Revisiting the Altman Definition of Distressed Debt and a New Mechanism for Measuring the Liquidity Premium of the High-Yield Market

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In 1990, buried in a report commissioned by Los Angeles based The Foothill Group and written by Professor Edward I. Altman, of the New York University Stern School of Business, was the simple definition quoted below:

Our new tests concentrate on distressed, not defaulted, debt whereby distressed is defined as a security with a current yield of 10% above comparable U.S. Treasury bonds. In all, 310 issues qualified over an 11 year sample period, 1978–1989. Incredibly, over one-half of these distressed securities eventually defaulted.

It was the first recorded instance we can find where precision was given to the term “distressed debt.” Since then, the definition has helped draw attention to what was at the time an under-researched segment of the fixed-income investment universe—distressed debt investing. Over the course of 20 years, distressed debt investing has been transformed from a small cottage industry into what is today a $300+ billion professional money management business, including some of the world’s most prominent hedge fund and private equity managers and proprietary traders at major investment banks. Investors were attracted to the strategy because distressed investing has generated among the most attractive absolute and risk-adjusted returns, relative to more conventional investment strategies (see Exhibit 1).3 However, despite the now-ubiquitous nature of the Altman definition, we believe that few investors have formally analyzed the predictive power of this definition, particularly when scrutinized under varying liquidity conditions.

Since the definition’s debut in 1990, we have found that most discussions regarding distressed debt have revolved around the “10%” (1,000 bps) risk premium threshold over U.S. treasuries. However, we believe that an equally important component of the definition, which receives little or no mention, is that “over one-half of these distressed securities eventually defaulted.” As we currently live through the third distressed cycle since the definition’s debut,4 many investors, ourselves included, find themselves asking a key question: “Is Altman’s definition of distressed debt still valid?”

As we began to seek answers to this question, we found ourselves raising additional questions. For example, Altman never ascribed a time-to-default when he first defined distressed securities in 1990, as he only asserted that such securities “eventually defaulted.” However, in a prior publication in 1989, Altman calculated annual and cumulative default and loss rates, over a 10-year period, based on credit ratings using a novel actuarial approach.5 As such, time-to-default was not calculated based on the 1,000 bp OAS threshold component of the definition of distressed. Therefore, we
also ask ourselves, on average, how long does it take distressed securities to default?—because from an investor’s perspective, the answer adds practicality. Furthermore, following Altman’s research for many years, we have learned that there are times, such as the period leading into the summer of 2007, where excess liquidity may overshadow the robustness of Altman’s own default prediction models. As such, we also explored the effect that overall market liquidity has had on the original definition over time.

In summary, the two key components of Altman’s definition of distressed debt are that:

1. The risk premium, over comparable U.S. treasury bonds, exceeds 10% points (or 1,000 bps);
2. Over half of such securities eventually default. 7

Because over half of these securities are assumed to eventually default, while the other half do not, these securities appear to be at an inflection point in their lifecycle and represent potential opportunities to investors, from both the long and short sides of the investment perspective. As such, when securities meet this definition of being “distressed,” they tend to appear on investors’ radar screens because the securities do not remain at distressed levels—at some point they either revert to more normal levels or they eventually default. A skillful distressed manager can hone in on such securities, by applying fundamental credit skills and knowledge of the bankruptcy process, and assess the likelihood of making money by either investing long (purchasing) or short (selling) based on his or her assessment of the most probable outcomes and timing assumptions. We endeavor to shed light on some of these important questions related to default rate, timing, and effects of liquidity on the Altman definition of distressed debt.

**PROCESS AND DATA**

We first set out to categorize high-yield securities into two groups: 1) “distressed” and 2) “non-distressed” based on the Altman definition. We use the Bank of America/Merrill Lynch High Yield Master II Index as the source of the data. We then calculate the realized monthly default rate for distressed securities in the sample, from January 1990 to December 2009. After determining the empirical long-term default rate for distressed securities, we observe mean-reverting characteristics while noting periods of large deviations from the long-term default rate average. This finding leads us to examine more closely periods where the default rate deviates significantly from its mean. In an effort to investigate this deviation, we use a bootstrap method that raises, or lowers, the 1,000 bp threshold (the Altman risk premium threshold component of the definition) sufficiently to cause the default rate for such distressed securities to reach their long-term average. The resultant time series therefore represents the premium (positive or negative), relative to the 1,000 bp threshold, that may not be fully reflected in the long-term default characteristics of such securities due to other market factors.

We hypothesize that such a premium may be related to temporary liquidity conditions because we observe that the default rate reverses to its long-term mean over the last two distressed cycles. We define this premium as the “High-Yield Liquidity Premium.” The intuition for this phenomenon lies in the increased availability of distressed securities relative to the overall high-yield market (as measured by the distressed ratio). 8 When there is a glut of liquidity, there are few distressed securities relative to the overall high-yield market, the few that are in a state of distress are likely to be the least creditworthy (i.e., without access to the liquidity glut) and thus to default at high rates. Whereas when there is a dearth of liquidity, there are large numbers of distressed securities, many of which are likely to be creditworthy, thus getting out of distress when liquidity returns and not defaulting. Another way to say this is that there is likely to be indiscriminate buying when there is a glut of liquidity (potential bad outcome for un-informed investors) and indiscriminate selling when there is a dearth of liquidity (potential good outcome for informed investors). This key finding is discussed in detail in the Bootstrap Analysis section.

The final part of the process decomposes the high-yield index option-adjusted spread (OAS) into a liquidity factor and a credit factor. Furthermore, the liquidity factor is mapped to a real-world proxy and an estimation model.
is specified, which adjusts the Altman 1,000 bp definitional threshold for the effects of varying liquidity conditions over time. We pursue this last part of the investigation in the Cluster Analysis and Modeling Liquidity sections.

