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ORIGINAL ARTICLE



Bottom-up versus top-down factor investing: an alpha forecasting perspective

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Abstract

In a recent discussion about efficient ways to combine multiple firm characteristics into a multifactor portfolio, a distinction was made between the bottom-up and top-down approach. Both approaches integrate characteristics with equal weights and ignore interaction effects from differences in informational content and correlations between the firm characteristics. The authors complement the bottom-up approach for the missing interaction effects by implementing a linear alpha forecasting framework. Bottom-up versus top-down factor investing is typically discussed using the assumption that all characteristics are equally priced, but the pricing impact of different firm characteristics can vary tremendously. The alpha forecasting perspective provides a theoretical motivation for factor investing and helps to compare the bottom-up and top-down approach with regard to the difference of informational content and interaction effects between firm characteristics. Taking into account the difference in informational content between firm characteristics leads to significant performance improvement in factor models with a high concentration of informational content. Equally weighted characteristics result in related performance irrespective of whether the bottom-up or top-down approach is applied.

Keywords Factor investing \cdot Top-down \cdot Bottom-up \cdot Smart beta \cdot Multifactor \cdot Alpha forecasting \cdot Stock screening \cdot Z-score \cdot Information coefficient \cdot Optimal orthogonal portfolio

JEL classification $G11 \cdot G12 \cdot G15 \cdot G17$

Factor investing, which is also called smart beta, aims to improve capitalization-weighted portfolios by tilting portfolio weights toward specific risk factors. Advocates of factor investing refer to well-performing backtest results caused by low-cost factor exposures. While cost-efficiency is a result of the rules-based approach, an overly simplistic adaptation of factor investing strategies can lead to many missconceptions,¹ especially in cases of the implementation of multifactor strategies.

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In a recent discussion about efficient ways to combine multiple firm characteristics into a multifactor portfolio, the top-down (TD) and bottom-up (BU) approach were differentiated. The TD method is a two-step approach that first builds the single-factor portfolios and then combines them into a multifactor portfolio. In contrast, the one-step BU approach integrates all firm characteristics simultaneously into a multifactor portfolio.

Across the recent literature, there has been no consensus on the superiority of one approach against the other. While Bender and Wang (2016), Clarke et al. (2016) as well as Fitzgibbons et al. (2017) demonstrated that the BU method leads to better performance results, Chow et al. (2018), Leippold and Rueegg (2018) and Amenc et al. (2018) reassessed the claim and found no such superiority. In an attempt to

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¹ In a position paper Amenc et al. (2016) discussed ten misconceptions about smart beta and separated them into groups of performance drivers, investability hurdles and strategy choices. Arnott et al. (2019) also detailed misconceptions and emphasized overfitting, crowding and nonnormal drawdowns.

balance this discussion, Ghayur et al. (2018) emphasized the increased efficiency of the BU approach in gaining a higher exposure to the chosen factors. They argued that, after the factor exposures of both approaches are matched, the advantage of the BU approach disappears. Lester (2019) also underscored the importance of factor exposures by analyzing how factor exposure translates into expected portfolio returns. The findings confirmed that, on average, factor returns and risk scale linearly with factor exposure. However, in the performance comparison between the TD and BU approach, factor exposures alone provided no sufficient answer to the dissent in the literature. Because, even without any exposure adjustments Amenc et al. (2018) and Leippold and Rueegg (2018) did not find significant performance differences between both approaches.

In this paper, we argue that the discussion has neglected pricing inequalities between the different factors. Both approaches integrate equally weighted characteristics and ignore interaction effects from differences in informational content and correlations between the firm characteristics. This neglect follows the questionable assumption that all characteristics are equally priced. The strong simplification of this assumption is demonstrated in the zoo of factors discussion. The 314 published factors documented by Harvey et al. (2016), as well as the postpublication decay findings of McLean and Pontiff (2016), provide reasonable explanations for doubting the relevancy of each individual factor. Additionally, the results motivate the construction of multifactor portfolios to diversify the factor risk posed by unpriced factors. Ignoring the different pricing relevancies of factors can lead to biased performance results. In particular, if the BU approach loads large weights on noisy factors, high exposure to these factors could lead to a disadvantage compared to the TD approach.

Avoiding the full range of interaction effects can not only lead to false performance statements but also ignores one of the main benefits of the BU approach. The BU approach can easily be extended to consider factor relevancy, while the TD approach is not able to do so without losing simplicity, which can be identified as one of its main benefits. To distinguish among multiple firm characteristics, we apply an alpha forecasting framework from Grinold and Kahn (2000, p. 263), which is closely related to a cross-sectional Fama-MacBeth (FM) regression on lagged firm characteristics. Lewellen (2015) showed that FM-based return forecasts correspond well with true expected returns and provide an effective way to combine multiple firm characteristics into a composite estimate of expected returns. Furthermore, Heinrich and Zurek (2019) exhibited the benefits of implementing a linear alpha forecasting model as an operational tool to combine multiple firm characteristics into a multifactor portfolio. They found that distinguishing between the informational content of firm characteristics outperforms the naïve scoring approach in well-defined factor models with a high dispersion in the informational content of firm characteristics. However, they primarily focused on the BU approach. Therefore, in this article, we conduct a horse race between the TD and BU approach, in which interaction effects and informational content differences between the selected firm characteristics are explicitly considered.

Our study contributes to the literature in various ways. By determining portfolio weights proportional to alpha forecasts, we present factor investing strategies from the perspective of the optimal orthogonal portfolio (OOP), formally used by MacKinlay and Pástor (2000). Based on this framework, it is possible to pinpoint the reasoning for an investment in a factor portfolio from the practical view of an investor who aims to beat a given benchmark portfolio. Since the implementation of the OOP can be interpreted as an investment in the missing risk factor portfolio, investors who believe that the given benchmark can be complemented by this factor should invest in the OOP, increasing the Sharpe Ratio of the overall portfolio. This perspective is not only helpful for operational portfolio management but might also be relevant for performance measurement and risk management.

Moreover, by the implementation of the alpha forecasting model within the BU approach, we evaluate the difference between the TD and BU approach with regard to the full range of interaction effects. This topic has not yet been addressed in the recent discussions and is especially important for practice since, in multifactor portfolios and even in single-factor portfolios, many investors attempt to diversify their factor investing risk by considering several firm characteristics. For example, the Fama-French proxy portfolio for value relies only on the book-to-market ratio, while the MSCI value index uses three additional firm characteristics.

With regard to the practical applicability of our study, we analyze the various approaches with factor portfolios defined according to an industry standard for MSCI factor portfolios. Overall, the entire multifactor portfolio contains 16 firm characteristics. Including stocks from the S&P 500, Stoxx Europe 600, and the Nikkei 225 index, the results are evaluated for three different data samples.

