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Abstract. Recent advances in pension product development seem to favour alternatives to the risk free asset so often used in financial theory. In this paper, we investigate other benchmarks of the financial model than the classical risk free asset; for example, a benchmark following an inflation index is just one important case. Modelling extra returns above the inflation of risky assets is important, for example, for actuarial applications aiming at providing real income forecasts for pensioners. We study market timing when three alternative benchmarks are considered: the risk free rate, inflation and the long bond yield. We conclude that forecasting future stock returns is of similar complexity for all three considered benchmarks. From a pension fund modelling perspective, it therefore seems that one should use the most convenient benchmark for the problem at hand.

Keywords. Benchmark, Cross validation, Prediction, Stock returns.

MSC: 62G99, 62M20, 91G70, 62P05.

1 Introduction

One of the key messages of the *Harvard Business Review* paper by the *Nobel Laureate* Robert Merton (Merton , 2014) was that pension forecasts should be in real terms. Perhaps, the simplest way of accommodating that challenge is to change the benchmark, i.e., the monetary unit everything is measured in terms of, to inflation rather than the risk free interest rate often used. In the three recent papers from the IFoA-sponsored project (Institute and Faculty of Actuaries, IFoA, is the UK's only chartered actuarial professional body) "Minimizing longevity and investment risk while optimizing future pension plans" – Donnelly et al. (2018) and Gerrard et al. (2018a, 2018b) – we assumed a risk free inflation fund rather than a risk free fund in the classical sense. In other words, these three recent pension product development papers suggest that we change the classical benchmark, i.e., the risk free asset, to inflation as the benchmark.

The previous papers did not consider the econometric challenges of using different benchmarks. The purpose of the current research is to make the first few investigations into suitable benchmark selection from an econometric perspective. We use the cross-validated time series approach of Nielsen and Sperlich (2003) and Scholz et al. (2015, 2016) to optimize the fully nonparametric statistical estimation and forecasting of the risky asset given the three

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different alternative choices of benchmarks: the risk free rate, inflation and the long-term bond yield. In our approach, we assess the performance in terms of forecasting next year's return – adjusted for the benchmark – given covariates such as earnings, dividend yield, short interest rate, long interest rate and inflation, as well as last year's lagged stock return. Our investigations show that earnings are always important while forecasting and that earnings should often be combined with something else to provide optimal forecasts. The best forecast for the inflation-corrected stock return is, for example, obtained when earnings are combined with the inflation index as a covariate.

The remaining of this paper is organized as follows. In Section 2, we present our underlying financial model and our validation criterion. In Section 3, we present our empirical findings from different validated scenarios. In Section 4, we extend from a dependent variable measured on the original nominal scale (single benchmarking approach) to the case with both the independent and dependent variables adjusted according to the benchmark (full benchmarking approach), and repeat the empirical study. Section 5 concludes.

2 The Underlying Financial Model and the Principle of Validation

First, we focus on nonlinear relationships between stock returns in excess of a reference rate or benchmark and a set of explanatory variables. We investigate different benchmark models and their predictability. As in Scholz et al. (2015), we apply a local linear smoother based on cross-validated smoothing parameters to the fully nonparametric models. As benchmarks, we consider the short-term interest rate, the long-term interest rate, and the inflation rate. More specifically, we investigate stock returns $S_t = (P_t + D_t)/P_{t-1}$, where D_t denotes the (nominal) dividends paid during year t and P_t the (nominal) stock price at the end of year t, in excess of a given benchmark $B_{t-1}^{(A)}$ (on the log-scale)

$$Y_t^{(A)} = \ln \frac{S_t}{B_{t-1}^{(A)}},$$

where $A \in \{R, L, C\}$,

$$B_t^{(R)} = 1 + \frac{R_t}{100}, \quad B_t^{(L)} = 1 + \frac{L_t}{100}, \quad B_t^{(C)} = \frac{CPI_t}{CPI_{t-1}},$$

