Where Has My Credit Premium Gone?
A Perspective on the Current US Corporate Bond Market

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Key Takeaways

- The Credit Risk Premium (CRP), though not widely understood or used, can offer valuable insight into expected credit returns.

- An accurate forecast of the CRP requires extensive default and downgrade data as well as sophisticated modeling. Our approach utilizes prices, credit ratings and macroeconomic data to model the expected CRP.

- Overall, the CRP is positive across sectors but is larger for lower-quality sectors. During tight CRP environments, like the current environment, the credit return outlook is modest, but importantly, not negative.

- Drawdown risk increases during the latter stages of a tight CRP environment. However, drawdowns, while sharp at times, are generally short lived and the ensuing recovery tends to be equally dramatic, suggesting timing can be difficult.

- Our analysis of the current tight CRP environment, as well as the past tight CRP regimes, reveals that while the excess return outlook may be diminished during these periods, it can be a fertile environment for collecting attractive coupons in high yield (currently more than 6%) while harvesting lower, but still positive, excess returns over Treasuries.

The primary concern of corporate bond investors is estimating the expected excess return above Treasuries in order to justify additional risk. The option-adjusted spread (OAS) of corporate bonds over Treasuries is frequently used to measure this expected excess return. We believe that the CRP is a better measure.

Essentially, bond spreads have two components. One is the expected loss from default and downgrade. The second is an “extra” premium for illiquidity and all other risks, commonly referred to as the CRP. Our historical analysis of the CRP suggests a strong correlation with excess returns and much of the cross-sectional variation in credit spreads can be attributable to the CRP. Further, our research indicates that the CRP can provide valuable insight into expected credit returns. We believe the ability to forecast the CRP should be of great interest to credit investors.

Here, we present analysis of the CRP’s behavior over time, propose a methodology for estimating the CRP, and share investment implications for the current market environment.

Calculating the Realized CRP

We begin with an analysis of the realized, or observed, CRP. We must note that the realized CRP is a theoretical construct that can only be calculated with perfect foresight. That is, if we know with certainty the number of bonds that will default and the number that will be downgraded over the next five years, we can then calculate the realized CRP as follows:

\[
\text{Realized CRP} = \text{Current OAS} - (5\text{-Year Realized Loss from Default} + 5\text{-Year Realized Loss from Downgrades})
\]

As the above formula implies, one must first calculate the realized loss from defaults and downgrades in order to arrive at the CRP. While we provide a detailed methodology for calculating the CRP in the appendix, on the next page is a high-level description for calculating realized CRP.
1. **Data:** Our analysis incorporates all US corporate bond data (within the Bloomberg Barclays US Corporate Bond Index and the Bloomberg Barclays Corporate High Yield Index) from January 2000 through March 2019.

2. **Categorization:** We categorize bonds into several groups, Aaa/Aa/A, Baa, Ba, B, Caa/Ca/C, and Default.

3. **Transition Matrix:** Our transition matrix calculates the actual percentage of bonds that defaulted, were downgraded or maintained their rating over our analysis period.

4. **Realized Loss from Default and Downgrade:** We combine the data from the transition matrix with loss-given-default (LGD) to measure the realized five-year loss rate from defaults and downgrades. *Please note that this part requires perfect foresight on losses and downgrades over the next five years.*

5. **Calculating the Realized CRP:** Finally, we calculate the CRP by subtracting the realized loss from default and downgrades for the current OAS.

Notably, the concept of loss from downgrade is not widely adopted; however, we find that explicitly incorporating expected downgrade losses is helpful for higher-rated issuers, Aaa/Aa/A rated bonds for example, as their probability of default is virtually non-existent. The figure below shows the average historical values since January 2000.

