QUANTITATIVE PORTFOLIO STRATEGIES

Value of Skill in Macro Strategies for Global Fixed Income Investing

- We explore the issues faced by portfolio managers trying to outperform a broad global benchmark using macro strategies.
- We select a set of strategies that express views on the main risk factors that drive global bond returns. These include exchange rates, yield curve shift and twist, and exposures to credit and core-plus asset classes. The strategies are designed such that each targets a singe type of risk exposure while remaining neutral to all others.
- A risk budgeting framework is used to monitor the risk of each strategy and keep overall portfolio risk at a desired level.
- We use an “imperfect foresight” approach to simulate the performance of each strategy at a given skill. Skill is simulated historically using the benefit of hindsight by tilting the investment choices toward the winning ones more often than randomly. Barring any external constraints, we find the performance of the various strategies to achieve similar results for a given level of skill. We demonstrate the performance impact of two specific types of constraints: the “no short” constraint for core-plus asset classes and the “no leverage” constraint for implementing duration views.
- We investigate various aspects of combining strategies, as strategy diversification should improve risk-adjusted performance. We describe a method for assigning risk budgets to multiple strategies.
- We study the optimal allocation of risk as a function of the skill at the various strategies and the correlations between them. Even if a manager is most skilled at a particular strategy, performance can be improved by allocating some of the risk budget to another strategy that offers significant diversification. Similarly, even though a core-plus strategy suffers from a “no short” constraint, it can be a beneficial component of a combination strategy, especially if it has low correlations with the core strategies.

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MOTIVATION

Global fixed income investors have experienced a major shift in the landscape over the past few years. Five years ago, global fixed income mandates were almost universally benchmarked against indices of global government debt, but there were many opportunities for astute managers to add value. A manager might have considered views on a dozen different currencies and yield curves before setting a portfolio's allocation. In the period leading up to EMU, convergence trades provided a consistent source of alpha for believers.

With monetary union a reality, global bond portfolio managers suddenly found themselves with a much smaller opportunity set for generating outperformance within the investment universe. There are now just a handful of currencies and yield curves on which to form views. To make matters worse, the increasing globalization of the world economy has made even those few remaining currencies more closely linked to each other. In particular, interest rate movements in the U.S. and Europe are more highly correlated than before.

In response to this loss of diversification within the global government debt universe, investors have sought to expand their efforts to new horizons. The most natural step is the inclusion of investment-grade credit and collateralized debt. The rapid rise of the Barclays Capital Global Aggregate Index, which now serves as a benchmark for debt portfolios totaling over $300 billion, attests to the strength of this trend. The search for higher returns and greater diversification has even prompted investors to look beyond investment-grade. More than $65 billion is currently benchmarked to the Global Universal Index, which combines the Global Aggregate with high yield and emerging markets debt. Even for portfolios still benchmarked against all-government indices, these additional asset classes may be used in many cases as out-of-index investments.

Building active management capabilities for all subsets of the Global Aggregate Index within a domestic boutique is likely to entail massive new investment to develop security selection skills and solve complex implementation issues. As an alternative way to maintain significant excess returns and attractive information ratios, many global fixed income managers adopt an investment framework based on macro-level asset allocation. This approach entails much lower entry cost, and can be implemented inexpensively and efficiently if derivatives are allowed. Many of these managers invest in non-index asset classes such as high-yield, credit, emerging market debt, and inflation-linked securities. The use of asset classes outside of the benchmark is often referred to as a "core+" strategy.

With the inclusion of these additional asset classes in the investment set, managers now have many choices of how to position their portfolios, from the macro to the micro level. The main question, of course, is where to focus the research effort. Of all the macro strategies available, will the best risk-adjusted returns be achieved by skilled timing of exposures to yield curves, foreign exchange rates, credit sectors, or core-plus asset classes? This study addresses this issue using the "imperfect foresight" methodology[1] to simulate skill at a broad set of macro strategies for global investing.

We include a fairly broad set of classical strategies based on yields and FX rates within the global government market. The first level is a global duration call, in which the portfolio chooses whether to go long or short duration on a global basis, with exposures taken in the same direction in all currencies. Next is a market duration strategy, in which a duration

[1] *Value of Security Selection versus Asset Allocation in Credit Markets: Part II—an "Imperfect Foresight" Study*, Lehman Brothers, June 2000.

overweight in one currency is offset by an underweight in another. Yield curve twist strategies (steepening or flattening) are implemented on a single-currency basis in each of the G3 currencies. The currency allocation is viewed as an independent decision that is layered on top of whatever bond positions are selected by cross-hedging to achieve the desired set of FX exposures.

We also investigate a number of strategies based on allocations to additional market segments. The sectors covered are investment-grade credit, high yield credit, emerging markets, and inflation-linked securities. While conceptually these are global strategies, we show example implementations of each of these strategies in a single-currency framework. We look at investment grade credits on an excess return basis versus treasuries in both the U.S. and euro markets, U.S. TIPS relative to U.S. Treasuries, and USD-denominated high yield and emerging market debt.

Risk Budgeting by Investment Committees

In our simulation of the various yield curve and foreign exchange strategies, we have included a simple model of a *risk budgeting* process. We recognize that *ex ante* risk analysis has become an intrinsic part of the portfolio management process. Before a particular strategy is implemented, the tracking error[2] incurred is projected based on the asset class volatilities and correlations observed to date. This allows a manager to scale the position sizes for each strategy to achieve a targeted amount of risk. This procedure allows us to compare the performance of different strategies operating under the same *ex ante* risk constraints, as opposed to simply analyzing the results on a risk-adjusted basis after the fact. It has been claimed[3] that the use of risk budgeting in this way can improve risk-adjusted performance by both increasing mean return and decreasing its volatility. In addition, we will discuss the use of risk budgeting to allot the total amount of risk among the various dimensions (or decision-makers).

Effect of Constraints

Portfolio managers often operate under mandates that include constraints of various types. Some constraints may be unavoidable due to regulatory or operational requirements; others serve to protect investors against various types of risk. When they curtail the ability of managers to implement their views fully, such constraints can reduce performance.

In this article, we will investigate the effect on performance of two relatively common types of constraints. The first is the long-only constraint that often governs the use of core-plus assets in a portfolio. Many global aggregate mandates allow (limited) long positions in high yield or emerging markets assets, but no short positions. As the index has zero weight in these assets, this allows managers to overweight these sectors but not to underweight them. When research results in a negative view on these assets, this view can not be put to use to enhance portfolio performance.

The second type of constraint that we consider is a related one that is often applied even within government bond markets—the “no leverage” or “cash” constraint. Under this constraint, a portfolio may consist only of long positions in cash and securities. If these

[2] racking error is the standard deviation of the performance difference between a portfolio and its benchmark. For a detailed discussion of the calculation of tracking error and risk model applications, see *The Lehman Brothers Multi-factor Risk Model*, Lehman Brothers, July 1999. In this paper, tracking error is not calculated using a multi-factor model, but with a simpler approach involving the covariance of asset class returns. However, the risk budgeting techniques that we discuss could be implemented using a multi-factor model as well.

[3] Lundin, Mark. “Risk Budgeting In Investment Management,” *Journal of Performance Measurement*, Summer 2002.

portfolios are positioned passively with respect to an index and managers wish to introduce a long duration view, they may not use a long futures position or buy additional bonds on a leveraged basis. Rather, they must sell shorter-dated securities and buy longer ones. In addition to the desired duration view, this introduces an unanticipated exposure to changes in the shape of the curve. We will investigate the performance impact of this effect.[4]

Combining Strategies

It is well known that risk-adjusted performance can be improved by diversifying the portfolio risk exposures among several different alpha-generation strategies. However, to get the full benefit of this diversification, it is important for the investment decisions in the various strategies to be made independently.

Toward the end of this article, we will explore various aspects of combining strategies. We show how risk budgeting may be applied to the allocation of risk to different strategies and discuss how the optimal allocation depends on the skills at the various strategies, as well as the correlations between them. We also report some empirically observed correlations among the various strategies investigated to help identify promising combinations.

In addition to the underlying correlations between two asset classes, correlations may be introduced in the decision process as well. For example, suppose a senior partner in an investment management firm makes an interest rate call. The managers of the corporate and core-plus portions of the portfolio are likely to reflect this view not only in their curve positioning, but also by overweighting market segments that are likely to outperform on a spread basis under the expected scenario. While this could further leverage the value of a correct interest rate call, it reduces the level of strategy diversification. We do not attempt to directly model this type of decision correlation in this article, but investors should keep in mind the benefits of keeping their various active management decisions as independent as possible.

[4] We recently addressed this topic using a combination of bonds and futures in the U.S. Treasury market. See "Cost of the No-Leverage Constraint in Duration Timing," Lehman Brothers, *Global Relative Value*, October 7, 2002.

DETAILED DESCRIPTION OF STRATEGIES AND METHODOLOGY

Historical Data

The study covers five currencies: EUR (DEM before 1999), USD, JPY, GBP, and CAD. For each currency, we gathered the following monthly data for the period from January 1, 1987, through December 31, 2002:

a) Exchange rates

b) 1-month deposit rates

c) Treasury bond index data

The Treasury bond index data were obtained from the components of the Barclays Capital Global Treasury Index corresponding to the five selected currencies. Each currency's index was divided into four maturity cells: 1-3 years, 3- 7 years, 7-10 years, and more than 10 years. For each maturity cell in each currency, we obtained a monthly time series of market value, duration, and total return. Market values and returns for each index are expressed in its local currency (i.e., no currency returns are included in the bond index data).

These were processed to obtain the following return series:

a) Returns on cash in each currency, with base currency EUR (DEM). This return includes both the return on cash and the FX return.

b) For each maturity cell in each market, the excess return of that cell over cash in its local currency.

To compare one type of macro investment strategy with another, it is important to ensure that the performance of each strategy is a pure reflection of the result of implementing a particular type of view. Thus, the monthly return on an FX strategy that shifts cash from one currency to another will include both the interest rate differential between the two currencies and the change in the exchange rate over the course of the month. All other strategies (yield curve, credit, core-plus) will be assumed to be carried out on a fully hedged basis, and performance will be measured in terms of excess return over cash in each local currency.

The returns on cash are used to measure the performance of FX strategies. The excess returns over cash in each currency are used to measure the performance of all yield curve strategies. These numbers are an idealization of the hedged returns over base currency cash, assuming perfect hedging. For example, consider a euro-based investor who goes long the 1-3 year sector of the U.S. Treasury Index. To hedge the FX exposure of this transaction, the investor effectively goes long euro cash and short USD cash. The difference between the return of this hedged index exposure and that of a pure euro cash investment is thus approximately the difference between the USD returns on the index and on USD cash. By taking this approximation, we make our results essentially independent of the base currency selected.

For the non-government asset classes, historical index data are not available for the full time period of the study. For each asset class, we have gathered index data going as far back as possible, as follows. For the Emerging Markets Index of dollar-denominated emerging market debt, we retrieved total returns in USD terms beginning in January 1993 and use these to calculate excess returns over USD cash. For U.S. high yield, we have data back to August 1988. Here, too, we subtract the returns on cash to obtain a time series of excess returns over USD cash. For euro-denominated investment grade credit, our index data are available back to September 1998. For this asset class, investment decisions will be guided by views on return relative to euro Treasuries, and any investment will come at the expense of the euro Treasury allocation. The return measure that we use is therefore excess returns over duration-matched EUR Treasuries. For U.S. investment grade credit, we use excess returns over duration-matched U.S. Treasuries, starting from August 1988. The final asset class that we will study is U.S. Treasury inflation-protected securities (TIPS). For a customized index of TIPS with maturities of 7-10 years, we obtained total returns (in USD terms) and real durations since February 1997. These were used to construct a series of excess returns for a hedged TIPS position relative to nominal U.S. Treasuries, as will be described below.

Risk Budgeting Approach

All of the investment strategies studied are expressed in terms of allocations to the asset classes described above. As a result, the historical returns of these asset classes can be used to form a simple ex ante risk estimate for any strategy. At the start of each month, we compute the covariance matrix among all of the different asset returns using historical return data up to that time. This covariance matrix is then used to estimate the tracking error volatility (TE) of each of the macro strategies to be considered. The position used to implement the strategy can then be scaled up or down so that the position taken each month is equal to a desired amount of risk—here set to 50 bp/year. This provides a realistic way to compare different strategies on a risk-equivalent basis.

To study a strategy based on ex ante risk estimation, we need to use some of the data to form the first covariance matrix before we begin strategy simulation. We have chosen to use three years of monthly return data for this purpose. As a result, although our data series begins in January 1987, our studies of strategy performance begin in January 1990. For the core-plus strategies, we have even shorter return histories. (For Euro corporates, for example, we have little more than three years of history all together.) In addition, there are mathematical complications involved in building a covariance matrix from asset return series of different lengths. Consequently, we have used this risk budgeting technique only for the four conventional strategies (global duration, market duration, curve twist, and FX).

For the core-plus strategies, we do not use this risk-budgeting approach to control the *ex ante* risk. Instead, we simply choose a constant position size of 5% of the portfolio and go long or short (neutral if shorts are not allowed) by this amount each month. We measure the statistics of this return series and obtain a risk-adjusted comparison with our other strategies by using information ratios.

Formulation of the Various Strategies

1) Global Duration Exposure

In the global duration timing strategy, a single decision is made each month to go long or short duration on a global basis. Duration is increased by the same amount in every currency, on a currency-hedged basis, with the amount selected to match a targeted amount of risk (e.g., 50 bp/year TE). Within each local currency, duration is increased by going long the entire market on a financed basis. That is, the active exposure to each maturity cell will be proportional to that cell's weight in the index. The strategy will choose each month between two positions: long all markets, as described above, and short all markets, which is exactly the negative of that position.

In practice, this strategy might be implemented using futures contracts to replicate the interest risk of the index in each currency. For the purposes of this study, we will assume that the portfolio borrows cash at the deposit rate to buy the index. Performance will be measured using index return over cash in each currency.

