A Bond-Picking Model for Corporate Bond Allocation

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The increased interest of active managers in corporate bonds and the recent turmoil experienced in credit markets have increased the need for well-diversified alpha models for this asset class. Stock-picking strategies have been using refined quantitative methods for a long time. Multifactor models based on company and stock fundamentals and/or technical factors are now widely applied by practitioners in order to pick the most promising stocks and to build either long–short or long-only equity portfolios. This multi-signal approach leads to well-diversified alpha models that process a number of information sources and synthesize the main sources of alpha.

The situation is quite different for active management of corporate bonds. The selection process still heavily relies on fundamental analysis and structural models that are consistent with the contingent claims approach (Merton [1974]) or on reduced-form models that extract default probabilities from actual credit prices (Duffie and Singleton [1999]). Structural and reduced-form models are able to identify corporate bonds with high default probabilities and are thus useful in excluding bonds with highly risky profiles from portfolios. Structural and reduced-form models can also be used as valuation tools in pricing corporate bonds and in distinguishing between over- and undervalued bonds. Nevertheless, approaches that use these models to increase alpha generation and improve bond selection have several critical shortcomings.

First, structural models, at least in their original form, tend to underestimate credit spreads; this bias, partly due to a liquidity premium, is greater the higher the bond’s credit quality and the shorter the bond’s maturity (Ericsson and Renault [2006]). A structural model is therefore not completely efficient at comparing corporate bonds on the basis of their relative misvaluations, limiting the structural model’s use as an active management tool.

Second, approaches using structural models are essentially mono signal and thus lack the diversification benefits that can be achieved by combining different signals. For instance, even if a structural model were able to perfectly price bonds, it takes time for the market to correct disequilibria. Thus, portfolios that are built on these types of valuation techniques may suffer large losses in the short to medium term. This is particularly true in periods of adverse market conditions and high market volatility (i.e., when market participants look at short-term rather than long-term indicators).

Therefore, as in stock selection, an active investment process for corporate bonds requires a multiple-alpha-source approach that explicitly accounts for the diversification benefits derived from the combination of alpha sources. A primary contribution of this article is to show the gain from signal combination when
applied to bond picking. We demonstrate that the combination of three kinds of signals—valuation signals, equity return signals, and earnings momentum signals—deliver consistent and stable performance.

Duffee [1999] and Castagnetti and Rossi [2006] provided strong evidence of mean-reversion effects that constitute the basis of our valuation signal. The interplay between equity and corporate bond returns at the company level has also been researched (Collin-Dufresne, Goldstein, and Martin [2001]), but only a few studies have explored the relevance of equity analyst data on corporate bond returns. Güntay and Hackbarth [2005] provided evidence on the change in the dispersion of analyst earnings forecasts on changes in credit spread, but to our knowledge the application of earnings revisions, or earnings momentum, strategies on corporate bonds has not yet been studied.

We show that such a strategy, when applied to corporate bond portfolio construction, generates substantial risk-adjusted returns. Following the important work of Sorensen et al. [2004], our approach for combining these signals simultaneously takes into account the signals’ relative abilities to generate returns and the diversification benefits provided by each signal. We provide a complete description of the different steps leading to the model and show results for the U.K. corporate bond market.

INDICATORS

The focus of our study is on forecasting the corporate bond-specific return, that is, the part of a corporate bond’s return not explained by its exposure to common factors. In order to perform our analysis, we had to select several types of indicators that capture the determinants of bond-specific returns. The choice of indicators is related to the following criteria:

• Each signal has to achieve consistent performance. This condition is obviously a necessary, but not sufficient, condition for obtaining superior performance, as it does not guarantee the stability and robustness of the performance path.

• Each signal has to exhibit a relatively low performance correlation with the other signals. As shown by Sorensen et al. [2004], this is a sufficient condition to generate a diversification effect provided by the efficient combination of information into a single indicator. When one indicator delivers poor performance, the others should ensure the relative stability of the strategy, limiting the depth and length of potential drawdowns.

Based on the preceding selection criteria, we selected three types of indicators: valuation indicators, earnings momentum indicators, and equity return indicators. We will show that these three indicators fulfill the required conditions and that the combined model shows significant and regular performance.