Our simulation and empirical findings point out the important role of the informational content structure within the alpha forecasting process. Ignoring the informational content by weighting all of the signals equally leads to related performance results irrespective of whether the TD or BU approach is applied. Therefore, our results reinforce the findings that, in the naïve alpha forecast case, the TD and BU approaches exhibit no significant performance differences. In contrast, if the BU approach is extended by the consideration of the full range of interaction effects, a significant performance improvement in factor models with a high concentration of informational content could be demonstrated.

The remainder of the paper is organized as follows. Section 1 introduces the linear alpha forecasting model and the simplified version of the naïve combination approach. Section 2 provides a simplified simulation example, which visualizes the importance of the full range of interaction effects within the bottom-up approach. Section 3 presents the data set and the applied firm characteristics, whereas Sect. 4 reports the findings of the empirical backtest, which includes the results of the long-only and long-short portfolios. Finally, Sect. 5 contains some concluding remarks.

Alpha forecasting

Following Treynor and Black (1973), the investment universe can be divided into an active portfolio A with i = 1, ..., N securities and a passive benchmark portfolio \mathbb{B} . Since the main purpose of this work lies in the comparison between the TD and BU approach, we concentrate on the weighting decision of A. We assume that the returns of Aand \mathbb{B} are uncorrelated. Therefore, \mathbb{A} represents the optimal orthogonal portfolio analyzed by MacKinlay and Pástor (2000), who showed that the OOP corresponds to the missing risk factor portfolio. Provided that the residual covariance matrix is in a restricted form,² the active weights of the missing risk factor portfolio are proportional to the securities' alpha parameters. In simplified terms, securities with a higher alpha forecast are represented by a greater weight within the portfolio. In accordance with Fama-French, we separate securities into a long and short portfolio. Stocks with an alpha forecast greater (less) than a specified quantile $\alpha_{at}^+(\alpha_{at}^-)$ are assigned to the long (short) portfolio:

$$a_{\text{long}} = \frac{\hat{\alpha}^+}{\mathbf{1}'\hat{\alpha}^+} \quad \text{with} \quad \hat{\alpha}^+ = \mathbb{1}_{\hat{\alpha} > a_{qt}^+} \circ \hat{\alpha}, \tag{1}$$

$$a_{\text{short}} = \frac{\hat{\alpha}^-}{\mathbf{1}'\hat{\alpha}^-} \quad \text{with} \quad \hat{\alpha}^- = \mathbb{1}_{\hat{\alpha} < \alpha_{q_t}^-} \circ \hat{\alpha}.$$
 (2)

In $\hat{\alpha}^+$, the symbol 1 denotes a vector of indicator variables with the value 1 for alphas greater than α_{qt}^+ and 0 for alphas less than α_{qt}^+ . An equivalent specification applies for $\hat{\alpha}^-$. Since they determine the number of the selected securities, we refer to α_{qt}^+ and α_{qt}^- as selection thresholds. Moreover, the symbol o denotes the entrywise product. In addition to longshort (LS) portfolios, we build long-only (LO) portfolios, wherein only the long portfolio is considered.

Since the weighting decision is only dependent on the securities' alphas, this perspective provides a motivation to apply factor portfolios with characteristic-based weighting schemes. In multifactor portfolios, the BU approach, as well as the TD approach, ranks stocks according to multiple firm characteristics. In the present literature, the main difference between the TD and BU approach can be found in the different treatments of the firm characteristic groups. While the TD approach separates the firm characteristics according to their factors, the BU approach integrates all of the characteristics simultaneously, resulting in the one-step solution of the BU, compared to the two-step solution of the TD approach. However, in both approaches, it is common practice to combine the firm characteristics into a weighted average over the scores of the single-firm characteristics. To avoid biased results from different signal distributions, z-scores are used. Heinrich and Zurek (2019) pointed out that the equally weighted z-score approach is a simplified version of alpha forecasting, and they called this the naïve z-score (NZ) approach:

$$\alpha_{NZ,i,t} = \sum_{m=1}^{M} \frac{1}{M} \frac{\left(g_{i,m,t-1} - E[g_{m,t-1}]\right)}{\sigma_{g_{m,t-1}}}.$$
(3)

We assume that security returns in the active portfolio follow a multivariate conditional normal distribution. As conditioning information, an amount of M different types of firm characteristics g, hereinafter referred to as signals, can be observed for each of the N companies. For simplification purposes, it has been assumed that these signals only have informational value for their specific company, indicating that signals from different companies do not correlate with each other or with returns from other companies. Further, we assume that signals are uncorrelated with benchmark returns so that benchmark timing can be disregarded. Under these conditions, it is possible to extend the NZ approach to account for the signals' cross-correlations and their informational content:

$$\boldsymbol{x}_{GK,i,t} = \boldsymbol{k} \, \boldsymbol{C}^{-1} \, \boldsymbol{z}_{i,t-1},$$

with

$$\boldsymbol{k} = \left(\operatorname{Corr}[R_{t}, g_{1,t-1}] \cdots \operatorname{Corr}[R_{t}, g_{M,t-1}] \right),$$
$$z_{i,t-1} = \begin{pmatrix} \frac{(g_{i,1,t-1} - E[g_{1,t-1}])}{\sigma_{g_{1,t-1}}} \\ \vdots \\ \frac{(g_{i,M,t-1} - E[g_{M,t-1}])}{\sigma_{g_{M,t-1}}} \end{pmatrix}.$$

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(4)

² The covariance is assumed to be diagonal and proportional to the identity matrix. Complementary information about this assumption can be found in MacKinlay and Pástor (2000, p. 887).

 R_t denotes the returns across the N securities at time t. Throughout the article, the term "return" on a given security denotes its return in excess of the riskless rate. $g_{m,t-1}$ are the corresponding companies' signal observations in t-1 of a specific firm characteristic m. The cross-correlations between lagged signals and returns in the $(1 \times M)$)-vector \boldsymbol{k} are called information coefficients (ICs), and they measure the signals' informational content. Heinrich and Zurek (2019) emphasized the important role of ICs in factor investing strategies and define this approach as GK alpha forecasting, inspired by the linear alpha forecasting model of Grinold and Kahn (2000). Moreover, ICs are one of the main determinants of the fundamental law of active management, which is a simplified framework to explain a portfolio's information ratio.³ The inverse of the signals' correlation matrix C^{-1} is responsible for ensuring that highly correlated signals will have a smaller impact on the alpha forecast and vice versa. The $(M \times 1)$ -vector $z_{i,t-1}$ represents the companies' standardized signal observations. Because factor investing strategies are based on cross-sectional anomalies, parameter estimation is conducted with regard to cross-sectional observations. Therefore, k and C will be the same for all securities. This outcome is equivalent to the assumption that a specific stock characteristic will have the same informational content and linear comovement with other signal types for all securities. To obtain ex-ante estimates, we estimate ICs and C from the time-series averages of their cross-sectional estimates.

