Discovery of key factors in hedge funds investment strategies using optimal IBA-based logical polynomials

Aleksa Radosavcevic[1], Ana Poledica[2] and Ilija Antovic[3]

[1] University of Belgrade - Faculty of Organizational Sciences, Belgrade, Serbia, ar20235065@student.fon.bg.ac.rs
[2] University of Belgrade - Faculty of Organizational Sciences, Belgrade, Serbia, ana.poledica@fon.bg.ac.rs
[3] University of Belgrade - Faculty of Organizational Sciences, Belgrade, Serbia, ilija.antovic@fon.bg.ac.rs

Abstract. For an increasing number of forecasting models based on computational intelligence, one of the most prioritized requests refers to the model's transparency, explainability and reproducibility. With the constant emergence of more complex investment instruments and strategies, challenges in financial time series forecasting are being amplified. Feature selection and aggregation are typical examples of such challenges. This paper examines the interpolative Boolean algebra (IBA) approach for discovery of optimal logical aggregation (LA) of key factors in Hedge Funds' (HF) investment strategies. IBA polynomials that serve as logical aggregation functions, are obtained as a product of a structure vector (SV) and corresponding atomic elements. To obtain optimal aggregation function for analyzed time series, structure vectors are optimized by iterating over all combinations of elements. The proposed approach is applied to four major groups (factors) of candidate inputs, first separately and then jointly, on five distinctive HFs' time series. The evaluation and robustness check are examined using standard multivariable linear regression and more complex, extreme gradient boosting algorithms. Lastly, feature aggregation using optimal IBA logical functions are benchmarked against original, non-restricted inputs. Test error analysis has demonstrated that IBA-based feature aggregation reduces errors, for most of the analyzed time series, when compared to the original feature set.

Keywords: interpolative Boolean algebra, feature aggregation, computational intelligence, financial time series, hedge funds

1 Introduction

As hedge funds (HFs) nearly doubled their globally managed assets from 2.6 trillion in 2015 to 4.9 trillion dollars in 2021 [1], their potential contribution to the overall systematic risk in financial markets continued to grow. Moreover, the fact that institutional investors, like social and pension funds started to increase allocations towards these investment vehicles, imposes monitoring and understanding of HFs' investment strategies.

This paper conducts empirical research focused on forecasting HFs' returns, considering a variety of investment styles, complex financial instruments and diverse asset classes as main portfolio constituents. HFs' strategies are represented as time series of observed cumulative quarterly returns, on 5 investment styles: Commodity Trading Advisors (CTA), Fixed Income Arbitrage (FIA), Global Macro (GM), Equity Long Short (ELS) and Equity Market Neutral (EMN). They are described by 4 major factor groups, intended to describe various macroeconomic, debt and capital market conditions following up on [2, 3] and [4] approaches. For the stakeholders, asset managers and investors, one of the most important aspects of an investment process are model transparency and explainability. Bearing in mind the complexity of investment strategies, feature engineering and feature selection are rather challenging tasks.

In computational intelligence, feature aggregation operators are widely used in building trustworthy forecasting models. Additionally, real-life data tends to suffer from issues like dependencies among the variables, strong correlation coefficients and multicollinearity. When traditional weighted sum, order weighted average, fuzzy t-norms are applied as aggregation operators, they are inadequate to capture all existing forms of logical interaction between attributes [12]. In such cases, logical aggregation based on interpolative Boolean algebra (IBA) is appropriate to develop more general models and complex structural representations [5, 6, 7]. IBA is a real-valued logic that could be used to model uncertainty or partial truth in a Boolean consistent manner [12, 13, 14]. Several research papers have proven that IBA-based LA improve decision making for problems in the financial domain, particularly in terms of transparency and explainability, e.g. in the case of sovereign credit rating forecasting [5, 6, 7], financial ratio analysis [8] or portfolio selection [9, 10]. One approach to construct IBA logical functions for a specific problem is to use domain expertise, as in [8-10, 18]. Another approach is to identify logical aggregations directly from specific data without prerequisites for domain expertise [5, 6, 7].

