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Research and Product Development Department

YMPB Global Fund Management

Tactical Asset Allocation Strategy Proposal

Summary

Responding to the demand by the Marketing Department, our team proposes a **Dynamic Equity WML Momentum Strategy** to diversify our active management products in the current market environment.

Market Update

U.S. equity market has fallen back to a level last seen in late 2016, entering bear market territory since March as the novel coronavirus fueled rapidly rising economic and market headwinds. We expect current volatile conditions to continue until a clear flattening of the infection curve and an oil production cut.

Target Investors

Professional investors who are sensitive to market volatility with a strong focus on a **long horizon.**

Strategy Description

On the principle of long run investment policy, the proposed dynamic equity WML momentum strategy aims at maximizing short-term expected utility by choosing a **dynamic series of weights** on a past-winner-minus-past-loser momentum portfolio. The leverage level of the portfolio is adjusted according to market volatility to maximize Sharpe Ratio. The baseline WML strategy **covers all sections of US listed equites**.

Strategy Estimation

Our analysis and empirical tests show that the dynamic strategy **outperforms** the market and static momentum portfolio in terms of Sharpe Ratio and cumulative returns, thanks to both the **robustness and resilience** of the strategy during bear markets.

Operational Development

Our Research and Product Development Department oversees the design, conception, construction and evaluation of the portfolio guided by the dynamic equity WML momentum strategy. For the entirety of its life cycle, the product will be managed by our Portfolio Management Department on a day-to-day basis.

Equity Momentum Based Asset Allocation Strategy

Design, construction and evaluation

1. Introduction

Tactical asset allocation (TAA) is among the most suitable investment tools available for navigating full market cycles. While TAA tends to lag in late bull markets, it offers opportunities across a full bull/bear market cycle. Among the greatest strengths of TAA is its mechanical, rules-based approach, which not only keeps the portfolio attuned with market conditions but also reduces the need for constant portfolio management.

Our proposal is a momentum based strategy: winner-minus-loser (WML) portfolio. Momentum strategies are based on a simple idea, stocks which have performed well in the past would continue to perform well. On the other hand, stocks which have performed poorly in the past would continue to perform poorly. This results in a profitable but straightforward strategy of buying past winners and selling past losers.

However, the static WML strategy demonstrates large negative premium in periods of market stress. An optimal dynamic WML momentum strategy is adjusted in which the WML portfolio is levered up or down over time to maximize the unconditional Sharpe ratio of the portfolio.

Compared with the basic WML portfolio over the whole period and a chosen subperiod for demonstrative purposes, the dynamic WML momentum portfolio significantly outperforms its static counterpart, delivering a Sharpe ratio twice as large with significant positive alpha.

2. US equity data and momentum strategy

2.1 US equity data

The data is obtained on individual US stocks from the Centre for Research in Security Prices which comprises ten decile portfolios constructed monthly based on past returns, encompassing NYSE, AMEX, and NASDAQ data. Among these ten, portfolio 1 (the Loser portfolio) contains the 10% worst performing stocks and portfolio 10 (the Winner portfolio) contains the best performing 10%. The Winner-minus-Loser (WML) is a zero-cost portfolio, which is structured as a long trade for the Winner portfolio and short for the Loser portfolio. The dataset covers the period from 1927 to January 2020.

In this paper, the market excess return is the value-weight return of all CRSP firms listed on the NYSE, AMEX, or NASDAQ minus the one-month Treasury bill rate (from Kenneth French’s data library).

2.2 Momentum portfolio performance

We initially focused on the cumulative returns of six portfolios: past Loser portfolio, past Winner portfolio, the risk-free asset, the market (the CRSP value-weighted index), and the WML portfolio.

For the long-short portfolio (WML), the cumulative log return is:

$$R(t,T) = \sum_{s=t+1}^{T}(r_{L,s} - r_{S,s} + r_{f,t})$$

With $r_{L,s}, r_{S,s}$ are log-returns over period s of winner and loser portfolios, $r_{f,t}$ is log-return of risk-free asset.

