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Are credit ratings procyclical?

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Abstract

This paper studies the influence of the state of the business cycle on credit ratings. In particular, we assess whether rating agencies are excessively procyclical in their assignment of ratings. Our analysis is based on a model of ratings determination that takes into account factors that measure the business and financial risks of firms, in addition to indicators of macroeconomic conditions. Utilising annual data on all US firms rated by Standard & Poor's, we find little evidence of procyclicality in ratings. By contrast, we find that initial ratings and rating changes exhibit excess sensitivity to the business cycle. The paper offers two explanations of these results

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Keywords: rating agencies, business cycles, credit risk, ordered probit, maximum likelihood

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Introduction[1]

"The ideal is to rate 'through the cycle'. There is no point in assigning high ratings to a company enjoying peak prosperity if that performance level is expected to be only temporary. Similarly, there is no need to lower ratings to reflect poor performance as long as one can reliably anticipate that better times are just around the corner." Standard & Poor's (2002, p 41).

Credit rating agencies claim that they rate "through the cycle". That is, a firm's credit rating, conditional on its underlying financial characteristics, should be independent of the state of the business cycle. In this paper, we examine whether this claim is true by empirically testing whether the state of the US economy is an important determinant of firm credit ratings, conditional on the financial and business characteristics of the rated firm.

We examine the universe of US firms rated by the agency Standard & Poor's (S&P) between 1981 and 2001. Using an ordered probit model to predict a firm's credit rating conditional on financial, business, and macroeconomic characteristics, we document the following results. When we examine a complete set of firms and ratings, we find very little evidence that credit ratings are influenced by the business cycle. However, we argue that these results may be suspect because the assumption implicit in the analysis is that each observation is reflective of an active decision being made by the rating agency. An alternative view is that due to resource constraints on the part of the rating agency, not every rating of every firm is accurate at all points in time. According to this view, some credit ratings become stale, simply because there has been little interest or little effort made to revisit the same firm over some finite time horizon. We thus conduct our analysis on a subset of our data for which we know with certainty that S&P has conducted a recent risk assessment. Repeating our empirical tests on the subset of observations where a rating has either just been issued or changed, we find that credit ratings exhibit excess sensitivity to the business cycle. In particular, conditional on the financial and business characteristics of the firm, newly announced credit ratings are related to the macroeconomy in a procyclical manner. That is, ratings are conditionally better during a boom and conditionally worse during a downturn.

The rest of the paper is organised as follows. Section 1 provides a brief literature review describing how measured risk relates to business cycles, in general, and how credit ratings have behaved through time, specifically. Section 2 provides details of the data used in this study. Section 3 outlines the ordered probit model and describes our two sampling techniques, which are designed to distinguish "fresh" ratings from those that may be "stale". Section 4 reports our results for our first data set, which includes all firms at an annual frequency. Section 5 describes our results when the sample is restricted to observations of new or recently changed ratings. Section 6 concludes.

1. Literature review

The financial system is procyclical. That is, measures of financial activity such as new bond issues and total bank lending tend to increase more during economic booms than during downturns. Much of this procyclicality might be explained by an "accelerator" model, such as the one discussed in Bernanke et al (1999). For example, higher levels of economic growth lead to higher values of potential collateral, thereby loosening credit constraints and making access to debt financing easier.

Another contributing factor to the financial system's procyclicality is that financial market participants behave as if risk is *countercyclical*.[2] For instance, bank loan standards tend to be most lax during

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[2] The claim that financial risk is countercyclical, however, is not universally accepted. Borio et al (2001), for example, argue an alternative view, namely that financial risk may actually be highest at business cycle peaks and that recessions merely represent a negative realisation of that risk. To the extent that measures of financial risk are inappropriately procyclical, the

economic booms (Lown et al (2000)) and banking supervisors have historically been most vigilant during downturns (Syron (1991)). Empirical models, too, tend to indicate a rise in risk during recessions.[3] For instance, Altman et al (2002) show that there is a relationship between the correlation of default probabilities and loss in the event of default and the business cycle. These authors argue that models that assume independence of default probabilities and loss-given-default will tend to underestimate the probability of severe losses during economic downturns. A study by Bangia et al (2002) documents the empirical significance of the procyclicality of credit quality changes by showing that estimated credit losses are much higher in a contraction relative to an expansion.

Unlike bank lending standards, bank supervisors and credit risk models, credit ratings are not supposed to vary in a procyclical manner. Instead, credit ratings are intended to distinguish the relatively risky firms (or specific bonds) from the relatively safe. To do so, credit ratings need not reflect an absolute measure of default risk, but are rather intended to be ordinal rankings of risk across a class of bonds or firms at a particular point in time. In fact, rating agencies insist that their ratings should be interpreted as ordinal rankings of default risk that are valid at all points in time rather than absolute measures of default probability that are constant through time (Moody's (2000)).

Historically, credit ratings were designed for the benefit of long-term buy-and-hold investors, who arguably were less concerned with credit events that affect a bond's market value in the short run but do not fundamentally affect the likelihood that the bond will be repaid in full at maturity. Thus, rating "through the cycle" became rating agencies' way of measuring risk that was immune to short-run variation in economic conditions. The longevity and success of agencies such as Standard and Poor's and Moody's suggest that the production of such risk measures has been highly valued by investors.

A casual investigation of ratings through time, however, suggests that credit ratings may be related to the business cycle. For instance, Graph1 plots the fraction of rating changes made by S&P that were upgrades in a given quarter. Shaded areas indicate recessions as defined by the National Bureau of Economic Research (NBER). Graph 1 suggests that during recessions, rating changes are far more likely to be downgrades than upgrades. Such empirical regularities have led to a closer examination of ratings behaviour over time. In one such study, Nickell et al (2000) examine the probability of the transition of a bond with a given rating to a different rating in a finite time period, conditioning on the state of the business cycle. They find that these so-called transition matrices tend to exhibit a higher frequency of downgrades during a recession and a higher occurrence of upgrades during booms. Their results, however, relate rating transitions to the state of the business cycle, without further conditioning on measures of true underlying default risk that may, in part, be procyclical. Thus, these studies cannot conclude that ratings are assigned in a procyclical manner, but only that ratings move procyclically.

Other studies have documented other predictable changes to credit ratings over time. For instance, Altman and Kao (1992) find that rating changes tend to exhibit serial correlation. That is, a downgrade is more likely to be followed by a subsequent downgrade than by an upgrade. Thus, rating changes are not independent, a finding that has been carefully modelled by Lando and Skødeberg (2002). Lucas and Lonski (1992) study Moody's ratings and show that the number of firms downgraded has increasingly exceeded the number of firms upgraded over time, suggesting that either the quality of firms has declined through time or that rating standards have become more stringent. Blume, Lim and MacKinlay (BLM) (1998) document that credit ratings have, on average, become worse through time, conditional on a set of variables that proxy for the financial and business risks of the rated firm. BLM argue that their results provide evidence in support of the notion that credit ratings have indeed become more stringent over time.

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financial system may be excessively procyclical. Lowe (2002), for instance, argues that a more careful treatment of macroeconomic conditions in credit risk models may lead to a financial system that is, appropriately, less procyclical.

3 For a review of how systematic factors are incorporated into credit risk models, see Allen and Saunders (2002).

2. Data

Our paper presents a joint examination of how all three aforementioned factors, (ie business risk, financial risk, macroeconomic conditions) influence the assignment of credit ratings. In particular, we include measures of the business cycle in the ordered probit empirical framework of BLM to determine whether credit ratings tend to be related to the cycle after conditioning on a set of variables that the rating agencies tell us are important. To conduct our analysis, we require three types of data in order to analyse how the business cycle influences the decisions of rating agencies. The first is data on ratings themselves; the second is data on firms' "fundamentals", ie measures of business and financial risk; the third is measures of the business cycle. These are discussed in turn.

2.1 Ratings

Credit ratings are applied to issuers (firms) and individual debt issues separately. We are interested in explaining ratings of firms, as these are the purest measure of default risk. They are intended to capture the basic ability and willingness of a firm to meet its ongoing financial obligations. Ratings of specific issues incorporate, in addition, an assessment of the likely amount of recovery in the event of default. Thus, the ratings of a particular issue need not coincide with the firm's overall credit rating for a variety of reasons related to recovery prospects, the most important of which is the relative seniority of the debt in question. While the cyclical behaviour of issue-specific ratings is of interest itself, the interaction between recovery rates and the cycle would introduce additional complicating factors into our analysis. Focusing on issuer ratings is sufficient to assess the influence of the cycle on rating determination.

The source of our data on issuer ratings is the S&P CreditPro database. Among the information items provided in this database is the rating of each US firm S&P has assessed, the date the rating became effective and, if applicable, the date a firm ceases to have a rating. Thus, a continuous record through time of each firm's rating history is available. Data in CreditPro begins on 1 January 1981 and for our sample ends on 27 December 2001.[4]

Our sample includes firms spanning the entire ratings spectrum, including both investment and speculative grade firms. To reduce the occurrences of rating categories without sufficient observations, we group firms into rating categories without consideration of notches (ie + or –). For example, our set of AA firms includes those with AA+, AA and AA– ratings. In total, then, our analysis focuses on 10 rating categories, ranging from AAA to D. To conduct our ordered probit analysis, we must assign numerical values to the rating categories. Without loss of generality, we assign 1 to AAA, 2 to AA, ... 10 to D.

2.2 Measures of business and financial risk

In assessing creditworthiness, S&P takes into account both business risk and financial risk. (See S&P (2002) for a detailed description of its rating methodology.) The analysis of business risk includes an assessment of industry characteristics, each firm's competitive position, firm size, management capability and organisational factors. By comparison, financial risk concerns the quality of a firm's accounting procedures, profitability, capital structure, cash flow situation, financial flexibility and, more generally, its overall financial policy. While business risk is seemingly more difficult to quantify than financial risk, both sets of factors nonetheless play an important role in the assignment of ratings.

We consider three variables meant to capture business risk. The first is *firm size*. Larger firms naturally tend to have more recognisable products and are more diversified, and therefore, all else equal, would tend to have lower business risk. We measure firm size in two ways: by the real market value of equity

[4] Standard & Poor's has provided credit ratings for more than 75 years. Indeed, a number of other studies have utilised ratings data prior to the beginning of our sample in 1981. While it would be possible to construct a database of ratings to include earlier time periods, Standard & Poor's currently only sells databases with ratings starting in 1981 due to various changes in methodology affecting comparisons of ratings across time periods. On this basis, we similarly restrict ourselves to data from 1981 onwards.

and by real total assets.[5] Measures of market value are obtained from the Center for Research in Security Prices (CRSP). COMPUSTAT is our source for firms' balance sheet data, including total assets and the four financial ratios to be discussed. The sign of the firm size variable is expected to be negative: larger firms should have better ratings (which means a lower value for the rating variable).

