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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. Utilizing annual data on all US firms rated by Standard & Poor's, we find that ratings do not generally exhibit excess sensitivity to the business cycle. In addition, we document that previously reported findings of a secular tightening of ratings standards are not robust to a more complete accounting of systematic changes to measures of risk.

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Keywords: Rating agencies; Business cycles; Credit risk

> 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)

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1. Introduction

Credit risk measurement has played an increasingly important role in the pricing of credit-risky instruments, asset allocation decisions and the development of integrated risk management systems (see, e.g., Duffie and Singleton, 2003). One important challenge in measuring credit risk is the identification of systematic risk exposures over the business cycle. In particular, there are several situations in which it may be desirable to have measures of credit risk that are unaffected by cyclical fluctuations (e.g. long-horizon investment strategies, capital allocation). Credit ratings can play a key role in this case. As is evident in the above quotation, one of the main goals of rating agencies is to assign ratings that are insensitive to undue cyclical influences.

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.

But what do rating agencies mean when they claim that they rate "through the cycle"? One interpretation, which we adopt here, is that a firm's rating should be independent of the state of the business cycle, conditional on its underlying financial and business characteristics. We examine whether ratings are *excessively procyclical* by empirically testing whether the state of the US economy is an important determinant of firm credit ratings after proper account is taken of firm-specific factors. [1] More specifically, our null hypothesis is that business cycle variables should not have a marginal effect on the rating assigned to a firm.

Even if rating agencies see through the cycle in making their assignments, it is nonetheless plausible that ratings will exhibit some degree of comovement with measures of aggregate economic activity. For instance, to the extent that changes in the financial and business prospects of firms are driven by long-lived fundamental shocks, and these shocks also induce business cycle fluctuations, we would expect to see the long-term creditworthiness of firms, and hence credit ratings, to covary positively with the cycle (see Löffler, 2003).

The difficulty in assessing whether ratings are excessively procyclical is in determining what is an appropriate degree of comovement between ratings and the cycle. In the context of our analysis, this issue is embodied in the choice of variables we use to capture the true long-term credit risk of firms. For this, we turn to the rating agencies themselves to tell us which factors they consider to be most important. The implicit assumption is that the rating agencies are best suited to have determined the most relevant factors that correlate with credit risk. Of course, we may fail to

[1] We will drop the modifier excessive and simply use the term procyclical when the context is clear.

account for certain financial and business risks, as the assessment of creditworthiness is ultimately subjective in nature. [2] Thus, it is only possible for us to test that ratings *might* be excessively procyclical, not that they are excessively procyclical. [3] To help address this problem, we estimate two benchmark models that allow us to perform what we refer to as "weak" and "strong" tests of procyclicality. Specifically, in addition to conditioning on firm-specific risk factors, the latter tests also take into account systematic time variation in the risk factors by including yearly cross-sectional averages of these variables in the model as well. We view this more stringent specification as our main test of excessive procyclicality.

We examine the universe of US firms rated by the agency Standard & Poor's (S&P) between 1981 and 2001. [4] 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 no evidence that credit ratings are unduly influenced by the business cycle. This conclusion is robust to three different measures of the state of the cycle and under various specifications of our model. However, it is not robust to our method for sampling the ratings data. In two important special cases, when we restrict our sample to only investment grade firms or to only initial ratings and rating changes, we do find evidence of procyclicality. It should be emphasized that our results directly apply to S&P's ratings only and may not hold for ratings from the other ratings agencies. [5]

One additional important result we obtain regards the trend behavior of ratings over time. 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 the standards of ratings agencies have indeed become more stringent over time. By contrast, when due account is taken of systematic changes in measures of risk, we find that this finding disappears, and in some cases, reverses itself. [6]

The rest of the paper is organized as follows. Section 2 provides a brief literature review describing how measured risk relates to business cycles, in general, and how

[2] For example, the recent period from 2000 to 2002 was one of both cyclical weakness and fundamental changes in the market's view of credit risk. The latter, which pertained to a significant re-evaluation of the riskiness of some industries such as telecoms and airlines, might not be adequately captured by our set of risk factors.

[3] Such problems of omitted variables can never be fully resolved and they are endemic to most statistical work in economics and finance.

[4] Our datasets include both non-financial and financial firms. However, non-financial firms dominate in our samples; for example, only 6.8% of the observations in our baseline sample correspond to financial, insurance or real estate firms.

[5] Using a different methodology, Cantor and Mann (2003b) examine the cyclical properties of Moody's ratings. They show that Moody's US ratings change by only a small fraction of one rating notch per year on average.

[6] Our results regarding trends thus complement the conclusion reached by Zhou (2001), who focuses on the default experience of cohorts of issuers grouped by rating category. Zhou finds that ratings standards were gradually relaxed throughout the 1970s and 1980s, eventually stabilizing in the early 1990s.

credit ratings have behaved through time, specifically. Section 3 provides details of the data used in this study. Section 4 outlines the ordered probit model and describes our sampling techniques. Section 5 reports results for our baseline data set, which includes all non-defaulting firms at an annual frequency. Section 6 provides analysis of the other two samples mentioned. Section 7 concludes.

