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Special Comment

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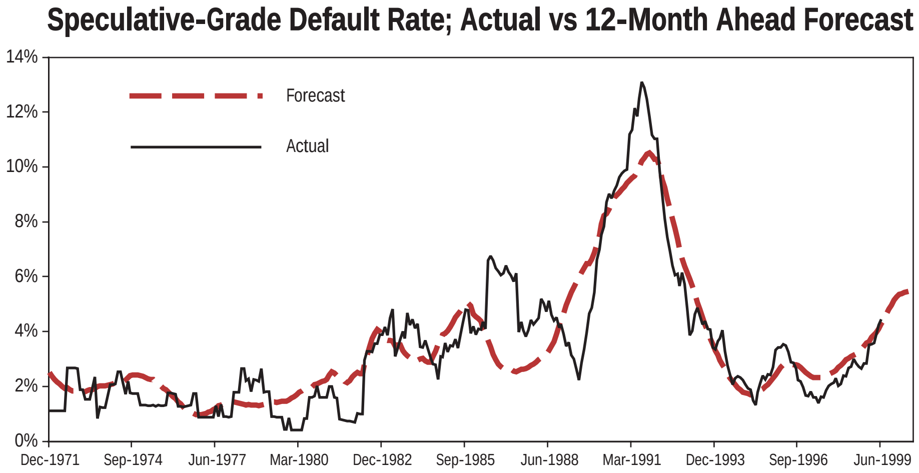
Predicting Default Rates: A Forecasting Model For Moody's Issuer-Based Default Rates

Summary

This study introduces a new model for predicting future default rates. The model leverages off of the statistical relationships underlying Moody's trailing 12-month issuer-based default rate — a widely monitored indicator of corporate credit quality — to offer a superior alternative to previous forecasting techniques. The model incorporates the effect on default rates of changes in the universe of issuers, both in terms of their credit ratings and the time since they first came to market (the "aging effect"), and of macroeconomic conditions as measured by the industrial production index and interest rate variables. The study finds that:

- The modeling of future monthly default *counts* has advantages over the modeling of default *rates* themselves, since the denominator of the default rate is known, up to a small adjustment for withdrawn issuers, 12 months in advance.
- The model generates 12-month-ahead forecasts which capture about 85% of the variation in the all-corporate trailing 12-month default rate and about 80% of the variation in the speculative-grade trailing 12-month default rate.
- Currently, our forecast model is projecting that default rates will trend higher over the next 12 months, but at a slower pace by the close of 1999. Default rates are expected to crest in the spring of 2000, at 2.2% for all-corporate and 5.5% for speculative grade issuers, as shown in the chart below.



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Introduction

Moody's trailing 12-month default rates are widely monitored indicators of corporate credit quality. In this report, we discuss in detail the calculation of these indicators and introduce a model that exploits the unique information structure of Moody's default rates to predict future monthly default rates.

In this study, we develop forecasting models for Moody's monthly speculative-grade and all corporate trailing 12-month default rates, which predict default rates up to 12 months out on a rolling basis. This differs from previous studies, which looked only at year-end annual default rates.

As in previous research, we consider predictor variables, which carry information about the size, relative credit quality, and age of the issuer pool, as well as the state of the macroeconomy. The specification of our model differs significantly, however, as we focus on predicting the monthly number of defaults rather than the default rate directly.

The Definition Of Moody's Trailing 12-month Default Rates

Moody's corporate default rate is easily interpreted as a measure of default risk on an issuer basis. The default rates we calculate are fractions in which the numerator represents the number of long-term debt issuers in the rated universe at the start of a given 12-month period that defaulted during that period. The denominator represents the number of issuers that could have defaulted during the period. (i.e. the total number of issuers rated at the start of the period minus the issuers who withdrew from the market for non-credit-related reasons over the 12 month period.).

We use the term *rating universe* to indicate the sample under consideration, which could be either the entire Moody's-rated universe (all-corporate), or a sub-grouping, such as speculative-grade. Moody's calculates corporate bond default rates for the universe of *Moody's-rated* corporate and sovereign long-term debt issuers only. Restricting our attention to Moody's-rated issuers allows us to ensure the accuracy of the inputs required for such calculations, including the timing of the issuers' market entry and exit, as well as the timing of default events. We sacrifice little by not including the non-rated segment of the market, since Moody's rates the vast majority of the global public long-term debt market as measured by par amount, and since accurate default information is often impossible to obtain for unrated or non-public issuers.

Moody's default rate calculation can be summarized succinctly mathematically. The trailing 12-month default rate for month *t* and rating universe *k* is calculated as,

$$D_{k,t} = \frac{\sum_{t-11}^{t} Y_{k,t}}{I_{k,t-11}} \qquad (1)$$

Where $D_{k,t}$ is the trailing 12-month default rate in month *t* for rating universe *k*. The numerator is a sum of the number of defaulters, *Y*, in month *t*, that were in the rating universe *k* as of *t-11*. The denominator, $I_{k,t}$ is the number of issuers left in the rating universe k in month t.

The denominator in equation (1) is a "slow moving" value, most of which is known with certainty 12-months in advance. The denominator is simply the number of rated issuers outstanding 12 months ago, adjusted to reflect the withdrawal from the market of some of those issuers.

The adjustment for withdrawals is important because the denominator is intended to represent the number of issuers who could potentially have defaulted in the subsequent 12-month period. The adjustment captures the natural attrition in the market from non-credit-related issuers exiting, and avoids overstating the number of issuers who could potentially default during the year.

