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Out of Sample Testing for O'Neil's Fundamental Stock Selection Strategy

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Abstract: We take a simple strategy that ranks stocks based on how they meet fundamental criterion outlined in the book How to Make Money in Stocks by Bill O'Neil (1988). We model it on a single benchmark the Dow Jones Industrial Average from 1999-2017 with no stop loss. Previous studies by Lutey, Hassan, Rayome (2018) modeled a study from 1999-2015 with a stop loss and showed favorable results. The purpose of our paper is to test the study, without a stop and then see how it holds up two years out of sample (2015-2017). The results show it outperforms the Dow Jones Industrial Average by a larger margin than the previous study. The results hold out of sample and on two additional benchmarks (The S&P 1500, and Nasdaq). We also test overlapping timeframes (1999-2017, 2010-2017, and 2015-2017) on all three benchmarks with favorable results. McLean and Pontiff (2016) show that characteristic studies with excess returns fall apart post publication. Our analysis is that the results are still favorable which have implications for individual money managers, student funds, and applications for industry and efficient market studies.

Keywords: Can Slim, Fundamental Analysis, Automated Trading, Algorithmic Trading, Nasdaq 100, Dow Jones, S&P 1500, Target Date Funds, Portfolio Management

1. Introduction

We take a strategy published on the Dow Jones Industrial average for selecting CAN SLIM Stops and remove the stop loss. We include data updated to 2017 and apply the system to additional benchmarks. McLean and Pontiff (2016) the findings point to mispricing as the source of predictability. Post-publication, stocks in characteristic portfolios experience higher volume, variance, and short interest, and higher correlations with portfolios that are based on published characteristics contribution for this is twofold. One we are showing the system applied without a stop loss on the DOW JONES benchmark which was not included in the previous study and we are extending the study two years into the future on data that was unavailable at the published end date. We also provide two additional benchmarks with the same rule set for robustness. This should alleviate any doubt in the CAN SLIM method to provide returns, however, it may not hold up to full academic scrutiny such as t-statistics or p-values for excess returns. It does, however, provide practical benefit and may be a useful system for student-managed funds. The weights follow Lutey et. al (2018)" The highest percent is given to Earnings growth versus the same quarter one year prior, within the industry; this is followed by earnings growth three-year average within the industry, and institutional shareholders within industry comparison. These are weighted at 35 percent, 25 percent, and 15 percent respectively. " The previous study looked back to 1999, 2005 and 2010 with a 2015 end date. Lutey *et al.* (2014) and Lutey *et al.* (2013) run studies that use the CAN SLIM system to find excess returns on the Nasdaq and S&P 500 respectively.

This paper shows the ranking system of Lutey *et al.* (2018) with no stop loss holds for two years post publication and on two additional benchmarks when tested for robustness. If there was any doubt in the system for picking stocks this would shed light on it.

Our study runs from 1999, 2010, and 2015 with a 2017 end date. We pay particular attention to the 2015-2017 period as it is on new data that was not available when the strategy was created. We also pay attention to the Nasdaq and S&P 1500 benchmarks as they also hold with the same rules which are made for the Dow Jones.

The initial study was 1999-2015 with a stop loss, modeled on the Dow Jones. Lutey, Hassan, Rayome (2018). The study was then re-evaluated without a stop loss and extended forward with real data by two years. It is evaluated on two additional benchmarks for robustness. What we find is that the strategy performs well on the Dow Jones in all periods. It also has strong performance on both the Nasdaq and S&P 1500. This solidifies the results as being more than just an anomaly.