2) Regional Duration Exposure

The regional duration strategy reflects skill at relative interest rate calls. A decision is made to increase duration in one currency and decrease it in another currency. The positions are offsetting in terms of contributions to duration, so the net effect on global duration is zero. The magnitudes of the exposures are set always to match the risk target. As above, duration positioning within each local currency is implemented by taking a leveraged position in the entire market proportional to index weights. In our simulation with five currencies, we consider 20 possible positions each month for this investment style: for each of the five currencies that one can go long, there are four possibilities of what to go short. To represent a group of managers who each implement one of these 20 positions each month, we will assign a selection probability to each position, as described below.

3) Curve Twist Exposures

The curve twist strategy reflects skill at selecting steepening/flattening positions in each local currency, on a duration-neutral basis. In each of the three major currencies (USD, EUR, JPY), we will consider an exposure to a twist in the yield curve, which is to be implemented by going long one half of the local market and short the other on a duration-neutral basis. For instance, to implement a steepening trade, we would overweight the short end of the curve and underweight the long end of the curve. To make this position duration-neutral, the contributions to duration of these two exposures need to offset each other. This will mean that the overweight at the short end will have a higher market value than the underweight at the long end, and we will have to borrow cash to make up the difference. The flattening trade will be exactly the opposite: the underweight to the short end of the curve frees up enough cash to overweight the long end and retain a positive cash position as well.

Unlike our treatment of market duration risk, we do not assume that a steepening play in one currency needs to be offset by a flattener in another currency. Instead, we treat the curve play in each currency as a separate strategy with two choices. We analyze the effectiveness of skilled curve twist timing separately in each currency. Later in this report, we will also investigate a combined strategy that independently implements views on curve shape in the three currencies.

4) Foreign Exchange Exposure

In this macro approach to portfolio management, the decision on what foreign exchange exposures to take on is totally independent of the interest rate view. A manager bullish on U.S. interest rates but not on the dollar can overweight the U.S. component of the index but short the currency in the FX markets. In this investment strategy, we isolate the FX component by assuming that the bond composition of the portfolio exactly matches the benchmark, and the entire difference between the two is an FX overlay that changes the allocations to the three main currencies. We will look at two different types of positions in the three currencies, for a total of six positions:

a) Long 1 short 2: long one currency by a certain percentage of market value, short each of the other two currencies by half this amount.

b) The symmetric positions of short one currency and long two.

In each month of our simulation, the manager in this style is faced with a choice among six strategies: he may go long (or short) any one of the three currencies versus the other two. In each case, the magnitude of the position is set so that the *ex ante* estimate of tracking error volatility matches the targeted 50 bp.

The returns on these overlay positions consist of two components: a pure "currency" return based on the change in exchange rates and an "income" return based on the deposit rates differential.

5) Emerging Markets Exposure

This is a market timing strategy based on skill at determining when to take on exposure to emerging markets as a core-plus asset. The return earned for going long this market is the excess return of the US dollar-denominated Barclays Capital Emerging Market Index over USD cash. (Any currency risk is assumed to be completely hedged.) At first, we investigate a long-only strategy in which the portfolio may either go long the market or stay neutral to it. In the sequel, we will remove the no-shorts constraint and investigate the performance when either long or short positions are permitted.

6) High Yield Exposure

As in the emerging markets strategy, we measure the performance due to market timing an exposure to the excess return of the Barclays Capital U.S. High Yield Index over USD cash. We will consider both a long-only strategy and a long-short variation.

7) Investment-Grade Credit Exposure

The decision is made each month whether to overweight investment-grade credit. This allocation, when made, is assumed to be based on a view of credit relative to treasuries. As such, the performance of the strategy is measured by the excess return of the relevant Barclays Capital credit index over duration-equivalent treasuries. We investigate this strategy in two markets, using the excess returns of the U.S. investment grade Credit Index and of the credit component of the Euro-Aggregate Index. Once again, no currency risk is assumed with this strategy, and both long-only and long-short versions are investigated. The investment-grade credit strategy may be viewed as a core-plus strategy by those with global government benchmarks, or as a core strategy versus the Global Aggregate, so both versions are relevant.

8) Inflation-Protection Exposure

A view on inflation may be reflected by taking a position in inflation-linked bonds. As a proxy for a long position in global inflation-linked treasuries, we consider an allocation to U.S. Treasury inflation-protected securities (TIPS), relative to U.S. Treasuries. The strategy will go long 7-10 year TIPS and short the 7-10 year portion of the Barclays Capital Treasury Index on a duration-neutral basis. As this is not necessarily a cash-neutral trade, the performance of this strategy is computed after adjusting for cash. That is, if the market value of the TIPS position is greater than that of the nominal Treasuries, the financing cost on the difference is subtracted from the TIPS return. Like all the other core-plus strategies, we consider both the long-only and the long-short cases.

A sample of the strategies considered is shown in Figure 1. We display the implementation of each strategy in terms of active allocations to the asset classes represented in the simple covariance matrix described above. All of the strategies shown have been scaled to achieve the same estimated tracking error volatility of 50 bp/year. It can be seen that correlations play a major role in determining what position sizes fall within risk limits for a given strategy. For example, the EUR-USD market duration strategy, which offsets a long duration exposure on the EUR curve with a short duration exposure in USD, is allowed to take larger position sizes (in market value terms, shown here, as well as in dollar duration terms) than the similar GBP-JPY strategy. The higher correlations between EUR and USD interest rates make the offsetting exposures more effective at reducing risk. Similarly, the yield curve twist exposures are larger still in terms of market value exposures, because long and short yields within a single currency are much more highly correlated than yields of different currencies.

Figure 1: Sample Strategies Scaled to a Target Tracking Error of 50 bp/Year, as of May 31, 2002, in %

		Market Duration Strategies			Curve Twist Strategies Curve			FX Strategies Long		
Asset	Global Duration	GBP-JPY	JPY-EUR	EUR-USD	JPY	EUR	USD	JPY	EUR	USD
GBP1-3	0.4	1.4								
GBP3-7	0.6	2.0								
GBP7-10	0.4	1.3								
GBP10+	0.9	3.0								
JPY1-3	0.7	-2.2	2.7		14.7					
JPY3-7	1.2	-3.9	4.6		25.7					
JPY7-10	0.7	-2.4	2.8		-10.8					
JPY10+	0.3	-1.0	1.1		-4.4					
CAD1-3	0.8									
CAD3-7	0.8									
CAD7-10	0.4									
CAD10+	0.8									
EUR1-3	0.9		-3.4	3.7		18.0				
EUR3-7	1.1		-4.3	4.5		22.4				
EUR7+	1.1		-4.4	4.7		-13.7				
USD1-3	0.9			-3.7			24.3			
USD3-7	0.6			-2.7			17.6			
USD7-10	0.3			-1.2			-2.6			
USD10+	1.0			-4.0			-8.5			
GBPcash										
JPYcash								4.5	-2.7	-2.4
CADcash										
EURcash								-2.3	5.4	-2.4
USDcash								-2.3	-2.7	4.9

Strategy Descriptions

Global Duration: Long market exposure (and short cash) in each currency with equal contributions to duration. No FX exposure.
Total (leveraged) long market exposure: 13.9% of portfolio value.

Market Duration: Directional calls on interest rates with no net global duration exposure.
Long the market (and short cash) in one currency; short the market (long cash) with same duration contribution in another.
Total market weights of leveraged long and short positions (yield curve exposures) in example strategies:

Long	Short
7.7% GBP	-9.5% JPY
11.3% JPY	-12.1% EUR
12.9% EUR	-11.7% USD

Curve Twist Strategies: Steepening or flattening positions within a single currency. No net duration or FX exposure.
Steepener: Long position in the short end of the curve vs. a short position in the long end (and cash).
Example Strategy: long 49% at the short end of the US curve vs. short -11.1% at the long end, for TE = 50 bp.
Even though this trade is the largest magnitude of those shown, the risks are largely offsetting, and TE is the same.

FX Strategy: Long one of the G3 currencies, short the other two in equal amounts.

Source: Barclays Capital

Figure 2: Illustration of Risk Budgeting, FX Allocation Strategy, as of May 31, 2002, in %

Strategy	Base Scale	Currency Allocations (Base Scale)			TE (bp/yr)	Scaling Factor	New Scale	Currency Allocations (Rescaled for Risk Budget)			TE (bp/yr)
		JPY	EUR	USD				JPY	EUR	USD	
Long JPY	5.0	**5.0**	-2.5	-2.5	**55.0**	91	4.5	**4.5**	-2.3	-2.3	**50.0**
Long EUR	5.0	-2.5	**5.0**	-2.5	**46.7**	107	5.4	-2.7	**5.4**	-2.7	**50.0**
Long USD	5.0	-2.5	-2.5	**5.0**	**51.4**	97	4.9	-2.4	-2.4	**4.9**	**50.0**

Source: Barclays Capital

In Figure 2, we illustrate how the risk budgeting technique is used to determine the strategy positions. First, the shape of a given position is specified in terms of a scaling variable *x*. In the FX allocation example shown here, the position "Long JPY" is defined as going long *x*% in JPY and short half this amount in both USD and EUR. A starting value is selected (here 5% is the base scale), and the risk can then be calculated. The resulting tracking error of 55 bp/year is greater than our target of 50 bp/year, so we need to reduce the position size. The ratio of the targeted risk budget to the risk of the base scale position gives a scaling factor of 91%, which is multiplied by the base scale to obtain the scale of the position to be implemented, here 4.5%. The same base scale and the same approach are applied to all three currencies; differences in the historical volatilities of the different currencies cause us to increase the size of the "Long EUR" position and decrease the other two to achieve the same risk of 50 bp/year. With this risk normalization technique, the value used for the base scale does not have any effect on the final scale of the position; starting with a larger base scale will merely result in a smaller scaling factor.

Simulation of Skill

What is management skill? In terms of results, one could say simply that a skillful manager outperforms more frequently than not. To do so, he may gather information of many different types, process it using some combination of quantitative methods and intuition, and forecast various types of market behavior.

In this study, to evaluate the performance of a skilled duration-timer versus that of an FX expert or a core-plus allocator, we do not attempt to model any of these complex decision-making processes. Rather, we simulate management skill based on results, using the "imperfect foresight" approach developed in earlier work.[5] If a manager is faced with two choices (such as whether to go long or short global duration), we can label these as "good" and "bad" based on our knowledge of the eventual outcome. The skill in selecting the winning strategy (the good choice) is assumed to range from 0% to 100%. At 0% skill, the manager has a 50% chance of selecting the winning strategy. At 100% skill, the manager makes the winning choice with certainty. Probabilities at intermediate skill levels are prorated. For example, at a 40% skill level, the probability of making the good choice is 0.5 + 0.5 x 0.4 = 0.70. Correspondingly, the probability of making the bad choice is 0.30.

For a decision in which the manager has more than two possible choices, we divide them into two groups based on the outcomes and continue along the same lines. For example, as discussed above, there are 20 different choices considered in our market duration strategy. However, ten of these positions are the negatives of the other ten. For example, long USD duration and short EUR duration is the exact opposite of long EUR duration and short USD duration, so in every month, one of these strategies will be a winner and the other will be a

[5] *Value of Security Selection versus Asset Allocation in Credit Markets: Part II—an "Imperfect Foresight" Study*, Lehman Brothers, June 2000.

loser. At 0% skill, each of the twenty choices will be chosen with an equal probability of 5%. At 100% skill, we will assign a 10% probability to each of the winning strategies and 0% to each of the losing ones.[6] At 40% skill, the probability of making each of the winning choices will be (5%) + (5% x 40%) = 7%. Figure 3 shows the probabilities assigned to each of the winning and losing choices, as a function of skill level, for strategies with different numbers of available choices.

Figure 3: Probability of the Right Choice as a Function of Skill Level, %

	Two Choices		Six Choices (FX)		Twenty Choices (Market Duration)	
Skill Level	Right	Wrong	Right	Wrong	Right	Wrong
0%	50.0	50.0	16.7	16.7	5.0	5.0
5%	52.5	47.5	17.5	15.8	5.3	4.8
10%	55.0	45.0	18.3	15.0	5.5	4.5
15%	57.5	42.5	19.2	14.2	5.8	4.3
20%	60.0	40.0	20.0	13.3	6.0	4.0
40%	70.0	30.0	23.3	10.0	7.0	3.0
60%	80.0	20.0	26.7	6.7	8.0	2.0
80%	90.0	10.0	30.0	3.3	9.0	1.0
100%	100.0	0.0	33.3	0.0	10.0	0.0

Source: Barclays Capital

The imperfect foresight methodology is illustrated in Figure 4, using the FX allocation task as an example. The six positions considered by our strategy are shown in the six right-most columns of the figure. Each shows an overweight or underweight of approximately 5% to one of the currencies, with an equal and opposite weight split among the other two. (The differences in position sizes are due to the risk budgeting process—bets that have historically been more risky are taken in smaller sizes.) In the unskilled case, we assume that a manager may choose any one of these positions with a probability of 1/6. For the month shown (May 2002), it turns out that the big story was a depreciation of the U.S. dollar versus the other two currencies. This caused all three strategies that were overweight the dollar to underperform and the three that underweight the dollar to outperform. The performance that would have been achieved by each strategy is shown underneath the column. In the 100% skill case, we assume that a manager definitely chose one of the winning positions, and we assign a probability of 1/3 to each of these and 0 to the losers. To simulate a manager with 20% skill, we interpolate between these two extremes to obtain the probabilities shown. The performance of such a manager for this month can thus be considered as a random variable following the discrete distribution given by these six returns and probabilities. We calculate the mean and standard deviation of this distribution. We repeat this procedure for each month in our study and aggregate the results over time. A similar procedure is followed for every strategy.

