A COMPARATIVE STUDY OF TRAILING AND FORWARD-LOOKING OPTIMAL PORTFOLIOS OF DJIA STOCKS

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ABSTRACT

This paper examines the performance of forward-looking optimal portfolios constructed primarily from DJIA (Dow Jones Industrial Average Index) stocks during the worst day of the year events in 2018 and 2020. The investigative question is: Is the performance of the forward-looking optimal portfolios superior to the performance of trailing optimal portfolios? This study uses forward-looking optimal portfolios constructed as proxies of contrarian investment portfolios. **JEL classifications**: G11; G14; G17

INTRODUCTION

The first event study examines the portfolio performance of the Dow Jones Industrial Average (DJIA) stocks plus four FAANG stocks around December 24, 2018, when DJIA hit its lowest point of the year 2018. The second event study deals with the portfolio performance of DJIA stocks around March 23, 2020, when DJIA hit its lowest point of the year 2020. This study chose two cases of lowest yearly points in 2018 and 2020 to examine the portfolio performance differences between the trailing and forward-looking optimal portfolios because contrarian investing would be more effective during such dramatic stock market periods when market efficiency suffers most. In this study, “winners” mean the top-half performers (i.e., performance ranks 1 through 17 in the 2018 case, the performance ranks 1 through 15 in the 2020 case), and “losers” mean the bottom-half performers (i.e., performance ranks 18 through 34 in the 2018 case, the performance ranks 16 through 30 in the 2020 case) during each of the two sub-sample periods. It analyzes the performance of the conventional, backward-looking (trailing) optimal portfolio constructed from the pool in the 2018 case using the daily data sample period from Oct. 18, 2018, to Dec. 24, 2018, and it analyzes the portfolio pool in the 2020 case using the daily data sample period from January 16, 2020, to March 23, 2020. As an alternative, it also analyzes the performance of the forward-looking optimal portfolios, based on a contrarian premise. In the first study, FAANG stocks are four stocks, Facebook (FB), Amazon (AMZN), Netflix (NFLX), and Alphabet (GOOG) stocks, because the fifth component of extended FAANG stock, Apple (AAPL) is already included in the DOW components. Apple (AAPL) became a DJIA stock in March 2015. However, FAANG stocks are excluded from the second event study.

This paper is organized as follows: the next section explains contrarian investing; the second section is a literature review; the third section describes the investigative design and methodology; the fourth section explains the findings; the final section sets forth a conclusion and further study. References and six tables presenting the key descriptive and analytical statistics of this study are placed at the back of the paper.

CONTRARIAN INVESTING EXPLAINED

The premise of contrarian investing is that investing the same way in which everyone else is thinking leads to wrong investing. That is, it is contrary to the herd instinct. In a way, contrarian investing is consistent with value investing in that the contrarian invests in mispriced investments that are undervalued by the market. Economist John Maynard Keynes was an early pioneer of implementing contrarian premises in active portfolio investment (Chambers and Dimson, 2013). For example, Keynes was an early contrarian investor when he managed the endowment for King's College, Cambridge from the 1920s to '40s in the sense that while most endowments invested mostly in land and fixed income securities, Keynes invested heavily in common stocks and outperformed the UK stock market.

David Dreman, a statistical contrarian investor, has been an advocate for contrarian investing focusing on low P/E ratio stocks. In a classic study, Dreman demonstrates that the contrarian investment strategies that employ low P/E ratio stocks have outperformed the S&P 500 over nine annualized periods for 50 years up to 12/31/2010 (Morningstar, Inc. 2011). The study shows that the Low P/E portfolio performed by +18.67%; S&P 500, +9.64%; High P/E portfolio, +9.87% based on the 50-year average annual return, 12/31/1960 to 12/31/2010, thereby the Low P/E portfolio outperformed both S&P 500 and the High P/E portfolio by wide margins.

Applying the premise of contrarian investing suggested by Dreman's Low P/E portfolio performance, this study constructs portfolio optimization based only on the pool of loser stocks among Dow and FAANG stocks in the 2018 case, Dow stocks only in the 2020 case. The proxy contrarian optimal portfolio construction is referred to as "forward-looking portfolio optimization" in this study, contrary to the conventional portfolio optimization or trailing portfolio optimization which is based only on historical properties of components of the portfolio pool.

LITERATURE REVIEW

The comparative underperformance of FAANG stocks during the first phase of the sample period of the first event study could be explained by a report by Keown (2019). Keown reported that the fabled "FAANG" (i.e., the extended FAANG) stocks, comprising Facebook Inc. FB, Amazon.com AMZN, Apple AAPL, Netflix NFLX, and Google parent Alphabet GOOG, have had a mixed year [2019], and the trade was no longer what it once was. As quoted in the report, Christopher Wood speculated that an optimistic trade war outcome expectation such as unexpectedly dropping existing tariffs could cause "global stocks soaring." Even though his speculation was not realized, the dramatic turnaround of performance of FAANG stocks in the second half of the sample period in the 2018 case was caused probably by rationalization from overreaction on tariff war concerns.