Moody's does not withdraw ratings because of changes in the credit quality of issuers. In each month, some issuers may call or have all outstanding debt mature without issuing any new debt. Alternatively, mergers or acquisitions may result in one issuer assuming all of the debt of another issuer, while defeasance or debt conversion of debt to equity can also result in a withdrawal of the issuer's bond rating.[1]

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[1] For a complete discussion of this adjustment and withdrawn ratings in general see Carty (1997) p.10.

These non-credit-related withdrawals may occur unevenly over any given 12-month period, but on average are approximately uniformly distributed through time. Our adjustment subtracts from the denominator the time-weighted average number of withdrawals during the previous 12 months. To make this adjustment, Moody's simply subtracts from the gross rated-issuer count 12 months ago, one-half of the issuers who withdrew from the bond market for non-credit related reasons during previous 12 months (in terms of equation (1), the period *t-11* to t).

An Overview Of Default Rate Forecasting Literature

Attempts to formulate a statistical model to forecast aggregate issuer-based default rates began with Fons (1991). In that study, Fons found that about 52% of the variation in historical default rates could be explained using only two factors, credit quality and the state of the economy. Credit quality was modeled by calculating an expected annual default rate for the high yield market. The expected annual default rate is simply the product of the historical average one-year default rates by rating category and the distribution of issuers holding each rating. In that study, Fons showed that the distribution of ratings provided a good indication of the overall trend in future default rates, and that the variations around that trend were contemporaneously correlated with changes in real GNP. The Fons model, then, consists of a regression equation in which the one-year speculative grade default rate deviation is a linear function of the current expected default rate and the Blue Chip consensus forecast of GNP growth.

Building upon the Fons framework, Helwege and Kleiman (1996) were able to explain the annual fluctuation in default rates with an accuracy, in terms of the adjusted-R-squared, as high as 81%. Among Helwege's and Kleiman's additions to the framework was an "aging" factor. The authors noted that few bonds default on their initial coupons. Consequently, one would expect seasoned bottom tier issuance—speculative grade bonds that have been outstanding for a few years—to have a greater influence on default rates than the current issuance of new speculative grade debt. Their model measured seasoned bottom tier issuance by the dollar amount of B3-rated issues outstanding lagged three years.

Helwege and Kleiman also suggested that macroeconomic factors may not affect defaults rates symmetrically over the business cycle. They considered the possibility that issues with speculative grade ratings may be more prone to default than their investment-grade counterparts if economic growth drops below a critical threshold. To measure this effect, they constructed a recession indicator variable that equals one if the economy experiences slow or negative growth (GDP growth of 1.5% or less). The authors multiplied their recession indicator by the expected default rate (based on modified rating categories) to form an interaction variable. Using this variable, they showed that a high percentage of bottom tier issuance is indeed more likely to spur an increase in default rates in the event of an economic downturn than is a distribution of higher tier speculative grade credits. Jonsson and Fridson (1996), and Jonsson, Fridson, and Zhong (1996) developed another set of aggregate default rate forecasting models similar to that of Helwege and Kleiman that were able to explain 86.5% of the variation in Moody's annual speculative-grade default rates. These models also studied the effects of credit quality, the macroeconomy, and aging factors, though in slightly different terms. Their models considered the effect of credit quality measured as the percentage of issuers rated B3 or lower. They also used seasoned bottom tier issuance as a variable to capture aging affects. Additionally, both studies considered various proxies for macroeconomic effects.

The Jonsson and Fridson (1996) study tested the explanatory power of two new variables: corporate profits as a percentage of Gross National Product and current liabilities of business failures. Jonsson, Fridson, and Zhong (1996) include the Nasdaq price-to-earnings ratio, the Standard and Poors price to earnings ratio, the difference between the S&P p/e ratio and the Nasdaq p/e ratio, and gross proceeds of initial public offerings. Rather than measuring the state of the economy, these variables are intended to assess investor optimism in the market, as well as the accessibility of the equity markets as alternative or supplemental sources of financing for risky borrowers. High price/earnings ratios and well-received IPOs are shown to be inversely related to default rates.

An Alternative Approach To Default Rate Forecasting

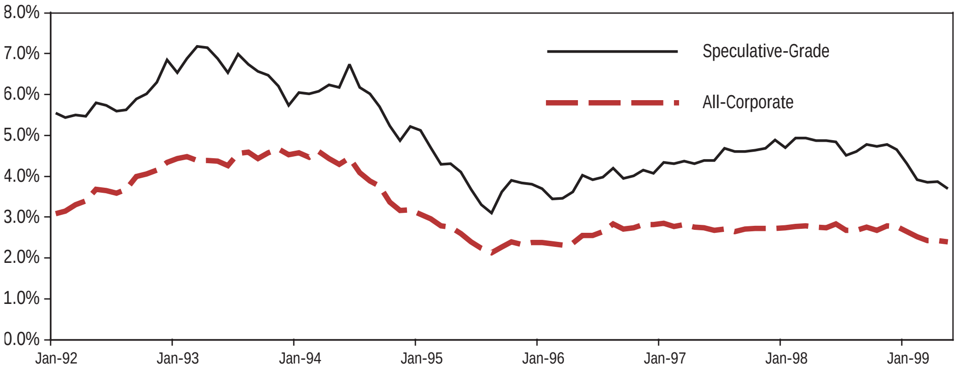
Most of the total variation and nearly all of the short term variation in default rates comes from changes in the number of defaulters over the past year, which is represented in the numerator in our framework.