The Bank of America/Merrill Lynch High Yield Master II Index (hereafter, "the Index") is a good representation of the investable U.S. high-yield bond market. Merrill Lynch has maintained historical information that tracks the characteristics of individual high-yield bonds, such as the option-adjusted spread, credit rating, par amount, and price, among other metrics, on a daily basis (monthly data were used in our research) for each constituent of the Index. However, the Index does not provide constituent bond-level data prior to 1997 (i.e., data are only available from 1997–2009), thus omitting a key period needed to test fully Altman's findings on an out-of-sample basis. Fortunately, with the assistance of Oleg Melentyev, a credit strategist at Bank of America/Merrill Lynch, we obtained unpublished and unverified bond-level data for the Index for the period of 1990 to 1996. We manually cleaned and verified the dataset using independent third-party sources as described below. Our investigation analyzed a total of 9,838 individual high-yield bond issues over a period of 240 months by combining the two databases (1990–1996 and 1997–2009), which span a contiguous 20-year period since the Altman definition was first published. By contrast, Altman analyzed 310 bond issues over an 11-year period, from 1978–1989, to arrive at his definition of distressed debt. Taken together with the original Altman study, the total period spans a minimum of two complete credit cycles (Cycle 1 and Cycle 2) and one contemporaneous partial credit cycle (Cycle 3) from 1978–2009.

We implemented a rule-based data cleaning methodology to maintain consistency and to preserve the integrity of the dataset. The 1990–1996 dataset was processed in three ways: 1) identifying all defaulted bond issues using the following sources: Bloomberg, Moody's Investors Service, and New York University Salomon Center; 2) verifying, and adjusting accordingly, the yield-to-worst information for each bond using the bond pricing function in Microsoft Excel; and 3) using, as a proxy for OAS data, the difference between the yield-to-worst and the yield on the U.S. Treasury 10-year bond for each individual bond issue (because OAS data were not available, this was done to be consistent with the 1997–2009 dataset). The 1997–2009 dataset was not altered.

To test Altman's findings, we used his definition of "distressed" debt to segregate the data. The entire database (1990–2009) was then sorted to extract all high-yield bonds with OAS greater than 1,000 bps to create a "Distressed" database (4,066 unique bond issues). Subsequently, on an ex post basis, the Distressed database was split into two databases: 1) Defaulted Distressed (1,164 unique bond issues) and 2) Non-Defaulted Distressed (2,902 unique bond issues). The Distressed database contained all bonds that at some point traded at an OAS greater than 1,000 bps and eventually defaulted. Similarly, the Non-Defaulted Distressed database contained all bonds that at some point traded at an OAS greater than 1,000 bps but never experienced an event of default. The difference between the number of unique bond issues in each of the databases is attributed to the time-to-default characteristics for the Defaulted Distressed group versus the time-to-non-distressed characteristics for the Non-Defaulted Distressed group.

Exhibit 2 shows the median values of OAS for the Defaulted Distressed and Non-Defaulted Distressed groups, respectively. Exhibit 3 shows the number of issues (bond count) included in each of these respective groups. We observe that over time, the two groups (Defaulted Distressed and Non-Defaulted Distressed) converge toward the end of the Improving state, both in terms of OAS and bond count, and diverge upon entering the Deteriorating state of a new cycle. However, during most of the time, the bond count of each of the two groups is generally the same, thus leading to the empirical long-term average default rate of approximately 50%. In general, the relationship between OAS and bond count is an inverse one when comparing the Defaulted Distressed group to the Non-Defaulted Distressed group. For example, during the course of the Deteriorating state, the OAS increases rapidly for the Defaulted Distressed group as compared to the Non-Defaulted Distressed group, while the bond count of the Non-Defaulted Distressed group outgrows its counterpart rapidly towards the end of the Deteriorating state.

In other words, in times of a deeply distressed environment, a large portion of the distressed universe can be characterized as having relatively low OAS volatility and never experiencing an event of default (the Non-Defaulted Distressed group). A useful insight for investors seeking to discern (ex ante) between securities that did not default (Non-Defaulted Distressed) and those that eventually
defaulter (Defaulted Distressed), may be to focus on the \textit{volatility characteristics of distressed securities.}

In summary, over Cycle 1 and Cycle 2 (Cycle 1 + 2),\textsuperscript{11} we observe that the long-term average of the OAS medians is 1,893 bps and 1,516 bps, for Defaulted Distressed and Non-Defaulted Distressed, respectively. We used the median to minimize the impact of outliers. A Student's $t$-test was performed on the difference of the
median OAS and the standard deviation of the median OAS of these two groups. The results show that the difference of the median and the difference of the standard deviations, for the two groups, are statistically significant. Additionally, we observe that the Defaulted Distressed data are significantly more volatile than the Non-Defaulted Distressed data (by a ratio of approximately 2.5:1). For example, the monthly standard deviation for the median OAS over this same period is 667 bps and 272 bps for Defaulted Distressed and Non-Defaulted Distressed, respectively.

DEFAULT RATE OF DISTRESSED SECURITIES

In order to measure the historical default rate of distressed securities, and perform an out-of-sample test on Altman’s original findings, we define the distressed default rate as the ratio of the number of securities in the Defaulted Distressed database to those in the total Distressed database. The Distressed Default Rate is based on issue count and is expressed in percentage points. The components of the definition are plotted in Exhibit 3.