The weakness of the trailing optimal portfolio construction lies in the fact that it favors high-performance stocks in terms of the return per unit of risk among the components of the portfolio pool based on the historical data. As evidenced by this study, the conventional optimal portfolio failed to capture any of the high-performance stocks in the second half of the sample period. Therefore, the conventional optimal portfolio construction based on past performance is no guarantee of similar results in the short-run future.

This study explores a forward-looking optimal portfolio proxy of DOW plus FAANG stocks constructed from the pool of 17 losers of DOW and FAANG stocks during the first sub-sample period and compares the performance of the proxy optimal portfolio with the performance of the trailing optimal portfolios of DOW stocks during the second sub-sample period.

The performance failure of the trailing optimal portfolio is a practical issue, despite the theoretical breakthrough by Markowitz's mean-variance portfolio optimization. The practical issue lies in the fact that past performance is no guarantee for future performance. For example, to overcome such a practical issue, Bielstein and Hanauer (2017) suggest using the ICC (Implied Cost of Capital) based on analysts' earnings forecasts as a forward-looking return estimate. Another possibility is that Jagannathan and Ma (2003) suggest focusing on the minimum variance portfolio (MVP) construction, which would mitigate the estimation errors. However, deriving the ultimate optimal portfolio from the MVP construction could be even more challenging.

If the forward-looking optimal portfolio proxy in this study is utilized effectively it could capture the winners of the second half of the sample period of this study. The practical goal of such forward-looking optimal portfolio construction would be to capture winners in the second sub-sample period in the short run. However, the trailing EGP optimal portfolio construction may still hold the investment merit in the long run.

INVESTIGATIVE DESIGN AND OPTIMAL PORTFOLIO CONSTRUCTION METHODOLOGY

The daily stock price data are adjusted for stock splits and dividends for the sample periods. The daily data for portfolio optimization are collected for 30 Dow components plus four FAANG stocks for 45 days before December 24, 2018. This section provides an operational and workable framework for constructing optimal portfolios of components. The application incorporates the capital asset pricing model, ways to find the excess return to risk ratios, and unsystematic risk measures. It finds specific weights for the optimal portfolio of components. It follows a sequence of steps to follow for finding the portfolio of components.

This study also examines the performance properties of optimal portfolios constructed with the DOW plus FAANG stocks, 34 stocks in total. The technique used for finding the optimal portfolio is the technique originally introduced by Elton, Gruber, and Padberg (1987) (EGP technique). The essential steps of the EGP technique are as follows. First, find the "excess return to beta ratios" for components and rank them from highest to lowest. This will rank the components in terms of relative performance based on return per unit of systematic risk contained. Second, calculate the nonmarket variance of each component by calculating the variance of the market proxy, or Dow Jones Industrial Average Index proxy, DIA (SPDR Dow Jones Industrial Average ETF). Then, it sets the cutoff ratio to include those components that qualify for the optimum mix. The optimum mix will consist of all components for which the individual component's "excess return to beta" ratio is greater than the cutoff rate. The model finds the individual component's C ratio by solving a mathematical objective function to maximize the tangency slope of excess return to the component's risk measure with the constraint that the sum of the proportions of individual components included in the mix equals one. The optimum cutoff ratio (C') is determined by finding the last individual component's C ratio, which is less than its "excess return to beta" ratio in the ordered list in the first step. After finding the qualified components for the optimum mix using the cutoff ratio (C'), calculate the percentage weight of each component for the optimal portfolio.

The percentage of ith component (Xi) in the optimum portfolio is:

$$X_i = Z_i / \sum_{i=1}^{n} Z_i * 100 \tag{1}$$

where:

$$Z_i = [ß_i / \sigma_{ei}^2]*[TI_i – C'] \tag{2}$$

where:
σ_{ei}^2= nonmarket variance of ith component.
TI_i = Treynor Index of ith component = $(R_i-R_f)/ ß_i$,
where:
R_f = risk free rate,
R_i = the rate of return of ith component,
$ß_i$ = the systematic risk of ith component,
C' = the optimum cutoff ratio.

This study constructs trailing, and forward-looking optimal portfolios constructed from the Dow plus FAANG stocks for the 2018 case but from DOW stocks only for the 2020 case. This paper examines the performance of the trailing optimal portfolios and the forward-looking optimal portfolios during the sub-sample periods after the event dates.

