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The Rise in Systematic Credit Investing

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Executive Summary

Systematic investing is based on the objective application of quantitative models informed by historical data throughout all stages of the investment process, including sector timing, security selection, portfolio construction, transaction cost optimization, and risk management. This form of investing, featuring a disciplined, diversified, and scientific approach to risk taking, has grown in popularity over the past two decades, particularly for equity portfolios.

In credit portfolio management, systematic investing has been slower to take hold. Credit portfolio managers have long taken a quantitative approach to risk, but a more qualitative fundamental approach to many other aspects of the management process. When controlling portfolio yield curve and industry exposures, managers employ quantitative risk models based on the variances and correlations of a set of risk factors. However, the selection of issuers and bonds has traditionally been based on a detailed bottom-up fundamental analysis. A positive view of a company's fundamentals has been a prerequisite for investing in its bonds. Essentially, this approach to credit portfolio management uses quantitative models to manage beta, but relies on fundamental analysis to generate alpha.

Many factors have contributed to the slower adoption in credit portfolios relative to equity. Credit markets are more complex, less transparent, and less liquid, complicating the implementation of systematic strategies. However, recent developments have lowered these frictions, paving the way for credit portfolios to reap the benefits of systematic investing.

In this white paper, we provide an overview of systematic investing as it applies to active management of credit portfolios. We also outline the key elements required to build a successful systematic strategy, which include: data-driven signals, adequate risk management, and efficient implementation.

1 Introduction

The piece is organized as follows:

Section 1 — Introduction

Section 2 — The Basics of Systematic Credit Investing We summarize the basic building blocks that comprise a systematic portfolio management process. First, we review the theoretical advantages of this approach, in which objective quantitative models are used to inform a diversified set of active risk exposures. Next, we address the associated concepts of risk factors and security selection signals, which form the basis for developing active views.[1] We discuss the measurement and control of systematic risk, as well as the monitoring of bond liquidity and steps to limit transaction costs. Optimal portfolio construction needs to continually steer the portfolio towards issuers with high systematic signal rankings and away from low-ranked companies. At the same time, portfolio risk exposures, along other dimensions, need to be carefully controlled and unnecessary turnover avoided. Finally, we discuss the execution capabilities that are essential for implementing these strategies efficiently in the real world, given liquidity conditions, the availability of credit securities and the market impact of trades.

Section 3 — Systematic Investing in Credit is Now Feasible We survey the liquidity and trading environment for credit securities. We analyze the key differences between equity and credit markets that slowed the adoption of systematic investing in the latter. We then review a number of recent changes in the credit trading environment relating to liquidity and transparency that have improved the prospects of systematic credit investing. These include a number of regulatory developments, as well as rapid growth in electronic trading, credit exchange-traded funds (ETFs), and portfolio trading.

Section 4 — Case Study: Developing a Realistic Systematic Credit Strategy We present a detailed case study of a systematic credit strategy utilizing value, momentum and sentiment signals derived from both credit and equity markets. We discuss several practical aspects of strategy implementation, including risk constraints, signal combination methodologies and transaction cost optimization. We backtest the combined strategy over the past two decades and show that its performance after transaction costs compares favorably to the reported track records of fundamental active managers. We also show that due to the low correlation between the performance of these two management styles, systematic active investing complements fundamental active strategies.

This paper is not a description of a specific systematic strategy. Rather, our goal is to highlight trends leading to broader adoption of systematic credit strategies, discuss considerations in forming these strategies and illustrate them by providing an example. We hope to draw the attention of credit investors to this investment style.

Section 5 — Key Takeaways

2 The Basics of Systematic Credit Investing

At the core of a systematic strategy lies a set of objective rules developed to optimize portfolio performance. These rules typically include two key stages. The first identifies which securities are more or less likely to perform well in the coming period, given the combined input from multiple mathematical models informed by historical data. The second finds the optimal way to tilt the portfolio towards the favored securities and away from the less-preferred ones, by taking many small active risk exposures — rather than a few large ones, and staying within the desired risk limits and controlling transaction costs. In this section, we review the key elements of this approach: strategy breadth, factors and signals, controls on risk and liquidity, portfolio optimization, and execution.

Strategy Breadth: The Key to Efficient Risk Taking

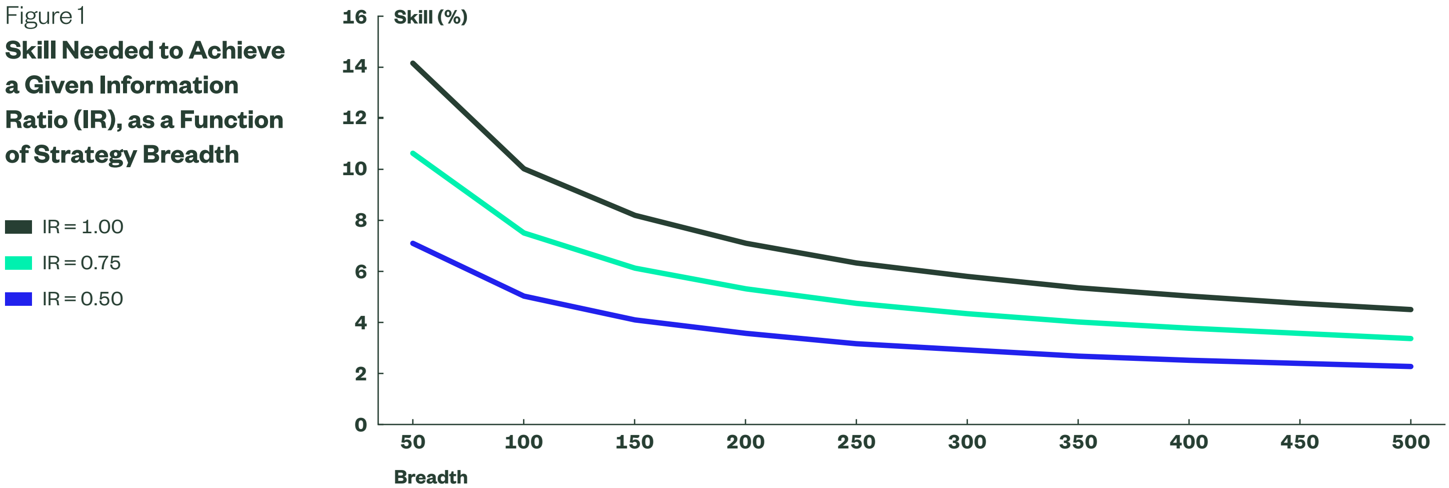
The key difference between systematic and traditional fundamental investing is the shift away from reliance on subjective analyst views. An analyst who studies a particular company in depth may develop a deep and comprehensive understanding of its business and financial condition, including the state of its management, the competitive environment in which it is operating, and its prospects. However, a human analyst may also be subject to behavioral biases, while a systematic strategy will carry out a purely impartial mathematical analysis. Furthermore, fundamental analysts typically cover just a small number of issuers and revisit their views infrequently, due to the effort required to carry out an analysis of this type. As a result, an investment program that relies on the subjective views of analysts typically takes a relatively small number of large active issuer exposures based on high-conviction calls. A systematic strategy, by contrast, is applied to every security in the investable universe, from which it produces a large number of small risk exposures, thus improving portfolio diversification and reducing risk.

The difference between these two approaches can be quantified using the “Fundamental Law of Active Management” developed by Grinold and Kahn.[2] They approximate the information ratio (IR) achievable by an active strategy (the average outperformance per unit of active risk) as a function of two key strategy attributes: breadth and skill. They define breadth (BR) as the number of independent investment decisions (or the number of independent underlying return forecasts) made by the manager each year. Skill is represented by the information coefficient (IC), defined as the correlation between the manager’s return forecasts and the subsequently realized returns (assuming that IC is the same for all forecasts). The achievable IR is then given by:

$$IR = IC \cdot \sqrt{BR}$$

Figure 1 shows the level of skill required to achieve a given information ratio according to this formula, as a function of strategy breadth. To achieve an information ratio of 1.0 with a breadth of 500 requires a skill level of just 4%, but to achieve the same information ratio with a breadth of only 100 would require skill of 10%. Even if a fundamental analyst may have a small advantage in the skill of each individual view, a systematic approach can overcome this edge by dramatically increasing strategy breadth.

Figure 1
Skill Needed to Achieve a Given Information Ratio (IR), as a Function of Strategy Breadth



Source: Barclays Research.

Factors and Signals

Systematic investing is closely linked with the idea of factor investing. The key concept is that financial markets are tightly interconnected, and there is much commonality among the returns of different securities. A factor is defined as a portfolio of securities exposed to a common source of systematic risk (e.g., sector, return, GDP growth). In fact, a large part of the variation of returns across a given market can be explained by the movement of a small number of factors. Confusion abounds when speaking about factors, however, because different market participants use the term in different ways. We need to distinguish between two types: risk factors and priced risk factors. To add to the confusion, priced factors are often hard to identify; we therefore rely on "style" factors to capture their effect.

As the basis for our discussion of different types of factors, let us consider the following representation of the capital asset pricing model (CAPM) for stock returns, the first and best-known factor model. For simplicity of notation, the returns of both asset i and the market are assumed to be their returns in excess of the risk-free rate:

$$R_{it} = \beta_i R_{Mt} + \varepsilon_{it}$$

In this, while there may be several common sources of risk that drive returns (i.e., risk factors), only one—the market cap-weighted portfolio of all assets — is a "priced" risk factor. The implication is that the return expected on a stock depends only on its exposure to the market portfolio, measured by its beta β_i, and the expected return on the market portfolio, namely the "equity risk premium."[3] Therefore, while the risk of a stock can be described by its exposure to different types of risk (e.g., company-specific risk), as represented by the term ϵ_i in the above equation, only the extent to which it moves in tandem with the market portfolio, captured by its β_i, is a determinant of both its risk and expected return.

Under the strict economic assumptions of the original CAPM, as put forward by Sharpe[4] and Lintner,[5] the expected return associated with non-market risk ϵ_i, widely referred to as the alpha α_i, is zero. However, the whole CAPM edifice collapses in real-life applications under the weight of this key zero-alpha implication, as established in the financial literature more than 40 years ago.[6] Intuitively, the implication of zero alpha discourages investors from gathering information and trading, preventing the market from ever reaching a CAPM-style equilibrium.

Consequently, a never-ending search for alpha — returns above those that compensate for market risk — has motivated investors and academics alike. For investors, finding securities that can generate this extra bit of return is the key to outperforming a benchmark. For academics, the identification of security or issuer characteristics that lead to statistically significant alpha in portfolio returns represents an anomaly, which can form the basis for introducing a new factor.

Compounding the problem, early attempts to generalize the CAPM to multi-factor models offered little relief, as additional factors were either hard to measure or not clearly identified.[7] Instead, we frequently rely on "style" factors, specifically well-diversified portfolios of securities sorted on observable characteristics believed to align with some dimension of expected returns.

The most prominent example of style factors comes from the work of Fama and French,[8] who identified two groups of common stocks that consistently earned returns in excess of those implied by their market exposures. They found that small stocks tend to outperform large ones, and stocks with low valuation (high book-to-market ratio) tend to outperform more highly valued ones. To account for these results, they proposed a three-factor model, in which size and value factors complement the market factor. Researchers next identified momentum as another characteristic that can help find stocks with potential for outperformance: stocks that have done well in the recent past tend to continue to do well. Momentum differs from the first three factors due to its dynamic nature and short horizon. Researchers have since uncovered a panoply of factors that capture systematic components of return, leading to what has been dubbed the "factor zoo."

Any factor will have returns that vary over time, and an expanded multi-factor version of the above equation can explain a large portion of the returns of any portfolio in terms of its factor exposures. Portfolios that match all known factor exposures of the benchmark should be expected to closely track its returns, as is the case for passive portfolios. Active managers seeking to outperform the benchmark will take active factor exposures relative to the benchmark. Factors can be categorized by how much of the return variation in the investment universe can be attributed to them. When building a risk model, the most important factors are the ones that capture the greatest percentage of overall return variance. Matching benchmark exposures to these is the key to constructing passive index-tracking portfolios. However, when building an active factor strategy, managers will seek to impose a steady overweight to the factors expected to generate positive outperformance and information ratios over the long term, namely the style factors.

Style factors are closely related to signals. The latter indicate the extent to which a given security should be considered to have a positive or negative exposure to a given style factor at a given point in time. For example, to form a value factor, we may start by calculating a signal that measures the extent to which a bond is rich or cheap relative to its peers. We can use this to construct a value factor by forming two portfolios: one of bonds with high value signals and one of bonds with low value signals. The difference between the two portfolio returns captures the return on the value factor.

Signals are a key input in systematic investing. Indeed, regardless of the role played by factor analysis, a portfolio is ultimately formed from individual securities. The decisions about which securities to buy or sell are determined based on the signals that measure their exposures to desirable factors.

Just as in equities, risk and style factors influence the returns of fixed income portfolios. Important risk factors include exposures to interest rates of different maturities, credit exposures to different industries and/or countries of company domicile, and FX exposures.

Exposure to certain credit style factors is also associated with outperformance of the market return. Some are thematically similar to known equity factors. For example, exposure to a value factor can be formed by an overweight to bonds that seem underpriced (i.e., trade at higher spreads) to their peers and to a momentum factor by an overweight to issuers that have performed well in recent months. We illustrate the performance achievable using credit style factors using a detailed case study in Section 4.

Controlling Risk in Fixed Income Portfolios

The key to achieving high risk-adjusted returns is to ensure that the active portfolio risk is concentrated almost exclusively in the intentional alpha-producing factor exposures. Unintentional risk exposure should be avoided to the extent possible. Furthermore, even the intended exposures should be constrained to prevent any one risk exposure from dominating portfolio risk.

Portfolio risk can be divided into two main categories: systematic and idiosyncratic risk. The former is the return volatility that can be traced to the movement of modeled risk factors, while the latter is due to issuer-specific effects. The main systematic risks for fixed-income portfolios are exposure to changes in interest rates, exposure to currency fluctuations in multi-currency portfolios, and changes in credit spreads. Different risk factor models have been proposed to measure these.