Since the TD approach does not take into account any interaction effects between characteristics from different factors, it would be unreasonable to apply the GK alpha forecasting model to this approach. In contrast, the proponents of the BU method predominantly emphasize interaction effects between firm characteristics as among its main benefits. However, the NZ combination only considers interactions from characteristics by allowing them to add up or cancel out each other. Although the application of equal weights on each characteristic disregards differences in informational content and the correlation between the firm characteristics, the NZ BU method leads to higher overall factor exposures, than the TD approach. However, especially in factor models with widely dispersed informational content, forcing characteristics to interact equally could skew the factor exposure to noisy characteristics or even characteristics with negative pricing impacts. Therefore, it is reasonable to question why the standard NZ BU method does not consider the full range of interaction effects, since the problem of the misallocation of factors with low information content could be remedied by utilizing the GK BU approach. The importance of interactions captured by ICs and correlations can be visualized in the following simplified simulation example.

Simplified simulation example

In the following simplified simulation example, a comparison is made among the TD, GK BU and the NZ BU approach regarding their factor exposures and alpha results. The framework of the simulation includes four stylized examples and is chosen to illustrate the possible impact of the entire spectrum of interaction effects. Therefore, a oneperiod setting with N = 500 securities is assumed, resulting in a simulated alpha observation for each of the 500 securities. Applying Eq. (4), we simulate the 500 alphas from a two-factor model with the conditioning signals x and y. The random signals are standard normal distributed and have two different settings of cross-correlations (corr). In the low signal corr setting, the characteristics are correlated with a coefficient of 0.1, whereas in the high corr setting, the signals' corr is 0.9. Moreover, we differentiate between two

Table 1Actual alpha resultsof the simplified simulationexample

Example	Actual portfo	olio alphas	
	TD (%)	NZ BU (%)	GK BU (%)
Low signal corr and low IC concentration	4.48	5.15	5.15
Low signal corr and high IC concentration	2.94	3.30	3.92
High signal corr and low IC concentration	4.45	3.92	3.92
High signal corr and high IC concentration	2.62	2.22	6.31

Actual portfolio alphas are determined by the sum of the weighted true alpha parameters. In the low (high) signal corr setting, the characteristics are correlated with a coefficient of 0.1 (0.9). In the low IC concentration case, the ICs of x and y have an equal value of 0.03. In the high IC concentration case, the y characteristic has an IC of 0.03, and x exhibits an IC of 0.01

³ Complementary work on the fundamental law of active management can be found in Clarke et al. (2002), Buckle (2004), Ye (2008) and Ding and Martin (2018).

Table 2 Factor exposures of the simplified simulation example	Example	Characteristic	Factor exp	osures	
simplified simulation example			TD	NZ BU	GK BU
	Low signal corr and low IC concentration	x	0.841	1.004	1.004
		У	0.801	0.885	GK BU 1.004 0.885 0.423 1.238 1.261 1.221 0.226
	Low signal corr and high IC concentration	х	0.841	1.004	0.423
		у	0.801	0.885	0.423 1.238
	High signal corr and low IC concentration	х	1.426	1.261	1.261
		у	1.391	1.221	1.221
	High signal corr and high IC concentration	х	1.426	1.261	0.226
		У	1.391	1.221	0.753

Factor exposures are calculated by the sum of the weighted characteristics' observations. In the low (high) signal corr setting, the characteristics are correlated with a coefficient of 0.1 (0.9). In the low IC concentration case, the ICs of x and y have an equal value of 0.03. In the high IC concentration case, the y characteristic has an IC of 0.03, and x exhibits an IC of 0.01

scenarios of IC concentration. In the low IC concentration case, the ICs of x and y have an equal value of 0.03. In the high IC concentration case, the y characteristic has an IC of 0.03, and x exhibits an IC of 0.01. In this simplified settings, any estimation errors are ignored. Moreover, it is assumed that the investor knows the true ICs and correlations of the GK BU approach, whereas the NZ BU approach uses the naïve alpha forecasts of equally weighted characteristics.

Further, only long-only portfolios are simulated for reasons of simplification. The GK BU and NZ BU approach selects all securities with an alpha higher than the median, and weight these securities according to Eq. (1). In contrast, the TD approach selects the top 25% securities with the highest firm characteristics for each factor portfolio, and it mixes the two portfolios by equal weights. The decision to increase the TD selection threshold from the median to the 0.75th-quantile are made in accordance with Ghayur et al. (2018), who adjusted the TD approach because of its lower factor exposure in the median threshold case.

To evaluate the performance, Table 1 shows the actual alpha results for all three strategies. The actual portfolio alphas are determined with the sum of the weighted true alpha parameters, where the weights are the actual strategy weights. Table 2 depicts the corresponding factor exposures, calculated from the weighted characteristics.

Since the ICs of the signals are assumed to be equivalent in cases of low IC concentration, there is no difference in the performance and exposure results between the NZ BU and GK BU approach. At low signal corr and low IC concentration, the BU approaches achieve slightly higher alphas compared to TD. The difference can be explained by slightly lower factor exposures within the TD approach. However, due to the low signal correlation, the realizations of the standard normal distributed characteristics are evenly scattered⁴ around zero. Therefore, in this case the BU and TD approaches lead to similar security selections, resulting in a small difference in factor exposures and associated performance results.

In the case of low signal corr and high IC concentration, the GK BU approach shows a 19% higher alpha value compared to the NZ BU method and a 33% higher value compared to the TD approach. While the TD and NZ BU exposures remain unchanged, the exposure of the GK BU approach shifts toward the y-characteristic. The GK BU approach benefits from the higher exposure in y, since the y-characteristic has three times more informational content than the x-characteristic. While the GK BU is able to adapt to the differences in the informational content, both the NZ BU and the TD approach neglect the differences, resulting in lower performance.

The examples of high correlation and low IC concentration show alpha results in favor of the TD approach. This is caused by the lower number of securities included in the TD approach. Due to the higher threshold, in combination with highly correlated signals, the TD approach selects fewer securities than the BU approaches. Therefore, the TD approach is able to generate a portfolio with a higher factor exposure. Since the IC concentration is low and the BU approaches also distribute their exposure to both characteristics equally, the higher factor exposure of the TD approach consequently leads to a higher alpha than the BU approaches.

