DTS$^{\text{SM}}$ (Duration Times Spread) -

A New Measure of Spread Exposure in Credit Portfolios

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ABSTRACT

The paper proposes a new measure of spread exposure for corporate bonds portfolios based on a detailed analysis of credit spread behavior. We find that changes in spreads are not parallel but rather linearly proportional to the level of spread, whereby bonds trading at wider spreads experience larger spread changes. Consequently, systematic spread volatility of a sector is proportional to its spread; similarly, the idiosyncratic spread volatility of a particular bond or issuer is proportional to its spread, irrespective of sector, maturity and time period. We confirm that the behavior of spreads results in excess return volatility being proportional to Duration Times Spread (DTS). We demonstrate the advantage of DTS over spread-duration in forecasting excess return volatility and portfolio construction and discuss the implications of our findings for the formulation of investment constraints, asset allocation, risk modeling and performance attribution.

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DTS (DURATION TIMES SPREAD) -

A NEW MEASURE OF SPREAD EXPOSURE IN CREDIT PORTFOLIOS

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.[1] Determining the set of active spread duration contributions 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 securities with the widest spreads within each cell. These bonds 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", because their spreads tend to react more strongly than the rest of the market to a

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.

To reflect the view that higher spread credits represent greater exposures to sector-specific risks, we propose a simple risk sensitivity measure that utilizes spreads as a fundamental part of the credit portfolio management process. We represent sector exposures by contributions to Duration Times Spread (DTS), computed as the product of market weight, spread duration, and spread. For example, an overweight of 5% to a market cell implemented by purchasing bonds with a spread of 80 bp and spread-duration of 3 years is equivalent to an overweight of 3% using bonds with an average spread of 50 bp and spread-duration of 8 years.

To understand the intuition behind the new measure we propose, consider the return due strictly to change in spread - R_{spread}. Let D denote the spread duration of a bond and s its spread; the spread change return[2] is then given by

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

It is quite easy to see that this 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 $(D \cdot s)$ is the sensitivity to a relative change in spread. Note that this notion of relative spread change provides for a formal expression of the rough idea mentioned earlier – that credits with wider spreads are riskier since they tend to experience greater spread changes.

In the absolute spread change approach (Equation 1) we can see that the volatility of excess returns can be approximated by

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

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

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

Given that the two representations above are equivalent, why should one of them be preferable to another?

In this paper we provide ample evidence that the advantage of the second approach, based on relative spread changes, is due to the stability of the associated volatility estimates. Using a large sample with over 560,000 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 relation holds for both investment-grade and high-yield credit irrespective of the sector, duration or time period. Additional analysis we conducted (to be published at a later date) found that these results are not confined to the realm of U.S. corporate bonds but also apply to European corporate bonds and credit default swaps (CDX and ITRAXX) regardless of the spread reference curve (e.g. Treasury or Libor). 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 the paper, we present evidence that the relative spread change approach offers increased insight into both of these sources of risk.

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ANALYSIS OF SPREAD BEHAVIOR OF CORPORATE BONDS

How should the risk associated with a particular market sector be measured? Typically, for lack of any better estimate, the historical volatility of a particular sector over some prior time period is used to forecast its volatility for the coming period.[3] 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 Lehman Brothers Credit Index between September 1989 and January 2005. It is clear that spread 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.

[FIGURE 1]

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.

[FIGURE 2]

As suggested by Equation 4, a potential remedy to the volatility instability problem is to approximate the absolute spread volatility (bp/month) by multiplying the historically observed relative spread volatility (%/month) by the current spread (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, and indicate a relationship between spread level and volatility.

Figure 3 plots side by side the volatility of absolute and relative spread changes of all bonds in the Lehman Brothers Credit 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 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. When we re-compute the two time-series excluding the four observations representing the period 8/98 – 11/98, 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 16 bp/month in 2002-3, growing by a factor of five. In contrast, relative spread volatility increases more modestly over the same time period, from 3%/month to 7%/month.

[FIGURE 3]

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.[4] Each point shown on the graph represents a particular sector-quality cell of the Lehman Brothers Credit Index, which is divided into 8 industry groups by 3 quality cells.[5] Points along the diagonal line reflect identical volatilities in both 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.

[FIGURE 4]

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.

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.

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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 issuer-specific (or idiosyncratic) spread volatility. 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 Lehman Brothers Credit Index historical database. The 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 Credit Index. For the sections of our study that include high yield bonds as well as investment grade, we augment the dataset with historical data from the Lehman Brothers 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) $$\Delta s_{i,t} = \Delta s_{J,t} + \Delta s_{i,t}^{idiosyncratic} \qquad i \in J$$

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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)
$$\frac{\Delta s_i}{s_i} = \frac{\Delta s_J}{s_J} + \frac{\Delta s_i^{idio}}{s_i} \quad \text{or} \quad \Delta s_i = s_i \cdot \frac{\Delta s_J}{s_J} + \Delta s_i^{idio}$$

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 as the basis of 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 reveals 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 Lehman Brothers Corporate Index against their beginning-of-month spreads in January 2001.[6] It is clear that this sector-wide rally was not characterized by a purely parallel shift; rather issuers with wider spreads tightened by more.

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[FIGURE 5]

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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^2 (97.1%) indicates that the model fit the data well.[7] 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^2 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.

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[FIGURE 6]

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 aggregate R^2 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. The last column of Figure 6 reports the aggregate R^2 for these regressions across all sectors and months. The relative model explains twice the variation in spreads (33%) as the parallel shift model (16.9%) and almost as much as the less restrictive combined model. The fact that only about a third of spread movements are explained is due to the fact that in many months, there is little systematic change in spreads, and spread changes are largely idiosyncratic. Still, the slope factor was statistically significant 73% of the time.

[FIGURE 7]

Figure 7 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

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examples of large parallel spread movements in which the slope factor moves in the opposite direction. This clear linear relationship between the shift and slope factors serves as an additional validation of the relative model.

Systematic Spread Volatility

The security-level analysis established that systematic changes in spreads are proportional to the systematic level of spread consistent with Equation 6. We now 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.

The credit index is first partitioned rather coarsely by sector (Financials, Industrials and Utilities) and then further subdivided by duration ('Short', 'Medium' and 'Long'). To ensure that every sector-duration cell is well-populated each month, we do not use pre-specified duration levels but rather divide each sector into three equally-populated duration groups.[8] In the last step, bonds in each sector-duration cell are assigned to one of several spread level buckets. To allow a detailed

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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, the Financial and Industrial sectors are divided into six spread buckets whereas the Utilities sector has only five spread buckets (a more detailed description of the partition and sample population can 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 spreads and spread changes. We then calculate the time series volatility of these systematic spread changes.[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).

[FIGURE 8]

The relation between the volatility of systematic spread changes and spread level is plotted in Figure 8, where each observation represents one of the 51 buckets in the partition. Figure 8, illustrates a clear relationship between spread volatility and spread level. Higher spreads are accompanied by higher volatilities for all sector-duration cells. Relatively minor differences can be seen between industrials and the other two broad sectors. Similarly, duration does not seem to have any significant systematic effect on the results.[10]

Nonetheless, the results shown in Figure 8 do not perfectly corroborate our hypothesis of proportional spread volatility, which would predict that all of our observations (or at least all

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observations within a given sector) should lie along a diagonal line that passes through the origin, of the form

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

While the points at the left side of Figure 8 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. The 250-300 bp spread region represents the boundary between investment grade and high yield bonds. 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 examine the relation between systematic spread change volatility and spread level beyond the 250 bp level, we repeat the analysis including all bonds rated Ba and B. This increases the sample size by roughly 35% to 565,602 observations. We employ the same sector x duration x spread partition, with the addition of several spread buckets to accommodate the widening of the spread range (the number of cells increases to 66).

Figure 9 plots the relationship between systematic spread volatility and spread level using both investment grade and high yield data. The linear relationship between the two now 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.

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The simple linear model of Equation 11 provides an excellent fit to the data, with θ equal to 9.1% if we use all observations or 9.4% if we exclude the three circled outliers. Hence, the results suggest 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 9]

Idiosyncratic Spread Volatility

To study the spread dependence of idiosyncratic spread volatility, we employ the same partition we used for the study of systematic spread volatility. Instead of the average spread change experienced within a given cell in a given month, we examine the dispersion of spread changes within each cell.

The idiosyncratic spread change of bond *i* in market cell *J* at time *t* is defined as the difference between its spread change and the average spread change for the cell in that month:

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

The volatility of idiosyncratic spread changes is then exactly equal to the cross sectional standard deviation of total spread changes.[11] Figure 10 shows a scatter plot of the cross-sectional volatility from all months and spread buckets including high-yield bonds. 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.

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[FIGURE 10]

To obtain a single measure of idiosyncratic spread volatility for each bucket, we pool all observations of idiosyncratic risk within a given market cell *J* over all bonds and all months, and compute the standard deviation. This pooled measure of idiosyncratic spread volatility per market cell is plotted in Figure 11 against the median spread of the cell.

The linear relationship between spread and spread volatility is strikingly clear. Observations which represent buckets populated almost exclusively by high-yield bonds exhibit more variation than those representing investment-grade bonds, but follow the exact same pattern. The regression results indicate a zero intercept, but the estimated slope coefficient (the relative volatility of idiosyncratic yield change) is somewhat larger than estimated previously, 11.5% vs. 9.4%).

[FIGURE 11]

Stability of Spread Behavior

We have established that spread volatility is linearly proportional to the level of spread. We now investigate the magnitude of time-variation in the spread slope or the change in spread volatility as spreads vary.