The denominator, consisting of the gross number of issuers minus the average number of withdrawals over the past 12 month, is a less volatile time series. Moreover, the gross number of issuers in the denominator is known with certainty 12 months in advance. Therefore, we can forecast the denominator by forecasting only the adjustment that will need to be made to reflect withdrawals.

Fortunately, there is a fairly stable historical relationship between the gross issuer count – the known quantity – and the adjustments. The adjustments have averaged about 4% and 2% for the speculative-grade and all-corporate categories, respectively, as shown in Exhibit 1 below. We therefore simply extrapolate this percentage using a simple autoregressive model to forecast the withdrawal adjustments over the known component of the denominators.

Exhibit 1

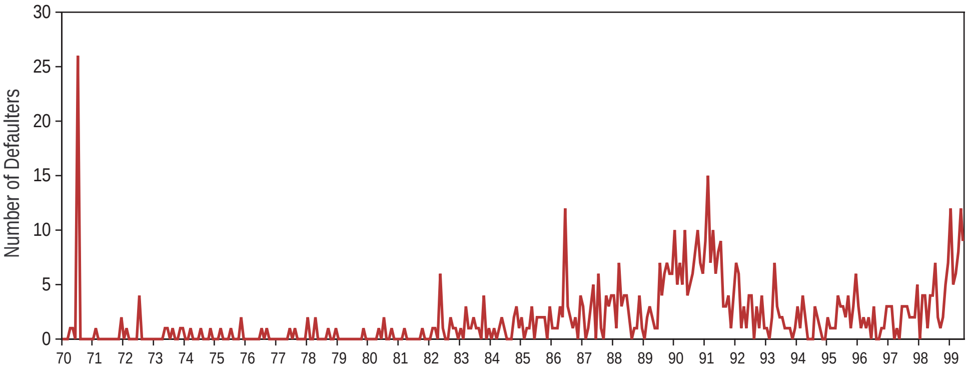
Rating Withdrawals as a Percentage of Gross Issuer Count 12 Months Ago



With the denominator in equation (1) forecast to a high degree of reliability, we can turn our attention to forecasting separately the terms of the summand in the numerator (the number of defaults we expect to occur in forward months). These are the specific unknown quantities with which we can project the issuer-based default rate 12 months into the future. Exhibit 2 shows the actual monthly default counts, the $Y_{k,t}$, on which the all-corporate default rates are based since 1970.

Exhibit 2

Monthly All-Corporate Default Counts, January 1970-June 1999



THE POISSON REGRESSION MODEL

To predict default counts, we need a statistical technique which will efficiently model non-negative *integer* values as a function of a set of explanatory variables. Because the number of potential defaulters is known, and because we can assume that the correlation of default events is small, the multinomial distribution would be a natural basis for such a model. In this case however, the number of defaults represents only a small fraction of the number of issuers, and so the multinomial distribution will be asymptotic to the Poisson distribution, which is easily represented in a regression model.[2]

The characterization of defaults as following a Poisson process is not new. Other models of aggregate default activity, including Duffie and Singleton (1997) and CSFP's CreditRisk+ portfolio risk management software, assume that defaults are governed by a Poisson process.

TESTING OUR ASSUMPTION ON CORRELATION

The appropriateness of the model depends in part, on whether defaults within weach month can be asuumed to be uncorrelated. While it is reasonable to assume that defaults in different industries are uncorrelated, we tested the same assumption *within* industries by looking for clusters of defaults in one or more industries in the highest default months from 1970 through June 1999. We found little evidence of industry default correlation.

Exhibit 3

Industry Representations in High Default Months

Month	Number of Defaults	Industry Groups
Jul-70	26	2
Jun-86	12	5
Jan-90	10	10
May-90	10	9
Oct-90	10	8
Feb-91	15	15
Apr-91	10	9
Dec-98	13	10

Two cases out of our sample of 342 monthly observations provide the exceptions that prove the rule. Most notably, July 1970 was a month in which 26 issuers defaulted, 25 of which were railroads thrown into insolvency by the default of Penn Central Railroad. Another example was June 1986, in which the default of the steel producer LTV Corp. prompted defaults by four other steel produces. Several oil and oil service companies also defaulted in that month.

Exhibit 3 shows the number of defaults for every month in which the default total was ten or higher and the corresponding number of industry groups represented in each month based on Moody's specific industry code. As the table indicates, there is typically a high degree of industrial diversity among defaulters.

APPLYING THE POISSON MODEL

Our model presumes that each month's count of bond defaulters is drawn from a Poisson distribution with parameter lambda;[3]

$$\Pr(Y_i = y_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!}, \quad y_i = 0,1,2,\ldots. \qquad (2)$$

Thus, the probability that the number of speculative-grade defaulters in, say, May is *n* is given by

$$\Pr(Y_{Spec,\,May} = n) = \frac{e^{-\lambda_{Spec,\,May}}\lambda_{Spec,\,May}^{\;n}}{n!} \qquad (3)$$

The mean of the Poisson distribution is λ and its standard deviation is λ½. Thus, (dropping the "spec" subscript for convenience) we want to find a formula for estimating λ_i — the Poisson parameter in each month i.

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[2] This exposition closely follows Greene (1997), Chapter 19.