At high signal corr and high IC concentration, the performance of the GK BU approach proves to be much better compared to NZ BU and TD, which can be explained by the relatively small IC value of x compared to the y characteristic. In combination with a high correlation between the signals, the x realizations are now treated negatively in

⁴ The realizations of the characteristics and the results of the security selection of the approaches are visualized in Fig. 5 in the "Appendix".

the alpha forecast of the GK BU approach. The GK BU approach reacts to the higher IC concentration by shifting exposure toward the y-variable, while the exposure of the x-variable decreases significantly. Although the unaffected TD exposure of the y-variable is almost twice as high, the redistribution of exposure to the variable with a higher IC leads to a significantly higher alpha in the GK BU approach.

If we compare both cases with low IC concentration, we can observe higher factor exposures for all strategies in the high signal corr case. However, the alpha results are higher in the low correlation case, showing that the higher correlation between the characteristics has a reducing effect on the performance, and factor exposures without the consideration of the cross-correlations between the characteristics are not sufficient to explain performance differences.

From the overall performance results in the high IC concentration cases, it can be concluded that an exposure distribution on signals with high informational content is much more important than the amount of the exposures. The improved results of the GK BU approach are not caused by an increase in the factor exposures but by a redistribution of exposures. The factor exposure of characteristics with high information content receives a greater weight than the exposure of characteristics with low informational content, leading to higher performance results of the GK BU approach, especially in the case of a high correlation between the signals. The GK BU approach can benefit in particular if the sign of the IC of a characteristic is inverted in the opposite direction, as initially assumed. A low IC concentration thus inevitably leads to similar performance results since the factor exposures are comparably distributed in all approaches. Under the condition of equally distributed factor exposures, approaches with a higher factor exposure show slightly higher alpha results. To challenge these findings in a realistic environment, we apply an out-of-sample backtest with a practical data set and a multifactor model.

Data

We investigate the backtest results for three different data samples. Apart from the S&P 500 (SPX), the Stoxx Europe 600 (STX) and the Nikkei 225 (NKY) are used as parent indices. The chosen indices represent the three most relevant developed equity markets and, as a whole, also cover the majority of many global benchmark indices, such as the MSCI World.⁵ Compared to other regions, Europe includes different currency areas. To ensure that currency effects do not influence the results, returns are measured in local currency. In particular, the assumption is made that currencies are hedged, whereby hedging costs are not considered.

The dataset⁶ contains firm characteristics and stock returns from the beginning of 2002 until the end of June 2020. The reasons for not expanding the time interval can be found in the decreasing data availability for the STX and NKY indices and in the observation of change points within the return generating process in the US market starting in 2002/2003. In accordance with Green et al. (2017), we observed a higher number of significant predictors of monthly US returns prior to 2002. Due to limited space, we do not account for time-varying predictability. However, the question of model misspecification is partly addressed by also including factor portfolios with a small number of significant predictors.

With value, growth, momentum, quality and low volatility, our investigation considers five well-known factors. Each factor is composed of several firm characteristics, whereby the entire sample comprises 16 characteristics. The composition of the factors is based on the MSCI⁷ factor portfolios, because they are widely accepted in the industry. In case of the low-volatility factor, we decided to deviate from the MSCI specification. The MSCI low-volatility factor uses a minimum variance approach to reduce the overall risk of the portfolio and thus differs from the other factors that are based purely on firm characteristics. Therefore, we apply the low-volatility factor using the characteristic-based method of Chow et al. (2014). This approach fits well to the construction methods of the other factors. Furthermore, from a return perspective, the authors found no evidence that the characteristic-based approach differs from the minimum-variance approach. Table 3 provides an overview of the applied factor portfolios and the corresponding firm characteristics.

To ensure that the most recent data are always available and the ongoing fluctuations in price-dependent data are taken into account, daily trailing data observations are used. Moreover, the calculation of accounting ratios is performed with the most actual data points. To guarantee that a higher z-score will imply a higher return and vice versa, the direction of the observations of debt to equity and earnings variability is changed by multiplying them by negative one. We adjust statistical outliers within our firm characteristics

 $^{^{5}}$ At the end of the investigation period, the chosen stock markets covered 92.4% of the MSCI World Index. The data for the calculation are based on the MSCI World weights reported by Bloomberg at the end of June 2020.

⁶ The dataset, including the reporting dates, is provided by the Bloomberg database.

⁷ The MSCI Global Investable Market Value and Growth Index Methodology (September 2017), the MSCI Quality Indexes Methodology (June 2017) and the MSCI Momentum Indexes Methodology (June 2017) are used as guidelines. Due to data availability, the factor specification differs in some respects from the MSCI standard, in particular by applying trailing instead of forward data.

Factor	Characteristic	Definition
Growth	Earnings Growth 1 Year (EPSG1Y)	$EPSG1Y_t = YoY EPS Growth_t$
	Earnings Growth 3 Years Average (EPSG3Y)	$EPSG3Y_t = \frac{1}{3}\sum_{t=1}^{3} YoY EPS Growth_t$
	Internal Growth Rate (IGR)	$IGR_t = \frac{TTM EPS_t}{BVPS} - \frac{TTM DPS_t}{BVPS}$
	Earnings Growth Trend (EPSGT)	$EPSGT_{t} = \frac{\rho_{EPS}}{1/5\sum_{i=1}^{5} EPS_{i} }$
	Sales Growth Trend (SPSGT)	$SPSGT_t = \frac{\beta_{SPS}}{1/5\sum_{t=1}^{5} SPS_t }$
Value	Dividend Yield (DivYld)	$\text{DivYld}_t = \frac{\text{TTM DPS}_t}{P}$
	Earnings to Price (EtP)	$\operatorname{EtP}_{t} = \frac{\operatorname{TTM} \operatorname{EPS}_{t}}{P}$
	Book to Price (BtP)	$BtP_t = \frac{BVPS_t}{P}$
	Cash Flow to Enterprise Value (CFOtEV)	$CFOtEV_t = \frac{TTM CFO_t}{EV}$
Quality	Return on Equity (RoE)	$\operatorname{RoE}_{t} = \frac{\operatorname{TTM} \operatorname{EPS}_{t}}{\operatorname{RVPS}}$
	Debt to Equity (DtE)	$DtE_t = \frac{TD_t}{RV}$
	Earnings Variability (EVar)	$EVar_{t} = \sqrt{\frac{1}{5}\sum_{t=1}^{5} \left(YoY \ EPS-Growth_{t} - \overline{YoY \ EPS-Growth_{t}} \right)^{2}}$
Momentum	6 Months Price Momentum (Pmom6M)	n-Months Price Momentum _t = $\frac{\left(\frac{P_{t-1}}{P_{t-n-1}}-1\right)-R_{f,t}}{\sigma}$
	12 Months Price Momentum (Pmom12M)	"mom,1
Low-volatility	Inverse Beta (InvB)	$\text{InvB}_t = \frac{1}{\theta_{tyt}}$
	Inverse Volatility (InvVola)	$\text{InvVola}_t = \frac{1}{\sigma_{tV,t}}$

