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# Modeling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions

by

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## Abstract

In credit modeling, default intensity is known to depend on firm-specific factors, notably credit rating, but variation in aggregate default rates over time presumably reflects changes in general economic conditions also. We fit Cox intensity models for defaults, as well as major upgrades and downgrades in credit rating, with both firm-specific factors and a broad range of macroeconomic variables. The sample covers all corporate issuers in Moody's corporate bond Default Research Database over the period 1981 - 2002. We find credit events are strongly influenced by ratings related factors, and also significantly affected by macroeconomic factors. Interestingly, while the coefficients on specific macro variables vary widely depending on which other variables are included in a specification, the estimated effects of the ratings-related factors are largely unchanged by the addition of macroeconomic variables to the model.



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# I. Introduction

Models of corporate default fall into two broad categories, structural models and reduced form models.[1] Structural models consider the evolution of the value of the firm, with default assumed to occur if firm value should fall below some insolvency threshold. Structural models have the practical advantage of being able to make use of the firm's current stock price. Stock returns are very sensitive to information about a firm's financial condition, and they are available daily, unlike accounting statements. But structural models also have serious drawbacks, including the need to take proper account of the firm's capital structure, which may be quite complex, and the difficulty in modeling important non-default credit events, such as a ratings downgrade.

Reduced form models, which are the focus of this paper, treat default as a random event that has a positive probability of occurrence for any firm at any time. In the basic reduced form model, a credit event corresponds to the first jump time of a Poisson process with a constant hazard rate. An "event" can be defined flexibly, to be default, downgrade or upgrade from one bond rating category to another, or any other well-defined change of state. The resulting model yields a Markov chain for the occurrence of credit events. The reduced form approach is widely used for credit risk analysis in both academic and real world research, e.g., Jarrow, Lando and Turnbull (1995) and (1997), Lando and Skodeberg (2002), Duffie et al (2005), and Koopman et al (2005).

The constant hazard rate formulation treats all bonds in a given credit class, often defined in terms of bond rating, as homogeneous with respect to their future prospects. But there is empirical evidence of non-Markovian behavior, such as the positive serial correlation in ratings changes known as "ratings drift." There also appear to be both time variation in default probabilities and cross-sectional variation across issuers within a given rating. For example, Altman and Kao (1992) showed the existence of ratings drift for firms that recently had a change in rating, and more recently Hamilton and Cantor (2004) found that the transition probabilities

[1] For an econometrician, these terms have quite precise meanings: a structural model specifies how each endogenous variable in the model is functionally related to the other endogenous variables and the exogenous variables. In the reduced form of the model, the structural equations are solved to express each endogenous variable only as a function of exogenous variables. However, credit researchers use these terms with less precision. Default and other credit events are assumed to be produced by underlying structural relationships that are too complex to be modeled explicitly. A reduced form credit model simply specifies the exogenous variables that are felt to be important without attempting to connect them explicitly to an underlying structure.

out of a rating class vary, depending on whether the bond entered its current rating by an upgrade or a downgrade. Christensen, et al (2004) modeled downward drift by introducing a hidden Markov chain. Other kinds of non-Markovian behavior were described by Lando and Skodeberg (2002) who found, for example, that the probability of a rating change diminishes the longer the bond stays in the same rating, by McDonald and Van de Gucht (1999) whose results suggested a nonmonotonic aging effect, and by Frydman and Schuermann **(**2008**)** who showed that a mixture of Markov chains statistically dominates a single Markov chain model.

Results reported by Hamilton, et al (2003), Hamilton and Cantor (2004) and Fledelius, et al **(**2004) indicate that within-class hazard rates for default and for ratings transitions vary considerably over time. These properties of credit risk exposure suggest that it may depend on macroeconomic factors. In particular, Bangia et al (2002) and Nickel, et al (2000) showed that upgrade, downgrade and default intensities differ over different economic regimes. Other studies that indicate sensitivity of default probability to macroeconomic factors include Kavvathas (2001), Carling et al (2002), Couderc and Renault (2004) and Duffie et al (2005). Huang and Kong (2003) demonstrated a connection between macroeconomic factors and credit risk by analyzing the impact of macroeconomic announcements on credit spreads.

In this paper, we formulate and estimate models for the occurrence of credit events, allowing the hazard rate for a given issuer to be a function of both firm-specific factors and macroeconomic conditions. The firm-specific factors we consider are all related to a firm's credit rating history. Keeping to the spirit of the reduced-form specification, we do not attempt to include factors tied to a firm's capital structure or stock returns, such as KMV's "distance to default," even though they have been shown to have considerable explanatory power in structural default models.[2]

Default is the most important change in credit quality, but hardly the only one that matters to investors. Indeed, the market will react to any change in perceived creditworthiness and yield spreads for the affected bonds will adjust to the new information. Moody's publishes tables of historical transition frequencies among the ratings categories and previous research on credit risk has attempted to estimate the full transition matrix for ratings changes.[3] We prefer to

[2] See Duffie, et al (2005) for example.
[3] See Hamilton, et al (2006), for an example of a historical ratings transition matrix. Nickell, Perraudin and Varotto (2000) explore the impact of overall "business cycle" conditions, along with the issuer's industry and country of domicile, on transition probabilities among ratings classes.

concentrate on the most important transitions rather than attempting to model the fine structure of the credit market.[4] We therefore focus on a few especially important credit events: transition from solvency into default, transition from investment grade (Moody's Baa and above) down to speculative grade (Ba or below), and the reverse (upgrade from speculative to investment grade).[5]

To estimate the hazard functions, we use the Cox regression model, a well-known and powerful technique in survival analysis.[6] This semi-parametric model accommodates both time-fixed and time-varying explanatory variables, called "covariates" in survival analysis. The focus on incorporating macroeconomic factors into hazard functions for credit events is a key distinguishing feature of our work. Use of a broad range of macro factors in the Cox hazard model has not been extensively explored before. Duffie, Saita, and Wang (2005) model the term structure of credit risk as depending on a small number of such factors.[7] Their focus, however, is on building a forecasting model for credit risk that incorporates the time-series properties of the macro factors. By contrast, we are interested in establishing "stylized facts" about which macro covariates are most important, and the nature of their impact on credit risk, including allowance for lagged effects. We do not attempt to predict the future values or the dynamics of those factors, which would require building forecasting models for them.

It seems intuitively obvious that macroeconomic conditions should affect credit risk. This is true both in absolute terms and also relative to the degree of credit risk implied by a bond rating. The latter fact is due to the rating agencies' practice of "rating through the cycle," i.e., assigning credit ratings based on each firm's creditworthiness relative to others in its cohort, and not adjusting the ratings when overall credit risk varies over the business cycle. But different

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[4] Jarrow, Lando and Turnbull (1997) modeled the ratings transition matrix, but faced the problem that many of the cells that involved transitions from a high rating to default or, in general, to a much different rating had no entries in their data. Yet one does not want to model such transitions as being impossible. Jarrow, Lando and Turnbull proposed a kind of "tweak" to deal with this problem; Kijima and Komoribayashi (1998) offered a more elegant solution. We minimize the problem by using broad ratings categories and eliminating from consideration transitions with too few occurrences.

[5] In an earlier version of this paper, we also broke down the speculative B and C grades and looked at their transitions separately. However, this did not provide much additional insight, beyond the observation that transitions for firms in the C categories tend to be more idiosyncratic and less obviously affected by macroeconomic factors than transitions for higher rated firms.

[6] Shumway (2001) demonstrates the statistical superiority of hazard models over static models that do not take into account the fact that a firm is exposed to the risk of a credit event over multiple periods.

[7] Their final specification includes the trailing one-year return on the S&P 500 index and the 3-month Treasury bill rate, along with distance to default and the firm's own stock return. They report that they explored a number of other macro covariates, but did not incorporate them in their final model.

researchers have obtained quite different results, depending on which macro variables were explored, how those variables entered the specifications (as contemporaneous values, with lags, or averaged over time), what other variables were included in the specification, and what time period was examined. Our comprehensive analysis sheds considerable light on these diverse results.

One defining property of a relevant macro factor is that it has a broad impact on the economy. Another is that one may expect most or all firms' creditworthiness to be affected by it. For example, an obvious candidate is the strength of the overall economy. But what is the best measure? Is it a high rate of GDP growth?; a low unemployment rate?; growth in industrial production?; high capacity utilization?; strength in a composite variable such as the Chicago Federal Reserve's National Activity Index?; the NBER's indicator of recession and expansion? Rather than trying to select one or a few of these possibilities a priori, we begin by specifying three broad classes of variables related to the overall level of economic activity (e.g., the unemployment rate, the rate of inflation, and the NBER recession indicator), the direction in which the economy is moving (e.g., the growth rates of GDP and industrial production) , and conditions in the financial markets (e.g., interest rates and stock market returns).

To look at how the estimated influence of each macro variable is affected by other variables included in the model, we examine four specifications. We first run each individual variable by itself, which indicates what the simplest possible specification, such as a simple correlation between the variable and a measure of credit risk, would show. Next, it is included as the single macro variable in a specification with the full set of firm-specific ratings-related covariates. In many cases, this produces a sharp change in the variable's significance level and even in the direction of its estimated effect. We then run the full set of firm-specific and macro covariates together in a single comprehensive specification. By including multiple variables in each broad class, these runs indicate which of the variables seem to have the strongest influence. But, clearly, multicollinearity among them tends to hold down significance levels. Finally, we employ a backward selection procedure that eliminates variables one at a time, leaving a substantially reduced specification with only statistically significant variables.

Our results show that, while adding macroeconomic factors to a specification with rating-related variables provides a highly significant increase in explanatory power, it is not easy to identify a small number of specific variables that dominate the field of alternative measures.

Moreover, in examining the stability of the estimated relationships over time, we find sizeable differences between the first half and the second half of our sample.

In short, our results show clearly how earlier studies might arrive at quite different conclusions based on fitting similar models with somewhat different specifications and sample periods. They call into question any strong conclusions that might be drawn from such research about the importance of any single macro variable among a set of related ones.

The ratings-based firm-specific factors we consider include the firm's current rating, its initial rating class, whether it entered its current rating by upgrade or by downgrade, and the length of time since the firm was first rated. By contrast with the results for macro variables, we find that the ratings-related variables perform consistently as expected, with higher ratings corresponding to significantly lower credit risk, and the ageing and ratings drift effects strongly confirmed. Interestingly, while the coefficients on specific macro variables vary widely depending on which other variables are included in a specification, the estimated effects of the ratings-related factors are largely unchanged by the addition of macroeconomic variables to the model.

In the next section, we describe the Cox hazards model that will be used throughout the paper. Sections III, IV and V describe, respectively, the ratings data from Moody's that is used to define the credit events we model, the ratings-based firm specific covariates, and the macroeconomic covariates used as explanatory variables. Sections VI, VII, and VIII present estimation results for defaults, downgrades from investment to speculative ratings classes, and upgrades from speculative to investment grade, respectively. In Section IX, we break the sample period in half to explore the stability of the estimated statistical relationships. Section X summarizes our results.

## II. The Cox Hazards Model

Ratings migrations can be treated like survival data if we consider the time an issuer spends in a rating class as a survival time. Our analysis, however, goes further and explores how the risk of a credit event, such as being upgraded or downgraded from a current rating class, depends on external (macroeconomic) and internal (firm-specific) factors, using the Cox(1972) hazard regression model as a statistical tool. This model has been very popular in the analysis of survival data in medicine and is becoming increasingly popular in finance. See, for example,

Buehler (2005), Henebry (1997), or Lane, et al (1986). In this section, we present a brief overview of the Cox model in the competing risks framework, which is a natural framework for our data. For a more extensive discussion see, e.g., Kalbfleisch and Prentice (2002) or Cox and Oakes (1984).

Let T be the time of exit of an issuer from its current rating class, measured from when it entered that class. This exit constitutes a credit event. It is important to keep in mind that, in our context, the time index t in $\lambda_j(t; Z(t))$ refers to the length of time since entering the current state, not calendar time. The fundamental object of analysis is a "spell," which is a time period that a given issuer remains continuously in a particular rating class. In our study, a "rating class" may refer to a single credit rating like Baa, but more frequently it will be an aggregated set of individual ratings, such as "all speculative grades." Exit from a rating class may occur due to a number of causes. For example, if the current rating is C, the cause of the exit could be upgrade, default or any non-credit reason for leaving the sample. We differentiate between exits due to credit events and to non-credit events.

To study how the risks of different types of credit events depend on covariates, we estimate the cause-specific hazard function for each type. For an event of type j out of J possibilities, this is the limiting conditional probability of occurrence given that there has been no event of any type prior to time t, and given a vector of time-dependent covariates Z(t):

$$\lambda_j(t; Z(t)) = \lim_{h \to 0} h^{-1} P(t \le T < t + h, J = j \mid t \le T, Z(t)), \quad j \in J \qquad (1)$$

To put it differently $\lambda_j(t;Z(t))$ represents the instantaneous hazard rate of a type j credit event occurring at time t given Z(t).

The Cox hazards regression model specifies $\lambda_j(t;Z(t))$ to be of the form:

$$\lambda_j(t; Z(t)) = \lambda_{0j}(t) \exp[\, \beta_j' Z(t) \,], \quad j \in J \qquad (2)$$

where $\beta_j$ is a column vector of regression coefficients, and $\lambda_{0j}(t)$ is an unspecified "baseline" function for spells of duration t. The Cox model is semiparametric: it consists of a nonparametric part, namely the baseline function $\lambda_{0j}(t)$, and the parametric part, $\exp[\beta_j'Z(t)]$. We note that each cause-specific hazard function has its own baseline function and its own vector of regression coefficients.

An important aspect of the Cox model is that, at any time t, the ratio of the hazard rates of a type j credit event for two different issuers does not involve the baseline hazard function.

Consequently, if the covariates are all time-independent, the ratio of hazard rates stays constant over time. For this reason, the Cox regression model is often referred to as the proportional hazards model. However, our covariates are time-dependent, so the ratio of hazard rates does change with t.

The parameter $\exp(\beta_j^p)$, $1 \le p \le P$, represents a relative change in the hazard rate resulting from a one unit increase in the value of the p'th covariate, holding all other covariates constant:

$$\exp(\beta_j^p) = \frac{\exp[\beta_j^p (Z^p + 1)]}{\exp[\beta_j^p Z^p]} \qquad (3)$$

We now discuss estimation of the parameters $\beta_j$, $j \in J$ in model (2). It can be shown that each cause-specific hazard function can be estimated separately using the so-called partial likelihood approach. The data used to estimate the parameters in $\lambda_j(t;Z(t))$ consist of all spells in a given rating class. Suppose that in the sample, $T_1 < T_2 < ... < T_N$ are distinct lengths of spells that ended with a type j credit event. If there are no simultaneous credit events, each $T_n$ will correspond to a single firm's credit event. Let $R_n$ denote the risk set at time $T_n$, that is, the set of issuers that experienced spells of at least length $T_n$ in the same credit class and were therefore at risk for credit event j just before $T_n$, $1 \le n < N$. The information needed to estimate $\lambda_j(t;Z(t))$ consists of the covariates for each firm in each set $R_n$ , that is, $\{Z_i(T_n), i \in R_n)$, $1 \le n < N\}$.

