THE IMPACT OF FANG STOCKS ON PORTFOLIO OPTIMIZATION WITH DOW STOCKS

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ABSTRACT

This paper examines the effects of FANG (Facebook, Amazon, Netflix, and Google) stocks added to the portfolio pool of DOW Index components on portfolio optimization. The investigative question is: Are FANG stocks good additions to the portfolio pool of DOW stocks for portfolio optimization? This paper uses Dec. 24, 2018 as the event date because the day marks the lowest point of DJIA of the year. It analyzes the performance for the holding period of 45 days from Dec. 24, 2018 to March 1, 2019. Then, it draws a conclusion regarding the usefulness of FANG stocks added to the DOW component pool for optimal portfolio construction. **JEL Classification**: G11, G14, G17

INTRODUCTION

The Dow Jones Industrial Average (DJIA) Index dramatically hit its lowest point of 2018 on December 24, 2018. It was an unusual event because the Christmas Eve day historically is not a typical down day. In this study, "winners" of the DOW plus FANG components mean the top-half performers (i.e., performance ranks 1 ~17) and "losers" mean the bottom-half performers (i.e., performance ranks 18~34) during each of the two sub-sample periods. Did the winners repeat their winning track for the subsequent two months after the event day of the DJIA Index in 2018? This paper investigates the performance of four FANG stocks (FB, AMZN, NFLX, and GOOG), originally coined by CNBC's Mad Money host Jim Cramer. It analyzes the performance in the context of the optimal portfolio constructed from the pool of Dow components plus FANG stocks combined, using the daily data sample period from Oct. 18, 2018 to Dec. 24, 2018.

According to S&P Dow Jones Indices (2019), while stock selection is not governed by quantitative rules, 1) a stock typically is added only if the company has an excellent reputation, demonstrates sustained growth and is of interest to a large number of investors; 2) companies should be incorporated and headquartered in the U.S.; 3) a plurality of revenues should be derived from the U.S.; 4) maintaining adequate sector representation within the index is also a consideration in the selection process for the Dow Jones Industrial Average™. With all these criteria considered, the FANG stocks would be excellent candidates for future additions to the DJIA.

This paper is organized as follows: the next section explains a brief background of FANG stocks; the third section is a literature review; the fourth section describes the investigative design and methodology; the fifth section explains the findings; the final section sets forth a conclusion and further study. Placed in the back of the paper, there are three tables presenting the key descriptive and analytical statistics of this study.

FANG STOCKS EXPLAINED

FANG stocks in this study are the four stocks, Facebook (FB), Amazon (AMZN), Netflix (NFLX), and Alphabet (GOOG) stocks, because the fifth component of extended FANG stock, Apple (AAPL) is solely included in the DOW components. FANG is the acronym coined by Jim Cramer originally referring to four stocks, Facebook Inc. (FB), Amazon.com Inc. (AMZN), Netflix Inc. (NFLX) and Alphabet Inc. (GOOGL or GOOG). It was later extended to include Apple Inc. (AAPL), sometimes referred to as FAANG, a further extension of the FANG. According to Grant (2017), Intercontinental Exchange launched an index tracking FANG stocks starting in November 2017, NYSE FANG+TM Index (ticker symbol, NYFANG), which offers exposure to "a select group of highly-traded growth stocks of next-generation technology and tech-enabled companies." The index also includes Alibaba Group Holding Ltd. (BABA), Baidu Inc. (BIDU), Nvidia Corp. (NVDA), Tesla (TSLA) and Twitter (TWTR) in addition to five of the extended FANG. S&P Index classifies Amazon in the consumer-discretionary sector; Alphabet, Facebook, and Netflix in the communications-services sector; Apple in the information-technology sector (Sector SPDR ETFs, 2019).