 Table 3
 Overview: factor strategies and firm characteristics

With: Share Price (P), Enterprise Value (EV), Total Debt (TD), Book Value (BV), Book Value per Share (BVPS), Earnings per Share (EPS), Sales per Share (SPS), Dividend per Share (DPS), Cash Flow from Operations (CFO), Year over Year (YoY), Trailing 12 Months (TTM). $\sigma_{mon,t}$ is the annualized volatility of weekly returns over last 3 years. The volatility $\sigma_{LV,t}$ and the CAPM beta $\beta_{LV,t}$ in the low-volatility factor are calculated using five-year daily data. For the calculation of EPSGT and SPSGT, the last 5 yearly restated EPS and SPS are used. β_{EPS} and β_{SPS} represent slope coefficients from regressions of yearly EPS and SPS observations against the number of months in the 5-year observation interval. For a calculation example of EPSGT and SPSGT, see the MSCI Global Investable Market Value and Growth Index Methodology (p. 32, 2017)

according to the method of DeMiguel et al. (2017). For this purpose, all of the observations greater (less) than the defined threshold are set equal to the third (first) quartile plus (minus) three times the interquartile range.

Since all three regions are subject to a different monetary policy environment, the risk-free rate for the respective equity market varies depending on the region. For the US market, the one-month T-bill rate is used. The three-month Euro Government Bond rate and the three-month Japan Treasury Discount Bill serve as proxies for their corresponding markets.⁸

Table 4 shows the time-series averages of the 222 crosssectional IC realizations within the chosen test period. To quantify the uncertainties in the inferences, bootstrap standard errors (SE) and 90% and 95% confidence intervals⁹ are calculated for 100,000 bootstrap resamples. The sample standard deviation of the average ICs, across the bootstrap samples, serves as an estimate of the standard error. Further the 5% (2.5%) and 95% (97.5%) centiles of the bootstrap samples for the mean ICs are calculated to obtain the lower and upper limits, respectively, of the confidence intervals.

The majority of signals show positive mean ICs, which are close to zero. Mean ICs where the confidence interval does not cross zero from the 5 (2.5) and 95 (97.5) percentiles of the 90% (95%) confidence interval are marked as significant. The number of significant mean ICs within the factors varies considerably. In terms of the informational content and the distribution of significant signals within the individual samples, three scenarios with different predictability are identified. The SPX multifactor model exhibits seven significant characteristics, corresponding to the case where an investor has identified a moderate number of exante predictors, and therefore, an accurate forecast is not likely. In contrast, the multifactor model of the STX sample

⁸ For Europe and Japan, maturities of three month have been used because one-month bills are not available.

 $^{^9}$ The according confidence intervals are shown in Table 7 in the "Appendix".

Factor	Characteristic	SPX		STX	STX		NKY	
		Mean	SE	Mean	SE	Mean	SE	
Growth	EPSG1Y	0.284	0.410	0.940**	0.350	1.516**	0.626	
	EPSG3Y	0.097	0.370	0.645	0.369	0.127	0.742	
	IGR	1.179**	0.475	0.969**	0.406	0.535	0.812	
	EPSGT	1.127*	0.583	1.792**	0.587	0.313	0.969	
	SPSGT	0.489	0.515	1.113**	0.511	- 0.897	1.196	
Value	DivYld	0.370	0.658	- 1.264	0.683	1.970**	0.704	
	EtP	-0.489	0.707	- 0.185	0.520	1.802**	0.817	
	BtP	-1.243*	0.746	- 2.429**	0.822	1.956**	0.881	
	CFOtEV	1.076*	0.601	1.048**	0.498	2.052**	0.730	
Quality	RoE	1.168**	0.515	2.398**	0.551	0.339	0.847	
	DtE	0.333	0.381	1.260**	0.476	0.639	0.828	
	EVar	0.204	0.420	-0.136	0.405	0.299	1.093	
Momentum	Pmom6M	0.448	0.801	1.472*	0.801	-0.928	0.925	
	Pmom12M	0.718	0.910	3.336**	0.883	- 0.301	0.925	
Low volatility	InvB	3.003**	0.852	2.842**	0.760	0.926	0.919	
	InvVola	2.422**	0.893	2.525**	0.809	0.848	0.977	

Table 4 Mean ICs and bootstrap results of the SPX, STX, and NKY samples

This table shows (in %) the means and bootstrap standard errors of the 222 IC realizations over the whole time interval of the SPX, STX and NKY samples from 100.000 bootstrap resamples. Mean ICs where the confidence interval does not cross zero from the 5 (2.5) and 95 (97.5) percentiles of the 90% (95%) confidence interval are market with one (two) asterisks



Fig.1 Average correlations between firm characteristics in the SPX sample

contains twelve significant mean ICs and represents a welldefined factor model. The NKY sample indicates a special situation because almost all of the informative predictors are clustered into one factor. In addition to the value factor, only the EPSG1Y characteristic is significant.

It is remarkable that the informational content of the individual characteristics varies greatly between the samples. Only the CFOtEV signal exhibits positive significant ICs in all of the samples. The opposite case is reflected by the momentum signals, which display significant characteristics in the STX sample, no significant, positive signals in the SPX sample and clearly negative but not significant values in the NKY sample. The poor predictive performance of momentum in the SPX sample is consistent with the results of Lewellen (2015), who attributed the poor performance to the financial crisis in 2008. The strong differences in the IC structure among the three samples underscore the importance of applying a heterogeneous investigation. Moreover, it also shows the need to compare the strategies in different scenarios to produce robust results.

Figures 1, 2 and 3 report heatmaps from the time-series averages of cross-correlations among the firm characteristics for each data sample. As the vast majority of correlation coefficients are less than 20%, most of the characteristics are uncorrelated. This outcome indicates that the consideration of multiple firm characteristics within a portfolio benefits from diversification effects. Nevertheless, some individual signal pairs, like RoE and IGR, Pmom6M and Pmom12M or InvB and InvVola appear to possess a high, positive correlation. Although the high correlations lead to a reducing effect



Fig.2 Average correlations between firm characteristics in the STX sample



Fig. 3 Average correlations between firm characteristics in the NKY sample

on the information content of the corresponding signals, the impact on the overall alpha forecast is rather limited since only a few signal pairs are affected. However, the correlation structure, especially for momentum and low volatility, has an influence on the assessment of the factor exposure, which is discussed in more detail in Sect. "4".