A spell in a given rating may end due to the occurrence of a credit event or a non-credit event, or because the end of the sample period is reached. In estimating $\lambda_j(t;Z(t))$, spells that end for any reason other than a type j credit event are treated as right-censored. A spell that is censored at time t will contribute to the risk sets for $T_n < t$ and will be excluded if $T_n \ge t$ .

The partial likelihood function for estimation of parameter $\beta_j$ is

$$L(\beta_j) = \prod_{n=1}^{N} \frac{\exp[\beta_j' Z_n(T_n)]}{\sum_{i \in R_n} \exp[\beta_j' Z_i(T_n)]} \qquad (4)$$

where n is the label of the issuer who experiences a type j event at time $T_n$. Issuers who do not experience a type j event contribute to the likelihood function through their presence in the risk sets $R_n$.

The n'th factor in the partial likelihood function

$$\frac{\exp[\beta_j' Z_n(T_n)]}{\sum_{i \in R_n} \exp[\beta_j' Z_i(T_n)]} \tag{5}$$

is the conditional probability that an issuer with covariates $Z_n(T_n)$ experiences a type j event at time $T_n$ given all issuers in $R_n$ and that exactly one issuer experiences the event at $T_n$.

Although in theory no more than one event can occur at a single instant, reporting of credit events in the real world is on a daily basis, which can lead to cases of ties, in which several firms experience an event with the same value of $T_n$. This happened in a small number of cases, requiring a modification of the algorithm, as described in footnote 8.[8]

The maximum likelihood estimator, $\hat{\beta}_j$ of $\beta_j$ is given by the value that maximizes $L(\beta_j)$. Under usual conditions $\hat{\beta}_j$ is asymptotically normally distributed with a covariance matrix that can be consistently estimated using the usual matrix of second derivatives of log $L(\beta_j)$. Inferences about inclusion or exclusion of the covariates can be based on standard likelihood ratio tests.

The essential feature of the partial likelihood method, first proposed by Cox(1972), is that it allows estimation of parameter $\beta_j$ in the hazard function without knowledge of the baseline function. If it is needed, the baseline hazard function can be estimated subsequently in a nonparametric fashion. Since the focus of our analysis is on the estimation of relative risk faced by the issuers we have used partial likelihood estimation for $\beta_j$. For discussion of estimation methods for $\lambda_{0j}(t)$ we refer the reader to the aforementioned references.

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[8] Suppose there are $d_n \geq 1$ events observed at time $T_n$. Let $D_n$ be the set of firms that experience an event. Let q denote any subset of $d_n$ firms drawn from the risk set $R_n$ and $Q_n$ be the collection of all of these subsets. The generalized version of the likelihood function (4) that incorporates ties can be written as

$$L(\beta_j) = \prod_{n=1}^{N} \frac{\exp[\beta_j' \sum_{k \in D_n} Z_k(T_n)]}{\sum_{q \in Q_n} \exp[\beta_j' \sum_{k \in q} Z_k(T_n)]}$$

For more details on the handling of ties, see SAS Online Doc 9.1.2, or Gail, et al (1981)

## III. Credit Ratings Data

Data on the history of credit events is drawn from Moody's Default Research Database, which contains information on over 11,000 issuers and more than 350,000 individual securities. The earliest data in the database come from the 1920s, but in view of the broad changes that have transformed the financial markets over the last 50 years, as well as the need to match credit data with other kinds of data with shorter available history, we limited our initial explorations to the period 1970 - 2002. The sample period we finally chose to investigate in depth is from 1981 - 2002. Table 1 provides short definitions for Moody's ratings. The rating classes Aaa, Aa, A and Baa are considered "investment grade" and the lower ratings are known as "speculative" or "junk" bond ratings. In 1992, Moody's added further subdivisions to the scale to indicate bonds that are relatively stronger or weaker than the average for their rating class (e.g., Baa1, Baa3), and subsequently, also a "Watchlist" covering bonds that Moody's believes may be close to a rating change, but one is not warranted yet. Although these finer gradations do contain information, we have not tried to make use of them in this study.[9] One reason is that that would substantially restrict the length of the historical sample we could cover.

Table 1 indicates that some firms rated in the C-categories have already defaulted. In case of a default, we use the date of default as recorded in the Moody's database as marking a transition from the previous ratings class into the default state. Thus, in our sample we only treat firms that have not defaulted as being members of ratings classes C, Ca, and Caa.

Moreover, when a firm's credit quality is degenerating, it is not uncommon for it to be downgraded in quick steps through more than one rating class. For example, a firm might be downgraded from B to Ca and then fall into default a few days later. We feel that in such a case it is more appropriate to consider this as a transition from B to default, ignoring the very short period it was in the Ca category. Therefore, any rating prior to default that lasted less than half a month (14 days) has been eliminated and the duration of the spell in the previous rating extended to include the very short time spent in the transitional rating.

An issuer's rating history may consist of spells in different credit classes. A spell may be complete or it may be right-censored. For example, in modeling the hazard rate of default from a speculative B or C rating, spells that end in default are complete and all other spells are

[9] See Hamilton and Cantor (2004).

considered to be right-censored for the purpose of estimating the default hazard rate. There are thus three ways in which a spell in a speculative grade may be right-censored: if the issuer is still in a speculative rating class at the end of the sample period, if the spell ends because the issuer's rating has been withdrawn (hereafter referred to as a transition into the WR category), or if it ends with an upgrade to investment grade (which is treated as right-censored in the partial likelihood approach, as described in Section II). The WR contingency may happen for several reasons, including a merger or extinction of all of a firm's rated debt through full repayment or defeasance. Completed spells contribute both to the numerator and denominator of the partial likelihood function in (4), while right-censored spells contribute only to the denominator.

Firms present at the start of the sample period begin with their current spells already under way. Such spells are called left-truncated. But since we know when left truncated spells entered their current rating class we can include them in the estimation, thus increasing estimation efficiency.

Table 2 summarizes the transitions we examine. Rather than attempting to model the fine structure of transitions among ratings classes and sub-classes, we consider only major transitions: from speculative grade to default, from investment grade down to speculative grade and from speculative grade up to investment grade.

Of 3422 spells for investment grade firms (Moody's Aaa, Aa, A, and Baa ratings), 1684 ended with no transition out of investment grade and 944 ended as WR, with their rating withdrawn. A downgrade from the investment class to a speculative rating occurred in 788 spells, of which nearly all were to a rating of Ba or B. In 5 cases, the transition was from an investment grade to a Caa, Ca, or C rating, and 6 investment grade firms ended in a direct transition into default. We do not attempt to model these latter two rare events.

Most important are the transitions into default, which overwhelmingly occurred from a speculative grade rating. There were 4327 spells in a speculative grade, of which 645 ended with an upgrade to investment grade, 1125 remained in a speculative grade at the end of the sample (912 in Ba or B and 213 in one of the C ratings), 1655 ended in WR, and 902 ended in default. We model the transitions for this combined sample of 902 firms that defaulted from any

Speculative grade. The last two lines in Table 2 show the breakdown of transitions from the B and C classes separately.[10]

Upgrades to investment grade were almost exclusively from the Ba and B ratings. Therefore, to measure significant improvements in credit quality, we consider the 641 ratings upgrades from Ba and B to investment grade.

## IV Firm-Specific Covariates

The list of potential factors that may have explanatory power for credit events is very long. In this study we consider two broad categories: factors derived from a firm's rating history and macroeconomic factors. We first discuss the four types of ratings-related firm-specific covariates:

Initial rating class. It is well known that "fallen angels" (firms that began as investment grade and were subsequently downgraded into junk status) tend to behave differently from firms that were initially rated as speculative grade.[11] We use two dummy variables to explore this effect, "Initial rating: Investment grade" and "Initial rating: C, Ca, Caa," with the former set to 1 for a firm that was initially investment grade, and the latter set to 1 for a firm that was initially rated in one of the C categories.

Current rating class A firm's current bond rating is the single most widely used measure of its credit quality. We form dummy variables and name them in the obvious way. For example, "Current rating: Ba" is set to 1 if the firm is currently rated Ba, and 0 otherwise.

Recent upgrade or downgrade Changes in credit quality show positive serial correlation, with a bond that has been recently downgraded being more likely to experience a further downgrade than one whose rating has not recently changed.[12] To capture this phenomenon, we constructed dummy variables for recent upgrades and downgrades. Some exploration with different specifications showed that the sizes and signs of the estimated coefficients on these dummies were quite variable and rarely significant for events more than 2 years old. In the specifications we report on here, we use 0,1 dummies to indicate an up- or downgrade within the last 2 years.

[10] Notice that the total number of transitions from the B and C categories exceeds the total from Any speculative grade, because of the different definitions of what constitutes a spell. For example, a transition from Caa to B is counted as a completed spell in line 4, but not in line 2, since both ratings are in the speculative category.
[11] See Mann, et al (2003).
[12] See Christensen, et al (2004).

Years since first rated It has been observed that newly rated firms are less likely to change rating within a given year than are more seasoned firms in the same ratings class.[13] For instance, it would be quite unlikely for a firm to default on a bond prior to its first scheduled coupon payment. To capture this, we use the length of time the firm has been rated as a firm-specific covariate. We do not necessarily expect the effect to be directly proportional to the number of years the firm has been rated, so this variable is entered in log form.

## V. Macroeconomic Covariates

We selected a total of 17 macroeconomic covariates, which we grouped into three categories: those related to the overall health of the macroeconomy ("General Macroeconomic Conditions"), those measuring whether economic conditions are improving or worsening ("Direction of the Economy"), and those that reflect current conditions in the financial markets ("Financial Market Conditions"). Some of the variables are obvious and unambiguous choices, like the unemployment rate. But in other cases, it was clear what we wanted to measure but not what variable would do so best: Which interest rate should we use? What is the most relevant indicator of whether economic conditions are getting better or worse?

We have tried to include variables that are obvious choices or have been explored in earlier research, including unemployment rate, inflation, and GDP growth, in part because our results will help shed light on the evidence from other studies. In addition to the obvious candidates, we examined a broad selection of macro variables that in some cases were highly correlated with one another, which led to some multicollinearity problems. We experimented with principal components as a way to extract a single common factor from a set of related variables, such as the three we use to indicate the direction of the economy, but the results were not especially illuminating, so we do not report on them here. As will be described in greater detail below, we ended up eliminating four of the most highly correlated covariates from the multivariate specifications, although we do report results for them in the univariate analyses. (Note that the terms univariate and multivariate here refer to specifications that include, respectively, just one, or multiple, macroeconomic covariates.) In the end, we report estimation results with firm-specific covariates and a set of 13 macro variables, and then obtain more

[13] See Altman (1998), for example.

parsimonious specifications using a backward selection procedure to eliminate those that were not statistically significant. [14]

General Macroeconomic Conditions

Casual reflection, with or without casual empiricism for support, suggests that a variety of broad economic conditions might influence corporate credit risk. We therefore tested several key economic indicators. Table 3 lists the variables used in the models and provides statistics on their means and standard deviations, as well as the sources.

Unemployment rate The unemployment rate is one of the most visible indicators of overall health of the macroeconomy. We examined both the level and the change in the seasonally adjusted monthly Civilian Unemployment Rate, constructed by the US Bureau of Labor Statistics. The change in unemployment, however, was ultimately dropped from the multivariate specification.

Inflation Inflation is widely understood to be an important economic variable, although in this case, it is unclear exactly what its effect should be. The common perception that inflation is bad for the economy might suggest that high inflation should increase default risk. But, from the perspective of a firm whose outstanding debt is in nominal dollars, inflation reduces the real value of its required debt service payments, which might make it less likely to default. We therefore include the monthly percentage change in the seasonally adjusted Consumer Price Index, with no prior expectation of the sign of its coefficient.

NBER recession indicator The National Bureau of Economic Research follows the evolution of the macroeconomy and designates periods of recession and expansion. The dates of a recession are from the most recent peak of economic activity to the trough of the economic contraction. Roughly speaking, a recession will be declared to be in progress if real GDP falls for two consecutive quarters, but the formal classification is made by the NBER's Business Cycle Dating Committee, which takes a number of relevant factors into consideration.[15] Our NBER recession indicator dummy variable is set to 1 for recession periods.

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[14] In addition to the macroeconomic variables described below, we investigated measures of the availability of cash to the corporate sector (e.g., the growth rate of corporate profits). However, the available proxy variables were not very closely connected to the factor we actually wanted (how easy or hard it was for a firm facing insolvency to raise new capital rather than being forced into bankruptcy), and they turned out to have very little explanatory power, so they were dropped from the analysis.

[15] A more complete discussion of the NBER's recession dating procedures is available on the NBER website, at URL: http://www.nber.org/cycles/recessions.html.

Chicago Fed National Activity Index (CFNAI) The large number of available series relating to the macroeconomy makes it very difficult to select the most important ones. To try to capture overall economic conditions in a single variable, the Chicago Federal Reserve publishes the CFNAI, a composite series that summarizes the behavior of 85 economic series in four broad categories: production and income; employment, unemployment and hours; personal consumption and housing; and sales, orders and inventories. The CFNAI is reported monthly in the form of a 3-month moving average.[16]

Capacity utilization One measure of demand conditions facing the corporate sector is how close current production is to maximum capacity. The Federal Reserve Statistical Release G17 shows monthly capacity utilization rates in percent, with 100 being maximum capacity.[17]

Real GDP actual minus potential The St. Louis Federal Reserve produces a series that estimates the potential real gross domestic product for the US. Real GDP was obtained from the U.S. Department of Commerce: Bureau of Economic Analysis. As this variable is defined in the estimation, it is negative on average, but an (algebraically) higher value corresponds to stronger economic conditions.

Industrial production actual minus trend Another way to estimate the current strength or weakness of the overall economy is to compare current economic output to its long-term trend. We therefore constructed a deviation from trend variable based on industrial production. The industrial production figures were downloaded from the same Federal Reserve website as capacity utilization. For each date t, we fitted a simple exponential growth equation to the series, ending 18 months before t and beginning 20 years earlier than that. The 18-month lag was chosen to be consistent with the way we handle lags in our specifications, as will be described in detail below. The choice of a 20-year moving window was arbitrary. The fitted equation was used to project industrial production forward to date t, and the variable used in the model is actual date t industrial production minus the trend value. Again, with this definition, a higher value corresponds to a stronger economy.

[16] Full detail on the components and construction of the CFNAI is available online at URL: http://www.chicagofed.org/economic_research_and_data/cfnai.cfm.

[17] The data were downloaded from the Federal Reserve website (URL: http://www.federalreserve.gov/releases/g17/).

