MATHGR5380 Multi-Asset Portfolio Management Project II:

Dynamic Two-Factor GTAA with 1% Risk and Monthly Rebalancing

ah3587 Angela Hong

kg2777 Kathi Gao

rt2702 Rui Tao

hc3021 Huilun Chen

tl2868 Tianshu Liu

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I. Introduction

As we studied in class, at country and global sector levels, empirical research has discovered factors within global equities. Among them the most prominent ones are value investing and momentum investing. The goal of our project is to create and back-test a dynamic two-factor long-short GTAA portfolio comprised of a combination of value and momentum factor portfolios, and to design and test efficacy of a dynamic factor weighting based on the volatility regime. The investment universe is comprised of 10 developed country equity index futures including Australia, Canada, Denmark, Spain, France, UK, Italy, Japan, Netherlands and United States with 34-year historical monthly data (from May 1984 to March 2018). Momentum is modeled as 12-month momentum with the most recent month skipped, and value is represented by the composite of forward E/P ratio and B/P ratio.

The structure of this paper is organized as follows. The first part describes the selected data, monthly index returns, and portfolio constructions that are used across the project. The next sections outline the method we use for risk model estimation and introduce the volatility regime variables. We then describe the dynamic weighting scheme based on the selected volatility regime. Finally, we show the back-test result using the combined portfolio.

II. Data

The raw data we use are monthly MSCI Index Levels for ten different countries from December 1972 to March 2018. We extract monthly index data from Daily MSCI Index Level, and calculate the monthly MSCI Index returns using:

(current month index - past month index) / (past month index)

The monthly MSCI Index returns are widely used across our project to calculate the monthly returns and cumulative returns of each portfolio.

III. Single Factor Investment

The portfolio consists of two factors, momentum and value. In the case of momentum, factor exposure is measured as the total return of country indices over 12-month horizon, skipping the most recent month due to short-term reversal effect at 1-month horizon. We buy the assets with high momentum and sell those with low momentum to capture profits. Index monthly momentum portfolio weight is thus calculated as:

w= (index momentum - average momentum)/standard deviation of cross-sectional momentum

In the case of value, factor exposure is measured as the composite of forward E/P and B/P from May 1984 to March 2018. Both E/P and B/P increase as risk premiums increase. We overweight assets with higher value measures and underweight those with lower value measures to capture the value risk premium. Index monthly momentum portfolio weight is thus calculated as:

w= (index value rank - average cross-sectional rank)/standard deviation of cross-sectional rank

We combine the weights calculated from E/P rank and B/P rank to get the composite portfolio weight in the value portfolio.

When constructing combined portfolios, in order to reconcile the time horizon, momentum portfolios from May 1984 to March 2018 are used along with corresponding value portfolios. The same time horizon applies to dynamic portfolio. The weight of index i at time t is calculated as:

$$w_{it} = w_{momentum} * \textit{scaled momentum factor weight at } t + (1-w_{momentum}) * \textit{scaled value factor weight at } t$$

IV. Risk Model Estimation

Given the monthly returns, we then use MATLAB to estimate our own risk model, COV(t), which is a 10x10 matrix containing variances of the asset on the diagonal and covariances of the assets off the diagonal. We use a 36-month trailing window, which is to estimate COV(t) by the most recent 36 months' returns. Therefore, even though we were given data from January 31, 1973, our risk estimation does not start until December 31, 1975. We also calculate risk for each period in MATLAB, using the formula:

$$Portfolio\ Risk_{(t)} = SQRT(w_{(t)} * COV^{A}_{(t)} * w'_{(t)}),$$

where $w'_{(t)}$ is the transpose of our portfolio weights, which is a 10*1 matrix. Note that here we should use annual COV(t). The COV(t) we obtained above is in monthly term as it is from monthly returns. Thus, for simplicity, we have multiplied COV(t) by 12 and used annualized covariance, $COV^{A}_{(t)}$, in the risk calculation. We have adapted the same method for risk estimation for all portfolios presented in this paper.

