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

by

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We thank Moody's Credit Market Research Fund and Moody's Investor Services for providing funding, data, and expert advice. We also thank Sanjiv Das, Stephen Brown, the Editor, Carl Chen, and seminar participants at NYU, Moody's, Columbia, Florida State, and Laval University for valuable comments and suggestions. The research was conducted while Weijian Liang was a Ph.D student at NYU.

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Abstract

In credit modeling, risk exposure depends on firm-specific factors, but it also varies with changes in general economic conditions. To explore how the macroeconomy affects credit risk, we fit Cox intensity models for defaults and for major transitions between investment grade and speculative credit ratings, using a broad range of macroeconomic variables. Firm-specific influences are taken into account through the firm's bond rating and its ratings history. We find that among all corporate issuers in Moody's corporate bond Default Research Database during the period 1981 - 2002, the intensity of occurrence of a credit event was strongly influenced by both macroeconomic and ratings-related factors. Interestingly, in all cases the estimated effects of the ratings-related factors were consistent with expectations and very robust when macroeconomic variables were added to the model. However, significance levels and even signs for some of the macro variable coefficients depended heavily on which other variables were included in a specification. This finding sheds some light on disparate results reported in earlier studies.

JEL Classification: G32, E44, G24

Keywords: Credit risk; Cox model; default risk; intensity model; bond ratings

1 Introduction

Models of corporate default fall into two broad categories, structural models and reduced form models. 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. They have the practical advantage of using the firm's current stock price, a sensitive barometer of its financial condition that is updated daily, unlike accounting statements that are only available quarterly.[1] But structural models pose difficult problems, including the need to value all of the components of a real world firm's complex capital structure, to model their dynamics and estimate those models empirically, and to specify exactly where the default boundary lies. This is a challenging task in itself, as the literature shows, and it becomes extremely difficult to introduce very many additional variables related to conditions in the macroeconomy. Moreover, important non-default credit events, such as a ratings downgrade, do not fit conveniently into the structural framework.

This paper focuses on the reduced form approach, which treats default as a random event that can strike any firm at any time. The paradigm might be thought of as a formalization and extension of the familiar ratings transition matrices published by Moody's and other ratings agencies.[2] 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 reduced form approach has been 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 (2007), and Koopman et al (2005).

The constant hazard rate formulation treats all issuers in a given credit class as homogeneous. But empirical evidence of non-Markovian behavior includes positive serial correlation in ratings changes, known as "ratings drift," time variation in default probabilities, and cross-sectional differences in credit risk across issuers within a given rating. For example, Altman and Kao (1992) found ratings drift among firms that recently had a change in rating, and Hamilton and Cantor (2004) showed that the transition probability out of a rating class depends on whether the bond entered its

[1] How quickly the ratings agencies update their ratings as a firm's creditworthiness deteriorates becomes an important issue in comparing the relative performance of the two approaches. Güttler and Wahrenburg (2007) present evidence that Moody's does so in a more timely manner than S&P.

[2] 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.

current rating by an upgrade or a downgrade.[3] Other kinds of non-Markovian behavior were described by Lando and Skodeberg (2002), who found that the probability of a rating change diminishes the longer the bond stays in the same rating; and by McDonald and Van de Gucht (1999), whose results suggested a nonmonotonic aging effect. 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 results support the belief that credit risk exposure is affected by conditions in the macroeconomy. In particular, Bangia et al (2002) and Nickel, et al (2000) found that upgrade, downgrade and default intensities differ across different economic regimes. Xie et al (2008) used the reduced form approach to extract (risk neutral) default intensities from investment grade corporate bond yields and found strong evidence of common factors, the strongest of which was the performance of the stock market. Numerous other studies showing that default probability is sensitive to macroeconomic factors include Kavvathas (2001), Carling et al (2002), Couderc and Renault (2004) and Duffie et al (2007). Huang and Kong (2003) demonstrated that macroeconomic announcements have a significant impact on credit spreads.

In this paper, we formulate and estimate extended reduced-form models for the occurrence of credit events, using the semi-parametric Cox regression model. This well-known approach adapted from survival analysis allows the hazard rate for a given issuer to be a function of both firm-specific factors and macroeconomic conditions.[4] In place of a formal structural model, we assume that the important factors tied to a firm's capital structure are adequately reflected in its current bond rating and its credit rating history. Our concentration is on assessing the relative importance of a much broader selection of macro variables, both individually and in combination, than has been carried out previously with the Cox hazard model.

Duffie, Saita, and Wang (2007) combined variables from both frameworks in developing a model for the term structure of credit risk as a function of a small number of structural and macro factors. But their focus on forecasting required building models for the time-series properties of

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[3] Christensen, et al (2004) modeled downward drift by introducing a hidden Markov chain. Subsequently, Frydman and Schuermann **(**2008**)** showed that a mixture of Markov chains statistically dominates a single Markov chain model.

[4] 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.

their factors, which strictly limited the number of variables that could be considered.[5] By contrast, we wish to establish "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.

