FEDERAL RESERVE BANK OF NEW YORK

CURRENT ISSUES IN ECONOMICS AND FINANCE

May 1996 Volume 2 Number 6

Understanding Aggregate Default Rates of High Yield Bonds

Jean Helwege and Paul Kleiman

What explains the wide swings in the default rate on high yield bonds in recent years? Differences in credit quality from year to year account for much of the observed variation in default rates, but economic conditions and the "age" of bonds have also played a role.

The market for high yield or speculative-grade bonds[1] has grown from $30 billion of outstanding bonds in 1980 to nearly $250 billion today. Over this period, the market has evolved from a collection of "fallen angels"—bonds that have lost their investment-grade rating—into an established capital market for raising funds.

Although the high yield market is now mature, its behavior during business cycle downturns is not well understood. During the severe recessions of 1980-82, when the market was in its infancy, few issuers of speculative bonds defaulted on their obligations to creditors. By contrast, in the mild recession of 1990-91, the default rate soared to 11 percent. These sharply divergent experiences raise the question: How does the high yield market typically respond to a slowing economy?

To understand the effects of recessions on default rates, we must first understand what causes the default rate to vary over time. This article explores the factors that help explain the past history of the aggregate high yield default rate. To begin our analysis, we consider existing statistical models that attribute variation in the default rate to changes in credit quality, macroeconomic conditions, and the "age" of bonds. We then build on this earlier work by clarifying the relative importance of each of the factors in the models and by refining the measures used.

Explaining Aggregate Default Rates

The fraction of all high yield issuers defaulting in a given year has fluctuated greatly in the recent past. Since 1981, the aggregate default rate *averaged* just under 4½ percent, but the level of aggregate defaults varied considerably from year to year. Defaults ranged from as high as 11 percent in 1991 to less than 2 percent in 1981 and 1994 (see chart). In 1986, the default rate rose considerably above the average, reaching 6 percent.

What explains these wide fluctuations in aggregate default rates? In recent years, researchers (Fons 1991 and Jonsson and Fridson 1996) have identified three factors that influence the pattern of defaults. First, they have shown that changes in the credit quality of speculative-grade bonds affect default rates over time. If the high yield market has a greater fraction of lower rated bonds, the aggregate default rate should rise in that year. Second, the state of the economy affects the aggregate default rate. Profits decline in downturns, leaving companies with less cash to pay their bondholders. Third, because defaults are most likely to occur three years after being issued, the length of time that risky bonds have been outstanding will influence the default rate. This last factor is known as the aging effect.

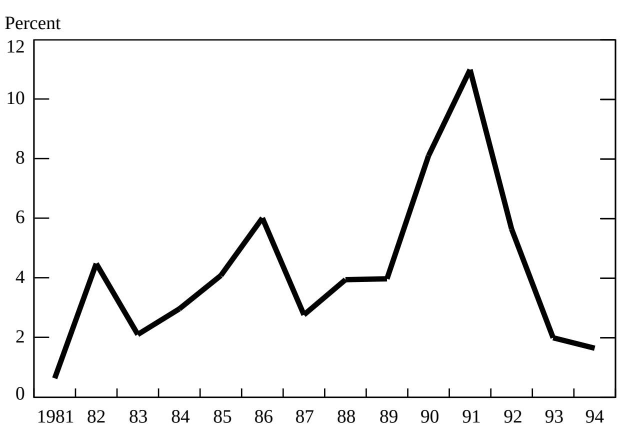
Fons constructed a statistical model that included two of these factors—credit quality and macroeconomic conditions.[2] He factored credit ratings into his model by calculating an expected default rate for the high yield market each year. The expected default rate is the default rate that would occur if firms in each major rating category defaulted according to historical patterns. To arrive at this rate, Fons multiplied the fraction of the speculative-grade market in a major rating category at the start of the year by the category's historical one-year default rate, repeated this for each category, and then added up the products. Fons used the Blue Chip consensus forecast of GDP growth at the start of the year to incorporate a prediction of macroeconomic effects on aggregate default rates.

Jonsson and Fridson modified the Fons model by including the aging effect and incorporating macroeconomic variables that were more closely tied to the financial health of corporations.[3] The authors accounted for aging by using the fraction of high yield bond issuance rated B3 or lower by Moody's *lagged* by three years. In essence, they combined two factors in one variable: the lag allows for the effect of aging, while the fraction of low-rated bonds measures credit quality in the market. Because predicted GDP was found to be only marginally significant, Jonsson and Fridson included two macroeconomic variables that had more explanatory power—corporate profits and the liabilities of failed firms.