2. Literature Review

The markets are said to be either weak form efficient, strong form efficient, or semi-strong form efficient (Fama and Blume, 1966). The weak form efficiency agrees that past prices cannot be used to make excess returns in the market and that they convey all available information. The strong form and semi strong form argue that the market prices include all available information including insider information and that market prices include only public and private information respectively. Previous research has suggested that stock prices are not always acting as random walks and that from time to time repeatable patterns exist that may be acted on (Lo *et al* (2000)). Furthermore it has been shown that the joint distribution between stock prices and volume can be used to forecast future returns (Blume *et al.*, 1999). There are a variety of technical indicators that are said to forecast the equity risk premium (Neeley *et al* (2013)), and moving averages have been shown to accurately time the volatility sorted decile portfolios (Han *et al.*, 2013). This paper seeks to ask the question whether fundamental analysis can outperform a broad market index. Using identified checklist criteria, stocks are ranked on their fundamentals such as earnings growth and sales growth. Following O'Neil (1988)'s research on previous stock market winners, stocks that broke out to have gains of 100% or more from 1950-1970 were said to have EPS growth in the most recent quarter up 70% from the same quarter one year prior. His work has been made popular by such student funds out of East Carolina University that outperformed the S&P 500 by 800% (as shown in AAII). Recently, markets have been shown to be comprised of nearly 70% algorithmic trading (Chan (2009)). There has also been a noted shift from the computerized trading post 1990 (Angel *et al.*, 2011). Investors typically fall in to two camps, either fundamental investors or technical investors. (Covel 2009). Fundamental investors ignore the semi-strong and strong forms of market efficiency while technical investors ignore the weak form. It is uncommon but becoming increasingly popular for investors to blend the two methods of analysis. In this paper we rely on entirely fundamental analysis without any use of past prices to forecast future returns. A study from Worcester Polytechnic Institute (Ambalangodage, 2019), shows that the O'Neil (1988) system performs well when compared to robo advisors. Typically individuals may use a target date fund for their retirement which de-invests risky assets as the individual becomes closer to retirement age. These funds have been shown to have a high probability of running out of money when analyzed using bootstrap analysis (Spitzer *et al* (2008)). Thus the O'Neil (1988) category may be fruitful for those individuals who want to manage their own stock protfolio. The drawbacks of such methods by O'Neil (1988) are that the methodology for most individuals can be subjective and difficult to replicate. Automating the stock selection may be a more appropriate method for individuals. Recent papers have supported automated algorithms (Zhang *et al.* 2019). McLean and Pontiff (2016) the findings point to mispricing as the source of predictability. Post-publication, stocks in characteristic portfolios experience higher volume, variance, and short interest, and higher correlations with portfolios that are based on published characteristics.

3. Data and Methodology

We use Standard and Poor's Compustat Snapshot Point in Time survivor free data. We use 1999-2017. We use $100,000 starting capital. Stocks are evaluated on fundamentals and ranked from highest to lowest against stocks in the same industry, and all available stocks. The ranking is limited to those stocks on the benchmark. Therefore, it the benchmark is the Dow Jones only Dow Jones stocks are considered. For the Nasdaq, only Nasdaq stocks etc. The rebalance period is every 4 weeks. Slippage is 0.5% and there is a $10 commission per entry and exit which today may be high considering many brokers are offering $0 commission or commissions as low as 0.05 per share. TD Ameritrade and Interactive Brokers are for example. For software we use portfolio123 as it gives a subscription based access to the Compustat and handles the back-end programming. We have an ideal weight of 10% per position with a maximum of 10 positions. The system may apply more or less weight and deviate up to 30%. The specific weights used for ranking stocks are described in the following section. We rank stocks on their ability to meet the following fundamental criterion. We first rank stocks based on their earnings and sales growth characteristics against stocks within the same industry. We then rank on their earnings growth against stocks in their benchmark.

Table 1: Trading Rules

EPS% Change Prior Year Quarter Industry	15%
Sales% Change Prior Year Quarter Industry	10%
EPS 3 Year Growth % Industry	20%
Sales 3 Year Growth % Industry	5%
EPS 3 Year Growth % Benchmark	15%
EPS% Change Prior Year Quarter Benchmark	35%

Source: Characteristic criteria for investing

We show that stocks that follow this via a ranking system are selected and held with monthly rebalancing. When a better stock meets the criteria and is available the next month it replaces the worst performing stock from the previous month. If stocks are acquired or delisted they are dropped. All of the data is point in time data and is survivor bias free. The initial sample of 1999-2017 is broken in to three overlapping sub periods. 1999-2017, 2010-2017 and 2015-2017. The sample is then evaluated on the Dow Jones Industrial Average (picking only Dow Jones Stocks). It holds an ideal number of 10 stocks. It can deviate however and apply greater weight to individual stocks based on how well they meet the ranking criteria. The system is then evaluated on two additional benchmarks, the Nasdaq and S&P 1500 which is a high growth index. Each benchmark shows similar results outlined in the following section.

4. Results

We run the study three separate times for each benchmark. We run it from 1999-2017. The study is then started over fresh in 2010 ending in 2017. We run it a third time from 2015-2017. Using the same weights from a previously published study ending in 2015. We then repeat this three times on each of the following benchmarks. The Dow Jones, the Nasdaq and the S&P 1500. Our results are summarized below.