[3] The Poisson distribution arises in cases where subsequent "draws," in this case monthly default counts, are independent. In fact, there is statistically significant autocorrelation in the variable to be modeled (monthly default counts) out to about five lags. Because we seek forecast models for this variable which exceed its autocorrelation range, we have not taken measures to eliminate this autocorrelation.

A good estimator for λ_i is one that makes the expected number of defaults in each month, using equation (2), as close as possible to the number of defaults that actually occurred. In order for the model to be a forecasting model, we can only use lagged observable variables in constructing our estimator for λ_i.

We use the log-linear version of the model, in which the log of λ_i is a linear function of other variables, i.e.

$$\ln\lambda_i = \beta' \mathrm{x}_i \,, \qquad (4)$$

where xi is a vector of explanatory variables, and b is a set of coefficients which is estimated using maximum-likelihood.

The log-linear formulation induces additivity on the right hand side of equation (4) which allows us to obtain separate coefficients for each variable we include. For example, if the model includes two variables— the percentage of issuers with speculative-grade ratings and industrial production — we would have

$$\ln\lambda_i = \beta_1 * \%\,\text{speculative-grade} + \beta_2 * \text{industrial production.} \qquad (5)$$

The variables that we found to be most useful as predictors of future default counts are outlined in the next section.

PREDICTORS OF DEFAULT ACTIVITY

This section describes the explanatory variables that were found to be useful predictors of future default counts. These variables include changes in overall credit quality, as measured by the percentage of the total universe rated speculative-grade and the percentage of the speculative grade universe rated in the Ba category. They also include an indication of the "aging effect" as measured by the number of speculative-grade issuers to come to market for the first time three years ago. Finally, they include macroeconomic indicators, notably the industrial production index and interest rates.

CHANGES IN CREDIT QUALITY

Since Fons (1991), forecasting models have typically included ratings as indicators of the overall credit quality of bond issuers. We included in our model two measures of the credit quality of the pool of Moody's-rated corporate bond issuers. The first is the relative size of the speculative-grade sub-universe, measured as the percentage of total rated issuers holding a senior unsecured rating of Ba1 or lower as of the first of each month. The second measure is the percentage of speculative-grade issuers whose senior unsecured rating is Ba (Ba1-Ba3). This measures the relative credit quality of the issuer pool within the spec-grade universe.

In each model formulation we examined, these two variables were highly statistically significant and had the expected signs, as shown the appendix. Other credit quality variables included in addition to or in place of these two, such as more refined breakdowns of the distribution of ratings, tended either to be statistically insignificant, incorrectly signed, or contributed to the in-sample fits in a marginal and inconsistent fashion.

THE AGING EFFECT

As described in Altman (1993), Jonsson and Fridson (1996) Carty (1997), and elsewhere, a bond issuers' likelihood of default may change as the issuer matures, a phenomenon know as the "aging effect." At the time of issuance, borrowers are flush with cash, and default is easy to avoid. In technical terms, the hazard rate of default is low. Over time, the hazard rate increases as cash generated from the debt issue is exhausted and the feasibility of the original business plan may be threatened by unforeseen events or changing business conditions.

For each issuer, a critical period will be reached when the success of the enterprise is most uncertain and, consequently, the hazard rate of default is at a maximum. If the issuer's plans are successfully implemented and begin to generate sufficient revenues to pay down the debt, the critical period has been survived and the probability of default falls.[4]

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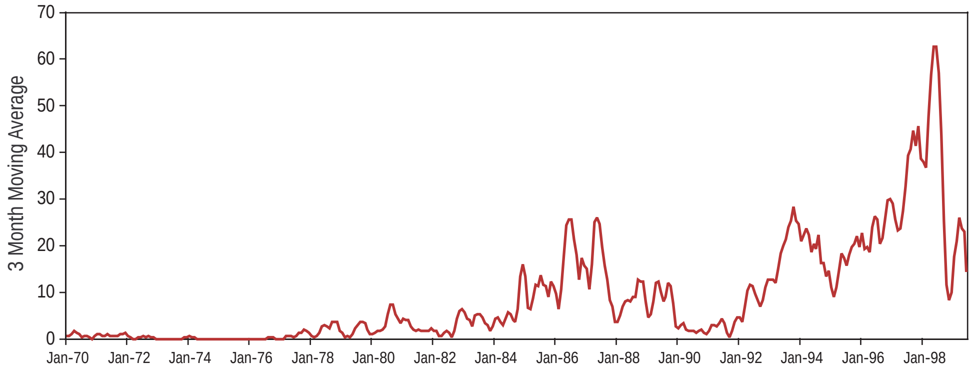
[4] Some analysts have argued that a new critical period will be produced for each bond that a company issues, since any separately financed project could precipitate a default. However, we find that seasoned, frequent issuers with long rating histories default very rarely and so focus on new entrants into the market.

While the timing of the critical period will vary for each issuer, the number of issuers operating in this critical period in any particular month should be positively related to the number of defaults in that month. A number of studies have estimated that, on average, the critical period tends to be in the neighborhood of three years after issuance. As a proxy for the aging effect, we therefore use the number of new rated issuers lagged by approximately three years. We focus on the number of first-time rated issuers, whose initial rating was speculative-grade (Ba1 or lower) at the senior unsecured level. New speculative-grade issuer counts are presented in Exhibit 4.

Unfortunately, as can be seen in Exhibit 4, the inflow of new bond issuers tends to vary considerably from month to month, which could inject unwanted volatility into the forecast model. Rather than arbitrarily smooth the series, we calculated the hazard rate of default at each point in time following first issuance.