For each bucket we compute the yearly systematic spread volatility and corresponding average spread level (i.e., using 12 months of average spread change).[12] We then regress these estimates of systematic spread volatility against an intercept and a spread slope factor. We follow the same approach idiosyncratic spread volatility except that we use the monthly cross-sectional volatility estimates.

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Panels A and B of Figure 12 present the yearly spread slope estimates and corresponding adjusted R^2. The results are plotted for investment-grade credit and separately when high-yield securities are included as well. The estimated coefficients are all highly significant, with *t*-statistics ranging between 15 and 30 for both systematic and idiosyncratic spread volatility. Not surprisingly, Figure 12 reveals that including high-yield data generally increases the spread estimate for both systematic and idiosyncratic volatility. The spike in volatility caused by the 1998 Russian crisis is evident in the large estimate of spread slope in 1998 (except for the case of idiosyncratic volatility with high-yield). Excluding 1998, the spread slope estimates are remarkably stable in light of the small number of observations used in the estimation.

[FIGURE 12]

Panel B of Figure 12 reveals that the explanatory power of the regressions is higher and more stable when high-yield securities are included. When we analyze investment-grade data only, the R^2 of our regressions goes as low as 40% for systematic volatility and 30% for idiosyncratic volatility. When we include high-yield data as well, the regression results are much better, achieving R^2 values consistently over 70% for systematic volatility and 60% for idiosyncratic volatility. Overall, this pattern confirms that relative spread changes characterize both investment-grade and high-yield credit.

A NEW MEASURE OF EXCESS RETURN VOLATILITY

What are the implications of spread proportionality? Which measure - DTS or spread-duration is more appropriate for representing the risk of credit securities? In this section we demonstrate that excess return volatility increases linearly with DTS, consistent with the formulation in Equation (4). Furthermore, portfolios with very different spreads and spread durations but with similar

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DTS exhibit the same excess return volatility. For example, a portfolio with a weighted spread of 200bp and spread duration of 2 years is equally risky as a portfolio with a spread of 100bp and spread duration of 4 years. We also show that using DTS generates improved estimates of future excess return volatility when compared with those calculated by simply employing spread duration.

DTS, Spread Duration and Excess Returns

If the volatility of both systematic and idiosyncratic spread changes is proportional to the level of spread, then the volatility of excess returns should be linearly related to DTS, with the proportionality factor equal to the volatility of relative spread changes over the corresponding period (see Equation 4).

To examine this prediction, each month bonds are assigned to quintiles based on their DTS value. 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. This formulation yields two empirical predictions:

(i)   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.

(ii)   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 13, strongly support both empirical predictions despite the fact that we do not control for industry, quality, maturity or any other effect.

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% which is in line with the estimated slope from the analysis of systematic spread volatility. 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; however, they continue to follow the same general relationship between DTS and volatility.

[FIGURE 13]

To fully appreciate the significance of the second result, Figure 14 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 buckets which are part of the second DTS quintile 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 bucket have average spread duration of 5.48 and trade at a spread of 54bp, while bonds in the bottom cell have spread duration of 2.53 and a spread of 127bp. Hence, a portfolio of high spread bonds with short duration can be as risky as a portfolio comprised of low spread bonds with high duration as long as they both have roughly the same DTS.[13]

[FIGURE 14]

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A Comparison of Excess Return Volatility Forecasts

A natural step to extend our analysis 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 directly compare the forecasting accuracy of the two measures, we conduct the following test: Every month, we compute the realized excess return of each of the 24 buckets that span the Lehman Brothers Credit Index (8 sectors x 3 credit ratings). 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.[14] 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.

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). A volatility measure that adjusts more quickly for changing market conditions should also 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.

Before we examine the results of the forecasting it may be helpful to look at the conditions under which the volatility forecasts generated by the two measures differ. If we explicitly write the expression for the ratio of the two measures at month *t* for some bucket *J*:

$$(13)\ Vol\ \text{ratio}_{J,t} = \frac{\sigma_t(\frac{\Delta s_J}{s_J}) \times \sum\limits_{i \in J} D_{i,t} \times s_{i,t}}{\sigma_t(\Delta s_J) \times \sum\limits_{i \in J} D_{i,t}} \cong \frac{\theta \times \sum\limits_{i \in J} D_{i,t} \times s_{i,t}}{\theta \times \bar{s}_{J,t} \times D_{J,t}}$$

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

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 15 displays the mean and standard deviation of the time series of normalized residuals separately for each volatility measure (each observation represents one of the 24 buckets). The normalized residuals are generated based on the entire history of returns that is available at the beginning of each month. In addition, Figure 15 shows the mean and standard deviation of the normalized residuals when the absolute spread change volatility is calculated over the previous 36 months only. This corresponds to the approach taken by many investors in periods of exceptionally low or high volatility, namely to rely only on recent data.

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. A close examination of the results did not identify any relation between the deviation from 1 and the sector - quality bucket.

[FIGURE 15]

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.[15]

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 16 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.

Not 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 16]

THE SCOPE OF DTS

Spread Volatility as Spreads Approach Zero

What do our findings imply for the level of spread volatility as spreads approach zero? Taking our results at face value suggests that there is no lower bound for volatility and that spread volatility should decline to almost zero for very low-spread securities. Spread volatility, however, is not driven solely by changes in credit risk but also by non credit-risk based factors. Non credit-risk based spread changes can result from "noise" (e.g., pricing errors), demand/supply imbalance (for example, when securities enter/exit the Lehman Brothers Corporate Index) and other factors.

Spread volatility (systematic or idiosyncratic) can therefore be represented as the sum of two terms: a constant term that reflects non credit-risk based spread volatility and a second term that represents spread volatility due to changes in credit risk (which may be approximated by a linear function of spread) as follows:

$$(14) \qquad \sigma(\Delta s) = \sqrt{\sigma^2_{non\ credit-risk} + \theta^2 \cdot s^2}$$

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Equation 14 makes it clear that for sufficiently high spreads, the second term dominates the first, and spread volatility can be well approximated by a linear function of spread, as we find for corporate bonds. As spreads tighten and approach zero, the first term dominates, and spread volatility should converge to some minimum "structural" level.

Agency debentures provide a natural framework to examine the behaviour of spread volatility for very low spreads. Because of market perception that securities issued by the three main agencies are backed by the U.S. Government, these securities typically trade at very low spreads. Between September 1989 and April 2005, the median spread at which agencies traded ranged between 20 and 50 bp except for a few distinct months. We employ the same approach as we did for corporates: each month, bonds are partitioned based on beginning-of-month spread level. Average spread change and median spread level are computed separately for each bucket. We then examine the relation between the time-series volatility and average (median) spread level of each bucket.

The sample spans roughly the same time period as for corporates (September 1989-April 2005) and includes all Aaa rated, non-callable debentures from the Lehman Brothers Agency Index.[16] As before, extreme observations (which reside in either the top or bottom percentile of the spread distribution) are discarded. Since the total number of observations (73,000) is about 17% of the corporate sample size, we use only eight spread buckets. The results are presented in Figure 17. For comparison, the spread volatility of long-duration financials which possess many of the same characteristics as agencies is shown as well.

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The plot in Figure 17 illustrates that spread volatility is roughly constant for spreads below 20 bp, and the level of "structural" systematic volatility is about 2.5-3.0 bp per month. Above 20 bp, the relation takes the usual linear shape and fits nicely with that of Long-Financials. A regression of spread volatility against spread level reveals a flatter slope than we estimated for corporates (5.7% versus 9%), consistent with Equation 14.[17] An analysis of idiosyncratic volatility indicates in a similar fashion that volatility increases moderately as spreads increase from 20 bp to 80 bp and indicate a "structural" volatility level of 4.0-4.5 bp/month. The fact that idiosyncratic "structural" volatility is higher than the corresponding systematic level is to be expected, as pricing noise should be more pronounced for individual securities.

To complete the analysis, the sample is partitioned into 12 DTS buckets and the excess return volatility of each bucket is plotted against its DTS (Figure 18). Similar to corporate bonds, excess return volatility increases linearly with DTS (the estimated slope from the regression is 9.8%, versus 8.8% for corporates). As the DTS approaches zero, however, there is a clear flattening of the relation, and volatility does not decline further. Indeed, the regression yields a significant intercept of 3 bp, which is consistent with our previous estimate for the "structural" level of systemic volatility.

DTS Across Seniority Classes

Probably, one of the most convincing evidence in support of the DTS concept was the fact that portfolios that are remarkably different in terms of their spread and spread-duration but where the product of the two (DTS) is similar, exhibit the same excess return volatility. Underpinning

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this result is the issue of whether credit risk is fully captured by spreads. If spreads incorporate on average all publicly available information related to credit risk then all portfolios with similar DTS should have the same level of excess return volatility. We re-examine this issue in the context of debt seniority by looking at portfolios comprised of bonds from different seniority classes (e.g. 'senior notes', 'debentures', etc) but with a very similar DTS. If spreads already incorporate the likelihood of default and the recovery value in such a case, then all portfolios should exhibit the same excess return volatility. Such a result would provide further support for our earlier findings.

Unlike credit rating which naturally lends itself to cross-sectional comparisons, constructing portfolios based on debt seniority presents a challenge. The classification of a bond as senior or subordinated is based on its payment priority in case of a default. The recovery value of any bond will be affected by the existence of other claims issued by the same issuer that are more or less senior to that bond. Across issuers however, the same seniority class does not necessarily imply a similar recovery value in case of a default. Furthermore, even for a given issuer it not always clear if a certain claim is senior to another claim (e.g. a debenture versus a senior note).[18] As a result, simply grouping bonds into portfolios based on the seniority class is inappropriate.