Following up on the previous implementations [5-10] of IBA in finance, this paper expands the realm of its applications in the field. HFs investment implies dealing with complex risk structures, often hard to identify, whereas the quantification of the overall risk exposures is a challenge. In this regard, the main task of the paper is to find an optimal IBA-based logical aggregation function for each investment strategy, composed of candidate factors [5, 9]. Similarly to the methods applied in previous research in [5, 6, 7], LA served as a feature aggregation technique to treat the problem of the discovery of key factors and corresponding constituents in HFs' investment strategies. Furthermore, it is examined whether IBA-based feature aggregation improves forecasting performance in terms of accuracy and explainability, by applying multivariable linear regression (MLR) and extreme gradient boosting (XGB) algorithms.

The paper is structured in the following manner: first, theoretical introduction of a general IBA methodology is given, followed up by a single and multi-factor overview of IBA-based feature aggregation. Next section is devoted to the experiments, where an empirical overview of the data, model development and experimental set up is given. Furthermore, results are discussed from a contextual point of view together with corresponding models and errors analysis. Conclusion marks are elaborated in the final part.

2 Theoretical Background

2.1 Interpolative Boolean Algebra

Interpolative Boolean algebra represents Boolean consistent, real valued [0, 1] realization of a Boolean algebra, formally built on the principle of structural functionality. It is a two-level algebra, which distinguishes between the structure of the logical function from its value realization [11, 12, 13]. Therefore, IBA on its symbolic level performs structural transformation of the logical function as binary vector representation, thus preserving the Boolean axioms. Once the structure of the logical function has been identified, on the second level, calculation of values within the [0, 1] interval is introduced, using generalized Boolean polynomials (GBP) and maintaining the properties of Boolean logic [11-15]. As focus of the paper is put on structural IBA polynomials, the following section will be devoted to structural transformations of the logical function and analyzing its binary forms as such. For optimization of the IBA structure vectors (SVs) values, different metaheuristic approaches have already been introduced, such as genetic algorithm [9, 10], differential evolution [5, 6, 7], and variable neighborhood search [16, 20].

2.2 IBA transformation of logical function

As proposed in [11, 12, 13], the principle of structural functionality implies that the structure determination precedes the calculation of the function arguments values. The structure of an element is determined by atoms included in it, so it is binary in its nature. This further implies that the structure vector is binary vector defined by the following expression:

$$\vec{\sigma} = \left[S \in P(\omega)^T\right] \quad (1),$$

where σ_f is the structure function of a logical function $f\left(x_1, ..., x_m\right)$, α_s is an atom of $BA(\omega) = P(P(\omega))$, and $P(\omega)$ is the power set of a set of free variables $\omega = \left\{x_1, ..., x_m\right\}$.

The structure vector $\vec{\sigma}$ contains information about which atoms are relevant/included in a logical function. It is obtained after iterating over all possible combinations of atoms. Such information is given by the structural function σ_f, defined by the following expression:

$$\sigma_f\left(\alpha_S\right) = \begin{cases} 1, & \alpha_S\left(x_1, \ldots, x_m\right) \wedge f\left(x_1, \ldots, x_m\right) = \alpha_S\left(x_1, \ldots, x_m\right) \\ 0, & \alpha_S\left(x_1, \ldots, x_m\right) \wedge f\left(x_1, \ldots, x_m\right) = \underline{0}. \end{cases} \quad (2).$$

After structure vectors have been identified, to obtain real-valued realization, in the next step IBA uses generalized Boolean polynomials (GBPs). GBP is a sum of the relevant atomic Boolean polynomials:

$$f \otimes (x_1, ..., x_m) = \sum_{\sigma_f(\alpha_S)=1 | S \in P(\Omega)} \left(\bigotimes_{x_i \in S} x_i \bigotimes_{x_j \in \Omega \setminus S} (1 - x_j) \right) \quad (3),$$

where $x_i \in [0, 1]$ and $\otimes$ is a generalized product (GP). On the value level, GP may be realized as a t-norm that produces values from the following interval [12]:

$$\left(x_1 + x_2 - 1,\ 0\right) \leq x_1 \otimes\ x_2 \leq \left(x_1,\ x_2\right) \quad (4).$$

There are three distinctive cases for realization of a generalized product: minimum, standard product, and Lukasiewicz operator [11, 12, 13]. In case there is no interaction/dependence between attributes, the standard product is appropriate as a GP operator. Attributes of the same nature or positively correlated ones are aggregated using the minimum operator. GP is realized as Lukasiewicz t-norm if attributes are negatively correlated. In case of complex expressions with diverse attributes by nature, attributes of the same nature should be aggregated first, followed by negatively correlated ones [17].

