QUANTITATIVE PORTFOLIO STRATEGIES

A New Measure of Spread Exposure in Credit Portfolios*

- We demonstrate that spread volatility of credit securities is proportional to spread level across a wide range of spreads. For every 100 bp of spread widening, volatility of spread increases by about 9 bp.
- Excess return volatility is proportional to Duration Times Spread (DTS). For every 100 bp of increase in DTS there is a 9 bp pickup in excess return volatility.
- This suggests that exposures to both credit sectors and individual issuers should be measured in terms of contributions to DTS rather than to duration alone.
- The product of DTS and long-term relative spread volatility is found to be a good predictor of excess return volatility, combining the stability of long-term averaging with quick reaction to changes in market risk conditions.
- We discuss the implications of our findings for the formulation of investment constraints, asset allocation, risk modeling and performance attribution.

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1. INTRODUCTION

The standard presentation of the asset allocation in a portfolio or a benchmark is in terms of percentage of market value. It is widely recognized that this is not sufficient for fixed-income portfolios, where differences in duration can cause two portfolios with the same allocation of market weights to have extremely different exposures to macro-level risks. As a result, many fixed-income portfolio managers have become accustomed to expressing their allocations in terms of contributions to duration – the product of the percentage of portfolio market value represented by a given market cell and the average duration of securities comprising that cell. This represents the sensitivity of the portfolio to a parallel shift in yields across all securities within this market cell. For credit portfolios in particular, the corresponding measure would be contributions to spread duration, measuring the sensitivity to a parallel shift in spreads. Determining the set of active spread duration contributions (the differences between the exposures of the portfolio and the benchmark) to market cells and/or issuers is one of the primary decisions taken by credit portfolio managers.

Yet all spread durations were not created equal. Just as one could create a portfolio that matches the benchmark exactly by market weights, but clearly takes more credit risk (e.g. by investing in the longest duration credits within each cell), one could match the benchmark exactly by spread duration contributions and still take more credit risk – by choosing the credits with the widest spreads within each cell. These credits presumably trade wider than their peer groups for a reason – that is, the market consensus has determined that they are more risky – and are often referred to as "high-beta" credits, because their spreads tend to react more strongly than the rest of the market to any systematic shock. Portfolio managers are well aware of this effect, but many tend to treat it as a secondary effect, rather than as an intrinsic part of the allocation process.

In this paper, we propose a simple risk sensitivity measure that utilizes spreads as a fundamental part of the credit portfolio management process. To reflect the view that higher spread credits represent greater exposures to sector-specific risks, we represent sector exposures by the product of market weight, spread duration, and spread. An overweight of 5% to a market cell implemented by purchasing bonds with a spread of 80 bp and a spread duration of 3 years will be considered to be of the same magnitude as an overweight of 3% using bonds with an average spread of 50 bp and a spread duration of 8 years. (0.05 x 0.80 x 3 = 0.03 x 0.50 x 8 = 0.12)

How does this make sense? As mentioned above, a portfolio's contribution to spread duration within a given market cell is its sensitivity to a parallel shift in spreads across all bonds in that cell. What is the intuition behind the new measure we propose - contribution to Duration Times Spread (DTS)?

In fact, the intuition is very clear. Let us look at a simple expression for the return of a given bond due strictly to change in spread R_{spread}. Let D denote the spread duration of the bond and s its spread; the spread change return[1] is then given by

$$(1)\quad R_{spread} = -D \cdot \Delta s$$

[1] Spread change return is closely related to excess return, the return advantage of a corporate bond over duration-matched Treasuries. Excess return can be approximated by the sum of the spread change return and an additional component due to spread carry.

It is quite easy to see that this equation is equivalent to

$$(2)\ R_{spread} = -D \cdot s \cdot \frac{\Delta s}{s}$$

That is, just as spread duration is the sensitivity to an absolute change in spread (e.g. spreads widen by 5 bp), DTS is the sensitivity to a relative change in spread (e.g. spreads increase by 5% of their current levels). Note that this notion of relative spread change provides for a formal expression of the rough idea discussed above – that credits with wider spreads are riskier since they tend to experience greater spread changes.

Given that the two representations above are equivalent, why should one of them be preferable to another? The advantage of the second approach, based on relative spread changes, is due to the stability of the associated volatility estimates. In the absolute spread change approach (equation 1), we can see that the volatility of excess returns can be approximated by

$$(3)\ \sigma_{return} \cong D \cdot \sigma_{spread}^{absolute}$$

while in the relative spread change approach of equation 2, excess return volatility follows

$$(4)\ \sigma_{return} \cong D \cdot s \cdot \sigma_{spread}^{relative}$$

Using a large sample with over 450,000 observations spanning the period 9/1989 – 1/2005, we demonstrate that the volatility of spread changes (both systematic and idiosyncratic) is indeed linearly proportional to spread level. This explains why relative spread volatilities of spread asset classes are much more stable than absolute spread volatilities, both across different sectors and credit quality tiers and also over time.

The paradigm shift we advocate has many implications for portfolio managers, both in terms of the way they manage exposures to industry and quality factors (systematic risk) and in terms of their approach to issuer exposures (non-systematic risk). Throughout this paper, we present evidence that the relative spread change approach offers increased insight into both of these sources of risk.

The remainder of this paper is divided into two parts. We first examine the behavior of spread changes of corporate bonds, and establish that absolute spread volatility is proportional to spread – both at the sector level and at the issuer level. These results apply to both investment grade and high yield credit. In the second part of the paper, we investigate what our findings imply for the management of portfolio's excess return volatility. We start by showing that bonds with very different spreads and spread durations but with similar product of the two exhibit the same excess return volatility. We then demonstrate that modeling spread changes in relative terms rather than absolute terms generates improved forward-looking estimates of excess return volatility. Finally, in a controlled index replication experiment, we show that matching index sector/quality allocations in terms of contributions to DTS can track the credit index more closely than matching the contributions to duration. We conclude with a discussion of the various implications of this research for portfolio managers.

2. ANALYSIS OF SPREAD BEHAVIOR OF CORPORATE BONDS

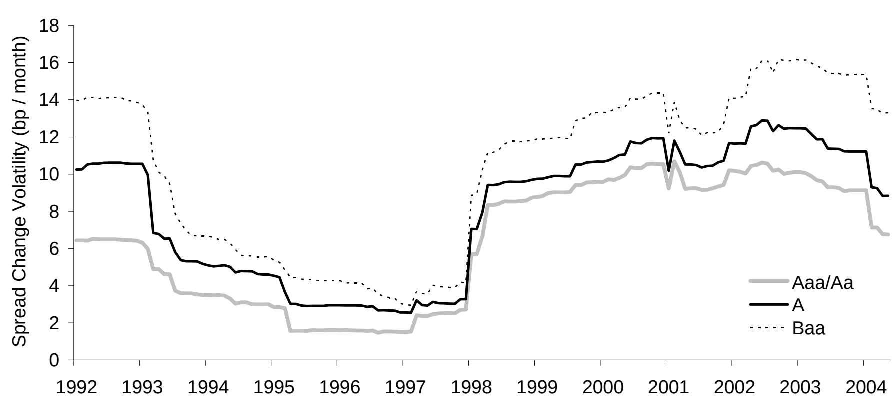
How can we get a good feeling for the amount of risk associated with a particular market sector? Most typically, for lack of any better estimate, the historical volatility of a particular sector over some prior time period is used to estimate its volatility for the coming period.[2] For this approach to be reliable, we would like to find that these volatilities are fairly stable. Unfortunately, this is not always the case.

As an example, Figure 1 shows the 36-month trailing volatility of spread changes for various credit ratings comprising the Barclays Capital Corporate Index between September 1992 and January 2005. It is clear that spread change volatility decreased substantially until 1998 and then increased significantly from 1998 through 2005. The dramatic rise in spread volatility since 1998 was only partially a response to the Russian crisis and the Long Term Capital Management debacle as volatility has not reverted to its pre-1998 level.

One explanation for the large variation in volatility during this time period is that spreads increased significantly for all credit asset classes. If the investment grade corporate universe is instead partitioned by spread levels, we find that the volatilities of the resulting spread buckets are considerably more stable, as seen in Figure 2. After an initial shock in 1998, the volatilities within each spread bucket revert almost exactly to their pre-1998 level (beginning in August 2001, exactly 36 months after the Russian crisis occurred). In this respect, one could relate the results of Figure 1 to an increase in spreads – both across the market and within each quality group.

As suggested by equation 4, our proposed remedy to the volatility instability problem is to approximate the absolute spread volatility (in bp/mo) by multiplying the historically observed relative spread volatility (in %/mo) by the current spread (in bp). This can help stabilize the process if relative spread volatility is more stable than absolute spread volatility. The results in Figure 2 point in this direction, since they show a clear relationship between spread level and volatility.

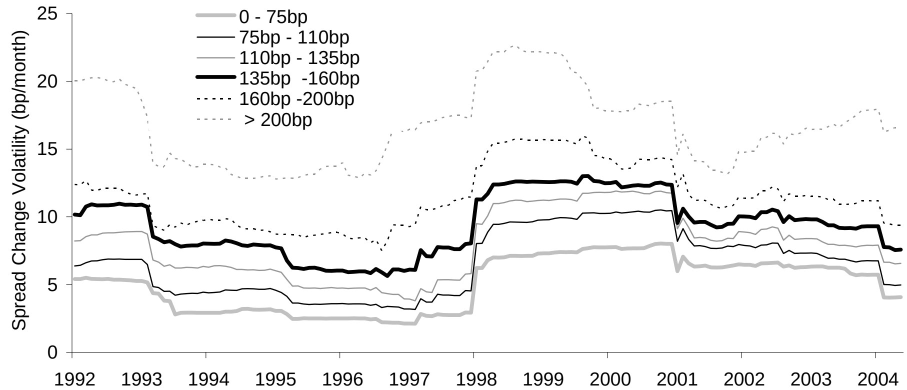
Figure 1: Spread Change Volatility by Credit Rating; Trailing 36 months (9/92 – 1/05), based on all bonds comprising the Barclays Capital corporate index



Source: Barclays Capital

[2] This practice leads to perennial questions about how much history should be used in such estimation. A longer time period leads to more stable estimates of volatility; a shorter time period (or a weighting scheme that gives more weight to recent observations) makes the estimate less stable, but better able to adapt to fundamental changes in the marketplace. In either case, the large swings in volatility that the market can experience mean that we are always trying to catch up to market events, and there will always be some amount of lag between the time of a volatility change and the time when it is first reflected in our estimates. We discuss this issue further in a later section.