To address these issues, we perform a more detailed analysis at the issuer level (identified by ticker). Each month, we construct two portfolios for each issuer, titled 'SENIOR' and 'SUBORD' which include all the securities (often just a single security) that are defined as senior and subordinated respectively. Months in which only one of the portfolios is populated are discarded. We first compute the market-weighted DTS and excess return for each portfolio and the DTS ratio of the 'SENIOR' portfolio to the 'SUBORD' portfolio. We then match the DTS of the 'SENIOR' portfolio to that of the 'SUBORD' portfolio (e.g. the DTS is scaled up or down)

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and adjust the excess return accordingly.[19] Hence for every issuer, we have a time-series of excess returns for two portfolios with the same DTS each month.

Using this approach for portfolio construction has clear advantages over the cross-sectional technique. First, it controls for any issuer-specific effect. Second, it accurately captures the relative seniority of different claims. Third, the fact that by construction the two portfolios have the same DTS has testable implications: the ratio of excess-return volatility of the two portfolios should be one on average. In addition, any difference in excess return should be relatively small and reflect only idiosyncratic risk (for example, one portfolio may include bonds that on average are smaller and 'older' than bonds in the second portfolio and are therefore less liquid).

Figure 19 presents the 25th percentile, 50th percentile and 75th percentile of the ratio of excess return volatility for the 'SUBORD' and 'SENIOR' portfolios as well as the difference in average excess returns. Since the relation among seniority classes is not always clear, the table presents these statistics for different compositions of the 'SUBORD' and 'SENIOR' portfolios.

For example, the second row reports the case in which the 'SUBORD' and 'SENIOR' portfolios include notes and senior notes respectively. There were a total of 353 different issuers with the two portfolios being populated over some time-period. The median ratio of excess returns volatilities is 0.94, and does not indicate a significant difference between the two portfolios. One quarter of the issuers exhibited ratios below 0.79, and one quarter of the issuers has ratios above 1.08, with the remaining half falling between these values. The typical performance of the two portfolios is also very similar and the median difference is 1 bp/month (e.g. the 'SUBORD' portfolio underperforms). The results reported for other portfolio compositions are similar (in particular the bottom row which represents the most inclusive case), and do not indicate the two portfolios exhibit different risk characteristics.

[FIGURE 19]

To examine the relation between DTS and excess returns volatility across various seniority classes, the 'SENIOR' and 'SUBORD' portfolios constructed for each issuer are assigned each month to one of the DTS quintiles. We then calculate the weighted excess return and DTS for each quintile (separately by seniority class). The two aggregate portfolios in each quintile have the exact same DTS since at the issuer-level the DTS of the 'SENIOR' and 'SUBORD' portfolios is equal by construction. As before, we compute the time-series volatility of excess returns and the average DTS of the ten portfolios.

Figure 20 presents the results of the analysis comparing senior notes to notes and senior debentures to subordinated debentures. The scatter plot shows that the linear relation between excess return volatility and DTS is preserved and that the slope does not depend on the seniority level. In both cases, there is an almost exact match between the volatilities of the 'SENIOR' and 'SUBORD' portfolios. We obtain similar results for other compositions of the two portfolios that are reported in Figure 19.

[FIGURE 20]

Summary and Implications for Portfolio Managers

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 560,000 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

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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. Those findings hold irrespective of sector, duration or time period.

In a sense, these results are not altogether surprising. The lognormal models typically used to represent changes in interest rates assume that changes in yield are proportional to current yield levels. Models for pricing credit derivatives have used a similar lognormal model to describe changes in credit spreads.[20] An assumption of lognormal spread changes would imply two things: that spread changes are proportional to spreads, and that the relative spread changes are normally distributed. Our results can be seen as providing empirical evidence to support the first of these assumptions, but not necessarily the second.

There are several implications for a portfolio manager who wishes to act on these results. 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 asset 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.

Second, our finding that the volatility of non-systematic return is proportional to DTS offers a simple mechanism for defining an issuer limit policy that enforces smaller positions in more risky credits. Many investors specify some ad-hoc weight-cap by credit quality to control issuer-risk.[21] Alternatively, we can 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

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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.

Should portfolio management tools such as risk and performance attribution models be modified to view sector exposures in terms of DTS contributions and sector spread changes in relative terms? The answer in our opinion is positive in both cases.

A risk model for any asset class is essentially a set of factors that characterize the main risks that securities in that asset class are exposed to. The risk of an individual security or portfolio is computed based on its risk loadings or sensitivity to the set of factors and their past realizations. For credit-risky securities, the traditional risk factors typically measure absolute spread changes based on a sector by quality partition which spans the universe of bonds. Specifying the risk factors in terms of relative spread changes instead, has two important benefits. First, such factors would exhibit more stability over time and allow better forward-looking risk forecasts. Second, the partition by quality would no longer be necessary to control risk and each sector can be represented by a single risk-factor. This would allow managers to express more focused views, essentially trading off the elimination of the quality based factors with a more finely grained partition by industry. Similarly, 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.

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.

Our investigation of the relationship between DTS and excess return volatility in this paper has focused almost entirely on investment grade credit in the U.S. We have also included in this study some results from U.S. high yield credit, which show that the paradigm of proportional spread changes carries through to high yield as well as for agency debentures. Additional analysis we have conducted established that all our results are valid for European corporate bonds as well as for credit default swaps. Furthermore, the findings are robust to the return horizon (monthly or weekly) and to the reference curve used to calculate the spreads (Treasury or Libor).

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. Traditionally, investment-grade credit portfolios are managed based on contributions to duration, while high yield portfolios are managed 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

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across the maturity spectrum, so that managing issuer contributions to DTS becomes roughly equivalent to managing issuer market weights.

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 anticipate a continued research in this area on several fronts, including extension to other asset classes, and implementation of DTS-based features into portfolio analytics offerings. In fact, work is currently under way to incorporate DTS as a risk sensitivity measure into credit components of the Lehman Brothers multi-factor risk model and performance attribution analysis.[22]

APPENDIX

The dataset used in the empirical analysis spans the period between 09/1989 and 01/2005 (a total of 185 months). The sample includes all the bonds that comprise the Lehman Brothers Credit 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 (trading at a price above 80 to mitigate potential default effects) which increases the number of observations by roughly 35% (from 416,783 to 565,602).

[FIGURE A1]

Spread figures are model-driven and can exhibit extreme values (especially since the methodology for computing option-adjusted-spreads has changed during the sample period). To mitigate the effect of outliers, observations where changes in spread fall above the 99th percentile

or below the 1st percentile are excluded. As a result, monthly spread changes included in our analysis range from -60bp to +78bp.

Figure A2 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 A2 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.

[FIGURE A2]

FIGURES

Figure 1. Spread Change Volatility by Credit Rating (trailing 36 months; 9/89 – 1/05)
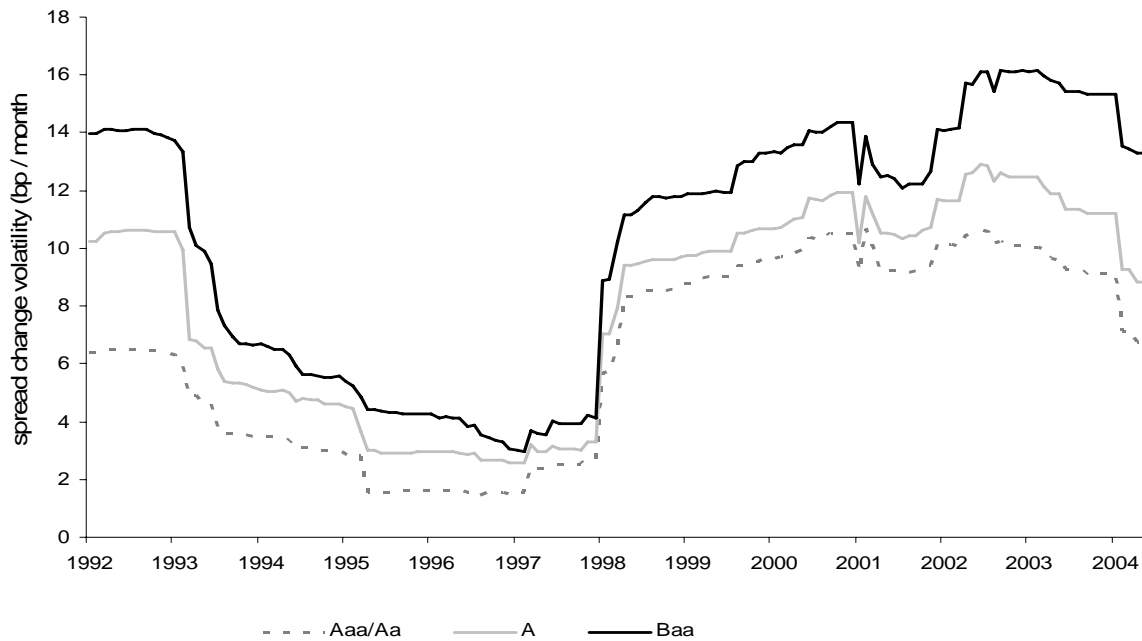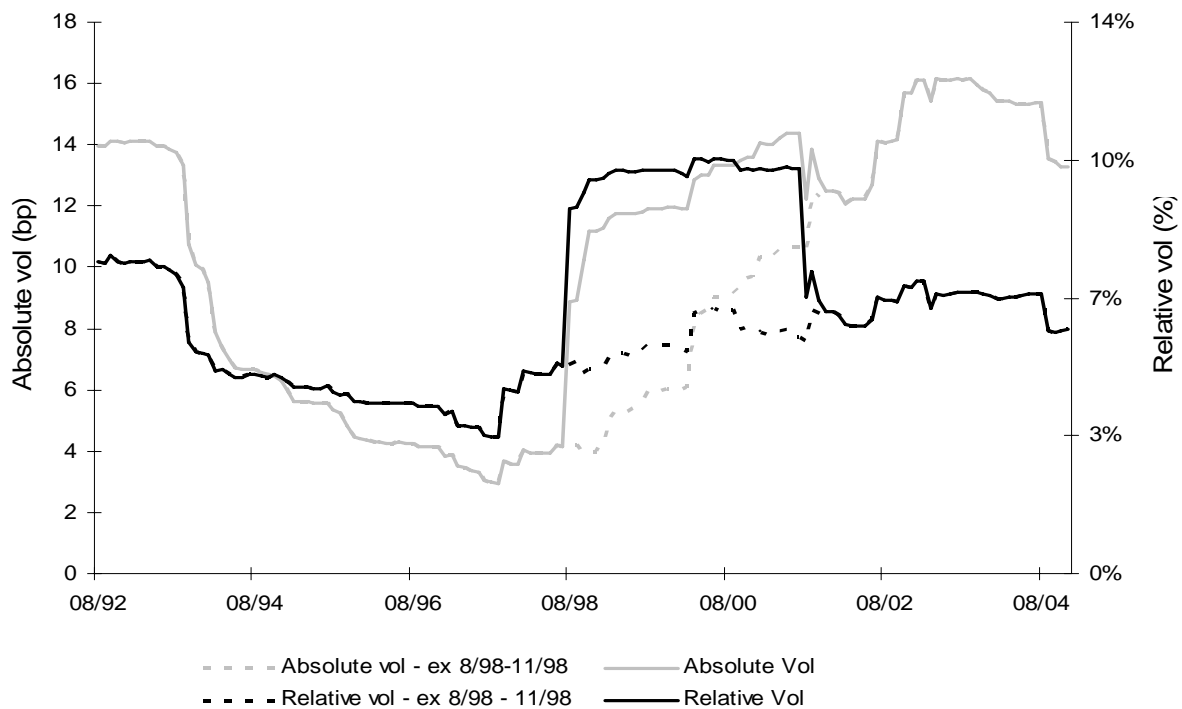