3 IBA-based approach to HFs strategies' factors discovery

In a proposed IBA setting, the presence of an arbitrary candidate variable, from a set of all possible inputs in a model, is analogous to the presence of an atom in the element's structure. This paper, in addition to identifying SVs of HF strategies represented as IBA polynomials, assesses the potential of such SVs as inputs for constructing forecasting models, where the goal is to predict cumulative returns over the next three months' period. Similarly to [6], the methodology of this paper is largely built around considering single and multi-aspect IBA vectors as candidate inputs in developing forecasting models.

As a standard step in the IBA framework [11-13], first it is necessary to perform normalization of input attributes and to analyze correlation matrix. These are the following steps:

1. Input preparation:
   a. Compute correlation matrix and analyze coefficients
   b. Normalize input attributes to unit interval
2. IBA-based feature aggregation:
   a. Define general IBA vectors for given input attributes
   b. Calculate GBPs applying appropriate operator
   c. Select optimal GBPs based on minimum error

In the next steps, for each analyzed HF strategy, based on optimal IBA feature aggregation functions, models' training and evaluation is performed.

3.1 Single Factor Approach

Among a variety of HFs investment styles and strategies, five representatives are selected, similarly to [4]: Commodity Trading Advisors, Equity Long Short, Equity Market Neutral, Fixed Income Arbitrage and Global Macro. To determine significant factors and corresponding variables for each of the strategies from *S = {CTA, GM, FIA, ELS, EMN}*, in the first step, IBA structural transformation of a logical function is applied separately using a set of 4 groups candidate factors (F), representing macroeconomic, debt, capital market conditions and trends: 3 interest rates (I), 3 bonds (B), 5 five factor asset pricing model (A), and 4 trend following (T) candidate inputs:

$$F = \left\{ \vec{I}^{3}, \vec{B}^{3}, \vec{A}^{5}, \vec{T}^{4} \right\} \quad (5).$$

For all strategies in *S*, each factor group ∈ F is evaluated separately, and optimal Single Factor (SF) models are selected based on evaluation metric. These initial vector structures have binary forms and input dimension shapes equal to the number of constituents in a corresponding factor group: 3 in case of interest rates and bonds, 5 in case of asset pricing and 4 trend following variables.

3.2 Multi Factor Approach

Next, starting from previously developed basic SFs, similarly to [5, 6, 7], more complex multi aspect or Multi Factor (MF) models are derived, by simultaneously considering all top performing models from all factor groups. Mathematically, the formation of a MF for a particular strategy in *S* is achieved by concatenating top performing SF models across all 4 risk factor groups ∈ *F* and forming a vector shape of 2^{n}, where *n* represents the sum of all risk factor groups shapes:

$$MF = \left\{ \vec{SF}^{3}_{I}, \vec{SF}^{3}_{B}, \vec{SF}^{5}_{A}, \vec{SF}^{4}_{T} \right\} \quad (6).$$

Individual SF models are ordered according to the order of factor groups in *F*, forming an MF input vector shape of 15.

4 Experiments

This section is structured in the following manner: first problem and data description are presented, where explanations regarding each HF strategy are given, together with a more detailed insight into each factor group constituents. Next, models' development process is explained, for both SF and MF models, with an overview of forecasting algorithms and objective function. Lastly, empirical findings, validation and test results for each strategy are presented and discussed.

4.1 Data

Monthly returns of HFs strategies have been acquired from Morningstar CISDM Database [21]. To describe performance of 5 main HFs strategies, quarterly performances (QPs) for each strategy has been calculated. Although each of the HF strategies is, to some extent, exposed to the same factors, the levels of exposures differ based on corresponding investment styles. For example, CTAs use managed futures contracts as the main financial instrument, while implementing various systematic and trend following strategies to speculate about future price of commodities like raw materials, like agricultural or mining products. Other strategies, like ELS and EMN are more focused on analyzing and trading stocks of the companies listed on stock exchanges. While ELS takes long positions in undervalued companies' stocks and short positions on overvalued stocks, it also employs financial instruments like options to hedge risks and leverage to amplify expected returns, EMN tends to minimize correlation to a broader equity market, by hedging risks such as currency, sector, and volatility. Contrary to equity-oriented strategies, FIA is more focused on trading companies mispriced debt securities, such as bonds and fixed income instruments, although it also implements hedging risky, high-yielding instruments by taking a position in corresponding companies' stock. Lastly, GM strategy is built around analyzing macroeconomic conditions and trends of countries or regions and investing in various asset classes like equities, commodities, fixed income instruments and hedging risks using futures, options, swaps and other derivatives.