In the following sections, we investigate the relationship of credit quality, the macroeconomy, and aging to default rates in greater detail. We improve on the models of Fons and Jonsson and Fridson by refining the variables they use to measure these three factors and by introducing an alternative method of gauging macroeconomic effects on default behavior. In addition, we use regression analysis to determine the relative importance of each of the factors in explaining yearly fluctuations of the default rate.

To evaluate a factor's contribution, we observe its effect on the adjusted R-squared of a regression model. Ranging from 0 to 100, the R-squared measures the percentage of variation in annual aggregate defaults that can be explained by the factors in the model. The adjusted R-squared approaches 100 when these factors account for most of the observed variation over time. A regression model with a high adjusted R-squared produces estimates of default rates that closely track actual rates.

Yearly Default Rate for the High Yield Bond Market



Source: Standard & Poor's.

Credit Ratings

Bond ratings summarize the risk of default for an individual bond. The safest bonds—AAA, AA, A, and BBB—have a one-year probability of default that is less than 0.1 percent.[4] Speculative-grade bonds—BB, B, and CCC—are considerably riskier. Analysts assign ratings to bonds by examining the issuing firm's financial and business risk, as well as the risk factors that are common to all firms in an industry. Ratings therefore can be viewed as a proxy for underlying indicators of financial strength. If the analysts are largely correct in their opinion of individual bonds, then collectively these bond ratings should help explain the variation in aggregate default rates from year to year.

In particular, the distribution of ratings in the high yield market at the beginning of a year should tell us a considerable amount about the aggregate default rate in that year. That is, when the ratings distribution of high yield bonds is tilted toward the riskier end of the scale, default rates should rise. The riskiest bonds issued in the high yield market are those at the lower end of the B category—rated B3 by Moody's or B- by Standard & Poor's (S&P)—and the CCC bonds. Indeed, default statistics calculated by Fons, Carty, and Kaufman (1994) indicate that B3 bonds are three times more likely to default than B1 bonds. Thus, the more bonds rated B3 or lower that exist at the beginning of the year, the more likely the default rate is to rise in that year.

We find that during the 1981-94 period, the expected default rate based on major ratings categories has significant explanatory power. The adjusted R-squared in a regression model including only the expected default rate is 34 percent, capturing just over a third of the variation in the aggregate default rate over time (see box). This explanatory power is substantial, especially considering that the expected default rate is based on only three categories—BB, B, and CCC.

We can refine our definition of the expected default rate by calculating the fraction of the high yield market in the modified letter categories—in the terminology of

S&P, the BB+, BB, BB-, B+, B, B-, and CCC categories.[5] Using data from S&P and Moody's on the distribution of bonds according to modified ratings, we recalculated the expected default rate from 1981 to 1994. Including this new measure of the expected default rate, rather than that based on major ratings categories, increases the adjusted R-squared of the model by 13 percentage points, to 47 percent (see box).

The statistical evidence clearly indicates that a high concentration of low-rated bonds at the beginning of the year is associated with above-average defaults during the year. Still, although credit ratings provide information about the aggregate default rate, more than half of the variation in defaults over time remains unexplained. We now turn to the second factor influencing default behavior, the state of the economy.

The Macroeconomy

A company's ability to pay its bondholders depends on the ability to generate profits, which may be sharply impaired in a recession. To assess the aggregate effect of economic shifts on high yield bond default rates, we can include a measure of general economic growth in our regression model. A natural measure of economic conditions is GDP growth. When GDP growth is included along with the expected default rate (using modified ratings categories), the adjusted R-squared rises to 60 percent, an increase of 13 percentage points (see box).

Those interested in forecasting the aggregate default rate for the coming calendar year might be tempted to use this regression model's estimates together with current ratings information and a prediction of economic growth, such as the Blue Chip forecast. However, the Blue Chip forecast for economic growth, like many macroeconomic forecasts, is known to systematically overpredict growth in recessions and underpredict it in booms, so the model would not work as well for predictions. Indeed, the same regression using forecast GDP instead of actual GDP explains only 54 percent of the observed variation—6 percentage points less than the regression using actual GDP.

As we noted earlier, alternative measures of general economic conditions are corporate profits as a percent of GDP and the current liabilities of failed businesses.

