Forecasting equity risk premium: there is no momentum of predictability for technical indicators

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1 Introduction

Forecasting equity risk premium has been examined by numerous papers. The historical average is proven to be a very stringent benchmark for forecasting is a rather difficult task. As Goyal and Welch [3] shows, some fundamental variables such as treasury bill rate or dividend yields can explain future stock returns to an extent in sample, but their out-of-sample forecasts are inferior to the historical average. Neely[1] compares the performance of technical indicators and fundamental variables based on their ability to forecast the risk premium, and finds that technical indicators are more useful for prediction during recessions, while fundamentals perform better during economic expansions. This implies that the predictive ability of a model based of a variable of either type is persistent, meaning that if it performed well in the recent past, then it is more likely do so in the current period. This phenomenon is called momentum of predictability (MoP) by Wang[2]. A MoP based strategy switches between the forecast of the model of interest and the historical average based on their performance in the past k months. Wang shows that MoP is present for fundamentals, which means that there is significant stock return predictability using a MoP-based forecast.

This paper examines a naturally arising issue: is there a similarly valuable momentum of predictability for technical indicators? Using data from January 1950 to December 2017, and a total of 14 variables (6 moving-average, 2 momentum, and 6 on-balance volume rules), , I perform a test of momentum predictability in the same framework as Wang, and find that there is some marginally significant dependence between past and current predictability for some of the indicators, especially with a lookback window of 6 months, but these findings are anything but convincing. Out of the 70 computed p-values, only 7 are lower than 5%, and none is lower than 1%. In contrast, Wang finds p-value lower than 1% for five different variables with multiple lookback periods. Based on these results, we can not reject the null hypothesis that there is no momentum of predictability.

To further address to controversial findings, I also perform a principal component analysis on the 14 variables. As a consequence of their nature, the technical indicators are highly correlated, so the first principal components, which explains over 70% of the variance, is used to build another MoP-based model. On an 5% level, there is significant dependence between the past 6-month and the current performance, but no dependence for the other lookback periods (1, 3, 9 and 12 months).

2 Data and descriptive statistics

This section describes the variables used in the analysis. The methodology of computing the technical indicators is the same as Neely.

I used 14 technical indicators to predict stock return, they are the same as the ones used by Neely. For the equity risk premium, the log of the value-weighted equity return including dividends minus the log of the lagged risk-free rate is used (available on Amit Goyal's homepage).

Out of the 14 variables, the first 6 are moving-average based rules, which generate a buy or sell signal ($S_{i,t} = 1$ or $S_{i,t} = 0$) at the end of period t by comparing two moving averages:

$$S_{i,t} = \begin{cases} 1 & if \quad MA_{s,t} \geq MA_{l,t} \\ 0 & \text{if} \quad \mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t} \end{cases}$$

where

$$\mathrm{MA}_{j,t} = \left(\frac{1}{\mathrm{j}}\right) \sum_{i=0}^{j-1} P_{t-i},$$

P_t is the level of the stock index, s and l are the lengths of the short and long MA ($s < l$). I analyze monthly MA rules with $s = 1, 2, 3$ and $l = 9, 12$, and denote the indicators with MA lengths s and l by MA(s, l).

Secondly, 2 momentum based strategies are used. A momentum rule strategy guves a buy signal if the current stock price is higher than its level m periods ago:

$$S_{i,t} = \begin{cases} 1 & if \quad P_t \geq P_{t-m} \\ 0 & \text{if} \quad P_t < P_{t-m}. \end{cases}$$

I employ monthly signals for m = 9,12 and denote them MOM(m) for m.

Thirdly, I consider 6 volume based strategies, which use trading volume as well as past price changes to identify market trends. I first compute the on-balance volume:

$$\mathrm{OBV}_t = \sum_{\mathrm{k}=1}^{\mathrm{t}} \mathrm{VOL}_k \mathrm{D}_k,$$

where VOL_k is the trading volume during period k, and D_k is a binary variable which takes the value 1 if $P_k \geq P_{k-1}$ and -1 otherwise. From OBV_t, we form a trading signal in the following way:

$$S_{i,t} = \begin{cases} 1 & if \quad MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 & \text{if} \quad \mathrm{MA}_{s,t}^{\mathrm{OBV}} \geq \mathrm{MA}_{l,t}^{\mathrm{OBV}}, \end{cases}$$

where

$$\mathrm{MA}_{j,t}^{\mathrm{OBV}} = \left(\frac{1}{\mathrm{j}}\right) \sum_{i=0}^{j-1} \mathrm{OBV}_{t-i},$$

I analyze volume-based rules for $s = 1, 2, 3$ and $l = 9, 12$.

