Score-based Portfolio Choice
Extended Abstract

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November 8, 2018

Factor investing has been ubiquitous in recent finance literature as a viable way of forming portfolios with favorable risk-return characteristics. While the standard approach to measuring factor exposure in academic studies is by performing a regression analysis of stock returns on a set of characteristics-sorted long-short portfolios (see, e.g., Fama and French, 2015; Hou, Xue, and Zhang, 2014), applications in the financial industry frequently asses factor exposure by using rank scores. Stocks are sorted with respect to characteristics which are associated with factors (e.g., book-to-market ratio or earnings yield are used to asses the *value* of a stock, return on equity or gross profits over total assets are used to proxy *profitability*) and these rank scores run directly into the portfolio-formation scheme, (see, e.g., Blitz and Van Vliet, 2007; Novy-Marx, 2013). I.e., the asset manager's strategy is to form a portfolio that maximizes some average compound score built from scores with respect to individual characteristics, thereby creating the desired factor exposure and in turn earning the associated factor premia.

Our study shows that for S&P 500 stocks the average portfolio score is a useful measure of factor exposure. In contrast to factor betas, which must be estimated from historical observations, scores are directly observable figures (the market beta is an exception). With score-based return expectations, stock characteristics are the essential primitives that determine portfolio selection. For applied portfolio management, a linear premium is of particular interest, since it allows to deduct return expectations simply from average scores. We show that the linearity assumption is confirmed for some of the chosen characteristics, but must be treated with care for others.

For this study, we select the characteristics underlying the five FF2015 factors used by Fama and French (2015). As a proxy for the market factor, we use the rank score from a sort with respect to beta (MS), for the size factor we score with respect to market capitalization (MC), for value we sore with respect to book-to-market ratio (BTM), for profitability the score with respect to gross profits over total assets (GPOA), finally for investment we use the score with respect to total asset growth (TAG). All these rank scores are normalized in order to lie equally spaced in the $[0, 1]$ interval. The scores are updated on a weekly basis and reflect the most current price and balance sheet information. Balance sheet and return data for the S&P500 have been downloaded from Datastream resulting in data from October 1989 until November 2017. All balance sheet characteristics are shifted in order to account for the backfill bias of Datastream data.

To measure the linear effect of the rank score on stock excess returns, we perform cross-sectional regressions of the excess returns on the stock characteristics

$$r_{i,t} - r_f = \alpha_t + \sum_{c=1}^{m} \gamma_{c,t} s_{c,t,i} + \epsilon_t$$

where $r_{i,t}$ denotes the return of stock i over the interval from t to $t+1$, r_f the risk-free return over the same period, α_t the intercept of the regression, $\gamma_{c,t}$ the return contribution for characteristic c from time t to $t+1$, m the number of characteristics under consideration, $s_{c,t,i}$ the rank score for characteristic c at time t for stock i, and ϵ_t the residual of the regression. Averaging return contributions γ_c over time shows that on average, a 1 pp increase in the BTM-score of a portfolio increases the expected portfolio return by 0.12 bp per week. An equivalent score increase for GPOA contributes 0.13 bp per week, whereas for TAG, the return contribution is 0.06 bp per week. In contrast, for MS and MC we did not find a significant return contribution, see Table 1.

Table 1: Multivariate regression results for return contribution γ

	MS	MC	BTM	GPOA	TAG
$\bar{\gamma}$	0.0919	0.0635	0.1180	0.1373	0.0572
σ_γ	3.3920	1.6139	2.0349	1.6693	1.1673
p-Value	0.2998	0.1319	0.0266**	0.0017***	0.0608*

Interestingly, particularly balance sheet items are ideal variables to implement with the score based method. Cross-checking our findings with the four factor model by Hou, et al. (2014) (Hou, Xue, and Zhang, 2014), we find that due to correlation between scores, the choice of characteristics crucially influences the estimate of the expected return contribution. In this study, an analytical solution to this problem is presented by correcting for collinearities in rank scores such that we neutralize unwanted changes in other factor scores and create a minimum tracking-error path for increasing only one desired rank score.

To conclude, in our study we construct a scoring-based portfolio choice based on normalized rank scores. We show that an increase in portfolio scores comes with a significant increase in portfolio return for BTM, GPOA and TAG. These results are robust also for longer time periods of 4 and 13 weeks for GPOA and TAG. The selection of the set of characteristics is of great importance for portfolio selection, as collinearity between characteristics occurs, but can be accounted for by the selection method introduced in this paper. For most of the characteristics, the linearity assumption is not rejected, but we show the limitations with respect to the BTM characteristic, where significant differences in return contribution between BTM-quintiles occur.

References

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