[6] In our original "imperfect foresight" study, we modeled skill in two different ways: skill at picking any winning strategy and skill at picking the best strategy. In th is report, we use skill at picking any winning strategy. In the other model, increasing skill would increase the probability of the single best choice to 100%, while decreasing the probabilities of all other choices.

Figure 4: Strategy Simulation Example: FX Allocation, 20% Skill, as of May 2002

Asset	Return (bp)	Long JPY	Long EUR	Long USD	Short JPY	Short EUR	Short USD
JPYcash	-24.5	**4.5%**	-2.7%	-2.4%	**-4.5%**	2.7%	2.4%
EURcash	27.7	-2.3%	**5.4%**	-2.4%	2.3%	**-5.4%**	2.4%
USDcash	-340.3	-2.3%	-2.7%	**4.9%**	2.3%	2.7%	**-4.9%**
Overall Strategy							
Return (bp)		6.0	11.3	-16.6	-6.0	-11.3	16.6
Selection Probabilities for:							
0% Skill		16.7%	16.7%	16.7%	16.7%	16.7%	16.7%
100% Skill		33.3%	33.3%	0.0%	0.0%	0.0%	33.3%
20%		20.0%	20.0%	13.3%	13.3%	13.3%	20.0%
$(R\text{-Mean})^2$		13.9	80.9	356.5	68.1	182.5	206.4
Mean Return		**2.3**					
Variance		**141.2**					
Volatility		11.9					

Source: Barclays Capital

Time Period Studied

To be fair, performance comparisons among different strategies should be carried out over the same time period. However, this study spans a broad range of asset classes, and the time period for which data is available is different for each. For the four strategies based on multi-currency yield curve and FX data (global duration, market duration, twist, and FX), we have assembled historical data from January 1987 through December 2002. We required at least three years of data for building the covariance matrix used in risk budgeting, so studies of strategy performance begin with January 1990.

In addition to analyzing results over the entire period, we will analyze performance over two sub-periods, before and after European Monetary Union (EMU) on January 1, 1999. There have been important structural changes in the markets since that time, and we will seek to identify their implications for global fixed-income management.

RESULTS FOR INDIVIDUAL STRATEGIES

The performance of the core strategies is summarized in Figure 5. For each strategy, at each skill level, we show both the mean outperformance and the overall standard deviation of outperformance, on an annualized basis. In addition, we show the ratio between these two quantities, known as the information ratio, the standard measure of risk-adjusted performance.

The first thing we will check is whether the risk budgeting procedure has succeeded in keeping tracking error close to the *ex ante* target of 50 bp/year. It can be seen that the realized standard deviations of outperformance (tracking error) are generally close to their targets. For several strategies, though, the realized tracking errors are smaller than the targets. This is true for the global duration and regional duration strategies, as well as for the curve twist strategy in EUR and JPY. Historical volatility is not always a good predictor of future volatility, and in these cases, volatility seems to have been overestimated, causing the positions to be smaller than they might have been. In the FX overlay strategy, the realized tracking error is a bit higher than the target, indicating that our historical volatility estimates were a bit low.

Figure 5: Performance Summary for Core Strategies, January 1990-December 2002

	Global Duration			Market Duration			FX Overlay in G3 Currencies		
Skill Level	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio
0%	0.0	44.9	0.00	0.0	44.7	0.00	0.0	52.5	0.00
5%	6.2	44.8	0.14	6.0	44.7	0.13	6.8	52.5	0.13
10%	12.3	44.7	0.28	12.0	44.6	0.27	13.6	52.3	0.26
15%	18.5	44.6	0.41	18.0	44.4	0.41	20.4	52.2	0.39
20%	24.6	44.3	0.56	24.0	44.2	0.54	27.2	51.9	0.52
40%	49.3	42.6	1.16	48.0	42.5	1.13	54.4	50.1	1.09
60%	73.9	39.5	1.87	72.0	39.6	1.82	81.6	46.9	1.74
80%	98.5	34.8	2.83	96.0	35.1	2.73	108.9	42.1	2.59
100%	123.2	27.5	4.48	120.0	28.3	4.23	136.1	34.9	3.90

	EUR Curve Twist			USD Curve Twist			JPY Curve Twist		
Skill Level	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Information Ratio
0%	0.0	42.6	0.00	0.0	52.8	0.00	0.0	39.8	0.00
5%	5.7	42.6	0.13	6.7	52.8	0.13	5.4	39.8	0.14
10%	11.3	42.5	0.27	13.4	52.6	0.26	10.9	39.7	0.27
15%	17.0	42.3	0.40	20.1	52.5	0.38	16.3	39.5	0.41
20%	22.7	42.1	0.54	26.9	52.2	0.51	21.7	39.3	0.55
40%	45.4	40.6	1.12	53.7	50.5	1.06	43.5	37.8	1.15
60%	68.0	37.8	1.80	80.6	47.4	1.70	65.2	35.1	1.86
80%	90.7	33.7	2.69	107.4	42.8	2.51	86.9	31.0	2.81
100%	113.4	27.4	4.14	134.3	35.9	3.74	108.7	24.6	4.41

Source: Barclays Capital

In general, we find that the mean outperformance of a given strategy increases linearly with skill. In addition, the volatility of outperformance tends to decrease at high skill levels. As a result, the increases in information ratios with greater skill are more than linear.

To understand this decrease in volatility with increasing skill, we can decompose the volatility of outperformance into two components: volatility across managers and volatility over time.[7] The first is the volatility across a population of managers implementing the same strategy at the same level of skill and represents the risk of making the wrong decision. The second is the volatility over time of the mean strategy return, reflecting the fact that some months offer more opportunity than others for a given strategy. These two components are shown in Figure 6 for the market duration strategy. The volatility over time tends to increase with skill. At high skills, the manager is able to exploit nearly every market opportunity, and this component of strategy outperformance mirrors market volatility. Yet the overall strategy volatility declines at high skills, due to the dramatic drop in the volatility over managers. The major risk in any allocation strategy is that of making the wrong decision. When this becomes highly unlikely, the risk is reduced accordingly.

In terms of information ratios, we find that the various strategies provide nearly identical performance for a given level of skill. For example, 10% skill gives information ratios ranging from 0.26 to 0.28. At 20% skill, results range from 0.51 through 0.56. All of the strategies shown in Figure 5 show an information ratio of exactly 0.0 at 0% skill. This is due to the method of implementation, in which 0% skill means we choose with equal weights from two symmetrical groups of positions. In each month for each strategy, there is an equal probability of going long and short each position, so the mean strategy outperformance is zero.

The performance of the core-plus strategies is similarly summarized in Figure 7. For these strategies, two cases are shown. In the first, the core-plus strategies are implemented with a long-only constraint. This corresponds to the way these strategies are commonly used in portfolios. In the second case, the long-only constraint is relaxed, and short positions (underweights) are allowed in all assets.

Figure 6: Decomposition of Volatility of Market Duration Strategy, January 1990-December 2002

Skill Level	Mean Outperformance (bp/yr)	Volatility Managers (bp/yr)	Volatility Time (bp/yr)	Volatility (bp/yr)	Information Ratio
0%	0.0	44.7	0.0	44.7	0.00
5%	6.0	44.7	0.8	44.7	0.13
10%	12.0	44.6	1.6	44.6	0.27
15%	18.0	44.4	2.4	44.4	0.41
20%	24.0	44.1	3.2	44.2	0.54
40%	48.0	42.0	6.4	42.5	1.13
60%	72.0	38.4	9.6	39.6	1.82
80%	96.0	32.7	12.8	35.1	2.73
100%	120.0	23.4	16.0	28.3	4.23

Source: Barclays Capital

[7] For a detailed discussion of this issue, see *Value of Security Selection versus Asset Allocation in Credit Markets: Part II—an "Imperfect Foresight" Study*, Lehman Brothers, June 2000.

The first set of results shown in Figure 7 corresponds to the long-only constraint. If managers have a positive view on the asset class, they include a 5% overweight to that asset class in their portfolios. If the view is negative, the asset class is excluded from the portfolio. The results therefore look very different from those of Figure 5. The lack of symmetry means that the 0% skill case no longer gives zero outperformance on average. Instead, each strategy has a mean return (and an information ratio) that partially reflects the performance of a long position in the selected asset class over the time period studied. As this bias is not indicative of either future performance or manager skill, especially because the different strategies cover different time periods, we have selected to remove it from the analysis. In the second set of results, the mean outperformance column is "de-meaned" by subtracting the mean outperformance at 0% skill from that at all skill levels. Comparing the resulting information ratios with those in Figure 5, it is clear that all of the core-plus strategies have much lower information ratios than the core strategies at the same skill levels.

In the third set of results in Figure 7, the long-only constraint has been relaxed, and short positions are allowed. This could correspond to the use of derivatives to implement a short position, or to the case in which these assets are included in the benchmark, thus making it possible to underweight the assets without actually shorting any securities. In the long-short case, the information ratios achieved are in line with those of the core strategies, with the exception of the euro credit strategy, which is implemented only over a relatively short time period.

This idea has been formalized by Grinold and Kahn[8] as the "fundamental law of active management." They show that the information ratio IR is a function of the information coefficient IC and the strategy breadth BR, given by

(1) $$IR = IC \cdot \sqrt{BR}\ .$$

The breadth is the number of independent decisions made each year, and the information coefficient is a measure of skill, defined as the correlation between forecasts and actual outcomes.

If we assume for a moment that our skill parameter is equivalent to Grinold and Kahn's IC, then this fundamental law can easily be applied to obtain a theoretical information ratio for a given skill level. As all of the strategies implemented here consist of a single decision made on a monthly basis, the strategy breadth on an annual basis is 12, and the fundamental law predicts a maximum information ratio of . In Figure 8, we plot the achieved information ratios as a function of skill against the theoretical maximum. Not only do all the strategies achieve similar information ratios when implemented with equal skill, but the observed values are very close to the theoretical ones.

Why do the observed information ratios not match the Grinold and Kahn results even more precisely? For low values of skill, the observed results are somewhat below the theoretical limit. For higher values of skill, the observed results can exceed the theoretical value. There are two distinct causes for these phenomena. The first is related to the difference in the way skill is represented in our work and in theirs. Grinold and Kahn assume that investment decisions are built upon an explicit forecast of asset returns, and the information coefficient is defined as the correlation between the forecast and realized returns.[9] Furthermore, the information ratios produced by the fundamental law assume that the manager follows an optimal management policy in which the amount of risk taken in a given month depends on

[8] Grinold, Richard C. and Ronald N. Kahn, *Active Portfolio Management*, 1999, McGraw-Hill.
[9] The notion that skill is essentially the ability to process all available information to produce a successful forecast has led Grinold and Kahn to use the term "information coefficient" (IC) to denote their measure of manager skill.

the return forecast. In our study, by contrast, the skill coefficient is used directly to model the investment decision, and the amount of risk is held to a constant amount each month by our risk budgeting process.

Figure 7: Performance Summary for Core-Plus Strategies

Long Only Results

	U.S. Credit (Aug 1988-Dec 2002)			Euro Credit (Jan 1999-Dec 2002)			Emerging Markets (Jan 1993-Dec 2002)			U.S. High Yield (Aug 1988-Dec 2002)			USD Inflation Protection (Feb 1997-Dec 2002)		
Skill Level	Mean Outperf (bp/yr)	Volat (bp/yr)	InformRatio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio
0%	0.1	7.0	0.02	0.2	3.4	0.07	18.8	53.4	0.35	6.4	25.4	0.25	-4.1	14.6	-0.28
5%	0.7	7.0	0.09	0.5	3.4	0.15	23.6	53.1	0.44	8.6	25.4	0.34	-2.7	14.6	-0.18
10%	1.2	6.9	0.17	0.8	3.4	0.23	28.3	52.8	0.54	10.8	25.3	0.43	-1.3	14.6	-0.09
15%	1.7	6.9	0.25	1.1	3.4	0.32	33.0	52.4	0.63	12.9	25.2	0.51	0.1	14.5	0.01
20%	2.2	6.9	0.32	1.4	3.4	0.41	37.8	51.9	0.73	15.1	25.1	0.60	1.5	14.5	0.10
40%	4.3	6.7	0.65	2.5	3.3	0.77	56.7	49.7	1.14	23.9	24.5	0.97	7.0	14.1	0.49
60%	6.4	6.4	1.00	3.6	3.1	1.17	75.6	46.8	1.61	32.6	23.7	1.38	12.5	13.6	0.92
80%	8.5	6.1	1.40	4.8	2.9	1.63	94.6	43.1	2.19	41.3	22.5	1.84	18.0	12.9	1.40
100%	10.6	5.7	1.87	5.9	2.7	2.18	113.5	38.2	2.97	50.1	20.9	2.39	23.6	11.9	1.98

Long Only Results (De-meaned)