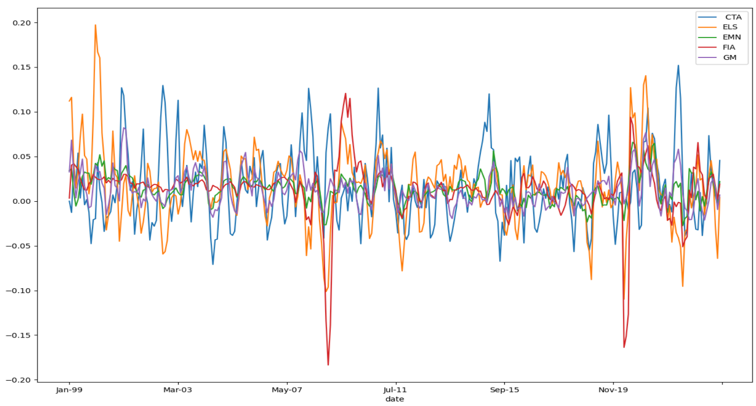

Figure 1: HFs strategies' quarterly performance

By taking a closer look at the timeline depicted on Figure 2, the environment conditions could be observed in each of the strategies quarterly performances, when looking at the peaks and drawdowns. Major ones are for example "dotcom" stock market bubble in early 2000s, global economic crisis and interest rates spikes in 2007/09 and covid crisis in 2019.

Following up on [4] approach, the investment environment in which HFs operate is described by 4 main groups of factors F, including short, mid and long-term interest rates, bonds with low, intermediate and investment grades obtained from FRED database [22]. Next, asset pricing risk factors and trend following factors were acquired from K. R. French's [23] and D. A. Hsieh's [24] data libraries respectively:

Table 1: HF's environment factors' descriptions and abbreviations:

Factors	Bonds Yields	Asset Pricing	Trend Following
3-month treasury bill (TB3SMFFM)	Investment grade (BAA)	Stock exchange performance (Mkt-RF)	Trend following strategies on bonds (PTFSBD)
5-year constant maturity (T5YFF)	High yield below investment grade (BBB)	Performance of small vs. large cap portfolios (SMB)	Trend following strategies on commodities (PTFSCOM)
10-year constant maturity (T10YFF)	High yield below investment grade (BCCC)	Performance of value vs. growth portfolios (HML)	Trend following strategies on interest rates (PTFSIR)
		Performance of robust vs. weak profitability portfolios (RMW)	Trend following strategies on stocks (PTFSSTK)
		Performance of conservative vs. aggressive portfolios (CMA)	

4.2 Experimental setup

In the first step, IBA polynomials for each strategy were constructed separately, using a single factor approach for each strategy ∈ S. Due to strong correlation coefficients among bond risk factors B, for GP a minimum operation is implemented (see Figure 2 in Appendix). Whereas for other factors product operation is used since there is no significant level of interaction detected. In addition to SF and MF models, non-restricted benchmark models have been constructed, including a full set of non-transformed model inputs, using MLR and XGB algorithms.

To assess the potential of IBA structure vectors in forecasting of HFs performances, in the first step, cumulative quarterly performances for each strategy are calculated using Equation (7) and shifted three steps backwards. The observed period covers the timeframe of 25 years, starting from January 1999 until December 2023, in a monthly resolution. The overall dataset is divided into train, validation and test sets, the last 3 years of data is used for models' testing. Lastly, all candidate model inputs have been normalized prior to model training.

As a forecasting algorithm, in the first step as a starting point, simple multivariable linear regression (MLR) has been implemented. However, due to its poor capability to capture non-linearity and spikes in time series, an extreme Gradient Boosting (XGB) is implemented in addition [18]. Therefore, it ensures generalization over different data distributions, accounting for non-linearity in the data and, due to parallel implementation, it can handle models with large numbers of candidate variables and offers fast compute time, particularly important for models' cross validation.