2. 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 may 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*, e.g. at its highest during economic downturns. [7] For instance, bank loan standards tend to be most lax during 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. [8] For instance, Altman et al. (2003) show that there is a relationship between the correlation of default rates 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) document 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

[7] 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 realization of that risk. To the extent that measures of financial risk are inappropriately countercyclical, the 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.

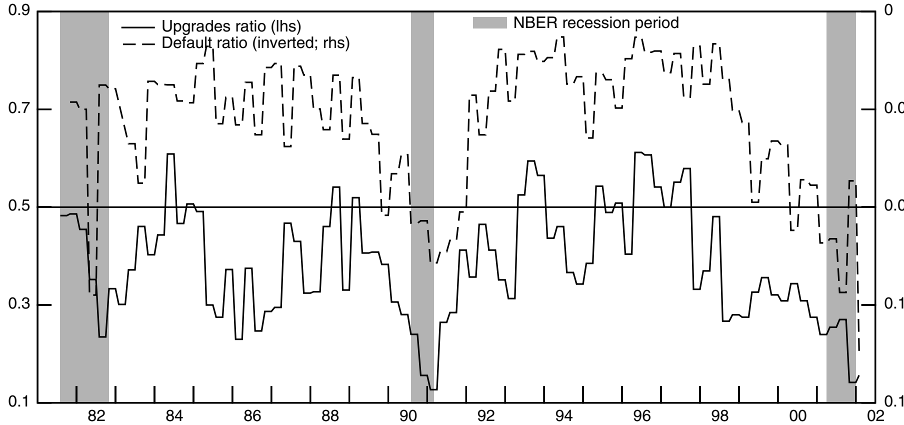
[8] For a review of how systematic factors are incorporated into credit risk models, see Allen and Saunders (2002).

in time rather than absolute measures of default probability that are constant through time (Cantor and Mann, 2003a).

A casual investigation of ratings through time, however, suggests that credit ratings may be related to the business cycle. For instance, Graph 1 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. Using a sample starting in 1920, Cantor and Mann (2003b) show that Moody's ratings are also positively correlated with cyclical indicators.

Such empirical regularities have led to a closer examination of ratings behavior 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. Nonetheless, ratings appear to be less procyclical than market-based measures of credit risk. For instance, Cantor and Mann (2003b) show that ratings are less cyclical than credit spreads and equity-based measures of credit risk. Catarineu-Rabell et al. (2003) provide evidence, on the basis of transition matrices, that downgrades from investment to speculative grade by the rating agencies during the 1990–1992 recession were much less than those that would have been implied by market-based models (i.e. a Merton-type model).

The analysis in most of these studies, however, is performed unconditionally with respect to the specific characteristics of firms. For example, Nickell et al. (2000) and



Graph 1. Downgrades and defaults across the business cycle.
Note. The solid line plots the number of upgrades as a fraction of all rating changes (upgrades plus downgrades); the dashed line plots the ratio of the number of firms that defaulted to the total number of rated firms. Each series is computed on a quarterly basis.

Bangia et al. (2002) 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. Löffler (2002) attempts to explain this by observing that the agencies appear to have an additional objective of avoiding near-term reversals in their rating assignments (see, e.g., Cantor, 2001). Thus, rating changes are not independent, a finding that has been carefully modeled 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.

Our empirical methodology most closely follows that of BLM (1998). BLM 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. We extend the analysis of BLM to consider both the secular and cyclical movements in credit ratings. We describe the details of our approach next.

3. Data

Our paper presents a joint examination of how three factors – business risk, financial risk, macroeconomic conditions – influence the assignment of credit ratings. Specifically, 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 analyze how the business cycle influences the decisions of rating agencies. The first is data on ratings themselves; the second is data on firms' "fundamentals", i.e. measures of business and financial risk; the third is measures of the business cycle. These are discussed in turn.

3.1. 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 behavior 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. [9]

Our sample includes firms spanning the entire ratings spectrum, including both investment and speculative grade firms. We group firms into rating categories without consideration of notches (i.e. + or −). For example, our set of AA firms includes those with AA+, AA and AA− ratings. There are three reasons for doing this. First, it restricts our attention to focus on larger cumulative rating changes (on average) which are, presumably, of greater economic significance. Second, it helps avoid a potentially artificial overweighting in our samples of those firms that experience a quick succession of rating changes, notch by notch, due to the agencies' practice of wishing to avoid the "ratings bounce" (see Löffler (2002, 2003) and the discussion below). Third, it helps to reduce the occurrences of rating categories with few observations.

To focus our analysis on the actions of a rating agency, we eliminate observations with a C or D rating. S&P and the other rating agencies have set out well-defined rules that determine whether a firm has defaulted and thus receives a D rating. [10] The C rating similarly involves little judgement by the agency. As noted by S&P (2002, p. 8), the C rating covers situations such as when a bankruptcy petition has been filed but obligations are still being met.