Table 2: CAN SLIM vs. Dow Jones

CAN SLIM vs	*1999-2017*		*2010-2017*		*2015-2017*	
Dow Jones	*Model*	*Dow Jones*	*Model*	*Dow Jones*	*Model*	*Dow Jones*
Monthly Samples	218	218	85	85	23	23
Drawdown	-59.16%	-53.78%	-16.40%	-16.82%	-13.05%	-14.48%
Beta	1.05	-	0.93	-	0.83	-
Standard Deviation	15.78%	14.32%	11.87%	12.02%	10.54%	11.81%
Sharpe	0.39	0.26	1.00	0.91	0.67	0.44
Sortino	0.52	0.35	1.39	1.25	0.97	0.68
Correlation	0.95	-	0.94	-	0.94	-
Total Return	243.72%	127.90%	119.03%	105.69%	18.63%	14.83%
Annual Return	7.03%	4.64%	11.64%	10.66%	8.96%	7.19%
Alpha	2.34%	-	1.80%	-	2.72%	-
Win Rate	66.67%	-	91.67%	-	80.00%	

Table 3: Can Slim vs. Nasdaq

CAN SLIM vs	*1999-2017*		*2010-2017*		*2015-2017*	
Nasdaq	*Model*	*Nasdaq*	*Model*	*Nasdaq*	*Model*	*Nasdaq*
Monthly Samples	218	218	85	85	23	23
Drawdown	-80.24%	-82.90%	-24.69%	-16.34%	-23.22%	-16.34%
Beta	0.95	-	1.05	-	1.07	-
Standard Deviation	31.34%	25.54%	18.54%	14.83%	17.71%	15.17%
Sharpe	0.35	0.29	1.06	1.14	1.27	0.55
Sortino	0.54	0.40	1.50	1.61	1.77	0.83
Correlation	0.77	-	0.84	-	0.92	-
Total Return	352.16%	195.65%	243.60%	198.15%	52.27%	20.33%
Annual Return	8.65%	6.14%	18.93%	16.58%	23.52%	9.74%
Alpha	4.09%	-	2.01%	-	14.57%	-
Win Rate	50.00%	-	87.50%	-	66.67%	

Table 4: Can Slim vs S&P 1500

CAN SLIM vs	*1999-2017*		*2010-2017*		*2015-2017*	
S&P 1500	*Model*	*S&P 1500*	*Model*	*S&P 1500*	*Model*	*S&P 1500*
Monthly Samples	218	218	85	85	23	23
Drawdown	-59.03%	-56.77%	-20.21%	-20.27%	-13.41%	-23.24%
Beta	0.92	-	0.93	-	0.68	-

contd. table 4

Standard Deviation	20.68%	14.84%	15.44%	12.71%	14.18%	13.87%
Sharpe	0.33	0.23	1.08	0.95	0.84	0.32
Sortino	0.46	0.30	1.51	1.31	1.18	0.44
Correlation	0.66	-	0.77	-	0.67	-
Total Return	217.81%	111.22%	189.28%	119.86%	26.25%	10.42%
Annual Return	6.57%	4.20%	16.09%	11.70%	12.43%	5.11%
Alpha	3.68%	-	5.65%	-	9.27%	-
Win Rate	63.16%		82.35%	-	73.33%	-

Table 2. Results Summarized.

The summary of the results show that the model is evaluated for 218 months (1999-2017), 85 months (2010-2017) and 23 months (2015-2017). We evaluate several risk metrics and compare them from the study to the benchmark. These include Maximum Drawdown, Beta, Standard Deviation, Sharpe Ratio, Sortino Ratio, Correlation with the Benchmark, Total Return, Annual Return, Alpha and a win rate.

4.1. Maximum Drawdown

The study overdraws the Dow Jones Industrial Average by 5.38% in the longest sample 1999-2017. The Dow Jones overdraws the study by 0.42% in the intermediate study 2010-2017, and by 1.43% on the shortest study 2015-2017.

The benchmark on the Nasdaq overdraws the study in 1999-2017 by 2.66%. The intermediate study 2010-2017 shows the study overdraws the benchmark by 8.34% and 9.83% in the shortest timeframe 2015-2017.

The study overdraws the S&P 1500 by 2.26% in the longest sample 1999-2017. The study performs better by 0.06% in the intermediate timeframe 2010-2017 and by 9.83% in the shortest time frame 2015-2017.

4.2. Beta

The study has a beta of around 1 for the long, and intermediate time frames on the Dow Jones (1.05, 0.93), and 0.83 for the shortest time frame. The beta is around 1 for the Nasdaq benchmark. 0.95, 1.05 and 1.07 for the Long, Intermediate and Short-Term time frames respectively. The beta is around 1 for the Long, and Intermediate time frames (0.95 and 0.93 respectively) for the S&P 1500 and 0.68 for the shortest timeframe.

This adds to the paper by Lutey, Hassan, and Rayome (2018) in that it provides an extended look at their model without a stop loss and on two years of forward tested data. The results for each overlapping timeframe are expanded below from the summary graphs above.