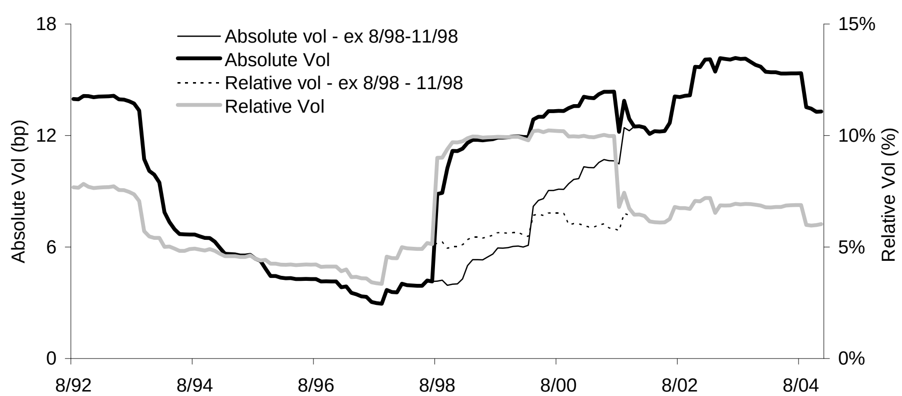
Figure 2: Spread Change Volatility by Spread Range; Trailing 36 months (9/92 – 1/05), based on all bonds comprising the Barclays Capital corporate index



Source: Barclays Capital

Figure 3 plots side by side the volatility of absolute and relative spread changes of all bonds in the Barclays Capital Corporate index rated Baa. (Relative spread changes are calculated simply as the ratio of spread change to the beginning of month spread level). The comparison illustrates that only a modest stability advantage is gained by measuring volatility of relative spread changes; however, the improvement is not as great as we might have hoped, and the figure seems to show that even relative spread changes are quite unstable. This apparent instability, however, is only due to the dramatic events that took place in the second half of 1998. We re-compute the two time-series excluding the four observations representing the period 8/98 – 11/98 and plot the two modified volatility time-series alongside the two original time-series. The difference between the modified time-series is striking. From a low of 3 bp/month in mid-1997, absolute spread volatility increases steadily through a high of 15 bp/month in 2002-3, growing by a factor of five. However, once we remove the effect of those few months in 1998, we find that relative spread volatility increases much more modestly over the same time period, from 3%/month to 7%/month.

Figure 3: Absolute and Relative Spread Change Volatility of Baa Credit; Trailing 36 months (9/92 – 1/05); Actual data is replaced with missing values for months that are excluded



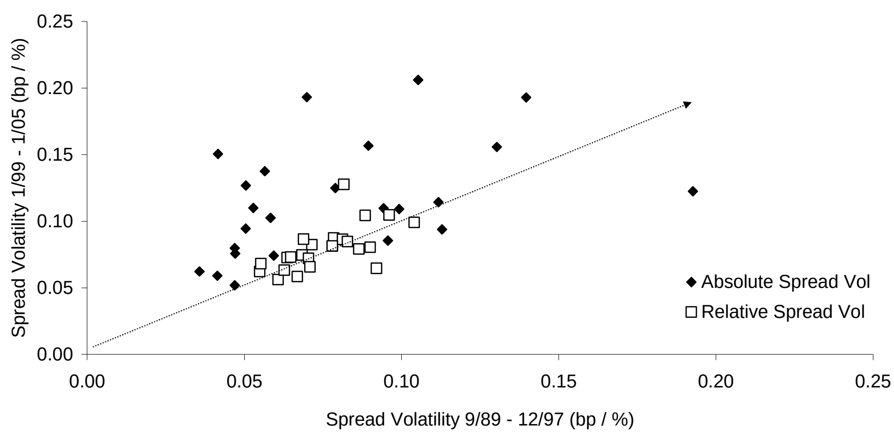
Source: Barclays Capital

Another demonstration of the enhanced stability of relative spreads is seen when comparing the volatilities of various market segments over distinct time periods. We have already identified 1998 as a critical turning point for the credit markets, due to the combined effect of the Russian default and the Long Term Capital Management crisis. To what extent is volatility information prior to 1998 relevant in the post-1998 period? In Figure 4, we plot pre-1998 volatility on the x-axis, and post-1998 volatility on the y-axis. We do this for two different measures of volatility: absolute spread volatility and relative spread volatility.[3] Each point shown on the graph represents a particular sector-quality cell of our Investment Grade Corporate Index, which we have divided into 8 industry groups and 3 quality cells.[4] Points along the diagonal line indicate that the volatilities are the same over the two time periods.

Two clear phenomena can be observed here. First, most of the observations representing absolute spread volatilities are located quite far above the line, pointing to an increase in volatility in the second period of the sample despite the fact that the events of 1998 are not reflected in the data. In contrast, relative spread volatilities are quite stable with almost all observations located on the 45 degrees line or very close to it. This is because the pick-up in volatility in the second period was accompanied by a similar increase in spreads. Second, relative spread volatilities of various sectors are quite tightly clustered, ranging from 5% to a bit over 10%, whereas the range of absolute volatilities is much wider, ranging from 5 bp/month to more than 20 bp/month.

The results presented so far clearly indicate that absolute spread volatility is highly unstable and tends to rise with increasing spread. Computing volatilities based on relative spread change however, generates a more stable time-series. These findings have important implications for the appropriate way of measuring excess return volatility and demonstrate the need to better understand the behavior of spread changes.

Figure 4: Absolute and Relative Spread Change Volatility Before and After 1998; Based on 8 sector X 3 credit rating partition of the corporate IG universe



Source: Barclays Capital

[3] To enable the two to be shown on the same set of axes, both absolute and relative spread volatility are expressed in units with similar magnitudes. However, the interpretation is different: an absolute spread change of 0.1 represents a 10 bp parallel shift across a sector, while a relative spread change of 0.1 means that all spreads in the sector move by 10% of their current values (e.g. from 50 to 55, from 200 to 220).

[4] The sector breakdown is: Banking, Finance, Basic Industry, Consumer Cyclical, Consumer Non-Cyclical, Communications, Energy and Utility.

To analyze the behavior of spread changes we first examine the dynamics of month-to-month changes in spreads of individual bonds. When spreads widen or tighten across a sector, do they tend to follow a pattern of parallel shift or one in which spread changes are proportional to spread? This key issue should determine how we measure exposures to systematic spread changes.

As a next step, we look at systematic spread volatility. If spreads change in a relative fashion then the volatility of systematic spread changes across a given sector of the market should be proportional to the average spread of that sector. This is true when comparing the risk of different sectors at a given point in time, or when examining the volatility of a given sector at different points in time.

To complete our analysis we also examine non-systematic spread volatility, or issuer risk. The dispersion of spread changes among the various issuers within a given market cell, or the extent by which the spread changes of individual issuers can deviate from those of the rest of the sector, also tends to be proportional to spread.

We investigate each of these issues using monthly spread data from the Barclays Capital Corporate Bond Index historical database. Our dataset spans more than 15 years, from September 1989 through January 2005, and contains monthly spreads, spread changes, durations, and excess returns for all bonds in the Corporate Bond Index. For the sections of our study that include high yield bonds as well as investment grade, we augment our dataset using historical data from our Barclays Capital High Yield Index. A more detailed description of the dataset can be found in the Appendix.

The dynamics of spread change

In order to understand why absolute spread volatility is so unstable, we first need to examine at a more fundamental level how spreads of individual securities change in a given month. One basic formulation of the change in spread of some bond *i* at time *t* is that the overall change is simply the sum of two parts: systematic and idiosyncratic:

(5) $\Delta s_{i,t} = \Delta s_{J,t} + \Delta s_{i,t}^{idiosyncratic} \qquad \mathrm{i} \in \mathrm{J}$

where *J* denotes some peer group of bonds with similar risk characteristics (i.e. such as Financials rated Baa with duration of up to 5 years). This formulation is equivalent to assuming that spreads change in a parallel fashion across all securities in a given market cell *J* (captured by $\Delta s_{J,t}$).

Alternatively, if changes in spreads are proportional to spread level then we have (omitting the subscript *t* for simplicity):

(6) $\frac{\Delta s_i}{s_i} = \frac{\Delta s_J}{s_J} + \frac{\Delta s_i^{idio}}{s_i}$ or $\Delta s_i = s_i \cdot \frac{\Delta s_J}{s_J} + \Delta s_i^{idio}$

Equation 6 reflects the idea that systematic spread changes are proportional to the current (systematic) spread level and that the sensitivity of each security to a systematic spread change depends on its level of spread. Higher spread securities are riskier in that they are affected more by a widening or tightening of spreads relative to lower spread securities with similar characteristics.

In order to analyze the behaviour of spread changes across different periods and market segments we use Equations 5 and 6 to formulate two regression models that we estimate. The first model corresponds to the parallel shift approach shown in Equation 5:

(7) $\Delta s_{i,t} = \alpha_{J,t} + \varepsilon_{i,t}$

The second model reflects the notion of a proportional shift in spreads as in Equation 6:

(8) $\Delta s_{i,t} = \beta_{J,t} \cdot s_{i,t} + \varepsilon_{i,t}$

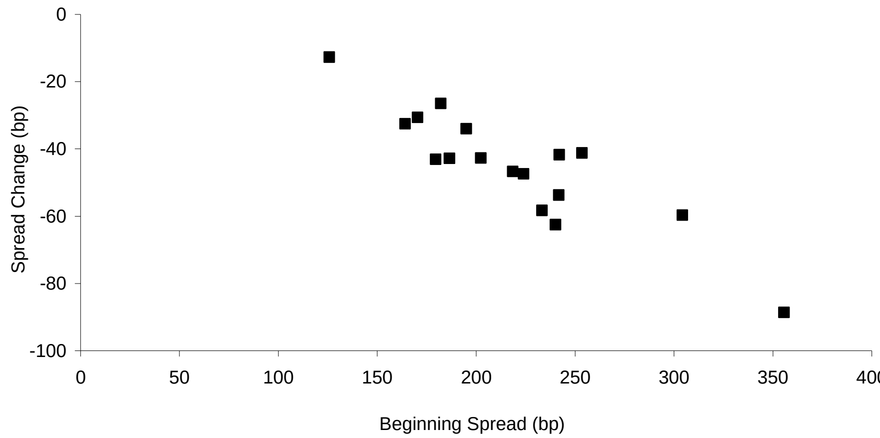
Comparing Equation 8 to Equation 6 shows that the slope coefficient we estimate $\beta_{J,t}$ corresponds to the proportional systematic spread change $\Delta s_{J,t} / s_{J,t}$. These two models are nested in a more general model that allows for both proportional and parallel spread changes to take place simultaneously:

(9) $\Delta s_{i,t} = \alpha_{J,t} + \beta_{J,t} \cdot s_{i,t} + \varepsilon_{i,t}$

Before we proceed with a full-scale estimation of the three models, we illustrate the idea with a specific example. Figure 5 shows changes in spreads experienced by large issuers that comprise the Communications sector of the Barclays Capital Corporate Index against their beginning-of-month spreads for the month of January 2001.[5] It is clear that this sector-wide rally was not characterized by a purely parallel shift; rather issuers with wider spreads tightened by more.