Explanatory Power of Credit Ratings, the Economy, and the Aging Factor

This box presents six regression estimates of aggregate default rate models. The adjusted R-squared measures each model's ability to explain the yearly fluctuations in aggregate defaults. A higher adjusted R-squared indicates greater explanatory power.

EDR_1 is the expected default rate calculated with major ratings categories (in S&P's terminology—BB, B, and CCC); **EDR_2** is the expected default rate calculated with modified ratings categories (in Moody's terminology—Ba1, Ba2, Ba3, B1, B2, B3, and Ca); **LAGB3** is the dollar amount of B3 or lower rated bonds issued, lagged by three years.

Regression Model	Adjusted R-Squared
Credit Ratings	
1) Default rate $= \underset{(-1.82)^{*}}{-8.26} + \underset{(2.78)^{**}}{2.88} \times EDR_1$	34%
2) Default rate $= \underset{(-2.70)^{*}}{-13.41} + \underset{(3.57)^{**}}{2.91} \times EDR_2$	47%
Macroeconomy	
3) Default rate $= \underset{(-2.19)^{*}}{-10.09} + \underset{(3.54)^{**}}{2.58} \times EDR_2 - \underset{(-2.17)^{*}}{0.52} \times GDP$	60%
4) Default rate $= \underset{(-2.53)^{*}}{-9.08} + \underset{(3.44)^{**}}{2.07} \times EDR_2 + \underset{(3.81)^{**}}{0.56} \times (\text{recession indicator} \times EDR_2)$	75%
Aging	
5) Default rate $= \underset{(1.93)^{*}}{1.12} + \underset{(6.67)^{**}}{12.53} \times LAGB3$	77%
6) Default rate $= \underset{(2.68)^{**}}{1.61} + \underset{(3.35)^{**}}{8.89} \times LAGB3 + \underset{(1.80)^{*}}{4.23} \times (\text{recession indicator} \times LAGB3)$	81%

* Significant at the 90 percent confidence level.

** Significant at the 95 percent confidence level.

Liabilities of failed businesses emerge as a significant factor in a regression, but they are in part an indicator of the degree to which corporations are unable to service their debt—the very variable we wish to explain! Corporate profits are significant only when business failure liabilities are also included in the regression model. Even if business failure liabilities were an independent factor in aggregate defaults, they are quite difficult to forecast (much more so than corporate profits). Consequently, these variables may be more helpful in explaining past history than in predicting future variation in defaults.

So far we have only considered measures of economic growth that vary continuously from weak to strong. These measures force changes in the economy to affect the aggregate default rate to the same extent regardless of the initial strength of the economy. That is, a slowdown of a strong economy, such as a drop in GDP growth from 6 to 5 percent, would be predicted to affect the aggregate default rate to the same degree as weakness in a fragile economy—say, a drop in growth from 2 to 1 percent. A more realistic specification of the model would include an indicator variable for weak economies. With an indicator variable, the aggregate default rate would be predicted to remain unchanged whenever the economy is strong. However, when the economy dips below a critical level of GDP growth—say, 1.5 percent—the aggregate default rate would be expected to rise.

Furthermore, one would expect more defaults in a downturn if during that time a greater proportion of companies had low ratings. For example, suppose GDP growth is only 1.0 percent this year. If most of the high yield market is rated B3 by Moody's, we would expect many of these risky firms to default with such sluggish growth. By contrast, if most of the bonds in the high yield market are rated Ba1, the highest speculative-grade rating, far fewer companies would be pushed into default by the slow economy.

We incorporate these two concepts in our model with a new variable—the product of changes in the economy and the level of credit quality of the companies in the market. First, we create a recession indicator variable that takes on the value of one if the economy experiences slow or negative growth, and zero otherwise.[6] Then we multiply this recession indicator by the expected default rate based on modified ratings. This new interaction variable raises the explanatory power of the model another 15 percentage points, to 75 percent (see box).

The interaction variable also sheds light on the dramatic difference in the aggregate default rates of 1981-82 and 1990-91. The rate during the mild recession of 1990-91 far exceeded the default rates during the severe recessions of the early 1980s because the fraction of risky bonds was much greater at the start of the 1990-91 recession.

The Aging Factor

The high yield bond market has cycles of issuance that roughly correspond to returns in the market: in years when returns are strong, more firms issue high yield bonds. In addition, the market is more receptive to riskier bonds at such times. These surges in issuance of riskier bonds can lead to a greater fraction of defaults in subsequent years.

