and sell-offs by panicked investors, likely as a result of bad news such as lower than expected earnings. The Overreaction Hypothesis suggests that the price will return to its average price over time, outperforming the market on its path back up. Conversely, under this theory large winners are left overvalued, fueled by an overreaction and surge in buying, just to return to the average price after time. If this hypothesis holds, it directly opposes all three forms of EMH.

Introduction to our Paper

The objective of this paper is to revisit the Overreaction Hypothesis, examining the performance of the top 5 and top 2 one-day percent losers in the S&P 500 over a time horizon of 10 years. Our data came from CRSP (The Center for Research in Stock Prices) and consists of every company that was at any time a constituent of the S&P 500 from 2009-2019. To ensure our study only looks at high volume stocks, low-price, low-volume/liquidity stocks were eliminated from our data set before analysis began. This ensures growing companies' performances prior to entering the S&P 500 are not included. The study is most similar to Atkins and Dyl's (1990), however, unlike the prior literature, we are only using information from companies with high volume, hoping to ensure that no profit is lost due to large bid-ask spreads.

The paper is structured as follows: Section II introduces relevant literature, including Atkins and Dyl (1990). Section III discusses our data and methodology. Section IV presents the main results of our analysis. Section V discusses our results as well as introduces any subsequent, more specific tests we run, and the results of said tests, and the paper ends with a final conclusion and summary.

Literature

Prior studies have shown substantial evidence of overreactions in the stock market, giving much credence to the idea of there being inefficiencies present in the market. Beginning with Kahneman and Tversky (1973), evidence was presented that individuals tend to give much more weight to recent data when making decisions and judgements. De Bondt and Thaler (1985), (1987) first tested these overreaction theories in the stock market by creating two portfolios; one of stocks that had demonstrated abnormal positive returns dubbed “winners”, and one of stocks that had demonstrated abnormal negative returns (“losers”). They subsequently found that the winners exhibited negative, market-adjusted returns, while the losers earned positive market-adjusted returns. De Bondt and Thaler’s findings motivated additional research, which has generally supported the original findings.

Following in De Bondt and Thaler’s footsteps, Brown and Harlow (1988) again found evidence of short-term corrections following negative events. Bremer and Sweeney (1991), using a design similar to De Bondt and Thaler (1985), examined short-term price movements from 1962 to 1986. They examined all cases where a Fortune 500 company had a one-day price change of 10% or greater (also examining cutoffs of 7.5% and 15%). By looking only at larger companies, the authors avoided the issue of bid-ask spreads being responsible for changes in prices. Bremer and Sweeney tracked stocks after jumps for a period of 20 days, finding that five days post price drop, stocks averaged a 3.95% gain, whereas the winners showed no excess returns during the period following their large gains.

While previous research showed evidence in support of stock market overreactions, no strategies to utilize these movements were created until Lehmann (1990). Using weekly returns, Lehmann studied whether a return reversal strategy could generate profits by financing the purchases of stocks that had underperformed the market during the previous week by short selling the stocks that had outperformed the market. Lehmann used all securities listed on the NYSE and AMEX from 1962 to 1986, weighing the dollar amounts invested in each stock to the stock's weekly excess return. Due to the large number of transactions each week (2000+) the profitability of the strategy depended on the size of transaction costs. Lehmann found that for a floor trader with assumed 0.1% transaction costs, the strategy would be extremely profitable, with a portfolio long $100 million of the losers and short $100 million of winners generating an average six-month profit of $38.77 million, with almost 2/3 of the profits coming from the losers in the portfolio. Following other previous studies, the winners and losers that had had the largest price changes demonstrated the largest reversals.