The other two measures of business risk are obtained from estimating the market model. Larger equity risk suggests that, all else equal, a firm would be less able to service its debt. Following BLM, we separate equity risk into *systematic* (or beta) and *idiosyncratic* (or non-beta) components, where the latter is measured using estimates of the standard error of the residual from the market model. A higher beta indicates that the nature of the firm's business may be relatively sensitive to aggregate business conditions; in other words, it provides a measure of the relative cyclicality of the firm's operations. By contrast, higher idiosyncratic variation in equity returns might proxy for factors unique to the firm, such as the abilities of management. The market model is estimated using 200 days of daily equity returns observed up to the reference date for each rating observation.[6] Daily data is obtained from CRSP. This includes total returns for each firm and, as a measure of total market return, the CRSP value-weighted index.[7] Dimson's (1979) procedure is used to adjust for non-synchronous trading effects. To abstract from large common shifts in the market model estimates, we standardise estimates of beta and the residual standard error by the averages across all firms' estimates for the year in which they are calculated.[8]

As with business risk, S&P considers a broad range of information in assessing the financial risk of firms; nonetheless, it has identified eight key financial ratios that presumably play a central role in its analysis. Of these eight key ratios, two pertain to each of four categories: fixed charge coverage, profitability, cash flow, and capital structure. Following BLM, we consider four ratios in total.

The first is a measure of *interest coverage*, defined as the sum of operating income after depreciation and interest expense relative to interest expense. Increases in operating income after depreciation should have a positive effect on improving ratings. Moreover, if operating income after depreciation is positive, then a decline in interest should be similarly positive. However, if operating income is negative, then a decline in interest expense will make this variable more negative even though this would presumably be a positive development at the margin. We therefore eliminate observations that have negative values for this ratio.

The marginal effect of an increase in operating income relative to interest expense is likely to be small for large (positive) values of the ratio. To account for this possibility, we follow BLM by allowing the interest coverage variable to have non-linear effects on ratings; in particular, the interest coverage variable is first transformed via a continuous piecewise-linear function. If C is the three-year average of the interest coverage ratio, we first set values of C greater than 100 to be equal to 100.[9] Next, we create four new variables, C_j (j = 1,2,3,4), defined according to:

	C_1	C_2	C_3	C_4
C ε [0,5)	C	0	0	0
C ε [5,10)	5	C – 5	0	0
C ε [10,20)	5	5	C – 10	0
C ε [20,100]	5	5	10	C – 20

5 Nominal quantities are deflated by the current monthly value of the CPI.

6 In a small number of cases, daily returns data is not available right up to and including the rating observation date. In some instances, daily data is not available for 200 consecutive business days. As long as 200 days of returns data is available within one year prior to the rating observation date, market model estimates are calculated, and hence the corresponding observation appears in the sample.

7 Estimates of the ordered probit models are robust to using the S&P 500 Index in place of the CRSP value-weighted index.

8 Since the observations in our data sets are dated throughout the year, one potential problem with standardising by calendar year sums is the lack of proximity of observations dated in the early and later part of a year. However, the results are qualitatively similar if we standardise by quarters or not at all.

9 The reason for taking a three-year average is discussed below.

The choice of regions over which to define the linear portions of the function follows BLM, and is motivated by the sharp skewness of the empirical distribution of C (discussed below). Increases in each of these variables are expected to have a non-negative effect in improving ratings, but their marginal impact should be declining from C_1 to C_4.

The second key ratio is the *operating income/sales* ratio, defined as operating income before depreciation relative to net sales. While not exactly identical, earnings and cash flow are strongly related, and this measure seeks to proxy for both concepts. Ultimately, cash is what is required to service debt obligations. High earnings margins are indicative of a firm's ability to generate significant cash. This can be particularly important for lower-grade issuers who typically have few outside options to cash on a short-term basis. More generally, high earnings reflect the value of the firm's assets. An increase in this ratio should lead to a better rating.

The third and fourth ratios are related to the capital structure of the firm: *long-term debt/assets* and *total debt/assets*. Leverage is a direct measure of the magnitude of a firm's debt obligations. Since issuer ratings refer to a firm's ability to attend to all its financial responsibilities, overall debt matters. However, since issuer ratings are closely tied to the ratings on senior unsecured long-term debt, the long-term debt ratio may be informative in its own right.[10] Increases in either of these ratios should be correlated with worse ratings (ie have positive coefficients).

S&P compares three-year averages of the ratios to "ratio guidelines". This is because their analysis "focuses on a firm's ability to meet these levels, on average, over a full business cycle" (S&P (2002, p 41)). Accordingly, we also take three-year averages of the four ratios. It is less clear how S&P aggregates other types of information, such as the measures of business risk presented above. In keeping with BLM, we do not take time averages of firm size or the market model estimates.

2.3 Trend and cycle

The purpose of this study is to assess whether, above and beyond the variables described in the previous subsection that are intended to capture the fundamental determinants of the risks of firms, ratings are influenced by secular and cyclical factors. In their study, BLM included time dummies in an ordered probit model and found that, conditionally, ratings have generally become worse over time. One interpretation of this finding is that S&P has applied an increasingly tougher standard through their sample period. We will similarly present estimates of a model with time dummies that will serve as a basis for comparing results using our sample to those in BLM.

However, time dummies do not distinguish between trend and cyclical effects. Separating trend from cycle requires an identifying assumption. For the sake of simplicity, we assume that secular changes to ratings, if present at all, is captured by a linear time trend.[11] If rating agencies have become tougher over time, all else equal, the trend should have a positive coefficient.

We utilise two types of business cycle indicators. The first is an indicator of recessions and expansions; the second is a continuous indicator of the state of the economy.

A distinction is often made between recessions and expansions, as there is an apparent asymmetry between these two phases of the cycle. The onset of a recession tends to be rapid, but the recession itself is short-lived. By contrast, expansions develop slowly and are of much longer duration. Thus, it is plausible that these two phases of the cycle might have a different impact on the behaviour of rating agencies, with recessions having a particularly strong impact due to their virulent nature. To capture this asymmetry, we make use of a recession index based on the NBER's dating of business cycle peaks (the start of recessions) and troughs (the end of recessions). The NBER does not employ a set of strict rules to determine the dating of recessions. However, the dating of peaks and troughs appears

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[10] The difference between these two ratios is that total debt includes debt in current liabilities in addition to long-term debt. BLM report having included average short-term borrowings in their measure of total debt. This item was not reported for most firms in our sample, however, so it was omitted altogether. It turns out that these two ratios are highly correlated. To deal with the potential problem of multicollinearity, we also report results for the ordered probit models after eliminating one of the measures.

[11] As a sensitivity check, we estimated all versions of the ordered probit models with a quadratic time trend instead, obtaining qualitatively similar results for the other variables in the model, including measures of the cycle.

to be largely driven by movements in the level of personal income, industrial production, sales and, especially in recent times, employment. The *NBER recession* indicator is set equal to –1 if the timing of an observation falls within an NBER recession period, and to 0 otherwise.[12] Defined in this way, we are making the assumption that only recessions might have a material impact on the behaviour of the rating agency. This hypothesis is consistent with the perception that agencies are too aggressive in downgrading ratings during bad economic times.[13] As can be seen in Graph 2, the NBER has identified only two relatively brief recessions over our sample period.

An alternative set of business cycle indicators that we consider seeks to capture both ups and downs in economic activity. The first measure is the *output growth gap*, defined as the difference between real GDP growth and potential GDP growth.[14] The output growth gap is a measure of excess demand that is meant to reflect whether economic conditions are relatively strong or weak compared to the sustainable rate of growth of economic activity. Our estimate of potential GDP growth is obtained from the Congressional Budget Office (CBO). Although it exhibits variation over time, fluctuations in potential growth are typically dominated by actual growth rates. As a consequence, the output growth gap has a high positive correlation with real GDP growth (see Graph 2). The growth gap tends to become negative before the start of an NBER recession and remains negative for a few quarters after a recession is over.

The second "symmetric" business cycle measure we consider is, unlike the output growth gap, a discrete-valued indicator of the relative rate of current real GDP growth. It is defined as follows. The histogram of annual real GDP growth rates for the entire sample period (at a quarterly frequency) is constructed. If the current quarterly observation of annual growth falls into the lower third of this distribution, the indicator is assigned a value of –1 for that quarter, a 0 if it falls in the middle third and a 1 if it falls in the upper third.[15] This indicator was used by Nickell et al (2000) to investigate rating transitions across the business cycle. Refer to Graph 2 once again to see the relationship between this indicator, labelled *discrete growth indicator*, and the other cyclical measures. As might be expected, this variable equals –1 during the two recessions denoted by the NBER but identifies more "down" periods, too. Similarly, it tends to be positively correlated with the output growth gap. However, by virtue of it being a discrete indicator that can take only three possible values, it necessarily provides a different characterisation of business cycle movements, both in terms of timing and magnitude, than the continuous-valued growth gap.

3. Ordered probit model

3.1 Model specification

Ratings are by their nature qualitative, discrete-valued indicators of creditworthiness. Ratings also have a natural ordering, with AAA best, AA next best and so on. We therefore make use of the ordered probit model in our empirical analysis, which allows us to relate the set of explanatory variables described in the previous section to the ratings.

The ordered probit model can be described as follows. Let R_{it} be the rating of firm *i* at time *t* and X_{it} a vector of observable variables available at time *t* that influence the determination of firm *i*'s rating. R_{it} is an integer-valued variable – recall the mapping discussed above: AAA = 1, AA = 2, ... D = 10. The components in X_{it} may or may not be specific to firm *i*. Consider an unobservable variable Z_{it} that

12 Specifically, the NBER dates peaks and troughs by the month. Since our rating and balance sheet data are identified by the day, we adopt the convention that each day in a month defined as a peak, and all days in subsequent months up to but not including the trough month, are assumed to be part of the recession. Peak and trough dates from the NBER can be found at www.nber.org.

13 Similar results are obtained if a recession is defined as at least two consecutive quarters of negative growth.

14 Actual and potential real GDP growth are measured on an annual (year-over-year) basis.

15 Analogous to the NBER recession indicator, the quarterly value is assigned to each day within the period for these latter two business cycle proxies.

maps values of X_{it} into R_{it}. The first part of the ordered probit model relates X_{it} to Z_{it} by means of a linear equation:

$$(1) \qquad Z_{it} = \beta\ X_{it} + \varepsilon_{it}$$

where β is a vector of slope coefficients and ε_{it} is an unobserved error term. The second part of the ordered probit model links Z_{it} to R_{it} according to:

$$(2) \qquad R_{it} = \begin{cases} 1 & \text{if } Z_{it} \in (\infty, \mu_1) \\ r & \text{if } Z_{it} \in [\mu_{r-1}, \mu_r), \quad r = 2, 3, ..., 9 \\ 10 & \text{if } Z_{it} \in [\mu_9, \infty) \end{cases}$$

where the parameters μ_i define the partitions of the range of Z_{it} associated with each value of a rating.