Default is the most important change in credit quality, but hardly the only one that matters to investors. Tables of historical transition frequencies among the ratings categories, and previous research on credit risk, have attempted to estimate the full transition matrix for ratings changes. We prefer to concentrate on the most important transitions rather than modeling the fine structure of the credit market.[6] We therefore focus on three 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 transition (upgrade from speculative to investment grade).[7]

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 expectation 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 as overall credit risk varies over the business cycle. But different 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.

A relevant macro factor should be one that has a broad impact on most firms' creditworthiness. 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

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[5] Their final specification included only four variables: 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.

[6] 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.

[7] 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.

production?; 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 choose among these possibilities a priori, we begin by grouping candidate variables into three broad classes: those related to general macroeconomic conditions (e.g., the unemployment rate, inflation, and the NBER recession indicator); those related to the direction in which the economy is moving (e.g., real GDP growth and the change in consumer sentiment); and a remaining set loosely categorized as indicators of financial market conditions (e.g., interest rates and stock market returns). The last group includes the recent default rate among corporate borrowers in order to examine potential "contagion" in the credit market. The 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.

To look at how the estimated influence of each macro variable is affected by other variables included in the model, we examine three specifications. First we include each one as the single macro variable in a specification with the full set of firm-specific ratings-related covariates. This indicates what the simplest specification with that macro variable would show, for example an initial exploratory analysis of the individual variables in a large set of candidates. We then run the full set of firm-specific and macro covariates together in a single comprehensive specification. In many cases, this produces a sharp change in the variable's significance level and even in the direction of its estimated effect. Finally, although most of the pairwise correlations among our macro variables are not that high, it seems clear that multicollinearity within the full set tends to hold down significance levels for individual coefficients. We therefore use stepwise regression to pare down the number of variables and obtain a third, parsimonious specification in which all of the estimated coefficients are statistically significant. This procedure is known as "backward selection" because it begins with the full set of covariates and eliminates the least significant ones, one at a time.

We find that adding macroeconomic factors into a specification with ratings-related variables produces a highly significant increase in explanatory power, but it is not easy to identify a small number of specific variables that dominate the field of alternative measures, and some of the seemingly obvious candidates turn out to have insignificant or anomalous coefficients when combined with other macro variables in more comprehensive specifications. For example, while they are highly significant when examined one at a time, none of the variables related to general macroeconomic conditions have any power in explaining defaults when combined with the other macro factors. Strength in the stock market as measured by the return on the S&P 500 index is estimated to have an anomalous effect, increasing the risk of default and reducing the chance of upgrade.

While failure to obtain a single dominant model specification for each transition may seem somewhat disappointing, we actually feel that this is one of our more important findings in helping to understand the complicated connection between credit risk and the macroeconomy. Our results show how earlier studies could arrive at quite different conclusions based on fitting similar but somewhat different models. They call into question any strong conclusions about the importance of any single macro variable among a set of related ones that might be drawn from such research. By contrast, the ratings-related variables perform consistently as expected, with higher ratings corresponding to significantly lower credit risk, and the aging and ratings drift effects strongly confirmed. Interestingly, while the coefficients on specific macro variables can change drastically depending on which other variables are included in the specification, the estimated effects of the ratings-related factors are largely unaffected by the addition of macroeconomic variables to the model.

The question of contagion in defaults has been widely debated: Holding other factors equal, does default by one firm increase the likelihood that other unrelated firms will also experience credit problems, independent of their objective creditworthiness? Or is the empirical observation that defaults appear to come in waves simply due to the fact that all firms are exposed to broad economic forces that affect credit risk for all of them at the same time?[8] We do not offer a definitive answer to this question, but our results do shed some light on it. Along with a large set of variables measuring various aspects of the economic environment, we include the overall default rate in the corporate sector over the recent past. Consistent with the existence of contagion in the credit market, we find that even after allowing for the effects of the macro factors included in the specification, a high corporate default rate over the last year is still associated with a highly significant increase in the hazard rate for default and a decrease for rating upgrades. The estimated effect on downgrades from investment to speculative grade is also positive, but not significant.

[8] Das, et al (2007) explored this issue with a cleverly designed time-changed hazard model and concluded that their finding of higher default correlation than the model could explain could be due to macroeconomic factors. Guo et al (2011) consider contagion across asset classes and find that credit spreads are impacted by shocks from stock prices as well as the real estate sector, especially during more volatile periods.

In the next section, we describe the Cox hazards model that will be used throughout the paper. Sections 3, 4 and 5 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 6, 7, and 8 present estimation results for defaults, for downgrades from investment to speculative ratings classes, and for upgrades from speculative to investment grade, respectively. Section 9 summarizes our results and concludes.

2 The Cox Hazard Model

The Cox hazard regression model proposed by Cox (1972) has been widely used in the analysis of survival data in medicine and has become popular in finance. See, for example, Buehler (2005), Henebry (1997), or Lane, et al (1986). Here we present a brief exposition of the Cox model in the competing risks framework, a natural framework for our data. For a more extensive discussion see Kalbfleisch and Prentice (2002) or Cox and Oakes (1984).

Let T be the amount of time that an issuer spends in a given rating class; we identify this time as a survival time for an issuer in that rating class. We will also refer to it as a "spell." 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 upgrade or downgrade, default or some non-credit reason. We differentiate between exits due to credit events and those due to non-credit events.