V. Volatility Regime

For volatility regime, we introduce a new variable $\sigma_{target}/\sigma_{momentum}$ as the volatility regime, which is a time series volatility based on the monthly index returns. σ_{target} is the specified constant target risk attributable to momentum factor, which is set to 1% in our portfolio, and $\sigma_{momentum}$ is the 12-month average of trailing risk of monthly returns to the original momentum portfolio. This dynamically weighting momentum portfolio by risk strategy is a revision of the work of Daniel J. Sandberg (2019, S&P Global).

VI. Dynamic Weighting Scheme

Based on our selected volatility regime, the weights of momentum and value are calculated as:

$$Momentum\ Weight = min\ (\ \sigma_{target}/\sigma_{momentum}\ ,\ 1.0)$$

$$Value\ Weight = 1 - Momentum\ Weight$$

The purpose of dynamic weighted model is to produce a larger information ratio, a lower drawdown and a positive shift in skew. So we use dynamic volatility regime to scale the leverage of the momentum portfolio to control the momentum's left tail risk, and to construct the equally-weighted portfolio.

It is noticed that our dynamic strategy does not perform better than the equal weighted strategy, and due to heavily-weighted value factor in the dynamic strategy, it has similar back-test results to the value factor portfolio. The reason is that based on the data, the information ratio of the momentum factor is lower than that of the value factor most of the time, which means the momentum portfolio has more risk but less profit than the value portfolio. Also, this point has been proved by the low proportion of momentum factor in our dynamic strategy.

VII. Back-test Results

From our back-test results, we first generated the graph below which displays the weights in value, momentum factors over time and volatility regime variable over time. In general, the volatility regime variable over time fluctuates around 0.5. However, it falls below 0.5 in recent years. In addition, our dynamic strategy has relatively stable weights in value and momentum factors over time.

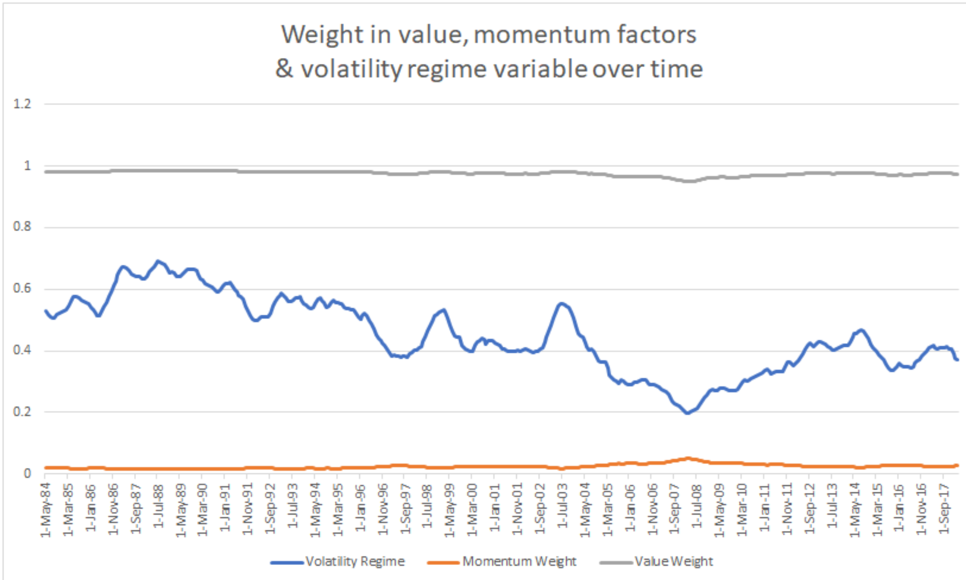

Figure 1

Comparing to the fixed-weights strategy, our dynamic strategy, though exhibits similar trends, does not seem to produce similarly high returns in practice. According to Figure 2, its cumulative return falls short of the fixed-weights counterpart over the years. In fact, in our back-test, the dynamic strategy only records an annualized return of 0.51% versus the annualized return of 0.68% from the fixed-weights strategy. The reason behind this poor performance is traceable, as we can see from Figure 1: our strategy puts too much weight on the value factor, which is between 95% and 100%, and it leads to the result of a performance similar to the value-factor-only strategy.

