A Portfolio Manager's Guide to Multi-Factor Fixed Income Risk Models and Their Applications[1]

Risk management is an integral part of the portfolio management process. Risk models are central to this practice, allowing managers to quantify and analyze the risk embedded in their portfolios. Risk models provide managers with insight into the major sources of risk in a portfolio, helping them to control their exposures and understand the contributions of different portfolio components to total risk. They help portfolio managers in their decision-making process by providing answers to important questions such as: How does my short duration position affect portfolio risk? Does my underweight in diversified financials hedge my overweight in banks? Risk models are also widely used in other areas, including portfolio construction, performance attribution and scenario analysis.

We discuss the structure of multi-factor fixed income risk models, the types of factors used in these models, and describe estimation techniques used in this context. We also illustrate the use of fixed income risk factor models in various applications, namely the analysis of portfolio risk, portfolio construction and scenario analysis. Throughout this paper, we use the Barclays Capital Global Risk Model[2] for illustration purposes. For completeness, we also refer to other possible approaches to constructing such a model.

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[2] The Barclays Capital Global Risk Model is available through POINT®, Barclays Capital portfolio management tool. It is a multi-currency cross-asset model that covers many different asset classes across the fixed income and equity markets, including derivatives in these markets. At the heart of the model is a covariance matrix of risk factors. The model has more than 500 factors, many specific to a particular asset class. The asset class models are periodically reviewed. Structure is imposed to increase the robustness of the estimation of such large covariance matrix. The model is estimated from historical data. It is calibrated using extensive security-level historical data and is updated on a monthly basis.

Quantifying Risk

Portfolio managers constantly monitor their exposures, typically net of a benchmark and routinely ask themselves: What is the portfolio duration? How risky is the overweight to credit? How does it relate to the exposure to mortgages? What is the exposure to specific issuers? Even when portfolio holdings and exposures are well known, portfolio managers increasingly rely on quantitative techniques to translate this information into a common risk language. Risk models can present a coherent view of the portfolio, its exposures, and how they correlate to each other. They can quantify the risk of each exposure and its contribution to the overall risk of the portfolio.

To start illustrating the motivation behind the risk models, let us assume that a portfolio manager wants to estimate and analyze the volatility of a large portfolio of fixed-income instruments. A straightforward idea would be to compute the volatility of the historical returns of the portfolio and use this measure to forecast future volatility. However, this framework does not provide insight into the relationships among different securities in the portfolio or among the major sources of risk. For instance, it does not assist a portfolio manager interested in diversifying a portfolio or constructing a portfolio that has better risk-adjusted performance. Additionally, the characteristics of a fixed-income portfolio change substantially over time (for instance, as instruments mature or are subject to credit events).

Instead of estimating the portfolio volatility using historical portfolio returns, a portfolio manager could use a different strategy. The portfolio return is a function of individual instrument returns (eg, Treasury securities, corporate bonds, credit derivatives, municipal bonds, interest rate swaps, etc) and the market weights of these securities in the portfolio. Using this, the forecast volatility of the portfolio (σ_P^f) can be computed as a function of the weights (w) and the covariance matrix ($\sum_S$) of the instrument returns in the portfolio:

$$\sigma_P^f = \sqrt{w^T \times \sum_S \times w}$$

where the superscript *T* denotes a matrix transpose. This covariance matrix can be broken down into individual instrument volatilities and the correlations between returns.

Volatilities measure the riskiness of individual instrument returns and correlations represent the relationships between the returns of different instruments. By measuring these correlations and volatilities, the portfolio manager can gain insight into her portfolio related to the riskiness of its different parts or how the portfolio can be diversified. As outlined above, to estimate the portfolio volatility we need to estimate the correlation between each pair of instruments. Unfortunately, this means that the number of parameters to be estimated grows quadratically with the number of instrument in the portfolio. For most practical portfolios, the relatively large number of constituents makes it difficult to estimate the relationship between instrument returns in a robust way. Moreover, this framework uses the history of individual instrument returns to forecast future security return volatility. However, instrument characteristics are dynamic; hence, using returns from different periods may not produce good forecasts. These drawbacks constitute the motivation for multi-factor risk models discussed in this paper.

A major characteristic of multi-factor models is their ability to describe the return of a portfolio using a relatively small set of variables, called factors. These factors should be designed to capture broad (systematic) market fluctuations, but should also be able to capture specific nuances of individual portfolios. For instance, a broad fixed-income market factor would capture the general movement in the fixed-income markets, but not the varying behavior across types of instruments. If, for example, a portfolio is heavily biased towards the long end of the US Treasury yield curve, or is tilted towards credit bonds of particular industries, the broad market factor may not allow for a good representation of the portfolio's return. Other factors might be needed to capture these more specific sources of risk.

Most factor models are linear and the total return is broken down into the sum of the contributions of the factors (referred to as the systematic return) and an idiosyncratic component. Systematic return is the component of total return due to movements in the common (market-wide) risk factors. On the other hand, idiosyncratic return can be described as the residual component that cannot be explained by the systematic factors. Under most factor models, idiosyncratic returns are uncorrelated across issuers. Therefore, correlations across securities of different issuers are driven by their exposures to the systematic risk factors, and the correlation between those factors.

The following equation demonstrates the systematic and the idiosyncratic components of total return for security *s*:

$$r_s = L_s \times F + \varepsilon_s$$

The systematic return is the product of the instrument's loadings (*L*, also called sensitivities) to the systematic risk factors and the returns of these factors (*F*). The idiosyncratic return is given by ε_s. Under this representation, the return is linear on the risk factors; therefore, we call these linear factor models.

Under these models, the portfolio volatility can be estimated as

$$\sigma_p^f = \sqrt{L_p^T \times \sum_F \times L_p + w^T \times \Omega \times w}$$

Here L_p are the loadings of the portfolio to the risk factors (determined as the weighted average of individual instrument loadings) and $\sum_F$ is the covariance matrix of factor returns. Ω is the covariance matrix of the idiosyncratic security returns. Typically, the idiosyncratic return of securities is assumed uncorrelated. Therefore, this covariance matrix is diagonal, with all elements outside its diagonal being zero. As a result, the idiosyncratic risk of the portfolio is diversified away as the number of securities in the portfolio increases. This is the diversification benefit attained when combining uncorrelated exposures.

For most practical portfolios, the number of factors is significantly smaller than the number of instruments in the portfolio. Therefore, the number of parameters in $\sum_F$ is much smaller than in $\sum_S$, leading to a generally more robust estimation. Moreover, the factors can be designed in such a way that they are more stable than individual stock returns, leading to models with potentially better predictability. In this setting, the changing nature of each particular instrument can be captured through its loadings to the different risk factors.

Another very important advantage of using factor models is the detailed insight they can provide into the structure and properties of portfolios. These models characterize instrument returns in terms of systematic factors that (can) have intuitive economic interpretations. Linear factor models can provide important insights regarding the major systematic and idiosyncratic sources of risk and return. This analysis can help managers to better understand their portfolios and can guide them through the different tasks they perform, such as rebalancing, hedging or tilting of their portfolios.

Naturally, the success of a risk model depends on its ability to interpret historical and current data in order to formulate estimates of future portfolio risk. It should therefore seek to discover properties of the data that are quasi-predictable; that is, that the error in the estimate of future realizations — given all information known today — is relatively small. For example, it is notoriously difficult to predict the expected return of a financial asset. On the other hand, historical data contain sufficient information to allow risk models to provide good estimates of the volatility of future returns. Nevertheless, one should not forget that even the most sophisticated risk model can provide only an estimate of risk. It is well known that financial markets are subject to event risk (ie, a sudden change in market conditions cause by geo-political or financial events). Such events are usually followed by a period of large negative returns on risky assets, large positive returns on assets considered to be safe havens, significantly higher volatility and very high (positive or negative) correlations. It is impossible for a risk model to predict when such events will occur. Therefore, it is useful to complement model-based risk management and portfolio construction with what-if analysis, which estimates portfolio return and risk under stressed conditions; that is, scenarios with extreme realizations of market returns and a covariance matrix with much higher volatilities and absolute correlations.

Fixed-Income Risk Models[3]

Fixed-income securities are exposed to many different types of risk. Multi-factor risk models in this area capture these risks by first identifying common sources along different dimensions, the systematic fixed-income risk factors. All risk not captured by these systematic factors is considered idiosyncratic and is determined by the choice of systematic risk factors. Typically, fixed-income systematic risk factors are divided into two sets: those that influence securities across asset classes (eg, yield curve risk) and those specific to a particular asset class (eg, prepayment risk in securitized products).

There are many ways to define systematic risk factors. For instance, they can be defined purely by statistical methods, observed in the markets (eg, a yield curve), or estimated from asset returns. In fixed-income, the standard approach is to use pricing models to calculate the analytics that are the natural candidates for risk factor loadings (L in the notation presented earlier). In this setting, the risk factors are either observable (eg, the movements in the yield curve) or estimated from regressing cross-sectional asset returns on instrument sensitivities. This is the approach taken in the Barclays Capital Global Risk Model, which is used for illustration throughout this paper[4].

In this risk model, the forecast risk of the portfolio is driven by a systematic and an idiosyncratic (also called specific, non-systematic, or concentration) component. The forecast systematic risk is a function of the mismatch between the portfolio and the benchmark in the exposures to the risk factors, such as yield curve or spreads. The (net) portfolio exposures are aggregated from security-level analytics. The systematic risk is also a function of the volatility of the risk factors, as well as of the correlations among risk factors. In this setting, the correlation of returns across securities is driven by the correlation of systematic risk factors these securities load on. Because the model uses security-level returns and analytics to estimate the factors, we can recover the idiosyncratic return for each security. This is the return net of all systematic factors. The use of detailed level analysis of idiosyncratic returns allows for the estimation of rich specifications of idiosyncratic risk.

[3] For a discussion of linear risk factor models in equity markets, please refer to Lazanas et al. (2011)
[4] See, for instance, Silva (2009).

Approaches to Analyzing Risk

Throughout this paper we analyze the risk of a particular bond portfolio, going through the various aspects of risk typically looked at by a manager. We assume the following:

- The Barclays Capital US Aggregate Index is the portfolio manager's benchmark.
- The portfolio manager believes interest rates are coming down. To capitalize on this view, she seeks to create a portfolio with interest-rate duration longer than the interest-rate duration of the benchmark. A portfolio with interest-rate duration that exceeds that of the benchmark is referred to as being "long duration" and it outperforms the benchmark when interest rates fall and all other market factors remain unchanged.
- The manager seeks a portfolio with a yield higher than that of the benchmark. Such a portfolio creates superior carry return (also known as income) relative to the benchmark but is subject to higher risks. The total yield of a portfolio can be broken down into a risk-free yield and a spread over the risk-free yield. Because the portfolio is expected to contain securities with longer maturities to satisfy the long duration target, it will earn a risk-free yield that differs from the risk-free yield of the benchmark (higher most of the time given that interest-rate curves are typically upward-sloping). To further enhance the portfolio yield, the manager wants to target a portfolio spread that is also higher than the benchmark spread. Higher spread typically exposes the portfolio to liquidity and issuer default risks. If defaults occur, or if the portfolio manager is forced to sell securities at a significant discount because of a lack of liquidity, the incurred losses may cancel out the higher yield advantage and could lead to portfolio underperformance relative to the benchmark. The manager must be comfortable that such risks are sufficiently compensated by the higher carry return associated with higher portfolio spread.
- The portfolio manager is required to maintain the difference between the returns of the portfolio and the benchmark at around 15bp, on a monthly basis. Thus, she must calibrate the long duration and high yield portfolio positions to abide by this constraint.