## The Direction of the Economy

Credit research often looks at economic strength in terms of the change in GDP or some similar measure of economic activity. This seems quite sensible: if the economy is growing rapidly, it is clearly in better health than if it is stagnant or shrinking. Yet, the time when the economy is able to grow the fastest is when there is a lot of slack. An economy with idle resources that can quickly be put back into production is capable of growing much faster than one at full employment. In other words, the most rapid GDP growth will tend to occur not when the economy is really strong, but when it is at the bottom of a recession and just beginning to turn around. From this perspective, it is less obvious that rapid growth in GDP should necessarily be associated with reduced default risk. We explore this issue with several measures of economic growth.

Real GDP growth The GDP figures were obtained from the St. Louis Fed, as mentioned above. Like many macro series, Real GDP is only available quarterly. As with all of the quarterly data, we created monthly series of real GDP growth rates simply by repeating the quarterly value for each month in the quarter. Note that the variable that enters the estimation is constructed from the monthly series as an 18-month distributed lag, as will be described in more detail below. This smoothes out what would otherwise be an undesirable pattern, with the month to month changes in these constructed monthly series being 0 for two months out of three followed by a large jump to the next quarterly level.

Growth of industrial production Real GDP comprises all economic activity, including government, noncorporate business, and other sectors which may be unrelated to credit conditions in the corporate sector. We therefore include the growth rate of industrial production as a possibly better targeted measure.

Change in unemployment This is the first difference in the monthly unemployment rate.

## Financial Market Conditions

We would like to measure how easy or difficult it is for firms to raise capital, especially firms that have non-negligible exposure to default risk. The overall level of interest rates is clearly a relevant variable. Conditions in the stock market should also be considered, and so should conditions in the credit markets.

Interest rates (3-month T- bill rate and 10-year Treasury yield) Other things equal, one might expect that high interest rates would also correspond to general tightness in the economy and increased difficulty in raising cash to make debt service payments.[18] As others have done, we used the 3-month Treasury bill rate as a measure of the tightness of the money market.[19] But corporate bonds have much longer maturities than this, so as a measure of the overall level of interest rates at a relevant maturity, we also included the US Treasury Constant Maturity 10-year Rate.

Stock market performance (S&P 500 return , S&P 500 volatility , Russell 2000 return) The performance of the stock market is an indicator of the general health of the corporate sector. Moreover, in a structural default risk model, the behavior of a firm's equity is a direct measure of default risk exposure. We include both the monthly return on the Standard and Poor's 500 stock index and its volatility as covariates. Volatility is estimated month by month as the annualized standard deviation of daily returns within the month. While the S&P index is commonly regarded as the best overall measure of stock market performance, it contains only the largest, and generally the most creditworthy, firms. To examine stock market performance of smaller firms, we also include the monthly return on the Russell 2000 index.[20]

Corporate credit spreads Ideally, we would like to use the corporate credit spread on high-yield bonds as an explanatory variable. However, due to the very thin markets for such bonds prior to the late 1980s, data series do not go back far enough to be useful in this exercise. We therefore have included the closest available match, which is the spread between corporate Baa yields and constant maturity 10 year Treasuries.[21]

Overall default rate for corporate bonds This series is constructed by Moody's. It measures the percent of all rated US corporations defaulting in the previous 12-month period. This variable should capture "contagion" in defaults, if indeed contagion exists, as well as the overall effect of other broad economic factors that we have not included specifically in the models.

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[18] Duffie, et al (2005), found that higher short term interest rates corresponded to lower overall credit quality.

[19] Previous studies that examined the influence of short term interest rates on default include Duffie, Saita and Wang(2005), and Keenan, et al (1999) who included the spread between the 10 year Treasury yield and 3 month T-bills.

[20] The Russell indexes include the Russell 3000, a market capitalization-weighted index of the largest 3000 US firms. The Russell 2000 is a cap-weighted index made up of firms 1001-3000 of the Russell 3000. Further detail is available from the Russell Investment Group, at URL: http://www.russell.com/indexes/.

[21] The corporate series was Moody's Baa Corporate Bond Yield series, as reported by the Federal Reserve in its H.15 Release, and downloaded from the St. Louis Fed website.

## Lags

Empirical default studies often introduce macroeconomic factors into models simply as contemporaneous variables. But to the extent that the macro factors are measuring aspects of the overall financial health of the corporate sector, it is not plausible that they would have an instantaneous effect on defaults. Rather, one expects that things like high interest rates or slow growth in the economy would lead, cumulatively, to a gradual increase in credit risk. We considered it quite important to allow lagged values of our macro covariates to enter the specification. But with a large number of individual series, adding lagged values into the specification without constraints would have led to far too many coefficients to fit. Instead, we impose a very basic lag structure on the data, such that each variable is a weighted average over a fixed window, with exponentially declining weights.

Let $\{x_t ; t = 1,...,T\}$ be the raw monthly data series for a given variable. $X_t$ represents the value used in the model for the x series in month t. $X_t$ is given by

$$X_t = \frac{\sum_{k=1}^{K} \delta^{k-1} \, x_{t-k}}{\sum_{k=1}^{K} \delta^{k-1}} \qquad (6)$$

where K is the length of the lag window and $\delta$ is the decay factor. This specification uses data up to the previous month. There is no a priori best choice for these parameters. We chose K = 18 months and $\delta = 0.88$, which amounts to a fairly rapid rate of decay in a medium-sized window. The weight on the current month's data is about 9 times as large as on the oldest data point in the average and the mean lag is 8.33 months. To gauge the effect of our assumptions, we explored lag windows of 12 and 24 months, and decay factors from 0.8 to 1.0 (no decay). The results were not especially sensitive to these choices, over a wide range of values. We settled on 18 months and 0.88 because they were in the middle of the range of values that we considered most plausible, and they seemed to produce reasonably good results in terms of statistical fit and robustness to small changes in the estimation sample. With an infinite lag length ($K = \infty$), at this decay rate, observations in the most recent 18 months would receive 90% of the total weight.

## Correlations

Before we move on to the presentation of estimation results, it is worthwhile to look at the correlations among our macro covariates, shown in Table 4. This will make clear why we found it necessary to eliminate several variables that were highly correlated with others, and also where we may anticipate possible effects of multicollinearity among the variables that have been retained.

Most of the correlations are quite moderate, with high values where they are to be expected. For example, the two interest rate variables (the 3-month T-Bill rate and the 10-year Treasury yield) have a correlation of 0.924 and the two stock market return variables (the S&P 500 return and the Russell 2000 return) have correlation of 0.749. But we also see that the variables Real GDP actual minus potential and Industrial production actual minus trend are highly correlated with each other and each is very highly negatively correlated with unemployment (highlighted by the box in column 1), as well as with some other variables. In the estimations, coefficients on these two variables often were significant but with opposite signs. We therefore show estimation results for them in the univariate analyses but drop them from the multivariate specifications. Capacity utilization was treated the same way: Although its highest correlations were with the two variables just mentioned, in fact Capacity utilization was rarely significant in any of the multivariate specifications, but its presence seemed to contribute to anomalous coefficients on other covariates.

The box in the third column indicates high correlation between the CFNAI and the three "Direction of the Economy" variables. Those variables are also highly correlated with each other, as indicated in the third box. Both Real GDP growth and the Growth of industrial production have been found to be important in earlier research, so we felt they should be kept in the specification, if possible, while the change in unemployment proved to be badly behaved in the multivariate specifications, so it was eliminated from those models. We kept the CFNAI, but the high correlation between it and the two remaining Direction of the Economy variables quite probably led to a certain degree of instability in its coefficient estimates. In the end, four variables were eliminated from the All Variables specifications: Capacity utilization, Deviation from Potential GDP, Industrial production actual minus trend, and the Change in unemployment.

## VI. Transitions into Default

The most important credit-related transition is from solvency into default. This section will focus on the effects of firm-specific and macroeconomic factors on transitions from a speculative grade into default.

### Individual Macro Factors

We first consider each macro factor individually, by estimating its impact on the hazard rate as a single covariate in a Cox specification, and also its marginal effect when added to a specification that includes the firm-specific factors. This will give some idea of each macro variable's potential importance and the direction of its effect. Multicollinearity is not a problem here because the macro variables enter these estimations one at a time, so we report estimation results for all of the variables, including those that will be excluded from the more comprehensive specifications. One reason to look at such simple and incomplete specifications is that they indicate what other researchers are likely to find in an exploratory investigation of how default is influenced by any one of these variables. The coefficient estimates for the firm-specific factors themselves will be presented below, in Table 6.

The left two columns of Table 5 show the univariate estimation results for default out of any speculative ratings class. The right side of the table reports coefficient estimates and p-values for each individual variable in a specification that includes a full set of ratings-based factors.

In the univariate estimations all of the variables measuring general macroeconomic conditions except inflation have highly significant p-values, but since a positive (negative) coefficient means that an increase in the covariate raises (reduces) the default hazard rate, only three coefficients have the expected signs. Unemployment has an anomalous negative coefficient (higher unemployment appears to reduce default intensity) in the univariate estimations, but the marginal contribution when it is combined with firm-specific variables is significantly positive. We did not have a prior expectation for the coefficient on inflation, which is tiny and insignificant on its own, but is significant and positive with firm-specific variables. In both specifications, being in a recession is strongly associated with an increased default hazard and a strong economy as measured by the CFNAI lowers default risk. A high rate of capacity utilization looks promising on its own, but it becomes insignificant, with the wrong sign, when firm-specific covariates are included. The two measures of economic output relative to potential

or relative to trend had anomalous positive signs in the univariate estimations, but they turn negative with firm-specific variables and the industrial production variable becomes significant.

For the Direction of the Economy variables, we find that rapid GDP growth is associated with a highly significant reduction in the default rate. The percentage growth of industrial production performs equally well, and the change in the unemployment rate also shows a large effect, with rising unemployment increasing default risk.

The third set of covariates relate to conditions in the financial markets. In the univariate estimations, higher interest rates appear to be consistent with reduced default hazard, but only the 10 year Treasury rate is significant. With firm-specific covariates, both interest rate variables are positive and significant, suggesting that high rates tend to increase default risk.

For the stock market variables, our prior is that rising stock prices should reduce default risk, but greater volatility may increase it. The univariate results are strongly consistent with this expectation, but with firm-specific variables, only the S&P 500 return enters significantly, and with what appears to be the wrong sign. A strong market for small stocks, as measured by the Russell 2000 by itself, appears to reduce default hazard significantly, but the coefficient becomes insignificant in the broader specification.

Last are the two measures of credit market conditions: the yield on Baa-rated corporates less the 10-year Treasury yield and the recent aggregate default rate on corporate bonds. By itself, a wider yield spread is associated with a significant increase in the default rate, but this does not carry through to the estimations with firm-specific dummies, where the sign is reversed. A higher corporate bond default rate overall is strongly associated with increased hazard rates.

## Comprehensive Specifications for Default Intensity

The univariate results in Table 5 are useful because they give a first indication of the overall impact of each of the variables. Table 6 presents results from more comprehensive specifications for transitions from any speculative grade to default.

To set the baseline, the first two columns of Table 6 present estimation results with only firm-specific ratings-related covariates. There is some evidence that having started with an investment grade rating gives a firm a lower risk of default, although the coefficient is not quite significant at the 5% level with just firm-specific covariates. Beginning with a rating in one of the C grades is strongly associated with a lower default risk, other things equal.

The next four dummy variables relate to the issuer's current rating class. The baseline is the lowest relevant rating category, i.e., C. In every case, the bond rating performs correctly, with all of the coefficients negative and significant, and with a higher rating always corresponding to a lower estimated hazard rate.

The next two variables deal with whether the issuer has been recently upgraded or downgraded. A firm that is weakening in credit quality may pass through a succession of lower ratings before eventually defaulting, so a recent downgrade presages possible further deterioration.[22] By contrast, an issuer that has recently been upgraded is unlikely to have an immediate reversal of fortune into default. The significant coefficients on the recent downgrade and upgrade variables strongly support this reasoning. The log(years since first rated) variable measures the length of time that the firm has been rated by Moody's, the idea being that a firm is relatively less likely to collapse into default shortly after receiving its initial rating than is a more seasoned firm. The positive and significant coefficient bears this out.

Now let us consider the effects of each of the macro variables when it is included in a comprehensive specification with all of the others, a complete set of 9 ratings-related variables and 13 macro factors. The second set of columns in Table 6, labeled "All variables," shows these results. The first column gives the estimated coefficient on the variable in its natural units, that is, the effect on the hazard of increasing the value of the covariate by 1.0. This makes it difficult to compare the relative importance of the macro covariates, when they have different scales. A good example is the growth of industrial production, for which Table 3 shows that an increase of 1.0 would be more than 3 standard deviations, while for the 10-year Treasury yield, an increase of 1.0 would be less than half a standard deviation. To better gauge the effective relative importance of these variables, the second column, labeled "std coef" gives standardized coefficient values for the macroeconomic covariates, obtained by multiplying each raw coefficient by the variable's standard deviation from Table 3. Measuring the effect on the default hazard when the variable increases by one standard deviation lets us better compare the effects of changes that have roughly similar probability of occurrence. The third All variables column gives the coefficient's estimated p-value.

The "All variables" specification includes 22 variables, with few of the macro covariates being statistically significant. To pare this down to a parsimonious specification, we weeded out

[22] Recall that we have eliminated transitions through ratings that last less than 14 days.

the variables that do not contribute significantly to explanatory power of the model with an automatic "backward selection" procedure. Starting with all variables included, the one variable with the least significant p-value was eliminated from the specification and the model was refitted. This process was repeated until all remaining coefficients were significant at the 5% level or better. The three rightmost columns show those results.

One of the first things to note is that the estimated coefficients and the p-values for the Firm-specific factors change very little when all of the macro variables are added, and all survive the backward selection process with essentially the same values. This indicates that the relevant information contained in the macro factors is incremental to that which is captured by the ratings-related covariates alone. This comforting result holds generally across all of the specifications and all of the credit transitions we consider in the paper.

In contrast to the results from Table 5, none of the four General macro factors comes anywhere close to statistical significance here, once other macro covariates are included in the specification, and none of them survives the backward selection process to enter the final specification. The Growth of industrial production is the single variable related to broad macroeconomic factors which performs well. It is negative and highly significant in the final specification.

Turning to the variables related to conditions in the financial markets, we see that the short term interest rate does not appear to influence the default hazard, but the 10-year Treasury rate does. Its positive coefficient indicates that high rates increase default risk, and its relatively large standard deviation means that the influence of the interest rate is substantial.

The two stock market return variables are significant, and both survive the backward selection process, but S&P 500 volatility is insignificant and is eliminated. A weak market for Russell 2000 small stocks significantly raises the default hazard, but the return on the S&P 500 index has an anomalous positive sign: a strong market for large firms is associated with increased default risk. We will see this odd result again, when we look at the other transitions: A strong market for S&P 500 stocks appears consistently to be bad news for the credit market.