[5] 'Large issuers' refers to issuers that have outstanding issues with market value in excess of 1% of the sector aggregate market value. There are a total of 17 issuers that represent 216 outstanding issues.

Figure 5: Average Spreads and Spread Changes for Large Issuers in the Communications Sector, as of January 2001



Source: Barclays Capital

Figure 6 reports the regression results when the three general models of spread change are fitted to the data in this specific example. The results verify that spreads in the Communication sector in January 2001 changed in a proportional fashion. The slope estimate is highly significant and the high R-square (97.1%) indicates that the model fit the data well. [6] The combined model which allows for a simultaneous parallel shift achieves only a slightly better fit (97.7%) and yields a somewhat unintuitive result: it shows that the sector widens by a parallel shift of 16 bp and simultaneously tightens by a relative spread change of -28%. We therefore estimate a fourth model, which is essentially a variant of the 'combined' model:

(10) $\Delta s_{i,t} = \overline{\alpha}_{J,t} + \beta_{J,t} \cdot (s_{i,t} - \overline{s}_{J,t}) + \varepsilon_{i,t}$

Normalizing spreads by subtracting the average spread level in equation 10 yields identical slope coefficients and R-squared to those generated by the 'combined model', but now the intercept $\overline{\alpha}_{J,t}$ represents the average spread change in the sample. This model expresses the month's events as a parallel tightening of -45 bp coupled by an additional relative shift, with a slope of -28%, that defines how much more spreads move for issuers with above-average spreads, and how much less they move for issuers with below-average spreads.

Figure 6: Regression Estimates of Various Models of Spread Change; Based on data for large issuers in the Communication sector as of January 2001

		Coefficients		T-stats		
Model	Equation	Shift (bp)	Slope (%)	Shift	Slope	R^2
Parallel	7	-45		-10.9		88.2%
Relative	8		-21%		-23.2	97.1%
Combined	9	16	-28%	2.0	-7.9	97.7%
Combined with normalized spread	10	-45	-28%	-24.1	-7.9	97.7%

Source: Barclays Capital

[6] Notice that since we compare models with and without an intercept, Figure 6 reports un-centered R^2 calculated using the total sum of squares (without subtracting the average spread change) rather then centered R^2.

We conduct a similar analysis to the one presented in Figure 6 using individual bond data in all eight sectors and 185 months included in the sample. Our hypothesis that the relative model provides in general an accurate description of the dynamic of spread changes has several testable implications. First, the overall R-squared for the relative model should be significantly better than that of the parallel model, and almost as good as that of the combined model. Second, we would like to find that the slope factor is statistically significant (as indicated by the t-statistic) in most months and sectors. Third, the realizations of the slope and the parallel shift factor in the combined model with normalized spread should be in the same direction, especially whenever the market experiences a large move. That is, in all significant spread changes, issues with wider spreads experience larger moves in the same direction.

We find support for all three implications. Figure 7 shows the aggregate R-squared for these regressions across all sectors and months. The relative model explains much more of the spread movement in the market than the parallel shift model and almost as much as the less restrictive combined model.

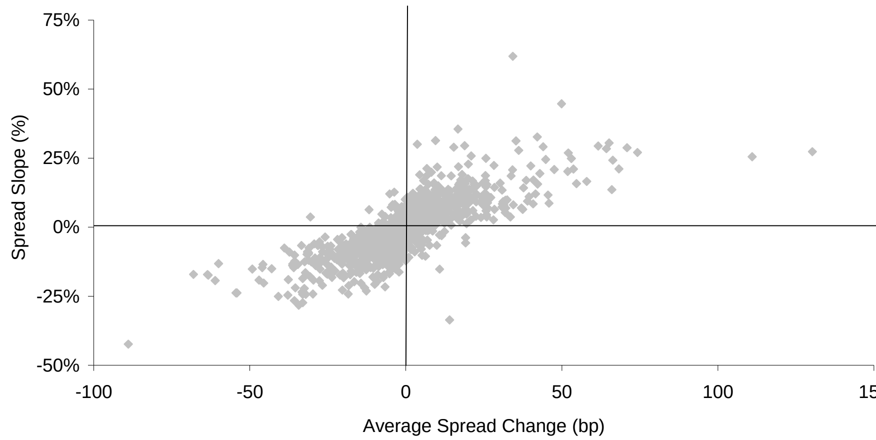
With respect to the second empirical implication, we find that the slope factor was statistically significant 73% of the time. The fact that in the combined model with normalized spreads, we find a clear linear relationship between the shift and slope factors serves as an additional validation of the relative model. The relatively low R-squared results shown in Figure 7 are due to the fact that in many months, there is little systematic change in spreads, and spread changes are largely idiosyncratic. Figure 8 shows that large spread changes are accompanied by slope changes in the same direction (the correlation between the two is 80%). That is, bonds that trade at wider spreads will widen by more in a widening and tighten by more in a rally. There are essentially no examples of large parallel spread movements in which the slope factor moves in the opposite direction.

Figure 7: Aggregate Fit of Various Models of Spread Change; Based on 1,480 individual regressions (185 months X 8 sectors)

Regression Model	Aggregate R-Squared
Combined	35.2%
Relative	33.0%
Parallel	16.9%

Source: Barclays Capital

Figure 8: Regression Coefficients For Shift And Slope Factors; Based on 1,480 individual regressions (185 months X 8 sectors)



Source: Barclays Capital

Systematic spread volatility

The security-level analysis in the previous section established (via the slope coefficient β) that systematic changes in spreads are proportional to the systematic level of spread consistent with the formulation in Equation 6. In this section we take a step further and examine the relation between systematic spread volatility and the level of spreads. To do this, we would like to partition our dataset by spread level, separately measure the volatility of each spread bucket, and examine the relationship between spread level and spread volatility.

However, the nature of the dataset presents several challenges. First, it is far from homogeneous – it contains bonds from different industries, credit qualities and maturities. Second, the spreads of corporate bonds have changed quite substantially during the course of the period studied, so that the populations of any fixed spread buckets vary substantially from one time period to another. Our goal was to design a partition fine enough that the bonds in each cell share similar risk characteristics, yet coarse enough so that our cells are sufficiently well populated over the course of the time period to give statistically meaningful results.

We have chosen to partition the corporate bond market rather coarsely by sector and duration, and then to subdivide each of these sector/duration cells by spread. We use three sectors (Financials, Industrials and Utilities) and three duration cells ('Short', 'Medium' and 'Long'). To ensure that each of these cells is well-populated each month, the division into three duration groups is not done based on pre-specified duration levels, but by dividing each sector cell each month into three equally-populated groups by duration[7]. Then, bonds in each sector/duration cell are further divided by spread level. To allow a detailed partitioning of the entire spread range while minimizing the number of months where a bucket is scarcely populated, the spread breakpoints differ from sector to sector. In addition,

[7] Our analysis shows that the distribution of spread duration varies significantly across time and therefore does not allow for a partition based on constant spread duration values.

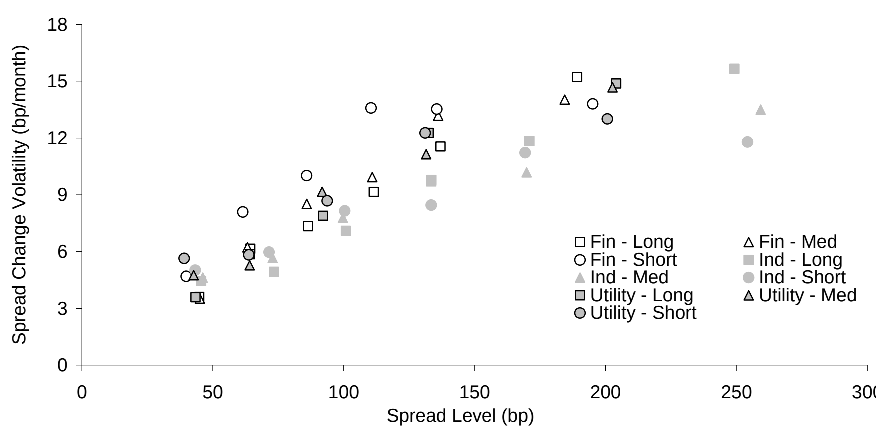
the Financial and Industrial sectors are divided into six spread buckets whereas the Utilities sector has only five spread buckets. Hence, based on this partition bonds in the sample are assigned to one of fifty-one buckets. Further detail on the precise definition of the partition and the sample populations assigned to each cell may be found in the Appendix.

The systematic spread change in cell *J* in month *t* can be represented simply as the average spread change across all bonds in that bucket in month *t*. Therefore, for each of the cells in the partition, we compute every month the median spread, the average spread change, and the cross-sectional standard deviation of spread change. This procedure produces 51 distinct time series datasets; each consists of a fairly homogeneous set of bonds for which we have monthly data on spreads and spread changes. We then calculate the average spread for each group over time, and the time series volatility of these systematic spread changes.[8]

Some caution is in order when using spread data. Spread figures are model-driven and can exhibit extreme values (especially since our modelling of option-adjusted-spreads has changed during the sample period). To mitigate the effect of outliers, observations that reflect extreme spread changes are excluded.[9] Similarly, the spread level for bucket *J* is calculated as the time-series average of the monthly median spread rather than the average spread.

The relation between the volatility of systematic spread changes and spread level is plotted in Figure 9, where each observation represents one of the 51 buckets in the partition. Figure 9, illustrates a clear relationship between spread volatility and spread level. Higher spreads are accompanied by higher volatilities for all sector/duration cells. The duration cells do not seem to have any significant systematic effect; relatively minor differences can be seen between industrials and the other two broad sectors.