Atkins and Dyl (1990) formed a different strategy, using the daily returns for all stocks on the NYSE from 1975 to 1984. The authors then selected the three stocks that experienced the largest percentage loss in value and the three that exhibited the largest percentage increase in value at close. Utilizing multiple forms of return analyses, Atkins and Dyl went on to find significant reversal in the largest percentage losers, demonstrating the presence of overreactions in the market. Contrary to Lehmann's findings, Atkins and Dyl found that profitability was not able to be achieved. This was due to transaction costs and the bid-ask spreads being large among these stocks, thus eliminating any gains that may have come from studied reversals.

Data

To begin, we gathered the daily opening price, closing price, and bid-ask spread data for every S&P constituent for a period from January 2, 2008, to December 31, 2019, from CRSP. The inclusion of 2008 is in an attempt to model during both periods of recession and growth. This resulted in a complete dataset of over 2,000,000 entries. To differentiate ourselves from Atkins and Dyl (1990), we narrowed down the dataset into stocks that have a bid-ask spread of $0.05 or lower in effort to ensure that both large price drops were not due to bid-ask spread gaps, and that market orders would not suffer from large differences between bid and ask price. To further eliminate smaller companies, we eliminated any stock with a price lower than 5.00 (the current lowest-priced stock on the S&P 500 is Ford, priced at $6.74 as of 3/5/2020). By narrowing our data in this manner, we limit our data to only include more liquid, frequently traded stocks. Using this new dataset, we sorted our data by daily percentage drops, and identified the Top 5 and Top 2 losers for each day, creating the two main datasets we used for our analysis. Our Top-5 list has 15,080 observations, and our Top-2 list has 6,032 observations.Table 1 shows the average price drop across our Top-5 and Top-2 data sets both by year and across the entire dataset.

Methodology

In each day for both our Top 5 and our Top 2 Datasets, we labeled the initial large percentage drops for each observation t_0. The following five days post-drop are subsequently labeled t_i such that:

$$t_i = \frac{Closing\ Price\ day\ i}{Closing\ Price\ day\ 0} - 1,\ i = 1, 2, \ldots, 5$$

Therefore, t_5 represents the price change by percentage from day 0 (day of initial drop) to day 5 following the initial drop. In addition, we also calculated t_{ij} such that:

$$t_{ij} = \frac{Closing\ Price\ day\ j}{Closing\ Price\ day\ i} - 1,\ \ j = i + 1$$

Therefore, in this calculation, t_{12} represents the price change by percentage from day 1 to day 2.

After calculating these values, we split both our Top 5 and Top 2 data sets into two groups, an in-sample and an out-of-sample. The designated in-sample years are 2008-2015, and designated out-of-sample years are 2016-2019. Using the results for t_i and t_{ij} for each year of our in-sample years, we averaged the values to find t_i or t_{ij} where we observe the highest returns by percentage, and applied the strategy to 2016-2019 to see if the same strategy results in the highest return in our out-of-sample years.

In Sample Results

In *Table 2* and *Table 3*, the return results on t_i and t_{ij} for our Top-5 in-sample data (2008-2015) is presented. Taking the averages of the returns across the in-sample horizon, t_i is positive for all *i*, meaning on average the-one day losers did show evidence of reversal. Of the eight years making up the in-sample data, t_5 was the highest performer five of those years. The exceptions are In 2008, when t_3 = 0.29%, in 2014 when t_4 = 0.30%, and in 2010 and 2015 when t_1 = -0.16% and -0.28%, respectively. Across our time-horizon, t_4 and t_5 both averaged the highest return, 0.18% on each trade. Therefore, if you had bought the top five biggest losers at the closing market price of day 0, on average, you would make 0.18% return on each trade if you closed out your position on day 4 or 5. In *Table 4* and *Table 5*, the return results on t_i and t_{ij} for our Top-2 in-sample data (2008-2015) is presented. The return tests on our Top-2 prove to be similar to our Top-5, with t_4 and t_5 again averaging the highest returns, this time 0.28% per trade.

These results suggest that in our out of sample test, t_4 and t_5 should again result in the highest returns for both our Top-5 and our Top-2 out-of-sample groups.