Exhibit 4

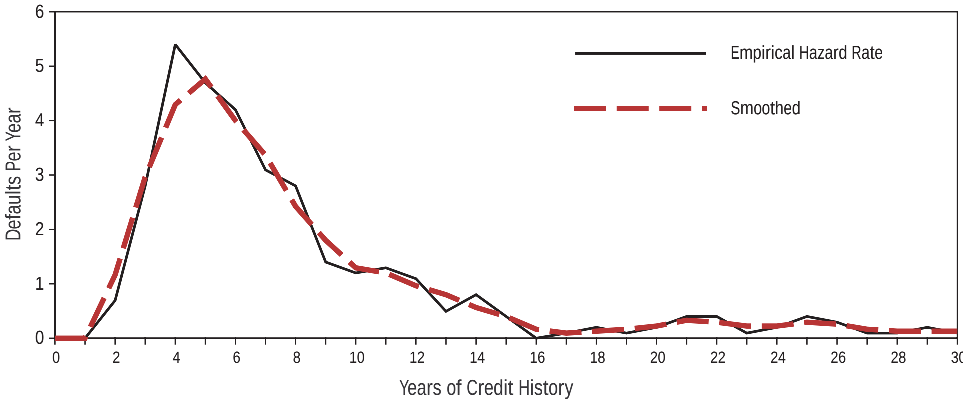
First Time Speculative-Grade Issuer Counts, January 1967-June 1999



Using our historical default database of over 15,000 bond issuers and some 2,200 defaulters, we found that the hazard rate of default did indeed start low, rising rapidly to a peak at about four years, and decreasing almost as rapidly out to about 10 years, as shown in Exhibit 5. We therefore accounted for the effect of lagged new issuance by including in the regression a weighted sum of lagged new issuer counts, where the weights are given by the smoothed hazard rate curve presented in Exhibit 5. We incorporated the same weighted sum of total new speculative-grade issuer counts into the forecasting equations for both the all-corporate and speculative-grade default rate series.

Exhibit 5

Hazard Rate of Default for New Issuers



MACROECONOMIC CONDITIONS

Because we are working with monthly data, we cannot use GDP as a proxy for the state of the economy as in Fons (1991). Instead, following Christiano (1986) and Artis et al. (1992), we considered the index of total industrial production (IP) adjusted by the producer price index. We examined IP levels and annual rates of change based on seasonally unadjusted data, at various lags and in combination with other credit quality and macroeconomic variables.

Like Fons (1991), who considered GDP as a predictor of the annual default rate, we did not find a strong relationship between lagged US IP and monthly default counts. This finding is not as strange as it may appear at first blush, as it is more reflective of changes in the capital markets than an indication that default frequency is independent of the economy. The difficulty in finding a relationship stems largely from two important periods. The first is the recessionary period around 1973, a time during which effective credit rationing in the bond market all but the largest and highest quality firms from issuing debt, which helped kept the default rate near zero even while IP growth was sharply negative.[5] The second is the period prior to the 1992 recession when IP growth was fairly robust, while the historically unique "junk-bond" market collapse drove the default rate to post WWII highs.

Moreover, the non-US component of Moody's-rated universe has grown sharply over the past ten years, and currently comprises nearly 38% of Moody's-rated issuers. Hence, a measure of US economic growth is an increasingly imperfect proxy for the population under consideration.

Even though the changing nature of the bond market has served to obscure the link between business-cycle-length fluctuations in the economy and default activity, changes in real IP can exhibit significant negative correlation with monthly default totals over shorter time horizons. Statistical significance for this variable, as measured by the t-statistic on the regression coefficient, can drop below the 95% confidence level over some specific time horizons. However, its significance tends to exceed the 95% confidence level in periods surrounding high default activity, and for this reason we retained this variable in the model. We also examined the linkage between interest rates and default counts. We found a statistically significant positive relationship between the 10-year bond yield and default counts, and a statistically significant positive relationship between the bond/bill spread and default counts. These relationships reflect the fact that periods of decreasing liquidity and slowing economic activity tend to be associated with rising interest rates and a steepening of the yield curve.

Testing The Forecast Results

We estimated forecast models for the speculative-grade and all-corporate default rates at the 12 month time horizon. The exact specifications for the final models are presented in the appendix. These included the following variables as regressors: the percentage of issuers with speculative grade senior unsecured ratings; the percentage of speculative-grade rated issuers with senior unsecured ratings in the Ba1 to Ba3 range; the annual rate of change of real monthly IP; sum of first time Moody's rated issuers over the previous 120 months weighted by the hazard rate at year *t* for lag *t*, the monthly average yield spread between the 10-year Treasury bond and the 90-day Treasury Bill; and interaction terms between these variables.

For both models, the denominator, net of withdrawals is known in advance. Forecasts of monthly withdrawal rates are generated using past withdrawal rates only[6], and average about 2% of all rated issuers, as described above. Therefore, the accuracy of the default rate forecast is almost entirely determined by the accuracy of the forecast numerators.

As explained in the previous section, we generate default counts by month and cumulate these into numerators. We then regress these fitted numerators against the actual numerators to obtain an overall measure of model fit.[7] Exhibit 6 below presents the r-squared values from the regressions of our fitted numerators on the actual numerators. These goodness of fit measures are nearly identical for the speculative-grade and all-corporate time series as, with investment-grade defaults being exceedingly rare, the difference between the numerators for these series is negligible. The difference between the two default rate time series derives almost entirely from differences in the denominators.