R_t is a short-term interest rate, L_t a long-term interest rate, and CPI_t the consumer price index for year t. The prediction problem is then

$$Y_t^{(A)} = m(X_{t-1}) + \xi_t,$$

and our aim is to forecast the excess stock returns $Y_t^{(A)}$ using popular predictive variables X_{t-1} such as the *dividend-by-price ratio* $d_{t-1} = D_{t-1}/P_{t-1}$, *earnings-by-price ratio* $e_{t-1} = E_{t-1}/P_{t-1}$, *short-term interest rate* $r_{t-1} = R_{t-1}/100$, *long-term interest rate* $l_{t-1} = L_{t-1}/100$, *inflation* $\pi_{t-1} = (CPI_{t-1} - CPI_{t-2})/CPI_{t-2}$, and also the excess stock return $Y_{t-1}^{(A)}$. The error terms ξ_t are zero-mean random variables given the past. We address the regression problem of estimating the conditional mean function $m(x) = E(Y^{(A)}|X = x)$ using i.i.d. pairs $\{(X_t, Y_t^{(A)})\}_{t=1}^T$ observed from a smooth joint density and its multivariate generalization.

For the purpose of model as well as bandwidth selection, we use a generalized version of the validated R^2, R_V^2, introduced by Nielsen and Sperlich (2003) based on leave-k-out cross-validation. This method of finding the smoothing parameter has shown to be suitable also in a time series context. Our validation criterion is defined as

$$R_V^2 = 1 - \frac{\sum_t \left(Y_t^{(A)} - \hat{m}_{-t}\right)^2}{\sum_t \left(Y_t^{(A)} - \bar{Y}_{-t}^{(A)}\right)^2},$$

where leave-k-out estimators are used: $\hat{m}_{-t}$ for the nonparametric function m and $\bar{Y}_{-t}^{(A)}$ for the unconditional mean of $Y_t^{(A)}$.

3 Predicting Excess Return of the Three Benchmarks: Inflation, Long Bond Yield, and Short Interest Rate

In what follows, we study the empirical findings of R_V^2 values based on different validated scenarios shown in Table 1. Overall, we find that earnings-by-price is the most important predictor, which works well as a predictor in itself, but sometimes even better when combined with other information. More specifically, the best two-dimensional predictor for the short interest benchmark R is either earnings-by-price and short-term interest rate or earnings-by-price and long-term interest rate. Both give a predictive R_V^2 value of 14.6%. The best two-dimensional predictor for the long-term interest benchmark L is earnings-by-price and long-term interest rate with $R_V^2 = 16.1\%$. Finally, the best two-dimensional predictor for the inflation benchmark C is earnings-by-price and inflation with an astonishing $R_V^2 = 21.2\%$. Given that the inflation benchmark might be the most important for many pension product applications, this high predictive power is very promising. If we constrain prediction to using only one-dimensional covariates, then earnings-by-price is the best predictor for both R and L with, respectively, $R_V^2 = 11.6\%$ and 12.8%, and inflation is the best one-dimensional predictor for C with $R_V^2 = 9.7\%$. Notice that these results are quite similar to those obtained in Scholz et al. (2015); slight differences are due to the extended data period 1872–2015 and the larger number of bandwidths on the analyzed grid.

4 The Full Benchmarking Approach

It could be argued that the independent variable in Section 3 is adjusted according to some benchmark, while the dependent variable is measured on the original nominal scale. In this section, we consider the case with both the independent and dependent variables adjusted according to the benchmark. For example, in the full benchmarking approach with benchmark inflation, excess returns are extra returns compared to inflation, and the covariate long-yield is excess long-yield compared to inflation. In pension research, for example, a model can be considered with benchmark inflation and all returns and covariates are net of inflation. This,

Table 1: Predictive power (%) for dependent variable $Y_t^{(A)}$. Explanatory variables X_{t-1}: $Y^{(A)}$ (where $A \in \{R, L, C\}$) excess stock return, d dividend-by-price, e earnings-by-price, r risk free rate, l long-term interest rate, π inflation.