To summarize, the portfolio manager has the mandate to track the benchmark, but is allowed to deviate from it up to a point to express views that may lead to superior returns. A portfolio manager with such a mandate is called an *enhanced indexer*. The amount of deviation allowed is called the risk budget (15bp in our example) and can be quantified using a risk model. The risk model produces an estimate of the volatility of the difference between the portfolio and the benchmark returns, called tracking error volatility (TEV). TEV gives the forecast magnitude of the typical tracking error. The manager should keep the portfolio's TEV at a level equal to or less than that specified in the risk budget. The final portfolio, which we will analyze, contains 50 securities and is consistent with the manager's views and risk budget.

Market Structure and Exposure Contributions

The first level of analysis that any portfolio manager usually performs is to compare the portfolio holdings in terms of market value with the holdings from the benchmark. For instance, Figure 1 shows that the composition of the portfolio has several important mismatches when compared with the benchmark. The portfolio is underweighted in Treasuries and government-related securities by 8.4%. This is offset by an overweight of 12.3% in corporates, especially in the financials sector. Other mismatches include an underweight in mortgage-backed securities (MBS) (-5.8%) and an overweight in commercial mortgage-backed securities (CMBS) (+2.1%).

Figure 1: Market Weights for Portfolio and Benchmark

Asset Class	Portfolio	Benchmark	Difference
Total	**100.0**	**100.0**	**0.0**
Treasury	30.2	32.1	-1.9
Government-related	5.8	12.3	-6.5
Corporate Industrials	9.0	9.7	-0.7
Corporate Utilities	2.9	2.1	0.8
Corporate Financials	18.6	6.4	12.2
MBS Agency	28.4	34.1	-5.8
ABS	0.0	0.3	-0.3
CMBS	5.2	3.1	2.1

Source: POINT, Barclays Capital

Interestingly, for an equity manager, this kind of information (applied, for example, to the various industries or sectors of the portfolio) would be key to the analysis of portfolio risk. For a fixed income portfolio, this is not the case. Although important, this analysis tells us very little about the true active exposures of a fixed income portfolio. What if the Treasuries in the portfolio have significantly longer duration than those in the benchmark – would we be really "short" in this asset class? What if the spreads from Financials in the portfolio are much smaller than those in the benchmark – is the weight mismatch that important?

To answer these questions, we turn to another aspect of our analysis: the exposure of the portfolio to major sources of risk. An example of such exposure is the duration of the portfolio. Other exposures typically monitored are spread duration, convexity, spread level and vega (if the portfolio has many securities with optionality, eg, mortgages or callable bonds). Figure 2 shows these analytics at the aggregate level for our portfolio, benchmark and the difference between them:

- The portfolio is long duration (+0.25 year), consistent with the manager's view on the direction of interest rate moves.
- In terms of spread duration, the mismatch is smaller (+0.11 year). The manager wants to minimize the exposure to spread changes as much as possible given the manager has no view on this source of risk. However, the spread duration mismatch cannot be zero because spread risk is related to other risks on which she does have a view, such as rates.
- The portfolio has significantly milder negative convexity than the benchmark (-0.15 vs -0.29). This is attributable to the smaller weight that MBS have in the portfolio.
- The portfolio has more negative vega, but the number is fairly small for both universes.
- Finally, the portfolio has significantly higher spreads (100bp) than the benchmark. This mismatch is consistent with the manager's goal of having a higher yield in her portfolio, when compared with the benchmark.

Figure 2: Aggregate Analytics

Analytics	Portfolio	Benchmark	Difference
Duration	4.55	4.30	0.25
Spread Duration	4.67	4.56	0.11
Convexity	-0.15	-0.29	0.13
Vega	-0.02	-0.01	-0.01
Spread	157	57	100

Source: POINT, Barclays Capital

The analysis in Figures 1 and 2 can be combined to deliver a more detailed picture of where the different exposures are coming from. Figure 3 shows this analysis for the duration of the portfolio, demonstrating that most of the mismatch in duration contribution (market weighted duration exposures) stems from the Treasury component of our portfolio (+0.21). Interestingly, even though we are short in Treasuries, we are long in duration for that asset class. This means that our Treasury portfolio would be negatively affected, when compared with the benchmark, by a rise in interest rates. Because we are short in Treasuries, this result must mean that our Treasury portfolio is longer in duration than the Treasury component of the benchmark. Conversely, a relatively small contribution to excess duration comes from our very large over-exposure to corporates. This means that, on average, the corporate bonds in the portfolio are significantly shorter in duration than those in the benchmark.

Figure 3: Duration Contribution per Asset Class

Duration Contribution	Portfolio	Benchmark	Difference
Total	**4.55**	**4.30**	**0.25**
Treasury	1.92	1.71	0.21
Government-Related	0.40	0.49	-0.09
Corporate	1.31	1.19	0.11
Securitized	0.92	0.90	0.02

Source: POINT, Barclays Capital

Adding Volatility and Correlations to the Analysis

The analysis above gives us some basic understanding of our exposures to different kinds of risk. However, it is still hard to understand how we can compare the level of risk across these different exposures. What is more risky, my long duration exposure of 0.25 years, or my extra spread of 100bp? How can I quantify the seriousness of the vega mismatch on my portfolio? Specifically, the risk of the portfolio is a function of the exposures to the risk factors, but also of how volatile (how "risky") each of the factors is.

To enhance the analysis, we bring volatilities into the picture. Figure 4 shows the outcome of this addition to our example. In particular, it displays the risk of the different exposures of the portfolio in isolation (that is, if the only active imbalances were those from that particular set of risk factors). For example, in this figure one can see that if the only active weight in the portfolio were the mismatch in the yield curve exposures, the risk of the portfolio would be 8.5bp per month. By adding volatilities to the analysis, we can now quantify that the mismatch of +0.25 years in duration "costs" the portfolio 8.5bp per month of extra volatility, when taken in isolation[5]. Similarly, if the only mismatch were the exposure to corporate spreads, the risk of the portfolio would be 5.1bp. Interestingly, we also see that both government-related and securitized sectors have non-trivial risk, despite having smaller imbalances in terms of market weights relative to corporates. By bringing volatilities into the analysis, we can compare and quantify the impact of each imbalance in the portfolio.

[5] Later in this paper we refer to this risk number as Isolated TEV.

Figure 4: Isolated Risk per Category

Risk Factors Categories	Risk
Curve	8.5
Volatility	1.7
Spread Government-Related	3.0
Spread Corporate	5.1
Spread Securitized	3.0

Source: POINT, Barclays Capital

For future reference, consider the volatility of the portfolio if all these sources of risk were independent (eg, correlations were zero). That number would be 10.9bp per month[6]. Of course, this scenario is unrealistic, as these sources of risk are not independent. Also, this analysis does not allow us to understand the interplay among imbalances. For instance, we know that the isolated risk associated with the curve is 8.5. But this value can be achieved by being long or short duration. So the isolated number does not allow us to understand the impact of the curve imbalance on the total risk of the portfolio. The net impact certainly depends on the sign of the imbalance. For instance, if the long exposure in the curve is diversified away by a long exposure in credit (due, for instance, to negative correlation between rates and credit spreads), a symmetric (short) curve exposure would add to the risk of the long exposure in credit. The risk is clearly smaller in the first case.

To alleviate these shortcomings, we bring correlations into the picture. They allow us to understand the net impact of the different exposures to the portfolio's total risk and to detect potential sources of diversification among the imbalances in the portfolio. Figure 5 reports the contribution of each of the risk factor groups to the total risk, once all correlations are taken into account. The total risk (9.3bp/month) is smaller than the zero-correlation risk calculated previously (10.9bp/month), indicating that the net imbalances of our portfolio are generally negatively correlated. The figure also allows us to isolate the main sources of risk as being curve (5.9bp/month) and credit spreads (2.4bp/month), in line with the evidence from the earlier analysis. In particular, the risk of the government-related and securitized spreads is significantly smaller once correlations are taken into account.

Figure 5: Correlated Risk per Category

Risk Factors Categories	Risk
Total	**9.3**
Curve	5.9
Volatility	0.1
Spread Government-Related	0.1
Spread Corporate	2.4
Spread Securitized	0.7

Source: POINT, Barclays Capital

The difference in analysis between the isolated and correlated risks reported in Figures 4 and 5 deserves more discussion. For simplicity, assume there are only two sources of risk in the portfolio – yield curve (Y) and spreads (S). The total systematic variance of the portfolio (P) can be calculated as follows:

[6] We calculate this number by taking the square root of the sum of squares of all the numbers in the table; 10.9 = (8.5^2+1.7^2+3.0^2+5.1^2+3.0^2)^0.5. Moreover, this number would represent the total *systematic* risk of the portfolio. This definition will be developed later in the paper.

$$VAR(P) = VAR(Y+S) = VAR(Y) + VAR(S) + 2COV(Y,S) =$$
$$= Y \times Y + S \times S + 2(Y \times S)$$

where we use the product X to represent variances and covariances. Another way to represent this summation is using the following matrix:

$$\begin{bmatrix} Y \times Y & Y \times S \\ Y \times S & S \times S \end{bmatrix}$$

The sum of the four elements in the matrix is the variance of the portfolio. The isolated risk (in standard deviation units) reported in Figure 4 is the square root of the diagonal terms. So the isolated risk due to spreads is represented as:

$$Risk_{Spreads}^{Isolated} = \sqrt{S \times S}\,.$$

It would be a function of the exposure to all spread factors, the volatilities of all these factors and the correlations among them.

The correlated risk reported in Figure 5 is:

$$Risk_{Spreads}^{correlated} = [Y \times S + S \times S] / \sqrt{VAR(P)}$$

that is, we sum all elements in the row of interest (row 1 for Y, row 2 for S) from the matrix above, and normalize it by the standard deviation of the portfolio. This statistic (1) takes into account correlations across groups of risk factors and (2) ensures that the correlated risks of all factors add up to the total risk of the portfolio given by[7]

$$Risk_{Curve}^{correlated} + Risk_{Spreads}^{correlated} = \sqrt{VAR(P)} = STD(P)$$

The difference between isolated and contribution to risk, given the interplay of the two sources ($2(Y \times S)$), is allocated equally to each source of risk. In cases when one type of risk on isolated basis is much smaller in magnitude than the other, the term may have an outsized effect. In sum, isolated risk takes into account only the individual behavior of each source of risk, while the contribution to correlated risk looks at the joint behavior of various risk sources.