Out-of-sample backtest

The backtest framework is chosen to resemble the realistic investing behavior of an institutional investor, with the aim of outperforming an underlying cap-weighted benchmark portfolio. This goal includes the consideration of long-only constraints, rebalancing costs, commonly used rebalancing frequencies and representative data sets. Regarding the data set, the backtest uses only point-in-time data, i.e., only firm characteristics that were available in the database at the current time.¹⁰ For the estimation period, a 5-year rolling window is used, which corresponds to 60 monthly observations. The out-of-sample evaluation interval starts in 2007 and ends in June 2020, whereby the analyzed results refer to the multifactor settings described in Sect. 3. Regarding the portfolio rebalancing, a monthly frequency is applied. Trading costs caused by the rebalancing are considered by quantifying the cost relevant volume with the portfolio turnover rate (PTR_t = $\sum_{i=1}^{N} |a_{i,t-1} - a_{i,t}|$). The PTR determines the percentage of the portfolio that causes trading costs. In this context, a PTR of 30% signifies that 15% of the old portfolio is sold. Subsequently, the incoming liquidity must be reinvested, and trading costs are incurred for 30% of the portfolio. Following Frazzini et al. (2018), the costs are assumed at ten basis points per traded volume. The calculated costs are demarcated on the day that they arise. Consequently, these costs lead to a direct reduction in the return on the rebalancing day. To avoid bias from industry-specific characteristics, all of the characteristics are z-score standardized¹¹ depending on their industrial specific cross-sectional expected values and standard deviations. For the securities' sector allocation, GICS sector classification codes are used.

To align the exposure of the BU and TD approach, the numbers of selected securities in both approaches are equated. Without matching, the constant number of stocks selected by the BU approaches differ from the varying number of stocks in the TD approach, which is caused by multiple-picking within the TD approach. Multiple-picking describes the case in which stocks exceed the selection threshold in several characteristics and are therefore included simultaneously in multiple factor portfolios. Since the number of stocks within the portfolio is reduced by this effect, uncontrolled exposure concentrations can occur, and the comparability between the TD and BU approach becomes arbitrary. In all three indices, the number of stocks affected by multiple-picking is nearly identical. Approximately 83% of the selected stocks are not affected, 14% are

¹⁰ We have not applied any restated data in the estimates, but have always used the values reported first.

¹¹ We have also conducted additional tests without sector standardization in which all results were confirmed.

included in two factors, 2% in three factors, and less than 1% are represented in four factors. Stocks that exceed the selection threshold in all five factors do not exist. For the purpose of controlling the number of securities, a varying selection threshold is used. The TD threshold is chosen to cover an average of 25% of the stocks inside the parent index. In the BU approaches, the number of stocks is adjusted accordingly for each rebalancing.

Backtest results

To examine the performance of the long-only (LO) and longshort (LS) portfolios in comparison with the associated capweighted benchmark portfolios, the annualized alpha parameters and information ratios for each strategy are reported in Table 5. The time series of monthly portfolio returns is used to compute the out-of-sample portfolio alphas, which are estimated from a regression of the portfolio returns against the associated benchmark returns. To determine the strategies' information ratios, the portfolios' alpha parameters are divided by the tracking errors, calculated from the standard deviations of the regression residuals.

Table 6 presents the corresponding average factor exposures of the individual factors for the LO and LS portfolios. The factor exposures are measured in accordance with Ghayur et al. (2018) by the weighted z-scores. Regarding the SPX sample, the only significant alpha result can be found in the LS GK BU approach. Furthermore, the LO results of the TD and NZ BU methods show negative performance, while the GK BU approach qualitatively shows a positive alpha. The poor performance for TD and NZ BU is not surprising since the SPX sample contains many firm characteristics with insignificant informational content. In such a case, maximizing exposure across all characteristics may result in high exposures to noisy characteristics. In contrast, the GK BU approach is able to align its distribution of characteristics with the ICs, resulting in lower exposure to noisy characteristics. The STX sample provides clearly different results, as the portfolio alphas are significantly positive in all three strategies. This outcome can be explained by the large amount of significant mean ICs within the sample. Contrary to the SPX sample, it is not advantageous to distinguish between the informational content. Due to higher tracking errors, the GK BU approach shows slightly lower information ratios, even though there is no significant difference between the approaches.

In the NKY sample, all of the characteristics with high information content are concentrated in the value factor. Consequently, the performance results are similar to the SPX sample. Unlike the NZ BU and TD approach, the GK BU approach is able to benefit from this IC structure and achieves significant outperformance in the LS portfolio. To determine the inference in the differences between the information ratios, we applied a Ledoit and Wolf (2008) test. With a p-value of 0.096, the LS portfolio of the GK BU approach appears to be significant against the TD method, at a level of 10%. Moreover, the qualitative information ratio result of the GK BU approach in the LO portfolio is much higher, although not significant.

The exposure results in Table 6 reveal that the strategies' factor exposures differ considerably. While the TD and the NZ BU approach maximize the overall exposures, the GK BU approach reaches much lower levels and even negative exposures in some factors. The factor exposures in the LS portfolios are on average twice¹² as large as in the LO portfolios. However, higher factor exposures do not automatically lead to better performance. While in the LS GK BU approach of the SPX and NKY sample, the alphas can be improved to a significant level, the alphas of the TD and NZ BU approach remain insignificant. Even in the STX sample, the information ratios are not significantly higher, although the LS alphas are almost twice as large as in the LO sample.

Interestingly, in all three samples, the highest exposures of the NZ BU and TD approach can be identified in momentum, low-volatility and in the growth factor, respectively. The large factor exposure variation of the TD approach can be mainly explained by the correlation structure of the characteristics within the factors. Momentum and low-volatility consist of two highly correlated characteristics, whereas the correlations of the characteristics within the quality factor are very low and in some cases negative. While in the case of momentum and low-volatility, the characteristics increase their factor exposure, the quality characteristics can cancel each other out and thus reduce the quality exposure. The correlation structure of the characteristics within the value and growth factors are quite similar. The correlations are low to medium, but positive. Hence, the cancelling effect within these factors is lower compared to the effect within the quality factor. However, characteristics of the value factor like BtP tend to be negatively correlated with most characteristics of the other factors. Therefore, it is likely that the securities selected from the other factors have lower value characteristics, resulting in an overall lower value exposure. Instead, the growth characteristics tend to show more positive correlations with other factor characteristics, which benefits the growth exposure. Especially the highly correlated characteristics IGR and RoE can be mentioned in this context. In addition, the high growth factor exposure of the NZ BU approach is partly caused by the large number of characteristics compared to the other factors. Because the NZ BU approach weights all characteristics equally, the factor with the most characteristics gains a higher overall

¹² Deviations from this observation can be explained by differences in the cross-correlations between the characteristics for securities in the short and long portfolios.

weight. This outcome indicates that the factor exposures are influenced by the factor model design.