The past winner has outperformed the losers significantly in the past, and the momentum strategy has performed well, albeit with large drawdowns after momentum reversed, notably in 2009 as shown in the Figure 1 below.

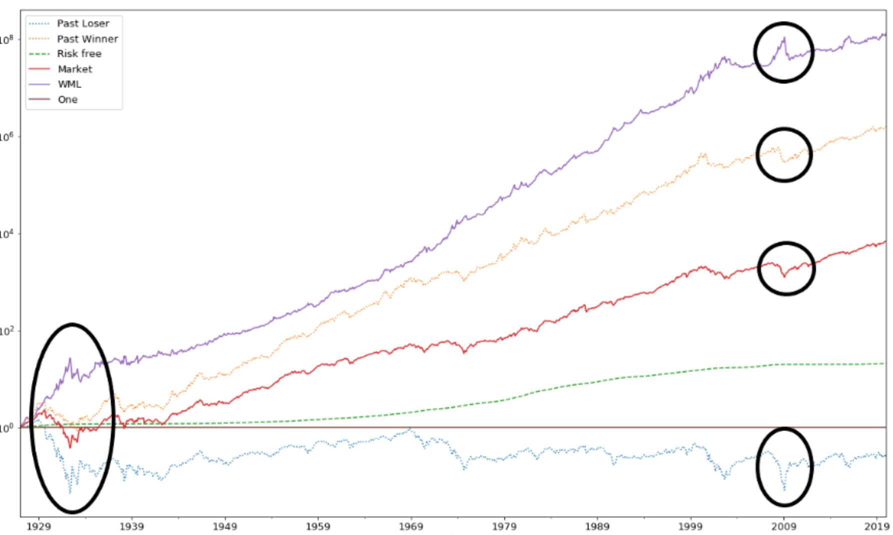

Figure1: Cumulative returns

We estimated a full-period regression specification of the form:

$$R_P - R_f = \alpha + \beta R_m$$

Where $R_P - R_f$presents the excess return of the 10 decile portfolios and WML portfolio, R_m is the return of the CRSP value-weighted index. SR and Skew denote the annualized Sharpe Ratio and the skewness of the monthly log returns.

	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10	WML	MARKET
Excess Return	-0.0475	0.0137	0.0311	0.0496	0.0544	0.0626	0.0707	0.0837	0.0921	0.121	0.168	0.0622
Sigma	0.325	0.269	0.235	0.213	0.2	0.197	0.189	0.183	0.194	0.225	0.254	0.184
SR	-0.146	0.0508	0.132	0.234	0.272	0.318	0.375	0.458	0.475	0.537	0.664	0.338
Alpha	-0.0119	-0.00563	-0.00341	-0.0014	-0.000757	-7.72e-05	0.000856	0.00213	0.00262	0.00465	0.0165	-1.73e-18
t_Alpha	-8.29	-5.36	-3.99	-2.0	-1.27	-0.152	1.63	3.98	4.11	4.59	8.02	-4.9
P-Values Alpha	3.12e-16	9.86e-08	6.94e-05	0.0454	0.204	0.879	0.103	7.4e-05	4.18e-05	4.95e-06	2.75e-15	1.09e-06
Beta	1.52	1.3	1.16	1.07	1.02	1.02	0.971	0.935	0.975	1.05	-0.478	1.0
Skew	0.0999	-0.0675	-0.124	0.134	-0.0627	-0.276	-0.728	-0.538	-0.807	-0.909	-0.826	-0.558

Table 1: Characteristics of the monthly momentum decile portfolio excess return

According to Table 1, the WML strategy has a large premium over the last century, which is consistent with existing literature. The Sharpe Ratio of the WML portfolio is 0.664, highest among the 11 portfolios and approximately double that of the market. The excess return of the winner (Decile 10), namely 12.1%, outperforms the loser (Decile 1), -4.75%. The beta of the winner portfolio is positive, with a high positive CAPM alpha of 4.65% annually (t-stat=4.59). Accordingly, the WML alpha over this period is the highest, where the t-statistic is significant.