Interest rate risk can be measured crudely by portfolio duration, which gives the sensitivity to a parallel shift in the yield curve. However, given the primary importance of the yield curve in determining bond prices, it is important to model non-parallel changes to the yield curve as well. Different approaches can be adopted to model such risk. For example, Litterman and Scheinkman[9] showed that three factors — yield curve shift, twist, and curvature — can account for well over 90% of variation in yield curve returns. Instead, we prefer the key rate duration[10] approach, which models exposures to yield changes at a number of key maturities along the curve. Although from a mathematical perspective, it is preferable to use a small number of orthogonal risk factors, many investors appreciate models that correspond intuitively to the way they view the market, even at the expense of some redundancy and correlation among the factors. In the case study in Section 4, we rely on constraints on the portfolio's active key rate duration exposures relative to the benchmark to limit tracking errors due to rate changes.

For measurement of systematic exposures to credit risk, there are, similarly, several possible approaches. A portfolio's spread duration gives its sensitivity to a parallel widening or tightening of spreads, but again this single number fails to capture all the possible ways in which spreads can change. They can widen for issuers in one industry while tightening in another. Therefore, many practitioners partition their portfolios and measure exposures to spread changes by industry as distinct, albeit correlated, risk factors.

Furthermore, even within a given industry, a parallel shift in spreads is not the most typical type of systematic change. As shown by Ben Dor et al.,[11] spreads often follow a pattern of relative spread changes in which bonds with wider spreads widen (or tighten) more, proportionally to their initial spreads. They show that sensitivity to this type of systematic spread change can be measured by contributions to duration times spread (DTS), which measures portfolio sensitivity to relative spread changes across a market segment. Constraints on active DTS exposures by industry thus serve to limit tracking errors due to systematic changes in corporate bond spreads.

For benchmarked portfolios, a key measure of risk is tracking error volatility (TEV), which is the volatility of the return difference between the portfolio and the benchmark. Systematic TEV can be modeled ex ante based on the differences between portfolio and benchmark exposures to risk factors, using the factors' variances and cross-correlations, which are estimated from historical data. Idiosyncratic TEV can be projected based on the differences in the issuer exposures (either in terms of percent of market value or contributions to DTS) between the portfolio and the benchmark. Systematic TEV can be effectively controlled by placing constraints on the allowed deviation between portfolio and benchmark risk factor exposures, as described above. Similarly, constraints on exposures to individual bonds and issuers can limit TEV from idiosyncratic and default risk. If tight constraints are imposed on all of these parameters, portfolios should be expected roughly to track the returns of the benchmark.

Navigating the Risk/Return Trade-Off

It follows that any attempt to improve portfolio performance relative to the benchmark by taking different exposures to systematic risk factors and/or issuers increases the risk of underperformance. Different types of portfolios are therefore available for investors with different risk appetites.

Beta/Indexing/Passive Replication In these strategies, investors construct portfolios designed to closely track the returns of a benchmark index. These will typically be structured to match all benchmark risk factor exposures as closely as possible, with a highly diversified issuer composition that carefully matches issuer exposures, at least for the largest benchmark positions. In equities, indexed portfolios may seek exactly to match benchmark exposures to all stocks in an index. For credit, where the index can contain a large number of bonds, many of them illiquid, passive replication may use a stratified sampling approach to create a portfolio very similar to the benchmark without precisely replicating its bond-level composition. Indexed portfolios are not expected to outperform their benchmarks, but they are expected to track their returns with very low TEV.

Smart Beta Standard benchmark indices are typically rules based and market weighted. This makes them highly transparent, but can lead to inefficiencies, such as risk concentrations in large issuers or industries. Smart beta strategies are designed with alternative sets of rules that aim to gain market exposure more efficiently, in line with client preferences. For example, a portfolio can be constructed that may place limits on issuer concentrations; may delay forced selling of securities when their characteristics change, such as downgraded bonds; may reflect different liquidity requirements or turnover; or may exhibit differences in characteristics such as quality, maturity and risk/return. Investors may choose smart beta portfolios in anticipation of achieving better risk-adjusted performance than that of standard benchmarks, but any such result will be due mostly to the difference between the customized index and the standard one. A smart beta portfolio will typically be managed passively with respect to the customized smart beta index and structured such that risks and returns closely track those of this alternative benchmark.

Fundamental Active In traditional active management, investors seek to outperform the benchmark index. To that end, they give their managers discretion to express their views through active exposures to risk factors and issuers. Such portfolios typically express views on duration timing and sector rotation, in addition to issuer selection. The portfolio mandate will specify an investment policy that details the allowable risk limits and alpha targets, which can vary greatly from one mandate to another.

Systematic Active In this paradigm, as in traditional fundamental active fixed income strategies, investors seek to outperform a benchmark index by taking active risk. However, rather than relying on manager discretion, systematic strategies follow a disciplined quantitative approach to selecting risk exposures relative to the index. Such portfolios take a large number of small active risk exposures, such as selecting securities, issuers or sectors deemed attractive by these models. These intended exposures have the potential to contribute to excess returns, while carefully controlling risk in all other dimensions. Systematic security selection strategies are expected to track their benchmarks more closely (i.e., with smaller TEV) than most fundamental active portfolios, with attractive risk-adjusted active performance.

The objective of systematic active strategies in fixed income is to outperform their benchmark indices, ideally over the full economic cycle. A second objective is to generate alpha whose magnitude makes these strategies competitive with fundamental active managers with less TEV, resulting in attractive information ratios relative to those managers.

A systematic, data-driven approach can be taken to any risk dimension and can be used to set active exposures to rates, industries, countries, foreign exchange and the like. Some of these macro timing strategies have been found to be challenging to implement, as they tend to have lower breadth than security selection, so greater skill is needed to arrive at a similar information ratio, as illustrated in Figure 1.[12] In many fundamental active funds, managers may carry a macro exposure to credit or duration that comprises a large portion of their portfolios' overall risk relative to the benchmark. These exposures may help improve carry, but will likely increase portfolio TEV. The greatest potential for achieving strategy breadth is found in the selection of specific bonds and issuers. Therefore, in this white paper, we focus on bond selection strategies, and carefully match the benchmark on all other risk dimensions.

Even after we have settled on a pure security selection strategy, different approaches can be taken to setting risk limits and outperformance targets. Tight risk limits can be set as described above, ensuring low volatility of tracking errors, and the desired outperformance will need to be achieved by consistently selecting bonds and/or issuers that outperform their risk-equivalent peers. This outperformance can be accomplished by selecting the securities that maximize the exposures to alpha factors while satisfying the constraints on risk factors. However, if constraints are set too tight, such a strategy may be limited in the amount of alpha that it can generate. For example, if a strategy is run with risk controls that keep its tracking error volatility down to 25bp/year, even if it achieves an attractive information ratio of 1.0, its annual alpha will be only 25bp. For more ambitious alpha targets, it might be necessary to relax some of these constraints. In particular, a value strategy seeks to overweight bonds that trade at wider spreads than their peers. Such a strategy will be unable to generate much traction if we force portfolio spreads to match those of the benchmark. To leave room for a value tilt to be expressed, it therefore may be desirable to allow portfolio spreads to be wider on average than those of the benchmark. While this may seem to expose the portfolio to a systematic overweight to credit, this effect is found to be smaller in practice than might have been expected, as risk and valuation are related. Ben Dor et al.[13] show that when a bond's spread is found to be wide to fair value, its risk tends to be lower than that projected by the DTS approach. Allowing for some tolerance in the portfolio optimization constraint when matching the benchmark spread is the approach we take, as discussed in Section 4.

Rates derivatives such as Treasury futures or interest rate swaps can be a useful tool for managing interest rate risk in a systematic credit portfolio. Clearly, for portfolios that utilize active rates strategies, futures allow an easy way to layer a rates view on top of a credit portfolio without requiring any changes to the portfolio itself. However, the flexibility they offer can be very valuable even to a portfolio based on a pure security selection approach. This is because in the absence of futures, the constraints designed to control rates exposures may interfere with credit selection. Imagine that a number of issuers that are favored in terms of their alpha factor exposures have outstanding bonds only around the 5-year part of the curve. The need to match the benchmark's exposure at this point on the curve may prevent the portfolio from buying all of these names and force it into less favored ones. However, if futures were allowed, the portfolio could choose the preferred issuer allocation, regardless of the positioning along the curve, and then apply a futures overlay to reposition the rates exposures along the curve to match the benchmark. Desclée and Polbennikov[14] have emphasized the importance of derivatives in allowing separate management of rates and credit views and demonstrated that a "no derivatives" constraint can give rise to a marked drop in efficiency in active credit portfolios.

Liquidity

The main impediment to systematic investing in credit has been the concern that corporate bonds are not sufficiently liquid to support this approach to portfolio management. Transaction costs are substantially higher in credit than in equity, and this is a large reason why systematic strategies have been more widely used in equity.[15]

It is therefore critical that any study of systematic credit strategies include liquidity considerations as a central part of the framework, in two ways. First, we must make sure that any proposed strategy is implementable. If an "optimal strategy" suggests buying bonds that are simply not available in the market or can be purchased only at very wide bid-offer spreads, it will not be executable in practice. To avoid this situation, a screening process must be put in place to make sure that the optimization process includes only sufficiently liquid bonds. Second, to evaluate the success of a strategy, it is important to include the effect of transaction costs. In a historical backtest, actual transaction costs are not known precisely, but access to historical liquidity measures makes it possible to estimate how much it would have cost to execute a given transaction at a particular point in time.

Barclays produces two sets of bond-level metrics of liquidity[16] that facilitate these processes. Liquidity Cost Scores (LCS) provide an estimate of the round-trip transaction cost of trading a bond, as a proportion of its market value, based on quotes from Barclays trading desks. This can be used to estimate transaction costs of simulated trades. LCS provide a conservative single-dealer estimate of transaction costs; a large execution desk will see a cross-market bid-offer that should enable it to trade at lower cost. Trade Efficiency Scores (TES) provide a ranking of the liquidity of corporate bonds, based on the combination of LCS with trading volume information obtained from TRACE. TES are stated as relative scores and are meant to identify tradable bonds in all market environments. Bonds indicated by TES to be in the most liquid tier will exhibit both low trading cost and high transaction volume relative to their peers. Screening bonds based on TES to form the eligible universe for an optimization thus provides an excellent way to make sure that the optimizer purchases only sufficiently liquid bonds.

Optimal Portfolio Construction

Once a number of signals have been identified, each of which has been found to be predictive of superior performance in its own right, the next step is to apply them to the task of constructing and maintaining a portfolio. From a theoretical standpoint, defining the optimal portfolio is straightforward: an optimization can be carried out to identify the portfolio of securities that maximizes the signal score while satisfying all of the constraints on systematic and idiosyncratic risk. To reflect liquidity considerations, the universe of securities supplied as candidates for inclusion in the portfolio can be restricted to those with liquidity metrics above a certain threshold.

At this point, we run into a number of frictions and tensions that may not have been addressed in the first step of signal identification and evaluation. First, as we attempt to integrate several different signals, we may find that they provide conflicting views regarding a particular issuer; we need to find the best way to make use of all available information. Is it better to form a separate portfolio based on each signal and then combine portfolios or first to combine the signals and then form a single portfolio? In either case, how should we determine the weights assigned to different signals? Second, we need to take steps to limit transaction costs while still keeping the portfolio tilted to securities with high systematic signal scores.

Managing Multiple Signals

Given multiple signals, each of which could be used on its own to construct a portfolio that is expected to outperform the benchmark, what is the best way to build a portfolio that takes advantage of the information content in all of them? One possibility might be to diversify the portfolio by dividing the assets and running separate smaller portfolios, one based on each signal. However, it is clear that this approach can give rise to inefficiency. When different signals point in different directions, one might end up being long the bond in one portfolio while shorting it in another. Even if care is taken to net out the positions before trading, such offsetting trades would essentially negate the possibility of a net return improvement from positioning in that name. It is thus more efficient first to combine signals and construct a single portfolio with high combined scores.[17] Polbennikov, Desclée and Dubois[18] illustrate this result with an example based on a combination of value and momentum strategies. They found that a portfolio constructed to optimize a 50/50 blend of value and momentum signals achieved significantly better performance — in terms of both average outperformance and information ratio — than a 50/50 blend of two portfolios that independently optimized each of the two signals on its own.

Even once the decision is made to combine signals, there are many different ways to do so. For our case study in Section 4, we will use a simple equal-weighting scheme in which the arithmetic average of three signals is used as the combined signal. However, as demonstrated by Ben Dor, Elnahal and Florig,[19] there are a number of additional techniques that can help refine the signal combination process and improve performance. First, it is important to understand the relationship between signal values and expected alpha. For some signals, this relationship may be nearly linear, while for others it may be highly non-linear. In this case, it can help performance significantly to transform the signals before combining them such that a unit difference in one signal relates to the same advantage in expected alpha as a unit difference in another. Another important question is whether the various signals that are to be combined are to be given equal weights, or whether some signals should be given greater weight. It might be beneficial to give greater weight to signals that have been more efficient at alpha generation in the past or to decrease the weight given to signals that are highly correlated with others. In any such approach based on historical performance, there is an additional question of whether these weights, once chosen, should remain fixed or whether they should be adjusted dynamically as new experience is accumulated. Dynamic updating can offer substantial benefits and can keep the overall strategy attuned to current market trends, but it can be prone to overfitting. In the paper by Ben Dor, Elnahal and Florig mentioned above, the authors present a robust approach to dynamically adjusting signal weights.

Efficiently Rebalancing the Portfolio

The high cost of trading in credit markets presents an ongoing challenge to active managers. Evaluating a proposed strategy in a simulated portfolio backtest, one can solve for the optimal portfolio at the start of each month and find that it generates substantial outperformance of the benchmark on a steady basis. However, these optimal portfolios can be very different from one month to the next; turnover can be so high that once estimated transaction costs are taken into account, the net active performance is negative. To avoid this pitfall of "churning" the portfolio, it is essential for the optimization process to recognize the prior month's holdings as the starting point for each monthly rebalancing and to include a mechanism for limiting turnover. Rebalancing transactions — which are necessary both for risk control and for maintaining positive tilts to all of our alpha factors — must be kept to the minimum amount necessary for achieving these goals.