Altman and Kishore (1995) show that low-rated bonds are less likely to default in the first year after issuance and most likely to default three years after issuance. There are two plausible reasons why defaults occur with a lag: First, companies that recently raised money in the bond markets are likely to have the cash to pay their creditors. Second, bond markets generally do not lend to companies in immediate danger of default.

The fraction of bonds rated B3 or lower and lagged by three years encompasses both this aging effect and the notion that very low-rated bonds tend to default more frequently. This variable by itself accounts for 77 percent of the variation in aggregate default rates over time (see box). Compared with the results for a model that includes just the expected default rate, this result represents an improvement in the adjusted R-squared of 30 percentage points (line 5 versus line 2 in the box), indicating a substantial role for aging.

The aging measure, however, may be correlated with economic activity. Issuance of riskier bonds increases when the capital markets are rising in anticipation of a strong economy. Three years after such a period, the economic environment is likely to be weaker. Thus, the strength of lagged issuance of B3 and lower rated bonds may incorporate macroeconomic effects as well as credit quality and aging. To isolate the effect of aging from both of these factors, we can compare the explanatory power of 1) a regression model with lagged B3 or lower issuance and the macroeconomic interaction variable and 2) a regression model with the expected default rate and the interaction variable (see box, line 6 versus line 4). This comparison suggests a much smaller, yet still important, role for aging. The adjusted R-squared with lagged B3 or lower issuance is only 6 percentage points higher (81 percent) than that of the model based on the expected default rate and macroeconomic interaction variable (75 percent).

The aging factor surely played a role in the surge in default rates in 1990 and 1991: issuance of low-rated bonds in 1987 and 1988 was more than triple its normal level. In contrast, such low-rated bonds were rarely issued in the late 1970s, suggesting a small role for aging in the recessions of 1980 and 1981-82.

The 1986 Puzzle

In 1986, speculative bond defaults jumped from 4 to 6 percent (see chart). Yet none of the factors explored in this article were present at that time: the economy was not in recession, the credit quality of the market was not tilted toward the lower end, and lagged new issuance had not peaked. What additional factor accounts for the spike in defaults?

The jump largely reflects the decline in oil and gas prices during 1986. Salomon Brothers (1992) calculates that half of the defaults on original-issue high yield bonds in 1986 were in the energy industry. The 1986 experience suggests that some of the variation in default rates not explained by our models may reflect industry-specific economic trends.

Weakness in one industry can affect the aggregate default rate because the high yield market is not well diversified. Even the well-established high yield market of 1988-92 had a number of industries that claimed a sizable 5 percent share or more of the market (Table 1). Nevertheless, if an overrepresented industry is to have a substantial impact on the aggregate default rate in any given year, it must experience a large number of defaults. We know that some high yield industries have recorded double-digit default rates (Table 2). But how often does an industry with a significant share of the market suffer numerous defaults? We calculate that since 1983, the high yield market experienced these conditions jointly seven times—contributing 1 percent or more to the aggregate default rate (Table 3). Moreover, this combination of conditions raised the rate by more than 1.5 percentage points on two occasions: oil and gas firms in 1986 and retailers in 1991.

Table 1
Industries with 5 Percent or More of the High Yield Bond Market, 1983-92

Industry	Average 1983-87 (Percent)	Industry	Average 1988-92 (Percent)
Oil and gas	10	Retail	10
Retail	7	Finance	7
Electronics	6	Oil and gas	6
Steel	5	Electronics	5
Home building and building products	5	Home building and building products	5

Source: Authors' calculations.

Table 2
Highest Industry Default Rates on High Yield Bonds, 1983-92

Industry	Percent of Issuers Defaulting	Year
Finance	23	1989
Textile and shoes	21	1990
Oil and gas	19	1986
Home building and building products	18	1990
Textile and shoes	17	1991
Retail	17	1991
Services	13	1991
Finance	13	1990
Oil and gas	12	1985
Air transportation	11	1990, 91

Sources: Salomon Brothers; authors' calculations.

Table 3
Largest Contributors to the Default Rate on High Yield Bonds, by Industry, 1983-92

Industry	Percent	Year
Oil and gas	1.7	1986
Retail	1.7	1991
Finance	1.3	1989
Oil and gas	1.2	1984, 85
Finance	1.1	1990
Home building and building products	1.0	1990
Memo:		
Average annual default rate for all industries	4.5	1981-94

Sources: Salomon Brothers; authors' calculations.