**Exhibit 1: Realized Five-Year Loss from Default, Downgrades and the CRP**

![Exhibit 1: Realized Five-Year Loss from Default, Downgrades and the CRP](image)

The realized data, unsurprisingly, shows that the CRP is positive on average and is larger for lower-quality sectors. For investment grade sectors, the CRP explains the majority of the spread. For high yield sectors, a notable component of the spread is attributable to the risk of default, and to a lesser extent, the risk of downgrade.

While some may dismiss the notion of the realized CRP as merely a theoretical exercise, we find it useful because it shows that realized excess returns are highly correlated with the realized CRP, as shown in Exhibit 2.
Estimating the Expected CRP

Given the high correlation shown above, we think an accurate forecast of the CRP provides a valuable projection of corporate bond excess returns. It is no small task to forecast the CRP, however, as there is no agreed-upon formula for such a calculation. As previously noted, we cannot directly estimate the CRP. Rather, we must first estimate the expected five-year loss from default and downgrade in order to arrive at an estimate of the CRP.

In the prior section, we described our derivation of the realized five-year loss from default and downgrade. To arrive at a forecast, our research suggests that combining the known data from the transition matrix along with changes in unemployment data can effectively predict loss rates across credit sectors. Our empirical research, consistent with more recent research, found that the change in unemployment rate, more so than other economic variables, effectively predicts the future state of a business cycle and better explains future variations in the cumulative loss rates across credit buckets. The initial steps are the same, but we share our high-level approach here.

1. **Data:** Our analysis incorporates all US corporate bond data (within the Bloomberg Barclays US Corporate Bond Index and the Bloomberg Barclays Corporate High Yield Index) from January 2000 through March 2019.

2. **Categorization:** We categorize bonds into several groups, Aaa/Aa/A, Baa, Ba, B, Caa/Ca/C, and Default.

3. **Transition Matrix:** Our transition matrix calculates the actual percentage of bonds that defaulted, were downgraded or maintained their rating over our analysis period.

4. **Unemployment Data to Forecast Loss from Default and Downgrade:** We combine the data generated from the transition matrix with historical changes in unemployment data (over the past four years) to arrive at a five-year loss forecast from default and downgrade. (Please see Exhibit 11 for a comparison of the expected versus realized loss from defaults).

5. **Calculating the Forecast CRP:** Finally, we calculate the forward CRP by subtracting the forecast loss from default and downgrades from the current spread.
Exhibit 3 shows the expected CRP as well as the expected five-year loss values from default and downgrades for all credit sectors. Similar to the realized observations, our estimates show that, on average, the CRP is positive across credit sectors and higher for the lower-rated sectors.

**Exhibit 3: Average OAS Decomposition Based on Expected Loss from Default and Downgrades**

The long-term average expected loss from default is noticeably greater for high yield sectors, especially in the CCC or lower issuers where the default component is almost 50% of the overall option-adjusted spread (OAS). The result makes both intuitive sense and aligns with the realized numbers in Exhibit 2. By contrast, for Aaa/Aa/A issuers the default component is approximately 6% of the OAS. As of March 31, 2019, the CRP is compressed across quality sectors but most noticeably in high yield sectors.

Looking more closely at the breakdown of high yield spreads across time (Exhibit 4), we can make a few additional observations. First, the majority of the variability in the overall OAS is attributable to the CRP. While the current forecast shows a slightly below average CRP, the tightest period for the CRP was between August 2003 and December 2007. During this period, the average CRP was an abnormally tight 0.10%. Two factors contributed to this tight CRP environment: a relatively low overall OAS and an elevated five-year expected loss from default.
Indeed, the average spread for high yield over this period (August 2003 to December 2007) was 3.6%, notably lower than the 5.5% average over our entire research history (January 2000 to March 2019). Similarly, the average five-year expected loss from default was 2.95%, significantly higher than the long-term average of 1.95%. The most recent tight environment, between 2017 and 2018, was less pronounced than the 2003 to 2007 period.