Figure 9: Time Series Volatility of Systematic Spread Changes versus Spread Level; Based on IG credit data and monthly observations (9/1989 – 1/2005)



Source: Barclays Capital

[8] Despite our efforts to ensure uniform cell populations, some cells are very sparsely populated (or even empty) in some months. Months where a cell is populated by less than 20 bonds are not used in the analysis. As a robustness check, we repeat the analysis using the entire available time series of systematic spread changes and a weighted volatility estimate (where the number of observations in each month is used as the weighing facto). The results are essentially unchanged.

[9] The entire dataset is filtered to exclude observations where changes in spread fall above the 99th percentile or below the 1st percentile. As a result, monthly spread changes included in our analysis range from -60bp to +78bp.

Nonetheless, the results shown in Figure 9 do not perfectly corroborate our hypothesis of proportional spread volatility, which would predict that all of our observations (or at least all observations within a given sector) should lie along a diagonal line that passes through the origin, of the form

$$(11)\ \sigma_{spread}^{absolute}(s) \cong \theta \cdot s\ .$$

While the points at the left side of Figure 9 seem to fit this description, the points to the right, representing higher spread levels, do not seem to continue along this line. Rather, volatility seems to flatten out beyond the 200 to 250 bp range. Is it possible that spread volatility does not continue to grow linearly when spreads increase beyond a certain point?

Before we reject our hypothesis, we should question the significance of these few highest-spread observations. This region of 200-300 bp spreads lies right on the boundary between investment grade and high yield. For a good part of the time period of our study, these spread cells are very lightly populated by our investment-grade bond sample. Due to our policy of excluding any cell with less than 20 bonds, the summary results for these cells may be less robust than desired.

To further examine the relation between systematic spread change volatility and spread level beyond the 200 bp level, we repeat the analysis including all bonds rated Ba and B during the same time period. This increases the sample size by roughly 35% from 416,783 observations to 565,602 observations. We use the same industry x duration x spread partition, with the addition of a few more spread buckets to accommodate the widening of the spread range. This expanded partition is shown in Figure 10, with the new spread buckets shaded.

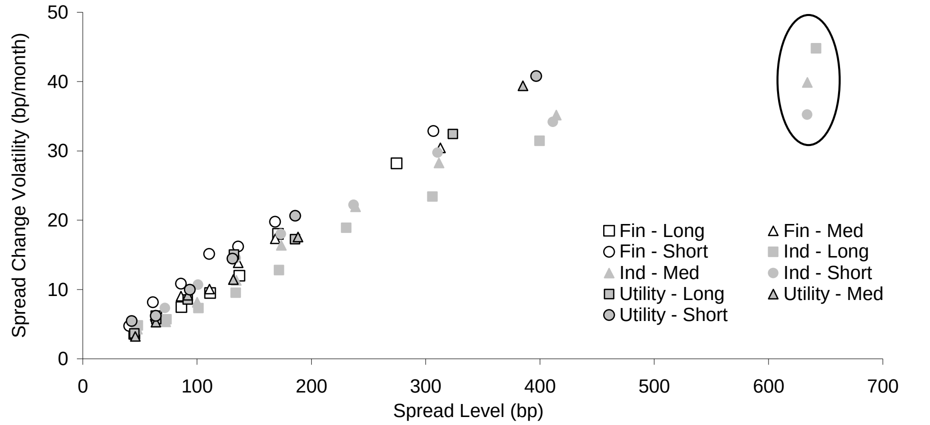
Figure 11 plots the relationship between systematic spread volatility and spread level using both investment grade and high yield data. We now find that the linear relationship we were looking for extends out through spreads of 400 bp. As before, the three observations that represent the highest spread bucket in industrials (circled) have somewhat lower than expected spread volatility. Once again, we suspect the statistical relevance of these most extreme data points. The simple linear model of equation 11 provides an excellent fit to the data shown in Figure 11, with θ equal to 9.1% if we use all the data points or 9.4% if we exclude the three circled outliers. Thus, our data shows that the historical volatility of systematic spread movements can be expressed quite compactly, with only minor dependence on sector or maturity, in terms of a relative spread change volatility of about 9% per month. That is, spread volatility for a market segment trading at 50 bp should be about 4.5 bp/month, while that of a market segment at 200 bp should be about 18 bp/month.

Figure 10: Corporate IG and HY Universe Partition by Sector and Spread Spread breakpoints are determined based on population of all bonds rated Aaa-B (9/1989 – 1/2005)

Spread Bucket	1	2	3	4	5	6	7	8	9
Financials	<50	50-75	75-100	100-125	125-150	150-200	>200		
Industrials	<60	60-85	85-120	120-150	150-200	200-275	275-350	350-500	>500
Utilities	<55	55-75	75-115	115-150	150-250	>250			

Source: Barclays Capital

Figure 11: Systematic Spread Change Volatility versus Spread Level Including HY Credit; Monthly observations for all bonds rated Aaa-B (9/1989 – 1/2005)



Source: Barclays Capital

Idiosyncratic spread changes

To study the spread dependence of idiosyncratic spread volatility, we use the same sector x duration x spread partition as in the previous section. Instead of the average spread change experienced within a given cell in a given month, we now examine the dispersion of spread changes across each cell. If we define idiosyncratic spread change of bond *i* in market cell *J*, at time *t* as the difference between its spread change and the average spread change for the cell in that month:

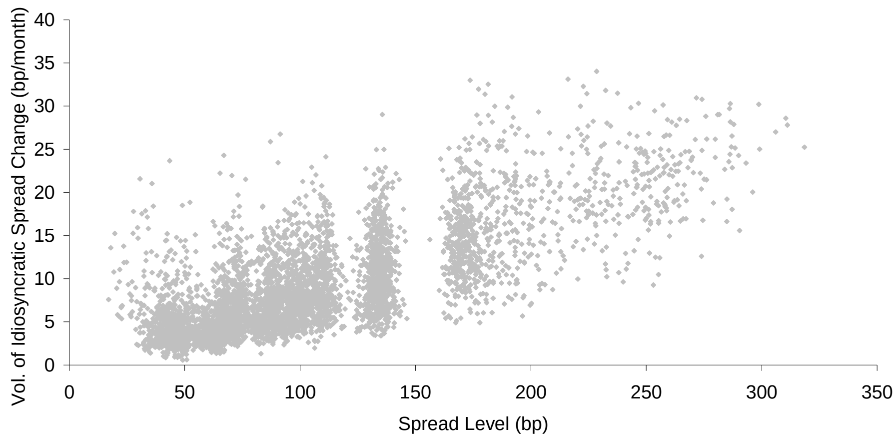
(12) $\Delta s_{i,t}^{idio} = \Delta s_{i,t} - \Delta s_{J,t}$.

Then the volatility of idiosyncratic spread changes is exactly equal to the cross sectional standard deviation of total spread changes.[10] Figure 12 shows a scatter plot of the cross-sectional volatility from all months and spread buckets. This plot clearly shows the general pattern of volatilities increasing with spread, as well as the relative paucity of data at the higher spread levels.

Next, we aggregate this data over time to obtain a single measure of idiosyncratic spread volatility for each market cell. We pool all observations of idiosyncratic risk within a given market cell *J* over all bonds and all months, and calculate their standard deviation. This pooled measure of idiosyncratic spread volatility per market cell is plotted in Figure 13 against the median spread of the cell.

[10] In order to be consistent with our formulation of relative spread change in equation 6, we should assume that the effect of the systematic spread change of bond i is proportional to its spread, and define idiosyncratic spread change as $\Delta s_{i,t}^{idio} = \Delta s_{i,t} - \left(s_{i,t} / s_{J,t}\right) \cdot \Delta s_{J,t}$. However, as we are carrying out this test over relatively narrow spread buckets, there is very little difference in practice between the two definitions.

Figure 12: Volatility of Idiosyncratic Spread Change versus Spread Level, Monthly calculations (9/1989 – 1/2005); Computed separately by sector, duration and spread bucket (N=5035)

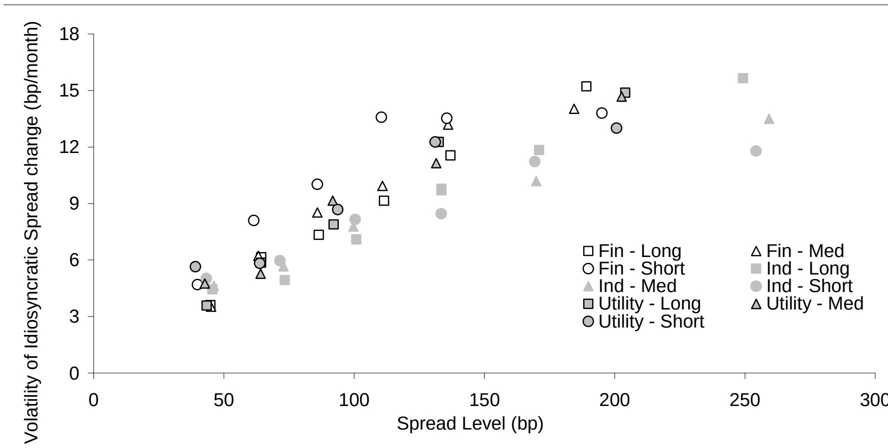


Source: Barclays Capital

In Figure 13, the linear relationship between spread and spread volatility is strikingly clear. A regression fit against this data (Figure 14) shows it to be consistent with equation 11. Unlike our results for the systematic spread volatility within investment-grade data only (Figure 9), the intercept of this regression is not significantly different from zero. In addition, we do not detect any significant slope differential among the three industries and the slope varies between 8.8% and 9.3%.

As before, we extend the analysis to include bonds rated Ba and B. To conserve space we only present the pooled cross sectional volatility results (Figure 15). The results clearly illustrate that observations which represent buckets populated almost exclusively by HY bonds seem to follow the same pattern as buckets populated mostly by IG bonds. However, observations representing HY bonds exhibit more variation than those representing IG bonds. Once again, the regression results indicate a zero intercept, but the estimated slope coefficient (the volatility of idiosyncratic yield change) is somewhat larger than estimated previously, 11.5% vs. 9.6%.

Figure 13: Pooled Idiosyncratic Spread Volatility versus Spread Level, Each observation represents the standard deviation of idiosyncratic spread changes aggregated across all sample months separately by sector, duration and spread bucket (N=51).