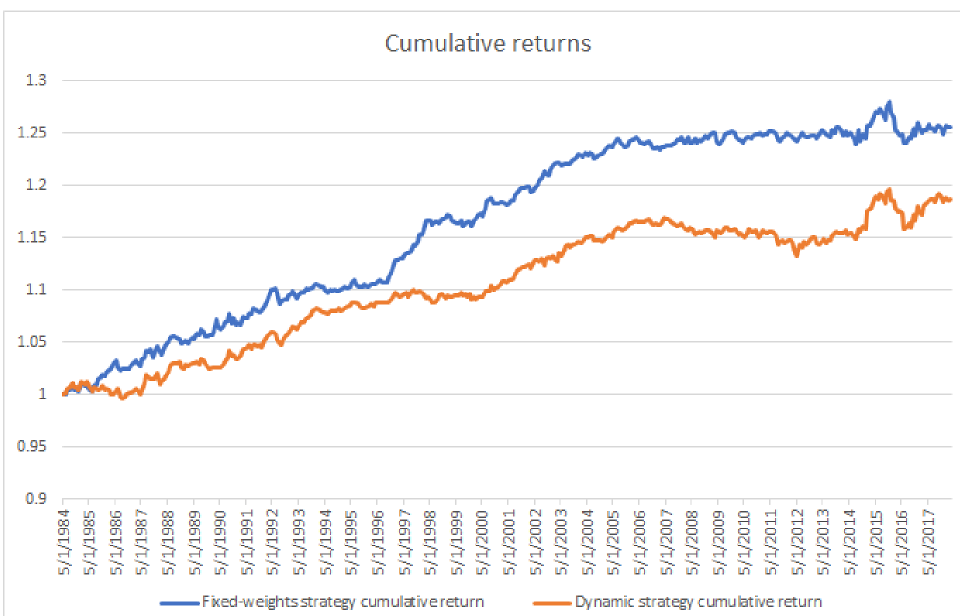

Figure 2

As shown in Figure 3 below, we can again observe that our dynamic strategy produces very similar outcome comparing to the value factor. While performing slightly better than either momentum or value factor portfolio with an annualized return of 0.51% and a return-to-risk ratio of 0.48, dynamic strategy is still overshadowed by fixed-weights strategy's 0.68% annualized return and 0.63 return-to-risk ratio. Another interesting observation is that average drawdown is improved when combining the two factors as dynamic strategy has 0.59% drawdown, and fixed-weights strategy has 0.42% -- both lower than the 1.04% and 0.63% of the momentum and value factors alone. Additionally, our dynamic strategy requires a much lower turnover rate than the fixed-weights strategy, which would result in lower transaction costs.

	Fixed-weights strategy statistics	Momentum	Value	**Dynamic stategy statistics**
Arithmetically Annualized return	0.68%	0.29%	0.50%	0.51%
Annualized realized risk	1.08%	1.08%	1.06%	1.06%
Annualized return-to-risk ratio	0.63	0.27	0.47	0.48
Geometrically annualized return	0.68%	0.28%	0.50%	0.51%
Average drawdown	0.42%	1.04%	0.63%	0.59%
Turnover	107.73%	102.72%	68.89%	69.25%

Figure 3

References

Daniel J. Sandberg (2019, January), "Value and Momentum: Everywhere, But Not All The Time" ,S&P Global Market Intelligence, Quantitative Research