Next, the five-year expected loss from the default component (Exhibit 5) is generally more stable and less sensitive to short-term economic fluctuations. However, the chart shows that the expected default component of the OAS reached elevated levels at least two years prior to the 2008 recession. The average expected loss from default was 1.77% (the median was 0.55%), with a standard deviation of 0.72%. The expected average loss from default between June 2006 and June 2008 was 2.80%, an event close to two standard deviations.
Two primary factors contributed to the elevated risk of default. First, although the prevailing macroeconomic environment between the tech bubble (2003) and the global financial crisis (2008) was generally one of stability (strong earnings growth, low volatility, etc.), the high yield market experienced a relatively high percentage of defaults between 2002 and 2004, which is an input to our calculation through the transition matrix. Second, the unemployment rate also contributed to higher expected loss from default. The response to the unemployment data suggests a counter-cyclical relationship to our expected loss. In other words, if unemployment is low now, in five years it is likely to be high (or at least higher), and vice versa. We can see in Exhibit 6 that between 2002 and 2004, unemployment was low and getting lower, which translated to higher forecast loss of default five years forward.

Exhibit 6: Expected Five-Year Loss from Default and Unemployment Rate

A Review of Tight CRP Environments

As observed in Exhibit 4, we are currently in a tight CRP environment—the type of environment that typically causes bond investors to pause. Mapping the CRP against realized credit excess returns across time, we look further into previous periods of a tight CRP in Exhibit 7. At a glance, we can see that the average contemporaneous monthly excess return during tight CRP regimes is generally in line with, or better than, the long-term average. However, excess returns tend to be lower on a forward 12-month basis, particularly during the tail end of each regime.

- The most prolonged period in which the CRP was below average was July 2003 to December 2007 (54 months). Over this period, the average CRP was 0.43%, well below the long-term average of 3.63%. The average monthly excess return for high yield bonds over this period was 0.31% and was positive 63% of the months (34 of 54 months). The realized subsequent 12-month excess return was +0.15%, which, while positive, is lower than the long-term average of 3.21%.

- The current tight CRP regime began in November 2016. While the length of time (29 months) has been notably shorter than the 2003 to 2007 period, the return metrics have been stronger and more consistent.

- We observed a shorter, less-pronounced, tight CRP period from September 2013 to August 2014 (12 months). During this period, the results were similar to the other two tight CRP regimes.
From a risk perspective, tight CRP environments appear to precede recessions (usually by several years) and may foretell periods of short-lived, sharp drawdowns. As noted in Exhibit 8, our analysis history covers two recession periods: the post tech-bubble and the financial crisis. While two recessions do not tell the full picture, it is interesting to note that:

- The tech-bubble recession of April to November 2001 was mild in nature and only lasted eight months. Perhaps because the market dislocations were concentrated in a few subsectors (primarily tech), the maximum excess return drawdown in high yield never exceeded 12%.

- The financial crisis period was broad based and much longer (18 months) than the tech bubble. During this crisis, the excess return max drawdown reached 33%. However, the recovery was very swift. From a low point of -33% in November 2008, the Bloomberg Barclays US Corporate High Yield Index recouped all losses in the subsequent five months.

Exhibit 8: High Yield CRP vs. Next 12-Month Excess Return over Treasuries

Source: Bloomberg Barclays, National Bureau of Economic Research, Mellon analysis.
What CRP Means for Investors

Over time, we expect the CRP mean revert toward its long-term average, but we think the CRP may remain tight for some time. Our CRP and default signals are not showing signs of economic distress or recession. Company fundamentals are stable, with corporate sales and earnings growth delivering robust year-over-year growth. Unemployment, a key input for our default and downgrade assumptions, is hovering near record lows, and the threat of inflation remains contained.