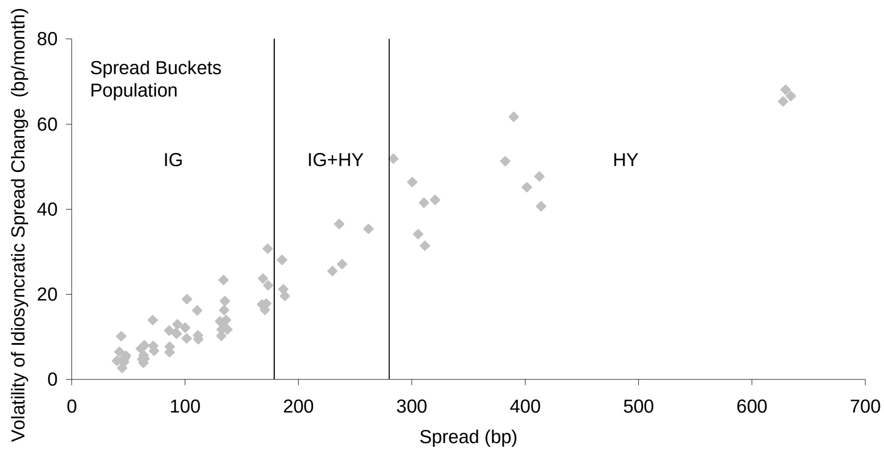
Source: Barclays Capital

Figure 14: Regression Estimates of the Relation Between Idiosyncratic Spread Volatility and Spread Level Based on sector X duration X spread partition described in section 2.2

	Coefficients	*t Stat*
Intercept	-0.001	-0.30
Fin-slope	0.093	18.32
Ind-slope	0.089	22.73
Util-slope	0.088	17.73
Adj. R^2 = 0.97	N=51	

Source: Barclays Capital

Figure 15: Pooled idiosyncratic Spread Volatility vs. Spread Level including HY Credit, Computed separately by sector, duration and spread bucket; Sample includes monthly observations for all bonds rated Aaa - B (9/1989 – 1/2005)



Source: Barclays Capital

A new Risk measure of excess return volatility

The results in the previous section demonstrated that both systematic and idiosyncratic spread changes are proportional to the level of spread. In this section we illustrate the implications of this relationship with respect to excess return volatility. Specifically, we show that the appropriate risk measure for credit securities is DTS rather than spread duration.

We first show that bonds with very different spreads and spread durations but with similar DTS exhibit the same excess return volatility. For example, a bond trading at a spread of 200bp with a spread duration of 2 is equally risky as a bond with a spread of 100bp and a spread duration of 4. Next, we examine excess return volatility forecasts generated using two risk measures: spread duration and DTS. The results suggest that using DTS provides more accurate forecasts with fewer instances of extreme excess return realizations.

Section 3.3 compares the efficacy of spread duration and DTS in the context of constructing portfolios with minimal tracking errors. We show that a replication strategy based on matching contributions to DTS tracks better than one based on matching contributions to spread duration.

DTS, Spread Duration and Excess returns

In the previous section, we established that the volatility of both systematic and idiosyncratic spread changes is proportional to the level of spread. Consequently, the volatility of excess returns over a given time period should be linearly related to DTS, with the proportionality factor equal to the volatility of relative spread changes over the same period.

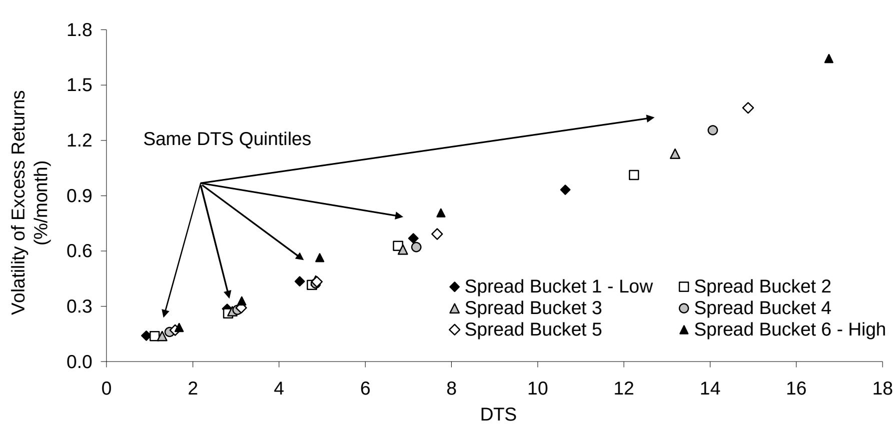
To examine this prediction, each month bonds are assigned to quintiles based on DTS. Each of these quintiles is further subdivided into 6 buckets based on spread. Every month the average excess returns and median DTS are calculated, and then the time-series volatility of excess returns and average DTS is calculated separately for each bucket.[11]

Our formulation yields two empirical predictions:

- Excess return volatility should increase linearly with DTS, where the ratio of the two (or slope) represents the volatility of relative spread changes we previously estimated.
- The level of excess return volatility should be approximately equal across spread buckets with a similar DTS characteristic.

The results of the analysis, presented in Figure 16, support both empirical predictions. First, it is clear that excess return volatility increases with the level of DTS and that a straight line through the origin provides an excellent fit. This is indeed confirmed by a regression of the excess return volatility on average DTS, which finds a fit of 98% and an insignificant intercept. (The slope estimate is 8.8%.) Second, consistent with prediction (ii), observations representing the same DTS quintile but with differing spread levels exhibit very similar excess return volatilities. The one exception to this is in the highest DTS quintile, where the subdivision by spread causes wide variations in DTS as well. As a result, the points no longer form a tight cluster, but they continue to follow the same general relationship between DTS and volatility.

Figure 16: Excess Return Volatility versus DTS; Based on monthly observations of all IG bonds (9/1989 – 1/2005);Bonds are first assigned to one of 5 DTS buckets and then further subdivided to 6 spread buckets



Source: Barclays Capital

[11] Notice that based on the previous findings that did not detect a significant industry effect, we do not explicitly control for industry. This allows us to use a finer DTS partition and also makes our results more robust.

To fully appreciate the significance of the second result, Figure 17 reports the average spread and spread duration for each of the 30 buckets. The table illustrates the extent of the differences among the spreads and corresponding spread durations of buckets with almost identical DTS. For example, the top and bottom spread cells in DTS bucket 2 (shown in bold) exhibit almost identical DTS values of 299 and 320 respectively. Yet, they have very different spread and spread duration characteristics: bonds comprising the top cell have an average spread duration of 5.48 and trade at a spread of 54bp, while bonds in the bottom cell have a spread duration of 2.53 and a spread of 127bp. Hence, high spread bonds with short duration can be as risky as low spread bonds with high duration.

Figure 17: Summary Statistics by DTS and Spread Buckets; Based on monthly observations of all IG bonds (9/1989 – 1/2005); Bonds are first assigned to one of 5 DTS buckets and then further subdivided to 6 spread buckets

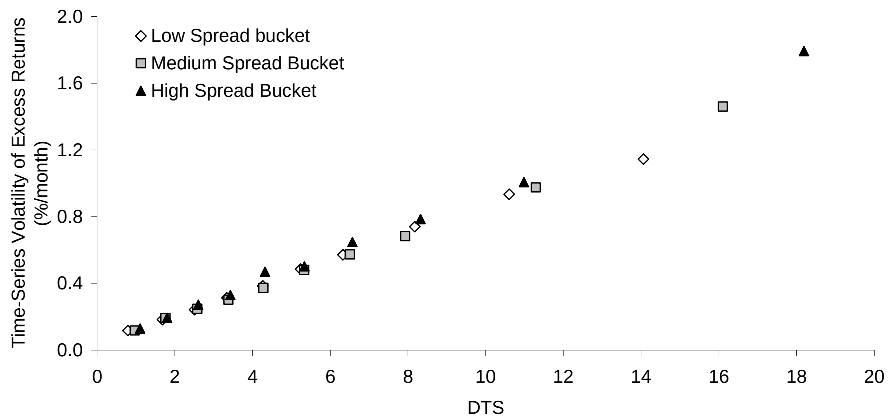
Panel A:	Spread	DTS buckets				
		Low	2	3	4	High
Spread Sub-Buckets	Low	41	**54**	64	77	97
	2	52	68	79	94	116
	3	60	78	88	106	135
	4	69	87	98	118	156
	5	79	99	112	135	184
	High	100	**127**	143	172	246

Panel B:	Spread Duration	DTS buckets				
		Low	2	3	4	High
Spread Sub-Buckets	Low	2.38	**5.48**	7.20	9.53	11.15
	2	2.19	4.24	6.12	7.17	10.62
	3	2.17	3.80	5.50	6.51	9.78
	4	2.17	3.54	4.96	6.09	9.09
	5	2.09	3.25	4.43	5.72	8.23
	High	1.65	**2.53**	3.52	4.53	6.91

Source: Barclays Capital

To verify that the results are not driven by the specific partition we used, Figure 18 presents the results of the analysis using a 10 x 3 partition. This partition has the same number of points as before, but allows a more detailed look at the relation between excess return volatility and DTS. The results in Figure 18 are very similar to those in Figure 16, with respect to the slope estimate (8.9% vs. 8.8%) and the overlapping of observations representing different spread buckets within the same DTS bucket.

Figure 18: Excess Return Volatility versus DTS; Based on monthly observations of all IG bonds (9/1989–1/2005); Bonds are first partitioned to 10 DTS buckets and then further subdivided to 3 spread buckets



Source: Barclays Capital

A comparison of excess return volatility forecasts

A natural step following the analysis in the previous section is to examine which approach provides a better forecast of the excess return volatility of a portfolio:

(i) Spread Duration X historical volatility of absolute spread change.

(ii) DTS X historical volatility of relative spread change.