In total, then, our analysis focuses on eight rating categories, ranging from AAA to CC. 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, ..., 8 to CC.

3.2. Measures of business and financial risk

In assessing creditworthiness, S&P takes into account both business risk and financial risk. (See Standard & Poor's (2002) for a detailed description of its rating

[9] S&P has provided credit ratings for more than 75 years. Indeed, a number of other studies have utilized 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, S&P 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.

[10] In contrast to S&P, Moody's does not even supply a rating for default.

methodology.) The analysis of business risk includes an assessment of industry characteristics, each firm's competitive position, firm size, management capability and organizational 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 recognizable 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 and by real total assets. [11] 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. [12] 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. [13] 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 standardize estimates of beta and the residual standard error by the averages across all firms' estimates for the year in which they are calculated. [14]

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 pre-

[11] Nominal quantities are deflated by the current monthly value of the CPI.

[12] 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.

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

[14] Since the observations in our data sets are dated throughout the year, one potential problem with standardizing 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 standardize by quarters or not at all.

sumably 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. [15] Next, we create four new variables, C_j ($j = 1, 2, 3, 4$), defined according to

	C_1	C_2	C_3	C_4
$C \in [0,5)$	C	0	0	0
$C \in [5,10)$	5	$C-5$	0	0
$C \in [10,20)$	5	5	$C-10$	0
$C \in [20,100]$	5	5	10	$C-20$

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 raise 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

[15] The reason for taking a three-year average is discussed below.

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. [16] Increases in either of these ratios should be correlated with worse ratings (i.e. 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.

Furthermore, we subtract the within-year cross-sectional averages from all of the business and financial risk variables. This helps to minimize the possibility that these demeaned measures are picking up purely cyclical or secular effects and thus more accurately capture relative credit quality. In addition, demeaning by yearly averages helps to reduce collinearity with the trend and cycle variables.

3.3. 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 a secular 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, are captured by a linear time trend. [17] If rating agencies have become tougher over time, all else equal, the trend should have a positive coefficient.

We utilize three measures of business cycle indicators. The first is an indicator of recessions and expansions; the second two are continuous indicators 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 reces-

[16] 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 multicolinearity, we also report results for the ordered probit models after eliminating one of the measures.

[17] As a sensitivity check, we estimated all versions of the ordered probit models with a quadratic time trend instead, obtaining qualitatively similar correlations between credit ratings and the other variables in the model, including measures of the cycle.

sion 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 behavior 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 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. [18] Defined in this way, we are making the assumption that only recessions might have a material impact on the behavior of the rating agency. This hypothesis is consistent with the perception that agencies are too aggressive in downgrading ratings during bad economic times. [19] As can be seen in Graph 2, the NBER has identified only two relatively brief recessions over our sample period.

Our second and third business cycle indicators that we consider seek to capture both ups and downs in economic activity. In particular, we use the *output growth gap*, defined as the difference between real GDP growth and potential GDP growth. [20] 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.

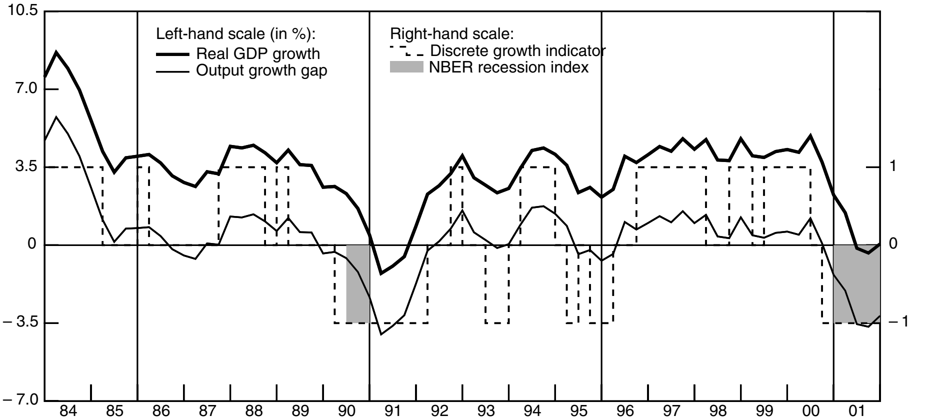
The other "symmetric" business cycle measure we consider is, unlike the output growth gap, a discrete-valued indicator of the relative rate of current real GDP growth. It is defined as follows. The histogram of annual real GDP growth rates for the entire sample period (at a quarterly frequency) is constructed. 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. [21] This indicator was used by

[18] 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.

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

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

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



Graph 2. Business cycle indicators.
Note. Real GDP growth and output gap are annual rates; see text for more detailed explanations of the series.

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, labeled *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 characterization of business cycle movements, both in terms of timing and magnitude, than the continuous-valued growth gap.