The measures of business and financial risk enter the model as part of the vector X_{it}. Systematic time variation in ratings can be captured by a set of time dummies, α_t, which would be included in X_{it}. One of the main findings in BLM was that α_t became larger over time, suggesting that rating agencies applied a progressively tougher standard, all else equal, as time passed.[16] We will estimate a version of the model that includes time dummies for each year. However, since we wish to assess the role of the business cycle on ratings, in most specifications we omit these variables and instead include terms in X_{it} to capture the trend and cycle separately.

We consider two distinct ways that measures of the business cycle might be related to ratings: either by shifting ratings up or down, even after accounting for firm-specific factors; or by changing the sensitivity of ratings to these other factors. Including a cyclical measure as an independent explanatory variable in X_{it} captures the first effect, whereas the second effect can be accounted for by interacting a cyclical measure with each firm-specific measure of business and financial risk. In addition, we investigate the possibility that ratings are influenced by the most recent observation on the financial ratios even when controlling for the (baseline measure) three-year average of each ratio. A significant conditional relationship between current financial ratios and ratings would be suggestive of excess sensitivity in the rating agency's decisions to contemporaneous macroeconomic conditions.

The partition points, or equivalently Z_{it}, are identified only up to affine transformations. This requires imposing two restrictions on the model, which we accomplish by assuming that ε_{it} has a standard normal distribution and that no intercept term appears in X_{it}. When time dummies are included in X_{it}, this latter assumption amounts to setting the dummy for the first year in the sample equal to 0; otherwise, when a linear trend is present, the intercept in the trend is set to 0.

3.2 Sampling methodology

An important issue is the construction of the estimation sample. One decision to be made is whether or not to restrict the subset of firms to include. A second decision concerns what constitutes an "observation" and the timing of its components.

In regard to firm type, one further contribution of this paper is that we consider firms with investment grade and speculative grade ratings, in contrast to BLM who analysed only the former. There are two reasons to consider low-rated firms. First, firms with poorer credit ratings are likely to be more sensitive to cyclical fluctuations, as suggested by models of imperfect information, such as the financial accelerator in Bernanke et al (1999). Hence, lower-rated firms might be subject to more intensive monitoring at critical points in the business cycle, particularly recessions. Second, omitting low-rated firms could also introduce a bias into our estimates. This would be the case, as is assumed here, if changes of a given magnitude in all of the components of X_{it} have the same *relative* effect on both investment grade and speculative grade issuers. Note that this assumption does not require a

[16] BLM report progressively smaller (more negative) time dummies since they assigned numerical values to ratings in the reverse order; see Figure 1 in their paper.

change of a given size in any component of X_{it} to have the same marginal effect across the ratings spectrum, because the regions corresponding to each rating class (as determined by the cut points, μ_i) may differ in length.

Another contribution of this paper is that we consider two different methods for converting the data into sample observations. Consider the nature of the variables being studied. Unless they are withdrawn, ratings are valid continuously through time. In principle, we could construct a continuous-time model of ratings, in contrast to the discrete-time ordered probit model in (1)-(2), if we also had access to continuously sampled data on the components of X_{it}. However, the components of X_{it} are observed only at discrete times. Market value and returns data used to obtain market model estimates are available at a daily frequency, whereas the business cycle indicators are available either daily or quarterly and the balance sheet data is observed annually.[17] Prior studies utilised samples of annual observations based on the observed frequency of balance sheets, including BLM, who used December as the reference month for the calculation of market model estimates and the determination of market value.

Our data set 1 is constructed in a similar manner to BLM, with the modification that the actual day of each firm's fiscal year-end is the reference date for identifying the state of the business cycle, obtaining market value and constructing the market model estimates (as described above). Thus, each firm can appear in the data set in multiple years, but at most once in each calendar year, as long as it has a rating at the time its annual balance sheet is reported. Constructing a sample in this way attempts to maximise the number of observations, keeping in mind the fact that much of the information on each firm is not updated frequently. The use of annual (say, versus monthly) observations tries to minimise the inclusion of observations that would effectively lead to "double-counting".

However, there is a potential problem with the sampling method used for data set 1. Specifically, monitoring is costly. It is unlikely that the rating agencies can devote proper resources to examining all rated firms on a continuous basis. This could lead to staleness in ratings, meaning that the link between the rating (of any given firm at any point in time) and the factors that influence its determination might not truly reflect the decision-making behaviour of the rating agency.

To combat this potential problem, we consider a second, alternative sample that focuses on *initial ratings* and *rating changes*. When a rating is first given or has changed, we can be relatively certain that the firm has been recently investigated by the rating agency. Since the date of such an event is temporally close to the time the actual monitoring has taken place, we can also be more certain that any decision by the agency was influenced, if at all, by economic conditions at the time – as identified in our empirical analysis. Specifically, an observation added to data set 2 has a date equal to when a firm obtains its first rating or its rating is changed. In general, these events do not occur on balance sheet dates. Thus, the financial ratios and total assets are based on the most recently available balance sheet information. By contrast, the daily frequency of market data still allows construction of the other variables using information up to the date of the rating action. According to our second data construction approach, a given firm may appear in data set 2 more than once in a calendar year if it experienced several rating changes during that year.[18]

While data set 2 has the advantage of minimising concern over staleness and disconnect in timing, a data set containing only initial ratings and changes unfortunately results in a significantly smaller sample of 2,353 observations, compared to 10,144 observations in data set 1. Econometrically, it also alters the nature of our conditional probability model. When we select observations on the basis of a rating change having taken place, the new rating cannot equal the old rating by construction. This implies that the support of the conditional distribution of Z_{it} is not the entire real line contrary to the assumption that ε_{it} is normally distributed in the model given by (1)-(2). Estimation of the ordered probit model using data set 2 therefore requires a modification to the standard form of the likelihood function (see the Appendix).

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[17] In principle, returns data could be observed at an intraday frequency. However, movements at this frequency are unlikely to be informative for our purposes.

[18] A lack of new balance sheet information does not pose a problem for the interpretation of our model. A rating may be altered even in the absence of new balance sheet data in the light of new market information, which is updated daily. Of course, a rating may also change simply in response to business cycle conditions, as investigated.

Table 1 shows the number of observations by rating and year for data set 1 (upper panel) and data set 2 (lower panel). In both data sets, the number of observations per year grows through time.[19] There does not appear to be any systematic pattern in the *number* of rating changes in years with business cycle peaks and troughs. Both samples are dominated by observations with ratings in categories A to B. At the ends of the ratings spectrum, there are relatively more high investment grade ratings in data set 1 and low speculative grade ratings in data set 2.

Descriptive statistics on the measures of business and financial risk are presented in Table 2 (data set 1) and Table 3 (data set 2). It can be seen, as noted above, that the interest coverage variable is highly skewed. For instance, the means are much larger than the medians. The distributions of the other variables are more symmetric. The means of each variable are roughly monotonic across rating categories in the expected way, except for the market-model beta. Notice that the average debt ratios of firms in default are lower than speculative grade issuers mainly as a consequence of the defaults themselves. The summary statistics on the explanatory variables presented in these tables will be helpful when interpreting the economic significance of the estimates of the ordered probit model.

4. Results for data set 1: balance sheet dating

Consider first estimates of the ordered probit model based on data set 1.[20] To determine whether or not there are important differences between our sample and the one used in BLM, Table 4 shows estimates of the model that includes time dummies (ie no trend or cycle variables), the three measures of business risk and the four financial ratios (extended to seven to account for the transformed interest coverage variable). On the whole, the estimates are very similar to those reported by BLM. Most of the coefficients have the right sign – two exceptions are the fourth transformation of the interest coverage variable, C_4 (the coefficient is positive), and total debt (negative) – and all are statistically significant at the 1% level.[21] As expected, the coefficients on the transformed interest coverage variable are roughly monotonic. The marginal effect of a given change in interest coverage at a low level (below five, ie C_1) is much larger than at values above five, although there is little economic difference in the coefficients on C_2 to C_4. Despite its statistical significance, the coefficient on C_4 is close to 0. An explanation of the estimate on total debt is offered below. The year dummies increase over time, confirming the result obtained by BLM. Graph 3 plots their estimates (see Figure 1 in their paper) against the values reported in Table 4. Higher drift in our time dummies is attributed to the fact that our sample contains below investment grade firms whose average ratings over time became relatively worse.[22]

Next, we investigate the role of trend and cycle. Table 5 presents estimates of our baseline specification, which includes the measures of business and financial risk in the model presented in Table 4, a linear trend and a measure of the cycle that enters X_{it} as an independent variable only. Each column corresponds to a different proxy of the business cycle. All of the estimates on the risk factors are statistically significant and are very similar in magnitude to those discussed above in Table 4. This is robust across measures of the cycle. The linear trend is statistically and economically significant as well. The estimates predict drift in the unobservable linking variable equal to 0.092 per year. One way to view the economic significance of this value is that it would take the typical AA-rated firm 7.5 years to become an A-rated firm, all else equal. Similarly, the typical BBB-rated firm would become a BB-rated firm after 6.9 years.[23] More importantly, the coefficient estimates on the cyclical variable suggest that ratings move *countercyclically* with the business cycle, although the strength of

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[19] The small number of observations in 2001 in data set 1 is due to the fact that the financial year-end for most companies is 31 December, while we were only able to get data up to 28 September.

[20] Only nine rating categories are considered in estimation of the ordered probit model based on data set 1 due to the lack of any observations with rating C (see Table 1).

[21] BLM also obtained the wrong sign on estimates of C_4 and total debt.

[22] Estimates of the partition points, μ_i (not reported), do not reveal anything unusual.

[23] By "typical", we mean a firm whose predicted value of Z_{it} from our ordered probit model would be equal to the midpoint of the interval of the distribution of Z_{it} that corresponds to the starting rating category.

this result varies across cycle measures. In general, we would expect to find no relationship (a zero coefficient) if the rating agencies "see through the cycle"; otherwise, if they overreact to the cycle, the coefficient should be negative. One possible explanation of the positive coefficient estimates obtained in the baseline is that the rating agencies indeed "see through the cycle", but our set of conditioning variables inadequately captures the nature of longer-term risks faced by firms. In particular, our measures of the risk factors may be *too* procyclical and the positive coefficients on the cycle variables serve to offset this.