To better understand the conditions under which the volatility forecasts generated by the two measures differ, we explicitly write the expression for the ratio of the two measures at month *t* for some bucket *J*:

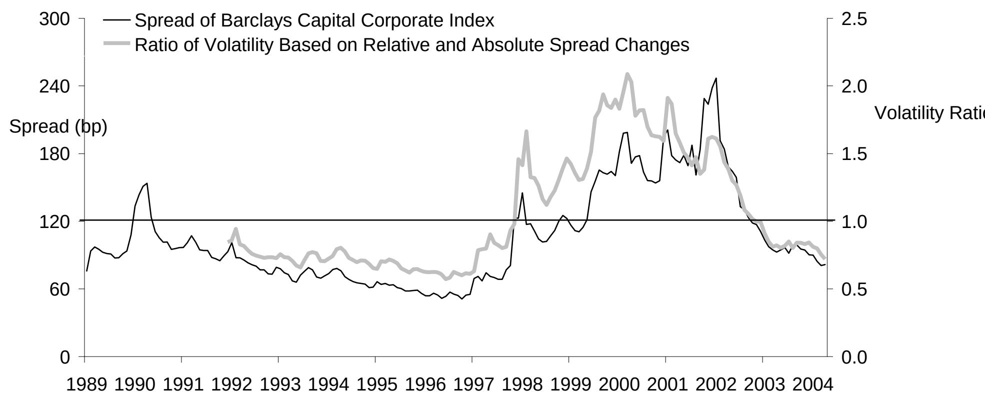
$$(13)\quad Vol\ \mathrm{ratio}_{\mathrm{J,t}} = \frac{\sigma\left(\frac{\Delta s_{J,t}}{s_{J,t}}\right) \times \sum_{i \in J} D_{i,t} \times s_{i,t}}{\sigma(\Delta s_{J,t}) \times \sum_{i \in J} D_{i,t}} \cong \frac{\theta \times \sum_{i \in J} D_{i,t} \times s_{i,t}}{\theta \times \bar{s}_{J,t} \times D_{J,t}}$$

$$\cong \frac{\sum_{i \in J} D_{i,t} \times (s_{J,t} + s_{i,t}^{idio})}{\bar{s}_{J,t} \times D_{J,t}} \cong \frac{s_{J,t} \times D_{J,t}}{\bar{s}_{J,t} \times D_{J,t}} = \frac{s_{J,t}}{\bar{s}_{J,t}}$$

Looking at equation 13 we see that the volatility measure based on relative spread changes reflects the current spread level of bucket *J* while the volatility measure based on absolute spread changes reflects the time-weighted average spread the bucket has exhibited over the volatility estimation period (denoted $\bar{s}_{J,t}$).

If, for example, the systematic spread level of bucket *J* over the estimation period was unchanged, the ratio would be equal to one. Otherwise, the ratio would be above or below one depending on whether the current spread is above or below the historical average. Using a shorter period for estimating spread change volatility will not necessarily reduce the difference between the two measures, if the long-term historical spread is a better reflection of the current spread environment than the recent past.

Figure 19: Ratio of Conditional Volatility Estimates and Spread on the Barclays Capital Corporate Index; Based on absolute and relative spread changes calculated using the entire available history since 9/1989



Source: Barclays Capital

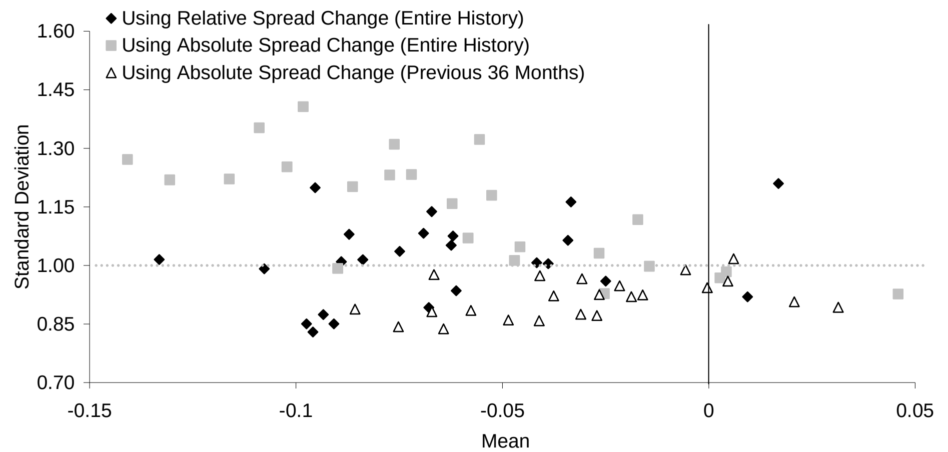
Figure 19 plots the time-series of volatility ratio using the 8 sector X 3 credit rating partition we have used before. Every month, two forecasts of excess return volatility are calculated using all available history at that time, based on absolute and relative spread changes. The volatility ratios computed separately for every bucket are then averaged to yield a representative volatility ratio for each month.

As we can expect, the volatility ratio tracks the index spread very closely. In the period between September 1992 and May 1998, spreads were relatively tight and the volatility ratio was below one indicating that using spread duration and absolute spread change volatility would have generated an upward biased volatility estimate. In contrast, the "Russian crisis" in late 1998 and periods of dramatic widening of spreads since have raised the volatility ratio to between 1.5 and 2. 0. Hence, the relative spread change volatility measure reacted in a much more timely manner to the change in spread environment than the measure based on absolute spread change.

To directly compare the forecasting accuracy of the two measures, we conduct the following test: In addition to the two volatility forecasts, each month we calculate the realized excess return of the 24 buckets. The carry component (spread/12) is stripped from the realized excess return, and the random part is then divided by one of the two forecasts of excess return volatility.[12] If the projected excess return volatility is an unbiased estimate of the "true" volatility, then the time-series volatility of these standardized excess return realizations should be very close to 1.

[12] Although the carry component is time-varying, we analyze each month's excess return conditioned on the beginning-of-month spread. We can therefore treat the carry component as deterministic.

Figure 20: Mean and Standard Deviation of Normalized Excess Return Realizations Conditional volatility, estimates are computed monthly by sector and credit quality based on the entire available history or previous 36 Months; Using monthly spread changes observations (9/89 – 1/05)



Source: Barclays Capital

Our premise is that relative spread change volatility is a more timely measure than absolute spread change volatility, since it can react almost instantaneously to a change in market conditions. Hence we expect the sample time-series standard deviation of excess returns to be closer to 1 when using (ii) then when using (i). Second, a volatility measure that is quicker to adjust for changing market conditions will generate less extreme realizations (i.e. realizations that fall above/below 2 or 3 standard deviations) relative to a measure which is slower to react.

Figure 20 displays the mean and standard deviation of the time series of normalized residuals (each observation represents one of the 24 buckets). The normalized residuals are generated using the two volatility measures using the entire available history for each month. In addition, Figure 20 shows the mean and standard deviation of normalized residuals when the absolute spread change volatility is calculated over the previous 36 months.

Comparing the three sets of observations reveals that using absolute spread changes produces downward (upward) biased estimates of volatility when using the entire available history (previous 36 months). As a result the average standard deviation of normalized excess returns using the entire and partial history is above and below one (1.14 and 0.92 respectively). In contrast the observations generated using relative spread changes are evenly spread around 1 and the average standard deviation of standardized excess returns is 1.01 (Figure 21 provides a detailed comparison by sector and credit rating).

These findings support our empirical prediction and are also consistent with the analysis of the ratio of the two volatility measures. Excess return volatility estimates based on absolute spread changes are very sensitive to the length of the estimation period: they may overreact when using too few data points and can be slow to adjust when using a long history. What is the optimal estimation period is not clear ex-ante when using absolute spread changes. In contrast, a longer estimation period is always desired when using proportional spread changes since it improves the accuracy of the proportionality factor, while at the same time the volatility estimate adjusts instantaneously because of the multiplication by the current spread level.[13]

[13] A longer estimation period is always desired as long as the proportionality factor is stable across periods, which we found to be the case.

Figure 21: Standard Deviation of Standardized Excess Returns Using Various Volatility Measures Using monthly observations (9/1992 – 1/2005)

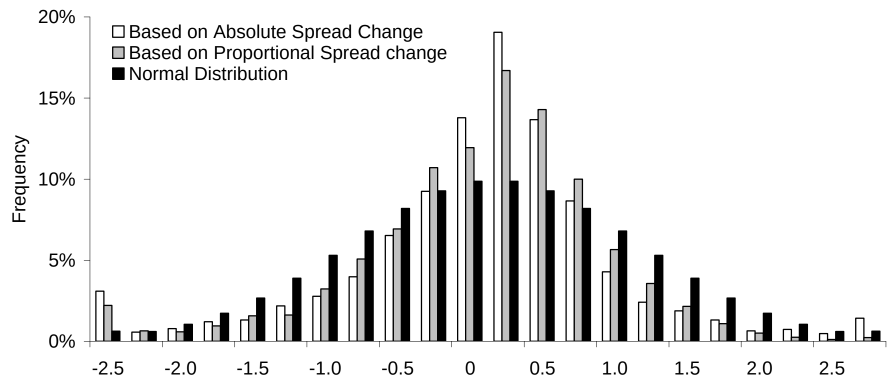
Market Cell		Absolute Spread Change		Relative Spread Change
Sector	Credit Rating	Entire Available History	Previous 36 Months	Entire Available History
Average		1.14	0.92	1.01
Banking	Aaa/Aa	0.93	0.92	1.20
	A	0.98	0.91	1.16
	Baa	0.93	0.91	1.21
Basic Industries	Aaa/Aa	1.32	0.94	1.06
	A	1.23	0.93	1.08
	Baa	1.01	0.95	1.00
Cyclicals	Aaa/Aa	1.03	0.99	1.14
	A	1.27	0.89	1.02
	Baa	1.07	0.92	1.01
Communications	Aaa/Aa	1.41	0.86	0.87
	A	1.22	0.84	0.85
	Baa	1.31	0.87	1.08
Energy	Aaa/Aa	1.22	0.84	0.85
	A	1.16	0.92	1.05
	Baa	1.00	1.02	0.96
Financials	Aaa/Aa	1.12	0.96	1.01
	A	1.05	0.87	0.94
	Baa	0.97	0.89	0.92
Non-Cyclicals	Aaa/Aa	1.18	0.97	1.04
	A	1.20	0.97	1.01
	Baa	0.99	0.98	0.99
Utilities	Aaa/Aa	1.25	0.88	0.83
	A	1.23	0.86	0.89
	Baa	1.35	0.88	1.08

Source: Barclays Capital

The second empirical prediction states that the percentage of extreme realizations (positive or negative) should be lower when using relative rather than absolute spread change volatility. Figure 22 plots a histogram of the standardized excess return realizations for all sector/quality cells based on the two volatility measures. For comparison, the standard normal distribution is also displayed.

No surprisingly, the histogram reveals that both volatility estimators generate distributions that are negatively skewed (-2.67 and -1.35 using the relative and absolute spread change based volatility measures). With respect to the percentage of outliers, 7.06% of the observations in the distribution based on absolute spread changes are located beyond 2 standard deviations from the mean. In the case of the distribution based on relative spread changes, the same figure is almost half, at 4.03%.