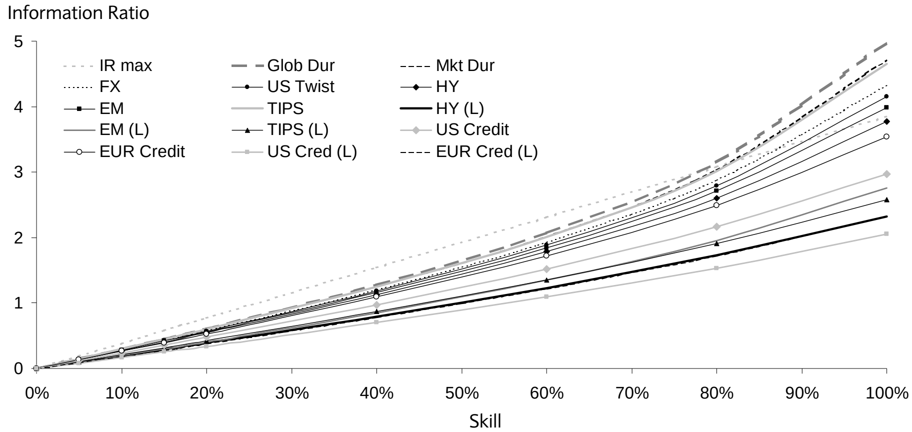
	U.S. Credit (Aug 1988-Dec 2002)			Euro Credit (Jan 1999-Dec 2002)			Emerging Markets (Jan 1993-Dec 2002)			U.S. High Yield (Aug 1988-Dec 2002)			USD Inflation Protection (Feb 1997-Dec 2002)		
Skill Level	Mean Outperf (bp/yr)	Volat (bp/yr)	InformRatio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio
0%	0.0	7.0	0.00	0.0	3.4	0.00	0.0	53.4	0.00	0.0	25.4	0.00	0.0	14.6	0.00
5%	0.5	7.0	0.08	0.3	3.4	0.08	4.7	53.1	0.09	2.2	25.4	0.09	1.4	14.6	0.09
10%	1.0	6.9	0.15	0.6	3.4	0.17	9.5	52.8	0.18	4.4	25.3	0.17	2.8	14.6	0.19
15%	1.6	6.9	0.23	0.9	3.4	0.25	14.2	52.4	0.27	6.6	25.2	0.26	4.1	14.5	0.29
20%	2.1	6.9	0.31	1.1	3.4	0.34	18.9	51.9	0.36	8.7	25.1	0.35	5.5	14.5	0.38
40%	4.2	6.7	0.63	2.3	3.3	0.70	37.9	49.7	0.76	17.5	24.5	0.71	11.1	14.1	0.78
60%	6.3	6.4	0.98	3.4	3.1	1.09	56.8	46.8	1.21	26.2	23.7	1.11	16.6	13.6	1.22
80%	8.4	6.1	1.38	4.6	2.9	1.55	75.7	43.1	1.76	35.0	22.5	1.55	22.1	12.9	1.72
100%	10.5	5.7	1.84	5.7	2.7	2.10	94.7	38.2	2.48	43.7	20.9	2.09	27.6	11.9	2.32

Long/Short Results

	U.S. Credit (Aug 1988-Dec 2002)			Euro Credit (Jan 1999-Dec 2002)			Emerging Markets (Jan 1993-Dec 2002)			U.S. High Yield (Aug 1988-Dec 2002)			USD Inflation Protection (Feb 1997-Dec 2002)		
Skill Level	Mean Outperf (bp/yr)	Volat (bp/yr)	InformRatio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio
0%	0.0	9.9	0.00	0.0	4.8	0.00	0.0	75.8	0.00	0.0	36.0	0.00	0.0	20.7	0.00
5%	1.0	9.9	0.11	0.6	4.8	0.12	9.5	75.8	0.12	4.4	36.0	0.12	2.8	20.6	0.13
10%	2.1	9.9	0.21	1.1	4.8	0.24	18.9	75.6	0.25	8.7	35.9	0.24	5.5	20.6	0.27
15%	3.1	9.8	0.32	1.7	4.8	0.36	28.4	75.4	0.38	13.1	35.8	0.37	8.3	20.5	0.40
20%	4.2	9.8	0.43	2.3	4.8	0.48	37.9	75.0	0.50	17.5	35.6	0.49	11.1	20.4	0.54
40%	8.4	9.6	0.87	4.6	4.6	0.98	75.7	72.6	1.04	35.0	34.6	1.01	22.1	19.7	1.12
60%	12.6	9.2	1.37	6.8	4.4	1.55	113.6	68.4	1.66	52.4	32.7	1.60	33.2	18.3	1.81
80%	16.8	8.6	1.94	9.1	4.1	2.24	151.5	62.1	2.44	69.9	29.8	2.34	44.2	16.3	2.72
100%	21.0	7.8	2.68	11.4	3.6	3.19	189.3	52.8	3.59	87.4	25.7	3.39	55.3	13.2	4.18

Source: Barclays Capital

Figure 8: Information Ratios for Different Strategies, as a Function of Skill, Compared with Theoretical Limit

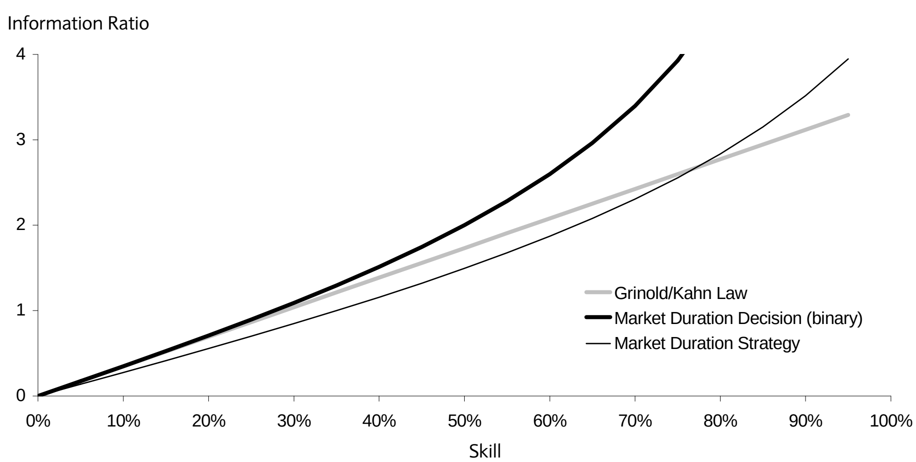


Source: Barclays Capital

Grinold and Kahn discuss a special case in which only the directionality of returns is forecast. In this case, both the forecast and realized returns are modeled by variables that take on only the values of +1 and -1. For this simple case, it can be shown that our definition of skill is equivalent to their information coefficient. To test the agreement of our results with the fundamental law, we recalculated the information ratios for our global duration strategy by replacing the time series of realized strategy returns with the sign of those returns. The results are shown in Figure 9. For low values of skill, the "decision information ratios" measured using this binary method exactly match the theoretical results.

While it shows agreement at low skill levels, Figure 9 accentuates the mismatch at high skill levels. The graphs of observed information ratios follow a concave upward pattern, while the Grinold and Kahn formula is linear with respect to IC. This is because by the authors' own admission, the formula is only an approximation, meant for use at low skill levels. It reflects the increase in outperformance that comes from increased skill, but not the decrease in volatility discussed above. While it may look dramatic in the figure, this non-linear effect is not particularly significant, as it appears only at unrealistically high levels of skill.

Figure 9: Information Ratio of Market Duration Strategy, Based on Actual Returns and on Binary Results Only, Compared with Theoretical Limit



Source: Barclays Capital

Effect of Constraints

In order for skilled managers to generate outperformance, they not only need to forecast the direction of the market successfully, but they also need to be able to take positions that capitalize on their views. A recent paper by Clarke et al. generalizes the work of Grinold and Kahn to include the effect of portfolio constraints.[10] In addition to the "information coefficient" (IC), which relates to allocation skill, the authors introduce a "transfer coefficient" (TC) that reflects the extent to which manager views may be implemented in the portfolio. Constraints lower the TC and, hence, the information ratio. While our methodology does not allow the direct calculation of a transfer coefficient,[11] we investigate the performance impact of certain constraints.

The results shown above for core-plus strategies illustrate the effect of portfolio management constraints on performance. An investment policy that disallows short positions in out-of-benchmark assets decreases the information ratios that can be achieved, because it allows managers to express views only in one direction. For example, Figure 7 shows that if the U.S. High Yield strategy could be carried out using long and short positions with 20% skill, it could achieve an information ratio of 0.49. The long-only constraint reduces this (after de-meaning) to 0.35 for the same skill level. Similar results are obtained for all of the strategies shown in Figure 7.

When dealing with core asset classes, the situation is different. Even though short positions may be disallowed, most views can be expressed in either direction in a benchmarked portfolio, since the active position is always constructed relative to the benchmark. A portfolio can go short duration relative to the benchmark, or underweight a particular asset class, without actually shorting any securities.

However, the imposition of a "no leverage" constraint limits the way in which a duration view can be implemented. In the strategies investigated above, we were careful to separate the duration view from the yield curve twist view. As shown in Figure 1, the long duration view is achieved by going long the entire government bond market in a given currency, on a financed basis, according to index weights. This strategy would be disallowed under a "no leverage" constraint. Instead, one would need to increase duration by overweighting longer-duration assets versus shorter ones. This method creates an unintended exposure to yield curve twist along with the duration exposure.

In reality, this unintentional twist exposure will generally reduce the value of the duration timing call. Going long duration will be accompanied by an unintended flattening position. There is strong evidence[12] that most yield curve rallies are accompanied by curve steepenings.

To simplify the analysis of this effect, we will investigate the performance implications of such a constraint on a single-currency basis. In Figure 10, we show the results of a single-currency duration timing strategy, in each of three currencies, using two different strategies. In the "pure duration" strategy, we follow the method used till now in this paper. The duration view is implemented by going long or short the index as a whole, on a leveraged basis when necessary. In the "cash neutral" strategy, the same amount of ex-ante tracking error is assumed, using a position that goes long or short duration by overweighting (or underweighting) the long half of the index versus the short half. In both cases, the skill level is assumed to refer to skill at making a pure duration call—that is, predicting the success or

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[10] Roger Clarke, Harindra de Silva, and Steven Thorley, "Portfolio Constraints and the Fundamental Law of Active Management," *Financial Analysts Journal*, September/October 2002, pp. 48-56.

[11] The transfer coefficient is defined as the correlation between the forecast residual returns on a set of assets and the portfolio weights in those assets. As our formulation of skill does not involve an explicit forecast, we cannot directly measure TC, but we can directly measure strategy performance with and without a given constraint.

[12] "Cost of the No-Leverage Constraint in Duration Timing," Lehman Brothers, *Global Relative Value*, October 7, 2002.

failure of the pure duration strategy. In this case, the unanticipated exposure to yield curve twist brings extra volatility that reduces the information ratio.

In a second experiment, we look at the performance using skill to predict both the shift and the twist in the curve. Skill at predicting the pure yield curve movement is first used to decide whether to go long or short; then skill at predicting the twist is used to decide whether to take a pure duration bet or to add on a steepener or a flattener. There are thus a total of six positions that can be selected: pure long, long flattener, long steepener, pure short, short flattener, and short steepener. Each of the six positions is scaled to achieve the same *ex ante* risk; therefore, the three variants of the long duration view typically entail different amounts of duration extension. The construction of the combined positions will be described in more detail in the following section.

The long flattener used in this combination is precisely the same as the cash neutral duration strategy described above. It achieves the long duration by overweighting the long end relative to the short. In the cash-constrained case, this is the only long position that the portfolio can take. (The long steepener is even more leveraged than the pure duration trade.) However, the short duration position is easy to achieve under the cash constraint, simply by shifting assets out of the entire index and into cash. This cash cushion allows the freedom to implement either a flattener or a steepener on top of the duration position if desired. As a result, the cash-constrained case can use four of the six positions available: either the long flattener, or any of the three short duration positions. We compare the unconstrained and constrained version of this strategy in Figure 11. Once again, we see that the no leverage constraint results in a decrease in information ratio.

Figure 10: Performance of Single-Currency Duration Timing in G3 Currencies, With and Without Cash Constraint, January 1990-December 2002

Pure Duration

Skill Level	Mean Outperf (bp/yr)	EUR TotalVolat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	USD TotalVolat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	JPY TotalVolat (bp/yr)	Inform Ratio
0%	0.0	51.3	0.00	0.0	46.0	0.00	0.0	42.3	0.00
5%	7.2	51.3	0.14	6.4	46.0	0.14	5.6	42.3	0.13
10%	14.5	51.1	0.28	12.7	45.8	0.28	11.1	42.2	0.26
15%	21.7	50.9	0.43	19.1	45.7	0.42	16.7	42.0	0.40
20%	28.9	50.6	0.57	25.5	45.4	0.56	22.3	41.8	0.53
40%	57.9	48.5	1.19	51.0	43.6	1.17	44.6	40.3	1.11
60%	86.8	44.8	1.94	76.4	40.4	1.89	66.9	37.7	1.78
80%	115.7	39.0	2.97	101.9	35.4	2.88	89.2	33.6	2.65
100%	144.6	29.9	4.84	127.4	27.7	4.60	111.5	27.6	4.04

Cash-Neutral Duration

Skill Level	Mean Outperf (bp/yr)	EUR TotalVolat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	USD TotalVolat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	JPY TotalVolat (bp/yr)	Inform Ratio
0%	0.0	53.4	0.00	0.0	48.1	0.00	0.0	41.9	0.00
5%	6.5	53.4	0.12	6.0	48.1	0.12	4.9	41.9	0.12
10%	13.0	53.3	0.24	12.0	48.0	0.25	9.8	41.8	0.23
15%	19.4	53.1	0.37	18.0	47.8	0.38	14.7	41.7	0.35
20%	25.9	52.9	0.49	24.0	47.6	0.50	19.6	41.5	0.47
40%	51.8	51.3	1.01	48.0	46.1	1.04	39.2	40.4	0.97
60%	77.8	48.5	1.60	72.0	43.5	1.66	58.8	38.4	1.53
80%	103.7	44.3	2.34	96.0	39.4	2.43	78.4	35.4	2.22
100%	129.6	38.3	3.39	119.9	33.5	3.58	98.0	31.1	3.15

Source: Barclays Capital

Figure 11: Performance of Combination Shift/Twist Strategy, With and Without Cash Constraint, January 1990-December 2002

Unconstrained

Skill Level	EUR Combined Shift/Twist			USD Combined Shift/Twist			JPY Combined Shift/Twist		
	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio
0%	0.0	50.5	0.00	0.0	46.7	0.00	0.0	42.6	0.00
5%	9.8	50.4	0.20	8.3	46.7	0.18	7.8	42.6	0.18
10%	19.7	50.3	0.39	16.6	46.6	0.36	15.5	42.5	0.36
15%	29.4	50.2	0.59	24.9	46.4	0.54	23.2	42.4	0.55
20%	39.2	49.9	0.79	33.2	46.2	0.72	30.9	42.3	0.73
40%	78.0	48.0	1.62	66.3	44.4	1.49	61.7	41.1	1.50
60%	116.4	44.8	2.60	99.2	41.2	2.41	92.2	39.1	2.36
80%	154.4	39.9	3.87	132.1	36.4	3.63	122.6	36.1	3.39
100%	192.0	32.8	5.86	164.8	29.0	5.69	152.7	32.0	4.78

Unconstrained

Skill Level	EUR Combined Shift/Twist			USD Combined Shift/Twist			JPY Combined Shift/Twist		
	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volat (bp/yr)	Inform Ratio
0%	-3.3	52.0	-0.06	-4.3	47.4	-0.09	-3.4	42.2	-0.08
5%	4.9	51.8	0.09	2.9	47.3	0.06	3.0	42.1	0.07
10%	13.0	51.6	0.25	10.0	47.2	0.21	9.3	42.0	0.22
15%	21.1	51.3	0.41	17.1	47.0	0.36	15.5	41.8	0.37
20%	29.1	51.0	0.57	24.2	46.7	0.52	21.7	41.6	0.52
40%	60.7	49.0	1.24	52.2	44.9	1.16	46.2	40.3	1.14
60%	91.4	45.8	2.00	79.9	42.0	1.90	70.0	38.4	1.82
80%	121.4	41.5	2.93	107.1	37.7	2.84	93.2	35.7	2.61
100%	150.5	35.7	4.22	133.9	31.7	4.22	115.7	32.4	3.57

Source: Barclays Capital.