Source: Lehman Brothers

Figure 2. Spread Change Volatility by Spread Range (trailing 36 months; 9/89 – 1/05)
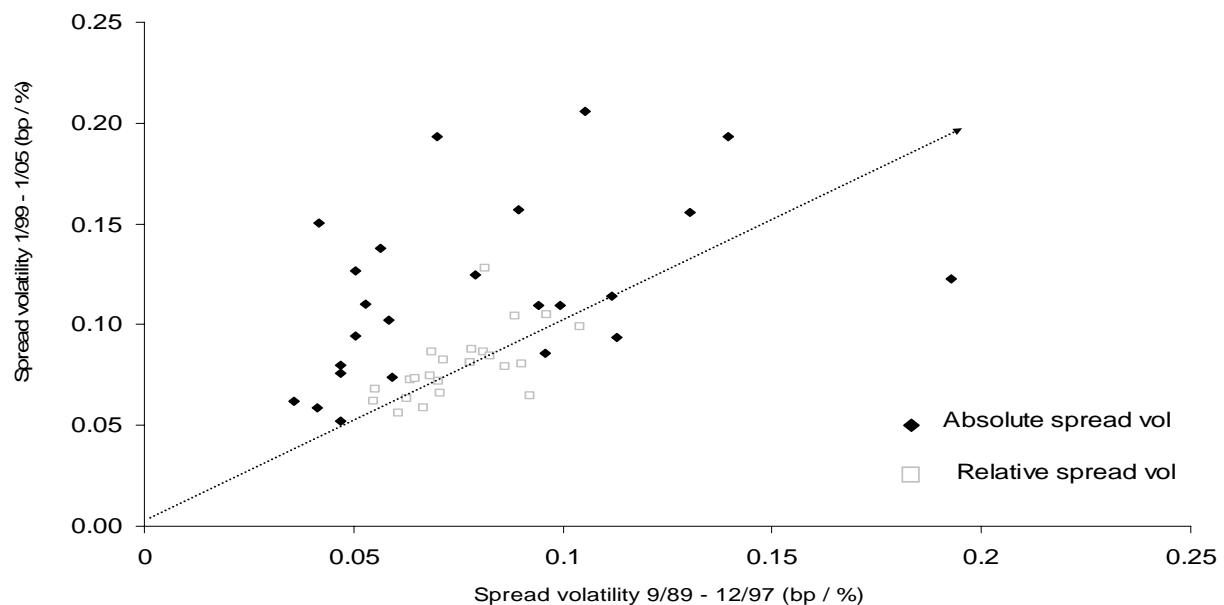

Source: Lehman Brothers

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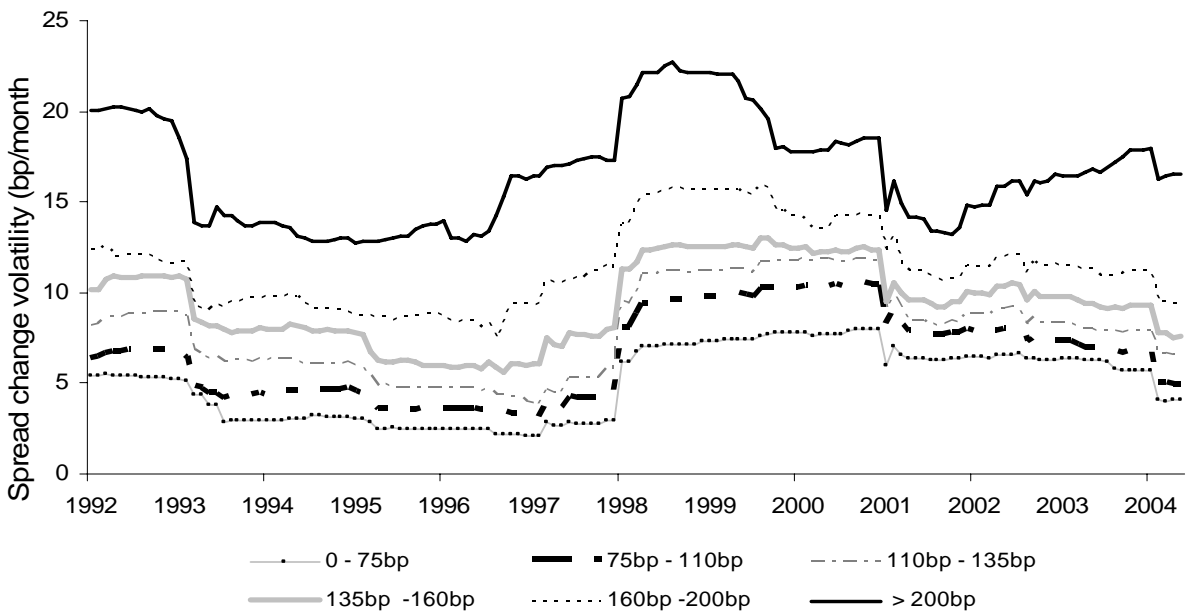
Figure 3. Absolute and Relative Spread Change Volatility of Baa Credit (trailing 36 months)

Actual data is replaced with missing values for months that are excluded.
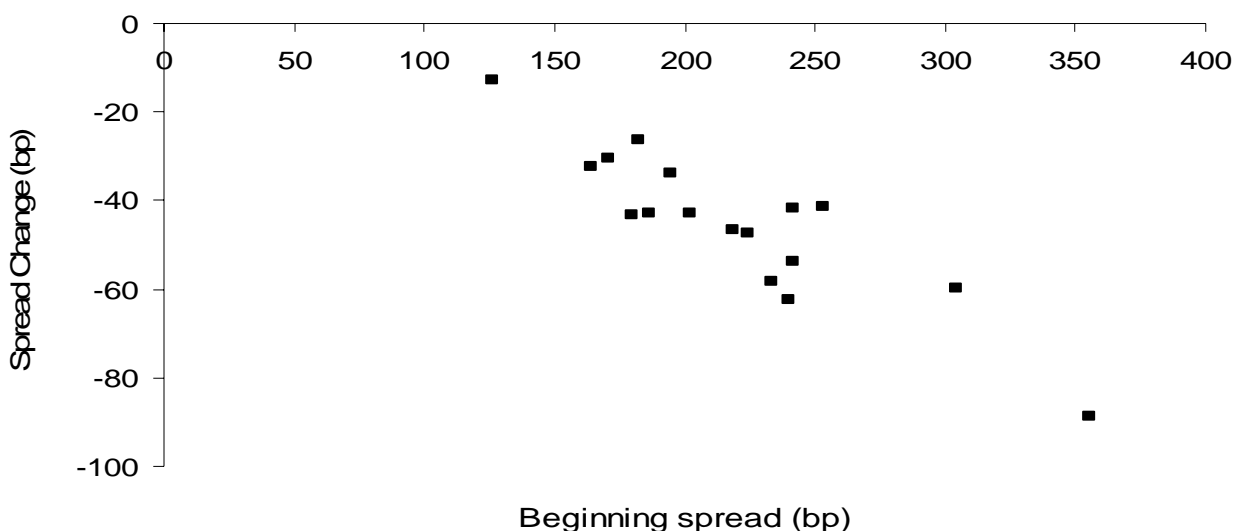Source: Lehman Brothers

Figure 4. Absolute and Relative Spread Change Volatility Before and After 1998

Based on 8 sectors x 3 credit ratings partition of the Lehman Brothers Credit Index.
Source: Lehman Brothers