We estimate the cause-specific hazard function to study how the risks of different types of credit events depend on covariates. For an event of type j among J possible event types, this is the limiting conditional probability of occurrence given a vector of time-dependent covariates Z (t) and given that no event of any type has occurred in the at-risk population prior to time 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 λ_j (t;Z(t)) represents the instantaneous hazard rate of a type j credit event occurring at time t given Z(t). Again, the time index t in λ_j(t; Z(t)) refers to the length of time since entering the current state, not calendar time.

The Cox hazard regression model specifies λ_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 β_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.

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:

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

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. The Cox regression model is often referred to as the "proportional hazards" model because, if the covariates are all calendar time-independent, the ratio of hazard rates is constant over time. However, our covariates are time-dependent, so the ratio of hazard rates does change with t.

We now discuss estimation of the parameters β_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, $1 \le n < N$, 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. 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 β_j is

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

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 the footnote.[9]

The maximum likelihood estimator, $\hat{\beta}_j$ of β_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 is that it allows estimation of parameters β_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 estimating relative risk faced by the issuers we have used partial likelihood

[9] 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) estimation for β_j. For discussion of estimation methods for $\lambda_{0j}(t)$ we refer the reader to the aforementioned references.

3 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 detail 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.[10]

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 considered

[10] 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. One reason is that that would substantially restrict the length of the historical sample we could cover. See Hamilton and Cantor (2004).

to be right-censored. 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. 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 firms with 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 category 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.[11]

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[11] 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.

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.

4 Rating History-Specific Covariates

Table 3 lists the variables used in the models and provides statistics on their means and standard deviations, as well as the sources. We consider four types of ratings-related firm-specific covariates:

Initial rating class: "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.[12] 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.[13] 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.

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.[14] 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

[12] See Mann, et al (2003).
[13] See Christensen, et al (2004). Güttler and Wharenburg (2007) also find serial correlation in Moody's ratings changes even after controlling for those by S&P, and vice versa.
[14] See Altman (1998), for example.

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.

5 Macroeconomic Covariates

We selected a total of 14 macroeconomic covariates, which we grouped into three categories: those related to the overall health of the economy ("General Macroeconomic Conditions"), those measuring whether economic conditions are improving or worsening ("Direction of the Economy"), and seven others that are broadly related to current conditions in the financial markets ("Financial Market Conditions").

5.1 General Macroeconomic Conditions

We examine four key indicators of broad economic conditions:

Unemployment rate: The unemployment rate is one of the most visible measures of overall health of the economy. High unemployment should increase the hazard of downgrade transitions and decrease the hazard of upgrade from speculative to investment grade.

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 increases 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 for the sign of its coefficient.

NBER recession indicator: The National Bureau of Economic Research follows the evolution of the macro economy 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

[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.

variable is set to 1 for recession periods. We expect its coefficient to be positive for downgrade transitions and negative for upgrades.

Chicago Fed National Activity Index (CFNAI): The large number of available series relating to the macro economy makes it very difficult to select the most important ones. To try to capture overall economic conditions in a single variable, the Federal Reserve Bank of Chicago 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] We expect the effect of a strong CFNAI to be negative for downgrade transitions and positive for upgrade transitions.

5.2 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 expansion. 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 low credit risk. We explore this issue with two measures of economic growth.

Real GDP growth: 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 simply by repeating the quarterly average growth rate 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.

[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.

Growth of Industrial Production: Real GDP comprises all economic activity, including government, non-corporate 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. We expect the estimated coefficients of the Direction of Economy variables to have negative signs for downgrade transitions and positive for an upgrade transition.

Change in Consumer Sentiment: A different gauge of the direction of the economy comes from a measure of "sentiment." Recent research has shown that behavior of consumers and investors is strongly influenced by their subjective sentiment.[17] Several measures are available, of which one of the best-known and most actively studied comes from the University of Michigan Survey of Consumer Sentiment, first reported in 1978. We use the change in Consumer Sentiment as a measure of how economic agents' subjective beliefs and expectations about the economy are evolving. We also explored an alternative measure of investor sentiment developed by Baker and Wurgler (2006). The results were quite similar, so we report only those with the Michigan Survey here.

5.3 Financial Market Conditions

A firm in financial distress may be able to extricate itself if it can obtain fresh funding from the market. 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: 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. As others have done, we used the 3-month T-bill rate as a measure of the tightness of the money market. 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.[18] We expect the coefficient on either interest rate variable to be positive in downgrade transitions and negative in the upgrade transition.

[17] See, for example, Lemmon and Portniaguina (2006) or Baker and Wurgler (2006).

[18] For example, Duffie, et al (2007), found that higher short term interest rates corresponded to lower overall credit quality. Keenan, et al (1999) included both the 10 year Treasury yield and the spread between the 10 year yield and 3 month T-bills, and found both variables to be positively associated with increased default rates.

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 model, a firm's default risk exposure is directly connected to the level and volatility of its stock price. While the Standard and Poor's 500 stock 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.[19] We also consider S&P monthly volatility as a potentially important predictor. Volatility is estimated month by month as the annualized standard deviation of daily returns within the month. Our prior expectation is that rising stock prices should reduce default risk, but greater volatility may increase it.