The most straightforward way to limit portfolio rotation is to impose a constraint on the maximum allowed turnover in a given month, say, 10%. However, a fixed limit on turnover may not be the most efficient way to control transaction costs. Due to changes in the liquidity environment, and depending on which bonds are traded, a 10% turnover in the portfolio can result in much higher transaction costs in one month than another. It might be more appropriate to place the constraint directly on transaction costs, rather than on turnover. Furthermore, there might be some months in which it is crucial to make a trade — e.g., when bonds outside the portfolio are viewed as much more attractive than the ones being held (or the signal for bonds currently in the portfolio turns strongly negative) — while in other months, the differences in signal values are less dramatic and the improvement in expected performance resulting from trading is much lower.

It therefore makes sense to allow larger transactions when the need is greater or to evaluate every trade to see if the improvement in signal scores that it produces justifies the transaction cost. This can be accomplished by changing the setup of the optimization problem. Rather than finding the portfolio that maximizes signal scores subject to risk and turnover constraints, we can find the portfolio that maximizes a composite objective function that rewards high signal scores but penalizes for estimated transaction costs. Ben Dor and Guan[20] compared the performance of three different approaches to controlling transaction costs in credit portfolio construction: a constraint on turnover, a constraint on transaction costs, and the incorporation of transaction costs into the objective function to maximize expected returns net of trading costs. They find that constraining estimated transaction costs gives better long-term performance than simply constraining turnover, and that incorporating transaction costs into the objective function can perform the best out of the three. However, both approaches require a more complicated estimation process than simply constraining turnover.

Delivering Efficient Implementation

Even after assembling all of the above machinery — signals, risk metrics, liquidity filters, accounting for transaction costs, signal combination methodology and the portfolio optimization process — there is one more step critical to the success of the strategy, namely, implementation. The asset manager's goal is to construct a portfolio of exposures that satisfy the targeted risk alignment and exhibit high sensitivity to the desired style factors. The optimization process provides a proposed set of trades that can accomplish this, given its a priori estimates of bond pricing and liquidity. However, it is crucial to obtain factor exposure at a sufficiently low trading cost so as not to affect negatively the overall performance potential of the strategy.

To that end, buy-side traders aim to purchase securities at or below the expected price in the optimizer. That is much easier said than done, especially in volatile markets. To assist in the process, portfolio managers and buy-side traders today have an increasingly rich data set of bond level liquidity metrics to work with, given the pricing transparency available as a result of the growth in electronic trading. This additional information can help to control and limit transaction costs, thereby improving the efficiency of implementation so as to generate the expected return of the strategy, arguably more reliably than was previously possible. Such efficiency can now be achieved generally via the secondary market, but also opportunistically through the primary/new issue market. In each instance, the implementation program will target specific spread levels and transaction costs to build the desired exposure. Leading institutional trading desks that manage large volumes of granular trade flows throughout the day are particularly well positioned to capitalize on this pricing data, resulting in improved execution and more efficient implementation.

No matter how much care is taken in the design of the optimization process to propose executable trades, there are bound to be surprises at execution time: pricing and availability for some bonds may turn out to be very different than the pricing inputs used at the time of optimization. To meet this challenge, the portfolio construction process needs to be pragmatic and allow for some flexibility to substitute specific bonds in the model portfolio in order to best achieve the goals of the rebalancing transaction, given the prevailing market conditions.

As a result, after rebalancing, the actual portfolio may not exactly match the model portfolio proposed by the optimizer. However, an experienced asset manager with advanced portfolio construction capabilities can employ several practical techniques that seek to alleviate implementation challenges and harness what has become known as *implementation alpha* along the way.

Here are several examples of these implementation techniques that an experienced asset manager can employ to improve the efficiency and reliability of execution:

- **Executing at better levels than the conservative pricing estimates used in optimization.** The optimization framework should use a conservative estimate of transaction costs. For example, Barclays LCS provide a single-dealer estimate of the bid-offer spread for a particular security. These single-dealer estimates tend to be conservative (i.e., higher than actual transaction costs), as the bid-offer viewed by a large execution desk across multiple dealers will likely result in lower costs. Furthermore, with the proliferation of electronic trading, and the availability of new trading protocols, finding the counterparty going in the opposite direction has never been easier. Advantageous execution levels can be achieved when buying directly from a bond owner or selling to a willing buyer, once one is found.

- **Incorporating insights from market flow dynamics into the construction process.** Sophisticated fixed income managers, particularly those who also manage a variety of large fixed income ETFs, enjoy real-time access to market flow dynamics and live pricing information. Often, market liquidity will coalesce around these ETF vehicles and be the first port of call when investors are looking to adjust market exposure, particularly on days when sentiment is changing. A manager can then use this real-time access to execute on those bonds considered in the strategy. This transaction flow information provides a reference not only as to the intraday direction of spreads, but also to the expected execution levels as these change with market conditions. These insights can then be brought to bear to exploit market liquidity as it arises, so as to reduce transaction costs in the continuous management of the strategy.

- **Monitoring spread levels and risk constraints in security watchlists.** Certain bonds may have high factor scores, but fall short of the necessary liquidity and spread requirements after transaction costs. Again, electronic trading enables managers to conduct continuous and anonymous surveillance of securities' pricing levels and market trade activity. Moreover, watchlists can be set up to rapidly (in some cases automatically) bid or offer bonds that have reached predetermined spread or price levels. It also facilitates, where necessary, the substitution of one high-scoring bond for another as their spread levels and liquidity costs change, to capture higher expected returns. By incorporating such quantitative trading and liquidity insights into the portfolio construction and maintenance process, a sophisticated manager can improve the efficiency and reliability of implementation outcomes in the ongoing management of systematic strategies.

- **Accessing primary markets.** The primary market premium is well known to fixed income investors; when new bonds come to market, they are priced attractively and at a concession to the issuer's spread in secondary trading. Managers can participate in primary issuance to benefit from this concession and gain a performance boost relative to existing bonds from the same issuer. Whereas new corporate bond issues enter standard bond indices at the end of the month of issue, at prices obtained from secondary market trading, a strategy of systematically buying new issues at primary issuance can help a portfolio outperform its benchmark. The magnitude of concessions and, hence, the alpha they can generate, vary with market supply and demand. A detailed study by Ben Dor and Xu[21] demonstrates that for a passive portfolio of US IG corporates, the average annual alpha generated by systematic application of such a strategy was 5-25 bp/year between 2007 and 2013. Therefore, it is worthwhile to ensure sufficient flexibility throughout the construction process to enable the manager to exploit this premium on issuers with high factor score that come to the primary market with a new bond deal.

To illustrate the performance potential of these implementation details, we present some data from an example portfolio, a passive fund managed by State Street Global Advisors (SSGA) against a broad US investment grade (IG) credit benchmark. Figure 2 shows a transaction cost analysis of this portfolio, comparing the average transaction costs realized in buy (Panel A) and sell (Panel B) transactions with those estimated by LCS. The costs realized by the portfolio on transactions in both directions are found to be consistently lower than the LCS-based estimates. Figure 3 attributes the performance of the portfolio relative to its benchmark to a number of mechanisms for adding value. During the 5½ year period shown, SSGA added a cumulative 149 basis points of implementation alpha from a combination of trading and turnover reduction, participation in primary markets, and security selection.

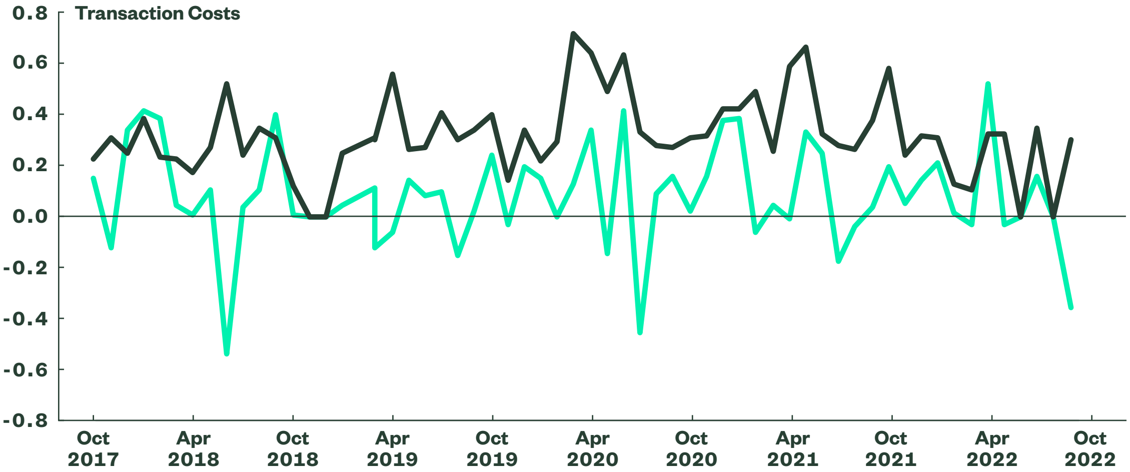
Figure 2

Transaction Cost Analysis of a Passive US IG Corporate Bond Portfolio

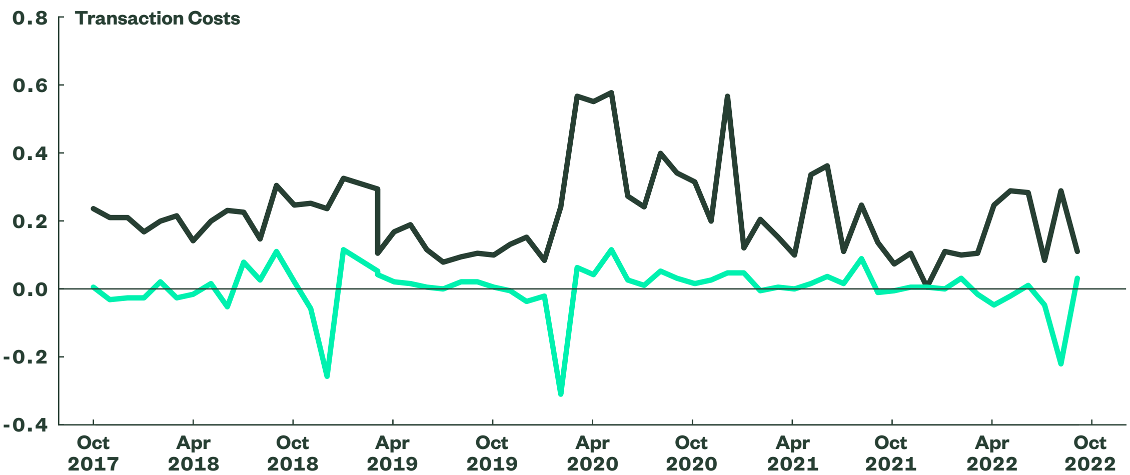
Order Weighted LCS

Effective Transaction Costs

Buy Transactions



Sell Transactions

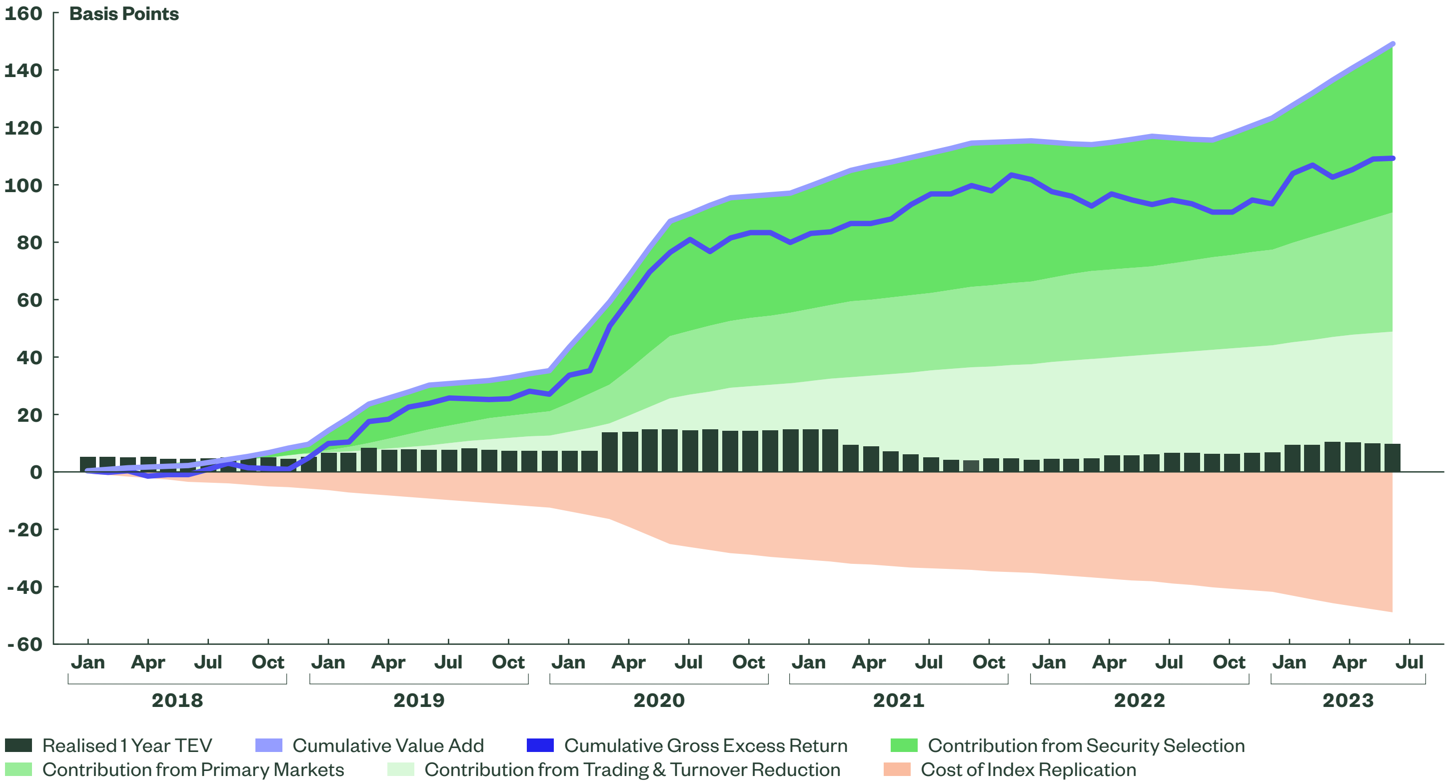


Source: State Street Global Advisors, Bloomberg Finance, L.P.
Note: Transaction cost analysis is conducted monthly on a representative account of a US Investment Grade Corporate Bond index strategy from October 2017 to September 2023. Effective transaction cost is calculated as [(Execution Price – BVAL Price) / BVAL Price] x 100. Bloomberg's definition of the BVAL Price states that "the time at which the price is taken for a particular bond is regionally based. Generally, bonds are priced at 3pm New York time for US markets."