Figure 5. **Average Spreads and Spread Changes for Large Issuers in the Communications Sector** (January 2001)

Source: Lehman Brothers

Figure 6. Regression Estimates of Various Models of Spread Change

Model	Equation	Coefficients		T-stats		R^2	
		Shift (bp)	Slope (%)	Shift	Slope	Jan-05	Aggregate
Parallel	7	-45		-10.9		88.2%	16.9%
Relative	8		-21%		-23.2	97.1%	33.0%
Combined	9	16	-28%	2	-7.9	97.7%	
Combined with normalized spread	10	-45	-28%	-24.1	-7.9	97.7%	35.2%

Based on data for large issuers in the Communication sector as of January 2001. The R^2 values reported in the last column are based on 1,480 individual regressions (185 months x 8 sectors).
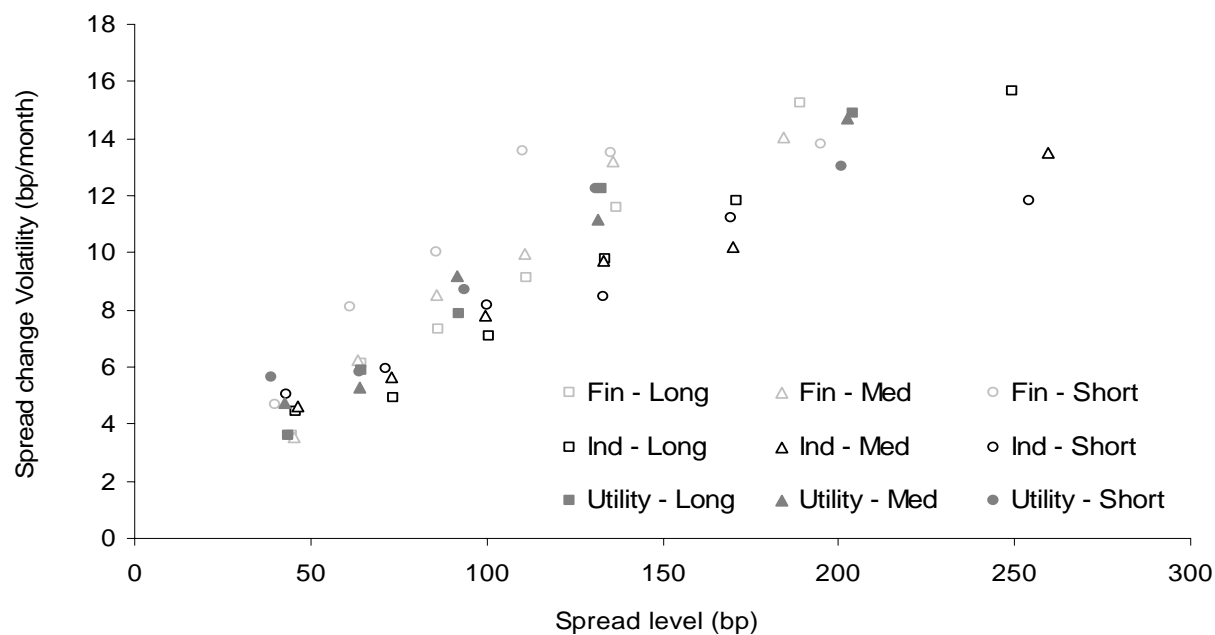Source: Lehman Brothers

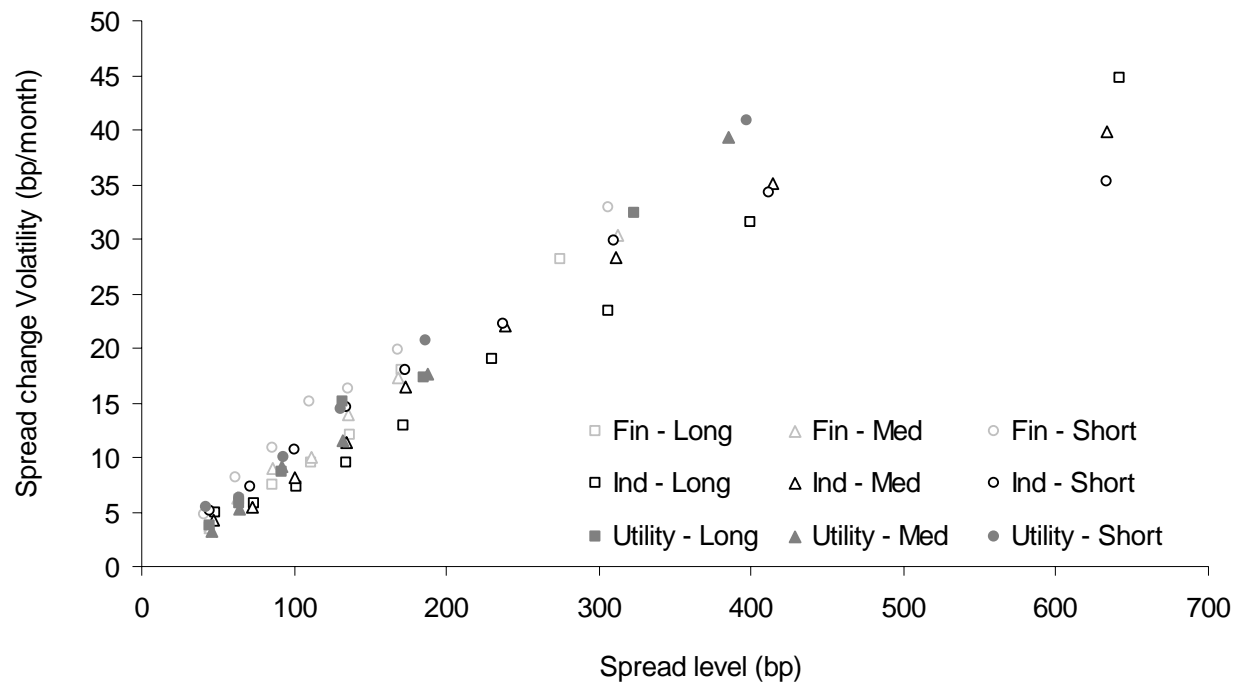**Figure 7. Regression Coefficients for Shift and Slope Factors**
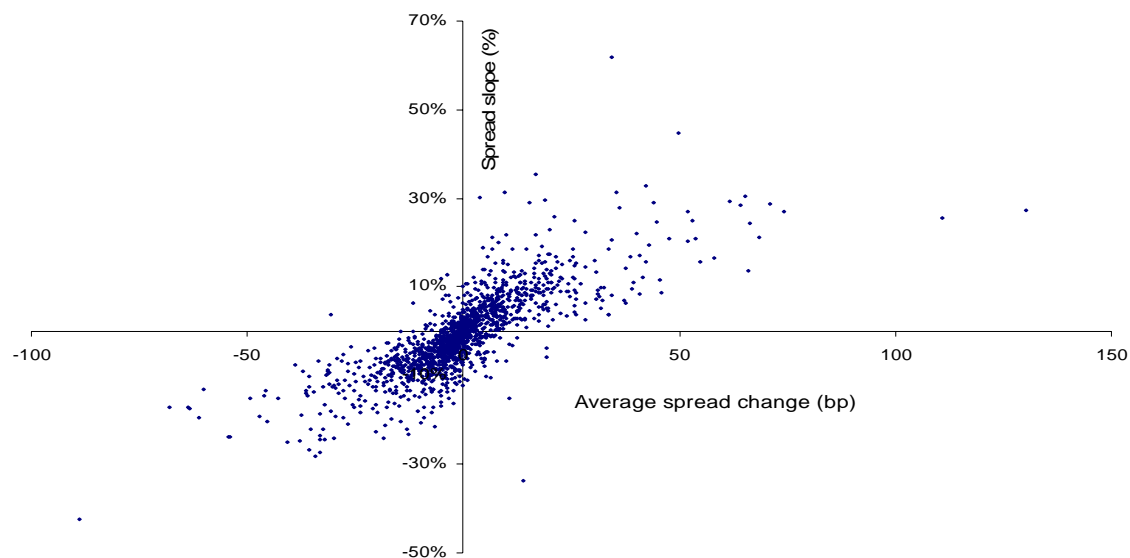
Source: Lehman Brothers

Figure 8. Time Series Volatility of Systematic Spread Changes versus Spread Level (9/89 – 1/05)
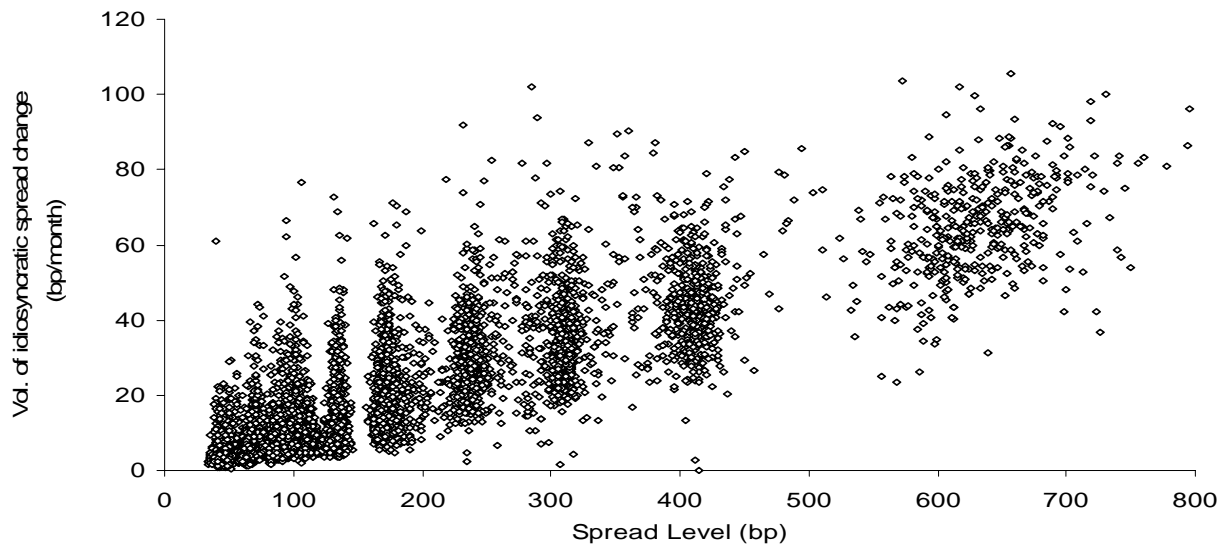