This has several implications for corporate bond investors. While the CRP tends to be positive over time, tighter CRP regimes leads to lower, but not necessarily negative, performance. We cannot completely eliminate the possibility of a drawdown since timing the market is a difficult proposition, and yet, investors who “sit this one out” potentially forfeit the opportunity to collect healthy 6% high yield coupons and possible positive excess returns. The current modestly below-average CRP suggests lower total returns, but we think it is a stable environment for harvesting high yield coupons. When backed by the currently stable corporate credit profile, we think investors should maintain their corporate credit allocations.

Methodology: Calculating the Credit Risk Premium

The credit spread is the difference between the yield of US corporate bonds and the duration-matched yield of risk-free bonds (US Treasuries). Credit spreads can be broken down into two components: Expected losses due to default or downgrade, and the credit risk premium, which is the additional compensation required to attract risk-averse investors to hold these risky assets (for illiquidity, volatility, etc.).

\[
\text{CRP} = (\text{Yield} - \text{Risk Free Rate}) - \text{Expected Loss (Default & Downgrades)}
\]

We use the OAS to measure the difference between yield and risk-free rates because it adjusts for embedded optionality and, therefore, is more comparable across different issues.

To estimate the CRP accurately, we must first have a robust estimate of the expected loss. Because understanding CRP behavior is central for corporate bond investors, considerable research has been dedicated to estimating the expected loss. Broadly speaking, most prior studies can be divided into two categories: reduced-form models and structural credit models. Ultimately, both approaches have been somewhat ineffective in estimating the long-term CRP as briefly summarized below.

1. Reduced-form models
   [Jarrow and Turnbull (1995) and Duffie and Singleton (1999)]

   These widely used studies utilize credit spreads as well as other market measures such as volatility to construct a risk-neutral term structure of conditional default probabilities. These studies assert that the variations in credit spreads can be explained solely by changes in expected defaults. Basically, a greater credit spread leads to higher frequency of default, which in turn leads to higher expected loss. We find that this process leads to an overestimation of the default probability. Additionally, the quality and quantity of data significantly impacts reduced-form models. In particular, periods of significant market dislocation may be particularly challenging from a modeling perspective due to volatility of data.
2. Structural credit models


This approach assumes a causal relationship among a set of variables (assets, debt, equity volatility, etc.) that results in an economic default, i.e. the value of the firm is such that it can no longer cover its obligations. Structural models may be able to discriminate expensive from cheap bonds (or defaulters from non-defaulters) based on the estimate of short-term default probabilities. However, the simplifying assumptions of structural models along several dimensions (normal distributions versus fat tails, lack of accountability for liquidity, etc.) introduce many questions about the accuracy of long-term estimates.

Our approach to estimating long-term CRP combines a reduced-form model with a macroeconomic model. Our reduced-form model (described in steps 2-4) is based on a transition-probability matrix. The macroeconomic model (described in steps 5-6) utilizes multiple regression on macro variables and the historical trend.

Our process can be summarized in the following steps:

1. Data

Our analysis is based on a monthly frequency of investment grade and high yield US corporate bonds between January 2000 and March 2019. We utilize Bloomberg Barclays data for measures of total returns, credit excess returns, as well as a suite of risk characteristics such as yields, option-adjusted spreads, durations, etc.

We categorize the bonds into six groups based on ratings: Aaa/Aa/A, Baa, Ba, B, Caa/Ca/C and Default. We combine Aaa/Aa/A rated bonds because these issuers are sparse. A similar rationale applies to merging Caa/Ca/C rated bonds.

2. Transition Matrix

Our transition matrix computes the annual default and transition probability for each credit sector.

The transition matrix describes the probabilities of moving along a spectrum of credit quality grades. We use the Bloomberg Barclays credit ratings, which combine scores from all three agencies (Moody’s, S&P and Fitch).

A continuous-time version of the transition matrix is called a generator matrix. We use a discrete version of a generator matrix on a monthly frequency. Each month we calculate the transition matrix from the preceding 12 months of data. In the abstract illustration below, \( P \) reflects transitions from rating to rating with the final bucket reflecting default. The subscript \( t \) refers to the time (month) when the matrix was estimated. An abstract illustration is followed by a recent example of the latest transition matrix (Exhibits 9 and 10).