The results for a systematic active portfolio are likely to differ somewhat from those realized in this largely passive one. An active portfolio will typically allow a larger TEV to the benchmark, and the systematic application of signals will target greater alpha from issuer selection. The role of primary issuance is likely to change as well. Whereas a passive portfolio will typically buy a small amount of every new issue that comes to market, a systematic active portfolio will seek to participate in new issues only from issuers with attractive signal scores, and it may do so in larger size. Finally, the application of execution skill to reduce transaction costs will take on a larger role in more actively traded portfolios. Thus, while the numbers may differ, the ability to add alpha in implementation is crucial for successful management of both passive and active portfolios.

Figure 3 **Consistently Adding Value in USD IG**

Value Added by Different Implementation Techniques for an Example State Street Global Advisors Portfolio



Source: State Street Global Advisors. Data as of January 2018 through June 2023.

Cumulative Value Add Contribution for a US IG Representative Account (All Data in Basis Points)

Year	Cost of Indexing	Trading & Turnover	Primary Markets	Security Selection	Total Added Value
2018	-5.70	6.44	0.07	3.19	9.70
2019	-6.55	6.26	8.24	11.05	25.55
2020	-17.58	18.17	16.05	27.37	61.58
2021	-5.05	6.66	4.26	7.13	18.05
2022	-6.75	6.51	4.54	-3.13	7.92
2023	-6.90	4.81	8.08	12.88	25.77
Total	**-48.53**	**48.84**	**41.24**	**58.49**	**148.57**

Source: State Street Global Advisors. Data as of January 2018 through June 2023.

3 Systematic Investing in Credit Is Now Feasible

Due to its clear advantages, investors have embraced systematic investing in equity markets. Algorithmic (systematic/quantitative) equity strategies for generating alpha have been very popular and highly developed for a long time. They cover a broad spectrum of time horizons, from milliseconds to months; most geographies; and a broad range of issuers with different market capitalizations. As noted above, fixed income investors have been slower to embrace this type of investing, with $30+ billion in systematic strategies across US, Euro, and Global IG credit strategies. This is due primarily to the more complex nature of credit markets.

However, over the past few years, several market and regulatory developments have led to slow but steady changes in the credit trading environment and reduced this asymmetry between credit and equities. In this section, we first review the key advantages that equity markets enjoyed historically. We then outline the various regulatory changes and technological advances that have dramatically improved liquidity and transparency in corporate bond trading, making systematic credit investing a viable and an attractive proposition for today's investors.

Systematic Equities Have a Head Start...

There are several reasons for the difference in the degree of adoption of quantitative alpha strategies between credit and equity markets. Success in systematic equities is driven predominantly by the information introduced to the portfolio through factor analysis, models and data. Implementation — sourcing the securities to construct the portfolio — is quite straightforward, given the simplicity of equity markets. Typically, each traded company is represented by a single stock; hence, every security in the major indices trades regularly every day. Equities are mostly exchange traded, and historical pricing, transaction and fundamental data have been broadly available from multiple vendors to academia and industry for decades. As a result, quantitative equity signals have been well researched, and standard sets of factors have emerged for alpha strategies and risk management. Corporate bond markets are more complex and substantially less liquid. A given company may have dozens of bonds outstanding, with different coupon levels, maturity dates, optionality, and seniority. Some of these, particularly older and smaller issues, may hardly trade at all. Until recently, corporate bonds traded mostly over-the-counter (OTC), and price discovery was opaque. The cost of trading credit was, thus, significantly higher than for equities, and in risk-off crises, trading in credit could come to a near halt. Few vendors offered bond-level historical pricing data and analytics. Bond security analytics require complex modeling of the price effect of interest rates and default expectations. These analytics need to be consistent across fixed income asset classes. Changes to these models often require updating analytics historically — always a costly endeavor. Most importantly, credit portfolio managers believed that algorithms based on historical patterns will always miss important bond characteristics and cannot be implemented in practice, due to high trading costs.

Corporate bond liquidity declined even further in the aftermath of the global financial crisis (GFC) of 2008, when regulators imposed a number of new constraints on financial institutions. Primary among these was the Dodd-Frank financial reform enacted in 2010. This legislation raised the regulatory capital requirements for banks, making it much more expensive for broker/dealers to maintain inventories of corporate bonds. Thus, even after the crisis had largely subsided, corporate bond markets remained substantially less liquid than they had been before the crisis. This manifested itself in a reduction in turnover and an increase in trading costs (as measured, for example, by average LCS) in the IG and high yield (HY) markets. These new regulations encouraged banks to reduce proprietary trading and move risks off their balance sheets. Investors at first responded to higher trading costs by trading less and concentrating their activity in the most liquid parts of the market, namely the largest and most recent issues. These changes allowed investors to keep costs under control, at the expense of limiting the scope of their portfolio strategy. Indeed, security selection strategies often rely on taking positions in smaller, lower-rated issuers, many of which remained difficult or very expensive to trade.

... But a Lane Has Cleared for Fixed Income

Responding to this need, market practice has evolved in a number of ways over the past decade to facilitate trading, despite the prevalence of smaller dealer balance sheets. This market evolution involves several interrelated processes that took place concurrently.[22]

Increased Agency Trading

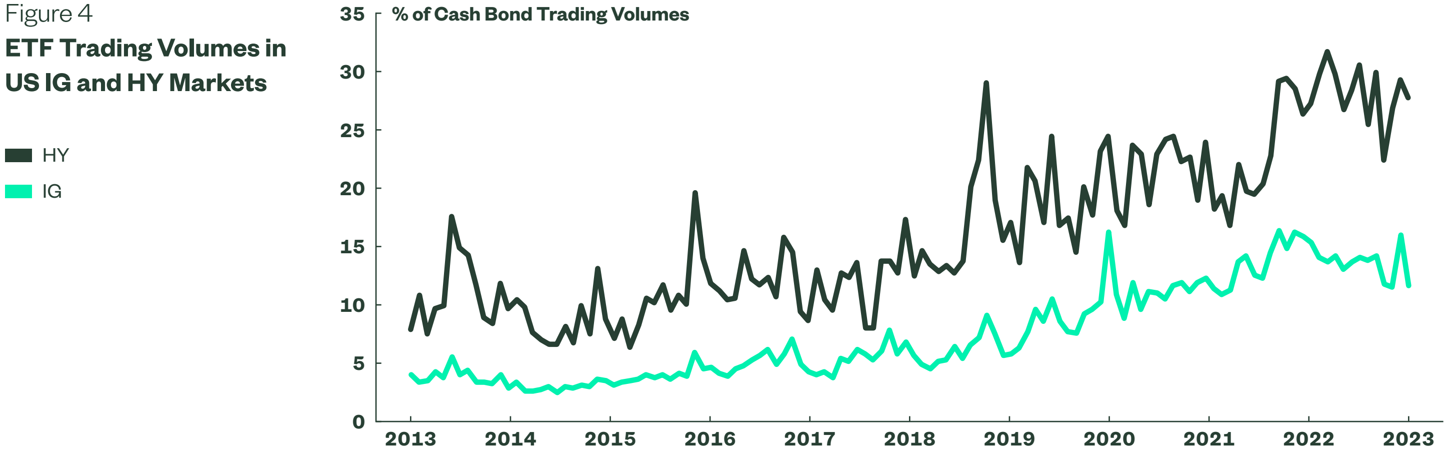
The need to maintain smaller balance sheets drove banks towards more of an agency model and encouraged them to participate in, or even develop, venues to match buyers with sellers. The extension of TRACE reporting requirements to include more OTC credit transactions gave researchers access to new trading data, increasing market transparency and opening new opportunities to study liquidity patterns. Market participants adopted new trading practices, aided in part by new technologies. The rise in the use of ETFs and portfolio trading in credit markets helped increase liquidity in otherwise illiquid segments of the bond market. Partially due to regulatory concerns, investment banks turned over production and dissemination of fixed income index data to vendors, which resulted in historical index data becoming more broadly available.

The first stage of market adaptation was marked by an increase in “agency trading,” as opposed to “principal trading.” Agency trading allows investors to trade less-liquid issues in a cost-effective manner, essentially trading by appointment. In this protocol, an investor gives a dealer an order, meaning the dealer is tasked with trading a specific bond at a specific price, and attempting to find the other side of the trade at (or close to) the requested price within a certain amount of time. If the market maker succeeds in finding a seller to match a buy order, it prints both sides of the trade at once; if not, the trade order goes unfilled. Using a detailed analysis of TRACE data, Meli and Gupta[23] demonstrated that agency trades, or near-simultaneous matched buy and sell orders on the same bond, result in significantly lower transaction costs than principal trades, in which the dealer holds the bond on its books for a longer time between the two legs of a transaction. They also found that the prevalence of agency trading increased substantially from 2010 to 2015, especially for older, and thus less liquid, issues.

Rise of Credit ETFs

Another market development that has changed the credit trading landscape has been the rise of credit ETFs and their trading volume from institutions. Since their introduction in the early 2000s, they have grown dramatically in total assets and trading volumes. While the total market value of IG bonds and the AUM of IG ETFs are substantially larger than those of their HY counterparts, the ETF volumes in the two markets have tended to have similar magnitudes, even as they have both had tremendous growth. To emphasize the growth in importance of ETF trading within the context of overall market activity, Figure 4 shows the growth of IG and HY ETF trading volumes as a percentage of the overall trading volumes in cash bonds.

Figure 4
ETF Trading Volumes in US IG and HY Markets



Source: Bloomberg. Note: Data based on HYG, JNK, SHYG, USHY, HYLB in HY and LQD, VCIT, VCSH, IGSB, IGIB in IG. Data from January 2013 through April 2023.

This increased ETF activity affects liquidity in the underlying bond markets in two different ways. One, it creates an easy way for a credit portfolio manager to handle cash inflows (outflows) by buying (selling) shares in passive credit ETFs, which tend to be more liquid than many individual bonds. This causes some trading volume that would have previously flowed into individual bonds to be redirected onto ETFs, thus reducing turnover and, hence, liquidity in the underlying bonds. However, secondly, the ETF ecosystem includes create/redeem activity, in which ETF shares are exchanged for baskets of individual bonds. This may serve to increase liquidity in the underlying bonds. Meli, Todorova, and Gupta[24] have investigated both of these effects in the US IG and HY markets. They find clear evidence that HY fund managers increasingly use ETFs to manage their liquidity needs relating to fund flows. This makes sense because the leading ETFs are much more liquid than the underlying HY bonds. In both HY and IG, they report that bonds included in the largest ETFs tend to have better liquidity than excluded bonds with similar characteristics.

Furthermore, the rise of credit ETFs and index investing has allowed new market entrants and established new trading protocols for portfolios of bonds and ETFs. Large index managers are now a significant source of liquidity across a wide range of securities because institutions often hold multiple bonds in a single-line instrument via ETFs. Banks may now have ETFs, bond portfolios and index CDS in the same book of trading. ETFs now provide intraday views of supply and demand on various fixed income securities and afford insights into clearing prices.

Technological Advancements

Several key technological advancements have also helped improve liquidity in credit markets. Request-for-quote (RFQ) systems,[25] introduced in the 1990s, have expanded to credit, list trading, basket trading, ETFs, and more recently, all-to-all trading. Large index managers that may hold tens of thousands of individual bonds can now leverage technology to find overlaps between their exposures, their "axes," or the bonds they would like to own or sell and the axes of other market participants. Technology also provides scannable data on liquidity indicators such as issue size and age across thousands of bonds, allowing portfolio managers to view the fragmented fixed income market efficiently and make optimal trade-offs at a portfolio level. These developments are particularly important in the fixed income market, where liquidity is a crucial element of investment decisions. Electronic trading on various platforms has increased steadily in volume.

O'Hara and Zhou[26] analyse trading data from MarketAxess and TRACE and show that the share of electronic trading in US IG corporate bonds, by volume, rose from about 10% in 2010 to about 25% in 2017. This effect is strongest for smaller trades; as of 2017, they show that nearly 50% of "odd-lot" trades of $100,000 to $1,000,000 trade electronically, while less than 10% of block trades of over $5,000,000 do. These larger institutional trades, which comprise more than half of total volume, still trade primarily by voice. However, the authors demonstrate that during this time, transaction costs decreased steadily for both electronic and voice-traded transactions.