The generic analysis just performed constitutes the first step in the description of the risk associated with a portfolio. The analysis refers to categories of risk factors (such as "curve" or "spreads"). However, a factor based risk model allows for a significantly deeper analysis of the imbalances the portfolio may have. Each of the risk categories referred to above can be described with a rich set of detailed risk factors. Typically, in a fixed income factor model, each asset class has a specific set of risk factors in addition to the potential set of factors common to all (eg, curve factors). These asset-specific risk factors are designed to capture the particular sources of risk the asset class is exposed to. In the following section, we go through a risk report built in such a way, emphasizing risk factors that are common or particular to the different asset classes. Along the way, we demonstrate how the report offers insights from both a risk management and a portfolio construction perspective.

[7] In this example we focus only on the systematic component of risk. Later, the normalization is with respect to the total risk of the portfolio, including idiosyncratic risk.

A Detailed Risk Report

In this section, we continue the analysis of the portfolio introduced previously, a 50-bond portfolio benchmarked against the Barclays Capital US Aggregate Index. The report package we present was generated using POINT®, Barclays Capital's cross-asset portfolio analysis and construction tool, and gives a very detailed picture of the risk embedded in the portfolio. The package is divided into four types of reports: summary reports, factor exposure reports, issue/issuer level reports and scenario analysis reports. Some of the information we reviewed earlier can be thought of as summary reports.

Summary Report

Figure 6 illustrates a typical risk summary statistics report. It shows that the portfolio has 50 positions from only 27 issuers. This implies limited ability to diversify idiosyncratic risk, as we will see below. The report confirms that the portfolio is long duration (OAD of 4.55 years versus 4.30 years for the benchmark) and has higher yield (yield to worst of 3.71% versus 2.83% for the benchmark) and coupon (4.73% versus 4.46% for the benchmark).

Figure 6: Summary Statistics Report

	Portfolio	Benchmark	
A. Parameters			
Positions	50	8191	
Issuers	27	787	
Currencies	1	1	
Market Value ($mn)	200	14,762	
Notional ($mn)	187	13,750	
B. Analytics			**Difference**
Coupon	4.73	4.46	0.27
Average Life	6.63	6.35	0.27
Yield to Worst	3.71	2.83	0.88
Spread	157	57	100
Duration	4.55	4.30	0.25
Vega	-0.02	-0.01	-0.01
Spread Duration	4.67	4.56	0.11
Convexity	-0.15	-0.29	0.13
C. Volatility			**TEV**
Systematic	162.9	158.0	9.3
Idiosyncratic	11.1	5.6	10.1
Total	163.3	158.1	13.7
D. Portfolio Beta			1.03

Source: POINT, Barclays Capital

Figure 6 also reports that the total volatility of the portfolio (163.3bp/month) is higher than that of the benchmark (158.1bp/month). This is not surprising: longer duration, higher spread and less diversification all tend to increase the volatility of a portfolio. Because of its higher volatility, we consider the portfolio to be riskier than the benchmark. Looking into the different components of the portfolio volatility, the figure reports that the idiosyncratic volatility of the portfolio is significantly smaller than that of the systematic (11.1bp/month versus 162.9bp/month, respectively). This is also expected from a portfolio of investment grade bonds. Given the fact that, by construction, the systematic and idiosyncratic components of risk are independent, we can calculate the total volatility of the portfolio as

$$TEV_{PTF} = \sqrt{162.9^2 + 11.1^2} = 163.3$$

There are two interesting observations regarding this number: first, the total volatility is smaller than the sum of the volatilities of the two components. This is the diversification benefit that comes from combining independent sources of risk. Second, the total volatility is very close to the systematic one. This may suggest that the idiosyncratic risk is irrelevant. That is an erroneous and dangerous conclusion. In particular, when managing against a benchmark, the focus should be on the net exposures and risk, not on their absolute counterparts. In Figure 6, the total TEV is reported as 13.7bp/month. This means that the model forecasts the portfolio monthly return to be typically no more than 14bp/month higher or lower than the return of the benchmark. This number is in line with the risk budget of our manager. The figure also reports idiosyncratic TEV of 10.1bp/month, which is greater than the systematic TEV (9.3). When measured against the benchmark, our major source of risk is idiosyncratic, contrary to the conclusion one could draw by looking only at the portfolio's volatility. The TEV of the portfolio is also greater than the difference between the volatilities of the portfolio and benchmark. It would be equal to the difference only if the portfolio and benchmark were perfectly correlated.

Finally, the report estimates the portfolio to have a beta of 1.03 to the benchmark. This statistic measures the *co-movement* between the portfolio and the benchmark. We can read it as follows: the model forecasts that a movement of 100bp in the benchmark leads to a movement of 103bp in the portfolio in the same direction. Note that a beta of less than one does not mean that the portfolio is less risky than the benchmark; it just means that the portfolio is less sensitive to movements in the benchmark. To see this more clearly, consider the limit case when the portfolio and benchmark are uncorrelated. The portfolio beta in this case is zero, but this does not mean that the portfolio has zero risk. Finally, one can compute many different "betas" for the portfolio or subcomponents of it[8]. A simple and widely used one is the "interest-rate duration beta", given by the ratio of the portfolio duration to that of the benchmark. In our case, the ratio is 4.55/4.30 = 1.06. This implies that the portfolio has a return from yield curve movements around 1.06 times larger than that of the benchmark. This beta is larger than the portfolio beta (1.03), meaning that net exposures to other factors (eg, spreads) "hedge" the portfolio's net curve risk.

This first summary report (Figure 6) gives us a glimpse into the risk of the portfolio. However, the manager wants to know in more detail what the sources of this risk are. Risk can be broken down along various dimensions, two of which we looked at briefly above: security groups (asset classes) and risk factors. The next two summary reports present the detailed risk breakdown along these two dimensions. In the first, risk is partitioned across different groups of risk factors. In the second, the partition is across groups of securities.

Figure 7 shows four different statistics associated with each set of risk factors. The first two were explored to an extent in Figure 4 and Figure 5[9]. The figure reports in the first column the isolated TEV, that is, the risk associated with that particular set of risk factors only. We see that in an isolated analysis, the systematic and idiosyncratic risks are balanced, at 9.3 and 10.1 respectively. The report also shows the isolated risk associated with the major components of systematic risk. As discussed before, all components of systematic risk have non-trivial isolated risk, but only curve and credit spreads are significant when we look into the contributions to TEV. If we look across factors, the major contributors are idiosyncratic risk, curve and credit spreads. Other systematic exposures are relatively small.

[8] For example, see Figure 13 later in this paper.

[9] Note that the contribution numbers are different than those from Figure 5, because there we reported the contribution to systematic—not total—risk.

Figure 7: Factor Partition – Risk Analysis

Risk Factor Group	Isolated TEV	Contribution to TEV	Liquidation Effect on TEV	TEV Elasticity (%)
Total	**13.7**	**13.7**	**-13.7**	**1.0**
Systematic Risk	9.3	6.3	-3.6	0.5
Curve	8.5	4.0	-1.5	0.3
Volatility	1.7	0.1	0.0	0.0
Government-Related Spreads	3.0	0.1	0.2	0.0
Corporate Spreads	5.1	1.6	-0.7	0.1
Securitized Spreads	3.0	0.5	-0.2	0.0
Idiosyncratic Risk	10.1	7.4	-4.4	0.5

Source: POINT, Barclays Capital

Another look into the correlation comes when we analyze the liquidation effect reported on the table. This number represents the change in TEV when we completely hedge that particular group of risk factors. For instance, if we hedge the curve component of our portfolio, our TEV drops by 1.5bp/month: from 13.7bp to 12.2bp. One may think that the drop is rather small, given the magnitude of isolated risk the curve represents. However, if we hedge the curve, we also eliminate the beneficial effect the negative correlation between curve and spreads has on the overall risk of the portfolio. Therefore, we have a more limited impact when hedging the curve risk. In fact, for this portfolio we see that hedging any particular set of risk factors has a limited effect on the overall risk.

The TEV elasticity reported in the last column gives further insight into how the TEV in the portfolio changes when the risk loadings are changed. Specifically, it tells us what the percentage change in TEV would be if we changed our exposure to that particular set of factors by 1%. If we reduce our exposure to corporate spreads by 1%, our TEV would fall by 0.1%.

Figure 8: Security Partition – Risk Analysis I

		Contribution to TEV		
Security Partition Bucket	NMW (%)	Systematic	Idiosyncratic	Total
Total	**0.0**	**6.3**	**7.4**	**13.7**
Treasuries	-2.0	2.9	0.2	3.1
Government Agencies	-5.4	0.5	0.4	0.9
Government Non-Agencies	-1.0	-1.4	0.1	-1.3
Corporates	12.4	3.4	4.3	7.7
MBS	-5.8	0.9	0.8	1.7
ABS	-0.3	0.0	0.0	0.0
CMBS	2.1	0.0	1.6	1.6

Source: POINT, Barclays Capital

We perform a similar analysis in Figure 8, but applied to a security partition. That is, instead of looking at individual sources of risk (eg, curve) across all securities, we now aggregate all sources of risk within a security and report analytics for different groups of these securities (eg, sub-portfolios). Figure 8 reports results when securities are grouped by asset class. It shows that the majority of risk (7.7bp/month) comes from the corporate component of the portfolio[10]. This sector is the primary contributor to both the portfolio's systematic and idiosyncratic components of risk. This is not surprising, given the portfolio's large net market weight (NMW) to this sector. There are two other important sources of risk. The first is the Treasuries sub-portfolio, with 3.1bp/month of risk. This risk comes mainly from the mismatch in duration. The second comes from the idiosyncratic risk of the CMBS component of the portfolio. Even though the NMW and systematic risk are not significant for this asset class, the relatively small number of (risky) CMBS positions in the portfolio causes it to have significant idiosyncratic risk (three securities in the portfolio versus 1,735 in the index). Since the portfolio manager is trying to replicate a very large benchmark with only 50 positions, she has to be very confident in the issuers selected. This report highlights the significant name risk to which the portfolio is exposed.

Figure 9 completes the analysis, reporting other important risk statistics about the different asset classes within the portfolio. These statistics mimic the analysis done in terms of risk factor partitions in Figure 7, so we will not repeat their definitions. We focus on the numbers. In particular, the isolated TEV from the corporate sector is 15.2bp/month, higher than the total risk of the portfolio. This means that the exposures to the other asset classes, on average, hedge our credit portfolio. The figure also reports that the agencies' isolated risk is very large. This is because of our large negative net exposure (-5.4%) to this asset class. But the risk is fully hedged by the other exposures of the portfolio (eg, long exposure to credit or long duration on Treasuries), so, overall, the risk contribution of this asset class is small, as previously discussed. We can even take the analysis a bit further: Figure 9 shows us, via the liquidation effect, that if we eliminate the imbalance that the portfolio has on agencies, we actually would raise the total risk of the portfolio by 2.0bp/month. In short, we would be eliminating the hedge this asset class provides to the global portfolio, therefore increasing its risk. The exposures to this asset class were clearly built to counteract other exposures in the portfolio. Finally, Figure 9 also reports the TEV elasticity of the different components of the portfolio. This number represents the percentage change in TEV if the NMW to that sub-portfolio changes by 1%, so we need to read the numbers with an opposite sign if the NMW is negative. In particular, if we increase the weight of the agency portfolio in absolute value (making it "more short") by 1%, we would actually increase the TEV by 0.1%. This result shows that the position in agencies provides hedging "on average", but further increasing the exposure to this sector would actually increase the risk of the portfolio. In other words, the hedging went beyond its optimal value.