Figure 22: Distribution of standardized excess returns; Based on observations (9/1992 – 1/2005) from all sectors and credit quality ratings



Source: Barclays Capital

Index replication by stratified sampling

In a final test of which risk measure is more appropriate, spread duration or DTS, we examine which can replicate an index with a smaller tracking error. As in the previous section, we use the 8 x 3 partition of the IG credit universe to construct a market weighted index and calculate each month the aggregate excess return, spread duration, DTS and spread. The replicating portfolio is constructed using one or two bonds from every bucket. In both cases the idea is similar: the replicating portfolio is not designed to match multiple index characteristics but only the aggregate spread duration or DTS. **Hence, the intention is not to create an "optimal" replication, but rather to focus on the relative efficacy of one measure against the other.**

Replication algorithms

Single bond replication – The algorithm selects from each bucket the bond that best matches the aggregate spread duration or DTS, and allocates the entire bucket weight in the index to it. Although the replication is not exact, the bonds that are selected typically match their respective bucket aggregate characteristic very closely. One caveat, however, is that the two bonds selected to represent a bucket under the two matching criteria are almost always different. As a result, the variation in tracking errors may reflect not only the difference between the two systematic risk measures, but also different levels of idiosyncratic risk.

Two-bond replication – This replication is much more complex but has two main advantages over the single bond replication. First, the same two bonds are used to match each cell's spread duration or DTS (with different weights), which addresses the issue of different idiosyncratic risk. Second, based on the matching criterion, the algorithm exactly matches either the bucket spread duration or DTS. Furthermore, in order to magnify the difference between the two competing risk measures, the two bonds are selected from each bucket such that they possess very different spread duration and DTS characteristics. As a result, the weights allocated to the two bonds within each cell are very different under the two matching criteria.

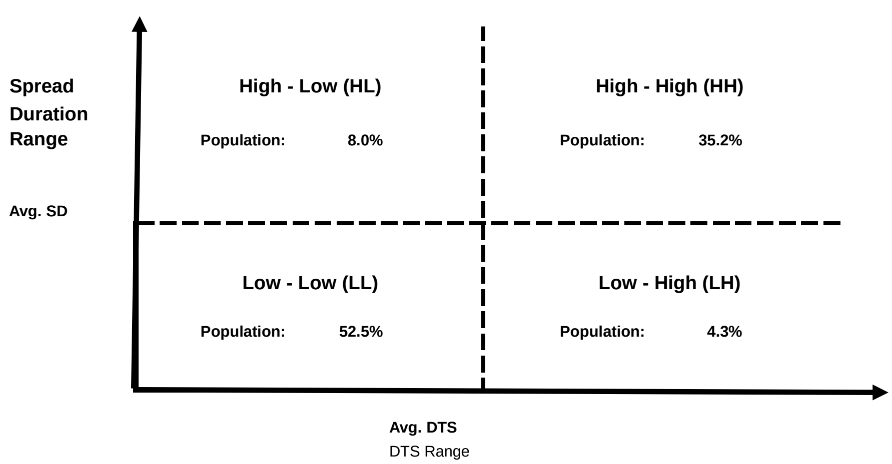
The replicating portfolio is constructed as follows: every month, all bonds in each bucket are assigned to one of four quadrants. The quadrants are defined using a 2 X 2 grid based on the market weighted spread duration and DTS (See Figure 23). Bonds with spread duration and DTS above the weighted mean are allocated to the upper right quadrant denoted "HH". Similarly, bonds with spread duration above the mean but DTS below the mean are allocated to the upper left quadrant ("HL") and so on.

The algorithm selects one bond from each of the "HL" and "LH" quadrants and calculates two sets of weights such that the two bonds exactly match either the spread duration or the DTS of the cell. Since, by construction, there is always one bond with spread duration or DTS above the bucket mean and a second bond with the same characteristic below the bucket mean, we are guaranteed to get exact replication with both bonds having positive weights.

The specific bonds that comprise the replicating portfolio are selected based on one of several criteria such as market value, spread, spread duration or DTS. Based on the first criterion, for example, the algorithm would select the largest bonds in the two quadrants. If, instead, the selection criterion is spread duration or DTS, the algorithm searches for the two bonds with the largest mismatch with respect to the selected characteristic. To achieve this, if the selection criterion is spread duration (DTS), the algorithm selects the bond with the highest (lowest) and lowest (highest) spread duration (DTS) from the "HL" and "LH" quadrants respectively. Thus, this algorithm not only insures that the weights of both bonds are positive, but also attempts to magnify the bond weights differential under the two matching criteria.

Since spread duration and DTS are highly correlated, the bond population within a bucket is not evenly divided among the quadrants. In fact, as Figure 23 shows, the "HL" and "LH" population comprise only 12.3% on average of a bucket population. This, in turn, implies that at least one of the "HL" or "LH" quadrants is not populated in about 25% of the over 4,300 period-cell pairs. Whenever the algorithm is unable to find a bond in either the "HL" or "LH" quadrants, it instead selects two bonds from the "HH" and "LL" quadrants.[14]

Figure 23. Illustration of Cell Partition by Spread Duration and DTS; Based on monthly observations (9/1989 – 1/2005) from all sectors and credit quality ratings



Source: Barclays Capital

[14] If the selection criterion is spread duration, then the algorithm selects the highest and lowest spread duration bonds from the "HH" and "LL" quadrants respectively. Alternatively, if the selection criterion is DTS, then the algorithm selects the lowest and highest DTS bonds from the "LL" and "HH" quadrants respectively.

Results

The replication results using both algorithms are presented in Figure 24. The table reports the monthly tracking error, as well as the average mismatch in overall spread and DTS relative to the index, for the matched spread duration replication. The same statistics are reported for the second replication except that the spread duration mismatch is reported instead. For the two-bond replications the figure also reports the average absolute difference in weights assigned to the same bond under the two matching criteria (the column titled “bucket” reports the difference within each bucket, whereas the column titled “overall index” weights the difference by the bucket weight in the index).

The first two rows report the results of the three replications that use a single bond from each cell. Matching the index market value of each cell using the largest issue results in a tracking error of 25.9 bp/month, partly because of overexposures both in terms of spread duration (long 0.82 on average) and DTS (long 1.01). By instead choosing the single bond in each cell that best matches spread duration, the tracking error is reduced to 17.5 bp/month; matching DTS does even better, bringing the tracking error down to 14.7 bp/month.

The two-bond-per-cell replications exhibit similar results. Choosing the bond with the highest market value in each selected cell quadrant, and then blending these two bonds together to match the cell’s market value as well as spread duration, brings TE down to 13.2 bp/month; blending the same two bonds to match cell market value and DTS improves the TE to 11.9 bp/month. We tried several different methods for selecting the two bonds in each cell, to help make our results more robust. Different criteria change the result somewhat, but in most cases the better TE is achieved by matching DTS rather than spread duration. The one exception was the case in which the bond with the largest spread was chosen within each cell quadrant, where the DTS replication had a slightly higher TE (14.9 bp/month vs. 14.5 bp/month for the duration-matched approach).

The differences between the two replication techniques are somewhat masked by the amount of idiosyncratic risk inherent in tracking the credit index with a portfolio of 24 or 48 bonds. A more extensive study of this variety might involve replication with a larger number of bonds, or simulation using some randomized mechanism for bond selection within a cell. Nevertheless, we feel that the results of this experiment confirm that matching DTS contributions provides better replication results than matching contributions to duration.

Figure 24: Replication Results Using Various Algorithms, Replication of the aggregate index is performed through matching the spread or DTS characteristic of each of the 24 cells in the partition (8 sectors X 3 credit quality groups); Based on monthly observations (9/1989 – 1/2005)

	Duration Matched Replication			Weight Differential		DTS Matched Replication		
		Mean Mismatch				TE (bp per month)	Mean Mismatch	
Bond Selection Criteria	TE (bp per month)	DTS	Spread (bp)	Bucket	Overall Index		Dur	Spread (bp)
Largest Issue	25.9	1.01	3.6	NA	NA	NA		
Single Bond	17.5	-0.18	2.3	NA	NA	14.7	0.27	4.9
Two Bond								
Market Value	13.2	0.28	13.3	29.0%	1.4%	11.9	0.14	6.4
Duration	14.6	-0.10	4.0	33.8%	1.5%	12.9	0.00	6.4
DTS	16.7	0.81	19.5	25.8%	1.2%	14.8	-0.06	8.1
Min Spread	14.3	-0.29	2.3	26.5%	1.1%	14.2	0.28	4.9
Max Spread	14.5	0.77	21.9	26.2%	1.1%	14.9	-0.08	10.5

Source: Barclays Capital

Summary and conclusions

This paper presents a detailed analysis of the behavior of spread changes. Using our extensive corporate bonds database, which spans 15 years and contains well over 400,000 observations, we demonstrate that spread changes are proportional to the level of spread. Systematic changes in spread across a sector tend to follow a pattern of relative spread change, in which bonds trading at wider spreads experience larger spread changes. The systematic spread volatility of a given sector (if viewed in terms of absolute spread changes) is proportional to the median spread in the sector; the non-systematic spread volatility of a particular bond or issuer is proportional to its spread as well.

For a portfolio manager who wishes to act on these results, there are many implications. First, the best measure of exposure to a systematic change in spread within a given sector or industry is not the contribution to spread duration, but the contribution to DTS. At many management firms, the targeted active exposures for a portfolio relative to its benchmark are expressed as contribution-to-duration overweights and underweights along a sector by quality grid – and reports on the actual portfolio follow the same format. In the relative spread change paradigm, managers would express their targeted overweights and underweights in terms of contributions to DTS instead.

If we take this approach to the limit, we can arrive at an even more radical departure from current practice. In the sector by quality management grid discussed above, the macro views of the manager are often expressed largely in terms of sectors or industries, and the role of the quality dimension is to control for the level of risk taken in implementing each view. If contributions to DTS are used to express industry exposures on a risk-weighted basis, then a further partition by quality may no longer be necessary. Instead, managers may view this as an opportunity to express more focused views, and slice the credit markets into a more finely grained partition by industry.

Second, our conclusion that non-systematic spread volatility is proportional to spread (and hence that the volatility of non-systematic return is proportional to DTS) suggests another way of defining issuer limits in a portfolio. In prior research on "Sufficient Diversification in

Credit Portfolios"[15], we focused on the return implications of credit rating downgrades, and emphasized that to reduce portfolio risk from downgrades, issuer limits should be much tighter for lower-rated issuers. For example, an investment policy might specify that no more than 1% of the portfolio market value can be invested in securities of any single Bbb-rated issuer, no more than 2% in any A-rated issuer, and no more than 4% in any Aa-rated issuer. Our current research addresses exposures to overall non-systematic returns, not specifically those connected with ratings transitions – yet it offers an even simpler mechanism for defining an issuer limit policy that enforces smaller positions in more risky credits. We can simply set a limit on the overall contribution to DTS for any single issuer. For example, say the product of market weight x spread x duration must be 5 or less. Then, a position in issuer A, with a spread of 100 bp and a duration of 5 years, could be up to 1% of portfolio market value; while a position in issuer B, with a spread of 150 and an average duration of 10 years, would be limited to 0.33%.