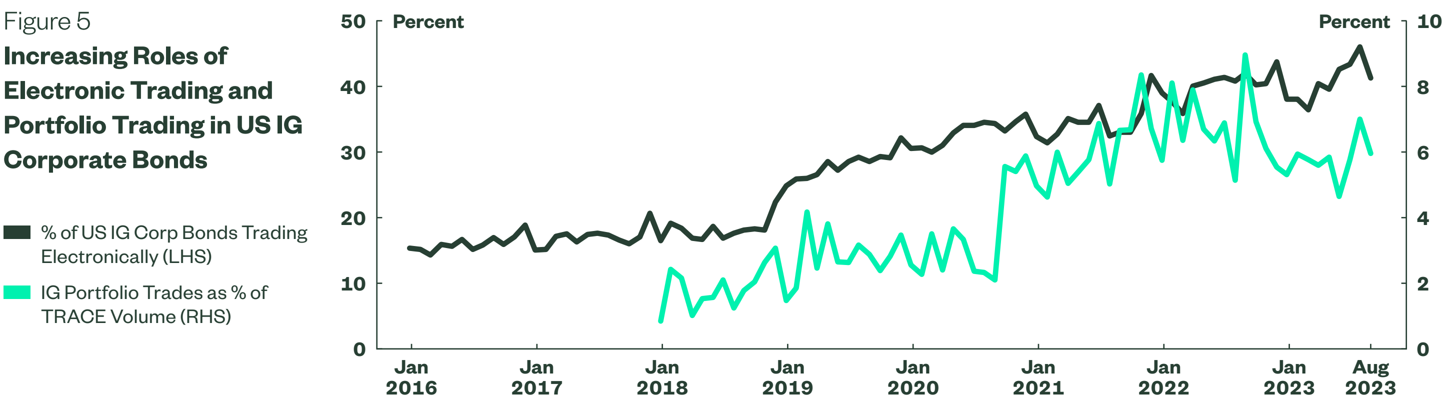
The rise in proprietary trading firms also strengthened liquidity in the financial system. Post-GFC, as banks grappled with new regulations, prop firms filled the void by making markets and offsetting the fall in liquidity caused by banks' lower appetite for holding risky assets on their balance sheets.

Portfolio Trading

Finally, portfolio trading has emerged as a growing force in credit markets. While ETF trading improved liquidity for many IG bonds, this effect was mostly limited to those owned by ETFs, which tend to be the most liquid ones in the market. This effect provided little help to managers who sought to express relative value views about less-liquid issuers. The latest innovation in corporate bond markets, portfolio trading, offers more such help. In this new custom protocol, an investor can submit to one or more dealers a request for a buy or sell quote on a basket of bonds to be purchased in a single transaction. The number of trades executed using this protocol has grown over the past few years. Meli and Todorova[27] have demonstrated that by including illiquid bonds in a portfolio trade along with more liquid ones, managers have been able to achieve a substantial reduction in transaction costs for the less-liquid bonds. Portfolio trading therefore presents an important new tool that enables systematic credit portfolio managers to transact efficiently in the securities with the desired factor exposures. Figure 5 details the recent growth in electronic trading and portfolio trading in the US IG corporate bond market over the past few years.

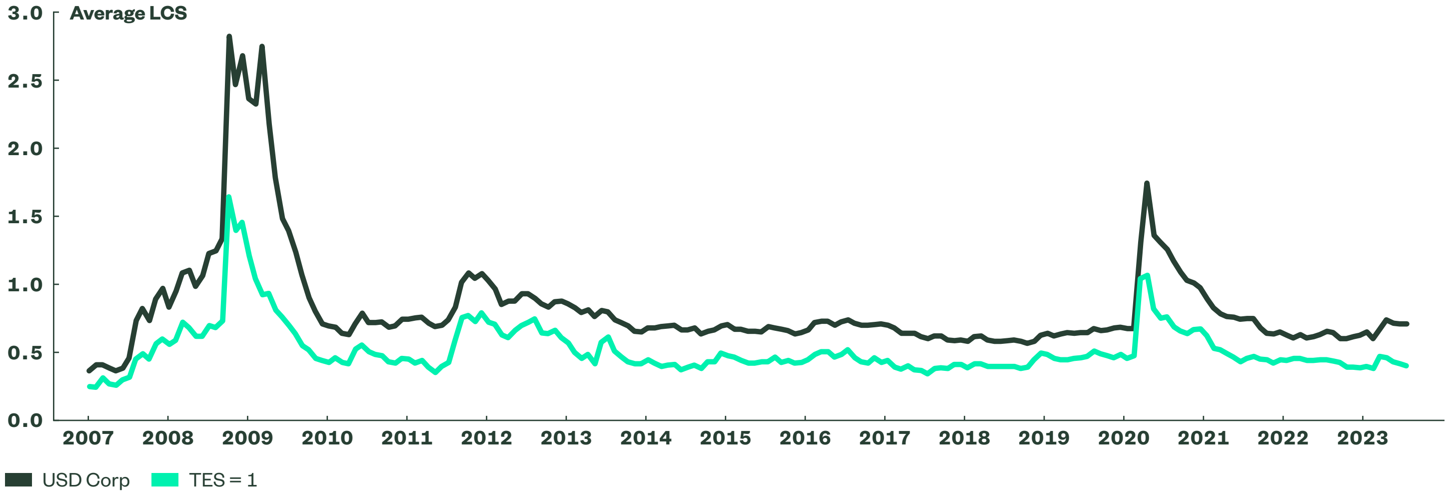
Figure 5

Increasing Roles of Electronic Trading and Portfolio Trading in US IG Corporate Bonds



Source: TRACE, Greenwich MarketView, Barclays Research. Note: Electronic calculations include all volume reported by the trading venues as fully electronic. Total volume as reported by TRACE. Data from January 2016 through September 2023.

Figure 6 **US IG Liquidity Has Improved Significantly Since 2010**



Source: Barclays Research. Data from January 2007 through July 2023.

Due to this combination of developments, corporate bond liquidity has improved substantially over the past decade, bringing down the cost of trading. Figure 6 shows how LCS has changed over time, for the average of all index bonds and for the most liquid segment, as measured by the TES. We see that trading costs declined steadily from 2012 through 2018, and again following the COVID-19 shock of 2020. While the average LCS for the index has increased somewhat in 2023, this has not had a significant effect for the most liquid bonds, for which LCS is near its 2017 low, with an average round-trip transaction cost of about 0.4%.

As a result of these changes in the trading environment, systematic active strategies in credit have now become viable. Information about individual bonds, including pricing, liquidity, credit rating, and other characteristics, is more readily available. New trading venues and protocols give managers more flexibility in execution.

Data-driven, systematic security selection can thrive in this information-rich environment. A systematic approach to credit selection casts a wider net when seeking opportunities, as it evaluates the entire security universe when considering opportunities versus the more focused fundamental strategies. Furthermore, systematic strategies do not typically hold large, concentrated positions in individual securities, but rather take a diversified approach, with many small exposures. This strategy type suits a trading environment that is tilted toward electronic and basket trading and allows investors to benefit from scale efficiencies.

4 Case Study: Developing a Realistic Systematic Credit Strategy

To flesh out the type of results that can realistically be expected from a systematic investment program, we present a detailed case study in the US IG corporate bond market. We start with three style factors that have been shown to be related to future outperformance, explore some of the key aspects of portfolio construction needed to integrate the corresponding signals into the ongoing rebalancing of the portfolio, and analyze the performance of the resulting strategy in backtests. A comparison of these results against a database of actual track records of active managers shows that the systematic strategy's risk-return trade-off compares favorably and is complementary to fundamental active strategy returns.

Examples of Style Factors

Value

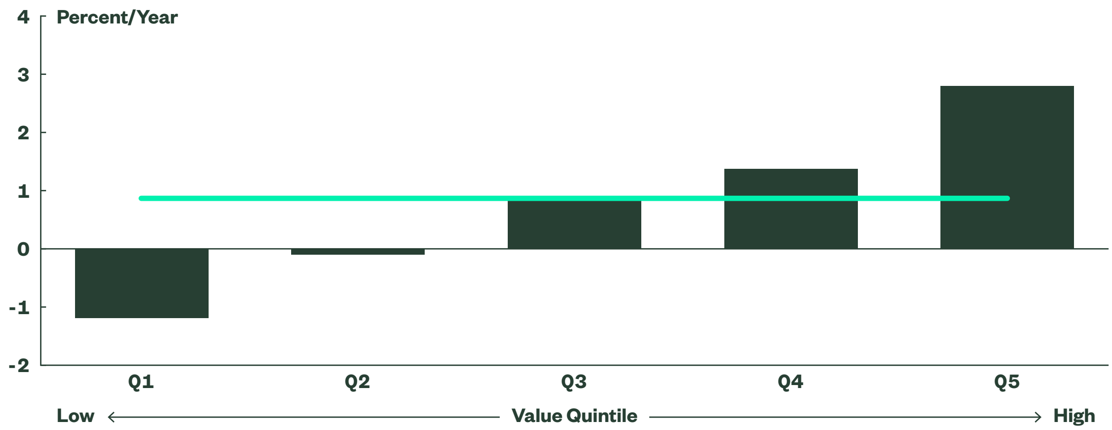
Value investing has been used successfully across all asset classes. The idea is simple: identify assets whose current market prices are below what a quantitative model infers to be their fair value. Eventually (and hopefully sooner rather than later), the market will adjust its views and these assets will appreciate relative to their peers as their price reverts to fair value. In the equity market, as previously discussed, Fama and French[28] formulated this approach in terms of ratios such as book-to-market value. However, the fair value of a corporation is very difficult to estimate, as it requires, among other aspects, predicting earnings far into the future. In credit markets, valuation is a much more precise science; the promised cash flows from a corporate bond, absent default, are known. These are discounted at a spread over the Treasury curve to arrive at the present value of the bond, where the spread used for a particular bond should be commensurate with its exposure to default risk. Relative value can, thus, be identified by comparing the spread of a bond to those of other similar securities.

A value measure described by Ben Dor et al[29] follows this logic, using a two-step approach to identify value in credit securities. In the first, the corporate bond market is partitioned into peer groups by industry and quality. At this stage, excess spread over the peer group average can be considered to be a first-order measure of value. However, there may be a good reason, based on company fundamentals, for the bonds of a given issuer to trade wide of their peers. To reflect this, a second step is carried out to determine how much of the excess spread of a bond is due to weaker fundamentals. The unexplained excess spread over the peer group is the measure of value that is then used to rank bonds within each peer group.

Backtests show that value, computed in this way, is a good predictor of corporate bond outperformance. Figure 7 shows that if we divide the corporate bond market into value quintiles and compute their respective long-term average risk-adjusted excess returns,[30] performance monotonically increases across quintiles, with the highest-value quintile earning excess returns of almost 3% per year, while the lowest-value quintile earns -1% per year.

Figure 7
Average Excess Returns by Value Quintile

Value Quintile
US Corp IG Index



Source: Bloomberg, Barclays Research. Data from February 2007 through September 2020. Data for US IG corporate bonds, DTS-adjusted.

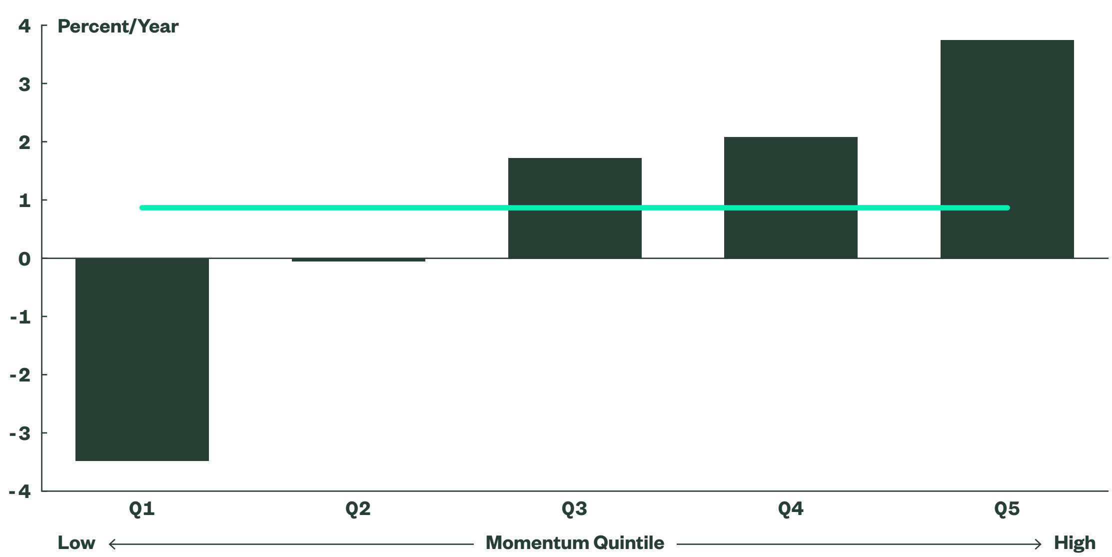
Momentum

Momentum is another pervasive investment theme across asset classes. Assets that have outperformed their peers often continue to do so. Many explanations for this phenomenon have been put forward based on behavioral economics, including herding, fear of missing out, and delayed integration of new information. Momentum can be applied within a single asset class, such as the assumption that a stock that has appreciated more than its peers in the past will continue to outperform.[31] Alternatively, it can be applied on a cross-asset-class basis: a company whose stock has outperformed in the recent past will have its bonds also outperform their credit peers. This is a logical expectation, given that the better liquidity in the stock market allows it to integrate new information much more quickly than the bond market.

Ben Dor et al[32] have shown that a cross-market momentum signal of this type, based on equity market momentum, has been strongly associated with bond market performance over the long term. As Figure 8 shows, bonds ranked in the top quintile by this momentum signal outperformed those in the bottom quintile by 7% per year in long-term average risk-adjusted excess returns.