Out of Sample Results

In *Table 6* and *Table 7*, our results for t_i are presented for Top-5 out-of-sample and Top-2 out-of-sample. In both Top-5 and Top-2, our two highest performing days were t_4 and t_5, as predicted by our in-sample test. For the Top-5 losers, t_4 returned 0.07% and t_5 returned 0.18% per trade. For the Top-2, t_4 returned 0.08% and t_5 returned 0.18% per trade. This confirms, then, that the most profitable strategy is to buy market price on close of day 0, and sell market price on close day 5.

Profitability Test

As stated above, in our analysis and subsequent findings within our data, we observed that the optimal strategy among our Top-5 and Top-2 lists was to buy the top losers at the closing price of day 0, and to hold and eventually sell these stocks at the closing price of day 5. Utilizing this strategy on our narrowed-down stock list, the issue of transaction costs observed by Atkins & Dyl is simplified, and bid-ask spreads do not play as big a part in our profitability analysis as they are incorporated in our strategy already.

We began our profitability test by creating a balance of $1,000,000 to be invested over our time horizon of January 2, 2008 to December 31, 2019. Seeing as returns for our first trades would only become available for reinvestment following a period of 5 days, we allowed a fixed trade amount for the first five days of our time horizon before beginning to allow a flexible percentage of our available balance to be reinvested. For our Top-5 list, we set a $32,000 trade size for each of the 25 trades that would occur during our first 5 days, leaving 20% of our original balance or $200,000 available, in addition to the returns from our first day of trades, for a flexible reinvestment. For our Top-2 list, we set a $80,000 trade size for each of the 10 trades that occured, again leaving $200,000 available in addition to our returns from the first day of trades for reinvestment. Beginning with the sixth day of trades for both lists, a new flexible trade size was implemented. This was a fixed percentage of our cash balance available for reinvestment, ranging, which we sensitized from 0.5% per trade to 20% per trade for our Top-5 list and from 1% per trade to 35% per trade for our Top-2 list.

Keeping a running track of our balance available for reinvestment, which included our trade returns lagged by 5 days and flexible trade sizes, we created our strategy. Once this strategy was applied to our data, we further sensitized our flexible trade size percentage to evaluate what strategies and trade sizes would have been the most profitable, if at all.

Beginning with our results from the Top-5 list as seen in *Table 10*, we found that our ending portfolio balance on December 31, 2019 increased monotonically with every .005 increase in our fixed percentage per trade, with the highest % per trade of 19.5% culminating in an ending portfolio value of $2,777,884. This represents a 278% gain over our time horizon, a substantial return, particularly when compared to the S&P 500's returns during the same time horizon of 220.7%. In *Table 9*, we see our results for our Top-2 list. Again, our observed ending portfolio balances increase subsequent increases in our fixed per-trade percentage, with the highest % per trade of 35% culminating in a final value of $2,144,875, a gain of 214%. While this final portfolio result does not beat the S&P 500's return of 220%, it is encouraging that our Top-2 Lists' returns do not lag by a considerable gap. It is worthwhile to note that after these fixed rates go over a certain percentage, our formula ceases to work, as our portfolio balance either drops to $0 due to us not leaving extra cash on hand to deal with drops, or rockets to absurd values such as with the case of 55% in our Top-2 list yielding a portfolio value of

$\$4.10 \times 10^{49}$. This is due to us creating money out of thin air once our percentage goes over 50% (seeing as we would have two trades which would each take over 50% of our value for that one day, corresponding to a value larger than 100% of our actual balance available). These extraneous results are why we capped our percentage invested per trade as we did.