Figure 9: Security Partition – Risk Analysis II

Security Partition Bucket	Isolated TEV	Liquidation Effect on TEV	TEV Elasticity (%)
Total	**13.7**	**-13.7**	**1.0**
Treasuries	7.4	-1.1	0.2
Government Agencies	9.1	2.0	0.1
Government Non-Agencies	6.7	2.7	-0.1
Corporates	15.2	0.6	0.6
MBS	5.8	-0.5	0.1
ABS	1.1	0.1	0.0
CMBS	5.1	-0.7	0.1

Source: POINT, Barclays Capital

[10] This result does not contradict the findings in Figure 7, where we see that curve is the major source of risk. Remember that the curve risk can come from our corporate sub-portfolio.

The summary reports give a very clear picture of the major sources of risk and how they relate to each other. Below, we give a more detailed analysis of individual systematic sources of risk.

Factor Exposure reports

At the heart of a multi factor risk model is the definition of the set of systematic factors that drive risk across the portfolio. As described above, a fixed income portfolio is exposed to different sorts of risk. In what follows, we focus on the three major types: curve, credit and prepayment risk. Specifically as regards the latter two, we use the credit and MBS component of the portfolio, respectively, to illustrate how to measure risks along these dimensions. Moreover, to keep the example simple, we show only a partial view of all relevant factors for these sources of risk. Later in this section we refer briefly to the other sources of risk to which a fixed-income portfolio may be exposed.

- Curve Risk

Curve risk is the major source of risk across fixed-income instruments. This kind of risk is embedded in virtually all fixed-income securities[11]; therefore, mismatches in curve profiles relative to a benchmark are often the main drivers of portfolio risk. As the previous analysis shows (eg, Figure 7), curve is the major source of risk in our particular portfolio.

When analyzing curve risk, we should use the curve of reference we are interested in. Depending on the portfolio and circumstances, this is typically the government or swap curve[12]. In calm periods, the behavior of the swap curve tends to match that of the government curve. However, during liquidity crises (eg, the Russian crisis of 1998 or the credit crisis of 2008), they can diverge significantly. To capture these different behaviors adequately, we analyze curve risk using the following breakdown: for government products, the curve risk is assessed using the government curve; for all other products in our portfolio (that usually trade off the swap curve), this risk is measured using both the Treasury curve and swap spreads (ie, the spreads between the swap and the government curve). Other decompositions are also possible.

The risk associated with each of these curves can be described by the portfolio's exposure to different points along the curve and a convexity term, and by how volatile and correlated the movement in these points of the curve is. For a typical portfolio, a good description of the curve can be achieved by looking at a relatively small number of points along the curve (called key rates), eg, 6-month, 2-year, 5-year, 10-year, 20-year, and 30-year. An alternative set of factors used to capture yield curve risk can be defined using statistical analysis of the historical realizations of the various yield curve points. The statistical method used most often is called principal component analysis (PCA). This method defines factors that are statistically independent of each other. Typically, three or four such factors are sufficient to explain the risk associated with changes of yields across the yield curve. PCA analysis has several shortcomings and must be used with caution. Using a larger set of economic factors, like the key-rate points described above, is more intuitive and captures the risk of specialized portfolios better. For these reasons, many portfolio managers favor the key-rates approach for most risk analysis problems.

Figure 10 details the risk in our portfolio associated with the US Treasury curve. It starts by describing all risk factors our portfolio or benchmark load on. As discussed above, we identify the six key-rate (KR) points in the curve plus the convexity term as the risk factors associated

[11] Exceptions are for instance floaters or distressed securities.
[12] Other curves that can be used are for instance the municipals (tax free) curve, derivatives-based curves, etc.

with US Treasury risk. They are described in the first column of panel A in the figure. They measure the risk associated with moves in that particular point in the curve. Exposure to these risk factors is measured by the key rate durations (KRD) for each of the six points. The description of the loading is in the second column of the figure, while values for the portfolio, benchmark and the difference are displayed in subsequent columns. Key-rate durations are also called partial durations, as they add up to approximately the duration of the portfolio. Their loadings are constructed by aggregating partial durations across (virtually) all the securities. For instance, for our portfolio, the sum of the key rate durations is 0.14 + 0.86 + 1.3 + 0.77 + 1.02 + 0.47 = 4.56, very close to the total duration of our portfolio. Their loadings are constructed by aggregating partial durations across all the securities.

Figure 10 shows significant mismatches in the duration profiles of our portfolio and its benchmark, namely at the 10-year and 20-year points on the curve. Specifically, we are short 0.36 years at the 10-year point and long 0.49 years at the 20-year point. How serious is this mismatch? Looking at the factor volatility column, it can be seen that these points on the curve have been very volatile, at around 40bp/month. If we interpret this volatility as a typical move, the first two columns of panel B show us the potential impact of such a movement in the return of our portfolio, net of benchmark. For instance, a typical move up (+44.2bp/month) in the 10-year point of the Treasury curve, when considered in isolation, will deliver a positive net return of 15.9bp[13]. In isolation, the positive impact is expected because we are short that point of the curve. More interesting may be the correlated number in the figure. It states the return impact but in a correlated fashion. In the scenario under analysis, a movement in the 10-year point will almost certainly involve a movement of the neighboring points in the curve. So, contrary to the positive isolated effect documented above, the correlated impact of a change up in the 10-year point is actually negative, at -5.0bp. This result is in line with the overall positive duration exposure of the portfolio: general (correlated) movements up in the curve have a negative impact on the portfolio's performance[14]. Moreover, and broadly speaking, the ratio of the correlated impact to the factor volatility gives us the model-implied partial empirical duration of the portfolio. For instance, if we focus on the 10-year point, we get 5.0/44.2 = 0.11. This smaller empirical duration is typical in portfolios with spread exposure. The spread exposure tends to empirically hedge some of the curve exposure, given the negative correlation between these two sources of risk. Finally, the figure shows the risk associated with convexity. We can see that the benchmark is significantly more negatively convex, so the portfolio is more protected than the benchmark from higher-order changes in the yield curve.

One can analyze many other statistics of interest with regard to the Treasury curve risk of the portfolio. Portfolio managers frequently want to know: If I want to reduce the risk of my portfolio by manipulating my Treasury curve exposure, what should I change? What is the most effective move? By how much would my risk actually change? The statistics reported in the columns "Marginal Contribution to TEV" and "TEV Elasticity (%)" of panel B are typically used to answer these questions. Regarding the marginal contributions, the 10-year point has the largest value, showing us that an increase (reduction) of one unit of exposure (in this case one year of duration) to the 10-year point leads to an increase (reduction) of around 16bp in

[13] This number is obtained by simply multiplying the net exposure by the factor volatility. The sign of the move depends on the interpretation of the factor. In the case of the yield curve movements we know that $R = -KRD \times \Delta KR$, where KRD is the duration associated with the KR point. In our example –(-0.36) x 44.2 = 15.9.

[14] This reversal is clearly related to the fact that the 10-year and the 20-year points in the curve are usually highly correlated. In our case our short position on the 10-year point is more than compensated by the positive exposure in the 20-year. Netting out, the 20-year effect (long duration) dominates when all changes are taken in a correlated fashion.

our TEV[15]. In other words, if we want to reduce risk by manipulating our exposure to the yield curve, the 10-year point seems to present the fastest track. In addition, the figure shows that all Treasury risk factors are associated with positive marginal contributions. This means that a rise in exposure to any of these factors increases the risk (TEV) of the portfolio. This conclusion holds, even for factors for which we have negative exposure (eg, the 10-year key-rate). The reason behind this result is our overall long duration exposure. If we add exposure to it, regardless of the specific point where we add it, we extend our duration even further, increasing the mismatch our portfolio has in terms of duration, and so increasing its risk[16]. This result holds because we take into consideration the correlations between the different points in the Treasury curve. Without correlations, the analysis would be much less clear.

Figure 10: Treasury Curve Risk

A. Exposures and Factor Volatility

Factor name	Units	Exposure Portfolio	Benchmark	Net	Factor Volatility
USD 6M key rate	KRD (Yr)	0.14	0.15	-0.01	36.0
USD 2Y key rate	KRD (Yr)	0.86	0.70	0.15	38.0
USD 5Y key rate	KRD (Yr)	1.30	1.25	0.05	44.3
USD 10Y key rate	KRD (Yr)	0.77	1.13	-0.36	44.2
USD 20Y key rate	KRD (Yr)	1.02	0.53	0.49	39.6
USD 30Y key rate	KRD (Yr)	0.47	0.53	-0.06	39.7
USD Convexity	OAC	-0.15	-0.29	0.13	8.4

B. Other Risk Statistics

Factor name	Return Impact of a Typical Move Isolated	Correlated	Marginal Contribution to TEV	TEV Elasticity (%)
USD 6M key rate	0.5	-2.4	6.3	0.0
USD 2Y key rate	-5.8	-4.5	12.2	0.1
USD 5Y key rate	-2.0	-4.5	14.5	0.0
USD 10Y key rate	15.9	-5.0	15.9	-0.4
USD 20Y key rate	-19.5	-5.2	14.9	0.5
USD 30Y key rate	2.5	-5.2	14.8	-0.1
USD Convexity	1.1	2.0	1.2	0.0

Source: POINT, Barclays Capital

Figure 10 also reports the TEV elasticity of each of the risk factors, a concept introduced earlier. The interpretation is similar to the marginal contribution, but with normalized changes (percentage changes). This normalization makes the numbers more comparable across different risk factors. It is also useful when considering leveraging the entire portfolio proportionally. In our case, if we increase the exposure to the 10-year key rate point by 10%, from -0.36 to something around -0.40 (effectively reducing our long duration exposure), our TEV would be reduced by 4% (from 13.7 to 13.2bp/month).

We now turn the analysis to the other component of the curve risk described above: the risk embedded into the portfolio exposure to swap spreads; that is, the differences between the swap and Treasury curves. Many securities trade against the swap curve, making it the

[15] The marginal contribution is the derivative of the TEV with respect to the loading of each factor, so its interpretation holds only locally. Therefore a more realistic reading may be that if we reduce the exposure to the 10-year by 0.1 years, the TEV would be reduced by around 1.6bp.
[16] This is a rationale very similar to the one used before, where we see all correlated impact with the same signal.

natural choice as the base risk curve for those markets. To unify the analysis with markets that use Treasuries as the base curve, we break the swap curve into the Treasury curve (analyzed in Figure 10) and excess over the Treasury — the swap spread.