We do not include the individual firm's own stock return as a covariate, even though it is an important factor in a standard structural model. One reason is that even in the structural framework, correctly understanding the connection between stock returns and a given firm's credit quality requires a fully specified structural model. But our main focus is on the way macroeconomic conditions affect credit risk, so we mainly want to abstract from firm-specific factors in that investigation. Rather than attempting to build a complete structural model for this purpose, we rely instead on the analysis done by Moody's, as reflected in the firm's bond rating. A second reason is that while a fall in the stock price may signal the market's perception that the firm's credit quality is diminishing, which may be very useful for forecasting future default, one thinks of it as a measure of credit quality but not as an independent causal factor, the way a general recession in the economy would be.

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, useful data series do not go back far enough for our work. We therefore have included the closest available match.[20] The expected sign on the credit spread is positive for downgrade transitions and negative for an upgrade.

[19] 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/.

[20] The corporate series is 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.

Overall default rate of corporate bonds: As mentioned above, there is considerable debate over whether "contagion" in corporate defaults exists. Moody's KMV tabulates the percent of all rated US corporations that have defaulted during the previous 12-month period. To the extent that the other macro variables in our specifications adequately capture the state of the macroeconomy, if there is significant contagion, the current default rate will be further elevated when there have been a lot of defaults in the recent past. The prior expectation is that the sign on the overall default rate will be positive for downgrade transitions and negative for an upgrade transition.

5. 4 Lags

Empirical 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 their effect on defaults would be instantaneous. 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 consider it quite important to include lagged values of our macro covariates in the specification. But with a large number of individual series, adding lagged values 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

$$X_t = \frac{\sum_{k=1}^{K} \delta^{k-1} \; x_{t-k}}{\sum_{k=1}^{K} \delta^{k-1}}, \tag{6}$$

where K is the length of the lag window and δ 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 δ = 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 18-month window we use would receive 90% of the total weight.

5.5 Correlations

The correlations among our macro covariates are shown in Table 4. 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. The CFNAI and two "Direction of the Economy" variables are also seen to be highly correlated with each other. We keep all of these highly correlated variables because it is not clear which are the best to use in our models. Whereas the CFNAI has not been used before, Real GDP growth and the Growth of industrial production have been found to be important in earlier research

6. 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.

6.1 Individual Macro Factors

Table 5 reports the estimated marginal effect of each macro factor when added to a Cox model that includes all of the rating history-specific factors. The coefficient estimates for the firm-specific factors themselves are presented in Table 6.

These results give some idea of each macro variable's potential importance and the direction of its effect when combined with rating specific variables. One reason to look at such simple specifications is that they indicate what other researchers are likely to find in an exploratory investigation of how default is influenced by each of these variables. The marginal effects of most of the macro factors are highly statistically significant. A positive (negative) coefficient means that an increase in the covariate raises (reduces) the hazard rate of default. The signs of the statistically significant estimated coefficients, except for the coefficient of S&P 500, agree with our prior expectations. We did not have a prior expectation for the coefficient on inflation, which is significant and positive in Table 5.

6.2 Comprehensive Specifications for Default Intensity

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 rating history-specific covariates. There is some evidence that having started with an investment grade rating gives a firm a lower risk of default, and 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 default 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.[21] 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 14 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, because 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

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

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. To save space, we only report standardized coefficients in Table 6. For the other transitions the ratios of standardized to raw coefficients are similar to what one sees here, although the raw coefficients differ.

The "All variables" specification includes 23 variables, with few of the macro covariates being statistically significant. To pare this down to a parsimonious specification, we used a stepwise regression to weed out the variables that do not contribute significantly to explanatory power of the model. 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 "backward selection" procedure 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 rating-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 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, once other macro covariates are included in the specification, and none of them survives the backward selection process to enter the final specification. The Change in Consumer Sentiment is the single variable related to broad macroeconomic conditions that performs well. It is negative and highly significant in the final specification. Growth of industrial production narrowly missed inclusion in the final specification, achieving a p-value of 0.080 in the final exclusion round.

Turning to the variables related to conditions in the financial markets, we see that of the two highly correlated interest rates, the 10-year Treasury yield makes it into the final backward selection model. 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 returns on the S&P 500 and the Russell 2000 index also survive the backward selection process. A strong market for small stocks significantly lowers the default intensity, but the return on the S&P 500 index still has an anomalous positive sign: a strong market for large firms is associated with increased default risk. This surprising result was also found by Duffie, et al (2007) in their estimation of default intensity. We will see the odd effect of the S&P 500 again in the estimated intensity of upgrade. By contrast, the recent corporate bond default rate has a highly statistically significant positive coefficient 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 (2007) 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 fully untangle this important issue 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 rating history-specific variables is rejected in favor of the All variables model (test statistic=178.02, df=14, p-value=0) as well as in favor of the backward selection model (test statistic=169.92, p-value=0). In fact, the backward selection model with only 5 of the original 14 macro variables is statistically indistinguishable from the All variables model, as seen from the last line of Table 6 (test statistic=8.10, df=9, p-value=0.524).

The second Goodness of Fit 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.