The goal of valuation indicators is to select bonds that are temporarily misvalued by the market compared to their underlying risk profile and to capture mean-reversion effects. A bond whose spread is higher than can be explained by its exposure to common factors and specific variables is considered to be underpriced and is thus expected to deliver higher specific returns than a bond whose spread is lower. In order to obtain the valuation signals, for each month we ran the cross-sectional regressions of corporate bond spreads on rating class, sector, and seniority class spreads (common factors) as well as on specific variables,

\[
sp_{kl} = \beta_{kl} + \beta_{k} sp_{k} + \beta_{l} sp_{l} + \sum_{m=1}^{M} \gamma_{ml} x_{ml} + \epsilon_{ijkl}
\]

where \(sp_{k}\) and \(sp_{l}\) represent the average spread of bonds belonging to rating class \(k\), sector \(j\), and seniority class \(l\), respectively. \(\{x_{1}, \ldots, x_{M}\}\) represents a set of specific variables that includes:

• a company profitability measure, in this case, the return on assets (i.e., net income divided by total assets), because a company that generates higher earnings is less likely to default;

• the volatility of related equity because, in the contingent claims approach, higher volatility increases the likelihood of reaching the default threshold.

The valuation signals are thus the residuals \(\epsilon_{ijkl}\) of the cross-sectional regressions.\(^1\)

Earnings momentum indicators refer to the revisions of a company’s expected cash flows for the current calendar year by the market consensus. Cash flow estimates reflect the ability of a company to maximize both profits and cash generated from its core operations, thus providing a view on the company’s earnings dynamics. Positive (negative) revisions of the cash flow estimate
variable for a particular company tend to translate into further positive (negative) revisions in the future, generating relatively higher (lower) bond returns. The cash flow momentum effect may arise because analysts slowly incorporate new information into their forecasts [Daniel, Hirshleifer, and Subrahmanyam [1998]] or due to a leader–follower effect (i.e., most analysts follow the forecasts of a few leaders). The positive impact of cash flow revisions on future returns is possible if the market does not fully price future revisions or, in other words, if the market, on a short-term horizon, slowly integrates positive (or negative) news of the company. This phenomenon has been extensively studied in the stock market (see Chan, Jegadeesh, and Lakonishok [1996] and Xu [2008]), but not in the bond market.

We can also exploit trading opportunities in the credit market by simply overweighting bonds with positive cash flow revisions and underweighting bonds with negative cash flow revisions. We used consensus analyst forecasts to estimate a company’s expected future cash flows. The global coverage of analysts, as well as their sheer number, strongly suggests that analysts’ consensus expectations for future earnings should be an informative indicator of market participants’ average expectation of a company’s risk profile. The momentum signal is

$$\text{Mom}_{t+1} = \frac{FY_{1t}}{FY_{1t-1}} - 1$$  \hspace{1cm} (2)

where FY₁ is the date t consensus cash flow forecast one-year ahead as provided by I/B/E/S. We chose to use the cash flow estimate rather than the earnings estimate because earnings from operations may be more easily subject to manipulation by a company’s management than are the cash flow statements.

The use of equity returns relies on structural models, such as Merton [1974], in which spreads reflect default probability. In this type of model, a default is triggered when a company’s value falls below a specified threshold, typically one that is closely related to the amount of the company’s outstanding debt. A negative equity return increases the likelihood of default. Thus, consistent with the findings of Kwan [1996] and Cheyette and Postler [2006], we expected bond and stock returns to be positively correlated.

Because our goal is to take positions based on the information available in the market, we used the lagged one-month equity return as our equity return signal. The persistent impact of lagged value for equity returns on bond returns can be explained by 1) a momentum effect on stock returns, which means that past equity returns predict current returns and thus should impact credit spread changes [Avramov, Jostova, and Philipov [2006]]; and 2) stock market movements that appear to precede changes in corporate bond spreads [Landin [2004]].

THE MODELING APPROACH

We model the expected specific returns (alphas) as a function of a bond’s intrinsic characteristics, which we call signals. Expected alphas are obtained through a linear combination of M signals. In matrix notation, the vector of forecasted alphas at time t is

$$\alpha_t = S w_t$$  \hspace{1cm} (3)

where w is a M x 1 vector of signal weights, S is a N x M matrix of raw signals, and α is a N x 1 vector of forecasted alphas, where N stands for the number of corporate bonds in the investment universe.