In our approach, all securities that trade against the swap curve (eg, all typical credit and securitized bonds) are exposed to both Treasury and swap spread (SS) risk. The analysis of the latter follows very closely that of the Treasury curve, so we highlight only the major risk characteristics of the portfolio along this dimension. Figure 11 shows that, in general, our exposure to the swap spreads is smaller than that of the Treasury curve. Remember that Treasuries do not load on this set of risk factors, so the market-weighted exposures are smaller. Looking at the profile of factor volatilities, it is clear that its term structure of volatilities is U-shaped, with the short end extremely volatile and the five-year point having the least volatility. When comparing with the Treasury curve volatility profile (Figure 10), we can see significant differences, the aftermath of a strong liquidity crisis. Regarding net exposures, Figure 11 shows that our largest mismatch is at the 30-year point, where we are short by 0.15 year. Interestingly, this is not the most expensive mismatch in terms of risk: when looking at the last column, we see that we would be able to change risk the most by manipulating the short end of our exposure to the swap spread curve, namely the six-month point.

Figure 11: Swap Spread (SS) Risk

Factor name	Exposure (SS-KRD)			Factor Volatility	Return Impact Correlated	Marginal Contribution to TEV
	Portfolio	Benchmark	Net			
6M SS	0.14	0.13	0.01	39.1	-2.1	5.8
2Y SS	0.52	0.47	0.04	20.4	-2.1	3.0
5Y SS	0.84	0.75	0.09	9.6	-2.0	1.4
10Y SS	0.71	0.68	0.03	14.1	1.7	-1.8
20Y SS	0.34	0.33	0.01	17.0	2.2	-2.7
30Y SS	0.06	0.20	-0.15	20.1	2.4	-3.5

Source: POINT, Barclays Capital

The previous figures help us to understand our exposures to the different types of curve risk and their impact on the return and risk of our portfolios. They also guide us as to changes we might introduce to modify the risk profile of the portfolio. We now turn to sources of risk that are more specific to particular asset classes. We start with the analysis of credit risk.

- Credit Risk

Instruments issued by corporations or entities that may default are said to have credit risk. Holders of these securities demand some extra yield – on top of the risk-free yield – to compensate for that risk. The extra yield is usually measured as a spread to a reference curve. For instance, for corporate bonds, the reference curve is usually the swap curve, so spread is typically quoted relative of this curve. The level of credit spreads determines to a large extent the portfolio's exposure to credit risk[17].

Several characteristics of credit bonds are naturally associated with systematic sources of credit spread risk. For instance, depending on the business cycle, particular industries may be going through especially tough times. So industry membership is a natural systematic source of risk. Similarly, bonds with different credit ratings are usually treated as having different

[17] Spreads are also compensation for sources of risk other than credit (eg, liquidity), but for the sake of our argument, we treat them as major indicators of credit risk.

levels of credit risk. Credit rating could also be used to measure systematic exposure to credit risk. Given these observations, it is common to see factor models for credit risk using industry and ratings as the major systematic risk factors. Recent research suggests that risk models that directly use the spreads of the bonds instead of their ratings to asses risk perform better for relatively short/medium horizons of analysis[18]. Under this approach, the loading of a particular bond to a credit risk factor would be the commonly used spread duration, but now multiplied by the bond's spread (the loading is termed DTS = *D*uration *T*imes *S*pread = OASD × OAS). By directly using the spread of the bond in the definition of the loading to the credit risk factors, we do not need to assign specific risk factors to capture the rating or any similar quality-like effect. It will be automatically captured by the bond's loading to the credit risk factor, and will adjust as the spread of the bond changes. We use different systematic risk factors only to distinguish among credit risks coming from different industries.[19]

The results of this approach to the analysis of our portfolio are displayed in Figure 12, which shows the typical industry risk factors associated with credit risk.

Figure 12: Credit Spread Risk

Factor name	Exposure (DTS)			Factor	Return Impact	Marginal Contribution to TEV
	Portfolio	Benchmark	Net	Volatility	Correlated	
IND Chemicals	0.00	0.03	-0.03	15.01	-0.39	0.43
IND Metals	0.00	0.06	-0.06	20.01	-0.16	0.23
IND Paper	0.00	0.01	-0.01	17.04	-0.40	0.49
IND Capital Goods	0.00	0.05	-0.05	14.98	-0.02	0.02
IND Div. Manufacturing	0.00	0.03	-0.03	14.21	-0.62	0.64
IND Auto	0.00	0.01	-0.01	22.18	-0.53	0.85
IND Consumer Cyclical	0.10	0.05	0.06	17.05	-0.26	0.32
IND Retail	0.00	0.05	-0.05	16.95	0.14	-0.17
IND Cons. Non-cyclical	0.00	0.13	-0.13	14.62	-0.22	0.24
IND Health Care	0.00	0.02	-0.02	14.07	0.13	-0.13
IND Pharmaceuticals	0.19	0.06	0.12	15.13	-0.34	0.37
IND Energy	0.12	0.20	-0.07	16.39	-0.29	0.34
IND Technology	0.00	0.06	-0.06	15.52	-0.11	0.12
IND Transportation	0.00	0.05	-0.05	15.09	-0.26	0.29
IND Media Cable	0.24	0.06	0.18	15.83	0.51	-0.58
IND Media Non-cable	0.00	0.04	-0.04	15.94	0.20	-0.23
IND Wirelines	0.09	0.17	-0.08	15.26	0.41	-0.45
IND Wireless	0.00	0.03	-0.03	14.87	1.06	-1.13
UTI Electric	0.28	0.20	0.08	15.79	-0.16	0.18
UTI Gas	0.09	0.10	-0.01	18.51	-0.41	0.55
FIN Banking	0.88	0.56	0.32	18.61	1.19	-1.59
FIN Brokerage	0.00	0.02	-0.02	15.90	1.47	-1.68
FIN Finance Companies	0.08	0.10	-0.02	20.64	0.68	-1.01
FIN Life & Health Insurance	0.12	0.11	0.01	19.96	0.58	-0.84
FIN P&C Insurance	0.00	0.06	-0.06	11.76	0.34	-0.29
FIN Reits	0.14	0.04	0.10	17.68	0.80	-1.02
Non Corporate	0.06	0.23	-0.17	25.27	0.28	-0.50

Source: POINT, Barclays Capital

[18] For details, please refer to Ben Dor et al. (2010).

[19] The general principle of a risk model is that the historical returns of assets contain information that can be used to estimate the future volatility of portfolio returns. However, good risk models must have the ability to translate the historical asset returns to the context of the current environment. This translation is made when designing a particular risk model/factor and delivers risk factors that are as invariant as possible. This invariance makes the estimation of the factor distribution much more robust. In the particular case of the DTS, by including the spread in the loading (instead of using only the typical spread duration), we change the nature of the risk factor being estimated. The factor now represents percentage change in spreads, instead of absolute changes in spreads. The former has a significantly more invariant distribution. For more details, please refer to Silva (2009a).

The portfolio has net positions in 27 industries, spanning all three major sectors: Industrials (IND), Utilities (UTI) and Financials (FIN). We saw before that we have a significant net exposure to financials in terms of market weights (12.2%; Figure 1). In terms of risk exposure, Figure 12 shows that the net DTS attached to the Banking industry is 0.32, clearly the highest across all sectors.[20] However, the marginal contribution to TEV that comes from that industry, although high, is comparable to other industries, namely Brokerage, for which the net exposure is close to zero. This means that these two industries are close substitutes in terms of the current portfolio holdings.

Another interesting point is highlighted by the fact that the marginal contribution is negative for all industries, even though some (such as Banking or Media Cable) are significantly overweighted. The analysis suggests that if we increase our risk exposure to Banking, our risk would actually decrease. This result is again driven by the strong negative correlation between spreads in financials and the yield curve. Therefore, the exposure in banking is actually helping hedge out our (more risky) long duration position. This kind of analysis is possible only when you account for the correlations across factors. It is also dependent on the quality of the model's correlation estimates.

Although the risk factors used to measure risk are predetermined in a linear factor model, there is extreme flexibility on the way the risk numbers can be aggregated and reported[21]. For example, as explained above, the risk model we use to generate the current risk reports does not use credit ratings as drivers of systematic credit risk. Instead, it relies on the DTS concept. However, once generated, the risk numbers can be reported using any portfolio partition.

As an example, Figure 13 shows the risk breakdown by rating, indicating that the majority of risk is coming from our AAA exposure (10.9bp/month), the bucket with the biggest mismatch in terms of net weight (-7.2%). This bucket includes Treasury and government-related securities, sectors that are underweighted in the portfolio leading to significant risk. This is clearer when we look into the isolated TEV numbers. If we had mismatches only on AAAs, the risk of our portfolio would be 37.4bp/month, instead of the actual 13.7bp; the other exposures (namely the one to single-As) hedge the risk from AAAs.

Figure 13: Risk per Rating

Rating	NMW (%)	TEV				Systematic Beta
		Contribution	Isolated	Liquidation	Elasticity (%)	
Total	0.0	13.7	13.7	-13.7	1.0	1.03
AAA	-7.2	10.9	37.4	22.2	0.8	1.12
AA1	-0.3	-0.2	1.0	0.2	0.0	0.00
AA2	0.2	0.3	3.3	0.1	0.0	1.10
AA3	-2.3	-1.3	6.7	2.6	-0.1	0.00
A1	-0.5	0.3	4.2	0.4	0.0	1.51
A2	7.1	3.6	11.2	1.0	0.3	0.77
A3	4.7	1.7	5.8	-0.5	0.1	0.65
BAA1	-0.1	0.3	3.7	0.2	0.0	1.51
BAA2	-3.3	-2.3	11.5	5.9	-0.2	0.00
BAA3	1.7	0.3	7.7	1.7	0.0	0.37

Source: POINT, Barclays Capital

[20] The DTS units used in the report are based on a OASD stated in years and an OAS in percentage points. Thus, a bond with an OASD = 5 and an OAS = 200bp would have a DTS of 5 × 2 =10. The DTS industry exposures are the market-weighted sum of the DTS of each of the securities in that industry.
[21] For a detailed methodology on how to performed this customized analysis, please see Silva (2009b).

Figure 13 also indicates the systematic betas associated with each of the rating sub-portfolios. These betas add up to the portfolio beta, when we use the portfolio weights (not NMW) as weights in the summation. For example, the figure allows us to infer that a movement of 10bp in the benchmark leads to an 11.2bp return in the AAA sub-component of the portfolio. On the other hand, the beta of 0.37 for the BAA3 component of the portfolio does not signal low volatility for this sub-portfolio. It mainly indicates low correlation with the benchmark, possibly a result of the significant role of idiosyncratic risk for this set of bonds. Systematic betas of zero identify buckets for which the portfolio has (close to) no holdings.

- Prepayment Risk

Securitized products are generally exposed to prepayment risk. The most common of the securitized products are the residential MBS (RMBS or simply MBS). These securities represent pools of deals that allow the borrower to prepay their debt before the maturity of the loan/deal, typically when prevailing lending rates are lower. This option means an extra risk to the holder of the security: the risk of holding cash exactly when reinvestment rates are low. Therefore, these securities have two major sources of risk: interest rates (including convexity) and prepayment risk.

Some part of the prepayment risk can be expressed as a function of interest rates via a prepayment model. This risk will be captured as part of interest-rate risk using the key-rate durations and the convexity. Convexity, which is usually negative for these instruments, is a significant source of risk. Negative convexity has a detrimental effect on the market value of an instrument – compared with one with positive or zero convexity – when interest rates move significantly in either direction. Indeed, decreasing interest rates cause prepayments to increase thereby reducing the price appreciation because of the falling rates. Conversely, rising interest rates intensify the price depreciation the instrument suffers with higher rates.