Figure 8
Average Excess Returns by Momentum Quintile

Momentum Quintile
US Corp IG Index

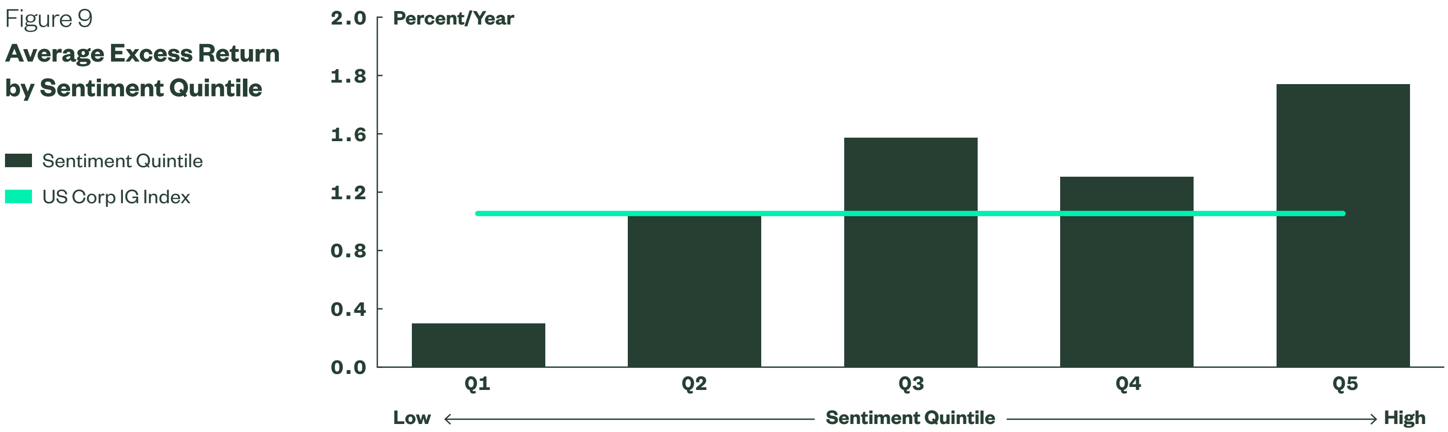


Source: Bloomberg, Barclays Research. Data from February 2007 through September 2020.

Sentiment

Sentiment is a broad category of information and essentially refers to anything that can give a directional indication of the public mood regarding a particular company or security. Sentiment indicators can be gleaned from news sources, social media feeds, or more traditional financial data such as options market positioning or short interest. For our case study, we will use an indicator based on short interest data from the equity market. Ben Dor et al[33] show that this indicator can be useful in predicting performance in the equity and credit markets. Figure 9 shows that corporate bonds in the top quintile, when ranked by this sentiment measure (i.e., bonds from the least shorted issuers), have outperformed the index, while those in the bottom quintile (bonds from the most shorted issuers) have underperformed.

Figure 9
Average Excess Return by Sentiment Quintile



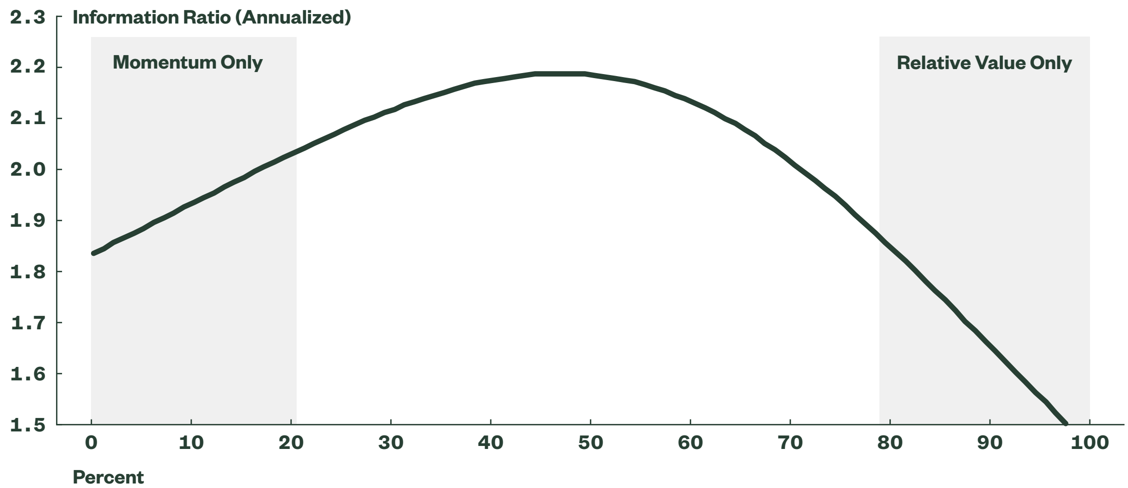
Source: Bloomberg, Compustat, FIS Astec Analytics, Barclays Research. Data from February 2007 through September 2020.

Combining Signals

When more than one signal is available for the same universe of securities, portfolio performance can be enhanced by basing security selection on the combination of all available signals. Diversification benefits obtained from combining factors increase as their cross-correlations decrease. This is because different factors do well under different market conditions, and even if one factor underperforms in a particular period, the other factors can shield the portfolio from large drawdowns. Polbennikov, Desclée and Dubois demonstrate this effect for value and momentum strategies. They find that portfolios with a value tilt tend to have procyclical performance, underperforming the index during credit market downturns. However, portfolios with a momentum tilt have tended to outperform during these incidents. The authors suggest that this type of diversification is a major reason that a combination of these two signals has achieved a higher information ratio in backtests than either signal on its own.

Figure 10 illustrates this diversification effect under the single-signal portfolio combination paradigm. Here, the highest-value quintile portfolio and the highest-momentum quintile portfolio are constructed separately, as described above, then mixed together using different allocations. We find that a blend of about 50% value and 50% momentum strategies achieves the best performance, with an information ratio of 2.2 (before transaction costs). Further, when combining signals instead of portfolios, even better performance can be achieved. In this case, the two signals were first averaged together using equal weights, and the portfolio was chosen as the top quintile of bonds by this composite signal. As shown in Figure 11, this portfolio earned substantially higher returns over the study period, outperforming the index by an average of 4.5%/year (before transaction costs). While it also exhibited greater TEV than the more diversified portfolio combination approach, it outperformed on a risk-adjusted basis, with an information ratio of 2.3 over the same period.

Figure 10
Information Ratio Achieved by Combination of Value and Momentum
Top-Quintile Portfolios



Source: Bloomberg, Barclays Research. Data from February 2007 through September 2020.

Figure 11
Performance of Value and Momentum Factors: Combining Signals versus Combining Portfolios

	Absolute Performance			Performance Relative to Index		
	Avg. Excess Return (%/Year)	**Excess Return Volatility (%/Year)**	**Information Ratio**	**Avg. Excess Return (%/Year)**	**TEV (%/Year)**	**Information Ratio**
Bloomberg US Corp IG	0.88	6.18	0.14	—	—	—
Top Value	2.80	6.56	0.43	1.92	1.31	1.47
Top Momentum	3.77	5.87	0.64	2.90	1.57	1.84
Combined Portfolios 50/50	**3.29**	**6.15**	**0.53**	**2.41**	**1.09**	**2.20**
Combined Signals 50/50	**5.38**	**5.94**	**0.90**	**4.50**	**1.95**	**2.31**

Source: Bloomberg, Barclays Research.

Portfolio Optimization in a More Realistic Setting: Matching Risk and Constraining Turnover

Quintile analysis of the type shown in Figures 7 through 11 is just one of the first steps in identifying a factor and demonstrating that it is informative with regard to future returns. The factor quintiles whose performance is depicted represent collections of bonds that vary from month to month and may differ substantially (from each other and from the index) in terms of important exposures to other factors. Furthermore, their performance is calculated by aggregating the bond-level monthly returns as reported by the respective indices, with no adjustment for transaction costs. Additional work is required to show that a given signal can be used to construct a diversified portfolio that can generate sustained alpha after transaction costs.

When constructing an actual portfolio to implement a systematic trading strategy, a more sophisticated approach is called for. As described above, the optimal portfolio cannot simply be formed from the set of bonds with the highest signal scores. First, the portfolio must be formed only from the subset of the bond universe that is sufficiently liquid to trade, to make execution viable. Second, it must maintain a close match to index risk characteristics, to minimize tracking error volatility relative to the benchmark. Third, transaction costs must be accounted for. This means that performance must be reported net of transaction costs and that the optimization process must consider what is already in the portfolio, so that trading costs can be controlled by a constraint on portfolio turnover.

Polbennikov, Desclée and Dubois followed such a procedure to construct a dynamically rebalanced portfolio based on a combination of value and momentum strategies, relative to the Bloomberg US IG Corporate Bond Index. In any given month, the set of bonds available to be purchased into the portfolio is restricted to the most liquid portion of the index, as measured by TES. Risk relative to the benchmark was controlled by constraints that targeted benchmark option-adjusted duration (OAD), option-adjusted spread (OAS) and DTS. Sector exposures of the portfolio were forced to match approximately those of the benchmark, as were exposures by credit rating and seniority. To limit the amount of issuer-specific risk taken by the strategy, upper bounds were placed on issuer overweights relative to the benchmark. Subject to these constraints, an optimization was run to find the set of transactions that maximize the combined signal score, which was a weighted average of the two signals. Within this tightly risk-controlled framework, the authors tested whether these signals can be used to construct a diversified portfolio that can generate sustained alpha even after transaction costs. To do so, they imposed a turnover budget — the maximum amount of portfolio turnover allowed in any month — and backtested the portfolio rebalancing for different values of the maximum allowed turnover.

This procedure was repeated at the start of each month, and the resulting optimal portfolio was used to calculate the strategy return for the subsequent month. Transaction costs were measured using LCS, which give a conservative estimate of the trading cost for each bond, and subtracted from the strategy returns. The performance of the value/momentum strategy, net of estimated transaction costs, is shown in Figure 12. Panel A shows that while transaction costs increase linearly with the allowed turnover, the outperformance generated by the strategy does not. Increasing the allowed turnover budget from zero leads to a steep increase in average alpha, but this levels off to a gentler slope above a critical level of about 10% turnover per month. As a result, as shown in Panel B, both the average alpha and the information ratio achieved by the strategy after transaction costs show a peak at a turnover of 11% per month in this backtest.

This exercise shows the critical importance of controlling turnover. If the optimization were run on an unconstrained basis, strategy performance net of transaction costs would have been negative, despite the high information content of the value and momentum signals. However, with turnover constrained to about 10% per month, the strategy was able steadily to outperform the benchmark on a risk-adjusted basis, generating a long-term information ratio of over 1.0 net of transaction costs.

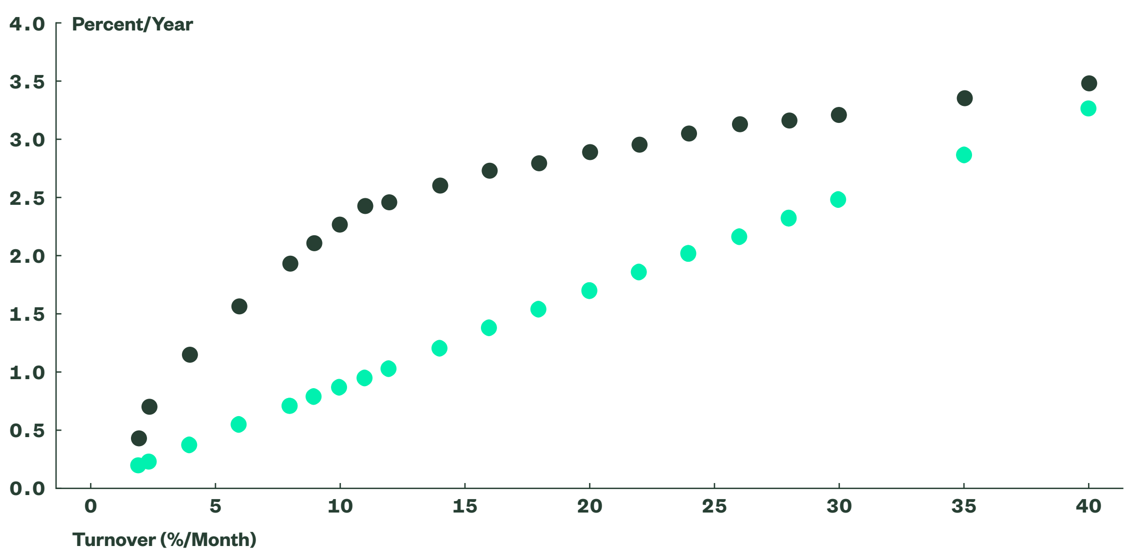
Figure 12a

Performance of Strategy Portfolios Over Index as a Function of Turnover

Average Excess Return Over Index and Transaction Costs versus Turnover Budget

Excess Return Over Index

Transaction Costs

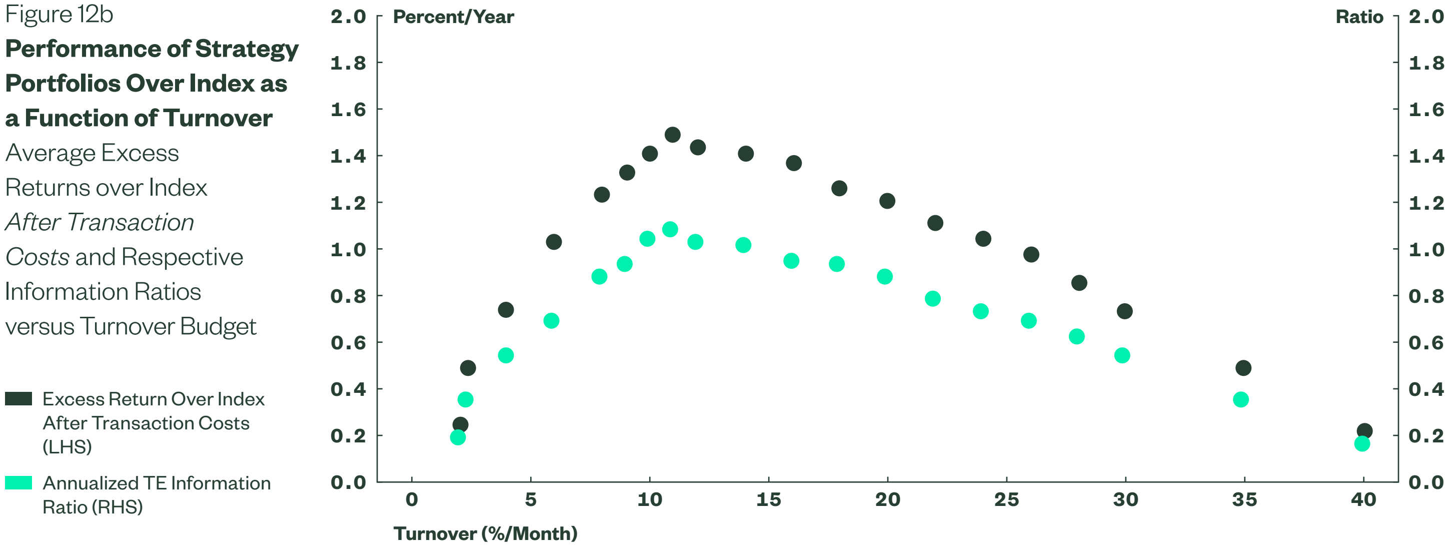


Source: Bloomberg, Barclays Research, data as of February 2007 through September 2020.