Finally, for the variables related to credit market conditions the yield spread between Baa corporates and 10 year Treasuries is estimated with an anomalous negative and significant coefficient when all 13 macro variables are in the model , but it is not retained in the backward selection model. By contrast, the overall corporate bond default rate has a highly statistically

significant positive coefficient, both when run with all of the macro variables and also in the backward selection model.

One of the major issues of concern with regard to credit risk is whether there is contagion in the credit market, such that default by one firm tends to precipitate defaults by others. Das, Duffie, Kapadia, and Saita (2005) present evidence that defaults do tend to cluster more than would be predicted by credit risk models, but they believe the effect may be more environmental in origin than due to contagion. They hypothesize that defaults cluster because unfavorable macroeconomic conditions affect many firms at the same time, rather than because bankruptcy by one firm infects other healthy but vulnerable firms and leads them to default. We do not attempt to examine this important issue in depth here, but because our models take account of a broad range of macroeconomic factors, we can say that the positive and significant coefficient on the Corporate bond default rate in the comprehensive specification is consistent with the existence of contagion in the credit market.

The last four lines in Table 6 provide measures of overall goodness of fit for the models. The first line shows -2 × log likelihood and the third line gives the values of the likelihood ratio test statistics and the p-values for testing the model with only firm specific variables against the All variables and backward selection models. The test statistic is obtained as the difference between the values of 2 x log-likelihood for a constrained model and for an unconstrained model that nests the first one, and it has a chi-squared distribution with degrees of freedom (df) equal to the number of constraints. The model with only firm specific variables is rejected in favor of the All variables model (test statistic=170.54, df=13, p-value=0) as well as in favor of the backward selection model (test statistic=161.55, p-value=0). In fact, the backward selection model with only 5 of the original 13 macro variables is statistically indistinguishable from the All variables model, as seen from the last line of Table 6 (test statistic=8.99, df=8, p-value=0.344).

The second line in Table 6 gives the Akaike Information Criterion (AIC), defined as

$$\text{AIC} = -2 \times \text{log-likelihood} + 2 \times \text{number of estimated coefficients}$$

The idea is that the log-likelihood measures the goodness of fit of the relationship, but this necessarily increases when more explanatory variables are added. The second term penalizes the specification for complexity. It is suggested that the model with the lowest AIC

should be selected, to optimize the tradeoff between increased explanatory power and overfitting. Here we see that the backward selection model achieves the best AIC value.

## VII. Downgrades from Investment to Speculative Grade

After default, probably the most important ratings transition is from investment grade (ratings Aaa, Aa, A, and Baa) down to speculative grade (Ba and below). A major reason for this is that many institutional investors will only hold investment grade bonds, either by covenant or by choice. A downgrade out of investment grade, as happened to General Motors and Ford in the spring of 2005, can cause considerable disruption in the market for that issuer's debt, as major investors divest the bonds from their portfolios.

In this section we estimate the effects of macroeconomic factors on this transition. An important difference from the previous section is that in modeling default, we are looking at events that are largely exogenous, whereas the other transitions we will examine represent decisions made by a credit rating agency. It is certainly possible that a given macroeconomic or firm-specific factor may have a different impact on the actual probability that a particular firm will default than on the future creditworthiness of that firm as perceived by a rating agency. Moreover, Moody's states explicitly that they do not try to make their ratings correspond one for one with absolute default probabilities as these fluctuate over time. Rather, they consider a bond's rating as a measure of its relative risk compared to other bonds in that ratings class.[23] That is, in bad economic times, expected default rates for all bonds may rise, but only bonds that change substantially more or less than the average bond with the same rating will be reclassified.

### Analysis of Individual Macro Factors

Like Table 5, Table 7 presents the results from univariate models with each of the macro variables as the single covariate, in the left two columns, and the marginal contribution of that variable in a specification with the full set of ratings-based firm-specific variables in the right-hand columns.

These results are quite striking, with every one of the variables being statistically significant at well under the 1% level, except for the unemployment rate in the univariate model ($p=0.084$) and no obviously anomalous signs. It is also noteworthy that the coefficient estimates are quite similar in size in the two different specifications.

[23] See Cantor and Mann (2003).

Both the NBER Recession indicator and the CFNAI come in with large coefficients, as do all three Direction of the Economy measures. The stock market variables appear to show that strong returns reduce the risk of downgrade, but volatility increases it. High risk premia in the bond market and a high overall default rate go along with higher probability of transitions from investment grade to speculative.

These results are interesting and quite consistent with our expectations, but because the macro variables are fairly highly correlated with one another, coefficient estimates change substantially when all macro variables are combined in a single model. Before discussing these results, we first analyze the model with only firm-specific factors.

Model with Firm-specific Factors Only

The leftmost columns in Table 8 present the estimates with only firm-specific factors. We see that if the issuer was originally rated investment grade, the hazard of being downgraded into a speculative rating category is significantly less than for a firm that started in a speculative grade.

The dummy variable "Current rating: Baa" is strong and highly significant, indicating a much greater chance of being downgraded from the lowest investment grade into "junk bond" status, than from a higher investment grade. This would be expected if Moody's were reluctant to downgrade a firm more than one (letter) rating at a time. For example, if the normal path for a Aa-rated firm that weakens substantially is to be downgraded first to A, then to Baa, and then eventually to a speculative grade rating, there will be many more downgrades to junk status from Baa than directly from higher grades. This will also lead to a kind of momentum or "ratings drift," such that a firm that has recently been downgraded into the Baa category is more likely to be downgraded again, than is a firm that has been Baa for several years. This reasoning is supported by the strong positive coefficient on "Downgraded within last 2 years," and the reverse logic for recent upgrades is also supported by the strong negative coefficient on "Upgraded within last 2 years." The last firm-specific covariate "log(years since first rated)" is not statistically significant and it is eliminated in the backward selection.

Before moving on to look at the specifications with macro covariates, notice that, as in Table 6, the coefficient point estimates and significance levels on these firm-specific variables are very similar across the different specifications, suggesting that to the extent that the macro

factors are able to add explanatory power to these models, it is incremental and largely orthogonal to the contribution of the firm-specific factors.

Models with All Macro Variables Included

The next pair of columns gives the results for a comprehensive specification with all of the macro factors together. These results illustrate the difficulty that arises with a large number of correlated macroeconomic variables. Eight out of thirteen coefficients on the macro covariates are estimated to be significant at the 0.001 level or better. Yet several of the signs are anomalous. Unemployment has a large and highly significant coefficient, but the negative sign means that high unemployment makes a downgrade less likely. A recession also reduces the risk of downgrade, although the coefficient is not significant. On the other hand, a strong economy as indicated by the CFNAI significantly increases the risk of a transition to speculative grade. Indeed, all four of the General macro factors have the "wrong" signs, and the two "Direction of the Economy" variables have offsetting signs.

The problem here may be largely the result of including many correlated macro variables in the same specification. In an attempt to find a more satisfactory specification, we separated the macro covariates into disjoint subsets: Macro Set 1 consisting of the four General Macroeconomic Conditions variables, and Macro Set 2 with the Direction of the Economy and the Financial Market variables. This produced two much better behaved alternatives.

With Macro Set 1, unemployment and recession are now estimated to be significantly positively related to downgrade risk; a strong CFNAI now produces a significant reduction in the hazard rate; and inflation becomes insignificant and drops out in the backward selection.

With Macro Set 2, positive Real GDP growth continues to produce a significant reduction in downgrade hazard, and while the Growth of industrial production still has an anomalous sign, it is less significant than before and drops out from the final specification. The signs on the Financial Market variables remain the same as in the full specification except for the small and insignificant coefficient on the T-Bill rate. High long term interest rates and a wide yield spread produce highly significant increases in the downgrade risk, while a strong stock market for small stocks reduces it.

Looking at the Goodness of Fit statistics we see that although some of the "nice" results from the univariate and single-macro variable specifications disappear when all of the variables enter the specification together, the improvement in goodness of fit is highly significant. Adding

the macro variables changes (-2 times) the log-likelihood value from 9546.00 with just firm-specific factors to 9272.87, an improvement of 273.13 at a cost of 13 degrees of freedom. The 0.001 critical value of a chi-squared distribution with 13 degrees of freedom is 34.5.

The two models with subsets of the macro variables are each significantly better than the model with only firm-specific covariates, both when all of the variables are included, as well as after backward selection. However, both of them also are significantly less good than the All variables specification, statistically. Backward selection eliminates two variables from Macro Set 1 and six variables from Macro Set 2, causing small reductions in log likelihood that are far from significant.

We have seen that some coefficient estimates come in with the "wrong" sign, indicating for example, that a stronger economy by that measure increased the risk of an adverse credit event. In trying to interpret what these mean, it is worth considering the following point. Since ratings are primarily relative rather than absolute measures of credit quality, Moody's does not necessarily downgrade a firm when its default risk has increased, if the increase reflects a general degradation of credit quality in the whole corporate sector. So it may be easier for a ratings agency to see that a given firm is doing badly when other firms are doing well than when all are experiencing difficulties. That is, it may not be inconsistent for a given firm to have a greater likelihood of being downgraded when the macroeconomy is strong than when it is weak. This logic does not apply to actual defaults, which depend on absolute, not relative, default probabilities, but it could play a role in the ratings agencies' behavior in downgrading a firm whose credit quality deteriorates more than what is expected for its cohort, or upgrading a firm whose credit quality improves relative to its peers.

## VIII. Upgrades to Investment Grade

The last two sections examined deterioration in credit quality. We now consider ratings upgrades. Again we do not attempt to model all upward transitions in credit rating, only the most important ones, which we take to be transitions from a speculative grade rating to investment class. There were only 4 cases in our sample of a firm with a rating in any of the C

classes jumping directly to investment grade, so we only consider upgrades from a B or Ba rating to one of the Investment grade ratings.[24]

Analysis of Individual Macro Factors

Table 9 shows the univariate estimation results for our macro factors. Variables related to a stronger economic environment are expected to have positive coefficients. Strikingly, when the general macro factors are considered one at a time, every one has the wrong sign, although only 3 are statistically significant. High unemployment, high inflation, and being in a recession all are estimated to increase the hazard rate for an upgrade, while a strong economy as measured by the CFNAI, high capacity utilization, and high real GDP or industrial production relative to their benchmarks all reduce the likelihood of an upgrade. Many of these anomalous signs are reversed when the variables are combined with ratings-based covariates, but only two of them are statistically significant, the recession indicator with a large and wrong-sign coefficient, and Industrial production actual minus trend, which is significantly positive but tiny.

The generally poor performance of these specifications with only a single macro variable in each continues for the Direction of the Economy variables, all three of which have the wrong signs in the univariate estimation. Two of them retain their anomalous signs when combined with the firm-specific covariates, with statistical significance (one has a p-value of .052).

Among the financial market variables, both interest rates are highly significantly positive on their own, but become very small and insignificant in the rightmost columns. The coefficients on the stock market variables are estimated with the wrong signs in 5 out of 6 cases, but none of them is significant at the 5% level. Only the two credit market variables get the expected negative signs--upgrades are less likely if credit spreads and defaults are high--but only the latter is significant.

Model with Firm-specific Factors Only

Table 10 presents estimation results for upgrades to investment class with all of the macro factors together. As before, we find that the coefficient point estimates and their significance levels for the firm-specific covariates are very similar for runs with and without the macro covariates. For "fallen angels" that were initially rated as investment grade but are

[24] We also examined upgrades within the speculative ratings classes, from a rating in one of the C categories into B or Ba. But, as we found in looking at other transitions involving firms in the C ratings classes, the results were rather muddy: these transitions seem to be more influenced by idiosyncratic factors than by macroeconomic conditions. To save space, we do not report these results here.

currently rated Ba or B, the probability of being upgraded back to investment grade is significantly greater than for an issuer that was originally rated as in a speculative grade B or Ba category. As expected, being in the higher of the two ratings classes, Ba, makes a very large positive difference to the hazard rate for an upgrade into investment grade.

Being downgraded within the last two years may reduce the chance of an upgrade, but the effect is not significant and the variable drops out in the backward selection. The scarcity of such cases in the sample is probably responsible for the weak performance of this variable. A recent upgrade has a strong positive and significant effect. The length of time the firm has been rated is also a positive and significant influence. This is consistent with the idea that Moody's credit analysts want to see a consistent record of good performance before concluding that a recently rated firm has improved its creditworthiness enough to justify an upgrade in its rating.

Models with All Macro Factors Included

Adding in all of our macro covariates produces several interesting results. Some of the odd results from the univariate regressions carry over to the comprehensive specifications, and some are reversed. Seven of the variables are dropped in the backward selection.

Consider first the general macroeconomic variables. Both high unemployment and inflation are now associated with a large and highly significant decrease in the intensity of upgrade from a speculative to an investment grade rating. Recession continues to receive a positive coefficient estimate, but it is not quite significant here and it is eliminated in the backward selection. The CFNAI has now reversed sign to become positive, but it remains insignificant.

The Direction of the Economy factors produce large but offsetting results. Real GDP growth seems to be bad news, but an increase in industrial production increases the intensity of upgrade. And both variables remain after the backward selection, with large, opposite sign, coefficients.

Coefficients on the interest rate variables are positive, and the 10-year Treasury yield enters the final specification with a highly significant coefficient, but it is also not obvious why high interest rates should make ratings upgrades more likely. Anomalous once again, a strong S&P 500 index significantly reduces the intensity of an upgrade. The Russell 2000 receives a positive coefficient, but it is not significant. The yield spread appears to have little effect, but the overall corporate default rate is a strong and significantly adverse factor for upgrades.

The specification with all of the macro variables improves (-2 times) the log-likelihood by a very highly statistically significant 126.79 over the model with only firm-specific covariates. Backward selection eliminates seven of the covariates and produces a model that is statistically indistinguishable from the All variables model and has the best AIC.

## IX. Robustness of Results over Different Sample Periods

We have seen a large number of estimation results for different credit transitions, some of which appeared fairly robust over different specifications, while others did not. But all of the estimations covered the same sample period, 1981 - 2002, so an important question arises as to how robust the results are to a change in the sample period. We have already alluded to the fact that we originally considered including the 1970s in the sample and decided against it because we felt that the economic environment was too different from what came afterwards. One example of this is that the 1970s was a period of sharply rising inflation, fueled by the first OPEC oil price shock and accommodative monetary policy, whereas inflation peaked and began falling rapidly in 1981 and has been fairly low and stable since then. Also, it was only starting in the 1980s that a bond could be brought to the market with a speculative grade rating at issue, so the composition of the population of firms in the lower ratings classes changed substantially after the 1970s.

Comparing the economic environment of the 1990s with the 1980s, it is easy to see changes potentially as important as those just mentioned. The 1980s began with a very sharp recession along with record inflation rates, followed by a period of relatively sluggish economic growth, punctuated by the 1987 stock market crash. By contrast, the 1990s were a period of generally strong economic growth with low inflation and stable credit markets, until the events around the Russian debt crisis and the Internet bubble towards the end of the decade. But by the end of our sample in 2002, there was another sharp drop in the stock market, a recession, and an increase in default rates to historic high levels.