Table 6 presents estimates of the ordered probit model under four alternative configurations for the composition of X_{it} for each of the cyclical indicators. The first four columns are results obtained using the NBER recession index and are to be compared to the baseline specification reported in column 1 of Table 5; similarly for the other two cyclical variables. For each cyclical measure, columns "1" and "2" present estimates of the ordered probit model that allow for different cyclical sensitivities: column 1 includes terms of the cycle interacted with the other variables, while column 2 adds the most recent observation on the ratios (ie without time averaging). These specifications paint a murkier picture than the baseline. The specifications with interaction terms either have (partially) offsetting effects (growth gap and discrete growth indicator), or the cyclical sensitivity, at least in terms of marginal statistical significance, is reversed (NBER).[24]

Columns "3" and "4" check for sensitivity of the baseline specification by replacing market value with total assets and dropping the fourth financial ratio, total debt/assets, respectively. Assets and market value both serve as a proxy for firm size. Data on market value is available at a higher frequency, which has both benefits (eg timeliness) and drawbacks (eg noise). In particular, market value may be *too* procyclical from the perspective of the rating agency, and may be a key factor in explaining the positive estimates of cycle found in the baseline. Indeed, when assets is included in the ordered probit model, the coefficient on cycle is not statistically significant for any of the cyclical measures. Lastly, when total debt is eliminated from the model, the coefficient on long-term debt falls to approximately 1.65 from 2.88, while the other parameters remain largely the same. In combination with the high positive correlation between the two debt measures (see above), these estimates suggest that the "wrong" sign on total debt in the baseline is due to multicollinearity.

One way to measure the goodness of fit of our ordered probit model specifications is to compare predicted ratings to actual ratings. The results of this are shown in Table 7. The upper panel reports predictions for the model with time dummies (ie corresponding to the estimates in Table 4), while the lower panel reports analogous results for the baseline model with, as an example, the NBER recession index (Table 5, column 1). Reading across each row gives the number of predictions in each category labelled across the top for all observations with an actual rating equal to the label in the leftmost column.[25] The results reflect a common feature of ordered probit models in that the highest (lower) categories tend to be under- (over-) predicted. However, most prediction errors are by one category only. One exception is firms in default. Here, even an investment grade rating is predicted for almost 10% of the firms with a D rating. Part of the reason is that, once in default, the level of debt of these firms is relatively low compared to most speculative grade firms that are not in default (see Table 2). The relative accuracy of the predictions for the model with time dummies is similar to what BLM found (see their Table 4), at least for investment grade firms. The predictions for speculative grade firms (which were not examined by BLM) are more dispersed.

More pertinent is the relative accuracy of the two models (Panel A versus Panel B). The broad conclusion is that there is little difference between the fit of the two models. There is a striking similarity in the total number of predictions of each rating category (compare the bottom row in each panel). Even the differences on an element by element basis are small. This suggests that little, if any, predictive power of the model is lost by replacing time dummies with a linear time trend and cyclical variable.

[24] Consider the case of the discrete growth indicator. The coefficient on cycle is estimated to be 0.3282 and is now statistically significant (compare to the corresponding estimate of 0.0236 in Table 5). However, this effect is offset by the significant, procyclical coefficients on the interaction terms involving market-model beta and market value.

[25] For example, the first row in Panel A shows that of the 225 observations with an actual rating of AAA, the model predicts a AAA rating for 36 of these, AA for 156 and A for 33.

Overall, the results based on data set 1 are mixed: statistical significance of countercyclicality varies across business cycle measures in our baseline case, and is generally not robust to changes in the set of explanatory variables. In some cases, procyclicality is even detected.

5. Results for data set 2: initial ratings and rating changes

Now consider estimates of the ordered probit model based on data set 2. Tables 8 and 9 are analogous to Tables 5 and 6 discussed in the previous section.[26] Turning first to the estimates of our baseline specification in Table 8, the main new result (compared to data set 1) is the *negative* coefficient on the cycle variables. Moreover, this coefficient is statistically significant at the 1% level for all three measures. This suggests that new ratings, whether an initial rating or a change in rating, exhibit excess sensitivity to the business cycle. Most of the other parameter estimates are similar in magnitude and statistical significance to those obtained using data set 1. One notable exception is the set of interest coverage variables: only C_1 is statistically significant now. Also, ratings drift is less noticeable in this sample as the coefficient on the linear trend is smaller (roughly 0.015 versus 0.023 in Table 5).

Table 9 presents estimates of alternative model specifications. When interaction terms with the cycle are included (case 1), the significant coefficients appear to offset each other in terms of their implications regarding the cyclical sensitivity of ratings. When financial ratios from the most recent balance sheet only are included (case 2), the current operating margin ratio has a significant negative marginal effect, indicating further procyclicality, though the three-year moving average of this ratio becomes insignificant. Replacing market value by assets (case 3) has little impact on the other parameters and dropping total debt from the model (case 4) leads to a much smaller estimated coefficient on long-term debt (as for data set 1). To summarise, the results in Table 9 give largely the same picture as the baseline. This contrasts with the situation for data set 1, where conflicting results with the baseline were obtained amongst the alternative specifications.

The goodness of fit of our ordered probit model for data set 2 is assessed by again comparing predicted ratings to actual ratings. The outcome of this is shown in Table 10 for our baseline specification using the NBER recession index. The ordered probit model seems to fit less well for data set 2 when compared to data set 1 (Panel B, Table 7), although the differences are not large and, arguably, are not economically significant. For instance, the model does not predict any AAA ratings, but there are only seven AAA observations in the sample. Perhaps more significant is that the number of predicted defaults (265) is relatively large compared to the number of actual defaults (83). This is mainly driven by the fact that the estimated partition points at the low end of the rating scale (CCC to D) are very close together.[27] In effect, the model cannot make precise distinctions between these categories on the basis of the variables studied, due in part to the fact (mentioned earlier) that debt ratios tend to improve once a firm defaults. But, again, there is only a small number of observations with an actual rating of CC or C in the sample, mitigating the economic importance of this failure of the model.

The results presented in Table 10 are indicative of the fit of the ordered probit model as a whole, but they do not shed light on the specific role played by the cyclical variables. The t-tests on coefficient estimates are a sign of statistical significance; however, the economic importance of the effect of cycle on ratings is difficult to discern from the coefficient estimates alone. One method to gauge this is to compare ratings predictions by changing the state of the cyclical measure included in the model. The results from this exercise are shown in Table 11. The table contains three distinct panels corresponding to each of the cyclical measures. In each panel, the values given across the columns correspond to the number of predicted ratings in each category when the cyclical variable is set equal

[26] Recall that, as discussed above, selecting observations on the basis of whether a rating change has occurred changes the conditioning set in our probability model. In particular, a number of ancillary parameters must also be estimated when data set 2 is used (see the Appendix). To conserve space, estimates of these parameters are not reported.

[27] Estimates of the partition points are –0.658 (CCC to CC), –0.632 (CC to C) and –0.629 (C to D).

to a "downturn", regardless of the actual state of the cycle corresponding to each observation. Similarly, the values across rows report predicted ratings when cycle is set to "upturn".[28]

The broad conclusion to be drawn from the table is that a shift in the state of the business cycle, all else equal, changes many ratings by one category at most. Changes in ratings are more pronounced for the higher and lower categories. For example, out of the 27 firms predicted to receive a AA rating when the output growth gap indicates an upturn, 20 of these would get an A rating if the growth gap were to instead signal a downturn. By contrast, the majority of firms rated BBB would maintain their rating under this switch in macroeconomic conditions. Nonetheless, 174 out of 836 firms receiving a BBB rating during an upturn would move to speculative grade (BB) in a downturn. The total number of rating changes would be 619 out of 2353 (26%).[29] Arguably, this number of rating changes dependent solely upon a switch in the state of the macroeconomy, *holding constant individual risk factors*, is economically significant.

6. Summary

It is a fact that the ratings of most firms change little. This could mean that the agencies are doing what they say they do, by taking a longer-run perspective and being reluctant to change ratings in response to short-term fluctuations in the status of a firm. The evidence we present based on one method for sampling the data (data set 1) largely supports this conclusion.

We argue, however, that there is a reason to be suspicious of the evidence based on data set 1 as providing a full characterisation of rating agency behaviour. In particular, the fact that the larger sample of ratings contains few changes and shows insensitivity to business cycle conditions might reflect a lack of continuous monitoring by the rating agencies. Our solution for dealing with this potential problem is to assess the cyclical sensitivity of ratings for dates when it can be determined that an explicit rating evaluation has been made; namely, when initial ratings or rating changes are applied. We find significant evidence, important from both a statistical and economic perspective, that ratings exhibit excess sensitivity to business cycle conditions. Even if irregular monitoring is not an issue for data set 1, our results still point to an overly procyclical reaction by the agencies when rating changes are indeed made.

Taken together, the evidence from the two data sets suggests that the behaviour of rating agencies might be captured by a threshold model with overshooting. Most of the time, ratings do not change. Rating agencies monitor the conditions of firms to a greater or lesser extent at any particular time, and generally do not react to small movements in the risk profile of firms. However, when rating agencies do make a change, they overreact relative to present conditions, and the nature of this overreaction is positively correlated with the state of the aggregate economy. This could be the consequence of excessive optimism (pessimism) during upturns (downturns) on the part of the rating agencies.

Another possible explanation is that, to some extent, what matters for the determination of ratings is what investors believe about the creditworthiness of firms even if these beliefs are not aligned to fundamentals. In this case, regardless of what quantitative measures of business and financial risk may indicate, it would be prudent for rating agencies to revise their assessment of default risk. Further work is needed to help disentangle the complex interactions between ratings, the independent assessment of credit risk by the market, the true risks faced by firms and the macroeconomy. This paper makes one step in documenting the nature of these relationships.

Finally, our findings may have implications for policymakers. Under proposed revisions to bank capital requirements advanced by the Basel Committee on Banking Supervision (BCBS (2001)), banks using a standardised approach to calculating their minimum required capital will base such requirements, whenever possible, on the credit ratings assigned to the companies to which they lend. To the extent

[28] Downturns and upturns correspond to values as currently defined for the NBER recession index (–1 and 0) and the discrete growth indicator (–1 and 1). The output growth gap is set equal to –0.015 for a downturn and 0.015 for an upturn.

[29] This figure is for the output growth gap. In fact, there are large discrepancies across cyclical measures. The result is even more dramatic for the NBER recession index (56%), but less strong for the discrete growth indicator (12%).

that ratings are procyclical, bank capital requirements will tend to be higher during downturns, further reducing credit supply during downturns.

Appendix: Computation of likelihood function for data set 2

One issue encountered in maximum likelihood estimation of the ordered probit model using data set 2 is censoring. This data set contains, in addition to the initial ratings of firms, rating changes. But when a firm experiences a rating change, by definition its current rating cannot equal its previous rating. For finite values of the cut points, this violates the assumption that ε_{it} is distributed normally because the support of the normal distribution is the entire real line (recall equations (1) and (2)). Notice that this issue does not arise for initial ratings or in data set 1 where observations are selected on the basis of the availability of balance sheet observations.