The remaining part of prepayment risk – that is not captured by the prepayment model – must be modeled with additional systematic risk factors. Typically, the volatility of prepayment speeds (and therefore of risk) on MBS securities depends on three characteristics: program/term of the deal, if the bond is priced at discount or premium (eg, if the coupon on the bond is bigger than the current mortgage rates) and how seasoned the bond is. This analysis suggests that the systematic risk factors in a risk model should span these three characteristics of the securities.

Figure 14: MBS (Spread) Prepayment Risk

	Exposure (OASD)			Factor	Return Impact	Marginal Contribution to TEV
Factor name	Portfolio	Benchmark	Net	Volatility	Correlated	
MBS New Discount	0.00	0.00	0.00	36.8	-1.2	3.3
MBS New Current	0.00	0.04	-0.04	24.5	-0.3	0.6
MBS New Premium	0.38	0.59	-0.21	29.7	-0.1	0.3
MBS Seasoned Current	0.00	0.00	0.00	25.5	-0.6	1.2
MBS Seasoned Premium	0.65	0.46	0.19	29.8	0.1	-0.2
MBS Ginnie Mae 30Y	0.31	0.21	0.10	6.1	-0.1	0.0
MBS Fannie Mae 15Y	0.00	0.11	-0.11	15.7	0.4	-0.4
MBS Ginnie Mae 15Y	0.00	0.01	-0.01	12.3	0.5	-0.4

Source: POINT, Barclays Capital

Figure 14 shows a potential set of risk factors that capture the three characteristics discussed above. Programs identified as having different pre-payment characteristics are the conventional (Fannie Mae) 30-year bonds (the base case used for the analysis), the 15-year conventional (Fannie Mae) bonds, as well as the Ginnie Mae 30- and 15-year bonds. The age of bonds is captured by factors distinguishing between new and aged deals. Finally, each bond is also classified by the price of the security – discount, current or premium. In this example there are no seasoned discounted bonds, given the current unprecedented level of mortgage rates. In terms of risk exposures, the figure shows that we are currently underweighting 15-year conventional bonds, and overweighting 30-year Ginnie Mae bonds.

- Interaction between Sources of Risk

So far we analyzed the major sources of spread risk: credit and prepayment. To do this, we conveniently used two asset classes – credit and agency RMBS, respectively – where one can argue that these sources of risk appear relatively isolated. However, recent developments have made very clear that these sources of risk appear simultaneously in other major asset classes, including non-agency RMBS, home equity loans and CMBS[22]. When designing a risk model for a particular asset class, one should be able to anticipate the nature of the risks the asset class exhibits currently or may encounter in the future. The design and ability to segregate between these two kinds of risk depends also on the richness of the bond indicatives and analytics available to the researcher. For this last point, it is imperative that the researcher understands well the pricing model and assumptions made to generate the analytics typically used as inputs in a risk model. This allows the user to fully understand the output of the model, as well as its applicability and shortcomings.

- Other Sources of Risk

There are other sources of systematic risk that may be important sources of risk for particular portfolios. Specific risk models can be designed to address them. We now mention some of them briefly.

Implied Volatility Risk: Many fixed income securities have embedded options (eg, callable bonds). This means that the expected future volatility (implied volatility[23]) of the interest rate or other discount curves used to price the security plays a role in the value of that option. If expected volatility increases, options generally become more expensive affecting the prices of bonds with embedded options. For example, callable bonds will become cheaper with increasing implied volatility because the bond holder is short optionality (the right of the issuer to call the bond). Therefore, the exposure of the portfolio to the implied volatility of the yield curve is also a source of risk that should be accounted for. The sensitivity of securities to changes of implied volatilities is measured by vega, which is calculated using the security pricing model. Implied volatility factors can be either calculated by the market prices of liquid fixed-income options (caps, floors and swaptions), or implied by the returns of bonds with embedded options within each asset class.

Liquidity Risk: Many fixed income securities are traded over-the-counter, in decentralized markets. Some trade infrequently, making them illiquid. It is therefore hard to establish their fair price, These bonds are exposed to liquidity risk. The holder of illiquid bonds would have to pay a higher price to liquidate its position, usually meaning selling at a discount. This discount is uncertain and varies across the business cycle. For instance, the discount can be significant in a liquidity crisis, such as the one of 2008. The uncertainty about this discount

[22] For more discussion, please refer to Gabudean (2009).
[23] The volatility is called implied because it is calculated from the market prices of liquid options with the help of an option-pricing model.

means that, everything equal, a more illiquid bond will be riskier. This extra risk can be captured through liquidity risk factors. For instance, in the Treasury markets, one generally refers to the difference in volatility between an on-the-run and an off-the-run Treasury bond as liquidity risk.

Inflation risk: Inflation-linked securities are priced based on the expectation of future inflation. Uncertainty about this variable adds to the volatility of the bond over and above the volatility from other sources of risk, such as the nominal interest rates. Expected inflation is not an observed variable in the marketplace but can be extracted from the prices on inflation-linked government bonds and inflation swaps. Expected inflation risk factors can be constructed by summarizing this information. The sensitivity of securities to expected inflation is calculated using a specialized pricing model and is usually called inflation duration.

Tax-Policy Risk: Many municipal securities are currently tax-exempt. This results in added benefit to their holders. This benefit – incorporated in the price of the security – depends on the level of exemption allowed. Uncertainty regarding tax policy – tax-policy risk – adds to the risk of these securities. Once again, tax-policy risk factors cannot be observed in the marketplace and must be extracted from the prices of municipal securities. The return of municipal securities in excess of interest rates is driven partially by tax-policy expectations changes. However, it is also driven by changes in the creditworthiness of the municipal issuers as well as other factors. In this case it is difficult to separate tax-policy risk factors from other factors driving municipal bond spreads. Therefore, instead of specific tax-policy factors we usually extract factors representing the overall spread risk of municipal securities. This exercise is performed in a similar way to the credit risk model, where securities are partitioned into groups of "similar" risk by geography, bond-type (general obligation vs. revenue), tax-status, etc[24].

Issue-Level Reports

The previous analysis focused on the systematic sources of risk. We now turn our attention to the idiosyncratic or security-specific risk embedded in our portfolio. This risk measures the volatility the portfolio has as a result of news specific to the individual issues/issuers it holds. Therefore, the idiosyncratic risk is independent across issuers and diversifies away as the number of issues in the portfolio increases: negative news about some issuers is canceled by positive news about others. For relatively small portfolios, the idiosyncratic risk may be a substantial component of the total risk. This can be seen in our example, as our portfolio has only 27 issuers. Figure 6 shows that the idiosyncratic volatility of our portfolio is 11.1bp/month, almost twice the idiosyncratic volatility of the benchmark (5.6bp/month). When looking at the tracking error volatility net of benchmark, Figure 7 shows that our specific risk is 10.1 bp/month and larger than the systematic component (9.3 bp/month). This means that, typically, a major component of the monthly net return is driven by events affecting only individual issues or issuers. Therefore, monitoring these individual exposures is of paramount importance.

The idiosyncratic risk of each bond is a function of two variables: its net market weight and its idiosyncratic volatility. This last parameter depends on the nature of the bond issuer. For instance, a bond from a distressed firm has much higher idiosyncratic volatility than one from a government-related agency.

Figure 15 provides a summary of the idiosyncratic risk for the top ten positions by market weight in our portfolio. Unsurprisingly, our top seven holdings are Treasuries and MBS

[24] For more discussion, please refer to Staal (2009).

securities, in line with the constitution of the index we are using as benchmark. Moreover, these positions have significant market weights, given that our portfolio contains only 50 securities. Although we see large concentrations, the idiosyncratic TEV for the top holdings is small, as they are not exposed to significant name risk. The last column of the table shows that from this group the largest idiosyncratic risk comes from two corporate bonds (issued by Comcast Cable Communication "CMCSA" and Merrill Lynch "BAC"). This is not surprising, as these are the type of securities with larger event risk. Even within corporates, idiosyncratic risk can be quite diverse, depending on the industry, duration and level of distress of the issuer (usually proxied by rating, in our model by the spread of the bond). For instance, the net positions of the CMCSA and BAC bonds are similar (2.2% and 2.1%, respectively), but even though the maturity of the BAC bond is significantly shorter, its spread is higher, delivering a higher idiosyncratic risk (2.9 versus 2.4bp/month). The fact that BAC is a firm from an industry (Financials) that experienced significant volatility in the recent past also contributes to higher idiosyncratic volatility. To manage the idiosyncratic risk in the portfolio one should pay particular attention to mismatches between the portfolio and benchmark for bonds with large spreads or long durations. These would tend to affect disproportionably the idiosyncratic risk of the portfolio.

Figure 15: Issue-Specific Risk

Identifier	Ticker	Description	Maturity	Spread (bp)	Market Weight (%)		Idiosyncratic TEV
					Portfolio	Net	
912828KF	US/T	US TREASURY NOTES	2/28/2014	4	5.4	5.2	0.4
912828KJ	US/T	US TREASURY NOTES	3/31/2014	3	5.0	4.8	0.4
912828JW	US/T	US TREASURY NOTES	12/31/2013	1	4.7	4.5	0.4
912828KN	US/T	US TREASURY NOTES	4/30/2014	2	3.8	3.6	0.3
FNA04409	FNMA	FNMA Conventional Long T. 30yr	3/1/2039	20	3.2	1.1	0.4
FGB04409	FHLMC	FHLM Gold Guar Single F. 30yr	3/1/2039	25	2.7	1.1	0.4
912810FT	US/T	US TREASURY BONDS	2/15/2036	-1	2.3	2.1	0.7
20029PAG	CMCSA	COMCAST CABLE COMMUNICATION	5/1/2017	222	2.2	2.2	2.4
59018YSU	BAC	MERRILL LYNCH & CO.	2/3/2014	300	2.1	2.1	2.9
912828KV	US/T	US TREASURY NOTES	5/31/2014	1	2.1	1.9	0.2

Source: POINT, Barclays Capital

Although important, the information in Figure 15 is not enough to assess fully the idiosyncratic risk embedded in the portfolio. For instance, a portfolio manager could buy credit protection on CMCSA through a credit default swap (CDS), thereby significantly reducing the net exposure to this issuer's bond. The position reported in this exhibit would still look significant because the CDS protection would not be reflected in it.

A better way is to look at idiosyncratic risk at the issuer rather than at the issue level. Although idiosyncratic risk is usually independent across issuers, one should not assume that the idiosyncratic risk of securities of the same issuer is uncorrelated because they are all subject to the same company-specific events. A good risk model should account for such correlation and try to quantify it for different issuer and security types. For example, all types of securities (bonds, equities, convertibles, etc) of an issuer in financial distress tend to move in a correlated fashion because they all represent claims to the same distressed assets. Adding more securities from such an issuer to a portfolio does not generally deliver additional diversification. On the other hand, securities from issuers in strong financial health can move quite differently from each other, driven mainly by liquidity or capital structure effects rather than credit. In this case, a portfolio manager can achieve some diversification of idiosyncratic risk (although limited) even when adding issues from that same issuer into the portfolio.