FINDINGS

Is the performance of forward-looking optimal portfolios of DOW stocks superior to the performance of the trailing optimal portfolios of DOW stocks? The findings show the answer is positive. Table 1A and Table 1B indicate the forward-looking EGP optimal portfolios outperformed the trailing EGP optimal portfolios in both 2018 and 2020 cases. As shown in the last column, the weighted-average performance rank

(15) of the forward-looking optimal portfolio is twice higher than the performance rank (30) of the trailing optimal portfolio in the 2018 case. In the 2020 case, the portfolio rank of the forward-looking optimal portfolio (18) is decisively higher than the portfolio rank of the trailing optimal portfolio (28). DIA performed slightly worse than the forward-looking optimal portfolio in terms of holding period returns in the 2018 case (+19.82% vs. +19.96%). However, DIA performed better than the forward-looking optimal portfolio in the 2020 case (+37.76% vs. +30.99%). None of the trailing optimal portfolio stocks in both 2018 and 2020 cases was a winner. The actual performance of the trailing optimal portfolio in the 2018 case was +5.27%, which is far inferior to the DIA's performance, +19.82%. The trailing optimal portfolios in both 2018 and 2020 cases were group winners in the first half (the optimally weighed group ranks, 3). But trailing optimal portfolios in both 2018 and 2020 were group losers in the second half (the group ranks, 30 and 28, respectively). However, two out of three stocks in the forward-looking optimal portfolio in both the 2018 and 2020 cases were winners.

Tables 2A and 2B show properties of the trailing optimal portfolios in the 2018 and 2020 cases. The 2018 portfolio consists of KO, MRK, MCD, PG, and VZ with heavily favoring KO (54.57% of the portfolio weight), all five of which turned out to be loser stocks during the second half of the sample period, as shown in Table 1A. The 2020 portfolio consists of VZ, MRK, and WMT with heavily favoring VZ (82.01% of the portfolio weight), all three of which turned out to be loser stocks as well. The comparatively poor performance of the trailing optimal portfolios after its construction raises a serious question of the usefulness of conventional backward-looking optimal portfolio construction at least in the short run. In sum, as for the trailing portfolio optimization, in both 2018 and 2020 cases, its hindsight was excellent, but its foresight was a failure. That is, past performance during the first half of the sample period of the trailing optimal portfolios in both 2018 and 2020 cases is not repeated in the second half of the sample period.

Table 3A and 3B show properties of the forward-looking optimal portfolios in the 2018 and 2020 cases. The 2018 portfolio consists of MSFT, CAT, and AXP with heavily favoring MSFT (65.5% of the portfolio weight), all three of which turned out to be the winner stocks during the second half of the sample period. The 2020 portfolio consists of KO, MMM, and NKE with heavily favoring KO (64.7% of the portfolio weight), two of which turn out to be the winner stocks during the second half of the sample period. The forward-looking optimal portfolios in both 2018 and 2020 cases are group losers in the first half (the group ranks, 19 and 17 respectively). The 2018 forward-looking optimal portfolio is group winner in the second half (group rank, 15), but the 2020 forward-looking optimal portfolio is group loser technically in the second half (group rank, 19, only 4 ranks lower than the winner rank). Even though two out of three stocks are winners, the heavily weighted KO is a technical loser (Rank 23). However, the holding period return in the second half (+30.99%) of the 2020 forward-looking optimal portfolio is not losing performance.

CONCLUSION AND FURTHER STUDY

The positive reversal performance during the second half of the sample periods in both 2018 and 2020 cases is dramatic. This indicates that Dow stocks did not behave efficiently during the sample periods. The worst day of the year event disrupted the pricing efficiency of stocks. The worst day of the year event made a significantly positive effect on the subsequent, second half of the sample periods. In summary, this study finds that it is fair to say that the forward-looking portfolio optimization decisively outperforms the trailing portfolio counterpart. Therefore, it may suggest the usefulness of contrarian thinking at least in the short run, particularly during the lowest points of stock market trend such as the worst day of the year events studied in this paper. However, it may be due to market inefficiency during such abnormal periods. That is, this study's finding may be due to the worst day of the year anomaly.

In the 2018 case, because of the poor performance of FAANG stocks during the first half of the sample period (the average group performance rank of 26 out of 34), any of the FAANG stocks were selected neither in the trailing optimal portfolio nor in the forward-looking optimal portfolio. The key reason for not being selected in the optimal portfolio is that the EGP optimization favors higher returns per unit of risk and the risk levels of FAANG stocks are too high to be included in the optimal portfolios.

The superior performance of forward-looking optimal portfolios during the sample test periods studied in this paper would be not universal. Also, this study's finding suggests a caveat to using trailing portfolio optimization for practical investment purposes. For further study, it would be worthwhile exploring the possibility of considering a more effective fair value estimation process and constructing forward-looking optimal portfolios using the futuristic return estimates rather than historical returns, thereby mitigating the negative influence of the high-risk nature of certain stocks like FAANG stocks. It also would be a future challenge to use S&P 500 stocks rather than DJIA stocks for portfolio optimization for performance comparisons since S&P 500 is a better market representation than DJIA.