Source: Lehman Brothers

Figure 9. Systematic Spread Volatility versus Spread Level (Investment grade + High yield bonds)

Monthly observations for all bonds rated Aaa-B (9/1989 – 1/2005).
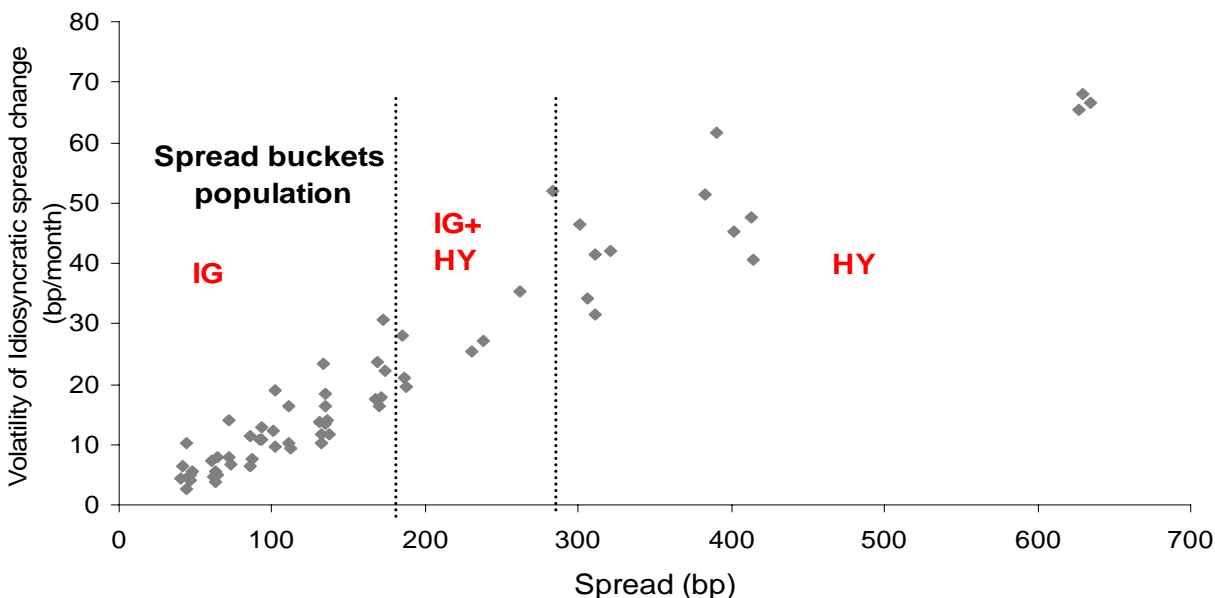Source: Lehman Brothers

Figure 10.   Volatility of Idiosyncratic Spread Change versus Spread Level

Monthly calculations (9/1989 – 1/2005) using all bonds rated Aaa - B; Computed separately by sector, duration and spread bucket (N=7250).
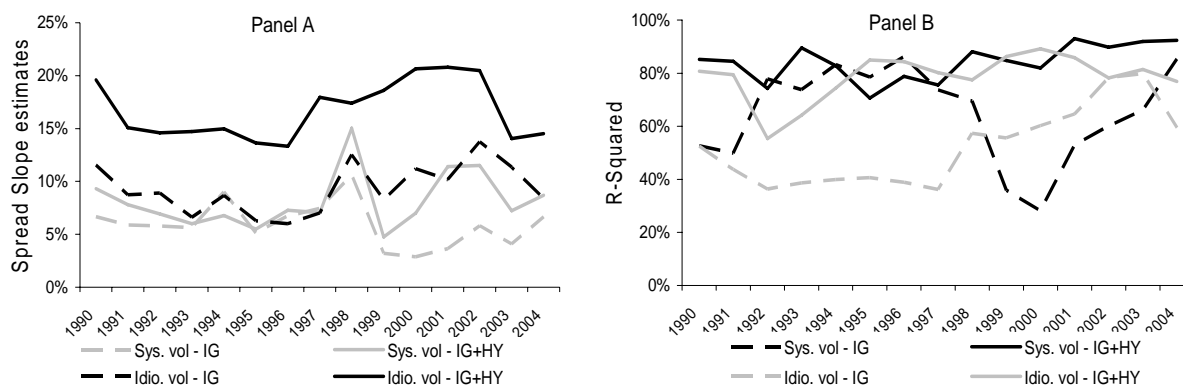Source: Lehman Brothers

**Figure 11.   Pooled idiosyncratic Spread Volatility vs. Spread Level**

Each observation represents the standard deviation of idiosyncratic spread changes aggregated across all sample months separately by sector, duration and spread bucket for all bonds rated Aaa - B (9/1989 – 1/2005)
Source: Lehman Brothers

Figure 12. Yearly Regression of Spread Volatility Against Spread Level (1/1990 – 12/2004)

Source: Lehman Brothers

Figure 13.   **Excess Return Volatility versus DTS** (9/1989 – 1/2005; Investment-grade credit)
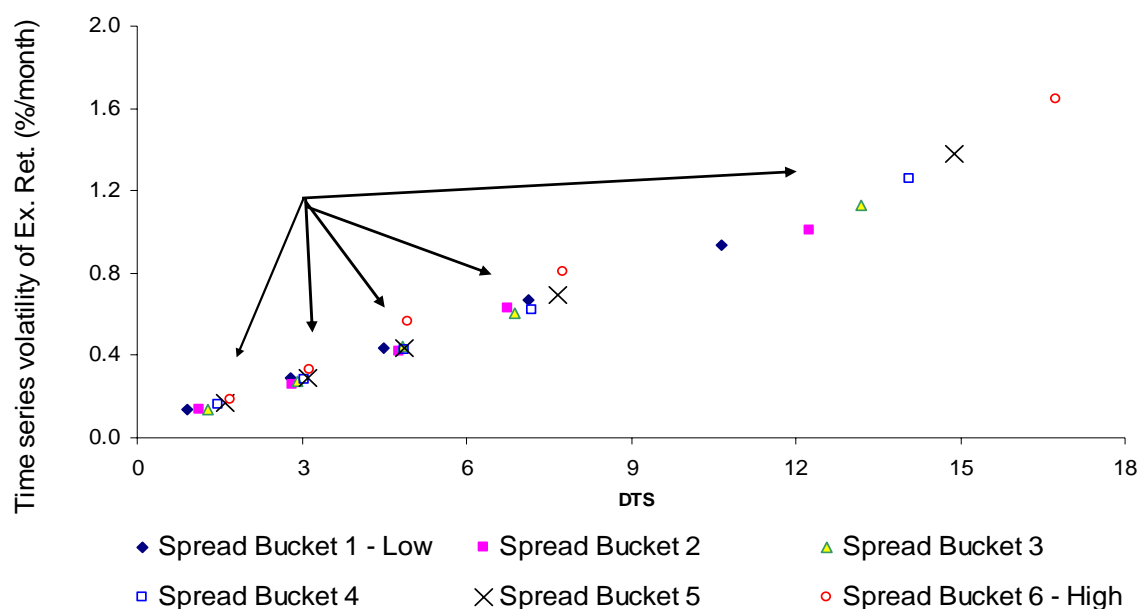
Bonds are first divided to DTS quintiles and then further sub-divided to six buckets by spread level.
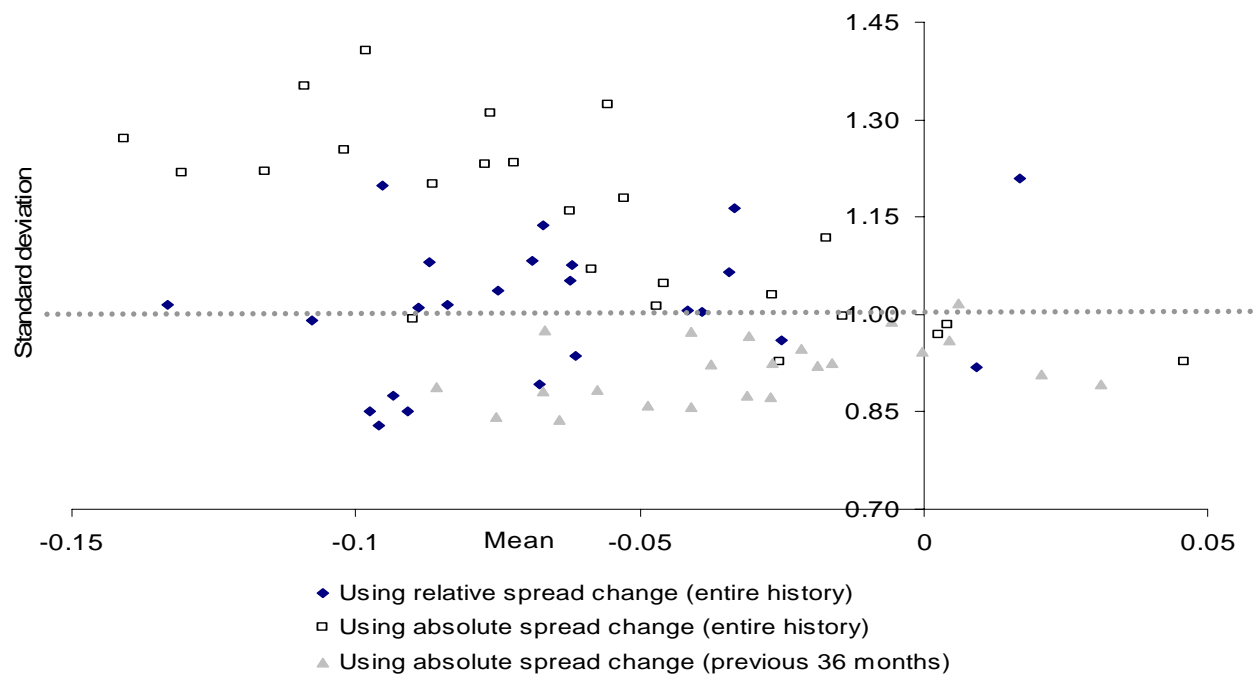Source: Lehman Brothers