To train forecasting models, factors' normalization has been performed, followed by a forward chaining 10-folds cross validation, where each folds' validation set contains 2.5 years of data. Models are evaluated on the test set, covering the period starting from July 2021 until the end 2023. To evaluate the fitness of a certain model candidate generated by structural function as depicted in Equation (3), the model's structure vector is passed to a decision tree based boosting algorithm [18], used to train and cross-validate the model's performance. As an evaluation metric, relative root mean squared error (RRMSE) is taken. Relative root mean squared error is a variant of root mean squared error (RMSE), which normalizes RMSE of a model in predicting values, by the target' s variable value and presents it as a percentage.

4.3 Results

IBA-based logical functions are optimized for each strategy and GBP polynomials for CTA strategy are given in Table 2. These GBP polynomials are used as inputs in regression models' training and evaluation.

Table 2: Commodity Trading Advisors - SF Models' validation performance:

Factors	*CTA GBPs*	*Val. RRMSE*
Interest Rates	*(TB3SMFFM ⊗ T10Y2Y) ⊗ (1 - T5YFF)*	*0.22*
Bonds	*(BAA ⊗ BCCC) ⊗ (1 - BBB)*	*0.23*
Asset Pricing	(HML ⊗ CMA) ⊗ (1 - (Mkt-RF)) ⊗ (1 - SMB) ⊗ (1 - RMW)	*0.19*
Trend Following	(PTFSBD ⊗ PTFSIR ⊗ PTFSSTK) ⊗ (1 - PTFSCOM)	*0.21*

From the empirical point of view, in the case of CTA, the MF approach provides superior results regardless of the regression algorithm. At the same time, from forecasting perspective, it represented the most difficult challenge, due to the spike in returns, occurring in the period March-May 2022. Therefore, both validation and test error are higher than for other strategies. Nevertheless, MF models based on XGB regressor have managed to capture the magnitude of the spike to some extent. When looking at CTA polynomial constituents, the structure is in line with the strategy definition, since there is a clear distinction between mid-term interest rates (T5YFF) on one side and short (TB3SMFFM) and long (T10Y2Y) interest rates. Similarly, when analyzing the trend following factors, it separates trend following proxies on commodities (PTFSCOM) from trend following proxies on other asset classes.

Next, in the cases of GM and FIA, an MF model based on XGB regressor has yielded the lowest error levels compared to all other strategies. Moreover, discrepancy between validation error of SF models and test error of MF model is not manifested as in case of CTA. When it comes to polynomial constituents, the implemented approach distinguishes between short term interest rates versus mid and long-term interest rates, indicating hedging investments based on a time horizon. When it comes to the bond polynomial constituents, the fact that investment grade bonds are assigned to the GM strategy is in line with this strategy's investment style and definition, as it prioritizes lower risk alternatives, e.g. governments' bonds. In the case of FIA strategy, primary focus is put on arbitrage between high yielding bonds of below investment grade on one side against moderate to low risky bonds on the other side. However, when analyzing the forecasted lines versus realized observations, the GM model tends to diverge from the ground truth, whereas the FIA model follows, to some extent, realized values.

Table 3: Test performance RRMSE comparison between SF, MF and Non-Restricted Benchmark Models:

Strategy	Non-Restricted		SF models		MF models	
	MLR	XGB	MLR	XGB	MLR	XGB
CTA	0.6865	0.3864	0.5244	0.2815	0.4577	**0.2348**
GM	0.3203	0.2425	0.2667	0.2458	0.2905	**0.2127**
FIA	0.3327	0.2254	0.3723	0.2803	0.3463	**0.2132**
ELS	0.2519	**0.1826**	0.3982	0.2602	0.3503	0.2045
EMN	0.2693	0.2038	0.2155	**0.1733**	0.2281	0.1993

Contrary to previous investment strategies, in the case of ELS, IBA polynomial couldn't overperform a XGB non-restricted benchmark (Table 3). This could be explained by the fact that, contrary to bonds and interest rates which are taken as such, Famma-French asset pricing factors were already derived based on a feature engineering process as a result of domain expertise and proprietary data on stocks of different market capitalization, coming from various industry sectors. Therefore, in combination with other factors, it is a challenging benchmark to overcome.
Interestingly, when forecasting EMN cumulative quarterly returns, a SF model overperformed other alternatives by a fair margin, resulting in the lowest error across all strategies and model alternatives (Table 3). This could be explained by the lowest volatility in this time series, as the returns fluctuate in the range of +/- 3.5%.