If our models could capture these industry-specific problems, their explanatory power would surely rise. Unfortunately, with so few years of data, there is no systematic way to incorporate these effects in a model. Researchers can, however, make a qualitative adjustment to their forecasts if they believe that the default rate in one of the largest industries in the high yield market will rise into the double digits.

Conclusion

We have examined three factors that influence the year-to-year variation in the aggregate default rate: the riskiness of the bonds outstanding in the market, the length of time they have been outstanding, and the state of the economy. Our analysis has shown that each plays a strong part in determining aggregate defaults, but credit quality appears to be the most influential factor. We also find that a downturn in the economy leads to many more defaults when the composition of the high yield market is skewed toward riskier bonds. The sharply divergent experiences in the recessions of the early 1980s and the recession of 1990-91 reflect differences in these factors: The early high yield market, with mostly fallen angels, had fewer risky bonds that were vulnerable to the recessionary pressures. The 1990-91 default rates, by contrast, reflected a very speculative high yield market in the late 1980s.

What does our investigation tell us about the likelihood of a sharp rise in default rates in the current period? Given the conditions in the high yield market at present, the default rate should not reach double digits in the near future. High yield investors have become more conservative since the late 1980s, often passing up offerings of B3 or lower rated bonds. Moreover, since 1991, many high yield firms have raised their ratings by issuing equity and lowering their debt burdens. This lower leverage further reduces the riskiness of the market. Thus, even if the economy were to slow, the effect on default rates should be moderate.

Notes

1. These bonds, pejoratively termed junk bonds, are rated BB, B, or CCC by Standard & Poor's (S&P) or Ba, B, or Caa by Moody's. The rating agencies further refine their assessments with indicators that move a bond's grade up or down a notch. For example, S&P B-rated bonds comprise those rated B, B-, and B+, where B+ is more creditworthy than B-, and Moody's B category comprises B1, B2, and B3 bonds, where B1 bonds are safer than B3 bonds.

2. We calculated the Fons model over the period 1981-94 and obtained the following results: actual default rate = -5.95 + 2.70 x expected default rate - 0.65 x Blue Chip GDP forecast. Only the coefficient for the the expected default rate was significant. The model's adjusted R-squared was 39 percent.

3. We calculated the Jonsson-Fridson model over the period 1981-94 and obtained the following results: actual default rate = 5.41 + 8.41 x lagged B- or lower issuance + 0.004 x current liabilities of failed business - 75.93 x corporate profits. All coefficients were significant with at least 90 percent confidence. The model's adjusted R-squared was 84 percent.

4. See Fons, Carty, and Kaufman (1994).

5. In theory, we could calculate the expected default rate using CCC+, CCC, and CCC- categories, but there are few such bonds.

6. We define slow growth as GDP growth of 1.5 percent or less. The results hardly change if the figure is increased or decreased by 0.5 percentage point.

References

Altman, Edward I., and Vellore Kishore. 1995. "Report on Defaults and Returns on High Yield Bonds: Analysis through 1994." New York University Salomon Center.

Brand, Leo, Thomas Kitto, and Reza Bahar. 1995. "Corporate Defaults Level Off in 1994." *Standard & Poor's CreditWeek*, May 1.

Fons, Jerome S. 1991. "An Approach to Forecasting Default Rates." *Moody's Special Report*, August.

Fons, Jerome S., Lea Carty, and Jeremy Kaufman. 1994. "Corporate Bond Defaults and Default Rates, 1970-1993." *Moody's Special Report*, January.

Jonsson, Jon G., and Martin Fridson. 1996. "Forecasting Default Rates on High Yield Bonds." *Journal of Fixed Income*. Forthcoming.

Salomon Brothers. 1992. *High Yield Default Study*.

About the Authors

Jean Helwege is an economist and Paul Kleiman a financial analyst in the Capital Markets Function of the Research and Market Analysis Group.

Current Issues in Economics and Finance is published by the Research and Market Analysis Group of the Federal Reserve Bank of New York. Dorothy Meadow Sobol is the editor.

Editorial Staff: Valerie LaPorte, Mike De Mott, Elizabeth Miranda
Production: Graphics and Publications Staff

Subscriptions to *Current Issues* are free. Write to the Public Information Department, Federal Reserve Bank of New York, 33 Liberty Street, New York, N.Y. 10045-0001, or call 212-720-6134. Back issues are also available.