To get an idea of how much the evolving economic environment may have affected the connection between macroeconomic factors and credit events, and therefore how robust our estimates are to the specific sample period we have chosen, we fitted separate coefficients for the periods 1981 - 1990 and 1991 - 2002. Note that the estimation procedure keeps the baseline

function the same but allows each covariate to have a different coefficient for spells in the two subperiods.

Table 11 compares coefficients estimated from the full sample and the two subperiods. Panels A-D, respectively, report results for the three major credit events we have examined: default from any speculative rating class, downgrade from an investment to a speculative rating with all macro factors included, downgrade from an investment to a speculative rating using subsets of the macro factors, and upgrade from speculative to investment grade.

Speculative Grades to Default

Panel A covers transitions into default. Looking first at the results for the firm-specific factors, there are no clear disparities across sample periods, although a few coefficients vary quite a bit in size. The most noticeable difference is in the backward selection results. In the earlier period, the point estimates on having a rating in a Caa or Ca category were negative--the default hazard was reduced relative to that for a firm rated C--but the effect was not significant at the 5% level and both dummies were eliminated in the backward selection. Similarly, the dummy on whether the bond was recently upgraded and the log(years since first rated) variable had the expected signs and reasonable magnitudes in the 1980s, but they were not statistically significant.

Table 6 showed that for the full sample period, none of the General Macroeconomic Conditions variables was close to statistically significant. That essentially negative result for these variables is seen in both subperiods, with the exception that the coefficient on inflation was significantly negative in the 1980s.

Overall, the coefficient estimate on Real GDP growth was anomalously positive, but insignificant, while it is negative, though still insignificant, in both of the subperiods. The coefficient on Growth of industrial production ends up large and significantly negative overall, although it is positive in the 1980s. After backward selection, this variable is retained in both the full sample and the 1990s subperiod, with a strongly negative and significant coefficient.

The Financial Market variables show several interesting results. The two interest rate variables get opposite signs in all three of the All variables estimations, but with backward selection, the T-Bill rate is positive and significant in the first subperiod and the 10-year yield is positive and significant in the later period and overall. Apparently, the specification needs to include some interest rate variable, but not both, and the effect is that high rates increase default

risk. The S&P 500 return, once again, is a significant and large adverse factor overall and in each subperiod. S&P volatility also increased default intensity, significantly in each subperiod but not overall. Positive returns on small stocks, as measured by the Russell 2000, significantly reduced the default hazard rate overall and in the earlier period, but not significantly during the 1990s. Finally, the yield spread was mostly wrong-signed and insignificant, except in the 1980s, but the overall corporate bond default rate was strongly positive overall and in the earlier period.

The Goodness of Fit statistics compare minus twice the log-likelihood of the full sample estimates, in which coefficients were constrained to be equal in the two subperiods, against that for the unconstrained model that allowed them to differ. This can only be done for the specifications with all variables included, because the backward selection models for the two subperiods are not nested in the one for the full sample. The difference was 81.29, which is highly significant for a chi-squared distribution with 22 degrees of freedom. As expected the test of the backward selection model against the model with all variables in the specification allowing coefficients to differ by subperiod, is statistically insignificant.

Downgrade from Investment to Speculative Grade

Panels B and C look at parameter stability in the model of ratings downgrades from an Investment to a Speculative grade. In Panel B, we report results using all of the macro variables in the All variables specification, while Panel C examines the stability of the two models based on the Macro Set 1 and Macro Set 2 subsets.

In Panel B, the coefficients on the Firm Specific Factors show fairly stable values in the two subperiods for the Current rating: Ba and the recent downgrade and upgrade variables. An initial rating of Investment grade is estimated to have a significant negative effect on the intensity of downgrade overall and in the 1990s, but not in the earlier subperiod, where the coefficient is positive and insignificant. The log(years since first rated) variable has the expected negative sign but it is never significant. As in Table 8, the macro factors exhibit quite erratic behavior when all of them are included in the specification. Those measuring General Macroeconomic Conditions have statistically significant coefficients in three out of four cases overall, but with anomalous signs: the adverse factors like high unemployment and being in a recession appear to reduce the risk of a downgrade, while strong economic conditions as measured by the CFNAI strongly increase downgrade intensity. None of these coefficients is statistically significant with the same sign in both subperiods.

The remaining macro variables exhibit similar erratic coefficient estimates. Not one of them is statistically significant with the same sign in both subperiods, although Real GDP growth comes close. The Goodness of Fit tests indicate that allowing the coefficients to differ in the two subperiods increases the log-likelihood by an amount that is highly statistically significant, while eliminating 16 of the variables by backward selection leaves a specification that is statistically no worse than the unconstrained model.

Panel C shows the results for both Macro Set 1, with the firm-specific and General Macroeconomic Conditions variables, and Macro Set 2, with the firm-specific and the Direction of the Economy and Financial Market variables. In both cases, the coefficients on the firm-specific variables are quite similar, both across subperiods and with the different subsets of macro variables. The exception is the dummy for having an initial rating in an investment grade. Overall, a firm that was initially rated in an investment grade has a lower intensity of being downgraded than one that began in a speculative grade, but the coefficient is positive in the earlier subperiod and it even is significant after backward selection for Macro Set 1.

In the reduced specification, the macro variables in Macro Set 1 perform much better, although some anomalies remain. The coefficients for inflation, recession, and CFNAI now have the expected signs overall and in the subperiods after backward selection. Only unemployment ends up statistically significant with the wrong sign, in the 1990s.

With Macro Set 2, we again see the offsetting effects of growth in real GDP and in industrial production. Strong GDP growth seems to diminish the hazard of downgrade but expansion in industrial production raises it. Only the former is significant overall, but both variables survive backward selection, with opposite signs, in the first subperiod, and neither does so in the second subperiod.

The variables related to financial market conditions did not do well for this transition. Not one of the seven variables had coefficient estimates of the same sign overall and in both subperiods, for example. After backward selection, the long term interest rate is significantly positive overall, but the coefficient is much larger in size and significantly negative in the later subperiod, while the T-Bill rate enters with a negative sign in the first subperiod and the 10-year rate is absent. The return on the S&P 500 is positive overall, but its coefficients are large and negative in both subperiods, significantly so after backward selection. These negative coefficients represent the only case we have seen where a strong S&P 500 does appear to be

favorable to the credit market. Stock market volatility has a tiny and insignificant coefficient overall, but it is negative and significant in the first subperiod (high volatility appears to reduce the risk of downgrade).

For the credit market variables, the yield spread is positive overall, but negative in the subperiods, with a very large coefficient in the second one. The corporate bond default rate is positive and not quite significant overall, but highly significant in the subperiods, with a large negative coefficient in the first and a large positive coefficient in the second, both of which survive backward selection.

The Goodness of Fit statistics indicate that the coefficients are significantly different in the two subperiods, and that backward selection does not significantly reduce the log-likelihood, for both Macro Sets.

Upgrade to Investment Class

Lastly, Panel D looks at upgrades from a speculative rating in the Ba or B category to investment grade.

The Firm-specific factors mostly performed as expected consistently in the two subperiods, with the exception being the dummy on whether the firm had been recently downgraded. The coefficient was negative in the whole sample, but far from statistical significance, and the subperiods produced significant coefficients, but of differing signs.

Among the general macro factors, unemployment is estimated with a strongly negative coefficient, and is retained in the backward selection for all three periods. Inflation has a highly significant negative coefficient in the full sample and the first subperiod, but it is positive and significant in the later period (though not retained in the backward selection). The recession dummy is anomalously positive but insignificant overall, but it is eliminated by backward selection in all periods. The CFNAI has a consistently positive coefficient, but it is only significant in the earlier period.

The Direction of the Economy factors do not do well for this transition. Real GDP growth is strong and significant overall and in the first subsample, but with an anomalous negative sign. The Growth of industrial production coefficient is positive and significant overall, but that hides the even larger coefficients, one positive and one negative, in the two subperiods. This may well be a case where multicollinearity due to the very high correlation between these

variables is playing a role. The two variables enter with opposite signs and mostly significant coefficients in each of the runs.

The results are somewhat messy for the variables relating to conditions in the financial markets, with few of them achieving statistical significance. None of the interest rate coefficients is significant in the All variables runs, although there does appear to be evidence of a positive influence of high interest rates on upgrades in the backward selection results. None of the stock market variables is significant with All variables, but the S&P 500 return does manage to achieve a small (anomalously) negative coefficient in the full sample backward selection. The yield spread is insignificant in both subperiods and overall, and it is consistently eliminated in the backward selection. Finally, the corporate bond default rate provides one of the strongest results in this Panel. It is consistently negative and significant, supporting the conclusion that, other things equal, upgrades are less common when defaults are prevalent.

The Goodness of Fit statistics confirm the impression from these results that the coefficient estimates for the macro factors did vary considerably between the early and later parts of the sample period. The difference in log-likelihood statistics was highly significant, with a p-value of $4.795 \times 10^{-17}$ on the hypothesis that the values were the same.

Our general conclusion from Table 11 regarding stability is that there are clear differences between the first half and the second half of our sample period, but most of the coefficients that were large and significant over the whole sample also showed up as important in the subsamples. The firm-specific factors showed the best overall behavior in terms of obeying our prior expectations and exhibiting consistency over time. Backward selection tended to amplify the apparent differences between the subperiods because different variables were excluded in each.

## X. Conclusions

This is the first study to examine such a broad range of macroeconomic factors in a Cox model specification for credit risk. In this framework, we have been able to increase the number of observations in our sample by working with individual firm data, rather than, say, aggregate default frequencies by ratings class as in earlier studies. We also have been able to access Moody's comprehensive database covering credit events in the full population of rated firms over a long time period. Finally, we limited the credit events under consideration to default and two

major changes of ratings class, which allowed larger numbers of firms in the "at risk" population for each type of transition. This first broad look at the problem suggests several conclusions.

Incorporating macroeconomic factors along with ratings-related variables in reduced form models of default intensity leads to a highly statistically significant increase in explanatory power. The size and sign of the estimated effect can vary substantially depending on whether the variable in question is examined by itself, as a single covariate in a specification with a full range of ratings-related variables, or in a comprehensive specification with other macro variables.

Our estimates of the effects of firm-specific factors confirm a variety of results from earlier studies. Specifically, we found that credit ratings reflected intensity differences correctly in every case. Higher rated firms had lower intensity of default than lower rated firms and had higher upgrade intensity. There is a "ratings drift" or "momentum" effect, by which a firm that has been downgraded (upgraded) in the recent past has a higher intensity of default or of being downgraded (upgraded) again than a firm in the same rating category that has not experienced a recent downgrade (upgrade). There is also evidence of an "aging" effect, such that the intensity of occurrence for a credit event depends on how long the firm has been rated. In particular, a recently rated firm has lower default intensity than a seasoned firm in the same ratings class. Similarly, a recently rated speculative grade firm in a B or Ba category has a lower intensity of being upgraded to the investment class.

We found that the intensity of occurrence of credit events was different for firms that began as investment grade and were subsequently downgraded into a speculative ratings class ("fallen angels"), and for firms that started as speculative and have been upgraded ("rising stars") than for firms that are still in the same broad, investment or speculative grade category, that they started in. One finding of considerable importance is that the coefficients on the ratings-based factors, and their significance levels, are only slightly affected by addition of macroeconomic factors to the specification. This implies that the information obtained from considering the macro data is incremental to that contained in a firm's credit rating history alone. However, the coefficients on the macro variables themselves are much less stable under different specifications, indicating that there is considerable correlation among them and overlap in the relevant information they contain relating to credit risk.

In models of the transition into default with macro covariates, none of the four measures of General Macroeconomic Conditions provided useful information about default hazards, when

firm-specific covariates and other macro variables were included in the specification. Unemployment, inflation, recession, and general economic conditions as measured by the CFNAI all were very far from statistical significance. Between the two measures of economic direction, Growth of industrial production seemed to perform better than the Real GDP growth rate--strong growth in industrial production reduced default risk--although the high correlation between these two variables probably produced some instability in the coefficient estimates. There was some evidence consistent with "contagion" in the credit markets. The overall default rate among corporate borrowers did enter as a significant covariate associated with an increase in the risk of default for an individual firm. However, in the breakdown by subperiod, the coefficient on this variable was negative and insignificant in the later subsample.

In models of the transition from an investment grade rating downwards to speculative grade, putting all of the macro covariates together into a single specification produced very noisy and anomalous results. Splitting them into one set containing the general macro variables and a second set with mostly financial market variables led to much more plausible coefficient estimates. Still, few of the macro factors worked very well. Many of the signs on the coefficients were wrong and they varied across the subperiods. Probably the best single variable was GDP growth: with a large, mostly significant, negative coefficient overall and in both subperiods, rapid GDP growth seems to lower the risk of downgrade. Like the general macro factors, the variables related to financial market conditions tended to have low statistical significance, with a number of anomalous signs.

In models of transitions to a higher ratings class, unemployment was the most important of the macro factors. High unemployment was strongly associated with a reduction in the intensity of an upgrade overall and in each of the subperiods, both before and after backward selection. Inflation appears to have been an unfavorable factor in the 1980s, but not in the second subperiod. Among the financial market variables, high interest rates were associated with a higher hazard rate for an upgrade, and a larger number of recent corporate defaults reduced the chance of upgrade.

With regard to the stability of the relationships over the 21 year sample, we found statistically significant differences in the coefficient point estimates between the 1980s and the 1990s. The differences in estimated parameters between the two subperiods are surely due in part to a lack of robustness in the model. But there have also been major changes in the

economy and the financial markets over this period, so at least some of the differences between the two halves of the sample must reflect real changes in how conditions in the macroeconomy affect corporate credit risk.

In summary, our results represent a broad first cut at incorporating a wide range of measures of the macroeconomic environment into reduced-form Cox models for the hazard rates of several important credit events. Further research along these lines is surely warranted and can be expected to refine our understanding of this important area.

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## Table 1

## Moody's Long-Term Rating Definitions

| | |
|---|---|
| Aaa | Obligations rated Aaa are judged to be of the highest quality, with minimal credit risk. |
| Aa | Obligations rated Aa are judged to be of high quality and are subject to very low credit risk. |
| A | Obligations rated A are considered upper-medium grade and are subject to low credit risk. |
| Baa | Obligations rated Baa are subject to moderate credit risk. They are considered medium-grade and as such may possess certain speculative characteristics. |
| Ba | Obligations rated Ba are judged to have speculative elements and are subject to substantial credit risk. |
| B | Obligations rated B are considered speculative and are subject to high credit risk. |
| Caa | Obligations rated Caa are judged to be of poor standing and are subject to very high credit risk. |
| Ca | Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest. |
| C | Obligations rated C are the lowest rated class of bonds and are typically in default, with little prospect for recovery of principal or interest. |

Source: Moody's KMV

# Table 2
# Numbers of transitions

| From \ To | Total | Investment grade | Any speculative grade | Ba and B | Caa, Ca, and C | Default | Withdrawn |
|---|---|---|---|---|---|---|---|
| **Investment grade** | 3422 | 1684 | 788 | 783 | 5 | 6 | 944 |
| **Any speculative grade** | 4327 | 645 | 1125 | 912 | 213 | 902 | 1655 |
| **Ba and B** | 4196 | 641 | 1624 | 912 | 746 | 448 | 1486 |
| **Caa, Ca, and C** | 942 | 4 | 315 | 102 | 213 | 454 | 169 |

**Notes:**

Moody's ratings classes Caa, Ca, and C contain some firms that have already defaulted. In our sample, we only count firms that have not defaulted as being in those classes.