Looking at the skewness of the portfolios, winner portfolio becomes more negatively skewed when it comes to more extreme deciles. The top winner decile's monthly skewness is -0.9 while the loser portfolio's (decile 1) is 0.1, which gives the WML portfolio over the period a negative monthly skewness of -0.83.

3. Risk exposure of WML strategy

As illustrated by Daniel and Moskowitz (2016- Momentum crashes), during bear markets, the WML portfolio is effectively short a call option on the market, and that option price is not fully reflected, leading to a high expected return on the loser portfolio and a lower expected return on the WML strategy. As market variance increases, the option price increases, suggesting that expected return on WML strategy is negatively correlated to market variance. Therefore, in this section, we investigate the risk exposure of the WML portfolio to market variance and the bear market indicator.

The bear market indicator is an ex ante market indicator, which equals to one if the cumulative CRSP VW index return in the past 24 months is negative, and zero otherwise. The market variance is constructed using daily market return data, rolling over the 126 days (6 months) preceding the start of month t.

To assess the risk exposure of the WML portfolio, we estimated a full-period regression of the following forms:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \tilde{\varepsilon}_t$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{\sigma_m^2} \hat{\sigma}_{m,t-1}^2 + \tilde{\varepsilon}_t$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \gamma_{\sigma_m^2} \hat{\sigma}_{m,t-1}^2 + \tilde{\varepsilon}_t$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2 + \tilde{\varepsilon}_t$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \gamma_{\sigma_m^2} \hat{\sigma}_{m,t-1}^2 + \gamma_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2 + \tilde{\varepsilon}_t$$

Where $I_{B,t-1}$presents the bear market indicator, $\hat{\sigma}_{m,t-1}^2$ is the variance of the market excess return.

	(1)	(2)	(3)	(4)	(5)
Const	0.0187	0.0212	0.0216	0.0185	0.0207
t_value Const	7.67	7.83	7.9	7.98	6.68
BI	-0.014		-0.00689		-0.00382
t_value BI	-2.34		-1.03		-0.454
VAR		-0.172	-0.143		-0.0989
t_value VAR		-3.12	-2.31		-1.03
BIVAR				-0.187	-0.0759
t_value BIVAR				-3.18	-0.603

Table 2: Momentum returns and risk factors

The regression result reports the estimated coefficients for the above set of time series regressions.

Regression 1 and 2 capture the two indicators independently, where these two betas are both negative, -0.014 and -0.172, and the intercepts are positive with significant t-statistics, noted as 7.67 and 7.83. Regression 3 reports both indicators and the results are consistent with regression 1 and 2, that momentum returns perform poorly in periods of high market stress, as indicated by bear markets and high volatility. For the interaction between the two factors, results from regression 4 and 5 show that returns tend to be poor (negative beta) during bear markets with high volatility.

Given the analysis from table 2, the conditional average return of the WML portfolio can be obtained through the specified regression method. Explicitly, based on the regression of the WML returns against the interaction between the bear market indicator and market volatility, the regression parameters can be used to project an expected returns for the static WML portfolio, which we will use when building our dynamic strategy.