Conclusion

Using our data and our subsequent analyses, we can say firmly that utilizing a strategy of buying top losers and holding for a period of time (in our case t=5 days) can yield a profitable outcome. This outcome and observation goes against the observations of Atkins & Dyl but does go nicely with the observations and studies of Lehmann, who did develop a profitable, albeit different, strategy. When comparing our returns from our Top-5 and Top 2 lists to the returns of the S&P 500 during our time horizon, we can see that the superior returns come from our Top-5 list, although both returns would be considered profitable on an absolute level. This result surely warrants additional research and testing. A potential reason for this difference may be due to the potential that the drops among the Top-2 losers every day were more warranted, due to larger issues within each stock, and thus the rebound may not have been as great as with the remaining three stocks within a Top-5 losers list. With our results, we can decisively state that the optimal strategy to produce returns would be to invest in the Top-5 list, using the data from our time horizons. Further studies could consider alternate time periods, extending the time each stock was held until sale past 5 days, changing the amount invested per stock as a percentage of the portfolio, or to analyze which types of stocks regressed more heavily than others.

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Tables & Figures:

Table 1

Average Daily Drop	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Top 5	-9.11%	-7.08%	-4.75%	-5.02%	-4.74%	-4.14%	-4.48%	-5.37%	-5.42%	-5.10%	-5.64%	-5.36%
Top 2	-11.10%	-8.61%	-5.70%	-6.04%	-5.90%	-6.65%	-5.56%	-6.65%	-6.61%	-6.29%	-7.01%	-6.71%

Table 2

Top 5 IS	T0	T1	T2	T3	T4	T5
2008	-9.11%	-0.02%	0.03%	0.29%	0.16%	0.05%
2009	-7.08%	0.73%	0.72%	0.90%	0.93%	0.99%
2010	-4.75%	-0.16%	-0.20%	-0.28%	-0.51%	-0.63%
2011	-5.02%	-0.03%	-0.06%	0.01%	0.10%	0.20%
2012	-4.74%	0.03%	0.10%	0.25%	0.43%	0.44%
2013	-4.14%	-0.09%	0.15%	0.31%	0.46%	0.66%
2014	-4.48%	0.07%	0.02%	0.19%	0.30%	0.25%
2015	-5.37%	-0.28%	-0.37%	-0.38%	-0.47%	-0.55%
Average	**-5.59%**	**0.03%**	**0.05%**	**0.16%**	**0.18%**	**0.18%**

Table 3

Top 5 IS	T0-1	T1-2	T2-3	T3-4	T4-5
2008	-0.02%	0.07%	0.28%	-0.04%	0.02%
2009	0.73%	0.04%	0.22%	0.04%	0.11%
2010	-0.16%	-0.05%	-0.08%	-0.22%	-0.12%
2011	-0.03%	-0.03%	0.07%	0.10%	0.09%
2012	0.03%	0.07%	0.15%	0.18%	0.03%
2013	-0.09%	0.24%	0.15%	0.15%	0.21%
2014	0.07%	-0.04%	0.15%	0.11%	-0.06%
2015	-0.28%	-0.11%	-0.01%	-0.10%	-0.07%
Average	**0.03%**	**0.02%**	**0.12%**	**0.03%**	**0.03%**

Table 4

Top 2 IS	T=0	T=1	T=2	T=3	T=4	T=5
2008	-11.10%	0.54%	0.35%	0.51%	0.58%	0.45%
2009	-8.61%	0.90%	0.83%	0.98%	0.92%	0.98%
2010	-5.70%	0.10%	0.11%	0.24%	0.38%	0.45%
2011	-6.04%	-0.13%	-0.09%	-0.02%	0.08%	0.19%
2012	-5.90%	0.00%	0.08%	0.28%	0.41%	0.26%
2013	-6.65%	0.04%	0.01%	0.04%	0.08%	0.18%
2014	-5.56%	0.26%	0.24%	0.33%	0.39%	0.32%
2015	-6.65%	-0.41%	-0.63%	-0.62%	-0.60%	-0.66%
Average	**-7.03%**	**0.16%**	**0.11%**	**0.22%**	**0.28%**	**0.28%**