Establishing issuer limits based on spreads has advantages and disadvantages relative to a ratings-based approach. One advantage, as described above, is the simplicity of specifying a single uniform limit that requires increasing diversification with increasing risk. The key difference between the two approaches, though, concerns the frequency which issuer limits are adjusted. In a ratings-based framework, bond positions that are within policy on the date of purchase will tend to remain in policy unless they are downgraded. A spread-based constraint, by contrast, is by its very nature continuously adjusted as spreads change. One possible result is that as spreads widen, a position which was in policy when purchased can drift over the allowable DTS limit. Strict enforcement of this policy, requiring forced sales to keep all issuer exposures to stay within the limit, could become very distracting to managers, and incur excessive transaction costs as spreads trade up and down. One possible solution would be to specify one threshold for new purchases and a higher one at which forced sales would be triggered. This could provide a mechanism that adapts to market events more quickly than the rating agencies without introducing undue instability. Another possible disadvantage of the DTS-based issuer caps is that it allows for large positions in low spread issuers and exposes the portfolio to "credit torpedoes". This too would argue for using the DTS-based approach in conjunction with caps on market weights.

Third, there could be hedging implications. Say a hedge fund manager has a view on the relative performance of two issuers within the same industry, and would like to capitalize on this view by going long issuer A and short issuer B in a market-neutral manner. How do we define market neutrality? A typical approach might be to match the dollar durations of the two bonds, or to go long and short CDS of the same maturities with the same notional amounts. However, if issuer A trades at a wider spread than issuer B, our results would indicate that a better hedge against market-wide spread changes would be obtained by using more of issuer B, so as to match the contributions to DTS on the two sides of the trade.

Our investigation of the relationship between DTS and excess return volatility in this paper has focused almost entirely on investment grade credit. However, there is good reason to believe that it carries over to other asset classes as well. We have included in this study some results from high yield credit, which show that the paradigm of proportional spread changes carries through to high yield as well. Indeed, we believe that perhaps one of the most useful applications of DTS will be in the management of core-plus portfolios that combine both investment-grade and high-yield assets. It might be typical to manage

[15] Sufficient Diversification in Credit Portfolios, Barclays Capital, May 2002.

investment-grade credit portfolios based on contributions to duration, and high yield portfolios based on market value weights; using contributions to DTS across both markets could help unify this process. Skeptics may point out that in high yield markets, especially when moving towards the distressed segment, neither durations nor spreads are particularly meaningful, and the market tends to trade on price, based on an estimated recovery value. A useful property of DTS in that context is that in the case of distressed issuers, where shorter duration securities tend to have artificially high spreads, DTS is fairly constant across the maturity spectrum, so that managing issuer contributions to DTS becomes roughly equivalent to managing issuer market weights.

The phenomenon of proportional spread volatility may extend beyond credit-risky securities. The fundamental idea that the mechanism by which spreads change is by a multiplicative factor rather than by a parallel shift could apply equally well to other spread sectors, such as mortgage-backed securities and other collateralized sectors. A preliminary investigation of the MBS sector indicates that this may indeed be the case; more research is required.

Should portfolio management tools such as risk analysis and performance attribution be modified to view sector exposures in terms of DTS contributions and sector spread changes in relative terms? For performance attribution, the answer is clear, because a key goal for attribution models is to match the allocation process as closely as possible. If and when a manager starts to state his allocation decisions in terms of DTS exposures, performance attribution should follow suit. For risk analysis, which is based largely on the results of regressions against individual bond returns similar to those discussed in sector 2.3, there is certainly room to question whether a more extensive use of DTS can improve the model[16]. The modelling team for the Barclays Capital Global Risk Model is currently exploring the possibility of revising the credit portion of the model. They will address whether such changes can significantly increase the accuracy of the model, and what their effect might be on issues ranging from the stability of the covariance matrix to the intuitive appeal of the risk factor exposures.

One practical difficulty that may arise in the implementation of DTS-based models is an increased vulnerability to pricing noise. For the most part, models of portfolio risk and reporting of active portfolio weights rely largely on structural information. Small discrepancies in asset pricing give rise to small discrepancies in market values, but potentially larger variations in spreads. Managers who rely heavily on contribution-to-DTS exposures will need to implement strict quality controls on pricing.

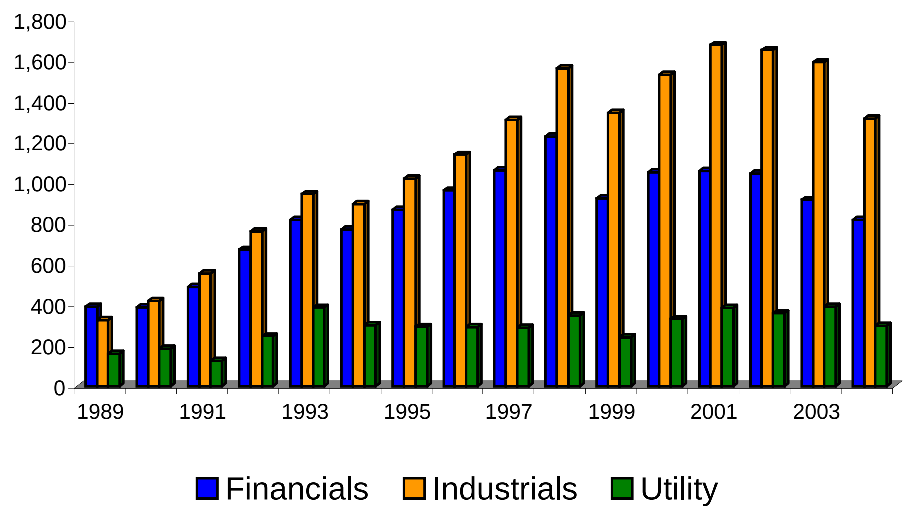
We believe that the DTS paradigm accurately represents the impact of spread changes on excess returns, and that its acceptance of this result could have wide-ranging effects on portfolio management practice throughout the industry. We look forward to continuing our research in this area on several fronts, including extension to other asset classes, and implementation of DTS-based features into our portfolio analytics offerings.

[16] The Barclays Capital risk model currently includes factors representing parallel shifts in spread along a 9x3 sector/quality partition, and a single credit slope factor similar to the one in equation (10), representing a further market-wide increase in wider-than-average spreads. For details, see **The Barclays Capital Global Risk Model: A Portfolio Manager's Guide**, Barclays Capital, April 2005.

Appendix

The dataset used in this paper spans the period between 09/1989 and 01/2005 (a total of 185 months). The sample includes all the bonds that comprise the Barclays Capital Corporate Index excluding (i) zero-coupon bonds (ii) callable bonds and (iii) bonds with non-positive spreads. The final dataset contains a total of 416,783 observations (see Figure A1 for a breakdown of the sample by sector and year). We also extend the analysis to include high yield bonds rated Ba and B[17] which increases the number of observations by roughly 35% (from 416,783 to 565,602).

Figure A1: Bond population by sector and time period; Sample includes IG bonds only; Number of bonds is as of December of each year



Source: Barclays Capital

Figure A-2 outlines the exact breakdown into spread buckets by industry and maturity we employ in analyzing the relation between spread volatility and spread level. A careful look reveals that because of the general tendency of spread to rise with maturity, the population of the 'Short' maturity bucket is concentrated in the lowest spread bucket (denoted by 1) while the opposite holds for the "Long" maturity bucket. Figure A-2 also reports for each bucket the percentage of months during the sample period where the bonds population exceeds 20. This statistic is of interest since months with less than 20 observations are filtered out from any volatility calculation. The percentage of months with sufficient number of observations varies between 30% and 50% for Utilities and 50%-80% for Financials and Industrials.

[17] We include bonds rated Ba or B only if their price is above 80 in order to screen potential default effects.

Figure A2: Sample partition by sector, duration and spread; Sample includes IG bonds only between 9/89 and 1/05

The table reports the breakdown into spread buckets, number of bonds in each cell and the percentage of months where a bucket is populated by more than 20 bonds.

Sector/ Maturity	Spread bucket / breakpoints					
	1	2	3	4	5	6
Financials	<0.50	0.50-0.75	0.75-1.00	1.00-1.25	1.25-1.50	>1.5
Short	16,881	13,201	9,351	5,296	2,677	4,004
	(50.8%)	(82.7%)	(64.9%)	(46.5%)	(30.8%)	(37.3%)
Medium	5,839	14,838	11,156	8,173	5,133	6,904
	(28.6%)	(65.4%)	(73.5%)	(61.6%)	(44.3%)	(48.1%)
Long	2,183	12,875	10,743	8,174	6,130	11,993
	(18.9%)	(54.6%)	(81.1%)	(73.0%)	(58.9%)	(55.1%)
Industrials	<0.60	0.60-0.85	0.85-1.20	1.20-1.50	1.50-2.00	>2.00
Short	22,794	13,705	12,172	7,670	6,277	6,167
	(84.9%)	(97.8%)	(78.9%)	(54.6%)	(48.6%)	(30.8%)
Medium	12,814	14,621	14,424	9,109	9,300	9,131
	(70.3%)	(85.4%)	(96.2%)	(65.4%)	(54.6%)	(43.2%)
Long	9,212	13,961	16,248	10,088	11,010	8,940
	(68.1%)	(81.6%)	(94.6%)	(69.7%)	(53.5%)	(40.5%)
Utilities	<0.55	0.55-0.75	0.75-1.15	1.15-1.50	>1.50	
Short	5,017	3,233	4,443	2,388	2,350	
	(46.5%)	(35.7%)	(48.6%)	(22.2%)	(16.8%)	
Medium	3,430	3,552	4,484	2,699	3,889	
	(41.1%)	(38.9%)	(41.1%)	(32.4%)	(23.2%)	
Long	3,030	3,199	4,457	2,653	2,350	
	(32.4%)	(40.5%)	(52.4%)	(25.4%)	(29.2%)	

Source: Barclays Capital

Analyst Certification(s)

We, Arik Ben Dor and Lev Dynkin, hereby certify (1) that the views expressed in this research report accurately reflect our personal views about any or all of the subject securities or issuers referred to in this research report and (2) no part of our compensation was, is or will be directly or indirectly related to the specific recommendations or views expressed in this research report.

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