The weighting scheme depends on the excess returns generated by each signal strategy; we give more weight to signals that achieve high returns than to signals that earn low returns. The weighting also depends on the correlations between the signals’ unique performances; we explicitly control for the covariation of the performance of individual signals because we do not want to introduce redundant information.

A very important relationship that we rely on is the similarity between signal combination and return combination in long–short allocations. Because forecasted alphas are a linear combination of signals, the return of a long–short strategy based on these forecasted alphas is, at any time, equal to a weighted average of the returns of long–short portfolios obtained by using each signal (see Sorensen et al. [2004]),

$$R^p_t = w^T R_t$$  \hspace{1cm} (4)

where R is the M x 1 vector of a single-signal long–short strategy’s annualized returns between t and t + 1, where the strategy refers to beta-neutral long–short allocations; R^p is the return of the beta-neutral long–short strategy using the combined score; and w is the vector of signal weights as previously mentioned. Therefore, each signal
has its own characteristics in terms of risk and return associated with their related long–short portfolios. As in portfolio theory, combining signals boils down to combining signal portfolios and thus to finding the weights that achieve the highest risk-adjusted return for the portfolio combination. Based on this representation of a portfolio’s return, maximizing the information ratio (IR) with respect to signal weights is given by

$$\max_w \frac{w^T E_{TS}[R]}{\sqrt{w^T \Sigma_R w}}$$

(5)

where $\Sigma_R$ is the $M \times M$ matrix of the variance and covariance of excess returns of long–short strategies based on individual signals. The matrix is assumed to be constant over time. $E_{TS}[-]$ is the time-series expectation operator.

The form of the IR is given in Equation (1). The solution takes the form of

$$w = \frac{1}{x} \sum_R^{-1} E_{TS}[R]$$

(6)

where $x$ is a scaling constant. In the next section, we will compare this optimal solution with an equally weighted scheme to highlight the impact of signal performance level and correlation on optimal signal combination.

**APPLICATION**

In this section, we will apply the methodology described in the previous section to build a multi-signal model based on the three types of indicators used in our study. The optimal combination of individual signals essentially depends on their respective performances and, therefore, on the target allocation characteristics. Our goal is to obtain a portfolio construction process that avoids unintended risk exposure and provides returns uncorrelated with tactical asset allocation, that is, sector allocation and/or rating allocation. Two ways are possible for avoiding exposure to risk factors: directly constraining the optimal portfolio by introducing explicit exposure constraints in the mean–variance optimization program (beta constraints) or beta-neutralizing alphas. The latter is the retained solution that we adopted.2 After the signals are risk adjusted, they are standardized.3 In our study, we performed unconstrained long–short mean–variance optimizations based on individual risk-adjusted signals and applied the solution for optimal weights given by Equation (6).

We tested our modeling approach in two markets—the U.K. and the euro zone. We will only present the results in the U.K. market, but the conclusions are qualitatively similar for the euro zone (the results are available on request). The universe includes corporate bonds in the Merrill Lynch U.K. Investment Grade Corporate Bond Index from January 2000 to July 2008. The inception date for the Merrill Lynch U.K. Corporate Bond Index is December 1996. But because the I/B/E/S (Institutional Brokers Estimate System) data on expected cash flows is available only from the end of 1999, the simulations begin in January 2000.

The main concern from an operational point of view is the liquidity of the selected bonds. We applied two filters to remove the less liquid bonds, which are characterized by prohibitive transaction costs. First, we limited the investment universe to bonds with a remaining term to maturity of 7 to 15 years, which corresponds to the most liquid parameter in the U.K. market. Second, we excluded at each date 20% of the less liquid bonds based on their outstanding amount. The result was a universe composed of between 105 bonds in January 2000 and 240 in July 2008. Data on the corporate bond spread, modified duration, rating, sector, and seniority are from Merrill Lynch. We used the option-adjusted spread to compute the spread momentum signal, valuation signal, and bond excess return. The third input is given by

$$r_{t-1,t} = sp_{t-1} - d_t \Delta sp_{t-1}$$

(7)

where $d_t$ is the modified duration. Consensus data for stock earnings and sales forecasts for the current calendar year were provided by I/B/E/S. The I/B/E/S data and one-month equity returns were obtained by matching corporate bond data with equity data. All indicators were computed on a monthly basis.