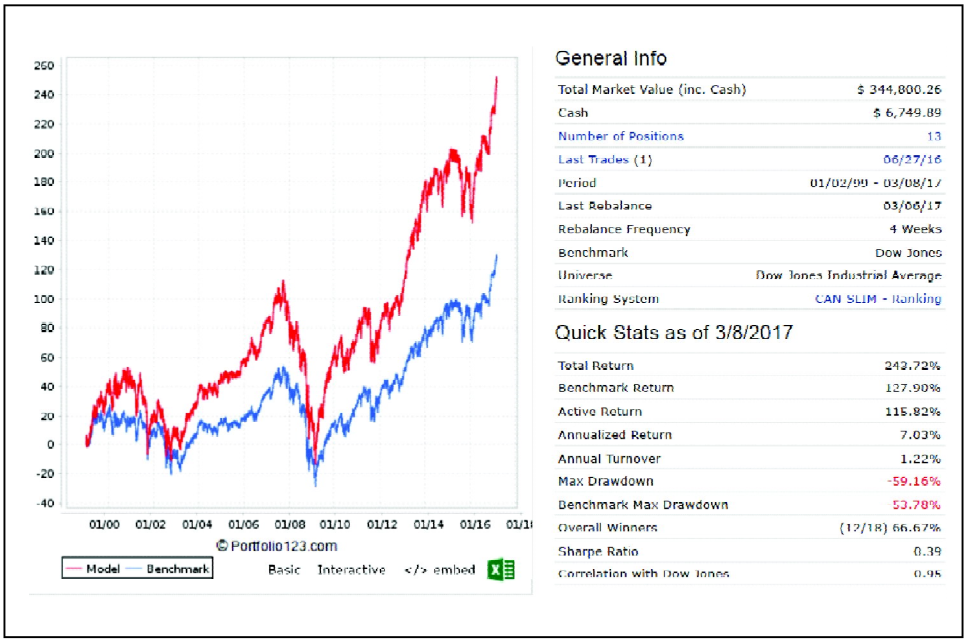

Figure 1: Dow Jones 2000-2017

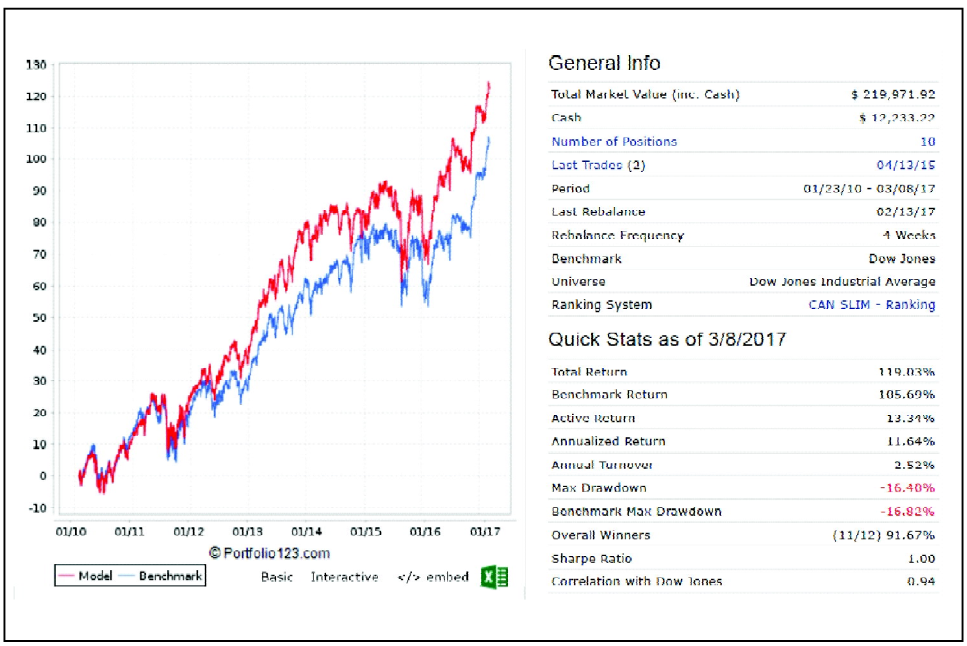

Figure 2: Dow Jones 2010-2017

General Info

Total Market Value (inc. Cash)	$ 119,419.28
Cash	$ 6,132.41
Number of Positions	10
Last Trades (10)	03/02/15
Period	02/28/15 - 02/24/17
Last Rebalance	01/30/17
Rebalance Frequency	4 Weeks
Benchmark	Dow Jones
Universe	Dow Jones Industrial Average
Ranking System	CAN SLIM - Ranking