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[5] During 1973-1977, high risk aversion by investors drove the percentage of speculative-grade issuers in the market down to an historic low of less than 23%.

[6] The withdrawal rates are forecast using an ARMA(2,2) model.

[7] Although these regressions do not satisfy the conditions of a classical regression model since the cumulation of default counts built into the numerator will produce autocorrelated errors, r-squared values still provide reasonable measures of goodness of fit.

While the numerator model fit is of interest, what is of greater interest is the accuracy of the forecasts for the default rates themselves. To measure this we construct our default rate forecasts by dividing the known denominators (adjusted by our forecast withdrawal rates) by the forecast numerators. We then regress these forecast default rates against the actual in-sample default rates to obtain a measure of total forecast fit. Exhibit 7 below presents the r-squared values from these total default rate regressions.

Exhibit 6

Goodness of Fit Measures

(R^2 From Regression of Fitted Numerators on Actual Numerators)

All Corporate	Speculative Grade
0.927	0.926

Exhibit 7

Goodness of Fit Measures

(R^2 From Regression of Fitted Default Rates Actual Default Rates)

All Corporate	Speculative Grade
0.850	0.796

Exhibit 8

All Corporate Default Rate Actual vs In-Sample Fit Plus 12-Month Out Forecast

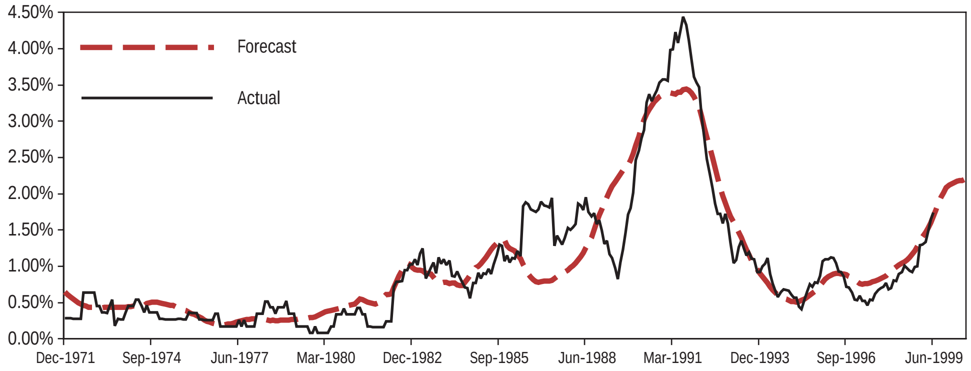
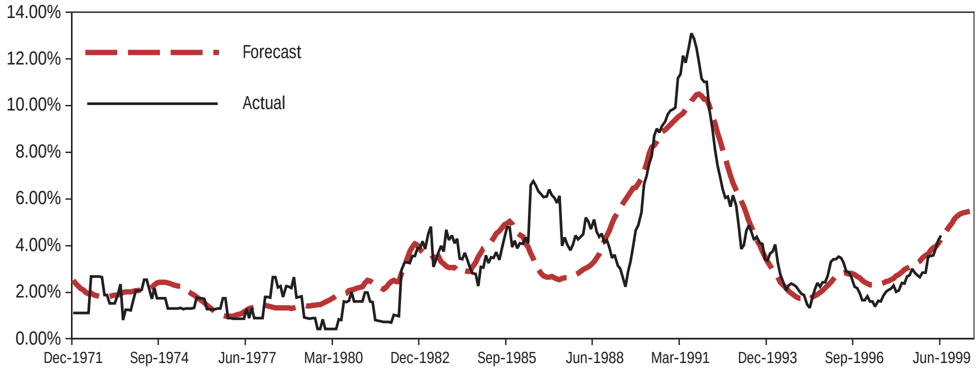


Exhibit 9

Speculative-Grade Default Rate Actual vs In-Sample Fit Plus 12-Month Out Forecast



Exhibits 6 through 9 show that for this sample the model is doing a good job of predicting default rate numerators and hence the default rates themselves. On average, about 90% of the variation in both the speculative-grade and all-corporate numerators can be explained by the model using data lagged 12 months. For the default rates themselves, about 79% of the variation in the speculative-grade default rate and about 84% of the variation in the all-corporate default rate are captured by the 12-month-ahead forecast equation.

Because we are forecasting monthly default rates, our goodness of fit measures are not comparable with earlier models of annual default rates. Monthly default rate time series are significantly more variable than annual time series, so capturing a given percentage of variation in monthly default rates is more difficult. However, our results compare favorably with Jonsson & Fridson's multivariate monthly model[8], which explained 54% of the variation in the monthly speculative-grade trailing 12-month default rate.

The forecast default rates in Exhibits 8 and 9 are based only on information which was known one year prior. The most notable error for both models was during the short-lived drop in default rates that occurred in the fall of 1987. Interestingly, as is evident from Exhibit 11, the use of increasingly lagged data and the consequent elimination of known values from the default rate numerator does not impair the model's performance.

While the ability of the model to fit the default rate time series using lagged information is quite strong, it is the ability of the model to forecast out-of-sample that determines the model's usefulness. Out-of-sample accuracy is measured by comparing the 12-month ahead forecasts for successive periods with the default rates that actually occurred 12 months later. Exhibits 14 and 15 show the out-of-sample forecasts vs. actual default rates for the all-corporate and speculative-grade series.