Distressed default rate = \frac{\text{Defaulted Distressed (number of securities)}}{\text{Defaulted Distressed (number of securities)} + \text{Non-Defaulted Distressed (number of securities)}}

As can be seen from Exhibit 4, the default rate for distressed securities has been near 50% over various long-term periods but volatile over shorter periods. Over Cycle 1, the Distressed Default Rate averaged 49%. Over Cycle 2, the Distressed Default Rate averaged 53%. When combining the last two cycles, Cycle 1 and Cycle 2, the Distressed Default Rate averaged 51%. However, when the current partial-cycle Cycle 3 (October 2007 to December 2009) is included, the average Distressed Default Rate drops to 48% over the period of January 1990 to December 2009. The Distressed Default Rate average for Cycle 3 is running at 21%, less than half of the prior two cycles. As will be discussed in the Time to Default section, we expect the Distressed Default Rate for Cycle 3 to continue to increase throughout the remainder of the current cycle.

EXHIBIT 4
Monthly Distressed Default Rate (1990–2009)
Exhibit 5 further shows that over the past two cycles (Cycle 1 + 2) the average Distressed Default Rate has historically been highest during the last state of the cycle (Static state at 61%). We also observe that the average default rate starts high (Deteriorating state), subsequently drops (Improving state), and eventually peaks (Static state).

WHAT DOMINATES THE ALTMAN DEFINITION?

Because the Altman definition has two components, either one could be equally as important as the other. Does one component dominate the definition? We explore answers to this question by attempting to understand the relationship between OAS threshold and default rate for the high-yield index at different threshold levels.

Exhibit 6 summarizes the relationship between default rate and a given OAS threshold for all constituents of the entire high-yield index. It shows that when controlling for the 1,000 bp OAS threshold, the empirical average default rate has been within a range of 48% to 51%, depending on the chosen period. Conversely, when controlling for the “50%” default rate definitional component, the OAS threshold has been within a range of 960 bps to 1,140 bps, depending on the chosen time period. Over the prior two cycles (Cycle 1 + 2), the OAS threshold and default rate definitional components converged close to the Altman definition. However, when the most recent partial-cycle is included (Cycle 3), the definitional threshold is elevated from 1,000 bps to 1,140 bps in order to reach the 50% empirical, long-term default rate. However, based on our findings in the Time to Default section of this article, it may be premature to redefine the distressed threshold as “1,140 bps” since the full effects of Cycle 3 have not been realized.

Exhibit 7 illustrates the inflection point between the OAS threshold and the default rate relationship by plotting the rate of change (slope) of the average default rate function (Exhibit 6). Over long periods (Cycle 1 and Cycle 2), we observe evidence of convergence of the rate of change of the default rate. As the OAS threshold moves from zero to approximately 500 bps, the default rate grows at an accelerated speed. When the OAS threshold is between 500 bps and 1,000 bps, the default rate grows at a decelerated speed.
EXHIBIT 6
Average Default Rate at Different HY OAS Threshold Level

Note: *Includes unfinished Cycle 3.

EXHIBIT 7
Rate of Change of Default Rate at Different OAS Levels
As shown by the band of dashed lines, beyond an OAS threshold of approximately 1,000-1,200 bps, the growth rate of the default rate converges at a near-constant speed.

Therefore, the 1,000-1,200 bp threshold level, which corresponds to the 51% long-term default rate over Cycle 1 and Cycle 2, lies close to the inflection point where the speed of the default rate stabilizes. Beyond the 1,000-1,200 bp threshold, every 20 bp increase in OAS threshold causes the default rate to increase by approximately 0.1%, a stable speed of increase as compared to data prior to the inflection point. This analysis provides additional support for the efficacy of the Altman definition.

In conclusion, we find empirical evidence that corroborates Altman’s original findings published in 1990. For the subsequent 20-year period of 1990–2009, we find that high-yield bonds with risk premiums in excess of 1,000 bps to comparable U.S. treasuries experience a long-term average default rate of 48% to 51%. Therefore, we believe that the 1,000 bp threshold is a good indicator of securities that experience a long-term default rate of approximately 50%.

However, equally important, we find that deviations from the Altman definition are significant over shorter periods and may be better explained by other market factors. As distressed debt investors, we inject our own view that it has been during periods of abnormally high or low levels of liquidity that the Altman definition has come under attack. These periods are typically at inflection points (regime shifts) with regard to market liquidity. Therefore, the 1,000 bp threshold is only valid for the long-term, full-cycle definition of distressed debt. At the 1,000 bp OAS-threshold level, distressed bonds experience a long-term average default rate of approximately 50%. However, over time, we expect the 1,000 bp threshold to move higher, or lower, to account for current liquidity conditions in order to satisfy the empirical 50% default rate. That is, when liquidity is scarce, an additional liquidity premium should be added to the threshold, and when liquidity is overly abundant, an additional liquidity premium should be subtracted.
from the threshold. By adjusting the long-term 1,000 bp threshold with this liquidity premium, we can better classify bonds that are fundamentally distressed, to better reflect their underlying creditworthiness. We attempt to quantify the effects of liquidity on the default rate of distressed securities in the Bootstrap Analysis section.

**TIME TO DEFAULT**

Exhibit 8 shows the distribution and cumulative distribution functions of the default rate of distressed securities in the high-yield index from 1990–2009. It attempts to quantify the time dimension associated with distressed securities that eventually defaulted, an area that Altman did not investigate in his original research. Constituents of this data set were distressed securities that eventually defaulted (Defaulted Distressed). The findings show that once a high-yield bond's OAS crosses the 1,000 bp threshold, approximately 45% of these securities eventually default within one year, 71% within two years, 83% within three years, 91% within four years, and 99% within seven years. We observe that the rate of change of the default rate accelerates most rapidly during the first 18 months after entering a state of distress.