COMBINING STRATEGIES

A cursory reading of the results presented above could easily lead to erroneous conclusions. We showed that the main determinant of strategy performance is skill, with all strategies achieving similar information ratios for a given skill level. From this, one might draw the conclusion that a manager should focus all his energy on the single strategy at which he has the most skill. Similarly, our demonstration that the long-only constraint puts core-plus strategies at a disadvantage might seem to indicate that this investment style is suboptimal and should never be used. Neither of these conclusions is correct.

In each of the above strategies, the portfolio takes on just a single active risk exposure each month. Whenever a wrong decision is made, the portfolio will underperform. Clearly, if several strategies are available that offer similar risk/reward profiles (i.e., if they can be carried out at the same skill), it would be advantageous to diversify the risk by taking several smaller exposures instead of one big one. In this way, a loss from one exposure can often be offset by a gain from another within the same month, leading to a much less volatile return series for a given level of outperformance. If the portfolio is being managed with a certain risk budget in mind, this reduction of risk due to strategy diversification can allow the manager to scale up the size of the combined strategy and boost the long-term outperformance.

In this section, we will explore the improvement in performance that can be achieved by combining strategies. We begin with a brief review of the basic theory - how much of an improvement in information ratio should one expect by combining strategies, and how do correlations affect this relationship? We then describe how we implement combined strategies in our risk budgeting framework and explore several practical issues with numeric examples. If one's skill is highest at one particular type of allocation, to what extent should one allocate risk to strategies with lower skills for the sake of diversification? Do core-plus strategies with a long-only constraint have a place in a combined strategy even though they do not look attractive on a stand-alone basis?

Theory of Combining Strategies: A Brief Review

Grinold and Kahn, in discussion of their fundamental law, point out that it is additive in the squared information ratios. That is, if strategies 1 through *n* could achieve information ratios IR_1 through IR_n if each were implemented on its own, then a combination of all *n* strategies can achieve an information ratio of

(2) $$IR_{combined} = \sqrt{IR_1^2 + IR_2^2 + \ldots + IR_n^2} \, .$$

If the *n* strategies all have the same information ratios, we can see that the combination of *n* strategies increases the information ratio by a factor of . This is closely related to the basic form of the fundamental law as expressed in equation (1) above. The combination of *n* strategies is equivalent to multiplying the breadth of the strategy by a factor *n*.

It is important to note that equation (2) is valid only if all of the n strategies are uncorrelated. The advantage offered by strategy diversification can be diminished by correlations among strategies. For example, if two strategies have the same information ratios, but have a correlation between them, then the information ratio is improved by a factor of

$$\sqrt{\frac{2}{1+\rho}} \, .$$

If the two strategies are uncorrelated ($\rho = 0$), then we obtain an improvement of as per equation (2). However, as ρ increases, this gain is reduced. In the limit of perfect correlation ($\rho = 1$), the two strategies are identical, and combining them does not add anything.[13] For a combination of more than two strategies, the math is a bit more complex, but the idea remains the same. Adding an additional strategy to the mix is effective only to the extent that it is uncorrelated to other strategies already included.

Combining Strategies in a Risk Budgeting Framework

Say we have decided to combine two different strategies. For each, we have decided what position we would take to implement it, and we have scaled it such that the risk taken is estimated to equal our overall target of 50 bp/year. How should we construct a blend of these two positions?

One interpretation of risk budgeting is that the total available risk is allocated in an additive manner. For example, we can scale each of our two positions by 0.5 such that each strategy gets a risk budget of 25 bp/year. This conservative approach assures that even if the two strategies are perfectly correlated, the overall risk of the position will equal the target.[14] However, if the correlation between the two strategies is relatively low, the risk of the combined strategy can be significantly lower than the target (by a factor of in the uncorrelated case). If we recall that outperformance is proportional to the amount of risk taken, we see that this will constrain the portfolio from achieving its potential outperformance.

A more aggressive approach is to assign risk budgets for each strategy using an assumption of independence. For example, if using two independent strategies, each could be assigned a risk budget of 35 bp/year ($50/\sqrt{2} \cong 35$). Such an approach could be justified if the strategies in question have a proven track record of uncorrelated historical behavior and/or if a manager is convinced by fundamentals that the two strategies are independent. The danger of this strategy is that if indeed the two strategies are correlated in the future, the strategy will have exceeded the risk budget and could suffer from unacceptably high return volatility.

In our risk management framework, we can construct a combination of strategies that gives a desired set of weights to the various strategies and has no more or less than the targeted amount of risk. We use a simple four-step construction method:

1) For each strategy, construct a position that reflects the current view and scale it such that its risk is equal to the full targeted amount as described above (e.g., 50 bp/year).

2) Apply a desired set of weights to the various strategies such that all the weights sum to one, and scale each strategy by the appropriate weight. Up to here, this is equivalent to the additive approach to risk budgeting.

3) Calculate the risk of the combined position using the covariance matrix (or a risk model of your choice).

4) Scale the combined position linearly so that its risk equals the risk target for the portfolio.

The method is illustrated in Figure 12, for a blend of the global duration and high yield strategies. In step 1, we find the position that would be needed to achieve an estimated tracking error of 50 bp/year for each strategy, as we have done throughout the study. For the global duration strategy, the position consists of going long each asset class in index

[13] Grinold and Kahn (cited above) actually present this relationship in the context of the information coefficient, showing that the combination of two correlated information sources with the same level of skill improves the information coefficient (and hence the information ratio) by this amount.

[14] This approach is similar in spirit to the traditional requirements for risk-based capital.

proportions. The position shown carries a global duration overweight of 0.83, with contributions evenly split across five markets, and the total position size represents 13.9% of the portfolio market value. For the high yield strategy, a leveraged position of 7.12% of portfolio market value is determined to have the same risk.[15]

In step 2, we blend the strategies by taking a weighted sum. In this case, we have used a blend of 75% of the global duration strategy and 25% of the high yield strategy.[16] Four different positions are considered: long both strategies (Long/Long), long global duration and short high yield (Long/Short), Short/Long, and Short/Short. As Short/Long and Short/Short are simply the negatives of the first two positions, they are not shown in the figure. The positions shown in this step are the ones that would be implemented if using the most conservative form of additive risk budgeting shown above. The global duration part of the position carries a TE of 37.5 bp, and the high yield part, treated alone, would exhibit a TE of 12.5 bp.

Figure 12: Building Combination Strategies Using the 4-Step Construction Method; 75% Global Duration, 25% High Yield as of November 30, 2002, in %

	Step 1: Individual Strategies Scaled to 50 bp/yr TE		Step 2: Form Blend of Strategies with Desired Weights (75/25)		Step 4: Rescale Each Blended Position to Hit Risk Target	
Asset	Global Dur (Scaled)	High Yield (Scaled)	Long/Long (Weighted)	Long/Short (Weighted)	Long/Long (Scaled)	Long/Short (Scaled)
GBP1-3	0.29	0.00	0.22	0.22	0.26	0.30
GBP3-7	0.60	0.00	0.45	0.45	0.54	0.61
GBP7-10	0.39	0.00	0.29	0.29	0.35	0.39
GBP10+	0.98	0.00	0.74	0.74	0.88	1.00
JPY1-3	0.70	0.00	0.53	0.53	0.63	0.71
JPY3-7	1.19	0.00	0.89	0.89	1.06	1.21
JPY7-10	0.71	0.00	0.54	0.54	0.64	0.73
JPY10+	0.31	0.00	0.23	0.23	0.27	0.31
CAD1-3	0.79	0.00	0.59	0.59	0.70	0.80
CAD3-7	0.81	0.00	0.60	0.60	0.72	0.82
CAD7-10	0.47	0.00	0.35	0.35	0.42	0.47
CAD10+	0.76	0.00	0.57	0.57	0.68	0.78
EUR1-3	0.85	0.00	0.64	0.64	0.76	0.86
EUR3-7	1.06	0.00	0.79	0.79	0.95	1.08
EUR7+	1.14	0.00	0.85	0.85	1.01	1.15
USD1-3	0.96	0.00	0.72	0.72	0.86	0.97
USD3-7	0.66	0.00	0.50	0.50	0.59	0.67
USD7-10	0.27	0.00	0.20	0.20	0.24	0.27
USD10+	0.96	0.00	0.72	0.72	0.85	0.97
GBPcash	0.00	0.00	0.00	0.00	0.00	0.00
JPYcash	0.00	0.00	0.00	0.00	0.00	0.00
CADcash	0.00	0.00	0.00	0.00	0.00	0.00
EURcash	0.00	0.00	0.00	0.00	0.00	0.00
USDcash	0.00	0.00	0.00	0.00	0.00	0.00
USHY	0.00	7.12	1.78	-1.78	2.12	-2.41
Step 3: Calculate Risk for Each Position Vector Using Covariance Matrix:						
TE (bp/yr)	**50.0**	**50.0**	**42.0**	**37.0**	**50.0**	**50.0**

Source: Barclays Capital

[15] For this example, we have extended the covariance matrix to include the high yield asset class as well.
[16] We shall see later that this allocation of risk budget is optimal for a particular mix of skills. Note that the absolute values of these initial weights do not affect the position that is ultimately selected; nor is it critical that the common risk level set in step 1 should be equal the total risk budget. The critical element is the ratios of the risk levels of the positions to be combined. Had we instead taken 300% of the global duration strategy and 100% of the high yield strategy, the normalization in step 4 would have yielded the same results.

Step 3 is to apply the covariance matrix to calculate the projected risk of these combined positions. Because the two strategies are not highly correlated, we find that the risk of the combined positions are significantly lower than 50 bp. This allows us to scale up the positions to take advantage of strategy diversification. This scaling is applied separately to each position. The tracking error measured for the Long/Long position is 42.0 bp, while that measured for the Long/Short position is 37.0. This reflects a small positive correlation between the two strategies. This increases the risk of going long in both (or short in both) relative to the uncorrelated case and decreases the risk of taking opposite positions.

In step 4, we scale the positions up such that the tracking error of each is equal to the risk target. As a result of the different risk estimates for the two positions shown, they are scaled by different amounts, and the position magnitudes for the Long/Short position are somewhat larger than those of the Long/Long position.

There are several advantages to this method. When combining correlated strategies, the resulting position does not take either too much or too little risk. In addition, it does not require any explicit assessment of the correlations among strategies, as this is implicitly provided by the use of the risk model.

One drawback to this method is that it does not offer the clean separation of responsibilities implied by the phrase "risk budgeting." The portfolio management process is often carried out hierarchically. Capital is allocated at the top level to different groups that then independently manage different parts of the portfolio. In the risk budgeting paradigm, one may think of assigning a certain amount of risk to the teams implementing the various strategies and then giving each team the freedom to apply that risk as it sees fit, independently of all the others. The framework outlined here calls for a more centralized management style, or at least a more cooperative one, with more interaction between the various management teams. In our example, the decisions to go short or long global duration can be made entirely independently of the decision to go short or long high yield. Each team suggests the position that represents its views, but then an analysis of the overall portfolio position is carried out to obtain the final scaling.

Pure Tilt Strategies

Before we proceed to more detailed applications of combination strategies, we will digress briefly to study the historical behavior of the individual strategies considered—or, more precisely, the positions from which these strategies were constructed. Our study has focused on the performance of various timing strategies. For each strategy considered, we use a skilled short-term forecast to adjust the position each month by choosing from a fixed menu of possible positions. In situations in which a longer-term trend is anticipated, it might be more appropriate to choose a single position and leave it in place for an extended period of time. Such a strategy, in which a portfolio takes a constant long-term exposure, is often referred to as a "tilt" strategy. This approach would clearly incur lower transaction costs than a timing strategy and could be quite successful in a consistent long-term trend.

As a control on our studies of performance with skill, we report the performance of the pure tilt strategies from which our skilled strategies were derived. That is, what performance would have been achieved by taking the long global duration position each month, instead of choosing between long and short in a skilled manner? How would one have performed by having the same yield curve positioning month after month—for example, long duration in USD and short duration in JPY? In market dimensions that experienced significant trends over the study period, it is interesting to see what skill levels would have been required for a market timer to outperform a pure tilt. In addition, the correlations among the pure tilt strategies can be instructive in helping to form effective combination strategies.