The model design effects have an arbitrary influence on the portfolio performance. For instance, the NZ BU and TD methods of the STX sample benefit from the effects, because low-volatility, momentum and growth are priced well. In the NZ-BU approach, the highly cross-correlated characteristics in the low-volatility and momentum factor are considered almost twice as much as all other characteristics. Since the ICs of the low-volatility characteristics in the SPX and additionally momentum in the STX are significantly positive, the NZ-BU approach benefits from these modeling effects. To quantify the impact of the modeling effect, we also calculated the performance results of a model which considers only one of the highly correlated characteristics within the momentum and low-volatility factor. In accordance with our argumentation, the model adjustments lead to lower alphas and information ratios,¹³ especially in the NZ BU approach of the SPX sample,¹⁴ whereas the GK BU approach is able to maintain the performance results. A counterexample can be observed in the NKY sample. Compared to the other methods, the GK BU approach is less affected by these arbitrary effects, and it overweights factors with higher informational content. The advantageous performance of the GK BU approach in the NKY sample can be deduced from the exposure distribution. Compared to other methods, the GK BU approach is able to adapt to the high informational content of the value characteristics, as reflected in a notably higher value exposure, while the remaining factors except low-volatility even show negative exposures.

The exposure results of the TD approach are in some cases counterintuitive to the significant characteristics found in Table 4. For example, in the SPX sample quality shows one significant characteristic, but the quality exposure is negative, while momentum has no significant characteristics and still receives the highest factor exposure. A reason for this outcome can be found in the calculation of the factors exposures, in which all characteristics are equally weighted. Therefore, in the GK-BU approach, the low exposure of quality in both the SPX and STX samples can also be explained by the cancelling effect of the low correlated characteristics within the quality factor. In addition, due to the low precision of the IC estimation, the noisy characteristics within the quality factor may interfere with the factor exposure. On the other hand, the momentum exposure in the SPX sample benefits due to its highly correlated characteristics, which are also negatively correlated with the value characteristics and positively correlated with all other

¹³ The performance results without the Pmom6M and InvVola characteristics are shown in Table 8 in the "Appendix".

¹⁴ The relative strength results for the LS strategies of SPX sample are shown in Fig. 7 in the "Appendix".

factors. Consequently, the momentum factor exposure benefits from both the low exposure in value and the positive exposures of the other factors. In the NKY sample, the exposure to the low-volatility factor is also high, even if the ICs are not significant. The small but positive correlations of the low-volatility characteristics with the value characteristics contribute to the low-volatility exposure.

Figure 4 depicts the relative strength result charts of the LS¹⁵ strategies for the SPX, STX and NKY samples. We calculate the relative strength as the ratio of price changes based on the log returns of the strategy portfolios compared to the benchmark portfolios, scaled to an initial value of 100. In SPX LS sample, the relative strength lines show that the GK BU approach is capable to generate continuous excess returns, while the NZ BU and TD approach have a longer interval of underperformance since 2008. In contrast, with the well-priced factor model of the STX sample, all of the approaches exhibit related and significant outperformance. A different picture is demonstrated by the NKY sample chart. Compared to the TD and NZ BU approach, the GK BU approach is able to benefit from the consideration of the high concentration of significant information coefficients in the value factor. The overweight in defensive stocks leads to a particularly high outperformance during the financial crisis in 2008. Thereafter, the curve flattened somewhat, but is still stronger compared to the TD and GK BU approach.

Overall, the backtest results confirm the propositions from the simplified simulation results. Without distinguishing between the informational content of the firm characteristics, the approaches lead to a related performance, regardless of whether the bottom-up or top-down approach is used. The discrimination between interaction effects is not necessary if all characteristics are priced equally well. However, if there is a difference in the informational content, characterized by a high concentration of significant mean ICs, the GK BU approach is able to obtain a higher alpha. Encouraged by the factor exposure results, it can be concluded that it is more important to affect the right factors than to maximize the factor exposures of all of the factors. Due to its ability to consider the full range of interaction effects, the BU approach has a major benefit over the TD approach.

Conclusion

In this article, we contribute to present TD versus BU approach discussion. Proponents of the BU approach argue that it benefits from considering interaction effects. However, both approaches integrate characteristics with equal

 $^{^{15}}$ The according results for the LO portfolios are shown in the "Appendix" in Fig. 6.

Table 5 Backtest results of theSPX, STX and NKY samples

Table 6 Average factor

exposures

Method	1	Alpha			Informatio	on ratio	
		SPX (%)	STX (%)	NKY (%)	SPX	STX	NKY
LO	TD	- 1.08	2.54**	- 0.85	- 0.26	0.58	- 0.16
	NZ BU	- 0.30	3.26***	-0.67	-0.08	0.73	-0.12
	GK BU	0.47	3.29**	2.36	0.08	0.53	0.26
LS	TD	1.89	5.22***	- 0.95	0.26	0.77	-0.10
	NZ BU	4.18	6.28***	0.66	0.44	0.85	0.05
	GK BU	5.53*	5.97***	5.74**	0.52	0.69	0.55

Significant alpha parameters are marked with asterisks. One, two or three asterisks represent the significance of the test, i.e., the rejection of the null hypothesis, with a level of probability of 10%, 5% and 1%, respectively

Factor Factor exposure Strategy Growth (%) Value (%) Quality (%) Momentum (%) Low-volatility (%) SPX LO TD 32.02 19.14 16.78 43.42 34.14 NZ BU 46.32 28.42 27.72 57.40 56.56 GK BU 15.45 7.09 - 16.32 20.67 17.61 STX TD 31.32 17.28 21.59 47.36 37.83 NZ BU 47.27 26.20 34.69 61.01 49.92 - 1.94 GK BU 22.04 12.30 36.19 28.79 NKY TD 36.71 10.75 19.35 43.30 34.68 NZ BU 51.23 49.70 53.47 32.16 36.36 GK BU - 8.95 - 20.53 - 3.21 56.55 29.73 SPX 77.31 LS TD 60.95 24.96 70.15 100.06 NZ BU 108.25 48.86 90.65 103.46 124.17 GK BU 39.21 -6.65 - 13.64 50.21 33.72 STX TD 60.58 13.34 67.82 82.89 86.48 NZ BU 104.38 44.03 89.21 111.03 102.80 GK BU 46.84 -9.0329.34 65.26 43.42 NKY 78.10 32.95 80.63 77.31 84.31 TD NZ BU 124.31 61.78 111.18 99.58 105.62 GK BU -8.60100.93 - 2.66 - 39.93 48.12

Factor exposures are determined by the weighted z-scores where the portfolio weights are applied. Averages are calculated from the time series of the cross-sectional results

weights, which can be identified as a naïve way of alpha forecasting. In the case of naïve alpha forecasts, we confirm the findings that the TD and BU approach show no significant performance differences. Moreover, the equal-weighted approach provides an explanation for the disagreement in previous studies. The findings from the simplified simulation, as well as from the out-of-sample backtest, indicate that uncontrolled differences in the informational content of the firm characteristics can lead to biased performance results.