Exhibit 9: Abstract Illustration of Transition Matrix

\[
\begin{array}{cccccc}
\text{Aaa/Aa/A} & \text{Baa} & \text{Ba} & \text{B} & \text{Caa/Ca/C} & \text{Default} \\
\downarrow & \downarrow & \downarrow & \downarrow & \downarrow & \downarrow \\
P_{11} & P_{21} & \ldots & \ldots & \ldots & \text{p}_{16} \\
P_{21} & P_{22} & \ldots & \ldots & \ldots & \text{p}_{26} \\
0 & 0 & 0 & 0 & 0 & 1 \\
\end{array}
\]

Survival fraction: \( S(t) \)

Defaulted fraction: \( D(t) \)
3. Term Structure of Default Losses

We combine the default probability from step two with loss-given-default (LGD) data to measure the term structure of realized five-year cumulative loss rates due to defaults. For example,

\[
\text{Loss(year T-5)} = \text{PD}_{T-5} \times \text{LGD},
\]

\[
\text{Loss(year T-4)} = (1-\text{PD}_{T-5}) \times \text{PD}_{T-4} \times \text{LGD}, \text{ through year T}.
\]

More generally, the cumulative loss rate due to defaults realized between t-n and t is

\[
L_{t-n}^i (r_i) = L_{t-(n-12),t-12}^i (r_i) + S_{n-12,t-12}^i (r_i) \times D_i \times \text{LGD}_t
\]

- \(r_i\): i-th rating bucket, where the Aaa/Aa/A group is assigned \(i=1\), Baa group assigned \(i=2\) and so on to the Default group, which has \(i=6\)
- \(S_i (r_i)\): Survived fraction in \(r_i\) bucket
- \(D_i (r_i)\): Defaulted fraction in \(r_i\) bucket
- \(\text{LGD}_t\): Loss-given default at the time t

We use constant LGD assumptions based on the long-term averages in Moody’s Default and Recovery database: 50% for Aaa/Aa/A, 60% for Baa/Ba/B and 70% for Caa/Ca/C. The LGD varies both over time and by industry with the highest losses during recessions. However, modeling LGD includes market timing and estimating time-varying industry trends and, therefore, would introduce noise into our model. We assume the loss happens during the month a company defaults on its debt even though the ultimate recovery is typically higher after the final resolution.

Consistent with our priors and intuition (Exhibit 11), the forecasted five-year default losses increase two-to-three years prior to recessions and tend to lead the realized default losses both into and out of recessions.
4. Term Structure of Downgrade Losses

Next, we calculate the term structure of downgrade losses on a five-year horizon. The loss rate is implied by bond prices. More specifically, we build five replicating portfolios, one for each year, and estimate the mark-to-market loss due to deterioration in the credit quality in each portfolio. One-year loss rate \( L_{t-12,t} \) for the rating bucket \( r_i \) is:

\[
L_{t-12,t}(r_i) = \sum_j S_t(r_i, r_j) \times \Delta P_t(r_i, r_j)
\]

Generalizing the previous formula to any period between \( t-n \) and \( t \), we arrive at the following equation for the realized cumulative loss rate:

\[
L_{t-n,t}(r_i) = L_{t-(n-12),t}(r_i) + \sum_{j} S_{t-(n-12),t-12}(r_i, r_j) \times \Delta P_{t-12}(r_i, r_j)
\]

- \( n = 60 \) for the 5-year cumulative loss rate
- \( \Delta P(r_i, r_j) \) Percentage price change for the event that rating \( r_i \) changed to \( r_j \), where \( r_i > r_j \)
- \( r_i \) i-th rating bucket
- \( L_{t-n,t} \) Cumulative loss rate between \( t-n \) and \( t \)
- \( S_t(r_i, r_j) \) Probability of credit downgrade from \( r_i \) to \( r_j \)