Figure 14.   **Summary Statistics by DTS and Spread Buckets**

Panel A:

Spread Sub-buckets	Spread	DTS buckets				
		Low	2	3	4	High
	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 Sub-buckets	Spread Duration	DTS buckets				
		Low	2	3	4	High
	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: Lehman Brothers

Figure 15.   Mean and Standard Deviation of Normalized Excess Return Realizations

- ◆ Using relative spread change (entire history)
- ☐ Using absolute spread change (entire history)
- ▲ Using absolute spread change (previous 36 months)

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).
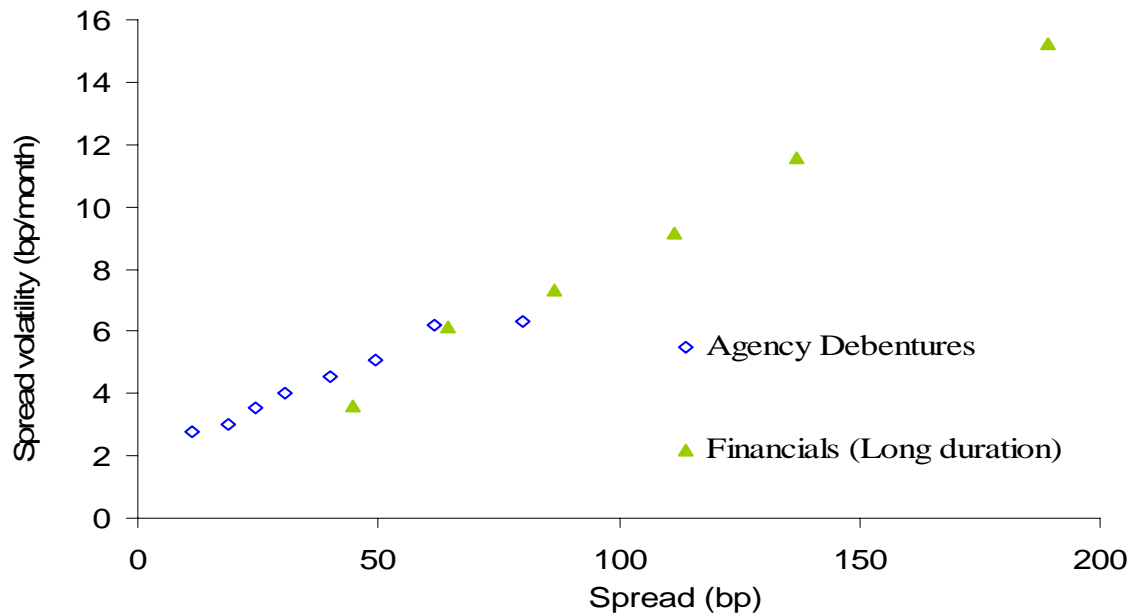Source: Lehman Brothers

Figure 16.   Distribution of standardized excess returns

- ☐ Based on absolute spread change
- ■ Based on proportional spread change
- ■ Normal Distribution
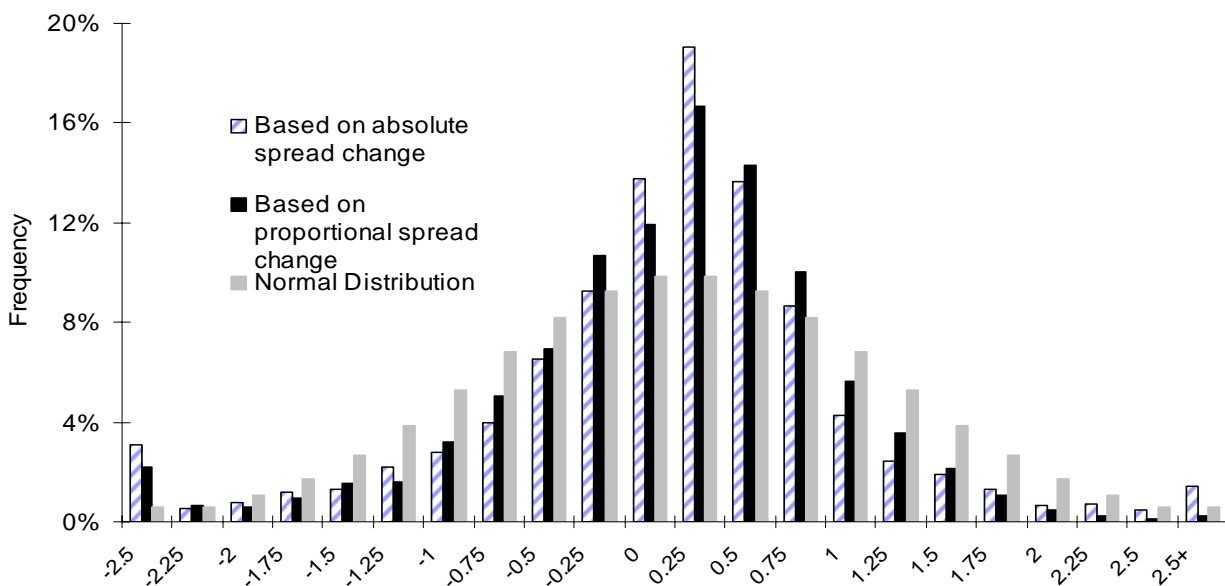
Based on observations (9/1992 – 1/2005) grouped across all sectors and credit ratings.
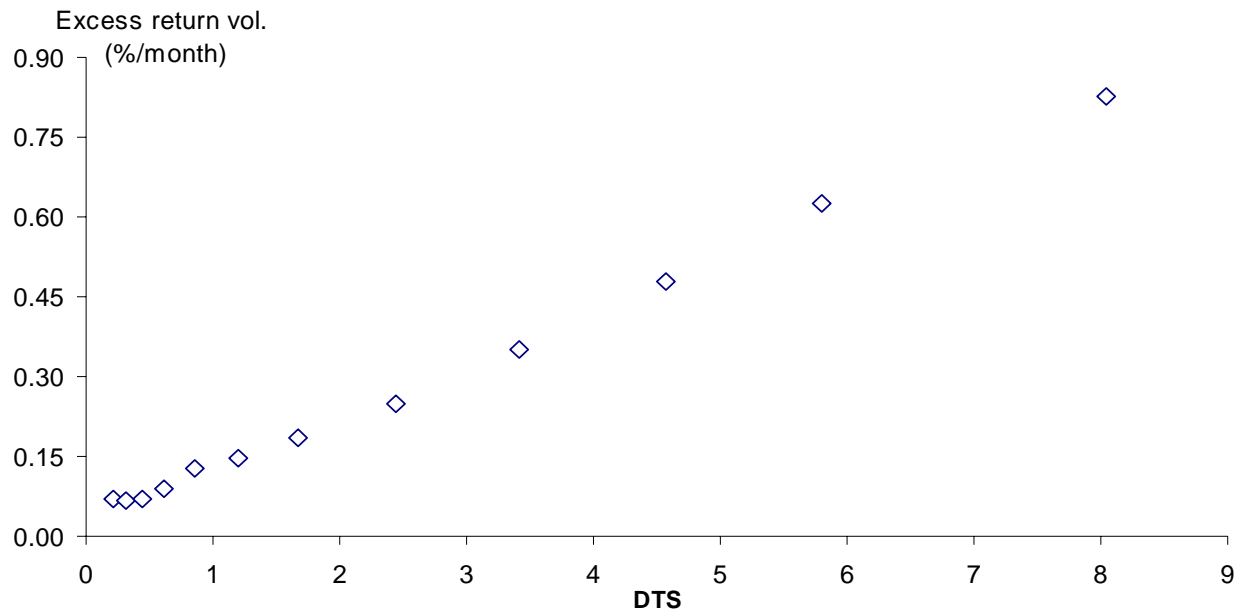Source: Lehman Brothers

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Figure 17. Systematic Spread Volatility Versus Spread Level of Agencies (9/1989 – 4/2005)

Based on all Aaa rated, non-callable debentures comprising the Lehman Brothers Agency Index.
Source: Lehman Brothers

Figure 18. Excess Return Volatility Versus DTS (9/1989 – 4/2005)

Bonds are assigned to one of twelve buckets based on DTS.
Source: Lehman Brothers