Spells shorter than 14 days are eliminated from the sample, and the spell in the previous rating class is extended to include the short period.

Transitions into the "Withdrawn" category occur when a firm's outstanding bonds mature, or disappear due to merger or another non-default reason.

Spells ending in a "Withdrawn" rating, or with no rating change at the end of the sample period are treated as right-censored

# TABLE 3
## Statistics on Model Covariates

| Variable | Mean | Standard deviation | Variable in Model | Source |
|---|---|---|---|---|
| **General Macroeconomic Conditions** | | | | |
| Unemployment rate | 6.295 | 1.500 | 18-month distributed lag | US Bureau of Labor Statistics* |
| Inflation | 3.706 | 2.021 | 18-month distributed lag | US Bureau of Labor Statistics* |
| NBER recession indicator | 0.12 | 0.327 | (0,1) dummy | National Bureau of Economic Research |
| CFNAI | -0.093 | 0.712 | 3-month moving average | Federal Reserve Bank of Chicago |
| Capacity utilization | 80.77 | 2.74 | 18-month distributed lag | Federal Reserve Board of Governors |
| Real GDP actual minus potential | -1.576 | 2.424 | 18-month distributed lag | Bureau of Economic Analysis and Congressional Budget Office |
| Industrial production actual minus trend | 0.237 | 8.625 | 18-month distributed lag | Federal Reserve Board of Governors |
| **Direction of the Economy** | | | | |
| Real GDP growth | 0.763 | 0.449 | 18-month distributed lag | US Bureau of Economic Analysis |
| Growth of industrial production | 0.220 | 0.288 | 18-month distributed lag | Federal Reserve Board of Governors |
| Change in unemployment rate | -0.0053 | 0.0747 | 18-month distributed lag | US Bureau of Labor Statistics* |
| **Financial Market Conditions** | | | | |
| 3-month T-Bill rate | 6.429 | 2.740 | 18-month distributed lag | Federal Reserve Statistical Release |
| Long-term interest rate (10-year Treasury) | 8.208 | 2.578 | 18-month distributed lag | Federal Reserve Bank of St. Louis |
| S&P 500 return | 0.904 | 1.240 | 18-month distributed lag | Wharton Research Data Services |
| S&P 500 volatility | 14.748 | 4.434 | 18-month distributed lag | Wharton Research Data Services |
| Russell 2000 Index return | 0.891 | 1.388 | 18-month distributed lag | Wharton Research Data Services |
| Yield spread (Baa - 10 Year Treasury) | 2.101 | 0.438 | 18-month distributed lag | Moody's and Federal Reserve Bank of St. Louis |
| Corporate bond default rate | 1.555 | 1.050 | 3-month moving average | Moody's KMV |
| **Firm Specific Factors** | | | | |
| Initial rating: Investment grade | | | (0,1) dummy | |
| Initial rating: C, Ca, Caa | | | (0,1) dummy | |
| Current rating: Ba | | | (0,1) dummy | |
| Current rating: B | | | (0,1) dummy | |
| Current rating: Caa | | | (0,1) dummy | |
| Current rating: Ca | | | (0,1) dummy | |
| Downgraded within last 2 years | | | (0,1) dummy | |
| Upgraded within last 2 years | | | (0,1) dummy | |
| log(years since first rated) | | | contemporaneous value | |

* Data series downloaded from the St. Louis Federal Reserve (URL: http://research.stlouisfed.org/fred2/).

**Table 4**
**Correlations Among Macroeconomic Variables**

| | Unemployment | Inflation | CFNAI | NBER recession | Capacity utilization | Real GDP Actual - Potential | Industrial prod'n actual - trend | Real GDP growth | Growth of industrial prod'n | Change in unemployment | 3-month T-Bill rate | 10-year Treasury yield | S&P 500 return | S&P 500 volatility | Russell 2000 return | Baa yield - 10 Year Treasury | Overall default rate |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Unemployment | 1.000 | 0.311 | 0.121 | 0.089 | -0.723 | -0.963 | -0.935 | -0.025 | -0.092 | 0.020 | 0.538 | 0.765 | 0.089 | -0.355 | 0.261 | 0.317 | -0.339 |
| Inflation | 0.311 | 1.000 | -0.319 | 0.399 | -0.043 | -0.349 | -0.487 | -0.264 | -0.254 | 0.246 | 0.797 | 0.673 | -0.168 | -0.045 | -0.023 | -0.013 | -0.204 |
| CFNAI | 0.121 | -0.319 | 1.000 | -0.716 | 0.035 | 0.002 | 0.078 | 0.815 | 0.839 | -0.795 | -0.264 | -0.141 | 0.357 | -0.128 | 0.249 | -0.163 | -0.339 |
| NBER recession indicator | 0.089 | 0.399 | -0.716 | 1.000 | -0.189 | -0.194 | -0.232 | -0.636 | -0.596 | 0.580 | 0.406 | 0.307 | -0.412 | 0.143 | -0.342 | 0.224 | 0.142 |
| Capacity utilization | -0.723 | -0.043 | 0.035 | -0.189 | 1.000 | 0.765 | 0.753 | 0.209 | 0.350 | -0.288 | -0.273 | -0.434 | 0.165 | -0.138 | -0.124 | -0.806 | -0.131 |
| Real GDP actual minus potential | -0.963 | -0.349 | 0.002 | -0.194 | 0.765 | 1.000 | 0.943 | 0.190 | 0.207 | -0.185 | -0.538 | -0.733 | 0.000 | 0.280 | -0.229 | -0.373 | 0.257 |
| Industrial prod'n actual minus trend | -0.935 | -0.487 | 0.078 | -0.232 | 0.753 | 0.943 | 1.000 | 0.208 | 0.302 | -0.196 | -0.633 | -0.814 | 0.098 | 0.242 | -0.146 | -0.416 | 0.156 |
| Real GDP growth | -0.025 | -0.264 | 0.815 | -0.636 | 0.209 | 0.190 | 0.208 | 1.000 | 0.854 | -0.887 | -0.175 | -0.085 | 0.286 | -0.107 | 0.074 | -0.338 | -0.396 |
| Growth of industrial prod'n | -0.092 | -0.254 | 0.839 | -0.596 | 0.350 | 0.207 | 0.302 | 0.854 | 1.000 | -0.864 | -0.280 | -0.220 | 0.289 | -0.158 | 0.046 | -0.489 | -0.428 |
| Change in unemployment | 0.020 | 0.246 | -0.795 | 0.580 | -0.288 | -0.185 | -0.196 | -0.887 | -0.864 | 1.000 | 0.204 | 0.110 | -0.233 | 0.203 | -0.022 | 0.381 | 0.420 |
| 3-month T-Bill rate | 0.538 | 0.797 | -0.264 | 0.406 | -0.273 | -0.538 | -0.633 | -0.175 | -0.280 | 0.204 | 1.000 | 0.924 | 0.032 | -0.077 | 0.064 | 0.086 | -0.360 |
| 10-year Treasury yield | 0.765 | 0.673 | -0.141 | 0.307 | -0.434 | -0.733 | -0.814 | -0.085 | -0.220 | 0.110 | 0.924 | 1.000 | 0.017 | -0.191 | 0.094 | 0.133 | -0.381 |
| S&P 500 return | 0.089 | -0.168 | 0.357 | -0.412 | 0.165 | 0.000 | 0.098 | 0.286 | 0.289 | -0.233 | 0.032 | 0.017 | 1.000 | -0.336 | 0.749 | -0.298 | -0.352 |
| S&P 500 volatility | -0.355 | -0.045 | -0.128 | 0.143 | -0.138 | 0.280 | 0.242 | -0.107 | -0.158 | 0.203 | -0.077 | -0.191 | -0.336 | 1.000 | -0.276 | 0.533 | 0.428 |
| Russell 2000 return | 0.261 | -0.023 | 0.249 | -0.342 | -0.124 | -0.229 | -0.146 | 0.074 | 0.046 | -0.022 | 0.064 | 0.094 | 0.749 | -0.276 | 1.000 | 0.022 | -0.205 |
| Baa yield - 10 Year Treasury | 0.317 | -0.013 | -0.163 | 0.224 | -0.806 | -0.373 | -0.416 | -0.338 | -0.489 | 0.381 | 0.086 | 0.133 | -0.298 | 0.533 | 0.022 | 1.000 | 0.329 |
| Overall corporate default rate | -0.339 | -0.204 | -0.339 | 0.142 | -0.131 | 0.257 | 0.156 | -0.396 | -0.428 | 0.420 | -0.360 | -0.381 | -0.352 | 0.428 | -0.205 | 0.329 | 1.000 |

# Table 5
# TRANSITIONS INTO DEFAULT
# Analysis of Individual Macro Factors

| | Univariate results | | Marginal contribution with firm specific variables | |
|---|---|---|---|---|
| | **coefficient** | **p-value** | **coefficient** | **p-value** |
| **General Macroeconomic Conditions** | | | | |
| Unemployment rate | -0.181 | 0.000 | 0.079 | 0.004 |
| Inflation | -0.002 | 0.938 | 0.146 | 0.000 |
| NBER recession indicator | 0.669 | 0.000 | 0.396 | 0.000 |
| CFNAI | -0.500 | 0.000 | -0.296 | 0.000 |
| Capacity utilization | -0.030 | 0.024 | 0.019 | 0.165 |
| Real GDP actual minus potential | 0.095 | 0.000 | -0.026 | 0.119 |
| Industrial production actual minus trend | 0.012 | 0.008 | -0.019 | 0.000 |
| **Direction of the Economy** | | | | |
| Real GDP growth | -0.713 | 0.000 | -0.409 | 0.000 |
| Growth of industrial production | -1.193 | 0.000 | -0.596 | 0.000 |
| Change in unemployment rate | 4.306 | 0.000 | 1.585 | 0.003 |
| **Financial Market Conditions** | | | | |
| 3-month T-Bill rate | -0.015 | 0.371 | 0.127 | 0.000 |
| Long-term interest rate (10-year Treasury) | -0.064 | 0.000 | 0.122 | 0.000 |
| S&P 500 return | -0.122 | 0.000 | 0.058 | 0.016 |
| S&P 500 volatility | 0.053 | 0.000 | -0.009 | 0.212 |
| Russell 2000 Index return | -0.092 | 0.000 | -0.010 | 0.685 |
| Yield spread (Baa - 10 Year Treasury) | 0.474 | 0.000 | -0.140 | 0.061 |
| Corporate bond default rate | 0.353 | 0.000 | 0.124 | 0.000 |

**Notes**

Sample period: Jan. 1981 - Nov. 2002.

As described in the text, spells of less than 14 days are reclassified, and most covariates enter as with exponentially weighted 18-month moving averages with a decay factor of 0.88.

The right panel reports the estimation results for each single variable in a model with these firm specific variables:

- Initial rating: Investment grade
- Initial rating: C, Ca, Caa
- Current rating: Ba
- Current rating: B
- Current rating: Caa
- Current rating: Ca
- Downgraded within last 2 years
- Upgraded within last 2 years
- log(years since first rated)

# Table 6
# TRANSITIONS FROM SPECULATIVE GRADE INTO DEFAULT

| | Firm specific only | | All variables | | | Backward Selection Model | | |
|---|---|---|---|---|---|---|---|---|
| | coefficient | p-value | coefficient | std coef | p-value | coefficient | std coef | p-value |
| **Firm Specific Factors** | | | | | | | | |
| Initial rating: Investment grade | -0.237 | 0.062 | -0.389 | -0.389 | 0.003 | -0.406 | -0.406 | 0.002 |
| Initial rating: C, Ca, Caa | -1.282 | 0.000 | -1.246 | -1.246 | 0.000 | -1.237 | -1.237 | 0.000 |
| Current rating: Ba | -5.305 | 0.000 | -5.640 | -5.640 | 0.000 | -5.624 | -5.624 | 0.000 |
| Current rating: B | -3.505 | 0.000 | -3.759 | -3.759 | 0.000 | -3.739 | -3.739 | 0.000 |
| Current rating: Caa | -1.630 | 0.000 | -1.720 | -1.720 | 0.000 | -1.708 | -1.708 | 0.000 |
| Current rating: Ca | -1.019 | 0.000 | -1.102 | -1.102 | 0.000 | -1.116 | -1.116 | 0.000 |
| Downgraded within last 2 years | 0.446 | 0.000 | 0.440 | 0.440 | 0.000 | 0.444 | 0.444 | 0.000 |
| Upgraded within last 2 years | -1.465 | 0.000 | -1.275 | -1.275 | 0.000 | -1.270 | -1.270 | 0.000 |
| log(years since first rated) | 0.141 | 0.013 | 0.132 | 0.132 | 0.023 | 0.132 | 0.132 | 0.023 |
| **General Macroeconomic Conditions** | | | | | | | | |
| Unemployment rate | | | -0.013 | -0.019 | 0.901 | | | |
| Inflation | | | 0.003 | 0.006 | 0.953 | | | |
| NBER recession indicator | | | 0.076 | 0.076 | 0.584 | | | |
| CFNAI | | | 0.005 | 0.003 | 0.976 | | | |
| **Direction of the Economy** | | | | | | | | |
| Real GDP growth | | | 0.311 | 0.140 | 0.192 | | | |
| Growth of industrial production | | | -1.006 | -0.290 | 0.022 | -0.520 | -0.150 | 0.002 |
| **Financial Market Conditions** | | | | | | | | |
| 3-month T-Bill rate | | | -0.001 | -0.003 | 0.991 | | | |
| Long-term interest rate (10-year Treasury) | | | 0.154 | 0.397 | 0.145 | 0.147 | 0.379 | 0.000 |
| S&P 500 return | | | 0.310 | 0.384 | 0.000 | 0.361 | 0.447 | 0.000 |
| S&P 500 volatility | | | 0.017 | 0.073 | 0.367 | | | |
| Russell 2000 Index return | | | -0.179 | -0.248 | 0.000 | -0.223 | -0.310 | 0.000 |
| Yield spread (Baa - 10 Year Treasury) | | | -0.327 | -0.143 | 0.145 | | | |
| Corporate bond default rate | | | 0.303 | 0.318 | 0.000 | 0.298 | 0.313 | 0.000 |

| **Goodness of Fit** | **statistic** | **statistic** | **p-value** | **statistic** | **p-value** |
|---|---|---|---|---|---|
| -2 x log(likelihood) | 11129.81 | 10959.27 | | 10968.25 | |
| Akaike Information Criterion | 11147.81 | 11003.27 | | 10996.25 | |
| Likelihood ratio test: model vs Firm specific only | | 170.54 | 0.000 | 161.55 | 0.000 |
| Likelihood ratio test: Final model vs All variables | | | | 8.99 | 0.344 |

**Notes**

Sample period: Jan. 1981 - Nov. 2002.