When we construct a sample based partly on rating changes, in effect we are interested in probabilities of the form:

$$P(R_{it} = j \mid X_{it}; R_{it} \neq R_{it-1}) \tag{A1}$$

Expanding (A1) by conditioning on the value of the previous rating and summing over the range of possible previous ratings, gives:

$$\begin{aligned} & P(R_{it} = j \mid X_{it}; R_{it} \neq R_{it-1}) \\ & = \sum_k P(R_{it} = j \mid X_{it}; R_{it} \neq R_{it-1}; R_{it-1} = k) \cdot P(R_{it-1} = k \mid X_{it}; R_{it} \neq R_{it-1}) \\ & = \sum_k P(R_{it} = j \mid X_{it}; R_{it} \neq k) \cdot P(R_{it-1} = k \mid X_{it}) \\ & = \sum_{k \neq j} \frac{P(R_{it} = j \mid X_{it}) \cdot P(R_{it-1} = k \mid X_{it})}{1 - P(R_{it} = k \mid X_{it})} \end{aligned} \tag{A2}$$

In the third line of (A2) it has been assumed that the rating of a firm in the previous period is independent of the firm's rating being changed in the current period. While it is possible to imagine situations where a particular rating might be partially responsible for inducing a change in rating (ie through "triggers"), the incidence and severity of such cases is likely to be minimal.

In principle, the mapping from X_{it} to R_{it-1} can differ from the mapping of X_{it} to R_{it}. We accommodate this by allowing the coefficients on X_{it} in the ordered probit model for R_{it-1}, which is analogous to (1)-(2), to differ from β. Denote the normal distribution function evaluated at x by $\Phi(x)$. The likelihood for each observation R_{it} (i = 1,2,...I; $t = t_{2,i}, t_{3,i}, \ldots t_{T(i),i}$), where $t_{2,i}$ and $t_{T(i),i}$ are the dates of the first and last rating changes of firm i in our sample, respectively, can be written as:

$$\sum_j \sum_{k \neq j} \frac{\left[\Phi(\mu_j - \beta X_{it}) - \Phi(\mu_{j-1} - \beta X_{it})\right] \cdot \left[\Phi(\mu_k - \tilde{\beta} X_{it}) - \Phi(\mu_{k-1} - \tilde{\beta} X_{it})\right]}{1 - \left[\Phi(\mu_k - \beta X_{it}) - \Phi(\mu_{k-1} - \beta X_{it})\right]} \cdot \chi(R_{it} = j) \tag{A3}$$

where $\mu_0 \equiv 0$, $\mu_{10} \equiv \infty$ and $\chi(E) = 1$ if E is true, 0 otherwise. The likelihood for an initial rating takes the standard form. The individual likelihood functions across all observations on initial ratings and rating changes are combined to give the (joint) likelihood function used in estimation.

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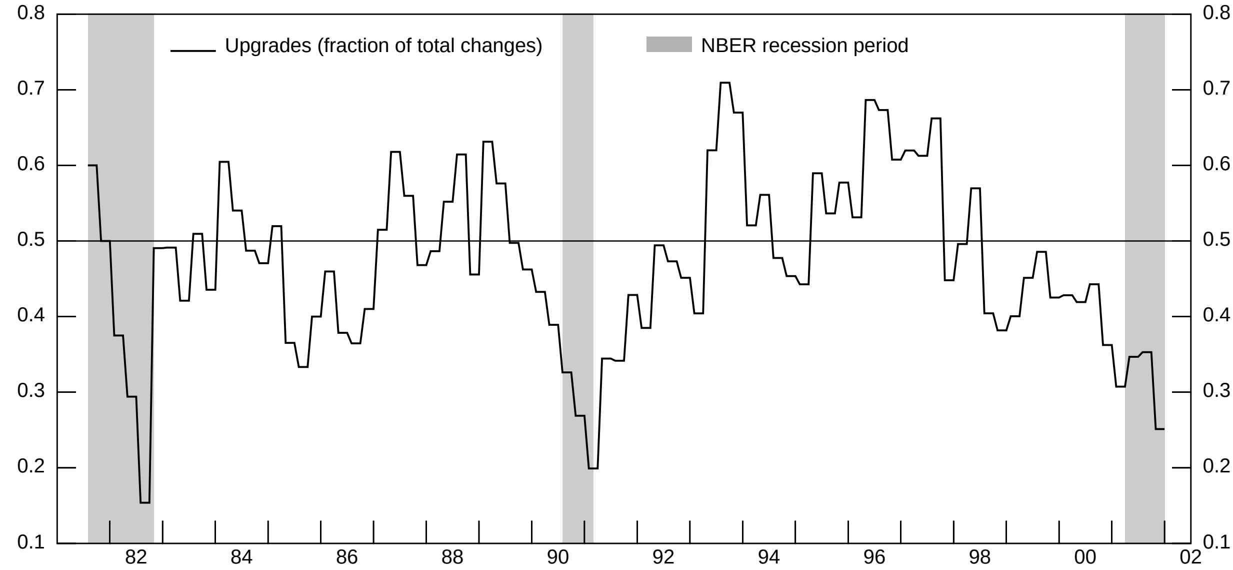
Graphs and Tables

Graph 1

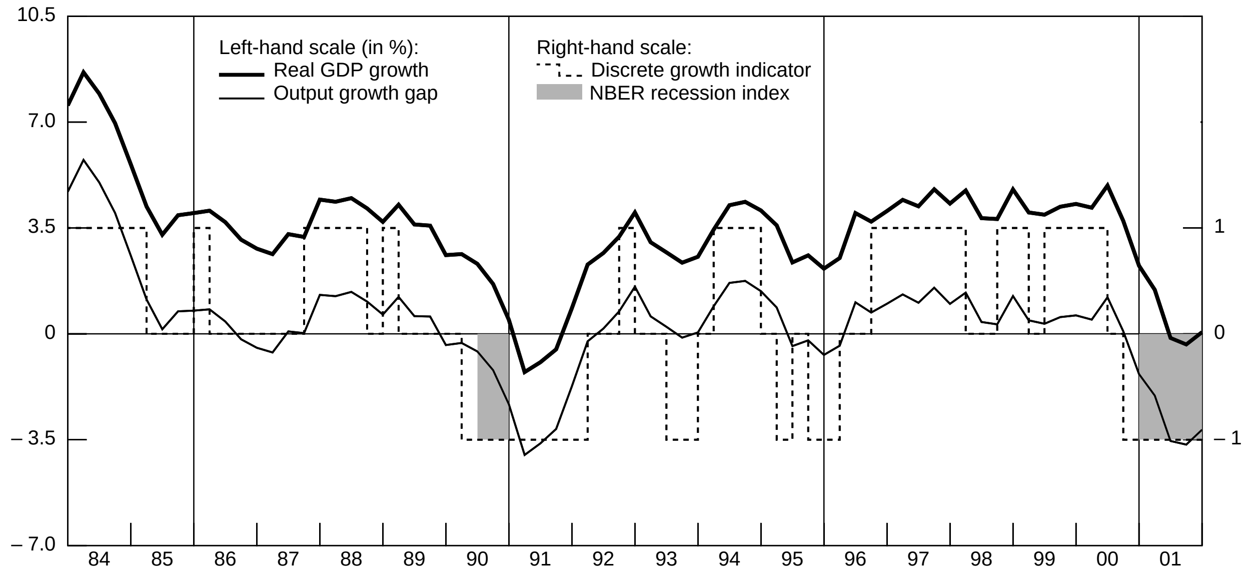
Fraction of ratings upgrades across the business cycle



Note: The solid line plots the number of upgrades as a fraction of all rating changes (upgrades plus downgrades) in each quarter.

Graph 2

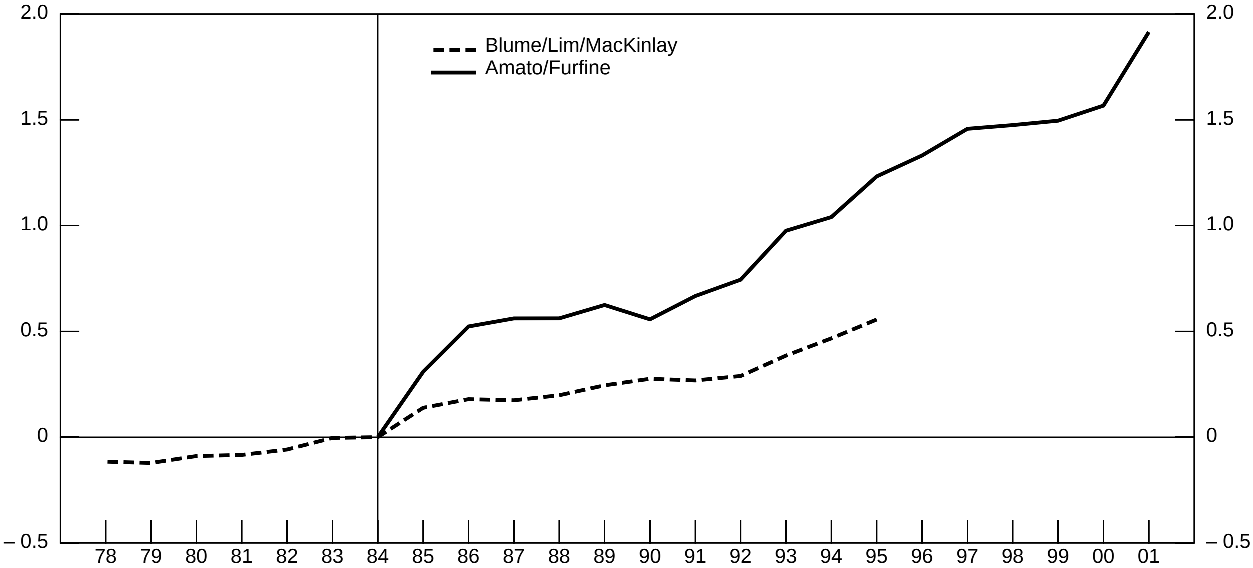
Business cycle indicators



Note: Real GDP growth and output gap are annual rates; see text for more detailed explanations of the series.

Graph 3

Time dummies from ordered probit model



Note: This graph plots estimates of the time dummies in the ordered probit model based on data set 1, which are presented in Table 4. These are compared to the estimates obtained by Blume et al (1998). To ease comparison, the estimates from Blume et al are re-based to equal 0 in 1984 as in the current study, and the sign is changed, due to the reverse definition of rating categories employed in the two studies.