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Figure 19. Summary Statistics for 'SENIOR' and 'SUBORD' Portfolios

Portfolio Composition		# of issuers	Ratio of Excess Return Volatility			Difference in Excess Returns (% / month)		
'SENIOR'	**'SUBORD'**		P_{25}	P_{50}	P_{75}	P_{25}	P_{50}	P_{75}
Senior debt	Subordinated debt	47	0.83	1.10	1.41	-0.15	-0.06	-0.01
Senior Notes	Notes	353	0.79	0.94	1.08	-0.08	-0.01	0.04
Sr. Debentures + Debentures	Sub. Debentures	46	0.80	0.94	1.04	-0.05	0.02	0.05
Sr. Debentures + Sr. Notes + Senior debt	Debentures + Sub. Debentures + Notes + Subordinated debt	535	0.80	0.93	1.08	-0.13	-0.04	0.01

Portfolios are constructed separately for each issuer; their composition is updated monthly based on the definition of senior and subordinated claims. The DTS of the 'SENIOR' portfolio is matched monthly to that of the 'SUBORD' portfolio and its excess return is adjusted accordingly.
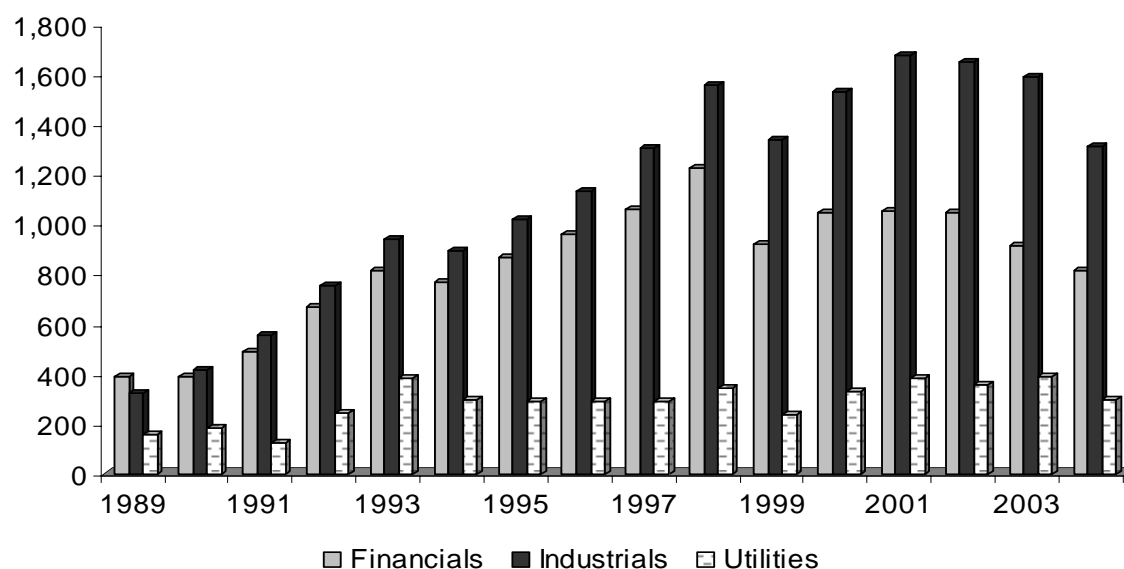Source: Lehman Brothers

Figure 20. Excess Return Volatility Versus DTS Across Seniority Classes
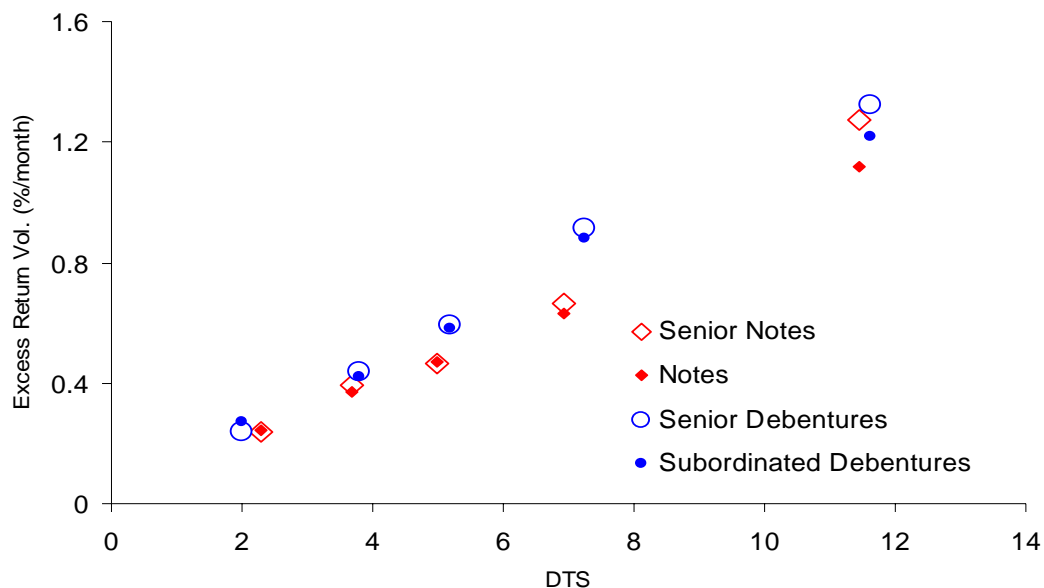
The 'SENIOR' and 'SUBORD' portfolios are divided into DTS quintiles and the weighted excess return and DTS is computed (separately by seniority class). The plot presents the time-series volatility of excess returns and the average DTS of the 10 aggregate portfolios composed of senior notes and notes or senior debentures and debentures.
Source: Lehman Brothers

Figure A1. Sample Population by Sector and Year

Investment grade bonds only; Number of bonds is as of December of each year.
Source: Lehman Brothers

Figure A2.   Sample Partition by Sector, Duration and Spread

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%)	

Sample includes IG bonds only between 9/89 and 1/05. The table reports the spread breakpoints, cell population and the percentage of months where a bucket is populated by more than 20 bonds.
Source: Lehman Brothers

ENDNOTES

[1] Spread is the constant (absolute) shift to the zero-coupon interest rates in all scenarios that is required to ensure that the model value of the bond (average value over all scenarios) equals the observed market price.

[2] Spread change return is closely related to excess return, the return a corporate bond earns in excess of that of a duration-matched Treasury bond. Excess return can be approximated by the sum of the spread change return and an additional component due to spread carry.

[3] 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.

[4] 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).

[5] The sector breakdown is: Banking, Finance, Basic Industry, Consumer Cyclical, Consumer Non-Cyclical, Communications, Energy and Utility. Bonds are assigned to one of three quality cells: Aaa/Aa , A and Baa.

[6] '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.

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

[8] We find that the distribution of spread duration varies significantly across time and therefore does not allow for a partition based on constant spread duration values.

[9] 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 weighing factor is the number of observations in each month). The results are essentially unchanged.

[10] Instead of a single spread coefficient, we also estimate an unconstrained model which allows the spread slope coefficient to vary by sector and duration as follows:

$$\sigma(\Delta s)_{i,d,s} = s_{i,d,s} \times (\beta + \beta_{Fin} \cdot I_{Fin} + \beta_{Ind} \cdot I_{Ind} + \beta_{Med} \cdot I_{Med} + \beta_{Long} \cdot I_{Long}) + \varepsilon_{i,d,s}$$ where i,d and s denote the sector - duration - spread combination of each observation. I_{Fin} and I_{Ind} are dummy variables equal to 1 if i ='Financials' or 'Industrials' respectively and zero otherwise. Similarly, I_{Med} and I_{Long} equal 1 if d = 'Medium' or 'Long' respectively and zero otherwise. The results confirm that relative spread volatility is not restricted to a single sector or maturity and that there is roughly 9 bp/month pickup in volatility for every 100 bp increase in spread.

[11] In order to be consistent with Equation 6, idiosyncratic spread change should be defined 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.

[12] Depending on the sample composition and population, this procedure produces between 38 and 66 observations yearly when examining systematic volatility, and 300-500 observations for idiosyncratic volatility. As before, only observations that represent buckets populated by at least 20 bonds during the entire year are included in the analysis.

[13] Our findings were not changed when we repeated the analysis using other partitions.

[14] 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.

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

[16] Including publicly issued debt of U.S. government agencies, quasi-federal corporations, and corporate or foreign debt guaranteed by the U.S. government (such as USAID securities).

[17] The results were unchanged when issues with a market value below $300 million were excluded or when non-U.S. agencies were excluded

[18] For example, when a bank is owned by a holding company owners of subordinated claim issued by the bank have priority in case of a default over owners of a senior claim issued by the holding company.

[19] Excess returns can be adjusted by the same scaling factor (ratio of DTS of the two portfolios) since they are linearly related to DTS. Notice also that if this was to be implemented in practice, we would need to take into account financing costs. However since we do not form a trading strategy but rather examine weather similar DTS portfolios exhibit similar excess return volatilities, borrowing costs can be ignored.

[20] For example, see Philipp Schönbucher, "A Libor market model with default risk", working paper, University of Bonn, 1999.

[21] For example, an investment policy may specify that no more than 1% of the portfolio market value can be invested in securities of any single Baa-rated issuer, no more than 2% in any A-rated issuer, and no more than 4% in any Aa-rated issuer

[22] For a description of the Lehman Brothers Risk Model and Performance Attribution methodology see Dynkin, Gould, Hyman, Konstantinovsky and Phelps. Quantitative Management of Bond Portfolios. Princeton: Princeton University Press, 2006. pp 677-810.