While the model forecast higher default rates than were actually observed following the 1992 recession, the recent performance of the model has been markedly better. In fact, if we consider the period from the second quarter of 1993 to the present, the out-of-sample forecasts have been quite good. Ninety percent confidence intervals for these 12-month ahead forecast errors over this recent period are presented in Exhibit 12.

Exhibit 10

12-Month-Ahead Out-of-Sample Forecast for All-Corporate Default Rate, June 1992-June 1998

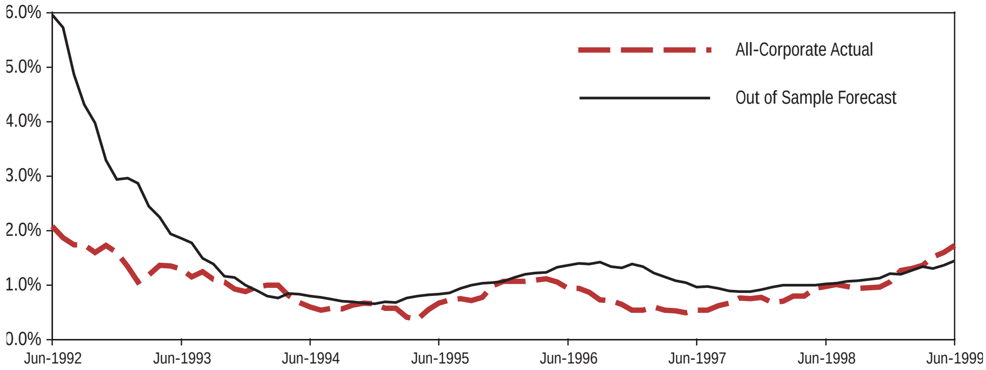
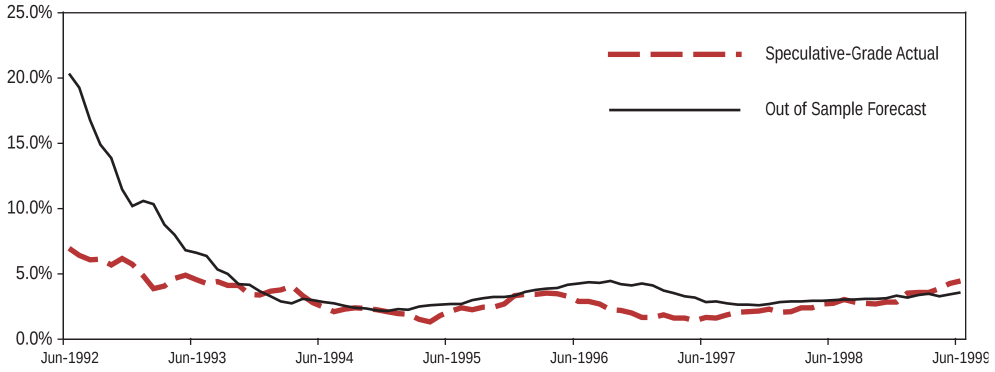


Exhibit 11

12-Month-Ahead Out-of-Sample Forecast for Speculative-Grade Default Rate, June 1992-June 1998



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[8] Jonsson and Fridson (1996), p.74.

Default Rate Forecast For The Next 12 Months

Exhibit 12

90% Confidence Intervals for 12-Month Ahead Out of Sample Forecast Errors

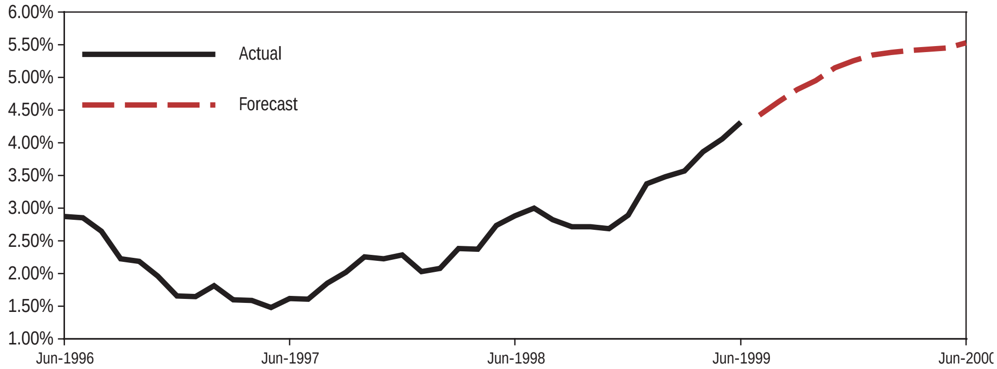
	10 Percent	90 percent
Speculative-Grade	-1.96%	0.21%
All-Corporate	-0.62%	0.04%

Exhibits 13 and 14 show actual and predicted default rates for both the speculative-grade and all-corporate universes, going out through June 2000. The forecast values are also presented in tabular form in the appendix. The forecasts show generally steady increases in default rates going forward, with a leveling off of both the all-corporate and speculative grade default rates beginning late in 1999. The model predicts default rates of 2.20% for all-corporate and 5.53x% for speculative grade isuers for the twelve-month period ending in June 2000.

Overall, these forecasts are reasonably consistent with the underlying fundamentals. Principally, the credit quality of Moody's-rated issuer pool has continued to trend lower over the past six months, albeit at an increasingly slower rate. This would suggest higher numbers of defaults going forward. The recent rise in interest rates and steepening of the yield curve is also contributing to the forecasts for higher default rates, while the industrial production variable is currently benign.

