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Elusive Return Predictability

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Overview

Forecasters of stock returns face a moving target that is changing over time and the more successful a particular forecasting approach has been in recent times, the more likely it is to have been detected and adopted by a wider group of investors which eventually render the model obsolete. Exogenous shocks to the markets will often alter the underlying assumptions and parameters of existing models, therefore making them ineffective.

Having established that a profitable long-term forecasting model is highly improbable, Timmermann examines historical data to discover that short-term predictability could and did exist. In the 1980s, typically reliable predictor variables such as dividend yields, financial ratios, and other economic figures failed during the strong bull market in the 1990s. Further out-sample studies into these models also found that the return predictability is either entirely absent or confined to particular intervals during this period. Timmermann seeks to explore empirically (using the US Stock market) the usefulness of a combination model in order to capture these momentary instances of predictability.

Empirical Testing to US Stock Returns (1959:12 – 2005:12)

Timmermann considers a suite of 11 forecasting models, of which 2 are combination models built on the other 9 standard models. The type of models are briefly explained below:

- **Prevailing Mean:** This is basically the simple average price of the past n samples of data
- **Auto-regressive (AR) specification/Factor Augmented AR/Logistic STAR models:** Forecasted price depends linearly on its own previous values, with parameters chosen to minimize the *Bayes Information Criterion* (BIC)¹
- **Exponential/Holt Smoothing:** Average price of the past n samples, with more weightage place on the more recent samples
- **One/Two-Layer Neural Net (NN):** Non-linear forecasting model with layers of “hidden” units which computes all inputs (i.e. market prices) before collated as one output.
- **Previous Best:** Using historical RMSE² as a criterion, select the forecast of best performing model in a given point in time
- **Equal-Weighted Average:** Takes the average forecast among all 9 standard models

The RMSE is a commonly utilized measure to the differences (i.e. sample standard deviation) between values predicted by a model and the actual values observed. The test results showed that in different time periods, the best performing models are typically different. Though the combination model “Equal Weighted Average” performed consistently better in the long run, it did so only marginally more than the prevailing mean; testing other approaches also yield similar results.

Adaptive Forecast Combination Approach

This basically highlights the fact that no single forecasting model or predictor variable can reliably perform better than the prevailing mean in the long-run; any return predictability is constrained to relatively short time intervals. Specifically, closer examination of the market data showed that major forecasting errors usually occur during structural changes in the market. Structural breaks in the market

¹ Bayes Information Criterion penalizes the selection of too many variables to avoid over-fitting in a model; the larger the value, the heavier the penalization

² Root Mean Square Difference: $RMSD(\hat{\theta}) = \sqrt{E((\hat{\theta} - \theta)^2)}$, where $\hat{\theta}$ is estimator value and θ is the observed value

are likely to affect individual forecasting models to varying degrees; hence this lends further support to the use of combination models to hedge against model instabilities. Timmermann proposed a simple adaptive combination approach which offers the flexibility of having access to multiple forecasting models as well as the mechanisms to adjust to changing market conditions. The main parameters and mechanism of this model are outlined as follows:

- Rolling window of $m = 18, 36, 60$ and 120 observations to estimate the out-sample $R^{2,3}$ value
- Check if any of the models produced an estimate \hat{R}^2 above a certain “hurdle” R_{\min}^2
 - Failure will set the combination forecast to the prevailing mean.
 - Success will set the combination forecast to the current estimate.

Note that there is a tradeoff between a high hurdle value R_{\min}^2 and the sensitivity of the adaptive combination model. Similarly, there is a trade-off between the length of the evaluation window m and the ability of the model to identify short periods of predictability. A simplified tabulation of the results of using this adaptive forecasting model is shown in Table 1.

Out-of-sample RMSE performance of the adaptive forecast combination approach vs. prevailing mean				
Window length (m)	Hurdle value	Hurdle exceedance	RMSE prevailing mean	RMSE adaptive model
18	0	0.52	15.759	15.709
	0.01	0.52	-	15.709
	0.02	0.5	-	15.716
	0.05	0.39	-	15.728
	0.1	0.2	-	15.725
	36	0	0.57	15.945
0.01		0.57	-	15.904
0.02		0.51	-	15.918
0.05		0.28	-	15.876
0.1		0.16	-	15.917
60		0	0.69	15.447
	0.01	0.6	-	15.456
	0.02	0.5	-	15.472
	0.05	0.31	-	15.423
	0.1	0.09	-	15.458
	120	0	0.86	15.454
0.01		0.54	-	15.42
0.02		0.41	-	15.412
0.05		0.18	-	15.463
0.1		0	-	15.454

Table 1: Green cells indicates RMSE values that are lower (i.e. better) than the prevailing mean

We can make the following observations from the results:

- For the smallest threshold value $R_{\min}^2 = 0$, the exceedance rate⁴ increases as m increases; this coincides with the claim that for a lower threshold, there is more noise being captured.
- On the other hand, for the highest threshold value $R_{\min}^2 = 0.1$, the exceedance rate decreases as m increases; this again coincides with the claim that in the long-run, it is very hard to build a model which can generate a high R^2 value consistently.
- Notice that for a shorter m , the adaptive model typically performs marginally better than the prevailing mean. On the other hand, model breakdown starts occurring when $m = 60$ or higher, reflecting the structural changes in the market during the 1990s.

Conclusion/Take-away

The difficulty of predicting financial returns in the market is exacerbated by market participants' attempts to identify and exploit any purported predictability, and it thus evolves constantly over time. In trying to build a valuable model or algorithm to capture market predictability, we need to consider the two factors:

- Prediction strength: A stronger forecast model will reduce its effective life compared to a weaker model

³ Sum of the square errors associated with the prevailing mean benchmark: $\hat{R}_{i,t-m+1,t}^2 = \mathbf{1} - \frac{e_{i,t-m+1,t} \times e_{i,t-m+1,t}}{\bar{e}_{i,t-m+1,t} \times \bar{e}_{i,t-m+1,t}}$, where $\bar{e}_{i,t-m+1,t}$ is the m -vector of out-sample forecast errors associated with the prevailing mean, and $e_{i,t-m+1,t}$ is the m -vector of the out-sample forecast errors from the i -th model measured between period $t - m + 1$ and t .

⁴ The exceedance rate is the rate at which a specific's model's performance exceed the threshold R^2 ; the higher the exceedance rate, the higher the number of forecasts will be used instead of the prevailing mean

- Forecast horizon: Longer term forecasts are more profitable yet almost impossible to achieve, while very short-term detection methods will likely capture too much noise

Ultimately, what we can learn from this particular paper is that there are no “holy grails” that are able to profit from the market consistently. Instead of trying to predict long-term market movements, it is more feasible to attempt to capture short-term predictability; developing a sustainable and effective investment model/strategy should involve constant adjustments and innovations to adapt to the immediate market conditions.

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