Table 1

Number of ratings by category and year

Data set 1: balance sheet dating

Year	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Total
1984	12	52	102	45	29	16	1	0	0	1	258
1985	12	66	124	70	41	26	2	0	0	3	344
1986	12	66	122	86	48	36	3	0	0	1	374
1987	13	65	134	94	58	46	4	0	0	2	416
1988	14	67	150	105	69	58	1	0	0	1	465
1989	14	68	160	116	71	53	4	0	0	4	490
1990	13	71	156	126	73	42	6	1	0	5	493
1991	13	69	160	123	73	34	4	0	0	11	487
1992	14	62	167	136	83	36	6	0	0	12	516
1993	12	58	178	143	109	52	4	0	0	12	568
1994	13	56	181	161	124	62	4	0	0	14	615
1995	13	57	189	176	147	92	5	0	0	13	692
1996	15	61	195	211	162	111	6	0	0	16	777
1997	14	54	201	235	186	128	4	0	0	13	835
1998	12	57	213	250	206	143	2	0	0	9	892
1999	14	49	202	260	215	149	3	0	0	10	902
2000	14	43	185	258	223	135	10	0	0	11	879
2001	1	3	20	41	54	17	1	0	0	4	141
Total	225	1,024	2,839	2,636	1,971	1,236	70	1	0	142	10,144

Data set 2: initial ratings and rating changes

Year	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Total
1984	0	0	2	0	1	1	0	0	0	0	4
1985	0	4	20	15	9	8	0	0	0	1	57
1986	0	6	22	25	9	7	7	0	0	2	78
1987	1	7	20	25	10	5	1	0	0	1	70
1988	0	5	20	22	22	17	0	0	0	0	86
1989	1	8	23	31	21	7	3	0	0	0	94
1990	0	7	30	31	14	9	9	1	0	3	104
1991	0	3	23	27	28	13	7	1	0	7	109
1992	1	3	33	31	22	8	5	0	0	3	106
1993	0	2	29	31	34	15	3	0	0	1	115
1994	1	4	16	38	22	14	4	0	0	2	101
1995	0	3	24	41	34	13	3	0	1	3	122
1996	0	4	33	43	45	23	2	0	0	1	151
1997	0	9	29	55	43	23	4	0	0	2	165
1998	2	7	37	66	58	41	9	0	0	5	225
1999	0	1	32	68	53	45	14	5	0	13	231
2000	0	7	37	66	58	47	21	4	0	12	252
2001	1	6	34	66	58	62	26	2	1	27	283
Total	7	86	464	681	541	358	118	13	2	83	2,353

Table 2

Statistics on business and financial risk variables: data set 1

Variables	Mean	Fractiles		
		0.25	**Median**	**0.75**
Interest coverage				
AAA-AA	13.30	5.13	8.38	16.11
A	8.80	4.03	5.42	8.59
BBB	6.48	3.16	4.25	6.36
BB	5.87	2.52	3.39	4.98
B	4.04	1.86	2.47	3.60
CCC-C	1.59	1.09	1.62	1.94
D	6.06	1.57	2.66	5.55
All	7.51	2.99	4.42	7.30
Operating margin				
AAA-AA	0.22	0.14	0.20	0.28
A	0.21	0.12	0.18	0.27
BBB	0.19	0.11	0.15	0.25
BB	0.16	0.09	0.13	0.20
B	0.16	0.08	0.12	0.19
CCC-C	0.16	0.05	0.10	0.20
D	0.12	0.07	0.11	0.16
All	0.19	0.10	0.16	0.24
Long-term debt				
AAA-AA	0.16	0.07	0.14	0.24
A	0.22	0.15	0.22	0.30
BBB	0.28	0.19	0.28	0.36
BB	0.40	0.27	0.37	0.48
B	0.47	0.32	0.45	0.59
CCC-C	0.55	0.40	0.51	0.69
D	0.33	0.14	0.29	0.45
All	0.30	0.17	0.28	0.38
Total debt				
AAA-AA	0.22	0.12	0.21	0.30
A	0.28	0.20	0.28	0.36
BBB	0.33	0.24	0.33	0.41
BB	0.44	0.31	0.41	0.52
B	0.52	0.38	0.50	0.63
CCC-C	0.66	0.50	0.61	0.76
D	0.46	0.22	0.36	0.57
All	0.35	0.22	0.33	0.43
Market value				
AAA-AA	15.59	14.42	15.58	16.82
A	14.63	13.76	14.69	15.55
BBB	14.05	13.20	14.04	14.80
BB	12.99	12.13	12.98	13.74
B	11.91	10.96	11.82	12.80
CCC-C	10.88	9.91	11.09	11.83
D	10.83	9.70	10.73	11.79
All	13.87	12.68	13.88	15.03

Table 2 (continued)

Statistics on business and financial risk variables: data set 1

Variables	Mean	Fractiles		
		0.25	**Median**	**0.75**
Market-model beta				
AAA-AA	0.93	0.58	0.92	1.26
A	0.91	0.49	0.88	1.24
BBB	0.92	0.51	0.85	1.24
BB	1.10	0.59	1.02	1.52
B	1.08	0.53	0.98	1.53
CCC-C	1.03	0.44	1.04	1.52
D	0.83	0.22	0.84	1.29
All	0.97	0.52	0.91	1.32
Market-model standard error				
AAA-AA	0.65	0.52	0.62	0.76
A	0.71	0.55	0.68	0.83
BBB	0.82	0.64	0.79	0.97
BB	1.14	0.87	1.07	1.34
B	1.50	1.12	1.40	1.74
CCC-C	2.43	1.61	2.18	3.00
D	2.44	1.46	2.17	3.15
All	0.94	0.63	0.82	1.11

Table 3

Statistics on business and financial risk variables: data set 2

Variables	Mean	Fractiles		
		0.25	**Median**	**0.75**
Interest coverage				
AAA-AA	12.63	5.05	8.31	17.31
A	9.34	4.03	5.53	8.90
BBB	6.53	3.23	4.44	6.39
BB	5.47	2.52	3.45	4.96
B	3.60	1.87	2.57	3.90
CCC-C	2.94	1.47	2.46	3.38
D	3.66	1.58	2.56	3.59
All	6.33	2.71	3.96	6.18
Operating margin				
AAA-AA	0.23	0.14	0.20	0.30
A	0.21	0.13	0.18	0.28
BBB	0.18	0.11	0.15	0.23
BB	0.16	0.08	0.13	0.20
B	0.16	0.07	0.11	0.19
CCC-C	0.18	0.07	0.15	0.23
D	0.17	0.07	0.14	0.20
All	0.18	0.10	0.15	0.23
Long-term debt				
AAA-AA	0.16	0.07	0.14	0.25
A	0.22	0.14	0.23	0.30
BBB	0.27	0.18	0.27	0.34
BB	0.38	0.25	0.34	0.45
B	0.44	0.31	0.41	0.55
CCC-C	0.45	0.32	0.44	0.55
D	0.45	0.32	0.45	0.56
All	0.32	0.20	0.30	0.41
Total debt				
AAA-AA	0.23	0.12	0.22	0.31
A	0.28	0.19	0.28	0.36
BBB	0.32	0.23	0.32	0.40
BB	0.42	0.30	0.39	0.50
B	0.49	0.36	0.47	0.61
CCC-C	0.52	0.41	0.52	0.64
D	0.55	0.39	0.52	0.64
All	0.38	0.25	0.35	0.47
Market value				
AAA-AA	15.70	14.50	15.77	16.86
A	14.87	14.08	14.96	15.67
BBB	14.32	13.59	14.32	15.01
BB	13.33	12.57	13.39	14.12
B	11.82	10.97	11.74	12.67
CCC-C	10.54	9.74	10.57	11.17
D	9.90	8.81	9.86	10.65
All	13.51	12.34	13.76	14.79

Table 3 (continued)

Statistics on business and financial risk variables: data set 2

Variables	Mean	Fractiles		
		0.25	**Median**	**0.75**
Market-model beta				
AAA-AA	0.98	0.56	0.97	1.29
A	0.87	0.51	0.87	1.20
BBB	0.90	0.50	0.84	1.25
BB	1.01	0.58	0.97	1.45
B	1.02	0.51	1.03	1.44
CCC-C	0.98	0.39	0.85	1.52
D	0.85	0.18	0.85	1.39
All	0.94	0.50	0.91	1.32
Market-model standard error				
AAA-AA	0.59	0.46	0.58	0.70
A	0.61	0.46	0.59	0.73
BBB	0.71	0.53	0.68	0.85
BB	0.93	0.71	0.89	1.11
B	1.35	1.05	1.29	1.54
CCC-C	1.19	1.46	1.79	2.23
D	2.29	1.57	2.00	2.69
All	0.96	0.59	0.79	1.14

Table 4

Estimates of ordered probit model with time dummies (data set 1)

Variable	Estimate	Variable	Estimate
Interest coverage (C_1)	–0.2589 (0.0140)**	1989	0.6246 (0.0840)**
Interest coverage (C_2)	–0.0400 (0.0095)**	1990	0.5569 (0.0839)**
Interest coverage (C_3)	–0.0431 (0.0069)**	1991	0.6671 (0.0844)**
Interest coverage (C_4)	0.0118 (0.0016)**	1992	0.7444 (0.0836)**
Operating margin	–1.1680 (0.0927)**	1993	0.9756 (0.0825)**
Long-term debt	2.8780 (0.1500)**	1994	1.0402 (0.0814)**
Total debt	–1.5012 (0.1523)**	1995	1.2326 (0.0804)**
Market value	–0.4242 (0.0091)**	1996	1.3314 (0.0794)**
Market-model beta	0.3310 (0.0179)**	1997	1.4576 (0.0790)**
Market-model standard error	1.0459 (0.0325)**	1998	1.4751 (0.0785)**
1985	0.3091 (0.0896)**	1999	1.4959 (0.0785)**
1986	0.5232 (0.0881)**	2000	1.5670 (0.0789)**
1987	0.5612 (0.0863)**	2001	1.9151 (0.1157)**
1988	0.5615 (0.0847)**		

Note: Standard errors in parentheses; * significant at 5%, ** significant at 1%.

Table 5

Estimates of ordered probit model with trend and cycle: baseline (data set 1)

Variable	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	–0.2498 (0.0139)**	–0.2502 (0.0139)**	–0.2504 (0.0139)**
Interest coverage (C_2)	–0.0377 (0.0095)**	–0.0376 (0.0095)**	–0.0377 (0.0095)**
Interest coverage (C_3)	–0.0430 (0.0069)**	–0.0428 (0.0069)**	–0.0427 (0.0069)**
Interest coverage (C_4)	0.0119 (0.0016)**	0.0118 (0.0016)**	0.0118 (0.0016)**
Operating margin	–1.1968 (0.0924)**	–1.1975 (0.0924)**	–1.1977 (0.0924)**
Long-term debt	2.8689 (0.1498)**	2.8766 (0.1498)**	2.8765 (0.1498)**
Total debt	–1.4800 (0.1519)**	–1.4886 (0.1519)**	–1.4905 (0.1519)**
Market value	–0.4241 (0.0091)**	–0.4230 (0.0091)**	–0.4228 (0.0091)**
Market-model beta	0.3303 (0.0178)**	0.3295 (0.0178)**	0.3292 (0.0178)**
Market-model standard error	1.0530 (0.0324)**	1.0531 (0.0324)**	1.0540 (0.0324)**
Linear trend	0.0226 (0.0006)**	0.0229 (0.0006)**	0.0227 (0.0006)**
Cycle	0.1913 (0.0487)**	1.7386 (0.8721)*	0.0236 (0.0128)

Note: See Table 4. The variable “Cycle” is set equal to the measure heading each column, respectively.