The results of the pure tilt positions for all of the core strategies are shown in Figure 13. In many cases, we find information ratios close to zero, indicating that gains and losses canceled out over the time period, leaving a small mean return relative to the volatility. However, in some cases, long-term trends over the course of the study period allowed certain pure tilt strategies to perform admirably well. When we separate the time period into the sub-periods before and after EMU, we find that most of these trends are very different in the two periods. All of the pure tilt strategies with information ratios greater than 0.5 are marked with asterisks. An overweight to JPY duration versus GBP or EUR duration produced an IR of 0.7 or 0.8 since EMU, but much less in the earlier period. The only pure tilt strategies that achieved information ratios above 0.5 in both halves of the study were the USD steepener, the All Twists strategy combining steepeners in all three G3 yield curves,[17] and the pure long global duration position, which produced an information ratio of 0.9 in the pre-EMU period and 0.6 since.

[17] The three twist positions used in this combination were scaled to the smaller limit of 29 bp/year in each currency so that the combination of all three twists would hit the 50 bp limit. This is similar to the combination strategy discussed in the next section, except that for this tilt strategy, the positions in the three currencies were always in the same direction.

Figure 13: Performance Summary of Various Pure Tilt Strategies over Different Time Periods

	Entire Time Period (1990-2002)			Before EMU (1990-1998)			Since EMU (1999-2002)		
	Mean	St Dev	IR	Mean	St Dev	IR	Mean	St Dev	IR
Market Duration Strategies									
Global Dur	37.5	43.7	0.9*	42.7	45.1	0.9*	26.1	40.6	0.6**
GBP-JPY	-8.5	52.6	-0.2	1.7	55.8	0.0	-31.6	44.4	-0.7
GBP-CAD	-10.1	41.3	-0.2	-6.2	45.7	-0.1	-18.8	29.2	-0.6
GBP-EUR	4.7	44.2	0.1	14.3	46.6	0.3	-16.8	37.7	-0.4
GBP-USD	-5.4	38.1	-0.1	5.0	40.5	0.1	-28.6	31.4	-0.9
JPY-GBP	8.5	52.6	0.2	-1.7	55.8	0.0	31.6	44.4	0.7*
JPY-CAD	-1.5	46.5	0.0	-8.0	49.3	-0.2	13.1	39.4	0.3
JPY-EUR	16.3	44.2	0.4	13.0	49.7	0.3	23.7	28.3	0.8*
JPY-USD	3.7	46.8	0.1	2.6	45.8	0.1	6.3	49.4	0.1
CAD-GBP	10.1	41.3	0.2	6.2	45.7	0.1	18.8	29.2	0.6*
CAD-JPY	1.5	46.5	0.0	8.0	49.3	0.2	-13.1	39.4	-0.3
CAD-EUR	15.7	43.2	0.4	19.9	48.5	0.4	6.3	28.0	0.2
CAD-USD	5.1	48.5	0.1	12.8	54.4	0.2	-12.1	31.7	-0.4
EUR-GBP	-4.7	44.2	-0.1	-14.3	46.6	-0.3	16.8	37.7	0.4
EUR-JPY	-16.3	44.2	-0.4	-13.0	49.7	-0.3	-23.7	28.3	-0.8
EUR-CAD	-15.7	43.2	-0.4	-19.9	48.5	-0.4	-6.3	28.0	-0.2
EUR-USD	-12.6	40.7	-0.3	-10.2	40.8	-0.2	-18.0	40.9	-0.4
USD-GBP	5.4	38.1	0.1	-5.0	40.5	-0.1	28.6	31.4	0.9*
USD-JPY	-3.7	46.8	-0.1	-2.6	45.8	-0.1	-6.3	49.4	-0.1
USD-CAD	-5.1	48.5	-0.1	-12.8	54.4	-0.2	12.1	31.7	0.4
USD-EUR	12.6	40.7	0.3	10.2	40.8	0.2	18.0	40.9	0.4
Twist Strategies									
JPY Twist	17.8	39.6	0.4	27.1	43.5	0.6*	-3.1	28.4	-0.1
EUR Twist	17.3	42.5	0.4	14.1	41.5	0.3	24.5	44.8	0.5*
USD Twist	38.1	51.8	0.7*	27.8	47.6	0.6*	61.1	60.1	1.0**
All Twists	42.2	48.1	0.9*	39.8	45.7	0.9*	47.6	53.5	0.9**
FX Strategies									
Long JPY	-2.5	58.1	0.0	3.1	62.6	0.0	-15.2	46.7	-0.3
Long EUR	-4.3	53.3	-0.1	-0.4	54.4	0.0	-13.2	51.4	-0.3
Long USD	6.9	45.8	0.2	-1.9	47.8	0.0	26.8	40.6	0.7*
Short JPY	2.5	58.1	0.0	-3.1	62.6	0.0	15.2	46.7	0.3
Short EUR	4.3	53.3	0.1	0.4	54.4	0.0	13.2	51.4	0.3
Short USD	-6.9	45.8	-0.2	1.9	47.8	0.0	-26.8	40.6	-0.7

* Indicates information ratio above 0.5 in a given time period.
** Indicates information ratio above 0.5 in all time periods shown.
Source: Barclays Capital

Figure 13 can also serve to check how well the realized tracking errors of the tilt strategies correspond to the *ex ante* limits placed upon them in strategy construction. Recall that each strategy was designed to achieve a tracking error of 50 bp/year. In the period before EMU, the realized tracking errors were reasonably close to this target for most strategies, with the largest TE realized by the FX strategies going long or short JPY. In the post-EMU period, many of the realized tracking errors were significantly lower. This is due to the fact that our covariance matrix was constructed each month using equally weighted data over a growing time window. At the start of 1990, the matrix was constructed using 36 months of data from 1987 through 1989. At the start of 1999, the matrix was constructed using 144 months of data from 1987 through 1998. This indicates that the volatility associated with many of these strategies has decreased over the past few years.

The question of how much historical data should be used when projecting risk is not a simple one, and various approaches have been taken. To avoid using out-of-date estimates, many market practitioners put greater emphasis on more recent data. This can be done with exponential weighting, or by using a shorter time window. The danger of this approach is that after a quiet period in the market, risk estimates may be too low when volatility next flares up. To investigate how our results might change, we repeated our study using a rolling three-year historical time window to calculate the covariance matrix. We found that the realized tracking errors were indeed closer to the target. However, when evaluated in terms of information ratios, there was little difference in the performance of the skilled strategies.

It is also interesting to look at the correlations among the historical outcomes of the pure tilt strategies. We calculated the correlations between each pair of pure tilt strategies over the entire time period and the two sub-periods. As the resulting matrices are quite large, we have selected a sampling of such correlations to display in Figure 14.

The market duration strategies experienced a major paradigm shift between one period and the other. For example, the correlation between the EUR-JPY strategy (long EUR duration and short JPY duration) and the EUR-USD strategy was 0.29 before EMU and changed sign to -0.55 after EMU. The correlations of the main market duration strategies (EUR-USD, USD-JPY, EUR-JPY) with the global duration strategy have changed dramatically as well. This is because Japanese interest rates have remained remarkably stable in the post-EMU period, linking the results of the global duration strategy more closely to rate changes in the USD and EUR markets. Large negative correlations between the long global duration tilt and several of the market duration strategies persist throughout the entire time period. It therefore appears that strategy diversification among the global duration strategy and the market duration strategy may not offer the best results in terms of risk-adjusted performance.

By contrast, we find that the correlations involving FX strategies have remained relatively stable over the time period studied. The strategies that go long the three major currencies have negative correlations with each other, as each strategy goes long one currency and short the other two. More important, the FX strategies tend to have relatively low correlations with both the global duration strategy and the market duration strategies. This shows that the FX allocation strategy is insensitive to interest rate movements and offers diversifying value.

The yield curve twist strategies also seem to offer good diversification of risk. While the changes in the slopes of the USD and EUR curves have been fairly highly correlated in the post-EMU period, these strategies tend to have low to moderate correlations with FX strategies, global duration, and market duration.

Figure 14: Pairwise Performance Correlations among Pure Tilt Strategies over Different Time Periods

		Pre-EMU	Post-EMU	Overall
EUR-JPY	EUR-USD	0.29	-0.55	0.12
EUR-JPY	EUR-GBP	0.10	-0.57	-0.01
EUR-GBP	EUR-USD	0.33	0.53	0.37
EUR-CAD	EUR-USD	0.61	0.72	0.61
USD-JPY	USD-GBP	0.25	0.45	0.30
Long Glob Dur	EUR-JPY	-0.32	0.47	-0.17
Long Glob Dur	EUR-USD	-0.51	-0.81	-0.59
Long Glob Dur	EUR-GBP	-0.66	-0.64	-0.66
Long Glob Dur	USD-JPY	0.13	0.75	0.31
Long Glob Dur	USD-GBP	-0.20	0.32	-0.09
FX Pairs				
Long JPY FX	Long EUR FX	-0.55	-0.64	-0.56
Long JPY FX	Long USD FX	-0.63	-0.50	-0.60
Long USD FX	Long EUR FX	-0.30	-0.35	-0.32
Long JPY FX	Long Glob Dur	0.07	0.04	0.06
Long EUR FX	Long Glob Dur	-0.07	0.17	0.00
Long USD FX	Long Glob Dur	0.01	-0.23	-0.05
Long JPY FX	JPY-EUR	-0.11	-0.08	-0.11
Long EUR FX	EUR-USD	-0.23	-0.18	-0.22
Long USD FX	USD-EUR	-0.17	-0.34	-0.21
Twist Pairs				
EUR Steepener	USD Steepener	0.04	0.53	0.23
EUR Steepener	JPY Steepener	0.09	-0.12	0.04
USD Steepener	JPY Steepener	-0.03	-0.12	-0.06
USD Steepener	USD-EUR	0.32	0.28	0.30
All 3 Steepeners	Long Glob Dur	0.10	0.23	0.14
EUR Steepener	Long EUR FX	-0.22	0.14	-0.11
USD Steepener	Long USD FX	-0.38	-0.28	-0.33
JPY Steepener	Long JPY FX	0.00	-0.05	-0.01
Core-Plus Pairs				
Emerging Mkts	Long Glob Dur	0.24	-0.05	0.15
High Yield	Long Glob Dur	0.33	-0.08	0.18
Euro Credit	Long Glob Dur	-1.00	-0.31	-0.31
USD Inflation	Long Glob Dur	-0.82	-0.78	-0.79
USD Inflation	USD-EUR	-0.82	-0.78	-0.75
Euro Credit	EUR Steepener	N/A	-0.38	-0.38
High Yield	USD Steepener	0.10	-0.28	-0.08
Emerging Mkts	USD Steepener	0.01	-0.22	-0.07
Emerging Mkts	High Yield	0.63	0.51	0.49
U.S. Credit	Long Glob Dur	-0.09	-0.35	-0.18
U.S. Credit	High Yield	0.55	0.77	0.67
U.S. Credit	Euro Credit	N/A	0.85	0.85
U.S. Credit	Long USD FX	0.31	0.20	0.24
U.S. Credit	USD-EUR	-0.19	-0.47	-0.30
U.S. Credit	USD Steepener	-0.26	-0.32	-0.29

Source: Barclay

Finally, among the core+ strategies, we find that both the emerging markets and high yield asset classes have low correlations with global duration and are good candidates for strategy diversification. However, it must be noted that there is a fairly high positive correlation between the two. The USD inflation strategy shows large negative correlations with the global duration tilt (and with USD-EUR) that persist throughout the entire time period and, thus, seems to offer less diversification potential. (Note that the sign of the correlation is not significant here—a high negative correlation is just as undesirable as a high positive correlation. The long position in the USD inflation strategy will be positively correlated with a short position in global duration, so these two strategies will share a common risk exposure. Ideally, we seek to combine strategies with correlations near zero.)

Excess returns of investment-grade credit exhibit fairly high positive correlations with total returns on high yield credit and moderate negative correlations with global duration, USD-EUR market duration, and USD twist. While the numeric values of these correlations may change over time, their direction and relative magnitudes seem to be quite stable.

Practical Applications: Examples of Combined Strategies

The reason correlations are so important to understand is that they play a major role in determining the performance of combined strategies. The fundamental law states that information ratios are additive in their squares—but only if all of the strategies are carried out independently. To the extent that two strategies (or two information sources) are correlated, the benefits of strategy diversification will be reduced.

We shall now take a look at some examples of combination strategies using different approaches. First, we will look at a combination of the yield curve twist strategies in the G3 currencies, in which we assume that the strategies are independent and assign a risk budget of 29 bp/year () to each. Second, we will examine the combination of yield curve shift and twist in each currency using our risk budgeting framework to separately match the overall risk target for each combination. Third, we will use this method to analyze a blend of the global duration and high yield strategies and address the issue of how to set the allocations to strategies with lower information ratios due to lower skill or implementation constraints.

Example 1: Combination Yield Curve Twist Strategy

In our first combination strategy, we choose to implement the yield curve twist strategy in all three G3 currencies simultaneously. Each month, a separate decision is made to put on either a steepener or a flattener in each currency. In this case, we assume that the strategies are independent, and we assign a risk budget of 29 bp/year () to each one. The results of this strategy are shown in Figure 15. The results for each single-currency twist strategy are simply scaled versions of those shown in Figure 5 with a risk budget of 50 bp. The mean and standard deviation of strategy returns are both divided by , and the information ratios for each skill level are therefore identical to those in Figure 5. The combination strategy diversifies among all three of these strategies at identical skill levels and, as a result, achieves information ratios that are better than any single strategy by a factor of about , as predicted by equation (2). We further find that the realized standard deviation of outperformance falls within our target of 50 bp/year.