To help us understand the net effect of all these points, it is useful to look at the idiosyncratic risk at the issuer level. When aggregating risk from the issue (as shown in Figure 15) to the issuer level, the correlations referred to above should be fully taken into account. Figure 16 shows the results of this exercise, for the ten issuers in our portfolio with the highest idiosyncratic TEV. Our riskiest exposure comes from Johnson & Johnson ("JNJ"), with 3.7bp/month of issuer risk. We can also observe that idiosyncratic TEV is not monotonic in the NMW: we have JNJ and President & Fellows of Harvard ("HARVRD") with the same NMW, but the former is significantly more risky (3.7 versus 2.0bp/month). It is possible to have important issuer risk even for names we do not have in our portfolio, if they have significant market weight in the benchmark.

Finally, note that because the idiosyncratic risk across issuers is independent, we can easily calculate the cumulative risk of several issuers. For example, the total idiosyncratic risk of the first two issuers is given by:

$$TEV_{idio}^{JNJ+D} = \sqrt{3.7^2 + 2.8^2} = 4.6$$

As is the case w ith most portfolios tracking a benchmark, most issuers present in the portfolio are overweighted relative to the benchmark. This is a natural consequence of the fact that, in practice, portfolios hold far fewer positions than the benchmark. It may be difficult for the manager to hold positive views on all issuers selected in the portfolio. In fact, some of these positions may be selected to build exposure to specific systematic factors, eg, a particular industry or asset class, and not to a particular issuer. However, it is important that the manager hold positive views for the issuers with the largest contribution to idiosyncratic risk. If this is not the case, the manager is assuming a significant unintended name risk that should be promptly taken out of the portfolio, in favor of another issuer with similar characteristics on which the manager does have a positive view. This interactive exercise can easily be performed with a flexible portfolio construction tool and the help of an optimizer.

Figure 16: Issuer Specific Risk

Ticker	Name	Sector	NMW (%)	Idiosyncratic TEV
JNJ	JOHNSON & JOHNSON	PHARMACEUTICALS	2.0	3.7
D	DOMINION RESOURCES INC	ELECTRIC	1.8	2.8
CMCSA	COMCAST CABLE COMMUNICATION	MEDIA_CABLE	2.0	2.1
BBT	BB&T CORPORATION	BANKING	2.0	2.1
HARVRD	PRES&FELLOWS OF HARVARD	INDUSTRIAL_OTHER	2.0	2.0
AXP	AMERICAN EXPRESS CREDIT	BANKING	1.7	1.8
MS	MORGAN STANLEY DEAN WITTER	BANKING	1.3	1.7
C	CITIGROUP INC	BANKING	1.5	1.7
BAC	MERRILL LYNCH & CO.	BANKING	1.6	1.6
RBS	CHARTER ONE BANK FSB	BANKING	1.6	1.4

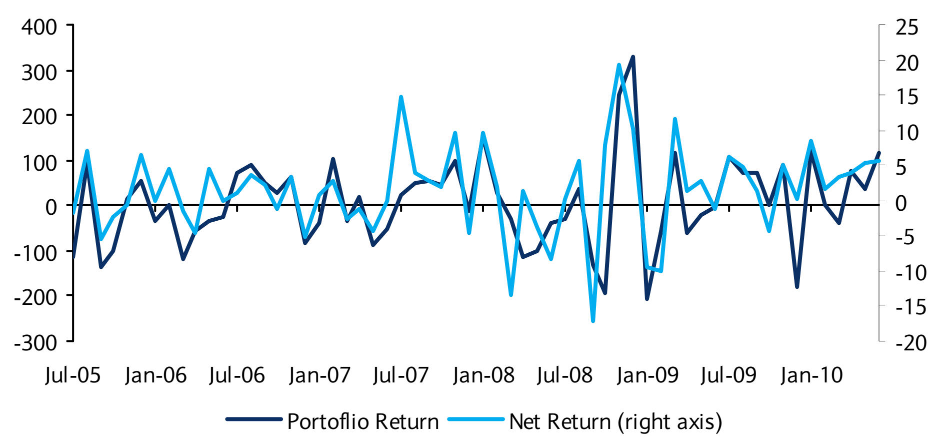
Source: POINT, Barclays Capital

Scenario Analysis Report

Scenario analysis provides additional perspective on the portfolio's risk. This exercise can be performed in several ways. For instance, a manager may want to re-price the whole portfolio under a particular scenario on risk factors, such as interest rates or spreads, and look at the hypothetical return under that scenario. Alternatively, a portfolio manager may wish to evaluate how the portfolio would have performed under particular historical scenarios (eg, the 1987 equity crash or the 1997 Asian crisis). One problem with this approach is the fact that, given the dynamic nature of the securities, the current portfolio with its current characteristics did not exist during such historical episodes. Some of the portfolio securities may have not even been issued during such periods. A solution might be to price the current securities with the market variables at the time. While a valid solution, it is difficult to implement because pricing models require inputs possibly not available during that period.

An alternative is to represent the current portfolio as the set of loadings to all systematic risk factors in a linear factor risk model. We can then multiply these loadings by the historical realizations of the risk factors. The result is a set of historical simulated systematic returns. Figure 17 presents these returns for our portfolio for five years finishing in June 2010. The dark line represents the portfolio returns and the lighter line represents the portfolio's return net of the benchmark. Note that this analysis uses only one set of static portfolio loadings. Therefore, these simulated returns can be interpreted as the hypothetical returns a portfolio with these characteristics would have, if submitted to the historical episodes. As expected, the largest volatility came with the crisis of 2008, when the portfolio registered returns between -200 and +300bp. The largest underperformance against the benchmark appeared in September 2008, followed by the largest outperformance two months after, both at about 20bp.

Figure 17: Historical Systematic Simulated Returns (basis points)



Source POINT, Barclays Capital

This analysis has some limitations, especially for the portfolio under consideration, where idiosyncratic exposure is a major source of risk. This kind of risk is always very hard to pin down and obviously less relevant from an historical perspective, as the issuers in our current portfolio may not have witnessed any particular major idiosyncratic event in the past. However, these and other kinds of historical scenario analysis are very important, as they give us some indication of the magnitude of historical returns our portfolio might have encountered. They are usually the starting point for any scenario analysis. The manager should always complement them with other non-historical scenarios relevant for the particular portfolio under analysis. In particular, the risk model can be used to express such scenarios, as discussed in the following section.

Applications of Risk Modeling

In this section we illustrate several risk model applications typically used for portfolio management. All applications make use of the fact that the risk model translates into a common, comparable set of numbers the imbalances the portfolio may have across many different dimensions. In some of applications – risk budgeting and portfolio rebalancing – an optimizer that uses the risk model as an input is the optimal setting to perform the exercise.

Portfolio Construction and Risk Budgeting

Portfolio managers can be divided broadly into indexers (those who measure their returns relative to a benchmark index) and absolute return managers (typically hedge fund managers). In between stand the enhanced indexers that we introduced previously in this report. All are typically subject to a risk budget that prescribes how much risk they are allowed to take to achieve their objectives: minimize transaction costs and match the index returns for the pure indexers, maximize the net return for the enhanced indexers, or maximize absolute returns for absolute return managers. In any of these cases, the manager has to merge all her views and constraints into a final portfolio. When constructing the portfolio, how can she manage the competing views, while respecting the risk budget? How can the views be combined to minimize the risk? What trade-offs can be made? Many different techniques can be used to structure portfolios in accordance to the manager views. In particular, risk models are widely used to perform this exercise. They perform this task in a simple and objective manner: they can measure how risky each view is and how correlated they are. The manager can then compare the risk with the expected return of each of the views and decide on the optimal allocation across her views.

An example of a portfolio construction exercise using the risk model is the one we performed to construct the portfolio analyzed in the previous section[25]. Figure 18 shows the exact problem we asked the optimizer to solve. We start the problem by defining an initial portfolio (empty in our case) and a tradable universe – the set of securities we allow the optimizer to buy or sell from. In our case, this is the Barclays Capital US Aggregate index with issues having at least $300mn of amount outstanding (first panel in the figure). The selection of this universe allows us to avoid having small issues in our portfolio, potentially increasing its liquidity. Pertaining to the risk model use, the second panel on the figure shows that the objective function used in the problem is to minimize Total TEV. This means we are giving leeway to the risk model to choose a portfolio from the tradable universe that minimizes the risk relative to the benchmark, in our case the Barclays Capital US Aggregate index. The third panel shows additional generic constraints we impose: we want a $100mn final portfolio with a maximum number of 50 securities. The fourth panel shows how we force the optimizer to tilt our portfolio to respect the portfolio manager's views: long duration against the benchmark between 0.25 and 0.30 year and spreads 100-150bp higher than the benchmark. The last panel imposes a maximum under/overweight of 2% per issuer, to

[25] The example is constructed using the POINT® Optimizer. For more details, please refer to Kumar (2010).

ensure proper diversification[26]. The characteristics of the portfolio resulting from this optimization problem were extensively analyzed in the previous section.

Figure 18: Portfolio Construction Optimization Set-up

Tradable Universe Options

No.	Name	Type	Trade/Buy/Sell	Long/Short
1	Initial Portfolio	Initial Portfolio	Buy and Sell	Long/Short
2	US Agg 300 Mln (System)	Index	Buy and Sell	Long Only

Objectives

(•) Minimize ( ) Maximize

No.	Attribute	Measure	Weight	Unit
1	Total TEV	Net vs Bmark	1.00	bps / mo
2	Systematic TEV	Net vs Bmark	0.00	bps / mo
3	Idiosyncratic TEV	Net vs Bmark	0.00	bps / mo

Common Constraints

Final Portfolio Cash (base currency): ( ) Long/Short ( ) Long Only ( ) Short Only (•) No Cash

E...	Description	Measure	Bound	Unit
☑	Budget: Final Portfolio Market Value	Change	100,000,000	USD
☑	Final portfolio maximum gross size	Target		USD
☑	Turnover: Maximum gross size of trades	Target		USD
☑	Maximum number of securities in final portfolio			
☑	Maximum number of trades		50	
☑	Minimum trade size	Target		USD

Constraints on each Issue/Issuer/Ticker

Universe Final Portfolio

No.	Soft	Penalty	Attribute	Universe	For Each	Measure	Lower Bound	Upper Bound	Unit
1	☐		Market Value [%]	Final Portfolio	Ticker	Net vs Bmark		2.00000	%

Constraints on values aggregated by Buckets

No.	Soft	...	Attribute	Universe	Measure	Lower Bound	Upper Bound	Unit
1	☐		OAD	Final Portfolio	Net vs Bmark	0.25	0.30	yrs
2	☐		OAS	Final Portfolio	Net vs Bmark	100.0	150.0	bps / yr

Source: POINT, Barclays Capital

[26] Another way to ensure diversification would be to include the minimization of the idiosyncratic TEV as a specific goal in the objective function.