Figure 12b

Performance of Strategy Portfolios Over Index as a Function of Turnover

Average Excess Returns over Index *After Transaction Costs* and Respective Information Ratios versus Turnover Budget



Source: Bloomberg, Barclays Research, data as of February 2007 through September 2020.

Measuring the Performance of a Systematic Credit Strategy

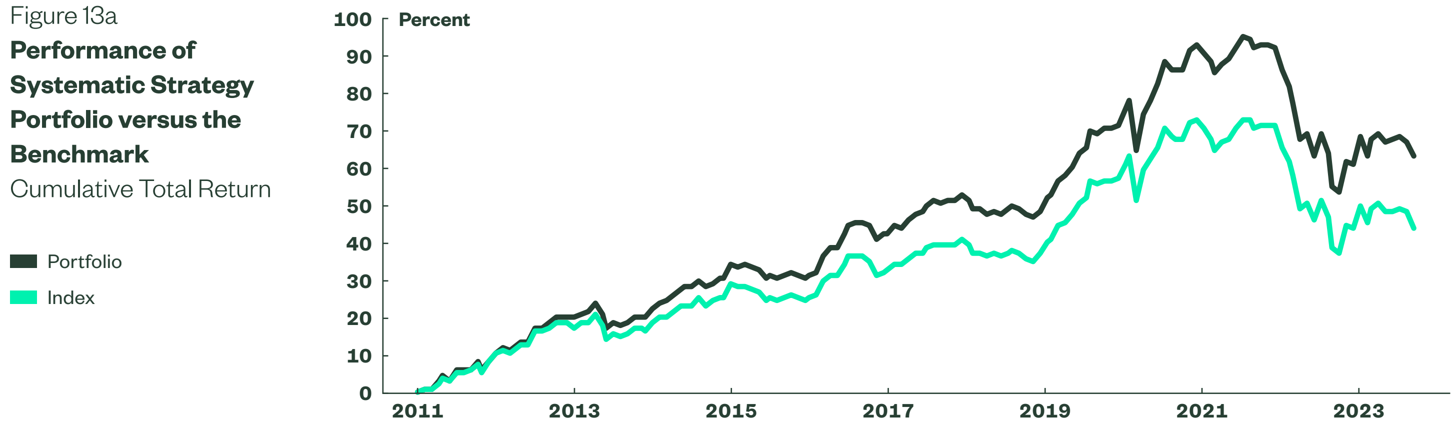
We now extend our backtest to incorporate all three of the quantitative signals outlined above, using a similar methodology for portfolio construction. With the help of these results, we can compare the potential performance of a systematically managed credit portfolio with that of more traditional active managers. The need for a realistic backtest stems from the lack of an industry track record in systematic credit management. Indeed, there are few asset managers running credit mandates on a systematic basis, and their live track records exist for only recent periods.

Our case study features a portfolio managed against the Bloomberg US IG Corporate Bond Index. As explained above, it must conform to a number of allocation and risk exposure limits relative to the index, which help keep its TEV small. Interest rate risk is controlled by constraints on portfolio OAD and KRDs; spread risk is controlled by constraints on DTS, both overall and by sector; and idiosyncratic risk is controlled by limits on issuer concentrations. Within these limits, the portfolio is systematically tilted to maximize its exposure to an equally weighted composite of our value, momentum and sentiment signals. Consistent with the spirit of relative-to-index management, the portfolio is rebalanced at each month-end. This frequency is synchronized with index rebalancing and ensures that the portfolio risk profile remains aligned with its benchmark. Periodic rebalancing is also needed to exploit the information contents of the signals considered.

The backtest includes a turnover limit of 10% per month.[34] This is motivated by several considerations. It needs to be large enough to control risk effectively relative to the index every month and to exploit the changing information in our signals, in line with the typical turnover in traditional actively managed credit portfolios. At the same time, turnover needs to be sufficiently low so that transaction costs do not overwhelm performance.[35] All backtest results are presented net of conservatively estimated transaction costs, based on LCS. This performance pattern is obtained with a purely rules-based approach, with the same set of rules being applied throughout the entire analysis. Results are therefore independent from any discretionary management decisions and free from any behavioral biases.

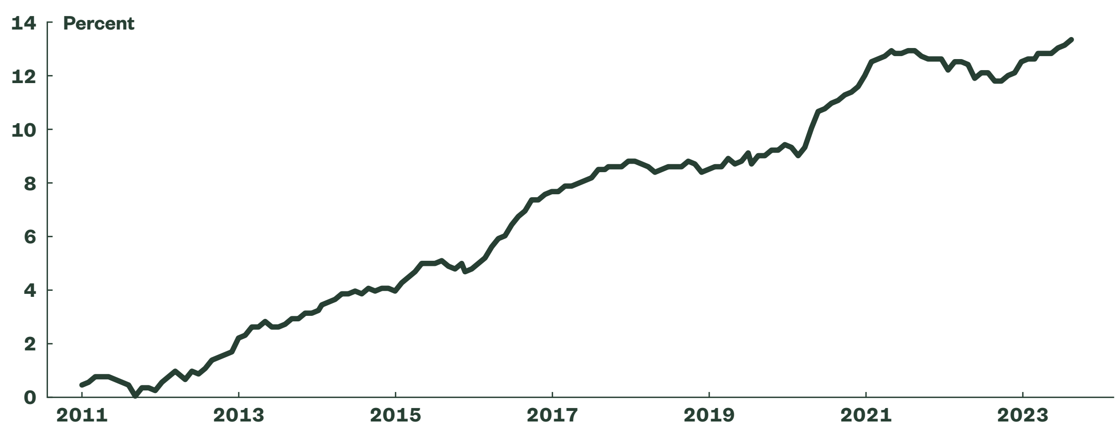
The results of our backtest, from January 2011 through September 2023, are shown in Figure 13. Over these nearly 13 years, the portfolio outperformed the index by 97bp annually after transaction costs. The annualized volatility of monthly tracking errors over the index was 61bp/y, resulting in an information ratio of 1.6. As shown in Panel B of Figure 13, the strategy has exhibited a pattern of consistent outperformance. While several drawdown episodes were observed, the maximum decrease was 100bp, and the strategy subsequently resumed its typical growth.

Figure 13a
Performance of Systematic Strategy Portfolio versus the Benchmark
Cumulative Total Return



Source: State Street Global Advisors, Barclays Research. Data as of January 2011 through September 2023.

Figure 13b
Performance of Systematic Strategy Portfolio versus the Benchmark
Cumulative Outperformance

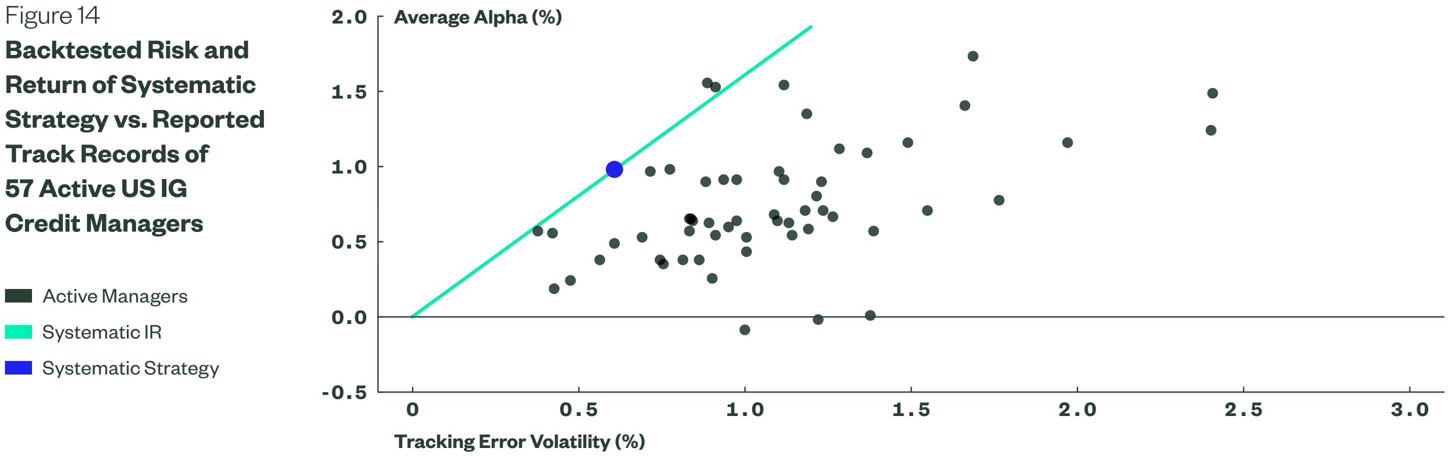


Source: State Street Global Advisors, Barclays Research. Data as of January 2011 through September 2023.

The backtested portfolio performance can be compared with the performance of traditional credit managers. To that effect, we turn to the eVestment[36] database and find a group of 57 institutional managers that have reported live track records of portfolios that they actively managed against the Bloomberg IG Corporate or Credit index from January 2011 through September 2023. Compared with this peer group, the systematic portfolio in our case study would have delivered a strong average outperformance over its benchmark (14th highest of 58). Due to its tight exposure limits and disciplined portfolio construction rules, the systematic portfolio's TEV was quite low relative to peers (7th lowest of 58). As a result, the systematic strategy would have had a high information ratio (3rd highest of 58). The risk-return characteristics of the systematic portfolio and actively managed peers are summarized in Figure 14. Only the two managers that appear above the dotted line achieved higher risk-adjusted returns than the systematic portfolio.

Figure 14

Backtested Risk and Return of Systematic Strategy vs. Reported Track Records of 57 Active US IG Credit Managers



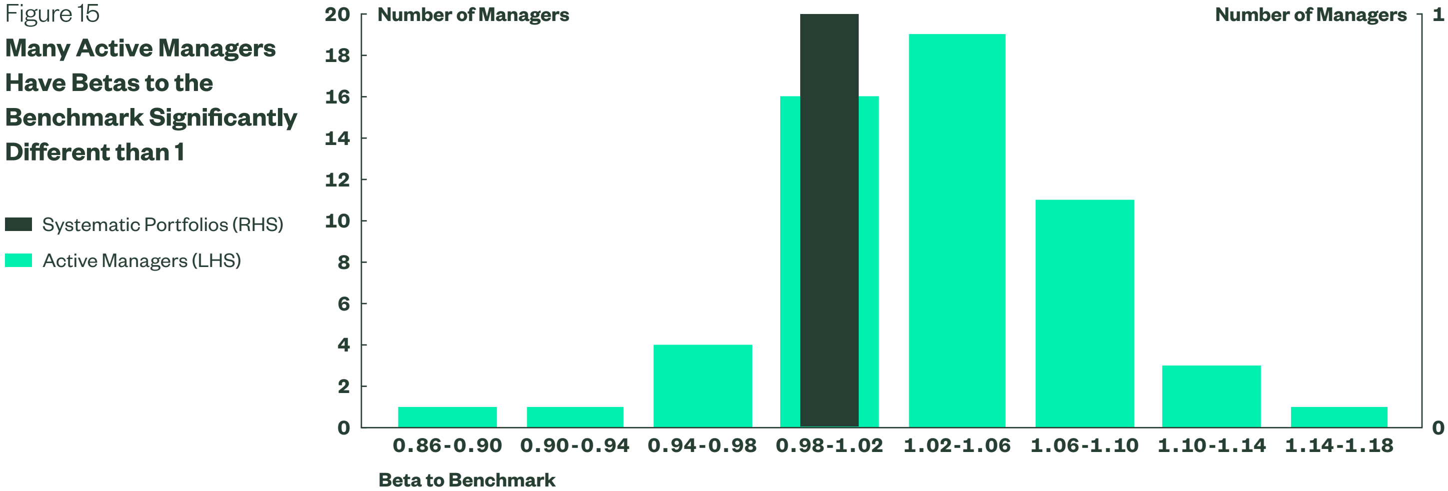
Source: State Street Global Advisors, eVestment, Barclays Research. Data as of January 2011 through September 2023. **The data displayed for the systematic backtest is a hypothetical example of Back-Tested Performance for illustrative purposes only and is not indicative of the past or future performance of any State Street Global Advisors product.** Back-tested results are not indicative of the past or future of any State Street Global Advisors product. The portion of results through September 30, 2023 represents a back-test of the systematic model, which means that those results were achieved by means of the retroactive application of the model which was developed with the benefit of hindsight. All data shown above does not represent the results of actual trading, and in fact, actual results could differ substantially, and there is the potential for loss as well as profit. Please reference Back-tested Methodology Disclosure for a description of the methodology used as well as an important discussion of the inherent limitations of back-tested results.

The active returns of the systematic portfolio were generally positively correlated with those of traditional peer managers: correlations between monthly returns of the systematic and any of the peers ranged from -0.16 to +0.62 over the past 13 years, with an average of 0.30. The average correlation with other managers was lower than that of 31 of the 57 peers considered. This indicates that a systematic mandate exploiting issuer selection strategies can usefully complement an allocation to traditional credit managers.

The systematic portfolio for which this backtest is constructed is designed to be close to the index at all times. In addition, it does not engage in any macro allocation decisions such as timing duration or the direction of overall credit spreads. Consequently, its overall market exposure, measured as beta relative to the index, is neutral. This is unlike most active managers, as shown in Figure 15. Indeed, the majority (35 of 56 active manager peers) had a beta significantly larger than one in the period considered, effectively over-exposing their sponsors to benchmark risk, while a few of them delivered below-market exposure. Only 21 of 56 peer managers produced performance that was not statistically significantly different from index beta over the past 13 years.