5 Conclusion

In this paper, the problem of identification of significant drivers that influence performance of diverse hedge fund investment strategies is tackled. The four groups of candidate factors are selected to represent macroeconomic, debt, capital market conditions and trends. The analyzed period covers the time horizon starting from 1999 until 2023, in a monthly resolution, where cumulative quarterly hedge fund returns were the forecasting targets, and the last 3 years of data is used for models' testing. To be able to draw general conclusions, the five investment styles are considered: Commodity Trading Advisors, Fixed Income Arbitrage, Global Macro, Equity Long Short and Equity Market Neutral.

The main idea was to make use of IBA-based logical polynomials as a feature aggregation technique. The optimal IBA polynomials for each factor group and investment strategy are extracted from the data. In other words, the optimal IBA structure vector is chosen based on minimal regression error as an objective function. Optimal IBA polynomials are further used in the challenging task of forecasting hedge funds' quarterly returns. The prediction models, multivariable linear regression and XGB, served as a framework to validate whether IBA-based feature aggregation improves forecasting compared to non-restricted input data.

In general, IBA-based feature reduction improves forecasting results for analyzed HFs index data. In the case where input features are already derived by experts (as in the Fama-French 5 factor model), additional IBA feature engineering does not significantly improve performance. However, the importance of the IBA approach is especially significant in case of insufficient domain expert knowledge for preprocessing and feature engineering. In such cases, the discovery of optimal IBA polynomials from the data automatically can be important for trustworthy decision making.

There are several directions for further research. For example, the proposed approach could be benchmarked against dimensionality reduction techniques, like linear or non-linear principal component analysis. In addition, following on [6, 7] and [16, 20] approaches, additional metaheuristics could be implemented to obtain real valued realization of IBA, thus skipping intermediate step and avoiding the usage of MLR and XGB. Lastly, the generalization capabilities of the proposed approach could be tested for time series forecasting beyond the financial domain.

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Appendix

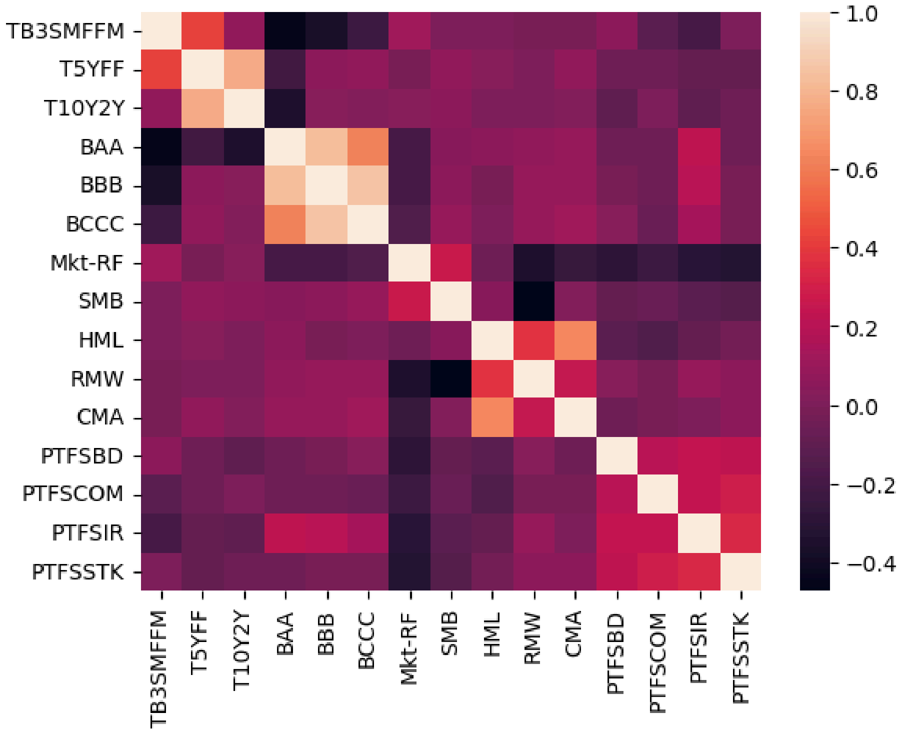

Figure 2: Factors’ correlation matrix