Using this framework, we quantify the second part of Altman's definition, that "over one-half of these distressed securities eventually defaulted." For the group of distressed securities that eventually default (Defaulted Distressed), it takes approximately 46 months for 90% of defaults to be realized. The median time-to-default is 14 months.

\[
\text{High Yield Liquidity Premium} = \begin{cases} 
\text{Max}(\text{OAS}) - 1000 & \text{if (DHLT_Rate}_{@}\_1000bp > 50\%) \\
\text{Min}(\text{OAS}) - 1000 & \text{if (DHLT_Rate}_{@}\_1000bp < = 50\%) \\
(45\% < = \text{DHLT_Rate}_{@}\_\text{OAS} < = 55\%) \text{ and } (\text{OAS} < 1000) & \\
(45\% < = \text{DHLT_Rate}_{@}\_\text{OAS} < = 55\%) \text{ and } (\text{OAS} > = 1000) & 
\end{cases}
\]

**BOOTSTRAP ANALYSIS: EXCESS SPREAD REQUIRED TO REACH 50% DISTRESSED DEFAULT RATE**

To investigate periods where the Altman definition deviates from its empirical long-term default rate, we apply a simple iterative process of raising, or lowering, the 1,000 bp threshold until 50% of the securities in the high-yield index are in a state of default on any given month. We call this process the bootstrap analysis. To reduce the variability of the calculations, we apply a band of 15 percentage points around the 50% long-term average. Therefore, the resultant time series consists of a spread premium (positive or negative), relative to 1,000 bps, where high-yield securities first enter a range of default rates between 45% and 55%. We define this time series as the High-Yield Liquidity Premium.

A qualitative way to think of the High-Yield Liquidity Premium is that it represents "excess spread" that an investor is compensated with (due to illiquid market conditions) when its value is positive. This is because the investor is not necessarily taking on additional default risk, relative to the long-term default rate, and instead being rewarded for providing liquidity to the distressed component of the high-yield index. The opposite is the case when the High-Yield Liquidity Premium is negative.

Exhibit 9 shows the High-Yield Liquidity Premium over time (solid vertical bars). Trend lines were added to highlight the cyclical nature of the data. The High-Yield Liquidity Premium peaks (positive value) during the latter part of the Deteriorating state and early part of the Improving state, and troughs (negative value) during the latter part of the Static state. The average High-Yield Liquidity Premium over each of the last two cycles is close to zero, at −15.0 bps for Cycle 1 and −14.8 bps for Cycle 2.

Although the computation for Cycle 3 was performed, the results are not finalized because the cycle has not concluded (shown in dashed vertical lines). We note that the most recent High-Yield Liquidity Premium data, Cycle 3 (C3), became extremely high during the third and fourth quarters of 2008 due to underestimation of realized default rates as caused by the lag effect described in the Time to Default section. Later in the Modeling Liquidity section, we provide forecasts for the High-Yield Liquidity Premium of Cycle 3 using various statistical estimation models.
Another way to interpret the High-Yield Liquidity Premium is that it temporarily redefines the risk premium threshold component of the Altman definition. This is because the High-Yield Liquidity Premium raises, or lowers, the 1,000 bps threshold so as to cause the Distressed Default Rate to reach its historical long-term average of approximately 50%. For example, when the High-Yield Liquidity Premium is +200 bps, the temporary definition of distressed is “OAS in excess of 1,200 bps” and when the High-Yield Liquidity Premium is −200 bps, the temporary definition of distressed is “OAS in excess of 800 bps.”

**CLUSTER ANALYSIS: FINDING OBSERVABLE MARKET FACTORS COMMON TO DISTRESSED DEBT**

Cluster analysis is a form of segmentation analysis that seeks to identify common sub-groups within the data population. The methodology attempts to identify clusters of data by calculating distances between data points and among the centroid of groups of closely situated data. We normalize each data set using the standard Z-transformation to avoid the possibility of generating false clusters when using data with different scaling factors.

The option-adjusted spread is the risk premium, over the comparable risk-free rate, after adjusting for the option premium embedded in bonds. In the case of high-yield debt, we hypothesize that this risk premium generally compensates investors for the combination of credit risk (default component of the OAS) and liquidity risk (liquidity component of the OAS).

High-yield OAS = Liquidity risk premium + Credit risk premium

In the next phase of the process, we attempt to identify the presence of these risk factors through the cluster analysis. We start out by introducing liquidity factors that are assumed to reflect systematic liquidity conditions related to the overall "financial system." We define these as Systematic Liquidity Factors. The factors that we test are: 1) USD two-year swap spread; 2) TBD spread; and, 3) three-month LIBOR minus Fed funds rate. Generally, these spreads represent the rates at which financial institutions fund their short-term activities by borrowing from
each other. Therefore, as financial institutions become more fearful of each other's ability to repay their obligations (i.e., counterparty risk), liquidity in the banking system quickly dissipates, and these spreads widen commensurately.

Next, we introduce a second set of factors that most purely incorporate corporate credit risk (i.e., default risk) and define them as Default Factors. In particular, we choose historical default rates for the high-yield market, over different time horizons and on an issue and issuer basis. These factors include: 1) Monthly Default Rate of the Merrill Lynch High Yield Master II Index (issue-based); 2) Quarterly Default Rate of the Merrill Lynch High Yield Master II Index (issue-based); 3) Moody's Monthly Default Rate (issuer-based); 4) Moody's Quarterly Default Rate (issuer-based); and 5) Moody's Last Twelve-Month Default Rate (issuer-based).

Next, we introduce a third set of factors that includes the full range of corporate bond spreads based on their credit ratings (investment grade to high yield)—from AAA to CCC and Below. We define this group as Corporate Credit Factors.

Exhibit 10 shows the results of the initial cluster analysis. As expected, we observe clustering along the lines of the three groups previously selected: 1) Systematic Liquidity Factors; 2) Corporate Credit Factors; and 3) Default Factors.