Exhibit 12 illustrates that the forecasted five-year downgrade losses are more volatile than the default losses. This is expected as the downgrade losses reflect shorter-lived contemporaneous trends.
5. Macro Model to Produce Forecast of Losses (Downgrade and Default)

From steps three and four, we are able to derive realized historical five-year losses from default and downgrade. To arrive at a forecast of forward or expected five-year loss, our empirical research, consistent with more recent research by Duffie (2017), found that the change in unemployment rate effectively predicts the future state of a business cycle and better explains future variations in the cumulative loss rates across all credit buckets.

We utilize multiple regression to forecast the expected five-year loss. More specifically, we estimate one-year change in the cumulative loss rate $L_{t-n,t}$ between periods $t-n$ and $t$, where $n=12$ months.

Using the change in the cumulative loss rate, as opposed to its level, improves the model from an econometric perspective. We utilize the following macro model:

$$L_{t-n,t} = \alpha + \sum_{i=0}^{3} \beta_i U_{t-i} + \gamma t + \epsilon_t$$

- $L_{t-n,t}$: Change in the cumulative loss rate between $t-n$ and $t$
- $U_t$: One-year change in unemployment rate (consensus forecast) at the year $t$
- $\gamma t$: To describe downward trend in cumulative loss rates over the time, an unobserved improvement in credit quality

After running the model twice, one time to estimate the change in downgrade loss and one time to estimate the change in default loss, we transform the change in f-year forward losses to units of spread assuming the recovery of the face value.
Exhibit 13 below provides the statistics and estimates for the loadings on the one-year change in default and downgrade losses. Summarizing the table:

- The regression model is statistically significant for both default and downgrade losses as indicated by F-statistic.
- The variance of the realized downgrade losses is nearly three times higher than that of the realized default losses, which explains lower $R^2$ values for the downgrade regression.
- Downgrade loss is both more sensitive and more statistically significant to the most recent change in unemployment relative to default loss.
- Default loss, on the contrary, is more impacted by lagged changes in the unemployment rate.
- The $\gamma$ loading is statistically significant for the term structure of defaults, which we can also observe in Exhibit 11.
- Finally, we note that the predictive power improves as we extend the prediction horizon from 12 months to the next five years (60 months) confirming our choice of the five-year CRP prediction. The intuition behind stronger prediction on the five-year horizon is that our macro explanatory variable, the change in unemployment rate, is a better predictor of long-term economic activity. (Exhibit 14).

**Exhibit 13: Regression Parameter Estimates**

<table>
<thead>
<tr>
<th>Ba rating</th>
<th>Default</th>
<th>Downgrade</th>
<th>Default</th>
<th>Downgrade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Term (months)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>24</td>
<td>36</td>
<td>48</td>
<td>60</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.007</td>
<td>0.008</td>
<td>0.010</td>
<td>0.010</td>
</tr>
<tr>
<td>d UNEMP(t0-12)</td>
<td>0.161</td>
<td>0.033</td>
<td>-0.057</td>
<td>-0.193</td>
</tr>
<tr>
<td>d UNEMP(t12-24)</td>
<td>-0.011</td>
<td>0.061</td>
<td>0.065</td>
<td>0.050</td>
</tr>
<tr>
<td>d UNEMP(t24-36)</td>
<td>0.020</td>
<td>0.2042</td>
<td>0.2123</td>
<td>0.2046</td>
</tr>
<tr>
<td>d UNEMP(t36-48)</td>
<td>0.153</td>
<td>0.329</td>
<td>0.486</td>
<td>0.651</td>
</tr>
<tr>
<td>Trend</td>
<td>-0.0002</td>
<td>-0.0001</td>
<td>-0.0002</td>
<td>-0.0001</td>
</tr>
<tr>
<td>R2-adjusted</td>
<td>27%</td>
<td>50%</td>
<td>61%</td>
<td>63%</td>
</tr>
<tr>
<td>F-statistic</td>
<td>22.6</td>
<td>61.1</td>
<td>101.7</td>
<td>171.8</td>
</tr>
<tr>
<td>Prob (F-statistic)</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*For the purposes of this exercise, the patterns observed for the Ba sector appear sufficiently consistent across all credit sectors. For completeness we provide the details for each sector in the appendix. All regressions are run at monthly frequency. Bold font indicates statistically significant loadings at 99% confidence. Numbers in italics are standard deviations.
6. Compute CRP