Quick Stats as of 2/24/2017

Total Return	18.63%
Benchmark Return	14.83%
Active Return	3.80%
Annualized Return	8.96%
Annual Turnover	0.00%
Max Drawdown	-13.05%
Benchmark Max Drawdown	-14.48%
Overall Winners	(8/10) 80.00%
Sharpe Ratio	0.67
Correlation with Dow Jones	0.94

Figure 3: Dow Jones 2015-2017

The last graph 2015-2017 is important because it takes the rule set from the previous strategy's published end date (2015) and tests until the current date (when the above study was formed). This is true out of sample testing as the data was not available or held out when the original model was created. It is only made available once we move forward in real time. There is a JF paper that discusses how stock predictive models fall apart after their publication date.

The same system can also be applied to the S&P 1500 and Nasdaq 100. Again noting the 2015-2017 periods. We discuss the S&P 1500 first. Then the Nasdaq 100. The results are similar over all of the time frames and all markets. It may be a useful tool for individual investors. It is possible that some time frames may have positive test statistics but it would not likely be robust.

We will show some graphs in the following section (after the S&P 1500, and Nasdaq 100 tests) that adapt the model of current earnings (addressed in the stock screener). These graphs likely have a positive test statistic but include technical analysis for entry (because the weights are so heavily based on earnings with no other criteria). We conclude the paper with a live adaption of the model using paper money and four years of forward testing applying the full system in freely available stock screeners and portfolios. This would be a ready to use model for individuals or student managed funds.