LITERATURE REVIEW

The phenomenal performance and volatility of FANG stocks in recent years could be discussed in the context of the Merton's (1987) attention hypothesis and the price-pressure hypothesis (PPH). The attention hypothesis would suggest that a temporary increase (or decrease) in returns and trading volumes could occur during media attention given to particular stocks. For example, one of the FANG components, NFLX (Netflix)'s price per share adjusted for dividends or stock splits was $7.84 on October 23, 2009, and $276.82 on October 25, 2019. The ten-year holding period return would be a phenomenal +3,431%. The gain of NFLX would have been not only caused by the media attention like Cramer's FANG designation but also probably caused by the sedentary lifestyle of retiring baby boomers favoring movie watching.

Poloncheck and Krehbiel (1994) compared the price and volume responses associated with changes in the DJIA and Dow Jones Transportation Averages. They found that firms added to the roster of the DJIA experienced significantly positive abnormal returns and significantly greater trading volume on the event date; however, firms added to the Transportation Average experienced neither event period abnormal returns nor increased trading volume. They attributed the lack of significant effects on the Transportation Average to much less media attention, supporting Merton's (1987) attention hypothesis.

The PPH assumes that a temporary increase (or decrease) in returns and volume results as firms are added to (or deleted from) an index around the announcement

day. The dramatic volatility associated with the performance of FANG stocks could be also explained by Harris and Gurel (1986) who confirmed the PPH in examining prices and volume surrounding changes in the composition of the S&P 500. The PPH assumes that investors who accommodate demand shifts must be compensated for the transaction costs and portfolio risks that they bear when they agree to immediately buy or sell securities, which they otherwise would not trade. They found that immediately after an addition to the index is announced, prices increased by more than 3 percent, but the increase was nearly fully reversed after two weeks. Therefore, as Intercontinental Exchange launched an index tracking FANG stocks starting in November 2017, NYSE FANG+TM Index (ticker symbol, NYFANG), additional pent-up demand for FANG stocks would have pushed the prices of FANG stocks further temporarily, then the price reversals were magnified during the first phase of the sample period of this study.

Lamoureux and Wansley (1987) supported the PPH. By examining market responses to changes in the S&P 500, they found that stocks added to (or deleted from) the index experienced a significant positive (or negative) announcement day excess return. The average announcement day trading volume for firms added to the S&P 500 was substantially larger than the average pre-period trading volume of traded stocks. Pruitt and Wei (1989) also supported the PPH by showing that institutional holdings increased when listing occurred.

Beneish and Gardner (1995), examining changes in the composition of the DJIA, found that the price and the trading volume of newly added DJIA firms were unaffected. However, firms removed from the index experienced significant price declines, which was consistent with the PPH. They believed that the market demanded an extra-return premium for higher trading costs due to relatively less information available to those stocks removed from the index. This suggested that the short-term demand curves of firms removed from the index would not be perfectly elastic, supporting the downward-sloping demand curve hypothesis.

The comparative underperformance of FANG stocks during the first phase of the sample period of this study could be explained by a report by Keown (2019). Keown reported that the fabled "FAANG" (i.e., the extended FANG) 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." If his speculation gets correct, then a dramatic turnaround of performance of FANG stocks, in particular, could resume.

INVESTIGATIVE DESIGN AND OPTIMAL PORTFOLIO CONSTRUCTION METHODOLOGY

This study uses data provided by Thomson Reuters. The daily stock price data are adjusted for stock splits and dividends for the sample periods. Applying to 30 Dow components plus four FANG stocks, this section discusses how to apply optimal portfolio theory to Dow and FANG stocks. The model constructs the optimal portfolio based on daily data of 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. This section shows a practical approach to find specific weights for a diversified optimal portfolio of components. It focuses on showing a sequence of steps to follow for finding an optimally diversified portfolio of components.

This study also examines the performance properties of optimal portfolios constructed with the DOW plus FANG 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).

Applying the capital asset pricing concept, the following model is used:

$$Ri = Rf + (Rm - Rf) * ßi \quad (1)$$

where:
Ri = expected rate of return of ith component,
Rf = expected risk-free return,
Rm = expected market rate of return,
ßi = the component beta; ith security›s systematic sensitivity of return with respect to the overall market.