4. Performance and drawback: Out-of-sample basic WML strategy

In order to project the one-month-ahead WML portfolio returns, we implement an expanding window regression by using the interactive coefficient contributed from Table1: the bear market indicator and market volatility. Here the $\hat{\gamma}_{0,t-1}$ and $\hat{\gamma}_{int,t-1}$ are obtained from a regression run from the start of our sample (1927-01-31) up through month t−1. To estimate the month t WML variance, the 126-day variance estimated through the last day of month t−1 is applied.

$$\widetilde{Mu}_{t-1} = \tilde{R}_{WML,t} = \gamma_0 + \gamma_{int,t-1} \cdot I_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1}$$

	Const	t-stat Const	Beta	t-stat Beta	Adj R Squared	BIVAR_t1	WML_Var_t1	Predicted_Mu	Weight
1937-06-30	0.0284	1.78	-0.0884	-0.505	-0.00758	0.0	0.0028	0.0284	0.677
1937-07-31	0.0278	1.76	-0.0843	-0.485	-0.00771	0.0	0.00769	0.0278	0.241
1937-08-31	0.027	1.73	-0.0797	-0.461	-0.00786	0.0	0.00818	0.027	0.22
1937-09-30	0.0268	1.74	-0.0785	-0.457	-0.00782	0.0	0.00789	0.0268	0.226
1937-10-31	0.0258	1.69	-0.0729	-0.427	-0.00801	0.0	0.00756	0.0258	0.228
...	...	...	...	...	...	...	...	...	...
2019-09-30	0.0186	7.99	-0.188	-3.18	0.00834	0.0	0.00348	0.0186	0.357
2019-10-31	0.0185	7.95	-0.187	-3.17	0.00825	0.0	0.00635	0.0185	0.194
2019-11-30	0.0185	7.97	-0.187	-3.17	0.00827	0.0	0.00658	0.0185	0.188
2019-12-31	0.0185	7.97	-0.187	-3.17	0.00825	0.0	0.00733	0.0185	0.168
2020-01-31	0.0184	7.94	-0.187	-3.16	0.00819	0.0	0.00705	0.0184	0.174

Table 3: Out-of-sample WML regression and predicted returns

As demonstrated, Table 3 and Figure 2 highlight the stability of predicted WML out-of-sample performance that remains positive in almost all cases when being compared realized WML portfolio. During extreme market conditions in 2009, both the predicted and realized returns sink to deep negative level, which demonstrates the effectiveness of our WML market-timing prediction model. During this period, our out-of-sample regression correctly estimates a large negative return for the WML portfolio following a momentum crash after the market bottomed out.

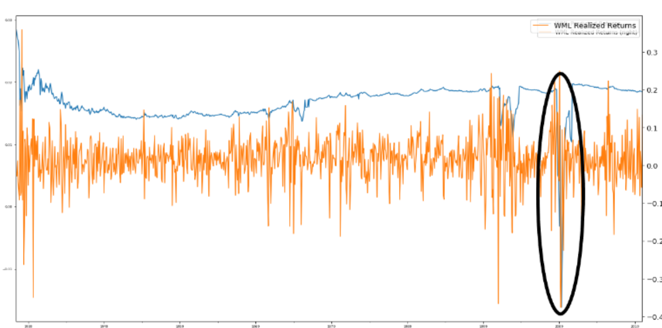

Figure 2: Predicted WML out-of-sample performance VS realized WML returns

This analysis shows that while the WML has performed well in terms of cumulative dollar returns from 1927, it is also prone to large drawdown after momentum crashed in the aftermath of financial crises, notably in the periods from 1932 to 1939 and 2009 to 2012.

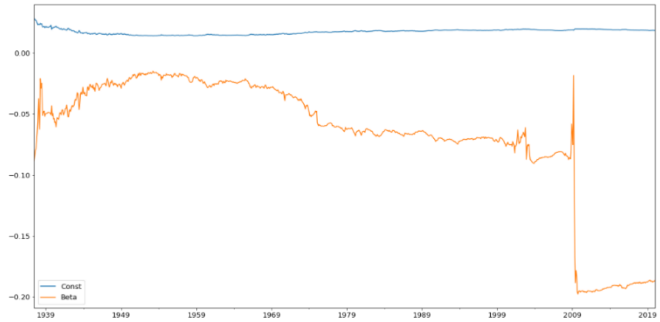

Figure 3: Out-of-sample prediction coefficient

In Figure 3, the beta stays negative and jumped dramatically lower during the bear market period in 2009 while the alpha (constant) remains positive and nearly unchanged, inferring that the WML momentum premium were relatively stable over time.