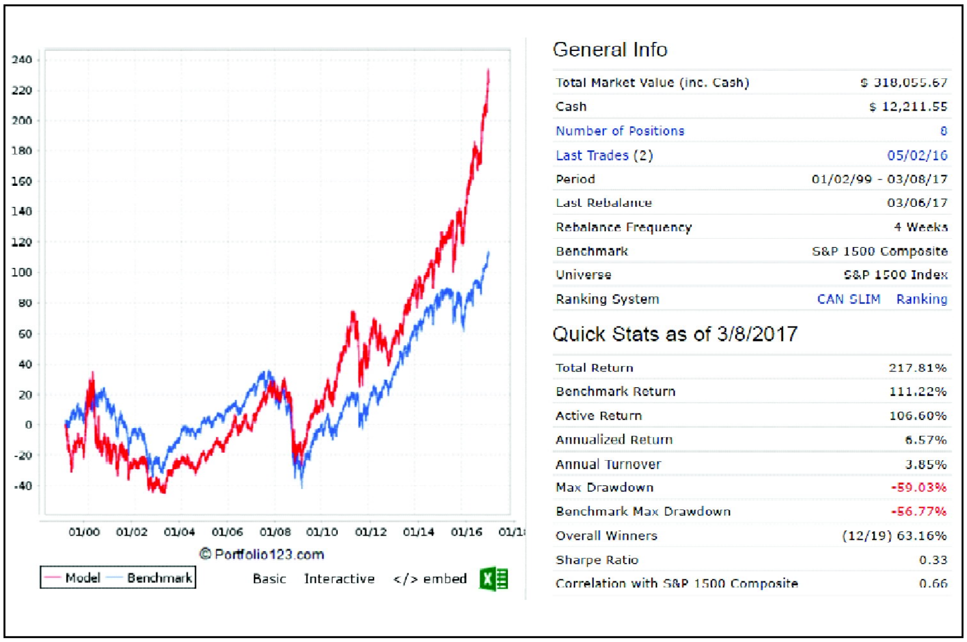

Figure 4: S&P 1500 2000-2017

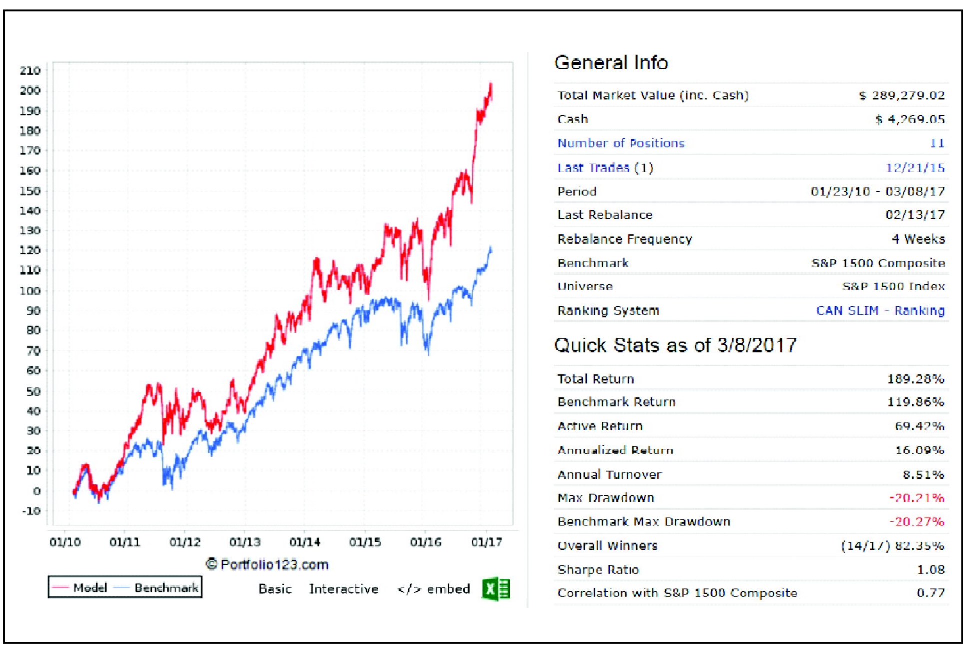

Figure 5: S&P 1500 2010-2017

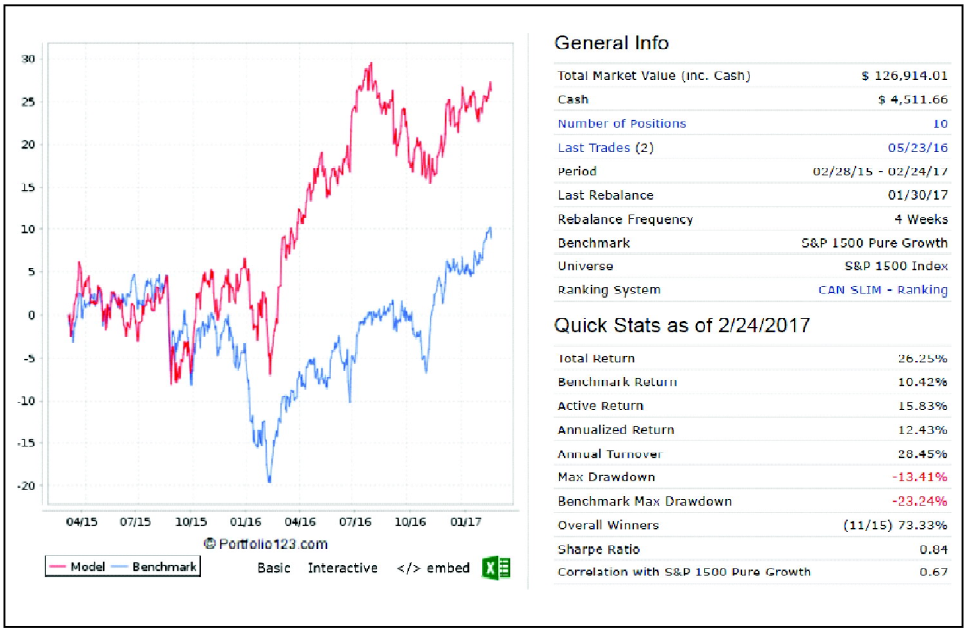

Figure 6: S&P 1500 2015-2017

These models all show similar results. Some perform better than the Dow Jones benchmark. Note the win percentage is nearly the same for the models between the two benchmarks. It is as high as 91% for the Dow Jones and consistent at 83% for the S&P 1500 in a similar period. Both models show the 1999-2017 strategy to have a 60% win rate (or thereabouts). All of the time frames outperform their benchmark. We now consider the Nasdaq 100 market. This is an interesting market because we've gone from 30 firms to 1500 and now we'll settle on 100. Notice how each market is only selecting from the available stock universe for that benchmark, but using the same ranking system. It is unifying the CAN SLIM method across available stock universes.

Again the model holds up and has a consistent and similar win ratio with the 2010-2017 period being the highest and >80%. The 1999-2017 period has a 50% win ratio which is lower but the market still overperforms. The results are not likely to be statistically significant when studied using P values but the later 2015-2017 market might. Note the returns are $100,000 to $152,903 compared to $100,000 to $120,330 inclusive of transaction and carrying costs.

We can also look at the current holdings over each of the 2015-2017 periods. These are the two years of out of sample data not included in the 1999-2015 study by Lutey, Hassan and Rayome (2018).