4. Ordered probit model

4.1. 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, ..., CC = 8. The components in X_{it} may or may not be specific to firm i. Consider an unobservable variable Z_{it} that 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:

$$Z_{it} = \beta X_{it} + \varepsilon_{it}, \tag{1}$$

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

$$R_{it} = \begin{cases} 1 & \text{if } Z_{it} \in (\infty, \mu_1), \\ r & \text{if } Z_{it} \in [\mu_{r-1}, \mu_r), \quad r = 2, 3, \ldots, 7, \\ 8 & \text{if } Z_{it} \in [\mu_7, \infty), \end{cases} \tag{2}$$

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. [22] 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.

As mentioned in the Introduction, we perform two tests to determine whether ratings are excessively procyclical. In the "weak" version (the Baseline 1 specification), we add a proxy measure of the cycle as an independent explanatory variable in X_{it}. A non-zero coefficient on this variable means that changes in the cycle shift ratings up or down. In the "strong" version (Baseline 2), we also include as independent terms in X_{it} the time series of the yearly cross-sectional averages of all financial variables. These annual averages do not solely measure the cyclical component in financial variables; they mix together both trend and cycle. Nonetheless, their inclusion may shed light on whether systematic time variation in the financial variables might explain any finding of a significant secular or cyclical influence on ratings.

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.

4.2. 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.

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

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 analyzed 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 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. Nevertheless, we check the robustness of our results by restricting the sample to investment grade firms only.

Table 1 shows the number of observations by rating and year in our baseline sample. [23] Note that the number of observations per year grows through time and that the sample is dominated by observations with ratings in categories A to B. [24]

Descriptive statistics on the measures of business and financial risk are presented in Table 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. 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.

An additional contribution of this paper is that we assess the sensitivity of our results to our method for constructing 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) and (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. [25] Prior studies utilized samples of annual observations based on the observed frequency of balance sheets, including BLM, who used

[23] For illustrative purposes, we have included observations with a C or D rating in the table, although these are omitted in estimation, as discussed above.

[24] The small number of observations in 2001 is due to the fact that the financial year-end for most companies is December 31, while we only have data through December 27.

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

Table 1
Number of ratings by category and year

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	1024	2839	2636	1971	1236	70	1	0	142	10,144

Note. Table 1 reports the ratings distribution of firms in our baseline sample. These data represent the complete set of firms for which we have both a rating and balance sheet information in the given year. Note, the decline in observations in 2001 is due to our sample period ending shortly before the end of 2001. Although we include information on C and D ratings, these observations are dropped from the empirical analysis.

December as the reference month for the calculation of market model estimates and the determination of market value.

Our baseline data sample 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 maximize 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 minimize the inclusion of observations that would effectively lead to "double-counting".

However, there is a potential problem with this sampling method. Specifically, monitoring is costly, and 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 behavior of the rating agency.

Table 2
Statistics on business and financial risk variables

Variables	Mean	Percentiles		
		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*)

Variables	Mean	Percentiles		
		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

Note. Table 2 reports summary statistics on the variables to be included in our ordered probit analysis. Although we include information on C and D ratings, these observations are dropped from the empirical analysis.

To combat this potential problem, in a second robustness check we analyze a sample that includes only *initial ratings* and *rating changes*. [26] 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 in this new sample 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.

[26] Using a rating change as a dependent variable 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) and (2). Estimation of the ordered probit model using this alternative sample therefore requires a modification to the standard form of the likelihood function (see Appendix A).

A given firm may appear in the alternative data set more than once in a calendar year if it experienced several rating changes during that year. [27] As mentioned above, rating agencies try to avoid reversals in the near term, and therefore change ratings in smaller steps than would otherwise be optimal solely on the basis of a firm's creditworthiness. Indeed, rating reversals are rare, unconditionally, even at a five-year horizon (see Cantor and Mann, 2003b). Including all rating changes without explicitly taking account of this additional objective of the agencies could be a source of specification error in our ordered probit model. However, this problem is mitigated somewhat by the fact that we have grouped together all notches in each letter category. As pointed out by Cantor and Mann (2003b), few firms experience rating changes of more than two notches over a one-year horizon. The downside of grouping notches is that our data set of initial ratings and rating changes contains many fewer observations (2,353) compared to our baseline sample (10,144).

5. Ordered probit estimation results

This section discusses estimation results of the ordered probit model based on our baseline data set. To determine whether or not there are important differences between our sample and the one used in BLM, Table 3 shows estimates of the model that includes time dummies (i.e. 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. [28] 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, i.e. 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 Fig. 1 in their paper) against the values reported in Table 3. 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. [29]

Next, we investigate the role of trend and cycle. Table 4 presents estimates of the Baseline 1 specification, which includes the measures of business and financial risk in

[27] 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.