A	$Y^{(A)}$	d	e	r	l	π	$Y^{(A)}, d$	$Y^{(A)}, e$	$Y^{(A)}, r$	$Y^{(A)}, l$	$Y^{(A)}, \pi$
R	-1.5	0.8	11.6	3.9	-0.1	-1.5	-1.6	7.7	1.9	-2.2	-2.7
L	-1.7	0.8	12.8	2.1	-0.1	-1.5	-1.4	8.2	0.0	-2.4	-3.0
C	-1.4	-0.1	7.9	1.1	-0.8	9.7	-1.6	5.0	-0.6	-2.5	9.4
A	d, e	d, r	d, l	d, π	e, r	e, l	e, π	r, l	r, π	l, π	
R	13.1	3.8	-1.0	-1.7	14.6	14.6	11.9	10.3	2.3	-2.1	
L	13.4	2.4	-0.5	-1.3	13.7	16.1	11.9	5.8	0.4	-2.2	
C	7.9	1.0	-1.2	9.7	6.1	7.6	21.2	6.5	9.0	9.3	

in turn, provides a simple scaling while working on long-term forecasts in real terms. The prediction problem is then

$$Y_t^{(A)} = m(X_{t-1}^{(A)}) + \xi_t,$$

where we use transformed predictive variables

$$X_{t-1}^{(A)} = \ln \frac{1 + X_{t-1}}{B_{t-1}^{(A)}}.$$

This model could be interpreted as a way of reducing dimensionality of the estimation procedure as $X_{t-1}^{(A)}$ combines an additional predictive variable in a multiplicative way. Results of the empirical study can be found in Table 2. We find that the full benchmarking approach is better than the single benchmarking approach of the previous section. The best two-dimensional predictor for the short interest benchmark R is earnings-by-price and inflation with a predictive power $R_V^2 = 18.8\%$ (increased from 14.4% in the previous section). The best two-dimensional predictor for the long-term interest benchmark L is earnings-by-price and short-term interest rate with $R_V^2 = 13.4\%$ (reduced from 16.1% in the previous section). The best two-dimensional predictor for the inflation benchmark C is earnings-by-price and dividend with $R_V^2 = 24.0\%$ (increased from 21.2% in the previous section). Again, given that the inflation benchmark might be the most important for many pension product applications, this high predictive power is very promising. When constraining prediction to using only one-dimensional covariates, earnings-by-price is the best one-dimensional in all three cases with $R_V^2 = 15.7\%$, 9.7% and 18.5% for predicting, respectively, returns in excess of short-term interest, long-term interest and inflation, compared to 11.6%, 12.8% and 9.7% in the previous section. It is particularly striking that earnings-by-price alone can deliver a predictive poser of 18.5% when full benchmarking is performed.

Table 2: Predictive power (%) for dependent variable $Y_t^{(A)}$. Explanatory variables $X_{t-1}^{(A)}$: $Y^{(A)}$ excess stock return, $d^{(A)}$ dividend-by-price, $e^{(A)}$ earnings-by-price, $r^{(A)}$ risk free rate, $l^{(A)}$ long-term interest rate, $\pi^{(A)}$ inflation; all transformed using the benchmark $B^{(A)}$, where $A \in \{R, L, C\}$.