Figure 15: Performance of Individual Curve Twist Strategies (Scaled) and Their Combination

	EUR Curve Twist			USD Curve Twist			JPY Curve Twist			G3 Combined Twists		
Skill Level	Mean Outperf (bp/yr)	Volatility (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Inform Ratio	Mean Outperf (bp/yr)	Volatility (bp/yr)	Inform Ratio
0%	0.0	24.6	0.00	0.0	30.5	0.00	0.0	23.0	0.00	0.0	45.4	0.00
5%	3.3	24.6	0.13	3.9	30.5	0.13	3.1	23.0	0.14	10.3	45.4	0.23
10%	6.5	24.5	0.27	7.8	30.4	0.26	6.3	22.9	0.27	20.6	45.3	0.45
15%	9.8	24.4	0.40	11.6	30.3	0.38	9.4	22.8	0.41	30.9	45.1	0.68
20%	13.1	24.3	0.54	15.5	30.1	0.51	12.5	22.7	0.55	41.1	44.9	0.92
40%	26.2	23.4	1.12	31.0	29.1	1.06	25.1	21.8	1.15	82.3	43.4	1.90
60%	39.3	21.8	1.80	46.5	27.4	1.70	37.6	20.3	1.86	123.4	40.8	3.03
80%	52.4	19.4	2.69	62.0	24.7	2.51	50.2	17.9	2.81	164.6	36.8	4.47
100%	65.5	15.8	4.14	77.5	20.8	3.74	62.7	14.2	4.41	205.7	30.9	6.66

Source: Barclays Capital

Example 2: Combination Shift and Twist Strategy

For our second example, we revisit the combination shift/twist strategy discussed above (Figure 11). In this strategy, we use skill to predict both the shift and the twist in the curve in a single-currency setting. In our earlier presentation, our focus was on the performance effects of the cash constraint. We now turn our attention to the construction of the strategy itself. In fact, the positions were defined using the four-step construction technique described above. In this strategy, we choose from a total of six positions: pure long, long flattener, long steepener, pure short, short flattener, and short steepener.

The construction begins by creating the cash-constrained long duration position described above, by overweighting the long-duration half of the index and underweighting the shorter half by the same market value. This position is the long flattener in our combined strategy. We then decompose this position into two parts: a pure duration trade that goes long the entire index on a leveraged basis to achieve the same duration exposure and a flattening trade that plays the long end against the short end on a duration-neutral basis. The long steepener is defined by combining the pure duration component of this decomposition with the equal and opposite twist exposure—we now overweigh the short end of the curve. For the pure long view, we omit the twist component of the trade entirely. We then estimated the tracking errors of each combination and scaled the positions to all have the same tracking error of 50 bp/year. As a result, the three variants of the long duration view typically entail different amounts of duration extension. The three possible short duration positions are each the negative of one of the long duration positions. In Figure 16, to highlight the advantage offered by this combination, we summarize the information ratios of the single-currency pure duration strategies from Figure 10, the pure twist strategies from Figure 5, and the unconstrained shift/twist combination strategies from Figure 11. As expected, combining these two largely independent strategies with equal skill gives a performance improvement of approximately relative to either strategy on its own.

Example 3: Blend of Global Duration and High Yield Strategies

In our third example, we will analyze the combination of the global duration and high yield strategies. The high yield strategy was shown in Figure 14 to have low correlation with the global duration strategy and, thus, seems like a good candidate for strategy diversification. In this context, we will investigate the role of the weights used to combine the two strategies and find the optimal weights for a two-strategy blend when the skills of the two strategies are unequal. Is it helpful to shift assets away from a more skilled strategy and into a less skilled one simply for the diversification benefit?

The detailed construction of the positions used in this strategy was illustrated in Figure 12 for a blend of 75% global duration and 25% high yield. We simulated the results of this strategy using our perfect foresight framework using various blends of the two strategies, as well as various skill levels at the two decisions. In Figure 17, we show the strategy results for this 75/25 mix, using 20% skill at global duration and only 10% skill at high yield. (In this example we have not included the long-only constraint for high yield; we make the assumption that we are allowed to short the high yield index.) By including a 25% allocation to the high yield strategy, the combined strategy achieves an information ratio of 0.599, compared with 0.553 for the global duration strategy alone. Diversification can help improve risk-adjusted performance even when skill in the secondary strategy is not as high as in the primary. These results are quite consistent with equation (2), which would predict an information ratio of if the two strategies were independent.

Figure 18 shows the dependence of strategy performance on the relative skill of the two strategies and the percent of risk budget allocated to each. In each case, we assume 20% skill at global duration allocation. The skill at high yield is varied from 0% to 20%, and the allocation to the high yield strategy is varied from 0% to 50%. When the high yield strategy is carried out at 0% skill (purely random decisions), its inclusion merely increases volatility without providing any outperformance, thus decreasing the information ratio; the optimal allocation in this case is clearly zero. For nonzero skill at high yield timing, we find that as we increase the allocation to high yield, the information ratio rises to a maximum and then decreases. As the skill level increases, so does the optimal allocation to high yield.

Figure 16: Performance Comparison of Shift/Twist Combination with Its Two Component Strategies

Information Ratios									
	EUR			USD			JPY		
Skill Level	Shift	Twist	Combo	Shift	Twist	Combo	Shift	Twist	Combo
0%	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5%	0.14	0.13	0.20	0.14	0.13	0.18	0.13	0.14	0.18
10%	0.28	0.27	0.39	0.28	0.26	0.36	0.26	0.27	0.36
15%	0.43	0.40	0.59	0.42	0.38	0.54	0.40	0.41	0.55
20%	0.57	0.54	0.79	0.56	0.51	0.72	0.53	0.55	0.73
40%	1.19	1.12	1.62	1.17	1.06	1.49	1.11	1.15	1.50
60%	1.94	1.80	2.60	1.89	1.70	2.41	1.78	1.86	2.36
80%	2.97	2.69	3.87	2.88	2.51	3.63	2.65	2.81	3.39
100%	4.84	4.14	5.86	4.60	3.74	5.69	4.04	4.41	4.78

Source: Barclays Capital

Figure 17: Performance of a 75/25 Combination of Global Duration and High Yield Strategies with Unequal Skills

Strategy	Mean Outperformance (bp/yr)	Volatility (bp/yr)	Information Ratio
Global Duration (20% Skill)	25.6	46.3	0.553
High Yield (10% Skill)	14.6	60.9	0.240
Blend (75% Global Duration, 25% High Yield)	28.6	47.8	0.599

Source: Barclays Capital

We can analytically find the optimum allocation for any such blend of two strategies. Assume strategies 1 and 2 are expected to outperform by α_1 and α_2, respectively, with tracking errors of σ_1 and σ_2, and that the correlation between the strategies is ρ. A blend of the two strategies with weights w_1 and w_2 will have an expected outperformance α and tracking error σ given by

$$\alpha = w_1\alpha_1 + w_2\alpha_2$$
$$\sigma^2 = w_1^2 VAR_1 + 2w_1w_2COV + w_2^2 VAR_2 = w_1^2\sigma_1^2 + 2w_1w_2\rho\sigma_1\sigma_2 + w_2^2\sigma_2^2 , \quad (3)$$

where the two weights are assumed to sum to one. We can express the information ratio as a function of these quantities and use this to find the blend of the two strategies that maximizes the information ratio. If we take the derivative of the information ratio $IR = \alpha/\sigma$ with respect to w_1 and set it to zero, we can show that the optimal weight for strategy 1 is given by

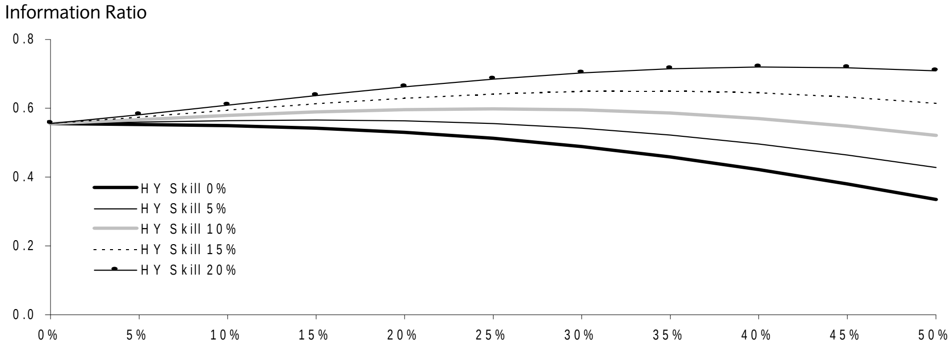
$$w_1^* = \frac{\alpha_1 VAR_2 - \alpha_2 COV}{\left(\alpha_1 VAR_2 - \alpha_2 COV\right) + \left(\alpha_2 VAR_1 - \alpha_1 COV\right)} . \quad (4)$$

If we make use of the fundamental law to express the expected outperformance in terms of the skill level and the strategy breadth of 12 (), we can reformulate this equation in terms of the strategy skills, volatilities, and correlation. Furthermore, if we assume that both of the individual strategies start with the same volatility, then this cancels out as well, leaving us with the simplified form:

$$w_1^* = \frac{s_1 - \rho s_2}{\left(s_1 - \rho s_2\right) + \left(s_2 - \rho s_1\right)} = \frac{s_1}{s_1 + s_2} + \frac{\rho}{1-\rho}\frac{s_1 - s_2}{s_1 + s_2} . \quad (5)$$

When the strategies are uncorrelated, the optimal allocation to a given strategy is proportional to skill.[18] As correlations are increased, the weight of the more skilled strategy is increased. This makes sense, as the allocation to a less skilled strategy is only justifiable to the extent that it provides diversification of risk.

Figure 18: Performance of Combination Global Duration/High Yield Strategy, with 20% Skill at Global Duration Timing and Several Skill Levels for High Yield Allocation, as a Function of High Yield Weight



Risk Allocation to High Yield Strategy
Source: Barclays Capital

[18] See Blitz, David C. and Jouke Hottinga, "Tracking Error Allocation," *Journal of Portfolio Management*, Summer 2001. The authors show that in the case of independent strategies, the optimal allocation of tracking error is proportional to the information ratios that can be achieved in each strategy. Our analysis shows, for the case of two correlated strategies, how the correlation modifies this conclusion.

In order to apply this technique to find the optimal blend, one needs to have estimates for all of the quantities in equation (3). In practice, the parameters most difficult to estimate may be the skill parameters, or equivalently, the alphas for each strategy. In our example, we have specified them from the outset, so the only parameter that is not clearly defined is the correlation. We can actually use equation (3) to back out the correlation ρ implied by the risk model. If we refer back to Figure 12, we see that the Long/Long position with a 75/25 weighting had a 42.0 bp/year tracking error before rescaling. If we set w_1 = 75%, w_2 = 25%, $\sigma_1 = \sigma_2$ = 50.0, and σ = 42.0 in equation (3), we can solve for ρ and find that it is 0.215. Using this value in equation (5), we find that the optimal blend of these two strategies at these skill levels is 75.8% in global duration timing and 24.2% in high yield timing. This is consistent with the pattern shown in Figure 18.

Concerning the inclusion of high yield and other core-plus strategies, there is one more point that we need to address. In this section, we have thus far analyzed the inclusion of high yield on a long-short basis. However, as discussed at length throughout this paper, many managers can include high yield and other core-plus strategies only as an overweight, but may not take short positions. When we analyzed these strategies on a stand-alone basis, we found that this limitation leads to a significant drag on performance. This is because under the long-only constraint, the manager is unable to take advantage of a negative view. Not only does this waste some of the manager's skill, but in months in which the view is negative, the risk budget is not used at all—the portfolio remained completely passive.

In a combined strategy, it may still be true that there is no way to act directly upon a negative view on a core-plus asset class. However, such a view does not need to result in under-utilization of the risk budget. For instance, in our combination of global duration and high yield, in months in which the outlook on high yield is negative, the portfolio would not stand idle, but would implement the pure global duration strategy at a risk level of 50 bp/year. In terms of Figure 12, the position taken to implement the Long/Short decision at the far right would now be the pure long global duration position at the far left, and a Short/Short decision would no longer correspond to the negative of Long/Long, but rather to the negative of the pure long global duration position (i.e., pure short global duration). We simulated the performance of this strategy and found that the information ratios were even higher than for the long-short case. This is due to the fact that the long-only high yield strategy has a positive bias over the time period of the study, as we saw in Figure 7. Due to the interaction between the long-only constraint, the blending of the strategies, and the risk scaling, it is not clear how to adjust for this bias properly.

The effect of the long-only constraint within one portion of a combined strategy is illustrated in Figure 19, using a different combination of strategies as an example. In a single-currency setting (USD), we combine views on duration and credit with different levels of skill. In the two top panels, we assume that the portfolio can go either long or short in both duration and credit. This might be an appropriate assumption for a portfolio benchmarked against the Barclays Capital Aggregate Index, where a negative view on credit can be expressed as an underweight.

In this case, we see much the same effect as in Figure 18. At the left of panel (a), all of the risk is allocated to the duration strategy, and performance is independent of the skill at credit timing. At the right, with 100% allocation to the credit strategy, performance increases linearly with credit skill and goes down to an information ratio of 0.0 for 0% credit skill. For any non-zero level of credit skill, the overall information ratio is increased by allocating some amount of risk to credit. As credit skill increases, so does the optimal risk allocation to credit, indicated by the location of the peak of the relevant curve. In panel (b), we hold credit skill constant at 20% and vary duration skill, with similar results.

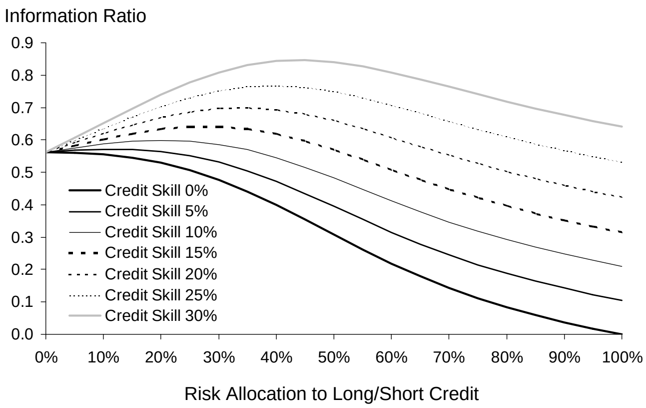
In panels (c) and (d) of Figure 19, we treat credit as a core-plus asset class and impose the long-only constraint. This would be an appropriate assumption for portfolios that incorporate credit against an all-government benchmark. Comparing panels (c) and (a), we find that the constraint affects performance in several ways. First of all, as expected, the overall information ratios achievable by the combined strategy are lower than in the unconstrained case. Second, the much narrower spread of the results toward the right-hand side of the graph indicates that the overall performance is less sensitive to credit skill. Third, even at 100% allocation to credit, the 0% credit skill case achieves a positive information ratio. A fourth effect can be found in panel (d), in which we find that the results for the 100% allocation to credit do not converge to a single point, but remain sensitive to the skill at duration timing.