Next, we introduce the High-Yield Liquidity Premium to search for observable market proxies. This is needed to add practicality to the analysis because the High-Yield Liquidity Premium is only known after a considerable time lag.

Exhibit 11 shows the results of the next iteration of the cluster analysis. The findings reveal the formation of three minor clusters, as defined below:

1. Low-Grade Credits Cluster: High-Yield Liquidity Premium and BBB to CCC and Below corporate credit spreads.

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**EXHIBIT 10**
Tree Diagram for 15 Variables

```
USD 2Y Swap Spread
  TED Spread
    3M Libor-FFR
      U.S. Corp AAA
      U.S. Corp AA
      U.S. Corp A
      U.S. Corp BBB
      U.S. Corp BB
      U.S. Corp B
      U.S. Corp CCC
    ML DR monthly
    ML DR qtrly
  Moody's DR LTM
  Moody's DR monthly
  Moody's DR qtrly

Ward's method
Euclidean distances

Systematic Liquidity Factors
  Corporate Credit Factors
  Default Factors

Linkage Distance
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*Revisiting the Altman Definition of Distressed Debt and a New Mechanism for Measuring the Liquidity Premium*
Exhibit 11
Tree Diagram for 16 Variables

2. High-Grade Credits Cluster: AAA to A corporate credit spreads.
3. Systematic Liquidity Cluster: USD two-year swap spread; TED spread; and three-month LIBOR minus Fed funds.

Additionally we observe the formation of two major clusters, as defined below:

1. Liquidity Cluster: Low-Grade Credits Cluster; High-Grade Credits Cluster; and Systematic Liquidity Cluster.
2. Credit Cluster: the various high-yield default rate measures.

The analysis generally groups individual components based on broad categorizations revolving around credit ratings, as expected, mainly along the lines of investment-grade and high-yield corporate credit ratings. The exception was BBB corporate credit spreads, which although belongs to the investment-grade category, is grouped with high yield. The High-Yield Liquidity Premium is grouped with high yield, although not surprisingly since its derivation is from the high-yield index. Together these factors form the Low-Grade Credits Cluster.

The next finding is that the Low-Grade Credits, the High-Grade Credits, and Systematic Liquidity minor clusters join to create a major cluster, which we define as the Liquidity Cluster. Together, all corporate credit spreads, the High-Yield Liquidity Premium, and Systematic Liquidity Factors form this major cluster. Given our assumption that the Systematic Liquidity Factors reflect overall financial-system liquidity and it is included in this cluster, we deduce that this major cluster has a dominant factor associated with liquidity.

We further find that the other major cluster is only associated with the Default Factors and define it as the Credit Cluster. These two major clusters (Liquidity Cluster and Credit Cluster) are very dissimilar from each other based on the linkage distance being near the maximum level.
Some interesting findings are that the lower-quality corporate credit spreads (BBB to CCC and below) are more closely associated with the higher-quality corporate credit spreads (AAA to A), and with Systematic Liquidity Factors, than with the Default Factors. We believe that this provides evidence that the dominant risk factor of corporate bond spreads is associated with liquidity. Based on the associations discerned by the overall Cluster Analysis, we draw two major conclusions: 1) an observable market proxy for the High-Yield Liquidity Premium is in fact related to liquidity and 2) liquidity is the dominant factor in explaining the variability of corporate credit spreads, which may indicate that the majority of the variance of the total spread premium is likely to be related to liquidity risk.

In an effort to find the best proxy for the High-Yield Liquidity Premium, the next phase of the process distills the factor set to the least and most efficacious quantity. Since we infer that the High-Yield Liquidity Premium is related to liquidity, we focus on the constituents of the Liquidity Cluster. Furthermore, since the High-Yield Liquidity Premium is related to corporate credit spreads, and because corporate credit spreads are very closely related to each other, we remove all such spreads except AAA corporate credit spreads. The removal of related factors helps refine the association among the fewer set of factors. Because AAA corporate debt issuers have historically experienced a near-zero (0.187%) cumulative default rate over a 20-year period, we deduce that its OAS should mainly reflect the liquidity risk premium. After making these changes to the dataset, we re-run the Cluster Analysis.

In Exhibit 12, we continue to observe two major clusters: 1) Liquidity Cluster and 2) Credit Cluster. Furthermore, the High-Yield Liquidity Premium and AAA corporate credit spreads form a sub-cluster that subsequently combines with the original Systematic Liquidity Factors sub-cluster. Therefore, we conclude that AAA corporate credit spreads should serve as a good observable market proxy for the High-Yield Liquidity Premium. Based on our hypothesis that the total option-adjusted spread for a high-yield bond is composed of a "liquidity

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**EXHIBIT 12**

Tree Diagram for 10 Variables

![Tree Diagram](image-url)
premium” and a “credit premium,” after having isolated the “liquidity premium” component, we then explore isolating the residual “credit premium” component. Given our finding that the High-Yield Liquidity Premium is a “liquidity” factor that is common to all high-yield credits, we subtract the High-Yield Liquidity Premium from the total high-yield index OAS. This leads us to arrive at what we hypothesize to be the credit premium component. We define this residual as the “Residual Credit Premium:”

\[
\text{Residual Credit Premium} = \text{High-yield index OAS} - \text{High-Yield Liquidity Premium}
\]

After introducing this factor into the Cluster Analysis, we observe that it combines with the Default Factors sub-cluster to form one of two major clusters (Credit Cluster).

Exhibit 13 shows the results of this final iteration of the Cluster Analysis, thereby completing the decomposition of the high-yield index OAS into a “liquidity” component (High-Yield Liquidity Premium) and a “credit” component (Residual Credit Premium).