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

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

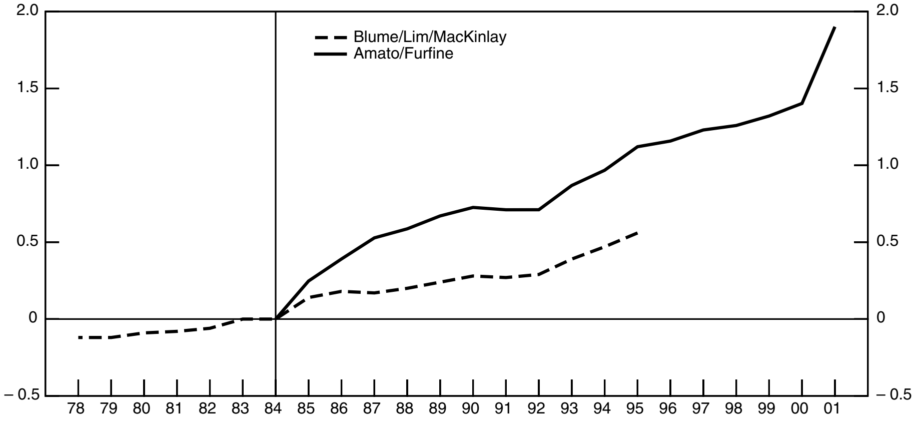
Table 3
Estimates of ordered probit model with time dummies

Variable	Estimate	Variable	Estimate
Interest coverage (C_1)	−0.2958 (0.0145)**	1988	−1.3143 (0.1084)**
Interest coverage (C_2)	−0.0331 (0.0097)**	1989	−1.2305 (0.1078)**
Interest coverage (C_3)	−0.0448 (0.0070)**	1990	−1.1753 (0.1077)**
Interest coverage (C_4)	0.0121 (0.0017)**	1991	−1.1905 (0.1080)**
Operating margin	−1.2762 (0.0945)**	1992	−1.1903 (0.1073)**
Long-term debt	3.3392 (0.1562)**	1993	−1.0325 (0.1062)**
Total debt	−1.5150 (0.1595)**	1994	−0.9335 (0.1054)**
Market value	−0.4232 (0.0094)**	1995	−0.7804 (0.1042)**
Market-model beta	0.3544 (0.0190)**	1996	−0.7434 (0.1032)**
Market-model standard error	1.1953 (0.0373)**	1997	−0.6714 (0.1026)**
1984	−1.9012 (0.1181)**	1998	−0.6424 (0.1021)**
1985	−1.6538 (0.1128)**	1999	−0.5807 (0.1020)**
1986	−1.5105 (0.1113)**	2000	−0.4990 (0.1022)**
1987	−1.3732 (0.1098)**		

Note. Standard errors in parentheses; *significant at 5%, **significant at 1%. Table 3 reports the estimates of our ordered probit estimation of credit ratings on measures of business and financial risk and a complete set of annual time dummies. The left-hand side variable is the credit rating of a firm at the time its most recent balance sheet date was released. In the analysis AAA ratings are assigned a "1", AA a "2", and so on until CC ratings, which are assigned an "8". That is, lower ratings reflect higher credit quality.

the model presented in Table 3, a linear trend and a measure of the cycle. Each column corresponds to a different proxy for 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 3. 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 0.076 per year. One way to view the economic significance of this value is that it would take the typical AA-rated firm 9.3 years to become an A-rated firm, all else equal. [30] Similarly, the typical BBB-rated

[30] 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.



Graph 3. Time dummies from ordered probit model.
Note. This graph plots estimates of the time dummies in the ordered probit model which are presented in Table 3. These are compared to the estimates obtained by Blume et al. (1998). To ease comparison, the estimates are re-based to equal 0 in 1984, and the signs of the estimates from Blume et al. have been switched due to the reverse definition of rating categories employed in the two studies.

firm would become a BB-rated firm after 8.8 years. However, this is evidence that only the absolute standards of rating agencies have changed through time. In particular, since ratings are intended to reflect relative risk across borrowers, this finding does not necessarily conflict with the agencies' own methodology. [31]

More importantly, even for the "weak" test of procyclicality documented in Table 4, the estimates generally support the notion that rating agencies "see through the cycle"; namely, for two of the three cyclical measures we cannot reject the hypothesis that their coefficients are zero. For the output growth gap, the coefficient is statistically significant at the 5% level and is negative, suggestive of procyclicality.

Table 5 gives estimates of the Baseline 2 specification, which includes the time series of yearly means of the financial variables. The coefficients on the firm-specific risk factors are almost identical to those above. By contrast, all of the coefficients on the linear trend and cycle variables change sign (with one exception), although most of the estimates are statistically insignificant. Thus, the inclusion in the model of the yearly means of financial variables has sharp implications for the interpretation of the cyclical and trend behavior of ratings. After taking account of systematic time variation in risk factors, our results show little evidence of either excessive cyclicality in ratings or ratings drift. [32]

[31] The results for the Baseline 2 specification are not subject to this criticism; see below.

[32] Because we do not decompose systematic variation in the risk factors into permanent and temporary components, a very difficult task in itself, it is possible that this test has imposed conditions that are *too stringent* on finding evidence of excessive procyclicality.