Since the naïve integration ignores interaction effects from differences in informational content and correlations between firm characteristics, this paper complements the bottom-up approach for the missing interaction effects by implementing an alpha forecasting framework. The empirical results show that the application of an alpha forecasting framework leads to significant performance improvement in factor models with a high concentration of informational content. In contrast, the naïve combination exhibits no performance differences between the approaches. The consideration of interaction effects between the applied firm characteristics is revealed to be an advantage of the bottom-up approach.

Our findings exhibit important practical implications. For the TD approach, the implementation of a linear alpha forecasting model conflicts with its most important benefit,



Fig. 4 Relative strength results of long-short multifactor portfolios. The relative strength results of all approaches in relation to their underlying indices are displayed by the colored lines

which can be found in its simplicity. The main difference between the TD and BU approach is the consideration of interaction effects. But the only way in which the common naïve BU approach is able to consider interaction effects is by allowing firm characteristics to add up or cancel out each other. Therefore, if practitioners decide on the bottom-up approach due to its ability to consider interaction effects, it seems to be a logical consequence of extending the approach for the full range of interaction effects. Without this extension, the BU approach provides no benefit compared to the TD approach. Further, even if portfolio managers still decide for the simple solution of the TD approach, our results provide reasonable arguments to test for the differences of informational content and correlations between firm characteristics. In cases with high concentrations of informational content or strongly correlated firm characteristics, portfolio managers might want to recalibrate their factor models to avoid unintended factor exposures.

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Appendix

See Figs. 5, 6, 7 and Tables 7, 8.



(c) High corr and low IC concentration









simultaneously selected by the BU and TD approach are represented by a (blue) circled plus sign. The (orange) plus sign without the circle depicts securities only selected by the BU approach. Securities selected solely by the TD approach have a (green) diamond sign, and those not included in any portfolio are marked with a (red) cross. For better visualization, the dashed line marks the selection border of the BU approach

Fig. 6 Relative strength results of long-only multifactor portfolios. The relative strength results of all approaches in relation to their underlying indices are displayed by the colored

lines



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Fig. 7 Relative strength results of long-short multifactor portfolios without Pmom6M and InvVola. The relative strength results of all approaches in relation to their underlying indices are displayed by the colored lines



Table 7 Confident	ce interval results	of the bootst	trap IC mean	S									
Factor	Characteristic	SPX				STX				NKY			
		0.05-Qt.	0.95-Qt.	0.025-Qt.	0.975-Qt.	0.05-Qt.	0.95-Qt.	0.025-Qt.	0.975-Qt.	0.05-Qt.	0.95-Qt.	0.025-Qt.	0.975-Qt.
Growth	EPSG1Y	- 0.389	0.958	- 0.519	1.088	0.365	1.516	0.254	1.626	0.487	2.546	0.285	2.745
	EPSG3Y	-0.511	0.708	-0.628	0.823	0.035	1.247	-0.081	1.365	-1.100	1.352	- 1.329	1.590
	IGR	0.400	1.965	0.248	2.114	0.298	1.634	0.170	1.758	-0.800	1.868	- 1.058	2.124
	EPSGT	0.165	2.085	-0.023	2.273	0.826	2.754	0.642	2.948	- 1.285	1.895	- 1.613	2.198
	SPSGT	-0.359	1.331	-0.524	1.493	0.272	1.953	0.113	2.117	- 2.862	1.065	- 3.252	1.442
Value	DivYld	-0.711	1.457	-0.922	1.664	-2.386	-0.140	- 2.602	0.076	0.822	3.144	0.603	3.362
	EtP	- 1.646	0.676	- 1.868	0.897	-1.043	0.671	-1.207	0.834	0.464	3.151	0.198	3.399
	BtP	- 2.463	-0.013	-2.702	0.220	-3.782	- 1.075	- 4.035	-0.819	0.506	3.403	0.227	3.682
	CFOtEV	0.091	2.067	- 0.099	2.256	0.233	1.874	0.073	2.035	0.852	3.255	0.622	3.483
Quality	RoE	0.323	2.019	0.155	2.177	1.493	3.301	1.317	3.479	-1.057	1.734	- 1.318	2.005
	DtE	-0.298	0.956	-0.418	1.076	0.479	2.043	0.333	2.191	-0.724	1.999	- 0.982	2.260
	EVar	- 0.489	0.894	-0.621	1.019	-0.804	0.530	- 0.935	0.657	- 1.526	2.086	- 1.886	2.422
Momentum	Pmom6M	-0.868	1.758	- 1.129	2.013	0.156	2.787	-0.105	3.038	- 2.453	0.587	- 2.747	0.874
	Pmom12M	-0.782	2.212	- 1.059	2.496	1.886	4.789	1.607	5.069	- 1.821	1.224	- 2.105	1.515
Low- Volatility	InvB	1.598	4.400	1.333	4.661	1.589	4.093	1.356	4.332	-0.593	2.430	-0.873	2.714
	InvVola	0.949	3.886	0.667	4.156	1.192	3.855	0.938	4.103	- 0.769	2.447	- 1.069	2.753
This table shows (in %) the 5 (2.5) a	nd 95 (97.5)	percentiles o	of the 90% (95	%) confidence	e interval of t	he bootstrap	IC means					

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Method		Alpha			Information rati	0	
		SPX (%)	STX (%)	NKY (%)	SPX	STX	NKY
ΓO	Π	- 1.05	2.37**	- 0.64	- 0.25	0.50	- 0.11
	NZ BU	- 1.12	3.04***	- 0.64	-0.26	0.57	-0.11
	GK BU	0.29	3.73**	3.11	0.05	0.69	0.35
LS	TD	1.35	4.83***	- 1.12	0.20	0.76	- 0.12
	NZ BU	1.99	5.82***	0.49	0.23	0.77	0.04
	GK BU	5.76*	7.92***	6.02**	0.53	0.82	0.60

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