Exhibit 14 shows that the Residual Credit Premium (solid vertical lines) has been relatively constant and positive over time throughout past two credit cycles. These characteristics seem to indicate that the credit quality of high-yield securities, as reflected by their credit ratings, has been consistent over time. In other words, when controlling for systematic/market liquidity conditions, the company-level fundamental credit metrics used to assess the creditworthiness of high-yield bonds have been relatively stable over time.

We note that the most recent Residual Credit Premium data, Cycle 3 (C3, shown in dashed lines), became significantly negative during the third and fourth quarters of 2008 due to underestimation of realized default rates as caused by the lag effect described in the Time to Default section.
E x h i b i t 1 4
Residual Credit Premium

MODELING LIQUIDITY: MARKET PROXY FOR THE HIGH-YIELD LIQUIDITY PREMIUM

This section endeavors to model the relationship between the High-Yield Liquidity Premium, which is not readily observable, and an observable market proxy. As discussed in the Time to Default section, there is a significant time lag before defaults are fully realized and the High-Yield Liquidity Premium is therefore stable. Due to the time required for distressed securities to default, it is not practical to directly measure the High-Yield Liquidity Premium contemporaneously.

Based on the results of the Cluster Analysis section, we select AAA corporate credit spreads as the observable market proxy. We model the relationship between the High-Yield Liquidity Premium and AAA corporate credit spreads (Exhibit 15) using two types of regression techniques—ordinary least squares (OLS) and stochastic beta (SBeta).20

Exhibit 15 shows the relationship between the High-Yield Liquidity Premium and AAA corporate credit spreads. The models were trained using data from January 1990 to August 2008. The last calculation of the High-Yield Liquidity Premium was chosen to be August 2008 to exclude the Lehman Brothers bankruptcy (September 15, 2008), which we assume to be an outlier for the purposes of the analysis. In addition, by selecting the last data point of August 2008 we allow for a posterior 15-month period (through December 2009) to better incorporate the effects of subsequent defaults, thus reducing the lag effect associated with the High-Yield Liquidity Premium, as discussed in the Time to Default section.

In order to estimate the High-Yield Liquidity Premium on an out-of-sample basis (September 2008 to
EXHIBIT 15
High-Yield Liquidity Premium and AAA Corporate Credit Spread

EXHIBIT 16
Beta Estimates of the High-Yield Liquidity Premium

Historical OLS Beta: $y = 10.1x - 692.04$

<table>
<thead>
<tr>
<th>Beta Type</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.35</td>
</tr>
<tr>
<td>S Beta</td>
<td>83%</td>
</tr>
<tr>
<td>Rolling 30 month OLS Beta</td>
<td>69%</td>
</tr>
<tr>
<td>Historical OLS Beta</td>
<td>35%</td>
</tr>
</tbody>
</table>
December 2009), we devise three models: 1) historical OLS linear regression; 2) 36-month rolling OLS linear regression (trailing 36-month sampling period); and 3) SBeta regression.

**Exhibit 17**
Model Specifications

<table>
<thead>
<tr>
<th>Historical OLS</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Stat</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>-692.04</td>
<td>66.60</td>
<td>-10.55</td>
<td>0.00</td>
</tr>
<tr>
<td>β</td>
<td>10.10</td>
<td>0.93</td>
<td>10.82</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Rolling 36 month OLS</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Stat</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>-526.72</td>
<td>40.71</td>
<td>-12.94</td>
<td>0.00</td>
</tr>
<tr>
<td>β</td>
<td>4.98</td>
<td>0.35</td>
<td>14.12</td>
<td>0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SBeta</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Stat</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>-418.98</td>
<td>73.90</td>
<td>-5.67</td>
<td>0.00</td>
</tr>
<tr>
<td>β mean</td>
<td>5.41</td>
<td>5.50</td>
<td>0.98</td>
<td>0.33</td>
</tr>
<tr>
<td>β persistence</td>
<td>0.96</td>
<td>0.03</td>
<td>38.40</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Exhibit 16 plots the three beta estimates of the High-Yield Liquidity Premium over time, as a function of AAA corporate credit spreads. The High-Yield Liquidity Premium is the dependent variable, whereas AAA corporate credit spread is the independent variable. The regression models exhibit $R^2$ values ranging from 35% for the historical OLS beta model to 83% for the SBeta model. The fact that SBeta exhibits better estimation results may indicate the existence of long-term, mean-reverting characteristics in the beta component. Exhibit 17 summarizes the various model specifications.

**Exhibit 18**
Estimated vs. Actual High-Yield Liquidity Premium

Exhibit 18 illustrates the results of the various models. The chart plots the actual High-Yield Liquidity Premium versus its out-of-sample estimations based on the rolling 36-month OLS, SBeta, and historical OLS models. The SBeta model estimates that the High-Yield Liquidity Premium last peaked near 2,000 bps (on October 2008), which is approximately twice higher than the peaks reached in 1990 and 2002. As of December 2009, the instantaneous High-Yield Liquidity Premium is estimated to be +19 bps.
EXHIBIT 19
High Yield Liquidity Premium with Estimations and Trend Line

EXHIBIT 20
Residual Credit Premium with Estimations
-33 bps, and -176 bps based on the historical OLS, SBeta, and rolling 36-month OLS models, respectively. We place a higher degree of confidence on the SBeta model estimate of -33 bps based on its relatively high R² of 83%.

Finally, using the SBeta model, we estimate the High-Yield Liquidity Premium for Cycle 3 as shown in Exhibit 19. Exhibit 20 shows the corresponding Residual Credit Premium for Cycle 3 as a result of the forecasted High-Yield Liquidity Premium. Estimated values for the High-Yield Liquidity Premium and Residual Credit Premium for Cycle 3 are shown in dashed lines in Exhibit 19 and Exhibit 20, respectively.