Portfolio Rebalancing

Most managers rebalance their portfolios at regular intervals to reflect changing views and market circumstances. For instance, as time goes by, the characteristics of the portfolio may drift away from targeted levels. This may be due to the aging of its holdings, market moves, or issuer-specific events such as downgrades or defaults. The periodic re-alignment of a portfolio to its investment guidelines is called portfolio rebalancing. Similar needs arise in many different contexts: when managers receive extra cash to invest, get small changes to their mandates, want to tilt positions towards their views, etc. Similar to portfolio construction, a risk model is very useful in the rebalancing exercise. During rebalancing, the portfolio manager typically seeks to sell bonds currently held and replace them with others having properties more consistent with the overall portfolio goals. Such buy-and-sell transactions are costly and their cost must be weighted against the benefit from moving the portfolio closer to its desired profile. A risk model can tell the managers how much risk reduction (or increase) a particular set of transactions can achieve so that they can evaluate the risk adjustment benefits relative to the transaction cost.

As an example, suppose a portfolio manager wants to tone down her heavy overweight on banking. She wants to cap that overweight at 5% and to do it with no more than 10 trades. Each trade should be larger than $1mn. Finally, assume she wants no change to the market value of the final portfolio. We can use a setup similar to that of Figure 18, but adjusting some of the constraints. Figure 19 shows the third and fourth panel from Figure 18, changed to allow for the new constraints. Specifically, in the first panel we allow for 10 trades (with a minimum of $1mn); in the second we include the extra constraint for the banking industry.

Figure 19: Portfolio Rebalancing Optimization Set-up

Common Constraints

Final Portfolio Cash (base currency): ○ Long/Short ○ Long Only ○ Short Only ◉ No Cash

E…	Description	Measure	Bound	Unit
☑	Budget: Final Portfolio Market Value	Change	0	USD
☑	Final portfolio maximum gross size	Target		USD
☑	Turnover: Maximum gross size of trades	Target		USD
☑	Maximum number of securities in final portfolio			
☑	Maximum number of trades		10	
☑	Minimum trade size	Target	1,000,000	USD

Constraints on values aggregated by Buckets

No.	Soft	…	Attribute	Universe	Measure	Lower Bound	Upper Bound	Unit
1	☐		OAD	Final Portfolio	Net vs Bmark	0.25	0.30	yrs
2	☐		OAS	Final Portfolio	Net vs Bmark	100.0	150.0	bps / yr
3	☐		Market Value [%]	Financial Inst. Banki…	Net vs Bmark	0.00000	5.00000	%

Source: POINT, Barclays Capital

Figure 20 shows the trading list suggested by the optimizer. Not surprisingly, the biggest sells are of financial companies. To replace them, the optimizer – using the risk model – recommends more holdings of Treasury and corporate bonds (we need these last to keep the net yield of the portfolio high). Remember that we concluded that our financial holdings were highly correlated with Treasuries, so the proposed swap is not surprising.

Interestingly, the extra constraint imposed on the optimization problem did not materially change the portfolio's risk. In fact, risk decreased to about 13bp/month. This is because of the extra three positions added to the portfolio, which now has 53 securities. The extra securities allowed the portfolio to reduce its systematic and idiosyncratic risk.

Figure 20: Proposed Trading List

BUYS			
Identifier	**Description**	**Position Amount**	**Market Value**
912828KV	US TREASURY NOTES	967,403	1,000,000
126650BK	CVS CORP-GLOBAL	1,696,069	1,518,408
98385XAJ	XTO ENERGY INC	2,097,746	2,508,567
FNA05009	FNMA Conventional Long T. 30yr	2,547,359	2,708,258
912828KF	US TREASURY NOTES	3,786,070	3,882,263
Total			**11,617,497**
SELLS			
Identifier	**Description**	**Position Amount**	**Market Value**
16132NAV	CHARTER ONE BANK FSB	-3,229,847	-3,370,981
05531FAF	BB&T CORPORATION	-2,425,413	-2,499,505
0258M0BZ	AMERICAN EXPRESS CREDIT	-2,021,013	-2,208,231
3133XN4B	FEDERAL HOME LOAN BANK	-1,818,417	-2,085,812
740816AB	PRES&FELLOWS OF HARVARD	-1,281,616	-1,452,968
Total			**-11,617,497**

Source: POINT, Barclays Capital

Scenario Analysis

Scenario analysis is a popular tool for risk management and portfolio construction. In this section, we illustrate a way to construct scenarios based on factor models. In this context, users express views on the returns of particular financial variables, indices, securities or risk factors and the scenario analysis tool (using the risk model) calculates their effect on the portfolio's (net) return.

Typically in this kind of scenario analysis, views are only partial. This means one can have specific views on how particular macro variables, asset classes, or risk factors will behave, but it is unlikely to have views on all risk factors the portfolio under analysis is exposed to. This is when risk models may be useful. At the heart of the linear factor models described in this paper is a set of risk factors and the covariance matrix between them. Under certain statistical assumptions, the covariance matrix can be used to "complete" specific partial views or scenarios and deliver a complete picture of the effect of the scenario in the return of the portfolio. Mechanically, what happens is the following: first, the manager translates the views into realizations of a subset of risk factors. Then the scenario is completed – using the risk model covariance matrix - to get the realizations of all risk factors. Finally, the portfolio's (net) loadings to all risk factors are used to get its (net) return under that scenario (by multiplying the loadings by the factor realizations under the scenario). This construction implies a set of assumptions that should be carefully understood. For instance, it is assumed that the manager can represent or translate views as risk factor returns. So a view about the unemployment rate, which is typically not used as a risk factor[27], cannot be used in this context. Also, to "complete" the scenario, we generally assume a stationary and normal multivariate distribution between all factors. These assumptions make this analysis less appropriate when looking at extreme events or regime shifts, for instance. However, it can be very useful in many other circumstances.

[27] Unemployment rate is not used as a factor in most short- and medium-term risk models.

As an example, consider using the scenario analysis to compute the model-implied scenario durations of the portfolio already analyzed in detail. To do this, we express our views as changes in the curve factors. In our risk model, these are represented by the six key-rate factors shown in Figure 10. In particular, to calculate the model-implied empirical duration, we assume that all six decrease by 25bp/month, broadly in line with our managers' views.

Figure 21 shows that under this scenario, the portfolio returns 99bp, against 93bp for the benchmark. As expected given the longer duration, the portfolio outperformed the benchmark. Because of the other exposures present in the portfolio and benchmark and their average negative correlation with the curve factors (eg, spreads), the duration implied by the scenario for our portfolio is only 3.96 (= 99 / 25), against the analytical 4.55 (Figure 2). The scenario shows a similar decrease in the benchmark's duration.

Figure 21: Scenario Analysis: Analytical and Model-Implied Durations

Universe	Return under scenario (bp)	Durations	
		Scenario (Model-Implied)	Analytical
Portfolio	99	3.96	4.55
Benchmark	93	3.72	4.30

Source: POINT, Barclays Capital

Another characteristic imposed while constructing the portfolio was a targeted higher spread. As Figure 2 shows, this resulted in an OAS for the portfolio of 157bp, against the 57bp of the benchmark. It would be interesting to evaluate the impact on the portfolio (net) return of a credit spread contraction of 10%. The portfolio is long spread duration (net OASD = 0.11, see Figure 2), so we may expect our portfolio to outperform in this scenario. To evaluate this episode, we analyze the results under two spread contraction scenarios: imposing no change in the yield curve (that is, an unchanged yield curve is part of the view) or allowing this change to be "completed" by the correlation matrix (that is, the change in the yield curve is not part of the scenario, we have no views about it, but we allow it to change in a way historically consistent with our spread view). Contrary to what one might expect, Figure 22 shows that the effect in the net return is minimal in both scenarios – our portfolio does not benefit from the spread contraction, when compared with the benchmark. The higher spread duration delivers no return advantage under this scenario. This is due to the many other exposures our portfolio has and that cannot be summarized by a small set of portfolio level analytics. The figure also shows that the absolute returns are quite different across the two scenarios. When one allows the rates to move in a correlated fashion with spreads, the net return drops to zero: all positive return from the spread contraction is cancelled by the probable increase in the level of the curve and our long duration exposure.

Figure 22: Scenario Analysis: Spread Contraction of 10%

	Restriction on YC movement	
Universe	No movement	Correlated
Portfolio	31	-3
Benchmark	32	0
Net	-1	-3

Source: POINT, Barclays Capital

These simple examples show how one can use reasonable scenarios to study the behavior of a portfolio or benchmark in different environments. This type of factor-based scenario analysis can significantly raise the intuition that a portfolio manager can gain from a risk model report.

Conclusion

Risk models describe the different imbalances of a portfolio using a common language. The imbalances are combined into a consistent and coherent analysis reported by the risk model. Risk models provide important insights regarding the different trade-offs existing in the portfolio. They provide guidance regarding how to balance them.

Risk models in fixed income are unique in two ways: First, the existence of good pricing models allows us to robustly calculate important analytics regarding the securities. These analytics can be used confidently as inputs into a risk model. Second, returns are not typically used directly to calibrate risk factors. Instead returns are first normalized into more invariant series (eg, returns normalized by the duration of the bond).

The fundamental systematic risk of all fixed income securities is interest rate and term structure risk. This is captured by factors representing risk-free rates and swap spreads of various maturities. Excess (of interest rates) systematic risk is captured by factors specific to each asset class. The most important components of such risk are credit risk and prepayment risk. Other important potential risks are volatility, liquidity, inflation or tax-policy. Idiosyncratic risk is diversified away in large portfolios and indices but can become a very significant component of total risk in small portfolios. The correlation of idiosyncratic risk of securities of the same issuer is non-zero and should be modeled carefully.

A good risk model provides detailed information about the exposures of a complex portfolio and can be a valuable tool for portfolio construction and management. It can help managers construct portfolios tracking a particular benchmark, express views subject to a given risk budget, and rebalance a portfolio while avoiding excessive transaction costs. Furthermore, by identifying the exposures where the portfolio has the highest risk sensitivity it can help a portfolio manager reduce (or increase) risk in the most effective way. The analysis can be significantly enhanced by using scenario analysis tools.

References

Ben Dor, A. Dynkin, L. Houweling, P. Hyman, J. Leeuwen, E. and Olaf Penninga, "A New Measure of Spread Exposure in Credit Portfolios," Barclays Capital, February 2010

Gabudean, R., "US Home Equity ABS Risk Model", Barclays Capital, October 2009

Kumar, A. , "The POINT Optimizer", Barclays Capital, June 2010

Lazanas, A. Silva, A. Staal, A. Cenk Ural, "Multi-Factor Equity Risk Models and Their Applications", *in Equity Valuation and Portfolio Management, by Frank J. Fabozzi and Harry M. Markowitz, John Wiley & Sons, 2011*

Silva, A., "Emerging Markets Risk Model: G4-Denominated Fixed Income Securities", Barclays Capital, December 2009

Silva, A. (a), "A Note on the New Approach to Credit in the Barclays Capital Global Risk Model", Barclays Capital, September 2009

Silva, A. (b), "Risk Attribution with Custom-Defined Risk Factors," Barclays Capital, August 2009

Staal, A., "US Municipal Bond Risk Model", Barclays Capital, July 2009

Analyst Certification(s)

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