7 Downgrades from Investment to Speculative Grade

After default, probably the most important ratings transition is from investment grade down to speculative grade. 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 result from decisions made by a credit rating agency. It is certainly possible that a given macroeconomic or rating-specific factor may have a different impact on the default intensity of a particular firm than on its future creditworthiness 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.[22] 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.

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[22] This is called "rating through the cycle." See Cantor and Mann (2003).

7.1 Analysis of Individual Macro Factors

Like Table 5, Table 7 shows the marginal contribution of each macro factor in a specification with the full set of ratings-based firm-specific variables. These results are quite striking: the marginal contribution of each macro factor is highly statistically significant (p-value=0) and the coefficients have no obviously anomalous signs.

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 rating-specific factors.

7.2 Model with Rating-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 in Table 8, as in Table 6, the coefficient point estimates and significance levels on the rating-specific variables are very similar across the different specifications, suggesting again that to the extent that the macro factors are able to add explanatory power to these models, it is incremental to the contribution of the rating-specific factors.

7.3 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 are estimated to be significant, but many of these coefficients have anomalous signs. Indeed, all four of the General macro factors have the "wrong" signs, and the first two "Direction of the Economy" variables have offsetting signs. Applying backward selection to the All variables specification, does not alleviate these problems.

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 Conditions 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, the four of the five variables that appear in the final backward selection model, Real GDP growth, Change in Consumer Sentiment, 10-year Treasury yield, and Yield Spread all show expected effects. Real GDP growth and rise in consumer sentiment produce significant reductions in downgrade hazard. A high long-term interest rate and a wide yield spread produce highly significant increases in the downgrade risk. But the Growth in industrial production survives the backward selection with a strong anomalously positive coefficient.

Looking at the backward selection models, we see that adding variables from either Macro set 1 or Macro set 2 to the rating-specific variables results in highly significant improvement in the goodness of fit statistics, 61.69 for the Macro set 1 and 196.67 for the Macro set 2. The AIC for the set 2 model is lower than for the set 1 model suggesting that the direction of the economy and financial market conditions variables influence the intensity of downgrade more than the general macroeconomic conditions variables do. Even so, the goodness of fit tests show that all of the subset models, with or without backward selection, are significantly worse than the specification that includes all variables. For this transition, we must base our preference for the more parsimonious models on their more plausible coefficient estimates than on their statistical power.

8 Upgrades to Investment Grade

We now consider the upgrade transition from speculative to investment grade. There were only 4 cases in our sample of a firm with a rating in any of the C ratings jumping directly to investment grade, so we only consider upgrades from a B or Ba rating to one of the Investment grade ratings.[23]

8.1 Analysis of Individual Macro Factors

Table 9 combines each macro economic variable with the rating specific covariates. The NBER recession indicator, Real GDP growth and the Corporate Bond default rate are each highly significant but, strikingly, the first two of these variables have the "wrong" signs. We expected that the variables related to stronger economic conditions (e.g., Real GDP growth) would have positive signs in the hazard for upgrade transition and those related to weaker conditions (e.g., the NBER recession indicator) negative signs.

This led us to investigate the issue of "wrong" signs. We estimated the upgrade hazard function with the NBER recession indicator as the sole variable, obtaining the coefficient of 0.51 with a p-value of 0.000, and also with Real GDP growth as the sole variable, which gave a coefficient of -0.319 with p-value =0.001, confirming the signs obtained in the marginal analysis. But empirically, there are more upgrades in expansions that in recessions (503 vs. 122), so we explored this issue further by re-estimating the coefficient of the NBER indicator using a parametric specification of the hazard function. By assuming a constant baseline hazard function, one can obtain an explicit estimator for the coefficient on the NBER recession indicator.[24] However, the test

[23] 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 the results here.

[24] The constant baseline assumption was employed in Duffie et al (2007), for example. The estimator of the exp(coefficient of NBER recession indicator) is of the form $(N_r/R) / (N_e/E)$, where R (E) is the total time that the firms spent in recession (expansion) and N_r (N_e) is the total number of upgrades in recession (expansion). Note that $(N_r/R) / (N_e/E)$ is the ratio of the hazard of upgrade in recession, (N_r/R), to the hazard of upgrade in expansion (N_e/E). For our sample, $N_r = 122$, $N_e = 503$, R=545,984 firm days and E=5,838,827 firm days, which results in $(N_r/R) / (N_e/E) = 2.6$. The coefficient on the NBER recession indicator =0.995, was positive and even larger than the 0.51 value obtained from the Cox model. (The derivation of this estimator can be obtained from the authors upon request.)

confirmed the positive sign for the NBER recession coefficient. There are decisively fewer upgrades in recessions than in expansions but the economy spends much more time in expansions, so it balances out mathematically to a higher chance of upgrade in recession that in expansion. This illustrates a key advantage of the hazard model, which focuses on the intensity of occurrence of a credit event rather than on its frequency. While frequency captures the direct effect of the macroeconomic environment, intensity weighs the frequency relative to the amount of time spent exposed to the risk factor.

The seemingly anomalous results in Table 9 suggest that it may be easier for Moody’s to identify a better performing firm relative to other firms in its cohort during a recession, when all firms are exposed to difficult economic conditions, than in an expansion when all firms are doing better. The negative sign on Real GDP growth is consistent with the hypothesis that a rising economy makes it more difficult for a rating agency to distinguish a more creditworthy firm from the others in its cohort.