One possible explanation for the poor performance of the WML portfolio during crisis derives from its construction. When market crashes, the outperformance of the WML portfolio comes from its short leg, i.e. stocks being short are crashing faster than stocks being long, hence the dramatic rises of the WML portfolio during the period when the market has not bottomed out yet. This translates into the fact that the WML portfolio is long low beta stocks and short high beta stocks. When the market eventually went up, this translates into large negative returns for the WML portfolio.

5. Expansion to dynamic WML strategy

Considering the momentum crashes in bear market, the basic WML strategy could be adjusted towards a dynamic momentum strategy using the expected return from our market-timing prediction model, the variance of the WML strategy and our risk tolerance. Inversely proportional to the volatility as the result of a Sharpe Ratio optimization routine, the optimal weight of dynamic portfolio is the central tenet of this strategy. See results in the last column of Table 3.

$$w_{t-1}^{*} = \left(\frac{1}{2\lambda}\right)\frac{\mu_{t-1}}{\sigma_{t-1}^{2}}$$

where $\mu_{t-1} \equiv E_{t-1}\left(R_{WML,t}\right)$ is the conditional expected return on the basic WML portfolio over the coming month (predicted returns in column 9 of Table3), $\sigma^2 \equiv E_{t-1}\left[\left(R_{WML,t}^{2} - \mu_{t-1}\right)^2\right]$ is the conditional variance of the basic WML portfolio return over the coming month, and λ is a time-independent scalar that scales or leverages the dynamic portfolio according to our risk tolerance. In line with the volatility of value-weighted market portfolio in the whole out-of-sample period, the λ (7.5 in this case) is chosen so that the volatility of dynamic WML strategy is scaled to be 19%. This λ does not affect the Sharpe Ratio of the dynamic WML strategy so choosing a certain value for λ is only to match the volatility of the market for comparison purposes.