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 (σ_{ei}^2) as follows:

$$\sigma_{ei}^2 = \sigma_i^2 - ß_i^2 * \sigma_m^2 \quad (2)$$

where:
σ_i^2= variance of ith component's rate of return,
σ_m^2= variance of the market's rate of return,
$ß_i$ = the component beta, i.e., ith component's systematic sensitivity of return with respect to the market proxy.

Third, set the cutoff ratio in order 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 to 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. Fourth, 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:

$$X_i = Z_i / \sum_{i=1}^{n} Z_i * 100 \quad (3)$$

where:

$$Z_i = [\beta_i / \sigma_{ei}^2]*[TI_i - C'] \quad (4)$$

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

After finding an optimal portfolio constructed from 34 Dow plus FANG stocks as of December 24, 2018, this paper examines the performance of the optimal portfolio and analyzes its performance comparisons with FANG, DIA, and DJIA surrounding the event date of December 24, 2018.

Testing Pricing Efficiency

This study uses the Wilcoxon Matched-Pairs Signed-Ranks Test to examine pricing efficiency before and after the worst day of the year event. The Wilcoxon signed-ranks applies to the holding period return (HPR) before and after the event day. The sum of the ranks corresponding to positive differences (Sp) and negative differences (Sn) are calculated. The test statistic (SPSS Statistical Algorithms, 1985) is:

$$Z = [\min (Sp, Sn) — (n(n+1)/4)]/[n(n+1)(2n+1)/24]^{1/2} \quad (5)$$

where n = number of cases with non-zero differences.

FINDINGS

As shown by Table 1, the five top performers during the 45-day period in terms of holding period returns (HPRs) before the worst day event were PG (the best performer), MCD, KO, MRK, and INTC, four of which were the components of the EGP optimal portfolio shown in Table 3. The five bottom performers during the first half of the sample period were NFLX (the worst performer), AAPL, GS, AMZN, and UTX, three of which were FANG stocks. The five top performers during the 45-day period in terms of HPRs after the worst day event were NFLX, BA, IBM, FB, and CSCO, two of which were FANG stocks; none of which were included in the EGP optimal portfolio. The five bottom performers during the second half of the sample period were VZ, PFE, UNH, WBA, and KO, none of which were FANG stocks; two of which were components of the EGP optimal portfolio. An equally-weighted FANG portfolio would have outperformed the EGP optimal portfolio decisively during the second half of the sample period (+31.22% vs. +5.27%). Four stocks are qualified to be consistent winners with the winning streaks highlighted with green in Table 1: CSCO, NIKE, INTC, V (the average group rank for two sub-sample periods, equally-

weighted, 8.5 out of 34) among which NIKE is the best consistent winner (the average rank for entire sample period, 7.5 out of 34). Any of the consistent winners were found neither in the EGP optimal portfolio nor in the FANG group.

Table 2 shows the results of the Wilcoxon signed ranks test regarding the performance consistency of Dow and FANG stocks. It shows a statistical confirmation that the worst day event of the year did interrupt the pricing efficiency of the Dow and FANG stocks in the short run. The 2-tailed significance, 0.000, with only one negative rank (KO), shows that the worst day of the year event caused significantly positive performance reversals for 33 out of 34 components during the sample periods. KO was the only exception that it performed worse in the second half compared to the first half. This result defies the randomness of stock price behavior in the short run.

Table 3 shows the EGP Optimal Portfolio constructed as of December 24, 2018. It consists of KO, MRK, MCD, PG, and VZ with heavily favoring KO (54.57% of the portfolio weight), which turned out to be the worst performer during the second half of the sample period. The actual performance of the optimal portfolio during the second half was +5.27%, which is inferior to the DJIA's performance, +19.43% and far inferior to the equally-weighted FANG group's performance, +31.22%. The optimal portfolio was a group winner in the first half (the optimally-weighed group rank, 3.1 out of 34). The optimal portfolio was a group loser in the second half (the optimally-weighted group rank, 29.7 out of 34). Because of the comparatively poor performance of the EGP optimal portfolio after its construction, it raises a question of the usefulness of conventional backward-looking optimal portfolio construction in terms of its realistic investment purpose at least in the short-run.