8.2 Model with Rating-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 rating-specific covariates are very similar for models with and without the macro covariates. For "fallen angels" that were initially rated as investment grade but are currently rated Ba or B, the intensity of being upgraded back to investment grade is significantly greater than for an issuer that was originally rated in a speculative 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 stepwise regression procedure. The scarcity of such cases in the sample may well be 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 has 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.

8.3 Models with All Macro Factors Included

We eliminated two variables from the All variables model for this table: Growth in industrial production and CFNAI. The first was eliminated because its coefficient was 0.000 with p-value = 0.998 when combined with rating-specific variables in Table 9. We eliminated CFNAI because its estimated coefficient for this transition was seriously affected by multicollinearity with Real GDP growth (correlation = 0.815 in Table 4). When CFNAI is included in the specification, both variables are retained in the backward selection model, with Real GDP growth having a highly significant negative coefficient, as in the marginal analysis, but the CFNAI coefficient reversing sign from its negative effect in the marginal analysis to become positive and highly significant.

Consider now the results in Table 10. Both high unemployment and inflation are now associated with a large and highly significant decrease in the intensity of upgrade. Recession continues to have a positive coefficient estimate, but it is not significant here and it is eliminated in the backward selection. The effect of Real GDP growth is highly significant, negative and larger than in the marginal analysis, while Change in Consumer Sentiment is insignificant and is eliminated in the backward selection.

The 3-month T-bill rate enters the final specification with a positive coefficient, but it is not obvious why high a interest rate should increase the upgrade intensity. Anomalous once again, a strong S&P 500 index is significantly associated with a reduced intensity of an upgrade. Finally the overall corporate default rate is a strong and significantly adverse factor for upgrades.

The final backward selection eliminates seven of the covariates and improves -2 times the log-likelihood by a highly significant 105.45 over the model with only rating–specific variables. This model is statistically indistinguishable from the All variables model and has the best AIC.

9 Conclusions

This is the first study to examine such a broad range of rating history related and 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 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 broad look at the problem suggests several conclusions. Overall, we confirmed that 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.

Our estimates of the effects of rating-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 of 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 variables is incremental to that contained in a firm's credit rating history alone.

In the model of the transition into default with macro covariates, none of the four measures of General market conditions provided useful information about default hazards when firm-specific covariates and other macro variables, i.e., direction of economy and financial conditions variables, were included in the specification. Similarly, in the estimation of the hazard of the downgrade transition (from an investment grade to speculative grade), the model with the direction of economy and financial conditions variables statistically dominated the model with the GMC variables. This leads to the general conclusion that the direction of economy and financial conditions variables play a more important role in modeling downgrade transitions than the GMC variables. For both downward transitions, the Change in Consumer Sentiment was a highly significant variable, but it did not provide any explanatory power for upgrades from speculative to investment categories.

Two GMC variables, unemployment and inflation, appear in the intensity model for the upgrade transition, in addition to Real GDP growth and three financial conditions variables. High unemployment and high inflation are both strongly associated with the reduction in the intensity of upgrade. Real GDP growth has a seemingly anomalous, but highly significant, negative effect on the intensity of upgrade. We suspect that this negative effect may indicate that it is easier for Moody’s to distinguish a more creditworthy firm from other firms in its cohort when most firms are doing badly than when they all are doing well.

In summary, our results represent a broad first cut at incorporating a wide range of measures of the macroeconomic environment and of firms’ rating histories 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
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	
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
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 Consumer Sentiment	0.0830	0.8140	18-month distributed lag	Univ. of Michigan Survey Research Center
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

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

Table 4
Correlations Among Macroeconomic Variables

	Unemployment	Inflation	NBER recession	CFNAI	Real GDP growth	Growth of industrial prod'n	Change in Consumer Sentiment	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	0.089	0.121	-0.025	-0.092	0.387	0.538	0.765	0.089	-0.355	0.261	0.317	-0.339
Inflation	0.311	1.000	0.399	-0.319	-0.264	-0.254	-0.059	0.797	0.673	-0.168	-0.045	-0.023	-0.013	-0.204
NBER recession indicator	0.089	0.399	1.000	-0.716	-0.636	-0.596	-0.405	0.406	0.307	-0.412	0.143	-0.342	0.224	0.142
CFNAI	0.121	-0.319	-0.716	1.000	0.815	0.839	0.574	-0.264	-0.141	0.357	-0.128	0.249	-0.163	-0.339
Real GDP growth	-0.025	-0.264	-0.636	0.815	1.000	0.854	0.428	-0.175	-0.085	0.286	-0.107	0.074	-0.338	-0.396
Growth of industrial prod'n	-0.092	-0.254	-0.596	0.839	0.854	1.000	0.440	-0.280	-0.220	0.289	-0.158	0.046	-0.489	-0.428
Change in Consumer Sentiment	0.387	-0.059	-0.405	0.574	0.428	0.440	1.000	0.055	0.163	0.399	-0.242	0.519	-0.028	-0.435
3-month T-Bill rate	0.538	0.797	0.406	-0.264	-0.175	-0.280	0.055	1.000	0.924	0.032	-0.077	0.064	0.086	-0.360
10-year Treasury yield	0.765	0.673	0.307	-0.141	-0.085	-0.220	0.163	0.924	1.000	0.017	-0.191	0.094	0.133	-0.381
S&P 500 return	0.089	-0.168	-0.412	0.357	0.286	0.289	0.399	0.032	0.017	1.000	-0.336	0.749	-0.298	-0.352
S&P 500 volatility	-0.355	-0.045	0.143	-0.128	-0.107	-0.158	-0.242	-0.077	-0.191	-0.336	1.000	-0.276	0.533	0.428
Russell 2000 return	0.261	-0.023	-0.342	0.249	0.074	0.046	0.519	0.064	0.094	0.749	-0.276	1.000	0.022	-0.205
Baa yield - 10 Year Treasury	0.317	-0.013	0.224	-0.163	-0.338	-0.489	-0.028	0.086	0.133	-0.298	0.533	0.022	1.000	0.329
Overall corporate default rate	-0.339	-0.204	0.142	-0.339	-0.396	-0.428	-0.435	-0.360	-0.381	-0.352	0.428	-0.205	0.329	1.000