Table 6

Estimates of ordered probit model with trend and cycle: alternative specifications (data set 1)

Variable	NBER recession				Output growth gap				Discrete growth indicator			
	1	2	3	4	1	2	3	4	1	2	3	4
Interest coverage (C_1)	–0.2466 (0.0143)**	–0.1985 (0.0214)**	–0.3635 (0.0141)**	–0.2162 (0.0135)**	–0.2520 (0.0142)**	–0.1981 (0.0214)**	–0.3636 (0.0141)**	–0.2166 (0.0135)**	–0.2551 (0.0143)**	–0.1992 (0.0214)**	–0.3639 (0.0141)**	–0.2167 (0.0135)**
Interest coverage (C_2)	–0.0344 (0.0098)**	–0.0230 (0.0138)	–0.0837 (0.0094)**	–0.0318 (0.0095)**	–0.0414 (0.0098)**	–0.0235 (0.0138)	–0.0836 (0.0094)**	–0.0317 (0.0095)**	–0.0395 (0.0098)**	–0.0241 (0.0138)	–0.0836 (0.0094)**	–0.0318 (0.0095)**
Interest coverage (C_3)	–0.0459 (0.0071)**	–0.0176 (0.0091)	–0.0563 (0.0069)**	–0.0396 (0.0069)**	–0.0393 (0.0072)**	–0.0173 (0.0091)	–0.0562 (0.0069)**	–0.0394 (0.0069)**	–0.0404 (0.0072)**	–0.0172 (0.0091)	–0.0562 (0.0069)**	–0.0392 (0.0069)**
Interest coverage (C_4)	0.0123 (0.0017)**	0.0107 (0.0023)**	0.0094 (0.0016)**	0.0126 (0.0016)**	0.0110 (0.0017)**	0.0106 (0.0023)**	0.0093 (0.0016)**	0.0125 (0.0016)**	0.0111 (0.0017)**	0.0106 (0.0023)**	0.0093 (0.0016)**	0.0125 (0.0016)**
Operating margin	–1.1986 (0.0946)**	–2.7044 (0.3648)**	–1.2706 (0.0921)**	–1.4247 (0.0893)**	–1.2175 (0.0952)**	–2.7060 (0.3647)**	–1.2695 (0.0921)**	–1.4271 (0.0893)**	–1.2141 (0.0957)**	–2.7125 (0.3647)**	–1.2715 (0.0922)**	–1.4276 (0.0893)**
Long-term debt	2.8511 (0.1547)**	1.1230 (0.3102)**	2.0174 (0.1524)**	1.6552 (0.0830)**	2.8891 (0.1522)**	1.1162 (0.3101)**	2.0219 (0.1524)**	1.6560 (0.0830)**	2.8751 (0.1522)**	1.1115 (0.3101)**	2.0186 (0.1524)**	1.6541 (0.0830)**
Total debt	–1.4814 (0.1575)**	0.3580 (0.3178)	–0.9147 (0.1526)**		–1.4680 (0.1538)**	0.3695 (0.3177)	–0.9207 (0.1526)**		–1.4563 (0.1539)**	0.3765 (0.3178)	–0.9179 (0.1526)**	
Market value	–0.4280 (0.0093)**	–0.4210 (0.0092)**		–0.4259 (0.0091)**	–0.4198 (0.0092)**	–0.4199 (0.0092)**		–0.4247 (0.0091)**	–0.4194 (0.0092)**	–0.4199 (0.0092)**		–0.4245 (0.0091)**
Total assets			–0.4256 (0.0096)**				–0.4256 (0.0096)**				–0.4257 (0.0096)**	
Market-model beta	0.3349 (0.0182)**	0.3235 (0.0179)**	0.2477 (0.0174)**	0.3153 (0.0178)**	0.3308 (0.0180)**	0.3225 (0.0179)**	0.2477 (0.0174)**	0.3142 (0.0177)**	0.3292 (0.0179)**	0.3220 (0.0179)**	0.2474 (0.0174)**	0.3139 (0.0177)**
Market-model standard error	1.0922 (0.0335)**	1.0560 (0.0327)**	1.1884 (0.0316)**	1.0307 (0.0324)**	1.0452 (0.0329)**	1.0560 (0.0327)**	1.1883 (0.0316)**	1.0304 (0.0324)**	1.0481 (0.0328)**	1.0575 (0.0327)**	1.1876 (0.0316)**	1.0315 (0.0324)**
Linear trend	0.0227 (0.0006)**	0.0226 (0.0006)**	0.0226 (0.0006)**	0.0221 (0.0006)**	0.0231 (0.0006)**	0.0228 (0.0006)**	0.0227 (0.0006)**	0.0224 (0.0006)**	0.0228 (0.0006)**	0.0227 (0.0006)**	0.0227 (0.0006)**	0.0222 (0.0006)**
Cycle	0.3276 (0.6220)	0.1851 (0.0488)**	0.0929 (0.0485)	0.2054 (0.0486)**	30.8549 (11.3632)**	1.7381 (0.8766)*	0.5036 (0.8702)	1.9958 (0.8711)*	0.3282 (0.1643)*	0.0230 (0.0128)	0.0170 (0.0127)	0.0268 (0.0127)*
C_1 * cycle	0.0741 (0.0631)				0.1020 (1.1039)				0.0219 (0.0160)			
C_2 * cycle	0.0747 (0.0436)				0.9844 (0.7600)				0.0034 (0.0113)			
C_3 * cycle	–0.0547 (0.0342)				–1.1932 (0.5608)*				–0.0108 (0.0082)			

Table 6 (continued)

Estimates of ordered probit model with trend and cycle: alternative specifications (data set 1)

Variable	NBER recession				Output growth gap				Discrete growth indicator			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
C_4 * cycle	0.0053 (0.0068)				0.2701 (0.1311)*				0.0028 (0.0019)			
Operating margin * cycle	0.0448 (0.4384)				6.0812 (7.6339)				0.0673 (0.1070)			
Long-term debt * cycle	0.0112 (0.6238)				1.2628 (11.7974)				0.1277 (0.1687)			
Total debt * cycle	–0.4953 (0.6081)				–14.2372 (11.9385)				–0.2907 (0.1721)			
Market value * cycle	–0.0565 (0.0384)				–2.3947 (0.6703)**				–0.0289 (0.0096)**			
Beta * cycle	–0.0044 (0.0903)				2.9848 (1.4626)*				0.0455 (0.0195)*			
Standard error * cycle	0.5087 (0.1309)**				3.7544 (2.4398)				0.0259 (0.0347)			
C_1 - current		–0.0620 (0.0196)**				–0.0630 (0.0197)**				–0.0618 (0.0196)**		
C_2 - current		–0.0079 (0.0139)				–0.0071 (0.0139)				–0.0064 (0.0139)		
C_3 - current		–0.0381 (0.0095)**				–0.0383 (0.0095)**				–0.0382 (0.0095)**		
C_4 - current		0.0029 (0.0025)				0.0029 (0.0025)				0.0029 (0.0025)		
Operating margin - current		1.5101 (0.3552)**				1.5107 (0.3551)**				1.5172 (0.3551)**		
Long-term debt - current		1.7260 (0.2683)**				1.7395 (0.2681)**				1.7438 (0.2680)**		
Total debt - current		–1.8162 (0.2693)**				–1.8343 (0.2689)**				–1.8422 (0.2690)**		

Note: See Table 5.

Table 7

Predicted versus actual ratings (data set 1)

Panel A: Model with time dummies

Actual rating	Predicted rating									
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**D**	**Total**
AAA	36	156	33	0	0	0	0	0	0	225
AA	9	249	678	87	1	0	0	0	0	1,204
A	0	95	2,030	691	22	1	0	0	0	2,839
BBB	0	4	893	1,390	342	6	0	0	1	2,636
BB	0	0	73	621	946	324	0	0	7	1,971
B	0	0	8	97	466	584	0	0	81	1,236
CCC	0	0	0	3	8	33	0	0	26	70
CC	0	0	0	0	0	0	0	0	1	1
D	0	0	5	7	33	60	0	0	37	142
Total	45	504	3,720	2,896	1,818	1,008	0	0	153	10,144

Panel B: Model with linear trend and NBER recession index

Actual rating	Predicted rating									
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**D**	**Total**
AAA	34	161	30	0	0	0	0	0	0	225
AA	8	252	678	85	1	0	0	0	0	1,024
A	0	98	2,007	712	21	1	0	0	0	2,839
BBB	0	4	899	1,392	333	7	0	0	1	2,636
BB	0	0	72	625	938	329	0	0	7	1,971
B	0	0	7	97	473	578	0	0	81	1,236
CCC	0	0	0	3	9	33	0	0	25	70
CC	0	0	0	0	0	0	0	0	1	1
D	0	0	5	6	32	62	0	0	37	142
Total	42	515	3,698	2,920	1,807	1,010	0	0	152	10,144

Note: Rating category C is not observed in data set 1 and, thus, is not explicitly included in the ordered probit model. As a consequence, predictions of C ratings cannot be identified.

Table 8

Estimates of ordered probit model with trend and cycle: baseline (data set 2)

Variable	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	–0.2110 (0.0301)**	–0.2076 (0.0298)**	–0.2054 (0.0300)**
Interest coverage (C_2)	–0.0427 (0.0220)	–0.0412 (0.0220)	–0.0349 (0.0220)
Interest coverage (C_3)	–0.0071 (0.0168)	–0.0114 (0.0169)	–0.0233 (0.0169)
Interest coverage (C_4)	0.0032 (0.0044)	0.0041 (0.0044)	0.0056 (0.0044)
Operating margin	–1.0640 (0.2143)**	–1.0678 (0.2162)**	–1.0783 (0.2136)**
Long-term debt	3.0628 (0.3978)**	3.1751 (0.4020)**	3.0675 (0.3993)**
Total debt	–1.4689 (0.3872)**	–1.5107 (0.3885)**	–1.4325 (0.3867)**
Market value	–0.3619 (0.0228)**	–0.3612 (0.0208)**	–0.3465 (0.0222)**
Market-model beta	0.0935 (0.0444)*	0.0920 (0.0448)*	0.0855 (0.0446)
Market-model standard error	2.0085 (0.1141)**	2.0803 (0.1159)**	1.9810 (0.1124)**
Linear trend	0.0147 (0.0024)**	0.0149 (0.0024)**	0.0161 (0.0024)**
Cycle	–0.4975 (0.0791)**	–12.1356 (1.7012)**	–0.0842 (0.0306)**

Note: See Table 5.