As described in the text, spells of less than 14 days are reclassified, and most covariates enter as exponentially weighted 18-month moving averages with a decay factor of 0.88.

# Table 7
## DOWNGRADE FROM INVESTMENT TO SPECULATIVE GRADE
## Analysis of Individual Macro Factors

| | Univariate results | | Marginal contribution with firm specific variables | |
|---|---|---|---|---|
| | coefficient | p-value | coefficient | p-value |
| **General Macroeconomic Conditions** | | | | |
| Unemployment rate | 0.042 | 0.084 | 0.077 | 0.001 |
| Inflation | 0.049 | 0.006 | 0.061 | 0.000 |
| NBER recession indicator | 0.695 | 0.000 | 0.643 | 0.000 |
| CFNAI | -0.381 | 0.000 | -0.341 | 0.000 |
| Capacity utilization | -0.108 | 0.000 | -0.092 | 0.000 |
| Real GDP actual minus potential | -0.044 | 0.003 | -0.061 | 0.000 |
| Industrial production actual minus trend | -0.026 | 0.000 | -0.029 | 0.000 |
| **Direction of the Economy** | | | | |
| Real GDP growth | -0.822 | 0.000 | -0.768 | 0.000 |
| Growth of industrial production | -1.291 | 0.000 | -1.138 | 0.000 |
| Change in unemployment rate | 4.708 | 0.000 | 4.153 | 0.000 |
| **Financial Market Conditions** | | | | |
| 3-month T-Bill rate | 0.074 | 0.000 | 0.090 | 0.000 |
| Long-term interest rate (10-year Treasury) | 0.072 | 0.000 | 0.094 | 0.000 |
| S&P 500 return | -0.247 | 0.000 | -0.186 | 0.000 |
| S&P 500 volatility | 0.052 | 0.000 | 0.031 | 0.000 |
| Russell 2000 Index return | -0.187 | 0.000 | -0.157 | 0.000 |
| Yield spread (Baa - 10 Year Treasury) | 0.837 | 0.000 | 0.636 | 0.000 |
| Corporate bond default rate | 0.206 | 0.000 | 0.127 | 0.000 |

**Notes**

See the Notes to Table 5.

# Table 8
# DOWNGRADE FROM INVESTMENT TO SPECULATIVE GRADE

| | Firm specific only | | All variables | | Macro Set 1 | | Set 1 Backward Sel'n | | Macro Set 2 | | Set 2 Backward Sel'n | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | -0.357 | 0.000 | -0.325 | 0.001 | -0.356 | 0.000 | -0.319 | 0.001 | -0.333 | 0.001 | -0.298 | 0.002 |
| Current rating: Baa | 2.734 | 0.000 | 2.721 | 0.000 | 2.734 | 0.000 | 2.744 | 0.000 | 2.719 | 0.000 | 2.724 | 0.000 |
| Downgraded within last 2 years | 0.820 | 0.000 | 0.795 | 0.000 | 0.839 | 0.000 | 0.833 | 0.000 | 0.804 | 0.000 | 0.807 | 0.000 |
| Upgraded within last 2 years | -0.823 | 0.000 | -0.753 | 0.000 | -0.790 | 0.000 | -0.828 | 0.000 | -0.760 | 0.000 | -0.788 | 0.000 |
| log(years since first rated) | -0.050 | 0.258 | -0.041 | 0.358 | -0.052 | 0.240 | | | -0.045 | 0.310 | | |
| **General Macroeconomic Conditions** | | | | | | | | | | | | |
| Unemployment rate | | | -0.687 | 0.000 | 0.092 | 0.001 | 0.085 | 0.000 | | | | |
| Inflation | | | -0.143 | 0.001 | -0.011 | 0.614 | | | | | | |
| NBER recession indicator | | | -0.258 | 0.118 | 0.298 | 0.042 | 0.286 | 0.047 | | | | |
| CFNAI | | | 0.573 | 0.000 | -0.241 | 0.002 | -0.236 | 0.002 | | | | |
| **Direction of the Economy** | | | | | | | | | | | | |
| Real GDP growth | | | -1.341 | 0.000 | | | | | -0.421 | 0.011 | -0.372 | 0.000 |
| Growth of industrial production | | | 0.533 | 0.211 | | | | | 0.250 | 0.406 | | |
| **Financial Market Conditions** | | | | | | | | | | | | |
| 3-month T-Bill rate | | | -0.091 | 0.215 | | | | | 0.040 | 0.370 | | |
| Long-term interest rate (10-year Treasury) | | | 0.570 | 0.000 | | | | | 0.075 | 0.103 | 0.094 | 0.000 |
| S&P 500 return | | | 0.054 | 0.367 | | | | | 0.070 | 0.166 | | |
| S&P 500 volatility | | | -0.062 | 0.000 | | | | | -0.005 | 0.724 | | |
| Russell 2000 Index return | | | -0.190 | 0.000 | | | | | -0.174 | 0.000 | -0.132 | 0.000 |
| Yield spread (Baa - 10 Year Treasury) | | | 1.201 | 0.000 | | | | | 0.570 | 0.000 | 0.465 | 0.000 |
| Corporate bond default rate | | | 0.086 | 0.128 | | | | | 0.095 | 0.062 | | |
| **Goodness of Fit** | **statistic** | | **statistic** | **p-value** | **statistic** | **p-value** | **statistic** | **p-value** | **statistic** | **p-value** | **statistic** | **p-value** |
| -2 x log(likelihood) | 9546.00 | | 9272.87 | | 9482.66 | | 9484.31 | | 9364.84 | | 9371.16 | |
| AIC (model) | 9556.00 | | 9308.87 | | 9500.66 | | 9498.31 | | 9392.84 | | 9387.16 | |
| Likelihood ratio test: Model vs Firm specific only | | | 273.13 | 0.000 | 63.34 | 0.000 | 61.69 | 0.000 | 181.16 | 0.000 | 174.84 | 0.000 |
| Likelihood ratio test: Subset vs All Variables | | | | | 209.80 | 0.000 | | | 91.98 | 0.000 | | |
| Likelihood ratio test on Backward Selection | | | | | | | 1.65 | 0.438 | | | 6.32 | 0.389 |

**Notes**

See Notes to Table 6.

# Table 9
# UPGRADE FROM B AND Ba TO INVESTMENT GRADE
## Analysis of Individual Macro Factors

| | Univariate results | | Marginal contribution with firm specific variables | |
|---|---|---|---|---|
| | coefficient | p-value | coefficient | p-value |
| **General Macroeconomic Conditions** | | | | |
| Unemployment rate | 0.076 | 0.009 | -0.053 | 0.080 |
| Inflation | 0.019 | 0.433 | -0.043 | 0.086 |
| NBER recession indicator | 0.510 | 0.000 | 0.449 | 0.000 |
| CFNAI | -0.109 | 0.081 | -0.114 | 0.055 |
| Capacity utilization | -0.004 | 0.801 | 0.028 | 0.096 |
| Real GDP actual minus potential | -0.049 | 0.007 | 0.028 | 0.143 |
| Industrial production actual minus trend | -0.006 | 0.257 | 0.016 | 0.002 |
| **Direction of the Economy** | | | | |
| Real GDP growth | -0.319 | 0.001 | -0.279 | 0.003 |
| Growth of industrial production | -0.040 | 0.788 | 0.000 | 0.998 |
| Change in unemployment rate | 1.187 | 0.054 | 1.136 | 0.052 |
| **Financial Market Conditions** | | | | |
| 3-month T-Bill rate | 0.081 | 0.000 | 0.025 | 0.132 |
| Long-term interest rate (10-year Treasury) | 0.077 | 0.000 | 0.004 | 0.802 |
| S&P 500 return | -0.006 | 0.841 | -0.025 | 0.423 |
| S&P 500 volatility | -0.016 | 0.070 | 0.003 | 0.735 |
| Russell 2000 Index return | -0.034 | 0.245 | -0.055 | 0.057 |
| Yield spread (Baa - 10 Year Treasury) | -0.145 | 0.127 | -0.139 | 0.153 |
| Corporate bond default rate | -0.264 | 0.000 | -0.187 | 0.000 |

**Notes**

See Notes to Table 5.

# Table 10
# UPGRADE FROM Ba and B TO INVESTMENT GRADE

| | Firm specific only | | All variables | | Backward Selection | |
|---|---|---|---|---|---|---|
| | **coefficient** | **p-value** | **coefficient** | **p-value** | **coefficient** | **p-value** |
| **Firm Specific Factors** | | | | | | |
| Initial rating: Investment grade | 0.363 | 0.001 | 0.436 | 0.000 | 0.430 | 0.000 |
| Current rating: Ba | 1.796 | 0.000 | 1.817 | 0.000 | 1.816 | 0.000 |
| Downgraded within last 2 years | -0.076 | 0.518 | -0.031 | 0.794 | | |
| Upgraded within last 2 years | 0.371 | 0.000 | 0.315 | 0.003 | 0.321 | 0.002 |
| log(years since first rated) | 0.333 | 0.000 | 0.317 | 0.000 | 0.318 | 0.000 |
| **General Macroeconomic Conditions** | | | | | | |
| Unemployment rate | | | -0.324 | 0.003 | -0.314 | 0.000 |
| Inflation | | | -0.276 | 0.000 | -0.256 | 0.000 |
| NBER recession indicator | | | 0.399 | 0.062 | | |
| CFNAI | | | 0.175 | 0.317 | | |
| **Direction of the Economy** | | | | | | |
| Real GDP growth | | | -1.192 | 0.000 | -1.256 | 0.000 |
| Growth of industrial production | | | 1.083 | 0.030 | 1.040 | 0.001 |
| **Financial Market Conditions** | | | | | | |
| 3-month T-Bill rate | | | 0.065 | 0.438 | | |
| Long-term interest rate (10-year Treasury) | | | 0.164 | 0.119 | 0.219 | 0.000 |
| S&P 500 return | | | -0.146 | 0.037 | -0.103 | 0.005 |
| S&P 500 volatility | | | -0.006 | 0.735 | | |
| Russell 2000 Index return | | | 0.060 | 0.264 | | |
| Yield spread (Baa - 10 Year Treasury) | | | 0.107 | 0.675 | | |
| Corporate bond default rate | | | -0.288 | 0.000 | -0.298 | 0.000 |
| **Goodness of Fit** | **statistic** | | **statistic** | **p-value** | **statistic** | **p-value** |
| -2 x log(likelihood) | 8469.44 | | 8342.65 | | 8349.88 | |
| AIC (model) | 8479.44 | | 8378.65 | | 8371.88 | |
| Likelihood ratio test: model vs Firm specific only | | | 126.79 | 0.000 | 119.56 | 0.000 |
| Likelihood ratio test: Final model vs All variables | | | | | 7.23 | 0.406 |

**Notes**

See Notes to Table 6.

## Table 11 -- DISJOINT SUBSAMPLES
## Sensitivity of Coefficient Estimates to Sample Period

### Panel A: All Speculative grades to default

| | All Variables | | | | | | Backward Selection | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | |
| | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | -0.389 | 0.003 | -0.341 | 0.083 | -0.463 | 0.005 | -0.406 | 0.002 | | | -0.447 | 0.005 |
| Initial rating: C, Ca, Caa | -1.246 | 0.000 | -2.606 | 0.011 | -1.248 | 0.000 | -1.237 | 0.000 | -2.485 | 0.014 | -1.225 | 0.000 |
| Current rating: Ba | -5.640 | 0.000 | -3.991 | 0.023 | -6.035 | 0.000 | -5.624 | 0.000 | -3.729 | 0.000 | -6.002 | 0.000 |
| Current rating: B | -3.759 | 0.000 | -2.216 | 0.206 | -3.982 | 0.000 | -3.739 | 0.000 | -1.881 | 0.000 | -3.954 | 0.000 |
| Current rating: Caa | -1.720 | 0.000 | -0.386 | 0.826 | -1.765 | 0.000 | -1.708 | 0.000 | | | -1.747 | 0.000 |
| Current rating: Ca | -1.102 | 0.000 | -0.110 | 0.951 | -1.062 | 0.000 | -1.116 | 0.000 | | | -1.034 | 0.000 |
| Downgraded within last 2 years | 0.440 | 0.000 | 0.849 | 0.000 | 0.243 | 0.018 | 0.444 | 0.000 | 0.830 | 0.000 | 0.240 | 0.018 |
| Upgraded within last 2 years | -1.275 | 0.000 | -1.135 | 0.113 | -1.288 | 0.001 | -1.270 | 0.000 | | | -1.298 | 0.001 |
| log(years since first rated) | 0.132 | 0.023 | 0.049 | 0.551 | 0.164 | 0.012 | 0.132 | 0.023 | | | 0.153 | 0.014 |
| **General Macroeconomic Conditions** | | | | | | | | | | | | |
| Unemployment rate | -0.013 | 0.901 | 0.069 | 0.832 | -0.052 | 0.792 | | | | | | |
| Inflation | 0.003 | 0.953 | -0.342 | 0.002 | 0.172 | 0.109 | | | -0.258 | 0.001 | | |
| NBER recession indicator | 0.076 | 0.584 | 0.010 | 0.981 | -0.090 | 0.624 | | | | | | |
| CFNAI | 0.005 | 0.976 | -0.239 | 0.426 | 0.159 | 0.564 | | | | | | |
| **Direction of the Economy** | | | | | | | | | | | | |
| Real GDP growth | 0.311 | 0.192 | -0.340 | 0.543 | -0.385 | 0.430 | | | | | | |
| Growth of industrial production | -1.006 | 0.022 | 0.898 | 0.257 | -1.677 | 0.104 | -0.520 | 0.002 | | | -1.220 | 0.000 |
| **Financial Market Conditions** | | | | | | | | | | | | |
| 3-month T-Bill rate | -0.001 | 0.991 | 0.359 | 0.035 | -0.116 | 0.559 | | | 0.247 | 0.000 | | |
| Long-term interest rate (10-year Treasury) | 0.154 | 0.145 | -0.120 | 0.581 | 0.296 | 0.314 | 0.147 | 0.000 | | | 0.308 | 0.000 |
| S&P 500 return | 0.310 | 0.000 | 0.482 | 0.027 | 0.343 | 0.000 | 0.361 | 0.000 | 0.502 | 0.001 | 0.203 | 0.000 |
| S&P 500 volatility | 0.017 | 0.367 | 0.090 | 0.012 | 0.055 | 0.070 | | | 0.079 | 0.002 | 0.051 | 0.000 |
| Russell 2000 Index return | -0.179 | 0.000 | -0.228 | 0.099 | -0.113 | 0.064 | -0.223 | 0.000 | -0.271 | 0.009 | | |
| Yield spread (Baa - 10 Year Treasury) | -0.327 | 0.145 | -0.972 | 0.244 | 0.047 | 0.935 | | | -0.789 | 0.001 | | |
| Corporate bond default rate | 0.303 | 0.000 | 0.310 | 0.050 | -0.137 | 0.402 | 0.298 | 0.000 | 0.376 | 0.000 | | |
| **Goodness of Fit** | | | | | | | | | | | | |
| -2 x log(likelihood) | 10959.27 | | 10877.98 | | | | | | 10896.23 | | | |
| Difference in 2 x log(likelihood) | | | 81.29 | | | | | | 18.25 | | | |
| p-value on H0 that the coefficients are the same in both subperiods | | | 0.000 | | | | | | | | | |
| p-value on backward selection for subperiods | | | | | | | | | 0.571 | | | |

**Notes:**

The model coefficients are estimated on the full sample and then with separate coefficients for spells during the period 1981-1990 and 1991-2002.