Table 4
Estimates of ordered probit model with trend and cycle – Baseline 1: weak test of procyclicality

Variable	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	−0.2925	−0.2926	−0.2925
	(0.0145)**	(0.0145)**	(0.0145)**
Interest coverage (C_2)	−0.0328	−0.0327	−0.0327
	(0.0097)**	(0.0097)**	(0.0097)**
Interest coverage (C_3)	−0.0452	−0.0451	−0.0452
	(0.0070)**	(0.0070)**	(0.0070)**
Interest coverage (C_4)	0.0120	0.0120	0.0120
	(0.0017)**	(0.0017)**	(0.0017)**
Operating margin	−1.2918	−1.2921	−1.2913
	(0.0943)**	(0.0943)**	(0.0943)**
Long-term debt	3.2966	3.2944	3.2951
	(0.1559)**	(0.1559)**	(0.1559)**
Total debt	−1.4881	−1.4859	−1.4872
	(0.1593)**	(0.1593)**	(0.1593)**
Market value	−0.4234	−0.4237	−0.4236
	(0.0094)**	(0.0094)**	(0.0094)**
Market-model beta	0.3553	0.3556	0.3556
	(0.0189)**	(0.0189)**	(0.0189)**
Market-model standard error	1.1931	1.1957	1.1945
	(0.0372)**	(0.0372)**	(0.0372)**
Linear trend	0.0191	0.0190	0.0191
	(0.0006)**	(0.0006)**	(0.0006)**
Cycle	−0.0053	−1.7879	−0.0163
	(0.0495)	(0.8888)*	(0.0130)

Note. Standard errors in parentheses; *significant at 5%; **significant at 1%. Table 4 reports the estimates of our ordered probit estimation of credit ratings on measures of business and financial risk, a linear trend, and three measures of business cycles. Each column reflects a different measure of the business cycle. The left-hand side variable is the credit rating of a firm at the time its most recent balance sheet date was released. In the analysis AAA ratings are assigned a "1", AA a "2", and so on until CC ratings, which are assigned an "8". That is, lower ratings reflect higher credit quality.

Finally, Table 6 presents evidence of the robustness of our results for our main data sample under three other alternative specifications of the explanatory variables. The first three columns are results obtained using the NBER recession index, which can be compared to the Baseline 1 estimates reported in column 1 of Table 4; similarly for the other two cyclical variables.

For each cyclical measure, column 1 adds the most recent observation on the ratios. [33] This is one additional test of procyclicality by examining whether ratings are also sensitive to current financial information in addition to financial ratios averaged across three years. In this case, the significance of the output growth gap term disappears, but the discrete growth indicator is now significant at the 5% level. The signs on some of the current ratios are as expected (e.g. long-term

[33] Recall that the standard set of ratios that are included in the model are three-year averages at the firm level, demeaned by the cross-sectional average within the current year.

Table 5
Estimates of ordered probit model with trend and cycle – Baseline 2: strong test of procyclicality

Variable	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	−0.2963	−0.2969	−0.2969
	(0.0145)**	(0.0145)**	(0.0145)**
Interest coverage (C_2)	−0.0330	−0.0329	−0.0330
	(0.0097)*	(0.0097)**	(0.0097)**
Interest coverage (C_3)	−0.0451	−0.0449	−0.0449
	(0.0070)**	(0.0070)**	(0.0070)**
Interest coverage (C_4)	0.0122	0.0121	0.0121
	(0.0017)**	(0.0017)**	(0.0017)**
Operating margin	−1.2670	−1.2644	−1.2649
	(0.0951)**	(0.0951)**	(0.0951)**
Long-term debt	3.3378	3.3437	3.3438
	(0.1563)**	(0.1563)**	(0.1563)**
Total debt	−1.5147	−1.5208	−1.5206
	(0.1597)**	(0.1596)**	(0.1596)**
Market value	−0.4229	−0.4225	−0.4225
	(0.0094)**	(0.0094)**	(0.0094)**
Market-model beta	0.3529	0.3527	0.3530
	(0.0190)**	(0.0190)**	(0.0190)**
Market-model standard error	1.1953	1.1935	1.1938
	(0.0373)**	(0.0373)**	(0.373)**
Linear trend	−0.0034	−0.0072	−0.0074
	(0.0067)	(0.0065)	(0.0065)
Cycle	0.1727	0.4216	−0.0074
	(0.0805)*	(1.2000)	(0.0165)
C_1 – yearly mean	−2.7444	−2.3432	−2.2124
	(0.7172)**	(0.7094)**	(0.6972)**
C_2 – yearly mean	2.1755	2.2708	2.0563
	(0.9733)*	(1.0141)*	(1.0056)*
C_3 – yearly mean	0.1635	0.1021	0.2404
	(1.3559)	(1.3710)	(1.3638)
C_4 – yearly mean	−0.0771	−0.0869	−0.0952
	(0.1090)	(0.1092)	(0.1094)
Operating margin – yearly mean	−6.4169	−8.2273	−7.6633
	(5.4878)	(5.5436)	(5.4638)
Long-term debt – yearly mean	20.5663	6.8921	8.2585
	(15.5916)	(14.2139)	(14.5569)
Total debt – yearly mean	0.9912	0.1946	0.2968
	(0.7263)	(0.6301)	(0.6564)
Market value – yearly mean	−2.8098	−0.8159	−0.7251
	(1.9418)	(1.7053)	(1.6750)
Market-model beta – yearly mean	−0.3119	0.1413	0.1416
	(0.3680)	(0.3004)	(0.3004)
Market-model standard error – yearly mean	−5.6593	8.0378	6.8389
	(14.6674)	(13.2123)	(13.4545)