**Univariate Simulation Results**

We performed beta-neutral long–short allocations with monthly rebalancing based on each individual risk-adjusted signal from January 2000 to July 2008.4 Exhibit 1 shows that the equity return strategy provides by far the highest risk-adjusted return among the four different strategies considered, with an annualized information ratio of 1.6, followed by the cash flow momentum strategy with an IR of 0.8, and the valuation strategy with an IR of 0.7.
To summarize, these results show that

- strategies relying on equity return factors generate substantial returns in line with structural model implications;
- it is possible to benefit from temporary over- or undervaluation of bond prices, which means that the fair value of a bond may be derived from the bond’s exposure to common factors, such as rating, sector, and seniority, and that prices tend to converge toward this fair value, even at a one-month horizon, which is the rebalancing horizon considered here;
- strategies based on analyst estimates revisions are also profitable in the credit market, so that the consensus view of an issuer's expected P&L figures provides valuable information about the way corporate bonds are priced by the market and may be used in quantitative screenings as a catalyst factor to adjust the positions taken in bonds on the basis of more traditional factors, such as valuation or equity return indicators.

Exhibit 1 shows that for the same optimization parameters (i.e., for the same ex ante tracking error), the valuation signal generates a slightly higher ex post tracking error than the other two strategies. Qian and Hua [2004] showed that part of a strategy’s tracking error comes from the consistency of forecast quality over time, which is represented by the standard deviation of the information coefficient (IC), or the cross-section correlation between forecasts and actual returns. With an IC volatility of 20%, the valuation signal provides a significantly less stable forecast of bond relative returns than the equity return signal with an IC volatility of 12% or the cash flow momentum signal with an IC volatility of 10%; hence, the tracking error gap.

The correlation of the different strategies reveals the diversification effect of signal combination, as shown in Exhibit 2. First, the complementary nature of long-term and short-term factors is evident in that the correlation between valuation and equity return strategies, on the one hand, and between valuation and earnings momentum strategies, on the other hand, are strongly statistically significant and negative, which is exactly what is required for the diversification to be effective. Second, even the correlations between strategies based on short-term signals are relatively low and nonstatistically different from zero at the 5% level.

But what drives these correlations? A closer look reveals that they are mainly driven by the way strategies behave in different market contexts. To evaluate the impact of market environment on each strategy, we segment the time horizon into different volatility contexts. The measure of volatility used is the difference between the 6-month and 18-month bond return monthly volatilities, both computed using the Merrill Lynch U.K. Investment Grade Corporate Bond Index. We split the time horizon into high- and low-volatility contexts based on the sign of the volatility measure; that is, if the 6-month volatility is higher than the 18-month volatility, then the period is considered volatile, and vice versa. Based on this sample breakdown, we compared the average returns and tracking errors of the high- and low-volatility context for each indicator.

Exhibit 3 shows that the three strategies respond differently to a change in volatility—the returns to the strategy based on the valuation signal are lower, and even negative, during high-volatility periods, whereas the returns to cash flow momentum and equity return portfolios are higher during high-volatility periods. The results are clear that the return profiles of each strategy are

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**Exhibit 1**

Beta-Neutral Long–Short Allocation Results, Monthly Rebalancing

<table>
<thead>
<tr>
<th></th>
<th>Annualized Excess Return</th>
<th>Tracking Error</th>
<th>Information Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valuation</td>
<td>1.78%</td>
<td>2.6%</td>
<td>0.7</td>
</tr>
<tr>
<td>Cash flow momentum</td>
<td>1.32%</td>
<td>1.7%</td>
<td>0.8</td>
</tr>
<tr>
<td>Equity return</td>
<td>3.2%</td>
<td>2%</td>
<td>1.6</td>
</tr>
</tbody>
</table>

Note: Optimization parameters are calibrated to deliver 2% tracking error for the strategy based on the equity return signal. Performance is calculated before transaction costs.