Table 5

Top 2 IS	T0-1	T1-2	T2-3	T3-4	T4-5
2008	0.54%	-0.16%	0.10%	0.21%	0.12%
2009	0.90%	-0.01%	0.24%	-0.03%	0.12%
2010	0.10%	0.02%	0.13%	0.13%	0.06%
2011	-0.13%	0.06%	0.07%	0.11%	0.11%
2012	0.00%	0.08%	0.20%	0.14%	-0.14%
2013	0.04%	-0.02%	0.03%	0.04%	0.09%
2014	0.26%	-0.03%	0.08%	0.06%	-0.08%
2015	-0.41%	-0.22%	0.00%	0.02%	-0.04%
Average	**0.16%**	**-0.04%**	**0.11%**	**0.09%**	**0.03%**

Table 6

Top 5 OOS	T=0	T=1	T=2	T=3	T=4	T=5
2016-2019	-5.38%	0.05%	0.00%	0.02%	0.07%	0.18%

Table 7

Top 2 OOS	T=0	T=1	T=2	T=3	T=4	T=5
2016-2019	-6.65%	0.04%	0.01%	0.04%	0.08%	0.18%

Table 8

Total	T=0	T=1	T=2	T=3	T=4	T=5
2008-2019	-6.90%	0.12%	0.08%	0.16%	0.21%	0.24%

Table 9

Top-5 Sensitivity Table	
% Per Trade	Final Balance
0.005	$ 1,213,434
0.010	$ 1,388,163
0.015	$ 1,537,486
0.020	$ 1,664,593
0.025	$ 1,772,783
0.030	$ 1,865,079
0.035	$ 1,944,102
0.040	$ 2,012,062
0.045	$ 2,070,796
0.050	$ 2,121,819
0.055	$ 2,166,384
0.060	$ 2,205,538
0.065	$ 2,240,181
0.070	$ 2,271,116
0.075	$ 2,299,079
0.080	$ 2,324,756
0.085	$ 2,348,771
0.090	$ 2,371,658
0.095	$ 2,393,825
0.100	$ 2,415,506
0.105	$ 2,436,751
0.110	$ 2,457,445
0.115	$ 2,477,379
0.120	$ 2,496,363
0.125	$ 2,514,353
0.130	$ 2,531,606
0.135	$ 2,548,777
0.140	$ 2,566,794
0.145	$ 2,586,322
0.150	$ 2,606,989
0.155	$ 2,627,229
0.160	$ 2,645,529
0.165	$ 2,662,290
0.170	$ 2,679,635
0.175	$ 2,698,264
0.180	$ 2,713,650
0.185	$ 2,711,513
0.190	$ 2,709,030
0.195	$ 2,777,884

Table 10

Top-2 Sensitivity Table	
% Per Trade	**Final Balance**
0.01	$ 1,179,078.54
0.02	$ 1,322,050.52
0.03	$ 1,446,604.44
0.04	$ 1,553,956.67
0.05	$ 1,645,803.26
0.06	$ 1,723,980.07
0.07	$ 1,790,277.30
0.08	$ 1,846,348.33
0.09	$ 1,893,672.79
0.10	$ 1,933,549.48
0.11	$ 1,967,104.20
0.12	$ 1,995,304.53
0.13	$ 2,018,976.91
0.14	$ 2,038,823.81
0.15	$ 2,055,440.01
0.16	$ 2,069,327.37
0.17	$ 2,080,908.23
0.18	$ 2,090,537.41
0.19	$ 2,098,513.05
0.20	$ 2,105,086.68
0.21	$ 2,110,472.64
0.22	$ 2,114,857.01
0.23	$ 2,118,405.88
0.24	$ 2,121,272.52
0.25	$ 2,123,602.75
0.26	$ 2,125,537.97
0.27	$ 2,127,215.23
0.28	$ 2,128,764.60
0.29	$ 2,130,304.85
0.30	$ 2,131,939.89
0.31	$ 2,133,759.41
0.32	$ 2,135,847.15
0.33	$ 2,138,298.43
0.34	$ 2,141,244.35
0.35	$ 2,144,875.45