Table 5
TRANSITIONS INTO DEFAULT
Analysis of Individual Macro Factors

	Marginal contribution with firm specific variables	
	coefficient	**p-value**
General Macroeconomic Conditions		
Unemployment rate	0.079	0.004
Inflation	0.146	0.000
NBER recession indicator	0.396	0.000
CFNAI	-0.296	0.000
Direction of the Economy		
Real GDP growth	-0.409	0.000
Growth of industrial production	-0.596	0.000
Change in Consumer Sentiment	-0.208	0.000
Financial Market Conditions		
3-month T-Bill rate	0.127	0.000
Long-term interest rate (10-year Treasury)	0.122	0.000
S&P 500 return	0.058	0.016
S&P 500 volatility	-0.009	0.212
Russell 2000 Index return	-0.010	0.685
Yield spread (Baa - 10 Year Treasury)	-0.140	0.061
Corporate bond default rate	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 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	-0.393	-0.393	0.003	-0.410	-0.410	0.002
Initial rating: C, Ca, Caa	-1.282	0.000	-1.247	-1.247	0.000	-1.247	-1.247	0.000
Current rating: Ba	-5.305	0.000	-5.658	-5.658	0.000	-5.668	-5.668	0.000
Current rating: B	-3.505	0.000	-3.775	-3.775	0.000	-3.780	-3.780	0.000
Current rating: Caa	-1.630	0.000	-1.730	-1.730	0.000	-1.734	-1.734	0.000
Current rating: Ca	-1.019	0.000	-1.112	-1.112	0.000	-1.132	-1.132	0.000
Downgraded within last 2 years	0.446	0.000	0.438	0.438	0.000	0.436	0.436	0.000
Upgraded within last 2 years	-1.465	0.000	-1.273	-1.273	0.000	-1.270	-1.270	0.000
log(years since first rated)	0.141	0.013	0.133	0.133	0.023	0.133	0.133	0.022
General Macroeconomic Conditions								
Unemployment rate			-0.016	-0.024	0.876			
Inflation			-0.008	-0.016	0.875			
NBER recession indicator			0.023	0.007	0.870			
CFNAI			0.115	0.082	0.468			
Direction of the Economy								
Real GDP growth			0.221	-3.821	0.360			
Growth of industrial production			-0.953	2.048	0.031			
Change in Consumer Sentiment			-0.176	-0.144	0.006	-0.219	-0.178	0.000
Financial Market Conditions								
3-month T-Bill rate			-0.011	-0.031	0.893			
Long-term interest rate (10-year Treasury)			0.177	0.457	0.093	0.166	0.429	0.000
S&P 500 return			0.306	0.379	0.000	0.307	0.380	0.000
S&P 500 volatility			0.018	0.078	0.330			
Russell 2000 Index return			-0.136	-0.188	0.003	-0.128	-0.177	0.000
Yield spread (Baa - 10 Year Treasury)			-0.309	-0.135	0.163			
Corporate bond default rate			0.282	0.296	0.000	0.309	0.324	0.000

Goodness of Fit	**statistic**	**statistic**	**p-value**	**statistic**	**p-value**
-2 x log(likelihood)	11129.81	10951.79		10959.89	
Akaike Information Criterion	11147.81	10997.79		10987.89	
Likelihood ratio test: model vs Firm specific only		178.02	0.000	169.92	0.000
Likelihood ratio test: Final model vs All variables				8.10	0.524