Now that we have estimated all required components, we can compute the credit risk premium by combining the contemporaneous OAS with the estimated five-year expected default and downgrade loss rates, and substituting these values into following formula:

\[ \text{CRP}_{sy} = \text{OAS} - \text{expected default loss} - \text{expected downgrade loss} \]

Overall, we believe the CRP produces an accurate prediction of future credit excess returns. In Exhibit 14, we plot the time series for CRP against the next 60-month realized excess returns. The correlation of these two time series is 0.75. It also illustrates how CRP may be countercyclical, in the sense that it increases during market recessions, but may not spike up dramatically in most market environments. General research on risk premia is consistent with this observation.

Exhibit 14: High Yield CRP and Subsequent 60-month Excess Return

Source: Bloomberg Barclays, National Bureau of Economic Research, Mellon analysis.
Appendix
CRP, Default and Downgrade for All Credit Sectors

High Yield CRP
Jan 2000 - Mar 2019

High Yield: 5-Year Expected Loss (Default)
Jan 2000 - Mar 2019

High Yield: 5-Year Expected Loss (Downgrade)
Jan 2000 - Mar 2019

High Yield Key:
- NBER Recession
- Ba
- B
- Caa
- Bloomberg Barclays US Corporate High Yield Index

Investment Grade: CRP
Jan 2000 - Mar 2019

Investment Grade: 5-Year Expected Loss (Default)
Jan 2000 - Mar 2019

Investment Grade: 5-Year Expected Loss (Downgrade)
Jan 2000 - Mar 2019

Investment Grade Key:
- NBER Recession
- Aaa/Aa/A
- Baa
- B
- IG

Source: Bloomberg Barclays, National Bureau of Economic Research, Mellon analysis.
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Eugene is a senior research analyst. He is responsible for conducting research for strategic beta, relative value credit and fixed income strategies. He also enhances current structural credit and convertible bond models, supports a variety of investment products, and performs independent research.

Eugene has been in the investment industry since 2008. Prior to joining the firm in 2011, he was head of quantitative research for the Golden State Fund at Evolution Capital Management. Previously, he worked as a quantitative research associate for the Shinsei Bank of Tokyo.

Eugene has been a guest lecturer in the MATLAB programming workshop in the MFE program at Berkeley since 2009.

Eugene is a Chartered Alternative Investment Analyst. He earned an MFE from the University of California at Berkeley and an MS in control systems and a BS in computer sciences from Riga Technical University.

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Syed is a global investment strategist. He is responsible for articulating the firm’s index, multi-asset and multi-factor strategies to clients and prospects, as well as participating in the refinement of current strategies and the development of new strategies. He works closely with sales and client service staff worldwide with an eye toward bringing innovative product solutions to client portfolios.

Prior to joining the firm in 2015, he was a client portfolio manager at American Century Investments, focused on active equity and multi-asset strategies. Previously, he worked as an investment strategist at BlackRock, primarily focused on active equity. Past roles include director of client service and portfolio management at AXA Rosenberg, portfolio manager at Innovest Capital Management, consultant at Barra, and programmer/analyst at Vestek Systems. Syed has been in the investment industry since 1987.

Syed holds the CFA® designation and he is a member of CFA Institute. He earned an MBA in finance from San Francisco State University and a BA in applied math from the University of California at Berkeley.
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