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TABLE 1A. COMPARATIVE PERFORMANCE PROPERTIES OF TRAILING VS. FORWARD-LOOKING EGP OPTIMAL PORTFOLIOS AND COMPONENTS OF DJIA STOCKS DURING 45 DAYS BEFORE AND AFTER DECEMBER 24, 2018

Index/Portfolio/Ticker	HPR,bef	HPR,aft	Rnk,bef	Rnk,aft
DIA (SPDR DJIA ETF)	-13.54%	+19.82%	22	15
Trailing EGP Optimal Portfolio:	+1.46%	**+5.27%**	3	**30**
MRK	-0.78%	14.76%	4	22
PG	8.87%	13.57%	1	26
MCD	2.71%	9.37%	2	29
VZ	-2.93%	8.49%	6	30
KO	1.56%	-1.26%	3	34
Forward-looking EGP Optimal Portfolio:	-12.97%	**+19.96%**	19	**15**
AXP	-12.97%	22.17%	20	13
MSFT	-12.87%	20.06%	18	15
CAT	-13.33%	18.30%	22	17

TABLE 1B. COMPARATIVE PERFORMANCE PROPERTIES OF TRAILING VS. FORWARD-LOOKING EGP OPTIMAL PORTFOLIOS AND THE COMPONENTS OF DJIA DURING 45 DAYS BEFORE AND AFTER MARCH 23, 2020

Index/Portfolio/Ticker	HPR,bef	HPR,aft	Rnk,bef	Rnk,aft
DIA (SPDR DJIA ETF)	-36.06%	+37.76%	20	13
Trailing EGP Optimal Portfolio:	-16.15%	**+11.33%**	3	**28**
VZ	-15.69%	+10.78%	2	28
MRK	-26.58%	+16.79%	10	27
WMT	-0.96 %	+7.65%	1	29
Forward-looking EGP Optimal Portfolio:	-34.20%	**+30.99%**	17	**19**
KO	-33.32%	+24.42%	16	23
MMM	-34.29%	+35.50%	17	14
NKE	-39.08%	+59.03%	22	2

Notes:
HPR = ((Ending Price – Beginning Price) + Dividend) / Beginning Price; however, in this study, the daily price data are already adjusted for dividends and stock splits, so the actual formula for HPR in this study is: (Ending Adjusted Price – Beginning Adjusted Price) / Beginning Adjusted Price.

HPR,bef; Rnk,bef = Holding Period Return; Performance Rank for 45 days before the benchmark day.

HPR,aft; Rnk,aft = Holding Period Return; Performance Rank for 45 days after the benchmark day.

The ranks for DIA and optimal portfolios are rounded.

Performance is based on closing prices adjusted for dividends and splits.

TABLE 2A. PROPERTIES OF TRAILING EGP OPTIMAL PORTFOLIO OF DJIAAS OF DECEMBER 24, 2018

Ticker	Wi
KO	0.546
MRK	0.2697
MCD	0.1092
PG	0.0625
VZ	0.0126

Expected Return Relative: 1.000396

Standard Deviation: 0.010514

Reward to Standard Deviation: .037632

Correlation Coefficient: .44

Notes: Wi = Portfolio weight of the ith component.

TABLE 2B. PROPERTIES OF TRAILING EGP OPTIMAL PORTFOLIO OF DJIA AS OF MARCH 23, 2020

Ticker	Wi
VZ	.820148
MRK	.121526
WMT	.058327

Expected Return Relative: .996404

Standard Deviation: .025849

Reward to Standard Deviation: -.139124

Correlation Coefficient: .73

Notes: Wi = Portfolio weight of the ith component.

TABLE 3A. PROPERTIES OF FORWARD-LOOKING EGP OPTIMAL PORTFOLIO OF DJIA AS OF DECEMBER 24, 2018

Ticker	Wi
MSFT	0.655
CAT	0.215
AXP	0.13

Expected Return Relative: .9968999

Standard Deviation: .02217

Reward to Standard Deviation: -.126025

Correlation Coefficient: .5751

Notes: Wi = Portfolio weight of the ith component.

TABLE 3B. PROPERTIES OF FORWARD-LOOKING EGP OPTIMAL PORTFOLIO OF DJIA AS OF MARCH 23, 2020

Ticker	Wi
KO	.647026
MMM	.239859
NKE	.113115

Expected Return Relative: .991288

Standard Deviation: .030577

Reward to Standard Deviation: -.284932

Correlation Coefficient: .7289

Notes: Wi = Portfolio weight of the ith component.