All of these phenomena stem from the same root cause. In the method we have used to construct our combination strategies, we do not allow the long-only constraint to cause us regularly to undershoot our risk target. Instead, whenever the constraint disallows a short credit position to implement a negative view on credit, the risk budgeting algorithm scales up the duration position accordingly. The actual risk allocation of the combination strategy is thus not perfectly reflected in panels (c) and (d) of Figure 19. A combination strategy with a nominal credit risk allocation of 50% will, in fact, be constructed as follows. When the credit view is positive, it will allocate the risk evenly between a long credit position and either a long or short duration position. When the credit view is negative, however, 100% of the risk budget will be allocated to the implementation of the duration view. This explains the reduced role of credit skill in determining the performance of the combined strategy, as well as the dependence on duration skill even when the risk allocation to credit is nominally 100%.

The incorporation of core-plus strategies in this manner greatly mitigates the performance effect of the long-only constraint. While a combination of duration and long-only credit may underperform its long-short counterpart, it should outperform a pure duration strategy. The major performance penalty that we saw in the single-strategy results in Figure 7 was due to underutilization of the risk budget, which is avoided in our combined strategies.

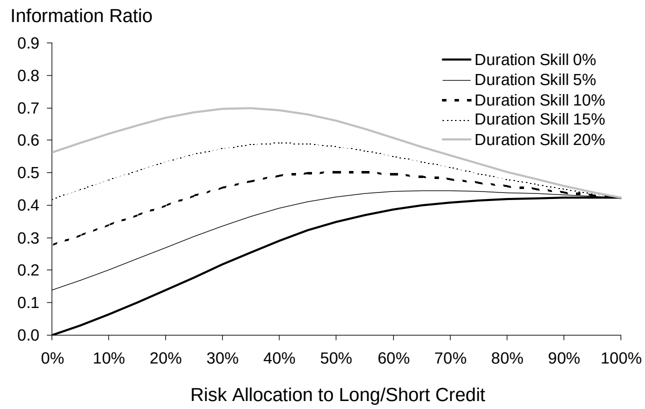
Figure 19. Information Ratios for a Combination of U.S. Duration Timing and U.S. Credit, August 1991-December 2002

a) Long/Short Credit, Fixed 20% Duration Skill, Varying Credit Skill



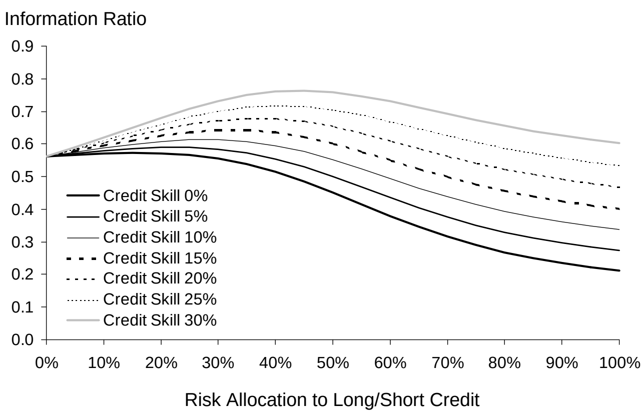
Source. Barclays Capital

b) Long/Short Credit, Fixed 20% Credit Skill, Varying Duration Skill



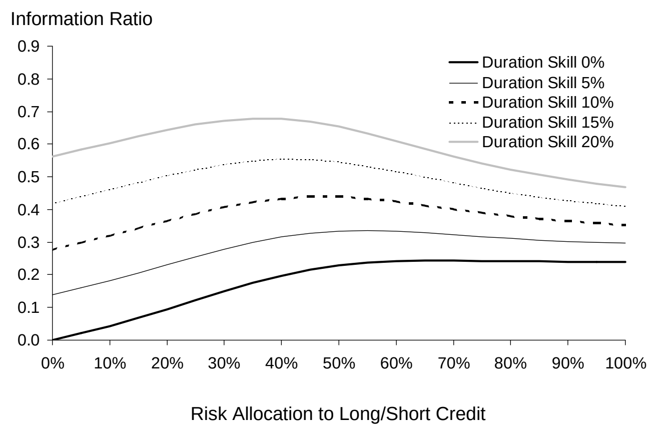
Source. Barclays Capital

c) Long-Only Credit, Fixed 20% Duration Skill, Varying Credit Skill



Source. Barclays Capital

d) Long-Only Credit, Fixed 20% Credit Skill, Varying Duration Skill



Source. Barclays Capital

Conclusion

In this paper, we have outlined the essential components of an investment management process that uses macro strategies to outperform a global fixed-income benchmark. First, we define a set of investment strategies that isolate different types of market views. Second, we establish a risk budgeting process by which we can control the amount of risk to be assigned to each strategy. Third, we have shown how strategies can be combined within this framework to achieve the best performance while adhering to a targeted tracking error.

We have explored the skilled implementation of a diverse set of pure strategies and confirmed that in each case, a given level of skill produces approximately the same information ratio. An open question remains—in which dimension is it easiest to achieve a given level of skill?

Another axiom that we have confirmed is that the constraints included in an investment policy have a direct impact on the information ratios that a skilled manager can achieve. We have seen that long-only constraints can cause skilled core-plus managers to achieve lower information ratios than they might in a long-short setting. This may argue for the selection of benchmarks that include all asset classes that may be used in the portfolio, thus allowing the portfolio to underweight, as well as overweight, each asset class.

Similarly, we found that a no-leverage constraint could cause a significant drag on the performance of duration-timing strategies, due to the forced inclusion of an unintended twist exposure with the implementation of a duration view. This evidence may encourage plan sponsors to allow the use of derivatives to enable more flexible expression of yield curve views.

The key to risk-adjusted performance is strategy diversification. One needs to spread the risk over multiple strategies, developing as high a skill level as possible in each. The big challenge is to keep the decision-making processes independent of each other. Correlations among the various macro strategies may form a limiting factor in determining just how much outperformance can be added by combining different macro strategies.

The need to maintain independence of decisions presents a dilemma for many managers. For example, suppose there is a well-established negative correlation between Treasury yields and corporate spreads, or that certain industry groups are expected to outperform in a market rally. Should the managers of these sectors key their decisions on the direction of their yield curve view? In practice, many often do. But if this occurs, the benefit of diversifying the active bets among many different strategies can be greatly diminished. The result of such activity will be positive correlation among the strategies, leading to higher volatility and lower information ratios.

Throughout this article, we have focused only on the systematic risks at the macro level. We have assumed the ability to earn the return on any index component when desired and to go in and out of these positions at will. These simplifications have helped us focus our attention on the core topic of macro strategies, but in the process, we have skirted some other important issues. In reality, every investment strategy entails some amount of non-systematic risk along with the desired macro exposure. This can affect the decision process in several ways. To minimize non-systematic risk, it can be helpful to select strategies involving indices that are easy to replicate. It also may help to use different types of instruments to replicate different portions of the market, to avoid correlations among the replication errors of different markets.[19] Of course, the decision of what specific instruments are used to implement a particular view is not just a source of non-systematic risk. If security selection is carried out skillfully, it has the potential to generate higher information ratios than any macro strategy, as it can incorporate a large number of independent decisions.[20]

One must also consider the transaction costs and liquidity risks that will be incurred in implementing a particular strategy. Macro positions in the liquid global government and currency markets can be modified with ease and at low cost, under almost all market conditions. In spread sectors, especially in core-plus markets, modifying macro positions is more complex. Not only is there greater non-systematic risk in replicating these indices, but the higher transaction costs and liquidity risks will typically require making strategy adjustments only over a longer time horizon.

What is the best mix of strategies for a global manager to develop? There is no single answer to this question. The goal is to develop high skill levels at several strategies that are not highly correlated. For a manager working under a fixed research budget, this elusive goal involves different types of tradeoffs. In many cases, a manager brings to the table expertise in a single type of strategy, and the cost of developing similar skills in other strategies will be much higher. This leans heavily toward a “play to your strength” strategy. However, we have demonstrated the benefits of allocating resources to a diversifying strategy, even with lower skill. How much of an investment will be required to build enough skill to justify allocating a significant portion of the risk budget? In the case of core-plus strategies, in addition to these considerations, the advantage of low correlations with other strategies needs to be considered against the disadvantage of the long-only constraint.

[19] For a detailed discussion of this topic, see *Replication with Derivatives: The Global Aggregate Index and the Japanese Aggregate Index*, Lehman Brothers, March 2001. It is shown there that a combination of Treasury futures, money market futures, and swaps can track the returns of various indices much better than Treasury futures alone, largely due to correlations among replication errors.

[20] Our studies of *Value of Security Selection versus Asset Allocation in Credit Markets* found evidence of much higher potential performance using security selection and traced this advantage to the much greater number of independent decisions.

APPENDIX: INTERPRETING THE STRATEGY INFORMATION RATIOS

In our tables of strategy performance, such as Figure 5, we show the information ratio that a given strategy achieves at a given skill level. How should these numbers be understood? In particular, how do they relate to the *ex post* information ratios recorded by actual managers in the real world?

For example, Figure 5 tells us that the market duration strategy, with 20% skill, recorded a mean outperformance of 24.0 bp/year with a tracking error volatility of 44.2 bp/year, for an information ratio of 0.54. However, this does not mean that every manager with this level of skill will record exactly these results if he uses this strategy. Rather, this *ex ante* information ratio represents the expected value of the information ratio that will be realized by any given manager. The realized IR can be higher or lower. The distribution of the realized information ratios has a standard deviation that depends on the length of time over which it is observed, and is approximately equal to , where *n* is the number of months of observed performance.

We tested this result using Monte Carlo simulation. We simulated 10,000 managers using the market duration strategy with 20% skill over the 149 months from January 1990 through May 2002. As indicated above, we know that the *ex ante* information ratio is 0.54, and we expect the realized IRs to be distributed around this mean with a standard deviation of In our simulation, we indeed found that the realized information ratios averaged 0.55 and that their standard deviation was 0.29. The values ranged from a minimum of -0.51 to a maximum of 1.64. Of the 10,000 managers, 293 of had negative information ratios. (This is in very good agreement with the Normal distribution, which would give a probability of 2.96% to negative outcomes given the above mean and standard deviation.)

The wide range of information ratios that can be realized by managers with the same amount of skill makes it difficult to back out an implied skill level from a realized information ratio. The best we can do is back out a range of reasonable values. Referring again to Figure 5, suppose that a manager realized an *ex post* information ratio of 0.55 over the 149-month sample period using the market duration strategy. It is certainly possible that this manager has 20% skill and achieved the IR that was expected for him. Yet it is also possible to have generated this result by starting with a much lower skill level (about 10%) with an *ex ante* IR of 0.27, one standard deviation below the mean, or a much higher one (about 30%) with an *ex ante* IR of 0.83. This rule of thumb of plus/minus one standard deviation thus defines an approximate skill range between 10% and 30%.

Repeating this analysis over a shorter observation period would give a wider window on skill. Say the manager achieved a realized information ratio of 0.55 over a five-year period. In this case, the standard deviation of realized IR is , and this could have been a reasonable outcome for a manager with an *ex ante* IR ranging anywhere from 0.1 to 1.0, or a skill range from 4% to 35%.

The information ratio is closely related to the t-statistic, a common measure of statistical significance. For a given excess return history, we can ask whether there is a reasonable chance that this performance was achieved totally by chance, by a manager with 0% skill. A statistical test of this possibility is carried out by calculating the t-statistic, the ratio of the average excess return to its standard error. If the t-statistic is greater than some critical value,[21] then the excess returns are deemed statistically significant, with less than a 5%

[21] Technically, the critical value depends on the number of degrees of freedom, which is one less than the number of time periods observed. In practice, critical values for 95% confidence are fairly close to 2.

possibility that they could have been generated by chance. Goodwin[22] has shown that the t-statistic is related to the information ratio by t-Statistic = , where T is the number of return periods included in the analysis. He points out that a realized information ratio of 0.5 achieved over nine periods has a t-statistic of 1.5 and is not "statistically significant," but the same information ratio maintained over 21 months has a t-statistic of 2.29 which is significant. However, he takes care to downplay the role of statistical significance, saying that its importance "should not be overstated." That said, we offer the following table[23] of realized information ratios that a manager would need to achieve over a given period of time to convince a skeptical scientist that the results cannot possibly be explained by luck. To prove that a 3-year track record is no fluke, the IR would need to be 0.98. Over a 10-year time frame, a sustained IR of 0.52 would suffice. These numbers are not meant to be used as a litmus test for evaluating realized performance. They simply offer another illustration of the common sense idea that a given IR is a surer sign of manager skill when it can be maintained for the long term.

Information Ratios Required to Prove Statistical Significance Monthly Observations, Annualized IR

Years	IR
2	1.21
3	0.98
5	0.75
10	0.52
15	0.43
20	0.37

[22] Thomas H. Goodwin, "The Information Ratio," *Financial Analysts Journal*, July/August 1998, pp. 34-43.
[23] The formula offered by Goodwin has been adjusted to reflect the use of monthly data and annualized information ratios. The information ratios shown here for *n* years are calculated as , using critical values at 95% confidence for the one-sided t-statistic based on the number of monthly observations.

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