A	$Y^{(A)}$	$d^{(A)}$	$e^{(A)}$	$r^{(A)}$	$l^{(A)}$	$\pi^{(A)}$	$Y^{(A)}, d^{(A)}$	$Y^{(A)}, e^{(A)}$	$Y^{(A)}, r^{(A)}$	$Y^{(A)}, l^{(A)}$	$Y^{(A)}, \pi^{(A)}$
R	-1.5	5.4	15.7	–	13.0	-1.2	3.6	13.0	–	8.6	-2.6
L	-1.7	1.1	9.7	8.7	–	-1.6	-1.4	5.5	4.4	–	-3.0
C	-1.4	10.9	18.5	6.0	10.0	–	10.6	17.2	5.2	9.3	–
A	$d^{(A)}, e^{(A)}$	$d^{(A)}, r^{(A)}$	$d^{(A)}, l^{(A)}$	$d^{(A)}, \pi^{(A)}$	$e^{(A)}, r^{(A)}$	$e^{(A)}, l^{(A)}$	$e^{(A)}, \pi^{(A)}$	$r^{(A)}, l^{(A)}$	$r^{(A)}, \pi^{(A)}$	$l^{(A)}, \pi^{(A)}$	
R	15.9	–	12.3	3.8	–	17.7	18.8	–	–	9.9	
L	10.9	8.0	–	-1.2	13.4	–	8.3	–	5.5	–	
C	24.0	10.4	10.2	–	22.6	21.9	–	14.4	–	–	

5 Conclusion

In this communication, we update and extend the validated predictive scores of Scholz et al. (2016). In particular, a few more years of data have been incorporated and the inflation and long-term interest benchmarks have been introduced to supplement the short-term interest rate benchmark which is by far the most commonly used in finance. This paper expresses an interest in going beyond this. Different benchmarks might be important, for example, when modelling returns in real terms (the inflation benchmark) or modelling returns in excess of long-term bond yield (long-term bond yield benchmark).

We also investigate the option of full or double benchmarking, meaning that, not only returns are benchmarked, but also the covariates used to predict them. This double benchmarking approach can also be seen as an example of a dimension reduction technique, where more information is included in the nonparametric prediction without extra cost in terms of increasing problem dimensionality. Recall that fully nonparametric models suffer in several aspects by the curse of dimensionality, in particular, as in our framework, where we confront sparsely distributed annual observations in higher dimensions. In statistics, it is well-known that importing more structure in the estimation process can help to reduce or circumvent such problems. For example, Nielsen and Sperlich (2003) investigate an additive functional structure in the context of predictability of excess stock returns (as proposed in the statistical literature by Stone , 1985). Their results indicate a more complex structure than additivity, as the fully nonparametric models always do better in terms of validated R^2 as the additive counterparts. Scholz et al. (2015) propose a semi-parametric bias reduction method for the purpose of importing more structure based on a multiplicative correction with a parametric pilot estimate.

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References

Donnelly, C., Guillen, M., Nielsen, J. P. and Pérez-Marín, A. M. (2018), *Implementing individual savings decisions for retirement with bounds on wealth.* ASTIN Bulletin **48**(1), 111-137.

Gerrard, R., Hiabu, M., Kyriakou, I. and Nielsen, J. P. (2018a), *Communication and personal selection of pension saver's financial risk.* Preprint.

Gerrard, R., Hiabu, M., Kyriakou, I. and Nielsen, J. P. (2018b), *Self-selection and risk sharing in a modern world of life-long annuities.* British Actuarial Journal (forthcoming).

Merton, R. C. (2014), *The crisis in retirement planning.* Harvard Business Review, **92**(7/8), 43-50.

Nielsen, J. P. and Sperlich, S. (2003), *Prediction of stock returns: A new way to look at it.* Astin Bulletin, **33**(2), 399-417.

Scholz, M., Nielsen, J. P. and Sperlich, S. (2015), *Nonparametric prediction of stock returns based on yearly data: The long-term view.* Insurance: Mathematics and Economics, **65**, 143-155.

Scholz, M., Sperlich, S. and Nielsen, J. P. (2016), *Nonparametric long term prediction of stock returns with generated bond yields.* Insurance: Mathematics and Economics, **69**, 82-96.

Stone, C. J. (1985), *Additive regression and other nonparametric models.* Annals of Statistics, **13**(2), 689-705.

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