CONCLUSION AND FURTHER STUDY

Did the winners or losers of DOW and FANG stocks repeat their winning or losing performance during the subsequent period after the worst day in 2018? The answer was affirmative no. Contrarily, the positive reversal performance during the second half of the sample period was dramatic. This indicates that Dow and FANG stocks did not behave efficiently during the sample period. The worst day of the year positively disrupted the Index's pricing efficiency. In fact, the worst day event made a significantly positive effect on the subsequent, second half of the sample period, supporting the notion, "buy low, sell high."

Because of the poor performance of FANG stocks during the first half of the sample period (the average group performance rank of 26.3 out of 34), none of FANG stocks was selected in the trailing optimal portfolio construction. However, the FANG stocks, winners as a group in the second half, did perform extremely well during the second half of the sample period (the equally-weighted FANG group's performance rank during the second half was 8.5 out of 34; the equally-weighted FANG group's HPR, aft was +31.22% vs. the DJIA's, +19.43%). Interestingly, one of the FANG stocks, Netflix (NFLX) performed the worst in the first half (Rank 34th) but the best in the second half (Rank 1st). The evidence confirms that FANG stocks showed high volatilities of performance.

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 include any of FANG stocks, so it failed to capture the high performance of FANG 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.

For further study, it would be worthwhile to explore the possibility of designing a forward optimal portfolio of DOW plus FANG stocks constructed with projected stock prices using forward or predicted earnings estimates as opposed to the trailing optimal portfolio construction. Such a forward optimal portfolio constructed from a combined pool of DOW plus FANG stocks could have speculative merit of short-term investing in practice, overcoming the failed performance of the trailing optimal portfolio construction in the short run demonstrated in this study. The failure of the trailing optimal portfolio is a practical issue, despite the theoretical breakthrough by Markowitz 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 as suggested by Jagannathan and Ma (2003), focus 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 optimal portfolio were designed effectively and applied in the same sample period of this study, it could have captured the winners of the second half of the sample period of this study, such as some of FAANG stocks and/or some of the four consistent winner stocks. The strategic goal of such forward optimal portfolio construction would be to capture consistent winners in the short run. A caveat would be that the conventional EGP optimal portfolio construction may still hold the investment merit in the long run. However, the long run is a misleading guide to speculative investing in the short run.

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TABLE 1. PERFORMANCE PROPERTIES OF DOW & FANG STOCKS DURING 45 DAYS BEFORE AND AFTER DECEMBER 24, 2018

Index/Portfolio/Ticker	HPR,bef	HPR,aft	Rnk,bef	Rnk,aft
DJIA (Dow Jones Industrial Average) Index	-14.13%	+19.43%		
DIA (SPDR DJIA ETF)	-13.54%	+19.82%		
Equally-Weighed FANG Portfolio (FB, AMZN, NFLX, GOOG)	-21.71%	+31.22%	26.3 (AVG)	8.5 (AVG)
EGP Optimal Portfolio	+1.46%	+5.27%	3.1 (AVG)	29.7 (AVG)
NFLX (Netflix)**	**-32.54%**	**52.78%**	**34**	**1**
BA (Boeing)	-17.76%	50.54%	27	2
IBM (IBM)	-16.55%	30.91%	26	3
FB **(Facebook)	**-19.92%**	**30.81%**	**29**	**4**
CSCO* (Cisco)	-11.39%	28.62%	14	5
NKE* (Nike)	-9.65%	28.32%	9	6
GS (Goldman Sachs)	-30.21%	27.28%	32	7
AMZN (Amazon)**	**-24.10%**	**24.39%**	**31**	**8**
UTX (United Technologies)	-20.39%	23.96%	30	9
XOM (ExxonMobil)	-19.15%	23.47%	28	10
INTC* (Intel)	-2.46%	23.05%	5	11
V* (Visa)	-12.45%	23.00%	17	12
AXP (American Express)	-12.97%	22.17%	20	13
CVX (Chevron)	-13.19%	22.05%	21	14
MSFT (Microsoft)	-12.87%	20.06%	18	15
AAPL (Apple)**	**-31.79%**	**19.68%**	**33**	**16**
CAT (Caterpillar)	-13.33%	18.30%	22	17
TRV (Travelers)	-9.44%	18.11%	8	18
HD (Home Depot)	-11.83%	17.09%	15	19
MMM (3M)	-10.25%	16.97%	10	20
GOOG (Google)**	**-10.27%**	**16.88%**	**11**	**21**
MRK* (Merck)***	***-0.78%***	***14.76%***	***4***	***22***
JPM (JPMorgan)	-14.76%	14.26%	24	23
WMT (Walmart)	-10.28%	14.11%	12	24
DIS (Disney)	-12.96%	13.61%	19	25
PG* (Procter & Gamble)***	***8.87%***	***13.57%***	***1***	***26***
JNJ (Johnson & Johnson)	-11.38%	13.37%	13	27
DWDP (DowDuPont)	-15.64%	9.40%	25	28