Note. Standard errors in parentheses; *significant at 5%; **significant at 1%. Table 5 reports the estimates of our ordered probit estimation of credit ratings on measures of business and financial risk, a linear trend, three measures of business cycles, as well as the time series average value of our independent risk measures. Each column reflects a different measure of the business cycle. The left-hand side variable is the credit rating of a firm at the time its most recent balance sheet date was released. In the analysis AAA ratings are assigned a "1", AA a "2", and so on until CC ratings, which are assigned an "8". That is, lower ratings reflect higher credit quality.

Table 6
Estimates of ordered probit model with trend and cycle: alternative specifications

Variable	NBER recession			Output growth gap			Discrete growth indicator		
	1	2	3	1	2	3	1	2	3
Interest coverage (C_1)	−0.2656	−0.4079	−0.2581	−0.2663	−0.4080	−0.2582	−0.2659	−0.4078	−0.2581
	(0.0225)**	(0.0148)**	(0.0140)**	(0.0226)**	(0.0148)**	(0.0140)**	(0. 0226)**	(0.0148)**	(0.0140)**
Interest coverage (C_2)	−0.0301	−0.0788	−0.0263	−0.0302	−0.0788	−0.0263	−0.0301	−0.0788	−0.0263
	(0.0141)	(0.0096)**	(0.0096)**	(0.0141)**	(0.0096)**	(0.0096)**	(0. 0141)*	(0.0096)**	(0.0096)**
Interest coverage (C_3)	−0.0189	−0.0582	−0.0418	−0.0189	−0.0582	−0.0417	−0.0189	−0.0582	−0.0418
	(0.0094)*	(0.0070)**	(0.0070)**	(0.0094)**	(0.0070)**	(0.0070)**	(0. 0094)**	(0.0070)**	(0.0070)**
Interest coverage (C_4)	0.0019	0.0096	0.0128	0.0119	0.0096	0.0128	0.0119	0.0096	0.0128
	(0.0023)**	(0.0017)**	(0.0017)**	(0.0023)**	(0.0017)**	(0.0017)**	(0. 0023)**	(0.0017)**	(0.0017)**
Operating margin	−2.3046	−1.3804	−1.5222	−2.2806	−1.3804	−1.5222	−2.2974	−1.3799	−1.5216
	(0.3772)**	(0.0940)**	(0.0910)**	(0.3775)**	(0.0940)**	(0.0910)**	(0. 3771)**	(0.0940)**	(0.0910)**
Long-term debt	1.1809	2.3779	2.0966	1.1831	2.3753	2.0963	1.1781	2.3769	2.0958
	(0.3538)**	(0.1583)**	(0.0881)**	(0.3543)**	(0.1583)**	(0.0881)**	(0. 3540)**	(0.1583)**	(0.0881)**
Total debt	−0.2785	−0.8722		−0.2747	−0.8700		−0.2737	−0.8716	
	(0.3696)	(0.1597)**		(0.3701)	(0.1597)**		(0.3699)	(0.1597)**	
Market value	−0.4172		−0.4248	−0.4175		−0.4251	−0.4174		−0.4250
	(0.0094)**		(0.0094)**	(0.0094)**		(0.0094)**	(0.0094)**		(0.0094)**
Total assets		−0.4223			−0.4225			−0.4223	
		(0.0100)**			(0.0100)**			(0.0100)**	
Market-model beta	0.3590	0.2717	0.3362	0.3594	0.2719	0.3365	0.3594	0.2718	0.3366
	(0.0191)**	(0.0184)**	(0.0188)**	(0.0191)**	(0.0184)**	(0.0188)**	(0. 0191)**	(0.0184)**	(0.0188)**
Market-model standard error	1.1766	1.3100	1.1814	1.1789	1.3122	1.1841	1.1779	1.3107	1.1828
	(0.0374)**	(0.0363)**	(0.0372)**	(0.0375)**	(0.0363)**	(0.0372)**	(0. 0375)**	(0.0363)**	(0.0372)**
Linear trend	0.0192	0.0196	0.0189	0.0192	0.0195	0.0188	0.0193	0.0196	0.0189
	(0.0006)**	(0.0006)**	(0.0006)**	(0.0006)**	(0.0006)**	(0.0006)**	(0. 0006)**	(0.0006)**	(0.0006)**
Cycle	0.0099	−0.0186	−0.0034	−1.5391	−1.6170	−1.8436	−0.0148	−0.0088	−0.0168
	(0.0496)	(0.0493)	(0.0495)	(0.8901)	(0.8861)	(0.8881)*	(0.0130)	(0. 0130)	(0.0130)
C_1 – current	−0.0451			−0.0444			−0.0448		
	(0.0206)*			(0.0206)*			(0.0206)*		
C_2 – current	0.0039			0.0041			0.0040		
	(0.0143)			(0.0143)			(0.0143)		
C_3 – current	−0.0402			−0.0402			−0.0401		
	(0.0098)**			(0.0098)**			(0.0098)**		