Exhibit 13

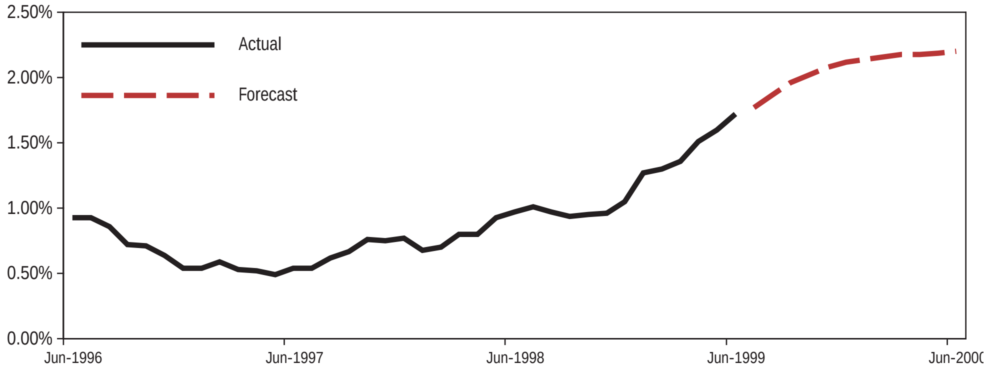
Speculative-Grade Default Rate and Current Forecast



The "aging effect" is also currently benign. New issuance reached a high in mid-1994, falling off steadily through 1995. New issuance accelerated dramatically in 1996, finally reaching a peak in the spring of 1998, followed by a precipitous decline in the wake of the Russian default in August of that year. Because of the approximate three-year lag, this fall-off is producing the current weak aging effect; however, this effect can be expected to place increasing upward pressure on default rates going forward.

Exhibit 14

All-Corporate Default Rate and Current Forecast



Summary And Conclusions

Several models to forecast the aggregate issuer-based default rate have been constructed since the original study conducted by Fonsin 1991. These models use measures of the credit quality of the issuer pool and lagged changes in market conditions, as well as macroeconomic variables, to forecast the default rate from six months to one year ahead.

We extend this research by providing a forecasting model similar in spirit to the Fons model, but which takes advantage of the fact that the denominator of the trailing 12-month default rate is a number which is known 12 months in advance except for the adjustment for withdrawals. These adjustments, which reduce the denominator by an average of 4%, are highly autocorrelated and can be forecast using lagged values only.

Therefore, we constructed a separate model appropriate for forecasting the numerator of the default rate, and combine forecasts of the numerator and denominator to obtain forecasts for the default rate itself. We use a discrete regression model to predict the monthly default totals directly. These monthly default totals sum to form the numerator of Moody's trailing 12-month default rate.

The model forecasts are able to explain about 88% of the variation in monthly trailing 12-month default totals (i.e. default rate numerators) 12 months ahead, for both the all-corporate and speculative-grade universes. Using these forecasted numerators and adjusted denominators, we explain about 85% of the monthly variation in the all-corporate default rate, and 80% for the speculative-grade default rate.

Our model is currently forecasting that both the all-corporate and speculative-grade default rates will continue to trend upward, but at a decreasing rate, leveling off in the spring of 2000. A stabilization of the credit quality of Moody's-rated universe as measured by the distribution of ratings, and a steady interest rate and economic environment will help bring this forecast to fruition. However, this forecast could prove optimistic if the large number of first-time speculative-grads issuers that entered the market in 1997 hit the "critical period" in their lifecycle over the next nine months. This would be increasingly likely were worldwide economic growth to slow over the next few quarters.

Moody's will continue to update the models described in this report, and will publish revised default rate forecasts along with our regular default commentaries. For monthly electronic updates, see the back cover of this report.

Appendix

MODEL SPECIFICATIONS AND COEFFICIENTS

Speculative-Grade Model Specification

Variable	Value	Std. Error	t value
(Intercept)	-4.784	0.479	-9.998
Industrial Production	2.598	0.926	2.807
New Speculative-Grade Issuers	0.111	0.026	4.355
Percent Speculative-Grade	11.071	1.109	9.981
10Year Treasury Yield	0.326	0.069	4.751
Treasury Bond/bill Spread	-0.155	0.043	-3.644
Ba % of Spec:Treasury Bond Yield	-0.254	0.102	-2.480

Residual Deviance: 461.3998 on 335 degrees of freedom

All-Corporate Model Specification

Variable	Value	Std. Error	t value
(Intercept)	-4.733	0.479	-9.886
Industrial Production	2.562	0.929	2.758
New Speculative-Grade Issuers	0.108	0.026	4.213
Percent Speculative-Grade	11.048	1.111	9.948
10Year Treasury Yield	0.328	0.069	4.770
Treasury Bond/bill Spread	-0.154	0.043	-3.614
Ba % of Spec:Treasury Bond Yield	-0.265	0.103	-2.581

Residual Deviance: 460.4543 on 335 degrees of freedom

Forecasts as of July 1999

	July	August	September	October	November	December
All-Corporate	1.77%	1.87%	1.96%	2.02%	2.08%	2.12%
Speculative-Grade	4.43%	4.63%	4.82%	4.96%	5.15%	5.26%

	January 2000	February	March	April	May	June
All-Corporate	2.14%	2.16%	2.18%	2.18%	2.19%	2.20%
Speculative-Grade	5.35%	5.39%	5.42%	5.44%	5.46%	5.52%

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