The market data of the S&P500 stock index is used from January 1950 to December 2017. Due to the lack of past data, we have observations for all technical indicators starting from December 2017. It is important to note that due to the long-term upward trend in the index level, technical indicators more often generate buy signal than not. More precisely, every indicators generates a buy

	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)
R^2_{OOS}	0.24%	0.66%	0.23%	0.73%	0.18%	0.01%	0.14%	0.16%

Table 1: $R^2_{OOS}$is positive for all variables, which implies stock return predictability

signal between 67 % and 73% of the time. We can observe that the indicators are highly correlated, with minimum correlation between two indicators being 0.44, and the minimum correlation between two indicators of the same type being 0.64.

3 Methodology of testing predictability

This section describes the way of testing the predictive performance of a forecasting model compared to the benchmark historical average model. The starting point is the following univariate linear regression:

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1},$$

where r_t is the aforementioned equity risk premium, x_t is a vector of predictive variables (in this case consisting of zeros and ones), and ε_t is an error-term assumed to be independent and identically distributed. Following literature and more specifically, the framework of Wang, I employ a recursive, expanding estimation window to generate out-of-sample forecasts. In particular, I divide the whole sample of T observations of r_t into an in-sample part containing the first M (in this study, $M = 180$) observations, and an out-of-sample part containing the remaining $N = T - M$ observations. The out-of sample forecast for some period $K + 1$, where $K \geq M$, $K < T$ is then given by

$$\hat{r}_{K+1} = \hat{\alpha}_K + \hat{\beta}_K x_K,$$

where $\hat{\alpha}_K$and $\hat{\beta}_K$ are OLS-estimates of α and β, respectively. These estimates are obtained by regressing $\{r_t\}_{t=2}^{K}$ on a constant and $\{x_t\}_{t=1}^{K-1}$. Throughout this process, a series of N out-of-sample forecasts are generated. We compare these forecasts to the benchmark model following the literature by using out-of-sample R^2. This is the defined as the percentage reduction in mean squared predictive error of the model of interest relative to the benchmark model. The R^2_{OOS} results are reported in Table2. We can observe that the R^2_{OOS} is positive for all of the indicators, suggesting the predictability of stock returns, although I do not test the significance of the difference between the models of interest and the benchmark model.

4 Testing the momentum of predictability

Wang defines momentum of predictability as the property whereby predictability present during a past period is also found in the current period. Therefore, we can say that momentum of predictability is present in a model, if it is more likely to outperform the benchmark model in the current period, if it did so in the recent past. Current and past predictability is defined based on the squared error of the predictions. Current predictability is given by:

$$cp = \left((r_t - \hat{r}_t)^2 < (r_t - \bar{r}_t)^2 \right),$$

a logical function, which thus takes the value 1,if the condition in the parenthesis is satisfied and -1 otherwise. Similarly,

$$pp\,(k) = \left(\sum_{j=t-k}^{t-1} (r_t - \hat{r}_t)^2 < \sum_{j=t-k}^{t-1} (r_t - \dot{r}_t)^2 \right),$$

where k is the lookback period. $pp\,(k)$ takes the value 1, when the model of interest produced a smaller sum of squared error than the benchmark model throughout the past k months., and -1 otherwise. I considered lookback periods of $k = 1, 3, 6, 9, 12$. I test the momentum of predictability under the null hypothesis that $pp\,(k)$ and cp_t are serially independent. For this purpose, I use the Pesaran-Timmermann statistic for directional accuracy testing.

Since I found the aforementioned test to be rather inadequately documented, I shortly include the methodology. The test compares whether the sign of an n-element vector x does a good job of forecasting the sign of an n-element vector y. First, we define the vectors

$$d_x = \begin{cases} 1 & where \quad x > 0 \\ 0 & \text{where} \quad \text{x} \leq 0 \end{cases},$$

$$d_y = \begin{cases} 1 & where \quad y > 0 \\ 0 & \text{where} \quad \text{y} \leq 0 \end{cases}, \quad l = 2$$

$$d_{xy} = \begin{cases} 1 & where \quad xy > 0 \\ 0 & \text{where} \quad \text{xy} \leq 0, \end{cases}$$

where xy is the elementwise product of the vectors x and y. For each of these three vector, let p_x, p_y, and p_{xy}be the proportion of 1's in d_x, d_y and d_{xy} respectively, and