General Info

Total Market Value (inc. Cash)	$ 453,713.55
Cash	$ 1,651.67
Number of Positions	7
Last Trades (1)	02/06/17
Period	01/02/99 - 03/08/17
Last Rebalance	03/06/17
Rebalance Frequency	4 Weeks
Benchmark	Nasdaq 100
Universe	Nasdaq 100
Ranking System	CAN SLIM - Ranking

Quick Stats as of 3/8/2017

Total Return	352.16%
Benchmark Return	195.65%
Active Return	156.51%
Annualized Return	8.65%
Annual Turnover	5.31%
Max Drawdown	-80.24%
Benchmark Max Drawdown	-82.90%
Overall Winners	(12/24) 50.00%
Sharpe Ratio	0.35
Correlation with Nasdaq 100	0.77

Figure 7: Nasdaq 2000-2017

General Info

Total Market Value (inc. Cash)	$ 343,637.00
Cash	$ 9,073.44
Number of Positions	10
Last Trades (2)	11/23/15
Period	01/23/10 - 03/08/17
Last Rebalance	02/13/17
Rebalance Frequency	4 Weeks
Benchmark	Nasdaq 100
Universe	Nasdaq 100
Ranking System	CAN SLIM - Ranking

Quick Stats as of 3/8/2017

Total Return	243.60%
Benchmark Return	198.15%
Active Return	45.45%
Annualized Return	18.93%
Annual Turnover	6.63%
Max Drawdown	-24.69%
Benchmark Max Drawdown	-16.34%
Overall Winners	(14/16) 87.50%
Sharpe Ratio	1.06
Correlation with Nasdaq 100	0.84

Figure 8: Nasdaq 2010-2017

General Info

Total Market Value (inc. Cash)	$ 152,903.39
Cash	$ 4,673.11
Number of Positions	11
Last Trades (1)	02/01/16
Period	02/28/15 - 02/24/17
Last Rebalance	01/30/17
Rebalance Frequency	4 Weeks
Benchmark	Nasdaq 100
Universe	Nasdaq 100
Ranking System	CAN SLIM - Ranking

Quick Stats as of 2/24/2017

Total Return	52.27%
Benchmark Return	20.33%
Active Return	31.95%
Annualized Return	23.52%
Annual Turnover	4.48%
Max Drawdown	-23.22%
Benchmark Max Drawdown	16.34%
Overall Winners	(8/12) 66.67%
Sharpe Ratio	1.27
Correlation with Nasdaq 100	0.92

Figure 9: Nasdaq 2015-2017

	Ticker		Weight	Return	Return $	Rank	Shares	Avg Shr Cost	Current Price	Value	Days Held	Sector
1	BA	[5D] [1Y]	9.66%	17.00%	1,675.86	63.3	65.0	$151.66	$177.44	$11,533.60	725	Industrials
2	CVX	[5D] [1Y]	8.58%	2.96%	293.96	13.3	93.0	$106.96	$110.12	$10,241.16	725	Energy
3	IBM	[5D] [1Y]	9.26%	11.50%	1,140.56	50.0	61.0	$162.65	$181.35	$11,062.35	725	Information Technology
4	JNJ	[5D] [1Y]	9.87%	18.60%	1,848.15	86.7	96.0	$103.48	$122.73	$11,782.08	725	Health Care
5	MRK	[5D] [1Y]	9.42%	12.82%	1,278.35	90.0	170.0	$58.64	$66.16	$11,247.20	725	Health Care
6	NKE	[5D] [1Y]	9.88%	18.72%	1,861.25	30.0	204.0	$48.74	$57.86	$11,803.44	725	Consumer Discretionary
7	PFE	[5D] [1Y]	8.35%	-0.01%	-1.36	40.0	291.0	$34.26	$34.26	$9,969.66	725	Health Care
8	UNH	[5D] [1Y]	11.88%	42.47%	4,228.74	56.7	87.0	$114.45	$163.06	$14,186.22	725	Health Care
9	V	[5D] [1Y]	10.37%	27.06%	2,636.93	96.7	140.0	$69.59	$88.43	$12,380.20	725	Information Technology
10	XOM	[5D] [1Y]	7.60%	-8.77%	-872.59	76.7	112.0	$88.87	$81.08	$9,080.96	725	Energy