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**Exhibit 2**

Correlation of Univariate Long–Short Strategies

<table>
<thead>
<tr>
<th></th>
<th>Cash Flow</th>
<th>Equity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valuation</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td>Cash flow momentum</td>
<td>−0.3%</td>
<td>100%</td>
</tr>
<tr>
<td>Equity return</td>
<td>−50%</td>
<td>−3%</td>
</tr>
</tbody>
</table>

Note: P-value in parenthesis.
significantly different in high- and low-volatility periods (see Exhibit 4).

What are the lessons of this contextual analysis? A first, and intuitive, lesson is that during market turmoil the market reacts more to short-term events, which is detrimental to strategies based on more fundamental signals. This phenomenon is well documented in the equity market, but less so in corporate bond markets. A second lesson is that a large part of the negative correlation between longer-term and short-term signals’ performances arises because they react differently depending on the market environment. To conclude, the capacity of equity return and momentum strategies to distinguish winners and losers during adverse market conditions should offset the valuation indicator underperformance and make the combination robust to changes in market context.

Combining the Signals

In this section, we will apply the methodology previously described for combining the signals. The optimal weights are reported in Exhibit 5.

The equity return signal represents roughly one-half of the final combination, which is in line with the relative level of its associated IR. The valuation signal benefits from its strong negative correlation with the equity return strategy to produce a higher weight than the cash flow momentum signal, although the valuation signal’s univariate performance is lower. In other words, the signal combination that maximizes the portfolio’s risk-adjusted return shapes the weight of the valuation signal to magnify the diversification effect it provides.

The overall information ratio of the combined signal is significantly higher than the information ratios of the underlying signals, illustrating the diversification benefits resulting from the particularly low correlations between strategies. We attained a high 2.5 annualized IR, which is a 60% increase compared to the 1.6 IR of the equity return strategy, the best performing univariate strategy, as shown in Exhibit 6.

The results are only slightly lower when we attribute equal weights to each signal, which proves that the combined strategy is robust to a change in signal weights. The diversification benefits are clear based on the tracking error of the combined strategy; the tracking error is now slightly less than 1%, while the lowest univariate strategy tracking error is 1.7%. The zero-investment combined strategy delivers a robust 2.4% annualized return, significantly different from zero as illustrated by the t-statistic reported in Exhibit 6. The performance of the strategy is regular as shown in Exhibit 7.
All the results reported thus far were obtained before transaction costs. The impact of transaction costs on the net return of active strategies can be sizeable, because the gross returns generated by applying allocation signals are generally low for corporate bonds compared to the potential costs incurred by rebalancing portfolios. This is especially true for strategies based on signals with low time persistence (i.e., low serial correlation), as the return forecasts experience frequent and large-scale changes, which generate high turnover (see Qian, Sorensen, and Hua [2007]). Reducing portfolio turnover is therefore essential for generating significant performance net of transaction costs. One simple and effective way to moderate the turnover is to increase the signal serial correlation by using a moving (weighted) average of signals,

$$\alpha_t = \sum_{\tau=0}^{\tau} \beta_{\tau} \alpha_{t-\tau}$$

As an illustration, we implemented a moving average of the combined signal with equal weights and two lags ($\beta_\tau = 1$ forall $\tau \in \{0,1,2\}$). The implementation costs retained in the example are the bid–ask spreads computed at the bond level. In order to implement a realistic allocation strategy, we filtered the less liquid bonds and excluded from the portfolio bonds whose bid–ask spreads were higher than 100 basis points. The returns were still positive and stable, with an information ratio equal to 1.8, as reported in Exhibits 7 and 8, and with a negative excess return in only one year, 2007. The negative return in 2007 was driven by the significant underperformance of the valuation indicator during the last quarter of 2007, illustrating once again the relatively poor performance of signals based on fundamentals during periods of market turmoil.