$$q_i = \frac{p_i\,(1 - p_i)}{n},$$

for $i = x, y, xy$. Now

$$p_* = p_x p_y + (1 - p_x)\,(1 - p_y)\,,$$

$$p_{xy}^{VAR} = \frac{p_*\,(1 - p_*)}{n},$$

k	MA(1,9)	MA(1,12)	MA(2,9)	MA(2,12)	MA(3,9)	MA(3,12)	MOM(9)	MOM(12)	VO[illegible]
1	0.540	0.669	0.753	0.947	0.654	0.861	0.736	0.575	0.[illegible]
3	0.508	0.364	0.489	0.565	0.428	0.330	0.291	0.329	0.[illegible]
6	0.066	0.137	0.036	0.314	0.080	0.104	0.044	0.096	0.[illegible]
9	0.278	0.287	0.119	0.458	0.121	0.158	0.389	0.341	0.[illegible]
12	0.013	0.018	0.148	0.366	0.068	0.260	0.137	0.839	0.[illegible]

Table 2: Results of testing the MoP. The p-values are much higher than in Wang's similar table, indicating there is no significant MoP for technical indicators

$$p_*^{VAR} = (2p_y - 1)^2 q_x + (2p_x - 1)^2 q_y + 4q_x q_y,$$

where p^* can be interpreted as the expected proportion of correct guesses of sign change assuming serial independence. The test statistic is given by the formula

$$PT = \frac{p_{xy} - p_*}{\sqrt{p_{xy}^{VAR} - p_*^{VAR}}},$$

which follows a standard normal distribution under the null hypothesis. The test results with the p-values are reported in Table3.

I find that 8 of the employed 14 variables has no significant momentum of predictability for any lookback period. The moving average based indicators MA(1,9), MA(1,12), MA(2,12), the momentum-based MOM(9) and the volume-based VOL(1,9) and VOL(2,9) show somewhat significant momentum of predictability (on a significance level of 5%) with one of the longer lookback periods ($k = 6, 9$ or 12), which. Moreover, none of the 70 p-values of Table3 is less than 1 percent, which suggests that there is no momentum of predictability for these 14 technical indicators.

5 MoP of different groups of technical indicators

Since different classes (moving-average, momentum, volume-based) of technical strategies tend to give more homogenous signals, I also analyse the performance of the average MA-based, momentum-based, and volume based strategies.

First, following Okunev, I compute monthly signals for 354 moving-average based strategies with $s = 1, 2, ..., 12$ and $l = 2, 3, ..., 36$ with $s < l$, meaning

$$\mathrm{MA}_t^{AVG} = \frac{\sum_{s=1}^{12} \sum_{l=s+1}^{36} IPC\left(\mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t}\right)}{354},$$

where I is the indicator function which takes the value 1 is the condition in the parenthesis is satisfied and 0 otherwise.

k	PC^{TECH}	MA^{AVG}	MOM^{AVG}	VOL^{AVG}
1	0.327	0.389	0.789	0.158
3	0.203	0.092	0.168	0.100
6	0.130	0.099	0.271	0.010
9	0.022	0.107	0.121	0.074
12	0.268	0.331	0.380	0.176

Table 3: p-values for serial dependency test current and past performance of PC^{TECH},MA^{AVG}, MOM^{AVG},and VOL^{AVG}strategies

Secondly, the average signal given by momentum based strategies is computed using MOM(m) for $m = 1, 2, ..., 36$:

$$\text{MOM}_t^{\text{AVG}} = \sum_{m=1}^{36} I\left(P_t \geq P_{t-m}\right).$$

Lastly, the average of the volume-based strategies is computed for the same short and long moving-averages as for simple MA-based strategies, meaning

$$\text{VOL}_t^{AVG} = \frac{\sum_{s=1}^{12} \sum_{l=s+1}^{36} I\left(\text{MA}_{s,t}^{\text{OBV}} \geq \text{MA}_{l,t}^{\text{OBV}}\right)}{354}$$

Furthermore, since all of them trying to extract the trend from price movements, technical indicators are highly correlated. Neely found that in the principal component analysis of the the14 technical indicators that paper employed, the first component explains over 70% of the variance. Considering this, I also analyse the momentum of predictability of the first principal component extracted from the PCA for the previously constructed 354 + 36 +354 = 744 strategies. This component, further denoted by PC^{TECH}still explains more than 55% of the variance in spite of the magnitudes larger number of variables.

After constructing these variables, I performed the same PT-test to test the momentum of predictability,the results of which are reported in Table3.

For the $\text{PC}^{\text{TECH}}$and VOL^{AVG}strategies, there is significant MoP on an 5% level for one lookback period, namely 9 months and 6 months, respectively. Considering the MA^{AVG} and MOM^{AVG}strategies, there is no significant MoP for any lookback period.

References

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