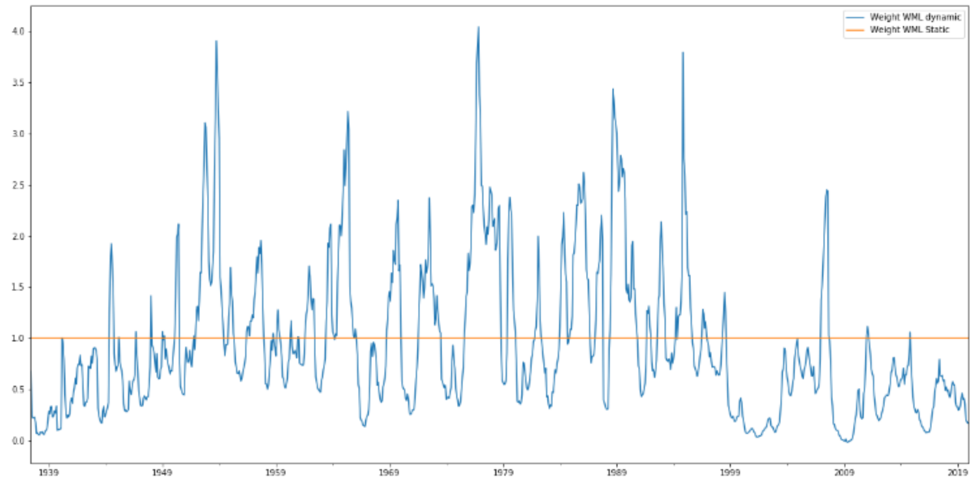

Figure 4: Basic WML strategy weight VS Dynamic WML strategy weight

As a benchmark, the position of basic MWL strategy is constantly equal to 1 made by going long $1 worth of the winning 10% and shorting $1 worth of the losing 10%. Pointed in Figure 4, the positions for dynamic WML strategy changes continuously. Higher volatility leads to lower weights and vice-versa. There were instances where our regression returns a negative weight for the WML portfolio, essentially shorting the WML in expectation of a momentum crash. However, as we adjust the weight of the WML portfolio according to a formula resulting from a Sharpe Ratio optimization routine, even when the predicted WML returns are negative, the strategy's short position is negligible. At these points of high stress, high market volatility and bear market conditions, the dynamic WML switches to risk free assets.

6. Performance comparison: dynamic and basic WML portfolio

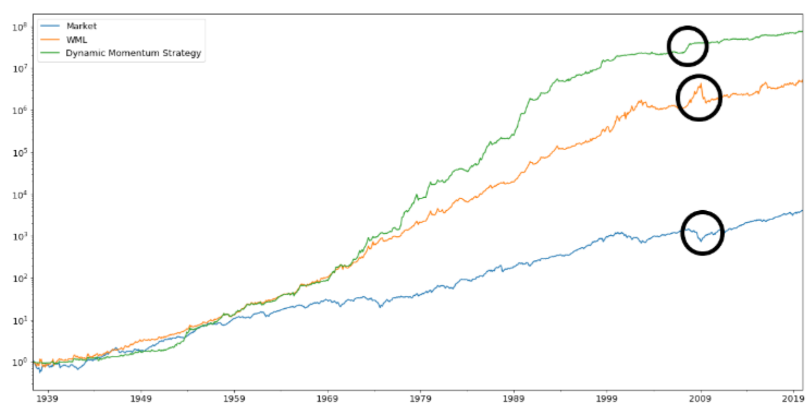

Figure 5: Full period performance comparison

Figure 5 plots the cumulative dollar value of the dynamic and static WML portfolios with one dollar being invested at inception. The dynamic WML portfolio significantly outperforms its static counterpart.

To further assess the characteristics of our dynamic WML portfolio, a shorter period is presented as follows, which encompasses the bear market of 2008 and 2009. Accordingly, the λ is lowered to 4 as the value-weighted market annualized volatility to meet the comparability principal.

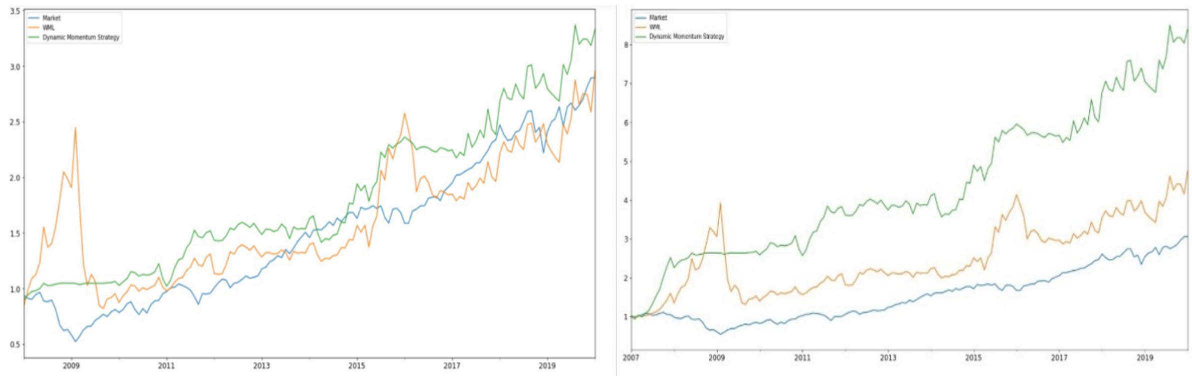

Figure 6 & 7: Performance comparison since 2007 with and without scaling strategy volatility

In Figures 6, the λ was chosen so that the volatility of the dynamic WML portfolio matches that of the market. In Figure 7, the λ was chosen so that the volatility of the dynamic WML portfolio is two third of that of the static WML portfolio. In both scenarios, the dynamic WML portfolio outperformed its static counterpart. The static WML portfolio crashed twice during the chosen timeframe, once in 2009 and once more in 2016. During these two periods, the dynamic portfolio scaled back and earned risk-free rates.