The average High-Yield Liquidity Premium over each of the prior two cycles, Cycle 1 and Cycle 2, was -15.0 bps and -14.8 bps, respectively (i.e., close to zero). For the current partial-cycle, Cycle 3 (October 2007 to December 2009), the average High-Yield Liquidity Premium is running at +587 bps, indicating a still-evolving credit cycle. However, the instantaneous High-Yield Liquidity Premium appears to have reached an inflection point in December 2009, turning from positive (lack of liquidity) to slightly negative (excess liquidity) for the first time during Cycle 3, at -33 bps based on the SBeta model forecast. This indicates the commencement of a shift in liquidity conditions towards equilibrium, as we expect the instantaneous High-Yield Liquidity Premium to remain negative for a sufficient length of time so as to cause the running average to converge to zero. We expect the Residual Credit Premium to continue to remain relatively stable and consistent with the characteristics of prior cycles.

CONCLUSION

Twenty years after the Altman definition of distressed debt was first published, we find strong empirical evidence supporting the definition’s efficacy over long periods of time. After analyzing 9,838 bond issues on an out-of-sample basis over the period of 1990–2009, we find that constituents of the Merrill Lynch High Yield Master II Index trading at risk premiums, over comparable U.S. treasuries, in excess of 1,000 bps, experienced a long-term average default rate between 48% and 51%—as postulated by Altman in 1990. Furthermore, we find that the relationship between the two Altman definitional components, risk premium threshold (1,000 bps) and default rate (50%), shows that the incremental default rate for each additional unit of premium threshold stabilizes at the intersection of the 960-1,140 bps premium threshold and at the long-term average default rate of 48% to 51%. We therefore conclude that the Altman definition has been highly effective at characterizing distressed debt over long periods of time.

Additionally, we introduce precision to the time-to-default dimension of the Altman definition, which had been silent on this point. For distressed securities that ultimately default, the median time-to-default is observed to be 14 months, with 90% of the population defaulting within 46 months. We also find that a differentiating factor between distressed securities that eventually defaulted and those that did not default is higher OAS volatility characteristics of the former.

Equally important, we find that the Altman definition does not hold over short periods of time due to the distortive effects of liquidity on default rates. However, we find that this phenomenon can be temporarily adjusted using a bootstrap method that controls for the default rate component of the Altman definition while varying the risk premium threshold component. The resultant adjustment is defined as the High-Yield Liquidity Premium, which is associated with liquidity factors based on cluster analysis. This method provides a practical approach to discern the liquidity premium embedded in the OAS of the high-yield market. We have found that there has been ongoing research regarding bond market liquidity since 1959, with varying degrees of scope and applicability. For example, Fisher in 1959 argued that the liquidity of corporate bonds is related to their “marketability,” which is proportional to the market value of the outstanding bond issue. Flemming in his 2003 article finds that the bid-ask spread of U.S. Treasury securities is useful in measuring liquidity because of the high transparency and high trading volume. However, Mahanti et al.’s 2008 article proposes for illiquid markets (corporate bonds), due to the lack of sufficient transaction information and the frequency thereof, the use of the ownership of securities to discern their accessibility by a dealer, as a proxy for liquidity. Prieswald et al., in 2010, find speculative-grade bonds to have lower liquidity and increased sensitivity to changes in liquidity as compared to investment-grade bonds.

The High-Yield Liquidity Premium exhibits high variability, with negative values corresponding to excess liquidity and positive values reflecting illiquidity in the high-yield market. Over each of the past two cycles, the average High-Yield Liquidity Premium has been near zero (-15 bps), indicating that liquidity equilibrium is reached over the course of full cycles despite interim imbalances (running average of +587 bps for the current cycle and an instantaneous value.
of -33 bps as of December 2009). Because the High-Yield Liquidity Premium is only observable after a considerable time lag due to the time-to-default characteristics of distressed debt, we use cluster analysis techniques to discern an observable market proxy (AAA corporate credit spreads). Finally, we add practicality to the analysis by introducing a stochastic beta regression model that adjusts the Altman premium threshold definitional component for concurrent liquidity conditions.

This finding leads to further decomposition of the high-yield index OAS, beyond the liquidity factor, into an additional credit component (Residual Credit Premium) that is derived from the total high-yield OAS, after subtracting the liquidity factor (High-Yield Liquidity Premium). Interestingly, the Residual Credit Premium is estimated to be relatively stable and positive (average of +507 bps) over the past 20-year period, which may reflect a consistent perception of the fundamental creditworthiness of high-yield bonds by investors and rating agencies when adjusting for contemporaneous liquidity conditions.

Finally, we conclude with the general observation that liquidity appears to be the dominant factor explaining the variability of the OAS for high-yield securities. It is also importantly related to the default rate characteristics of distressed securities.

ENDNOTES

The authors would like to thank Oleg Melentyev of Bank of America/Merrill Lynch for his assistance in providing us with the previously unpublished Merrill Lynch High Yield Master II Index data for the period of 1990-1996. Without this data, the analysis would not have been complete. Additionally, the authors would like to thank Dr. Jerome B. Baezel, Dr. George Shows, and S. Sloan Walker III for reviewing earlier drafts of this article and providing their insights and feedback.


Hedge Fund Research, PreQin Ltd., Morgan Stanley AIP.

The HFR LBD: Distressed/Restructuring Index is a non-investable index composed of hedge fund managers pursuing a distressed investment strategy. Source: Hedge Fund Research Inc.