**CONCLUSIONS**

In this article, we have developed a multifactor model for corporate bonds that combines multiple alpha sources. We have analyzed three alpha factors—valuation, estimates revision, and equity return. First, we reported that, in line with structural model implications, past equity return is a robust indicator of current corporate bond returns regardless of the market context. Second, we showed that the revision of analyst forecasts on a company’s future cash flows is a good signal of short-term change in a company’s financial health and can be particularly efficient at delivering returns during periods of high

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**EXHIBIT 6**

Combined Score Beta-Neutral Long–Short Allocation Results

<table>
<thead>
<tr>
<th></th>
<th>Annualized Excess Return</th>
<th>Tracking Error</th>
<th>IR</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal weights</td>
<td>2.42%</td>
<td>0.95%</td>
<td>2.5</td>
<td>7.4</td>
</tr>
<tr>
<td>Equal weights</td>
<td>2.10%</td>
<td>0.95%</td>
<td>2.2</td>
<td>6.5</td>
</tr>
</tbody>
</table>

**EXHIBIT 7**

Combined Strategy Cumulative Excess Return

**EXHIBIT 8**

Result Net of Transaction Costs, January–July 2008

<table>
<thead>
<tr>
<th></th>
<th>Annualized Excess Return</th>
<th>Tracking Error</th>
<th>Information Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Whole Horizon</td>
<td>1.2%</td>
<td>0.7%</td>
<td>1.8</td>
</tr>
<tr>
<td>2000</td>
<td>2.8%</td>
<td>0.8%</td>
<td>3.5</td>
</tr>
<tr>
<td>2001</td>
<td>0.5%</td>
<td>0.4%</td>
<td>1.5</td>
</tr>
<tr>
<td>2002</td>
<td>2.7%</td>
<td>1.1%</td>
<td>2.5</td>
</tr>
<tr>
<td>2003</td>
<td>2.7%</td>
<td>0.6%</td>
<td>4.7</td>
</tr>
<tr>
<td>2004</td>
<td>0.5%</td>
<td>0.5%</td>
<td>1.1</td>
</tr>
<tr>
<td>2005</td>
<td>0.3%</td>
<td>0.4%</td>
<td>0.7</td>
</tr>
<tr>
<td>2006</td>
<td>0.4%</td>
<td>0.2%</td>
<td>2.0</td>
</tr>
<tr>
<td>2007</td>
<td>-0.3%</td>
<td>0.3%</td>
<td>-1.1</td>
</tr>
<tr>
<td>2008*</td>
<td>1.4%</td>
<td>1.0%</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Transaction Costs

All the results reported thus far were obtained before transaction costs. The impact of transaction costs on the net return of active strategies can be sizeable, because the...
This result provides the demonstration that the dynamics of market views about a company’s expected P&L figures has a significant impact on corporate bond returns. Lastly, our results indicate that the valuation of a bond based on its exposure to common risk factors and to company-specific factors delivers significant returns during periods of low volatility.

This result is consistent with three complementary explanations. First, market participants focus on fundamentals in the medium term and long term. Second, when the price of risk is not too high, the fair value of a corporate bond can be estimated based on a reduced-form-model approach. And third, the corporate bond market is efficient, on average, which means that a bond’s price fluctuates around its fair value. A corollary to this last point is that investment opportunities may arise from temporary over- or undervaluation.

We have shown that because these indicators respond differently, depending on the market context, their performance correlation is low and the diversification effect is substantial. It is thus possible to obtain superior performance by efficiently combining them as illustrated by our analysis using the U.K. corporate bond market.

ENDNOTES

1We test whether the apparent mispricing relative to ratings peers could be explained by the credit outlook that the rating agency provides as a supplement to the rating. (We thank an anonymous referee for suggesting this.) Credit outlooks, however, do not increase the capacity of our valuation model to identify fair value spread, because the information they provide are redundant with the equity-volatility variable already included in the model.

2For the sake of simplicity and transparency, the risk model used for beta-neutralizing signals is a modified version of the Heston and Rouwenhorst [1994] model applied to corporate bonds, with three risk factors, namely, rating, sector, and seniority.

3For a given risk aversion, a change in signal cross-section dispersion modifies the cross-section dispersion of optimal active holdings in the portfolio and induces a change in the target tracking error. We have observed that this change in signal dispersion does not reflect any increase in investment opportunity, hence, the standardization.

4The risk aversion parameter is set to be identical for all simulations and is calibrated to obtain a 2% ex post tracking error for the equity return strategy.

REFERENCES


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