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

	Marginal contribution with firm specific variables	
	coefficient	p-value
General Macroeconomic Conditions		
Unemployment rate	0.077	0.001
Inflation	0.061	0.000
NBER recession indicator	0.643	0.000
CFNAI	-0.341	0.000
Direction of the Economy		
Real GDP growth	-0.768	0.000
Growth of industrial production	-1.138	0.000
Change in Consumer Sentiment	-0.348	0.000
Financial Market Conditions		
3-month T-Bill rate	0.090	0.000
Long-term interest rate (10-year Treasury)	0.094	0.000
S&P 500 return	-0.186	0.000
S&P 500 volatility	0.031	0.000
Russell 2000 Index return	-0.157	0.000
Yield spread (Baa - 10 Year Treasury)	0.636	0.000
Corporate bond default rate	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	-0.326	0.001	-0.356	0.000	-0.319	0.001	-0.334	0.001	-0.300	0.002
Current rating: Baa	2.734	0.000	2.729	0.000	2.734	0.000	2.744	0.000	2.725	0.000	2.732	0.000
Downgraded within last 2 years	0.820	0.000	0.787	0.000	0.839	0.000	0.833	0.000	0.797	0.000	0.798	0.000
Upgraded within last 2 years	-0.823	0.000	-0.754	0.000	-0.790	0.000	-0.828	0.000	-0.759	0.000	-0.792	0.000
log(years since first rated)	-0.050	0.258	-0.041	0.356	-0.052	0.240			-0.046	0.303		
General Macroeconomic Conditions												
Unemployment rate			-0.632	0.000	0.092	0.001	0.085	0.000				
Inflation			-0.151	0.001	-0.011	0.614						
NBER recession indicator			-0.347	0.118	0.298	0.042	0.286	0.047				
CFNAI			0.637	0.000	-0.241	0.002	-0.236	0.002				
Direction of the Economy												
Real GDP growth			-1.348	0.000					-0.395	0.016	-0.411	0.011
Growth of industrial production			0.752	0.077					0.615	0.045	0.646	0.022
Change in Consumer Sentiment			-0.335	0.000					-0.295	0.000	-0.363	0.000
Financial Market Conditions												
3-month T-Bill rate			-0.082	0.262					0.010	0.821		
Long-term interest rate (10-year Treasury)			0.558	0.000					0.115	0.013	0.120	0.000
S&P 500 return			0.002	0.979					0.037	0.465		
S&P 500 volatility			-0.059	0.001					-0.009	0.511		
Russell 2000 Index return			-0.084	0.113					-0.075	0.122		
Yield spread (Baa - 10 Year Treasury)			1.201	0.000					0.711	0.000	0.674	0.000
Corporate bond default rate			0.054	0.345					0.052	0.329		
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		9249.59		9482.66		9484.31		9344.53		9349.33	
AIC (model)	9556.00		9287.59		9500.66		9498.31		9374.53		9367.33	
Likelihood ratio test: Model vs Firm specific only			296.41	0.000	63.34	0.000	61.69	0.000	201.47	0.000	196.67	0.000
Likelihood ratio test: Subset vs All Variables					233.07	0.000	234.72	0.000	94.94	0.000	99.74	0.000
Likelihood ratio test on Backward Selection							1.65	0.438			4.80	0.570

Notes

See Notes to Table 6.

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

	Marginal contribution with firm specific variables	
	coefficient	p-value
General Macroeconomic Conditions		
Unemployment rate	-0.053	0.080
Inflation	-0.043	0.086
NBER recession indicator	0.449	0.000
CFNAI	-0.114	0.055
Direction of the Economy		
Real GDP growth	-0.279	0.003
Growth of industrial production	0.000	0.998
Change in Consumer Sentiment	-0.080	0.108
Financial Market Conditions		
3-month T-Bill rate	0.025	0.132
Long-term interest rate (10-year Treasury)	0.004	0.802
S&P 500 return	-0.025	0.423
S&P 500 volatility	0.003	0.735
Russell 2000 Index return	-0.055	0.057
Yield spread (Baa - 10 Year Treasury)	-0.139	0.153
Corporate bond default rate	-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	0.433	0.000	0.433	0.000
Current rating: Ba	1.796	0.000	1.820	0.000	1.825	0.000
Downgraded within last 2 years	-0.076	0.518	-0.031	0.793		
Upgraded within last 2 years	0.371	0.000	0.310	0.003	0.321	0.002
log(years since first rated)	0.333	0.000	0.316	0.000	0.312	0.000
General Macroeconomic Conditions						
Unemployment rate			-0.140	0.169	-0.172	0.000
Inflation			-0.255	0.000	-0.236	0.000
NBER recession indicator			0.233	0.243		
Direction of the Economy						
Real GDP growth			-0.642	0.000	-0.664	0.000
Change in Consumer Sentiment			-0.028	0.725		
Financial Market Conditions						
3-month T-Bill rate			0.082	0.333	0.127	0.000
Long-term interest rate (10-year Treasury)			0.046	0.647		
S&P 500 return			-0.167	0.019	-0.127	0.001
S&P 500 volatility			0.023	0.170		
Russell 2000 Index return			0.068	0.238		
Yield spread (Baa - 10 Year Treasury)			-0.306	0.148		
Corporate bond default rate			-0.377	0.000	-0.382	0.000

Goodness of Fit	**statistic**		**statistic**	**p-value**	**statistic**	**p-value**
-2 x log(likelihood)	8466.88		8356.10		8361.43	
AIC (model)	8478.88		8390.10		8381.43	
Likelihood ratio test: model vs Firm specific only			110.79	0.000	105.45	0.000
Likelihood ratio test: Final model vs All variables					5.33	0.619

Notes

See Notes to Table 6.