As mentioned, the systematic portfolio did not outperform the benchmark every month and exhibited some drawdown episodes. One possible reason for underperformance is that portfolio construction parameters, in particular, turnover control, prevent rebalancing from reflecting rapidly changing signal values. This problem could be addressed with more advanced techniques of managing transaction costs than using just a 10% limit on monthly turnover.

Figure 15
Many Active Managers Have Betas to the Benchmark Significantly Different than 1



Source: State Street Global Advisors, eVestment, Barclays Research.

Portfolio underperformance can also appear when selection signals are not predictive of bond performance. For example, a value signal would not be expected to perform very well in the presence of indiscriminate purchases by value-insensitive investors such as central banks as they engaged in quantitative easing. Also, market environments characterized by low dispersion in spreads and, hence, in signal value across issuers, are not favorable to relative value strategies for bond selection. Momentum strategies can be vulnerable to sudden reversal. Sentiment strategies might be more suited to avoiding risky names than to selecting outperformers and may not be able fully to prevent the effect of adverse market environments on overall strategy performance.

Longer term, there is of course a risk that systematic signals might be arbitraged away as they become commoditized. We would argue that while signal performance cannot be guaranteed, some persistence should be expected when their definition rests on sound economic and empirical findings documented and backtested over decades. Relative value can be measured much more objectively in credit than in equity, given the known cash flow schedules of corporate bonds. In addition to spread carry, relative value captures mean reversion in spread, in which bonds that trade wide to their peers tend to revert to fair value. This could be due simply to a realignment of investor views, or to corrective actions taken by corporate issuers as they seek to maintain access to the primary bond market and competitive funding rates. This behavior is likely to persist.

Similarly, momentum, especially cross-asset momentum, is an empirical fact observed for decades; sentiment, as represented by short interest activity, is an objective, measurable and intuitive indicator of the active views of informed investors.

Moving from a backtest to practical implementation can entail significant challenges. It is natural to wonder whether any backtest is realistic enough to be compared with the realized returns of active managers and, accordingly, whether practical remedies can be applied when running live credit portfolios. Two aspects of the analysis deserve scrutiny: the identification of bonds deemed liquid enough to be included in rebalancing and the measurement of transaction costs. The backtest presented here filters the investment universe to limit it to securities with high trading volume and low estimated transaction costs. Although it narrows the transaction universe to a fraction of the index universe, such a filter might not always be fully effective and could lead to the strategy's attempting to trade bonds that are difficult to source. Implementing a systematic strategy should therefore come with the freedom to perform substitutions, replacing bonds that are hard to trade with similar ones with high signal values. In addition, the growth in electronic trading, in particular in portfolio trading of corporate bonds, should facilitate the synchronized execution of baskets of bonds.

Transaction costs are estimated conservatively in the backtest, using bid-ask quotes from a single broker-dealer. The trading desk of an institutional investor should be able to put multiple broker-dealers in competition and therefore improve on such quotes. A possible factor to consider when evaluating the prospect for implementing systematic strategies is size: a large, high-volume execution desk should have better visibility on bond liquidity and be in a better position to control transaction costs.

5 Key Takeaways

We can now summarize the key elements required to build a successful systematic strategy.

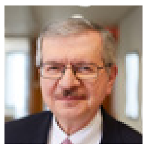
The first essential ingredient for a systematic strategy is a suite of signals that can help drive outperformance. These should identify bonds and/or issuers that are expected to deliver returns in excess of their peers with a similar risk profile. This information provides the directional basis for portfolio positioning at each rebalancing opportunity, subject to various constraints.

The second key component is a comprehensive approach to managing risk. To achieve the most risk-efficient performance gains, applying an intentional portfolio tilt towards desirable factor exposures should not come at the expense of taking unintentional risk in other dimensions. By carefully controlling exposures to all key risk factors while maximizing exposure to desired style factors, a systematic approach can sharpen the focus on performance-enhancing views and improve the information ratio.

The third requirement is an efficient implementation framework. In a theoretical exercise, we can calculate an optimal portfolio at the start of each month, track its performance, rebalance it without worrying about turnover, and show that it outperforms the benchmark before transaction costs. However, the turnover required for such rebalancing is likely to be significant, and the transaction costs could curtail, or even negate entirely, any outperformance benefits from the portfolio positioning. It is therefore critical that at each rebalancing date, the portfolio optimization is cognizant of current positioning and evaluates the trade-off between the signal-improving benefits of any potential trades against the transaction costs required to execute them. This requires that the execution framework integrate as much knowledge as possible of the liquidity landscape. Regardless, it is unreasonable to expect that the trades suggested by an optimizer will always be easy to execute. It is thus imperative to have an experienced, large-scale execution team that is able to understand the complex interactions between signals and risk exposures and is market savvy enough to be able to substitute hard-to-source bonds with more tradable alternatives to obtain the desired exposures within the constraints imposed by market liquidity.

With recent improvements in credit market liquidity and transparency, many of the barriers that previously hindered the implementation of systematic investing in credit have been lowered. Systematic investing presents investors with an attractive alternative to fundamental active management. It harnesses quantitative models to build a highly diversified portfolio that avoids taking any large risks relative to the benchmark, but reflects a steady tilt towards factors that have historically been associated with outperformance. In our case study, we show that the backtested risk/return performance of a systematic credit portfolio compares favorably to the historical track record of active credit managers and has low correlations with their active returns. Thus, if a part of a fundamentally managed credit portfolio is allocated to systematic credit, it could provide effective diversification of active risk. Furthermore, the algorithmic nature of systematic investing should allow it to be delivered at a lower cost than a traditional actively managed alternative.

Authors



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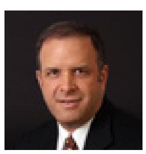

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Matt has a BA in Philosophy from Saint Anselm College, graduated with an MBA from Bentley College and has earned the Chartered Financial Analyst designation.

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Arkady earned the Chartered Financial Analyst designation in 2017 and is a member of the CFA Institute and the Boston Security Analysts Society. He holds a Master of International Business from The Fletcher School of Law and Diplomacy at Tufts University, and a BA in Quantitative Economics from Tufts University.

Endnotes

1 While the term "systematic strategy" can refer to any algorithmic data-driven signal — be it duration timing, sector rotation or security selection — in this article, we focus mainly on bond selection strategies and carefully match the benchmark in all other risk dimensions.

2 Grinold, Richard R. and Kahn, Ronald N., *Active Portfolio Management*, Second Edition, McGraw-Hill, New York, 1999, p. 148.

3 The expected return on the market portfolio is the equity risk premium of the market; however, in the representation of the CAPM in the formula $R_{it}=\beta_i R_{Mt}+\varepsilon_{it}$, we refer to the equity risk premium of the individual stock.

4 Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance*, 19:3, pp. 425-442.

5 Linter, J. 1965. "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics*, 47:1, pp. 13-37.

6 Grossman, S.J., and J.E. Stiglitz. 1980. "On the Impossibility of Informationally Efficient Markets," *American Economic Review*, 70:3, pp. 393-408.

7 For example, systematic downside risk in the three-moment CAPM of Rubinstein (1973) and Kraus and Litzenberger (1976) is difficult to measure ex-ante. Similarly, the hedging portfolios in the ICAPM of Merton (1973) and the factors in the APT of Ross (1976) are not precisely identified.

8 Fama, E. F., and French, K. R., "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics* 33, 1:3-56, 1993.

9 Litterman, R. and Scheinkman, J. (1991) "Common Factors Affecting Bond Returns", *The Journal of Fixed Income*, 1, 54-61, http://dx.doi.org/10.3905/jfi.1991.692347.

10 Ho, Thomas S. Y., "Key Rate Durations: Measures of Interest Rate Risks", *The Journal of Fixed Income*, September, 1992, 29-44.

11 Ben Dor, A., L. Dynkin, J. Hyman, P. Houweling, E. van Leeuwen, O. Penninga, DTS (Duration Times Spread), *Journal of Portfolio Management*, Winter 2007, 33(2): 77-100.

12 If such a macro strategy can be shown to be highly effective, it can be advantageous to include it, with appropriate risk controls, into a systematic portfolio. Strategies based on macro exposures have the advantage that they can often be executed using very liquid instruments, with substantially lower transaction costs. This allows breadth to be increased by adjusting views and positions more frequently. However, such high-frequency strategies are beyond the scope of this article and generally not expected in credit portfolios.

13 Arik Ben Dor, Albert Desclée, Jingling Guan, Alberto Pellicioli, and Simon Polbennikov, *The Relationship between Mispricing and Risk under DTS: Analysis and Implications for Investors*, Barclays Research, 5 May 2022.

14 Albert Desclée and Simon Polbennikov, *A Case for Rates Derivatives in Active Credit Portfolios*, Barclays Research, 27 January 2020.

15 In Section 3, we explore this issue in depth and review a number of developments that have improved liquidity in credit markets over the past decade.

16 Konstantinovsky, V., K. Y. Ng, and B. D. Phelps. 2016. "Measuring Bond-Level Liquidity," *The Journal of Portfolio Management* 42 (4): 116–128.

17 For a demonstration of the superiority of combining signals over combining portfolios in the context of equity style factors, see Shaun Fitzgibbons, Jacques Friedman, Lukasz Pomorski, and Laura Serban, "Long-Only Style Investing: Don't Just Mix, Integrate", *The Journal of Investing*, Winter 2017, pp. 153-164.

18 Simon Polbennikov, Albert Desclée, and Mathieu Dubois, "Implementing Value and Momentum Strategies in Credit Portfolios", *The Journal of Portfolio Management*, Quantitative Special Issue 2021, pp. 82-98.

19 Arik Ben Dor, Kareem Elnahal, and Stephan Florig, *Evaluating and Combining Systematic Credit Signals*, Barclays Research, 16 February 2023.

20 Arik Ben Dor and Jingling Guan, *Optimal Portfolio Construction: Incorporating Transaction Costs*, Barclays Research, June 2022.

21 Arik Ben Dor and Jason Xu, *Concessions in Corporate Bond Issuance: Magnitude, Determinants, and Post-Issuance Dynamics*, Barclays Research, January 2015.

22 For a more detailed description of this process of changes to corporate bond liquidity, see Arik Ben Dor, Albert Desclée, Lev Dynkin, Jay Hyman, Jeff Meli, and Simon Polbennikov, "Quantitative Management of Credit Portfolios", *The Journal of Fixed Income*, 30th Anniversary Special Issue 2022.

23 Meli, J., and S. Gupta. 2016. *Behavior Modification*, Barclays Research, June 8, 2016.

24 Meli, J., Z. Todorova, and S. Gupta. 2021. *The Rise of Institutional Investors in Bond ETFs* January 27, 2021. http://dx.doi.org/10.2139/ssrn.3774473.

25 An RFQ is a protocol in which platform users may query platform market-makers to request prices on an order of a particular size. Source: Bank for International Settlements.

26 O'Hara, Maureen and Zhou, Xing Alex, "The Electronic Evolution of Corporate Bond Dealers," *Journal of Financial Economics*, 140:2, May 2021, pages 368-390, https://doi.org/10.1016/j.jfineco.2021.01.001.

27 Meli, Jeffrey and Todorova, Zornitsa, "Portfolio Trading in Corporate Bond Markets" (December 5, 2022). Available at SSRN: https://ssrn.com/abstract=4295453 or http://dx.doi.org/10.2139/ssrn.4295453.

28 Fama, E. F., and French, K. R., "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 1: 3-56, 1993.

29 Ben Dor, A., Desclée, A., Dynkin, L., Hyman, J. and Polbennikov, S., *Systematic Investing in Credit*, Wiley, 2021, Chapter 13: Relative Value Investing in Credit Using Excess Spread to Peers.

30 Bond selection for quintile portfolios follows strict ranking by the selected signal, with no regard for risk exposures. To make sure that differences in returns are not influenced by random exposures to macro risk factors, we adjust the quantile portfolio returns in two ways. First, we use excess returns over duration-matched Treasuries rather than total returns to remove the effect of yield curve exposures. Second, the average excess returns of the quantile portfolios are scaled by DTS such that they can be compared on a risk-equivalent basis.

31 This is actually a rather complex example. Momentum is such a strong force in equity investing that it often leads to overshoot, which is then followed by a reversal. As a result, rather than looking at the past 12 months of performance, the standard equity momentum factor excludes the past one month from its performance record (see, for example, Fama, E. F. and K. R. French, “Size, value and momentum in international stock returns” (2012), *Journal of Financial Economics*, 105:3, pp. 457-472). In fact, a separate factor based on the past one-month performance is used in the opposite direction, to measure the exposure to a short-term reversal factor.

32 Ben Dor, A., Desclée, A., Dynkin, L., Hyman, J. and Polbennikov, S., *Systematic Investing in Credit*, Wiley, 2021, Chapter 15: Equity Momentum in Credit.

33 Ben Dor, A., Desclée, A., Dynkin, L., Hyman, J. and Polbennikov, S., *Systematic Investing in Credit*, Wiley, 2021, Chapter 21: Equity Short Interest as a Signal for Credit Investing.

34 One somewhat unfortunate but unavoidable result of constrained turnover is that portfolio composition and performance are path-dependent: a portfolio initiated at an earlier or later date would have slightly different performance. We have carried out robustness checks on sensitivity to the start date of the backtest, but do not report them for the sake of brevity.

35 This static turnover budget approach is used for simplicity. However, as discussed in the previous section, other approaches can be more efficient, as the need for risk-motivated rebalancing and the expected value, net of transaction costs, of the selection signals can change over time. More sophisticated approaches could potentially improve strategy efficiency relative to the reported results.

36 eVestment, a part of Nasdaq, provides institutional investment data, analytics and market intelligence covering public and private markets.

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* Pensions & Investments Research Center, as of December 31, 2022.

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