The three distinct distressed cycles that have occurred, since the term "distressed debt" was coined by Altman in 1990, are defined below:


Our definition of default is consistent with the Altman and Moody's definition: 1) rated "D"; 2) miss a coupon payment; 3) fail to repay principal; 4) file for bankruptcy; 5) enter into a distressed exchange offer; or 6) fail to cure covenant breaches within a pre-specified time period.

The distressed ratio refers to the ratio of distressed securities (OAS greater than 1,000 bps) to the total universe of high-yield securities. It serves as a good measure for the overall level of distress experienced by the high yield market.

The Merrill Lynch High Yield Master II Index (Bloomberg ticker: H0A0) tracks the performance of U.S. dollar-denominated below-investment-grade corporate debt publicly issued in the U.S. domestic market. Qualifying securities must have a below-investment-grade rating (based on an average of Moody's, S&P, and Fitch) and an investment-grade-rated country of risk (based on an average of Moody's, S&P, and Fitch foreign currency long-term sovereign debt ratings). In addition, qualifying securities must have at least one year remaining term to final maturity, a fixed-coupon schedule and a minimum amount outstanding of $100 million. Original issue zero coupon bonds, "global" securities (debt issued simultaneously in the Eurobond and U.S. domestic bond markets), 144a securities, and pay-in-kind securities, including toggle notes, qualify for inclusion in the Index. Callable perpetual securities qualify provided they are at least one year from the first call date. Fixed-to-floating rate securities also qualify provided they are callable within the fixed-rate period and are at least one year from the last call prior to the date the bond transitions from a fixed to a floating rate security. Taxable and tax-exempt U.S. municipal, DRD-eligible, and defaulted securities are excluded from the Index. Inception date: August 31, 1986. Index constituents are capitalization weighted based on their current amount outstanding. Source: Bank of America/Merrill Lynch.

Regression analysis shows the following relation between OAS and (YTW - 10-yr UST): y = 0.8497x + 5.6145; R² = 0.9133.
Deteriorating = "DBT"; Improving = "IMP"; and Static = "STA"; Cycle 1 = "C1"; Cycle 2 = "C2"; Cycle 3 = "C3."

The one-tailed Student's t-test on the difference between these two groups (Defaulted Distressed and Non-Defaulted Distressed) sets the alternative hypothesis to be that the measurement (median OAS or the standard deviation of the median OAS) for the Defaulted Distressed group is greater than the Non-Defaulted Distressed group by certain amount. By setting the confidence interval to be 95% and 99%, respectively, the difference between these two groups is greater than the amount specified in the table below:

<table>
<thead>
<tr>
<th>Confidence Interval</th>
<th>Median OAS (bp)</th>
<th>SDEV of Median OAS (bp)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cycle 1 + Cycle 2</td>
<td>Cycle 1</td>
</tr>
<tr>
<td>95%</td>
<td>&gt;306</td>
<td>&gt;192</td>
</tr>
<tr>
<td>99%</td>
<td>&gt;278</td>
<td>&gt;142</td>
</tr>
</tbody>
</table>

The OAS threshold is defined as the minimum option-adjusted spread required to cause a certain default rate among securities in the index.

No High-Yield Liquidity Premium was available for the period of March 1993 to April 1994 due to the lack of securities available to reach the 50% threshold default rate at any given spread-threshold level.

Cluster analysis comprises different algorithms, distance measures and amalgamation rules to group similar data into respective categories. There are several algorithms such as Joining, Two-Way Joining, and k-Means. We employ the Joining (Tree Clustering) algorithm, which successively joins data together into a larger cluster. Next, we establish our distance measures. We use Euclidean distance to measure the linkage distances, which is a geometric distance in multi-dimensional space: distance \((d(x,y)) = (d1 - y1)^2\). Because this measure may be greatly affected by different scales, we normalize the data. In our case the linkage distances are composed of normalized spreads and percentage rates. Finally, we define our amalgamation or linkage rules to determine when two clusters are sufficiently similar to be linked together. The shorter the linkage distance, the more similarity among the sub-groups being linked. We use Ward's method, which attempts to minimize the sum of squares (dispersion) in the amalgamation formed at each step. The analysis was performed using the STATISTICA analytical software package.

Errors associated with the use of different units of measurement and differing minimum and maximum values among the various data sets. The Z-transformation returns a new data set with a mean of zero and a standard deviation of one.


Source for AAA to CCC corporate credit OAS: Bank of America/Merrill Lynch. We used (Yield-to-Worst – 10-yr U.S. Treasury yield) as a proxy for OAS for the 1990–1997 period since OAS data was not available.


The stochastic beta model (SBeta) assumes that beta is time-variant and follows a mean-reversion pattern with a stochastic component. Beta is assumed to have the form of:

\[
\beta_{pt} = \alpha_{p} + \delta_{p}(\beta_{pt-1} - \alpha_{p}) + \sigma_{pp}v_{pt} \text{ where } v_{pt} \sim N(0,1)
\]

where

\[
\alpha_{p} \text{ is the long term mean of beta;}
\]
\[
\delta_{p} \text{ is the beta persistence;}
\]
\[
\sigma_{pp} \text{ measures beta volatility}
\]

SBeta estimation process employs the Bayes Inference method, which revises the prior estimation based on new information to obtain the posterior estimation. As a result, SBeta has a lesser lag effect, when compared to OLS, in developing a stable estimation model. A Gibbs Sampling Method, a type of Markov Chain Monte Carlo (MCMC) method is used to estimate the parameters via iterations until the values converge. Source: Gergana Jostova and Alexander Philippov, "Bayesian Analysis of Stochastic Betas," *Journal of Financial and Quantitative Analysis*, Vol. 40, No. 4 (December 2005), pp. 747-778.

The results are from October 1990 to August 2008. \(R^2\) numbers for SBeta and rolling 36-month OLS are based on out-of-sample estimations; the \(R^2\) numbers for historical OLS are based on in-sample estimations.


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