7. Portfolio performance evaluation and further expansion

	Market	WML	Dynamic Momentum Strategy
Average excess return	0.0656	0.152	0.185
SD	0.157	0.224	0.174
Sharpe Ratio	0.417	0.68	1.06
Appraisal Ratio	0.0133	0.285	0.368

Table 4: Evaluation of performance

Table 4 evaluates the performance of the two WML based portfolio. As expected, the dynamic WML portfolio achieved a very good Sharpe Ratio of 1.06. Again, we would like to stress that the Sharpe Ratio is not affected by risk tolerance, proxied by the chosen λ. The Appraisal Ratio is also improved compared to the static WML portfolio as shown in Table 4.

We also show common risk adjusted metrics for our dynamic portfolio. The average excess return shown in Table 5 and the tracking error are both annualized. The former indicates whether the strategy outperforms its benchmark on average and the latter measures the consistency of this outperformance. The Information Ratio (IR) is the ratio between the two. Grinold and Kahn (1995), asserted that an IR of 0.5 is "good", 0.75 "very good" and 1.0 "exceptional". The consensus among the investment profession is that an IR of .20 or .30 is superior, which states that the dynamic WML portfolio demonstrates good skills on the part of the manager.

	Against CW Market
Excess return	0.119
Tracking error	0.237
Information Ratio	0.503

Table 5: Performance against market benchmark

In addition, we have also considered the practical application of this portfolio by running the same regression and out-of-sample tests for an equally weighted WML (EWWML) portfolio. Everything is the same, except for the weights assigned to each stock in each leg of the static WML portfolio. With an equal weighting scheme, we expect transaction costs to be significantly lower and the practicality of our dynamic strategy would be improved.

Table 6 and 7 evaluates the performance of the dynamic EWWML portfolio. Compared to its cap-weighted counterparts, we do not observe significant differences especially in terms of Sharpe Ratio. The Appraisal Ratio, however, is slightly reduced. On the other hand, the dynamic EWWML portfolio has significantly higher Information Ratio. Considering these results, we strongly believe that a dynamic EWWML portfolio would most likely perform on par with or surpass our original dynamic EWWML portfolio thanks to its lower transaction costs.

	Market	WML	Dynamic Momentum Strategy
Average excess return	0.065601	0.12822	0.2397
SD	0.1572	0.20349	0.22781
Sharpe Ratio	0.41732	0.63011	1.0522
Appraisal Ratio	0.092462	0.26568	0.34442

Table 6: Evaluation of performance for the dynamic EWWML portfolio

	Against CW Market
Excess return	0.1741
Tracking error	0.27433
Information Ratio	0.63464

Table 7: Performance against market benchmark for the dynamic EWWML portfolio

Conclusion

The popular (static WML) momentum premium is widely tested and verified to fall dramatically in the aftermath of stressed bear markets (momentum crashes). Statistically, it can be avoided with a dynamic WML portfolio that is scaled by the ratio between its predicted return and past variance.

As our out-of-sample results show, the dynamic WML portfolio significantly outperforms its static counterpart, with double the Sharpe ratio and significant positive alpha thanks to the scaling back on the risky asset (in this case the WML portfolio) during stressed bear conditions.

Taking the dynamic strategy with higher turnover into consideration, a monthly rebalancing schedule and day-to-day monitoring is feasible to achieve better execution and lower transaction costs.

In conclusion, we strongly recommend including this portfolio in our product range for further commercialization towards our investor base.

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