Table 9

Estimates of ordered probit model with trend and cycle: alternative specifications (data set 2)

Variable	NBER recession				Output growth gap				Discrete growth indicator			
	1	2	3	4	1	2	3	4	1	2	3	4
Interest coverage (C_1)	–0.2111	–0.1811	–0.3038	–0.1870	–0.2066	–0.1736	–0.3011	–0.1846	–0.2111	–0.1539	–0.2959	–0.1838
	(0.0312)**	(0.0411)**	(0.0322)**	(0.0292)**	(0.0297)**	(0.0429)**	(0.0323)**	(0.0292)**	(0.0297)**	(0.0428)**	(0.0321)**	(0.0293)**
Interest coverage (C_2)	–0.0705	–0.0233	–0.0637	–0.0349	–0.0462	–0.0246	–0.0655	–0.0349	–0.0355	–0.0186	–0.0599	–0.0342
	(0.0237)**	(0.0283)	(0.0225)**	(0.0219)	(0.0221)*	(0.0292)	(0.0225)**	(0.0220)	(0.0220)	(0.0291)	(0.0225)**	(0.0219)
Interest coverage (C_3)	0.0043	–0.0251	–0.0212	–0.0119	–0.0062	–0.0161	–0.0200	–0.0108	–0.0174	–0.0180	–0.0234	–0.0072
	(0.0178)	(0.0205)	(0.0172)	(0.0168)	(0.0170)	(0.0208)	(0.0171)	(0.0168)	(0.0175)	(0.0208)	(0.0170)	(0.0169)
Interest coverage (C_4)	0.0048	–0.0054	0.0024	0.0049	0.0028	–0.0024	0.0025	0.0051	0.0034	–0.0027	0.0028	0.0040
	(0.0046)	(0.0058)	(0.0044)	(0.0044)	(0.0045)	(0.0058)	(0.0044)	(0.0045)	(0.0046)	(0.0057)	(0.0044)	(0.0044)
Operating margin	–1.0989	0.4753	–1.3190	–1.2417	–1.0603	0.5233	–1.2883	–1.2328	–1.1158	0.5420	–1.3364	–1.2209
	(0.2273)**	(0.7438)	(0.2149)**	(0.2131)**	(0.2171)**	(0.8025)	(0.2132)**	(0.2132)**	(0.2165)**	(0.8023)	(0.2118)**	(0.2108)**
Long-term debt	2.7308	2.5733	2.8134	1.8475	3.0343	2.6457	2.8972	1.8704	3.0467	2.7001	2.8613	1.8130
	(0.4142)**	(0.6837)**	(0.4021)**	(0.2250)**	(0.4043)**	(0.7596)**	(0.4015)**	(0.2252)**	(0.4000)**	(0.7612)**	(0.4014)**	(0.2215)**
Total debt	–1.1750	–2.7418	–1.5023		–1.3947	–2.7580	–1.5629		–1.4460	–2.8388	–1.4769	
	(0.4073)**	(0.7329)**	(0.3877)**		(0.3918)**	(0.8009)**	(0.3867)**		(0.3892)**	(0.8026)**	(0.3859)**	
Market value	–0.3508	–0.3578		–0.3634	–0.3575	–0.3493		–0.3645	–0.3682	–0.3514		–0.3688
	(0.0221)**	(0.0200)**		(0.0214)**	(0.0210)**	(0.0212)**		(0.0212)**	(0.0208)**	(0.0215)**		(0.0221)**
Total assets			–0.2063				–0.2076				–0.1937	
			(0.0221)**				(0.0223)**				(0.0217)**	
Market-model beta	0.0698	0.1372	–0.0913	0.0820	0.0747	0.1413	–0.0905	0.0833	0.0748	0.1406	–0.1070	0.0788
	(0.0472)	(0.0425)**	(0.0429)*	(0.0447)	(0.0451)	(0.0448)**	(0.0430)*	(0.0448)	(0.0446)	(0.0444)**	(0.0428)*	(0.0443)
Market-model standard error	2.0684	1.6424	2.4573	2.0302	2.0799	1.9048	2.4955	2.0535	1.9569	1.8325	2.4476	1.9424
	(0.1176)**	(0.0979)**	(0.1023)**	(0.1202)**	(0.1164)**	(0.1077)**	(0.1011)**	(0.1189)**	(0.1116)**	(0.1034)**	(0.1003)**	(0.1160)**
Linear trend	0.0149	0.0144	0.0141	0.0141	0.0149	0.0150	0.0141	0.0142	0.0161	0.0162	0.0155	0.0155
	(0.0024)**	(0.0023)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**	(0.0024)**
Cycle	–2.1401	–0.4211	–0.6029	–0.4789	–58.4429	–10.8934	–14.8959	–11.7492	–0.9983	–0.0717	–0.1146	–0.0799
	(1.0592)*	(0.0766)**	(0.0789)**	(0.0794)**	(22.7704)*	(1.7009)**	(1.6953)**	(1.6960)**	(0.4118)*	(0.0306)*	(0.0305)**	(0.0305)**
C_1 * cycle	0.0198				1.7702				0.0674			
	(0.1024)				(2.0962)				(0.0359)			
C_2 * cycle	–0.1862				–2.2436				–0.0286			
	(0.0643)**				(1.4231)				(0.0269)			
C_3 * cycle	0.0534				0.3167				0.0095			
	(0.0622)				(1.2215)				(0.0223)			

Table 9 (continued)

Estimates of ordered probit model with trend and cycle: alternative specifications (data set 2)

Variable	NBER recession				Output growth gap				Discrete growth indicator			
	1	2	3	4	1	2	3	4	1	2	3	4
C_4 * cycle	0.0340 (0.0191)				0.3683 (0.3460)				0.0064 (0.0054)			
Operating margin * cycle	–0.0902 (0.6984)				–8.6892 (15.5999)				0.1289 (0.2607)			
Long-term debt * cycle	–3.8358 (1.3736)**				–65.4472 (27.9977)*				–0.6922 (0.4786)			
Total debt * cycle	3.3996 (1.3942)*				77.1834 (28.2989)**				1.2390 (0.4851)*			
Market value * cycle	0.1091 (0.0585)				2.4913 (1.2863)				0.0277 (0.0240)			
Beta * cycle	–0.1659 (0.1506)				–2.0555 (3.0863)				–0.0128 (0.0533)			
Standard error * cycle	0.4174 (0.3382)				3.0806 (7.1210)				0.0591 (0.1192)			
C_1 - current		–0.0622 (0.0388)				–0.0689 (0.0403)				–0.0910 (0.0400)*		
C_2 - current		–0.0148 (0.0298)				–0.0084 (0.0306)				–0.0051 (0.0305)		
C_3 - current		0.0076 (0.0216)				0.0077 (0.0217)				0.0034 (0.0216)		
C_4 - current		0.0072 (0.0059)				0.0057 (0.0058)				0.0075 (0.0058)		
Operating margin - current		–1.4962 (0.7327)*				–1.6541 (0.7875)*				–1.6928 (0.7878)*		
Long-term debt - current		0.4319 (0.5487)				0.6499 (0.6542)				0.5198 (0.6563)		
Total debt - current		1.0961 (0.5903)				1.1344 (0.6886)				1.2989 (0.6900)		

Note: See Table 5.

Table 10

Predicted versus actual ratings using the NBER recession index (data set 2)

Actual rating	Predicted rating										
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**C**	**D**	**Total**
AAA	0	1	4	2	0	0	0	0	0	0	7
AA	0	10	54	19	3	0	0	0	0	0	86
A	0	2	233	210	18	0	0	0	0	1	464
BBB	0	1	132	423	115	8	1	0	0	1	681
BB	0	0	3	184	259	76	8	2	0	9	541
B	0	0	1	10	100	124	27	2	1	93	358
CCC	0	0	0	3	13	16	8	0	0	78	118
CC	0	0	0	0	0	1	1	0	0	11	13
C	0	0	0	0	1	0	0	0	0	1	2
D	0	0	0	1	4	7	0	0	0	71	83
Total	0	14	427	852	513	232	45	4	1	265	2,353

Table 11

Effect of cycle on predicted ratings (data set 2)

Panel A: NBER recession index

Predicted rating during upturn	**Predicted rating during downturn**										
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**C**	**D**	**Total**
AAA	0	0	0	0	0	0	0	0	0	0	0
AA	0	3	13	0	0	0	0	0	0	0	16
A	0	0	190	267	0	0	0	0	0	0	457
BBB	0	0	0	592	254	0	0	0	0	0	846
BB	0	0	0	0	371	135	0	0	0	0	506
B	0	0	0	0	0	134	45	4	1	42	226
CCC	0	0	0	0	0	0	0	0	0	46	46
CC	0	0	0	0	0	0	0	0	0	5	5
C	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	251	251
Total	0	3	203	859	625	269	45	4	1	344	2,353

Panel B: Output growth gap

Predicted rating during upturn	**Predicted rating during downturn**										
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**C**	**D**	**Total**
AAA	0	0	0	0	0	0	0	0	0	0	0
AA	0	7	20	0	0	0	0	0	0	0	27
A	0	0	323	216	0	0	0	0	0	0	539
BBB	0	0	0	662	174	0	0	0	0	0	836
BB	0	0	0	0	355	97	0	0	0	0	452
B	0	0	0	0	0	145	48	5	0	11	209
CCC	0	0	0	0	0	0	0	0	0	46	46
CC	0	0	0	0	0	0	0	0	0	2	2
C	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	242	242
Total	0	7	343	878	529	242	48	5	0	301	2,353

Table 11 (continued)

Effect of cycle on predicted ratings (data set 2)

Panel C: Discrete growth indicator

Predicted rating during upturn	Predicted rating during downturn										
	AAA	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**CC**	**C**	**D**	**Total**
AAA	0	0	0	0	0	0	0	0	0	0	0
AA	0	12	4	0	0	0	0	0	0	0	16
A	0	0	376	91	0	0	0	0	0	0	467
BBB	0	0	0	784	68	0	0	0	0	0	852
BB	0	0	0	0	448	52	0	0	0	0	500
B	0	0	0	0	0	188	28	0	0	0	216
CCC	0	0	0	0	0	0	23	3	0	23	49
CC	0	0	0	0	0	0	0	0	0	6	6
C	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	0	0	0	0	247	247
Total	0	12	380	875	516	240	51	3	0	276	2,353

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