MCD (McDonald's)***	***2.71%***	***9.37%***	***2***	***29***
VZ (Verizon)***	***-2.93%***	***8.49%***	***6***	***30***
PFE (Pfizer)	-7.13%	7.86%	7	31
UNH (United Health)	-12.42%	5.67%	16	32
WBA (Walgreens Boots Alliance)	-14.32%	2.69%	23	33
KO (Coca-Cola)***	***1.56%***	***-1.26%***	***3***	***34***

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 December 24, 2018.
HPR,aft; Rnk,aft = Holding Period Return; Performance Rank for 45 days after December 24, 2018.
AVG = Average.

Performance is based on closing prices adjusted for dividends and splits.
* Four consistent winner stocks.
** Five FAANG (FANG + AAPL) stocks.
*** Five stocks in italicized and bold are components of the EGP optimal portfolio constructed as of December 24, 2018.

TABLE 2. PERFORMANCE CONSISTENCY OF DOW AND FANG STOCKS WILCOXON SIGNED RANKS TEST

		N	Mean Rank	Sum of Ranks
VAR00004 – VAR00003	Negative Ranks	1[a]	1.00	1.00
	Positive Ranks	33[b]	18.00	594.00
	Ties	0[c]		
	Total	34		

Notes:
a. VAR00004 < VAR00003
b. VAR00004 > VAR00003
c. VAR00004 = VAR00003
VAR00003 = HPR,bef
VAR00004 = HPR,aft

Test Statistics[b]

	VAR00004 - VAR00003
Z	-5.071[a]
Asymp. Sig. (2-tailed)	.000

Notes:
a. Based on negative ranks.
b. Wilcoxon Signed Ranks Test.
HPR,bef = Holding Period Return for 45 days before December 24, 2018.
HPR,aft = Holding Period Return for 45 days after December 24, 2018.
Performance is based on holding period returns calculated, using daily closing prices adjusted for dividends and splits.

TABLE 3. PROPERTIES OF EGP OPTIMAL PORTFOLIO AS OF DECEMBER 24, 2018

Ticker	Wi	HPR,bef,i	HPR,aft,i	Rnk,bef,i	Rnk,aft,i
KO	0.546	1.56%	-1.26%	3	34
MRK	0.2697	-0.78%	14.76%	4	22
MCD	0.1092	2.71%	9.37%	2	29
PG	0.0625	8.87%	13.57%	1	26
VZ	0.0126	-2.93%	8.49%	6	30
EGP Optimal Portfolio		1.46%	5.27%	3.1 (Average)	29.7 (Average)
Expected Return Relative: 1.000396 Standard Deviation: 0.010514 Reward to Standard Deviation: .037632					

Notes:

Wi = Portfolio weight of the ith component.
HPR,bef,i; Rnk,bef,i = Holding Period Return; Performance Rank for 45 days before December 24, 2018 of the ith component.
HPR,aft,i; Rnk,aft,i = Holding Period Return; Performance Rank for 45 days after December 24, 2018 of the ith component.