(*) Avg Shr Cost includes commissions

Figure 10: Current (2017) Holdings Dow Jones

	Ticker		Weight	Return	Return $	Rank	Shares	Avg Shr Cost	Current Price	Value	Days Held	Sector
1	CPT	[5D] [1Y]	9.03%	15.26%	1,516.84	97.3	136.0	$73.09	$84.24	$11,456.64	725	Real Estate
2	DEI	[5D] [1Y]	13.30%	36.58%	4,519.75	97.3	417.0	$29.63	$40.47	$16,875.99	669	Real Estate
3	EQR	[5D] [1Y]	15.53%	-7.68%	-1,639.08	85.1	314.0	$68.00	$62.78	$19,712.92	277	Real Estate
4	GGP	[5D] [1Y]	6.75%	-14.14%	-1,410.49	99.6	342.0	$29.17	$25.05	$8,567.10	725	Real Estate
5	HST	[5D] [1Y]	6.70%	-14.95%	-1,494.56	66.0	472.0	$21.18	$18.01	$8,500.72	725	Real Estate
6	KBH	[5D] [1Y]	9.67%	22.76%	2,275.66	74.6	712.0	$14.04	$17.24	$12,274.88	725	Consumer Discretionary
7	LAMR	[5D] [1Y]	10.05%	27.74%	2,768.72	94.6	171.0	$58.38	$74.57	$12,751.47	725	Real Estate
8	PLD	[5D] [1Y]	9.34%	18.88%	1,882.30	98.5	232.0	$42.97	$51.08	$11,850.56	725	Real Estate
9	REG	[5D] [1Y]	8.58%	4.41%	459.88	59.8	153.0	$68.18	$71.19	$10,892.07	697	Real Estate
10	TCO	[5D] [1Y]	7.50%	-4.10%	-407.50	46.0	136.0	$73.00	$70.00	$9,520.00	725	Real Estate

(*) Avg Shr Cost includes commissions

Figure 11: Current (2017) Holdings S&P 1500

	Ticker		Weight	Return	Return $	Rank	Shares	Avg Shr Cost	Current Price	Value	Days Held	Sector
1	AMZN	[5D] [1Y]	14.37%	120.61%	12,014.63	51.0	26.0	$383.14	$845.24	$21,976.24	725	Consumer Discretionary
2	ATVI	[5D] [1Y]	12.69%	94.16%	9,410.31	74.5	426.0	$23.46	$45.55	$19,404.30	725	Information Technology
3	CTXS	[5D] [1Y]	8.13%	25.02%	2,487.24	95.1	155.0	$64.13	$80.18	$12,427.90	725	Information Technology
4	EA	[5D] [1Y]	9.79%	50.44%	5,019.82	55.9	173.0	$57.52	$86.54	$14,971.42	725	Information Technology
5	EBAY	[5D] [1Y]	3.83%	-41.17%	-4,099.77	98.0	172.0	$57.90	$34.06	$5,858.32	725	Information Technology
6	FOXA	[5D] [1Y]	5.69%	-13.06%	-1,306.46	53.9	284.0	$35.21	$30.61	$8,693.24	725	Consumer Discretionary
7	GILD	[5D] [1Y]	4.35%	-33.34%	-3,323.74	63.7	95.0	$104.93	$69.94	$6,644.30	725	Health Care
8	LVNTA	[5D] [1Y]	7.08%	8.59%	856.81	75.5	247.0	$40.37	$43.84	$10,828.48	725	Consumer Discretionary
9	MAR	[5D] [1Y]	8.60%	5.87%	728.56	23.5	151.0	$82.26	$87.08	$13,149.08	669	Consumer Discretionary
10	NVDA	[5D] [1Y]	16.99%	244.57%	18,435.75	89.2	256.0	$29.45	$101.46	$25,973.76	389	Information Technology
11	REGN	[5D] [1Y]	5.43%	-13.80%	-1,329.08	61.8	23.0	$418.80	$361.01	$8,303.23	725	Health Care

(*) Avg Shr Cost includes commissions

Figure 12: Current (2017) Holdings Nasdaq

The next step in this line of research is to see if it continues to holds going forward. Could keep updating this and see how well it holds. This would be done by running a live data feed from the portfolio selection models for each benchmark to three separate accounts. They would be evaluated going forward over rolling periods. 1 year, 3 year and 5 year and then eventually going live with real capital if applicable.

5. Conclusion

This paper shows promising results for automating the stock selection strategy outlined by O'Neil (1988). Placing a high emphasis on current earnings growth reiterates O'Neil's point that top performing stocks had abnormally high levels of earnings growth in the most recent quarter. The automated algorithm has important implications for fund managers and individuals who want to manage their own retirement, student investment funds, and market efficiency testing. The algorithm out performed 3 separate benchmarks over 3 overlapping time periods. It was originally modeled in 2015 and published in 2018 by Lutey et al (2018). McLean and Pontiff (2016) suggest that strategies that outperform a benchmark fall apart post publication. This paper takes the ranking system from Lutey et al (2018) and extends it two full years past their end of sample date and applies it to additional benchmarks for robustness while removing the stop loss criteria. This focuses entirely on fundamental analysis and ignores any form of past prices violating the weak form efficeincy. The purpose here is to automate portfolio selection for individuals while accounting for transaction costs.

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