As described in the text, spells of less than 14 days are reclassified, and most covariates enter as exponentially weighted 18-month moving averages with a decay factor of 0.88.

## Table 11, continued
## Sensitivity of Coefficient Estimates to Sample Period
### Panel B: Downgrade from Investment to Speculative grade -- All Macro Variables

| | All Variables | | | | | | Backward Selection | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | |
| | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | -0.325 | 0.001 | 0.201 | 0.251 | -0.614 | 0.000 | -0.293 | 0.002 | | | -0.608 | 0.000 |
| Current rating: Baa | 2.721 | 0.000 | 2.328 | 0.000 | 3.835 | 0.000 | 2.723 | 0.000 | 2.331 | 0.000 | 3.716 | 0.000 |
| Downgraded within last 2 years | 0.795 | 0.000 | 0.506 | 0.000 | 1.000 | 0.000 | 0.806 | 0.000 | 0.508 | 0.000 | 0.997 | 0.000 |
| Upgraded within last 2 years | -0.753 | 0.000 | -0.930 | 0.000 | -0.628 | 0.001 | -0.779 | 0.000 | -0.996 | 0.000 | -0.656 | 0.001 |
| log(years since first rated) | -0.041 | 0.358 | -0.028 | 0.620 | -0.023 | 0.664 | | | | | | |
| **General Macroeconomic Conditions** | | | | | | | | | | | | |
| Unemployment rate | -0.687 | 0.000 | -0.528 | 0.063 | -0.069 | 0.769 | -0.588 | 0.000 | -0.283 | 0.000 | | |
| Inflation | -0.143 | 0.001 | -0.247 | 0.000 | 0.121 | 0.324 | -0.158 | 0.000 | -0.210 | 0.000 | | |
| NBER recession indicator | -0.258 | 0.118 | -0.017 | 0.964 | -0.293 | 0.220 | -0.317 | 0.048 | | | | |
| CFNAI | 0.573 | 0.000 | 0.835 | 0.000 | -0.729 | 0.037 | 0.652 | 0.000 | 0.800 | 0.000 | -0.949 | 0.001 |
| **Direction of the Economy** | | | | | | | | | | | | |
| Real GDP growth | -1.341 | 0.000 | -2.003 | 0.000 | -1.072 | 0.083 | -1.228 | 0.000 | -1.790 | 0.000 | | |
| Growth of industrial production | 0.533 | 0.211 | 0.622 | 0.281 | 2.413 | 0.051 | | | | | 1.692 | 0.012 |
| **Financial Market Conditions** | | | | | | | | | | | | |
| 3-month T-Bill rate | -0.091 | 0.215 | -0.019 | 0.882 | -0.193 | 0.407 | | | | | -0.235 | 0.001 |
| Long-term interest rate (10-year Treasury) | 0.570 | 0.000 | 0.203 | 0.262 | -0.771 | 0.028 | 0.432 | 0.000 | | | -0.841 | 0.000 |
| S&P 500 return | 0.054 | 0.367 | -0.242 | 0.192 | -0.047 | 0.652 | | | -0.339 | 0.000 | | |
| S&P 500 volatility | -0.062 | 0.000 | -0.113 | 0.000 | 0.006 | 0.866 | -0.049 | 0.002 | -0.106 | 0.000 | | |
| Russell 2000 Index return | -0.190 | 0.000 | -0.022 | 0.861 | 0.018 | 0.815 | -0.174 | 0.000 | | | | |
| Yield spread (Baa - 10 Year Treasury) | 1.201 | 0.000 | 0.298 | 0.665 | -1.730 | 0.003 | 0.997 | 0.000 | | | -2.352 | 0.000 |
| Corporate bond default rate | 0.086 | 0.128 | -0.446 | 0.007 | 0.740 | 0.000 | | | -0.550 | 0.000 | 0.990 | 0.000 |
| **Goodness of Fit** | | | | | | | | | | | | |
| -2 x log(likelihood) | 9272.87 | | 9145.02 | | | | | | 9159.70 | | | |
| Difference in 2 x log(likelihood) | | | 127.85 | | | | | | 14.68 | | | |
| p-value on H0 that the coefficients are the same in both subperiods | | | 0.000 | | | | | | | | | |
| p-value on backward selection for subperiods | | | | | | | | | 0.548 | | | |

## Table 11, continued
## Sensitivity of Coefficient Estimates to Sample Period
### Panel C: Downgrade from Investment to Speculative grade -- Macro Subsets 1 and 2

| | All Variables | | | | | | Backward Selection | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | |
| | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value |
| **MACRO SUBSET 1** | | | | | | | | | | | | |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | -0.356 | 0.000 | 0.299 | 0.082 | -0.677 | 0.000 | -0.319 | 0.001 | 0.331 | 0.048 | -0.658 | 0.000 |
| Current rating: Baa | 2.734 | 0.000 | 2.418 | 0.000 | 3.510 | 0.000 | 2.744 | 0.000 | 2.438 | 0.000 | 3.456 | 0.000 |
| Downgraded within last 2 years | 0.839 | 0.000 | 0.428 | 0.000 | 1.084 | 0.000 | 0.833 | 0.000 | 0.423 | 0.000 | 1.079 | 0.000 |
| Upgraded within last 2 years | -0.790 | 0.000 | -0.991 | 0.000 | -0.673 | 0.001 | -0.828 | 0.000 | -1.009 | 0.000 | -0.693 | 0.000 |
| log(years since first rated) | -0.052 | 0.240 | -0.014 | 0.807 | -0.040 | 0.442 | | | | | | |
| **General Macroeconomic Conditions** | | | | | | | | | | | | |
| Unemployment rate | 0.092 | 0.001 | 0.009 | 0.802 | -0.146 | 0.004 | 0.085 | 0.000 | | | -0.144 | 0.003 |
| Inflation | -0.011 | 0.614 | -0.097 | 0.001 | -0.215 | 0.000 | | | -0.093 | 0.002 | -0.225 | 0.000 |
| NBER recession indicator | 0.298 | 0.042 | 0.822 | 0.000 | -0.345 | 0.076 | 0.286 | 0.047 | 0.909 | 0.000 | | |
| CFNAI | -0.241 | 0.002 | -0.051 | 0.621 | -0.642 | 0.000 | -0.236 | 0.002 | | | -0.498 | 0.000 |
| **Goodness of Fit** | | | | | | | | | | | | |
| -2 x log(likelihood) | 9482.66 | | 9332.82 | | | | | | 9336.98 | | | |
| Difference in 2 x log(likelihood) | | | 149.84 | | | | | | 4.15 | | | |
| p-value on H0 that the coefficients are the same in both subperiods | | | 0.00 | | | | | | | | | |
| p-value on backward selection for subperiods | | | | | | | | | 0.53 | | | |
| **MACRO SUBSET 2** | | | | | | | | | | | | |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | -0.333 | 0.001 | 0.233 | 0.187 | -0.630 | 0.000 | -0.298 | 0.002 | | | -0.613 | 0.000 |
| Current rating: Baa | 2.719 | 0.000 | 2.350 | 0.000 | 3.708 | 0.000 | 2.724 | 0.000 | 2.330 | 0.000 | 3.704 | 0.000 |
| Downgraded within last 2 years | 0.804 | 0.000 | 0.513 | 0.000 | 1.006 | 0.000 | 0.807 | 0.000 | 0.520 | 0.000 | 1.010 | 0.000 |
| Upgraded within last 2 years | -0.760 | 0.000 | -0.922 | 0.000 | -0.644 | 0.001 | -0.788 | 0.000 | -0.991 | 0.000 | -0.660 | 0.001 |
| log(years since first rated) | -0.045 | 0.310 | -0.025 | 0.661 | -0.026 | 0.624 | | | | | | |
| **Direction of the Economy** | | | | | | | | | | | | |
| Real GDP growth | -0.421 | 0.011 | -1.823 | 0.000 | -0.979 | 0.101 | -0.372 | 0.000 | -1.609 | 0.000 | | |
| Growth of industrial production | 0.250 | 0.406 | 1.204 | 0.004 | 1.014 | 0.247 | | | 0.966 | 0.008 | | |
| **Financial Market Conditions** | | | | | | | | | | | | |
| 3-month T-Bill rate | 0.040 | 0.370 | -0.379 | 0.000 | -0.081 | 0.457 | | | -0.294 | 0.000 | | |
| Long-term interest rate (10-year Treasury) | 0.075 | 0.103 | 0.081 | 0.359 | -0.790 | 0.000 | 0.094 | 0.000 | | | -0.818 | 0.000 |
| S&P 500 return | 0.070 | 0.166 | -0.424 | 0.006 | -0.130 | 0.137 | | | -0.301 | 0.000 | -0.162 | 0.002 |
| S&P 500 volatility | -0.005 | 0.724 | -0.142 | 0.000 | 0.023 | 0.462 | | | -0.131 | 0.000 | | |
| Russell 2000 Index return | -0.174 | 0.000 | 0.114 | 0.284 | 0.036 | 0.593 | -0.132 | 0.000 | | | | |
| Yield spread (Baa - 10 Year Treasury) | 0.570 | 0.000 | -0.105 | 0.627 | -2.109 | 0.000 | 0.465 | 0.000 | | | -2.277 | 0.000 |
| Corporate bond default rate | 0.095 | 0.062 | -0.552 | 0.000 | 0.738 | 0.000 | | | -0.612 | 0.000 | 0.857 | 0.000 |
| **Goodness of Fit** | | | | | | | | | | | | |
| -2 x log(likelihood) | 9364.84 | | 9194.70 | | | | | | 9203.05 | | | |
| Difference in 2 x log(likelihood) | | | 170.14 | | | | | | 8.35 | | | |
| p-value on H0 that the coefficients are the same in both subperiods | | | 0.00 | | | | | | | | | |
| p-value on backward selection for subperiods | | | | | | | | | 0.68 | | | |

## Table 11, continued
## Sensitivity of Coefficient Estimates to Sample Period

### Panel D: Upgrade from Ba and B to Investment grade

| | All Variables | | | | | | Backward Selection | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | | Spells in all years 1981-2002 | | Spells in years 1981-1990 | | Spells in years 1991-2002 | |
| | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value | coefficient | p-value |
| **Firm Specific Factors** | | | | | | | | | | | | |
| Initial rating: Investment grade | 0.436 | 0.000 | 0.327 | 0.090 | 0.479 | 0.001 | 0.430 | 0.000 | | | 0.460 | 0.001 |
| Current rating: Ba | 1.817 | 0.000 | 2.109 | 0.000 | 1.797 | 0.000 | 1.816 | 0.000 | 2.048 | 0.000 | 1.841 | 0.000 |
| Downgraded within last 2 years | -0.031 | 0.794 | 0.428 | 0.021 | -0.320 | 0.036 | | | 0.495 | 0.006 | -0.361 | 0.015 |
| Upgraded within last 2 years | 0.315 | 0.003 | 0.703 | 0.001 | 0.183 | 0.124 | 0.321 | 0.002 | 0.693 | 0.001 | | |
| log(years since first rated) | 0.317 | 0.000 | 0.546 | 0.000 | 0.198 | 0.001 | 0.318 | 0.000 | 0.627 | 0.000 | 0.218 | 0.000 |
| **General Macroeconomic Conditions** | | | | | | | | | | | | |
| Unemployment rate | -0.324 | 0.003 | -0.685 | 0.055 | -0.359 | 0.081 | -0.314 | 0.000 | -0.886 | 0.000 | -0.144 | 0.002 |
| Inflation | -0.276 | 0.000 | -0.655 | 0.000 | 0.305 | 0.027 | -0.256 | 0.000 | -0.629 | 0.000 | | |
| NBER recession indicator | 0.399 | 0.062 | 0.917 | 0.088 | -0.060 | 0.841 | | | | | | |
| CFNAI | 0.175 | 0.317 | 0.658 | 0.021 | 0.402 | 0.219 | | | 0.616 | 0.013 | | |
| **Direction of the Economy** | | | | | | | | | | | | |
| Real GDP growth | -1.192 | 0.000 | -2.055 | 0.000 | 0.321 | 0.559 | -1.256 | 0.000 | -2.517 | 0.000 | | |
| Growth of industrial production | 1.083 | 0.030 | 2.162 | 0.008 | -2.590 | 0.035 | 1.040 | 0.001 | 2.803 | 0.000 | | |
| **Financial Market Conditions** | | | | | | | | | | | | |
| 3-month T-Bill rate | 0.065 | 0.438 | 0.304 | 0.091 | -0.342 | 0.121 | | | 0.272 | 0.045 | | |
| Long-term interest rate (10-year Treasury) | 0.164 | 0.119 | 0.278 | 0.221 | 0.178 | 0.535 | 0.219 | 0.000 | 0.566 | 0.000 | | |
| S&P 500 return | -0.146 | 0.037 | -0.241 | 0.288 | 0.141 | 0.172 | -0.103 | 0.005 | | | | |
| S&P 500 volatility | -0.006 | 0.735 | 0.012 | 0.763 | 0.041 | 0.255 | | | | | | |
| Russell 2000 Index return | 0.060 | 0.264 | 0.196 | 0.185 | -0.026 | 0.713 | | | | | | |
| Yield spread (Baa - 10 Year Treasury) | 0.107 | 0.675 | -0.485 | 0.599 | -0.741 | 0.235 | | | | | | |
| Corporate bond default rate | -0.288 | 0.000 | -0.345 | 0.092 | -0.308 | 0.097 | -0.298 | 0.000 | | | -0.142 | 0.002 |
| **Goodness of Fit** | | | | | | | | | | | | |
| -2 x log(likelihood) | 8342.65 | | 8222.96 | | | | | | 8245.24 | | | |
| Difference in 2 x log(likelihood) | | | 119.69 | | | | | | 22.28 | | | |
| p-value on H0 that the coefficients are the same in both subperiods | | | 0.000 | | | | | | | | | |
| p-value on backward selection for subperiods | | | | | | | | | 0.271 | | | |