Table 6 (*continued*)

Variable	NBER recession			Output growth gap			Discrete growth indicator		
	1	2	3	1	2	3	1	2	3
C_4 – current	0.0005			0.0005			0.0005		
	(0.0025)			(0.0025)			(0.0025)		
Operating margin – current	1.0251			1.0005			1.0180		
	(0.3685)**			(0.3689)**			(0.3684)**		
Long-term debt – current	2.1599			2.1562			2.1617		
	(0.3170)**			(0.3176)**			(0.3173)**		
Total debt – current	−1.2714			−1.2733			−1.2754		
	(0.3255)**			(0.3262)**			(0.3259)**		

Note. Standard errors in parentheses; *significant at 5%; **significant at 1%. Table 6 reports robustness checks regarding the empirical specification of our ordered probit estimation of credit ratings on measures of business and financial risk, a linear trend, and three measures of business cycles. These results are comparable to those of Table 4, although each column has a slightly different empirical specification. Each group of three columns reflects a different measure of the business cycle. The left-hand side variable is the credit rating of a firm at the time its most recent balance sheet date was released. In the analysis AAA ratings are assigned a “1”, AA a “2”, and so on until CC ratings, which are assigned an “8”. That is, lower ratings reflect higher credit quality.

debt is positive), but others are not (e.g. operating margin is positive), making it difficult to provide a clean interpretation of these results.

Columns 2 and 3 check for sensitivity 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 (e.g. timeliness) and drawbacks (e.g. noise). When asset size is included in the ordered probit model, the results are basically unchanged (in particular, no evidence of procyclicality). When total debt is eliminated from the model, the coefficient on long-term debt falls to approximately 2.1 from 2.4, 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 reported above is due to multicolinearity.

Overall, the results for our main data sample do not indicate the presence of procyclicality in ratings. In only 3 out of 15 specifications does the cycle enter significantly, and in one of those three, it enters in a countercyclical direction (under our more stringent test).

One way to measure the goodness of fit of our ordered probit model specifications is to compare predicted ratings to actual ratings. The outcome of this is shown in Table 7. Panel A reports predictions for the model with time dummies (i.e. corresponding to the estimates in Table 3), while Panels B and C report analogous results for the Baseline 1 and 2 specifications, respectively. The output growth gap is used as the measure of cycle. Reading across each row gives the number of predictions in each category labeled across the top for all observations with an actual rating equal to the label in the leftmost column. [34] The results reflect a common feature of ordered probit models in that the highest and lowest categories tend to be under-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 various models (i.e. across panels). The broad conclusion is that there is little difference in fit. It is striking the 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 (Panel A versus Panel B). Moreover, the inclusion of the yearly means in the Baseline 2 specification does not improve much upon the predictive power of the more restricted Baseline 1 configuration (Panel B versus Panel C).

6. Alternative sample selections

In this section we assess the sensitivity of our results to changes to our sampling methodology. First, we restrict our sample to investment-grade ratings only. In the

[34] 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 45 of these, AA for 147 and A for 33.

Table 7
Predicted versus actual ratings

Actual rating	Predicted rating								
	AAA	AA	A	BBB	BB	B	CCC	CC	Total
Panel A: Model with time dummies									
AAA	45	147	33	0	0	0	0	0	225
AA	9	275	653	86	1	0	0	0	1024
A	0	111	2009	695	23	1	0	0	2839
BBB	0	4	880	1385	356	10	1	0	2636
BB	0	0	70	614	930	352	5	0	1971
B	0	0	7	90	460	641	38	0	1236
CCC	0	0	0	3	8	40	16	3	70
CC	0	0	0	0	0	0	1	0	1
Total	54	537	3652	2873	1778	1044	61	3	10,002
Panel B: Model with linear trend and output growth gap (Baseline 1)									
AAA	38	156	31	0	0	0	0	0	225
AA	8	265	666	84	1	0	0	0	1024
A	0	100	2023	696	19	1	0	0	2839
BBB	0	4	868	1409	345	9	1	0	2636
BB	0	0	73	613	923	357	5	0	1971
B	0	0	7	89	459	642	39	0	1236
CCC	0	0	0	3	8	40	16	3	70
CC	0	0	0	0	0	0	1	0	1
Total	46	525	3668	2894	1755	1049	62	3	10,002
Panel C: Model with linear trend and output growth gap (Baseline 2)									
AAA	43	150	32	0	0	0	0	0	225
AA	9	274	657	83	1	0	0	0	1024
A	0	115	2004	694	25	1	0	0	2839
BBB	0	4	885	1387	350	9	1	0	2636
BB	0	0	71	611	926	358	5	0	1971
B	0	0	7	92	454	644	39	0	1236
CCC	0	0	0	3	7	42	15	3	70
CC	0	0	0	0	0	0	1	0	1
Total	52	543	3656	2870	1763	1054	61	3	10,002

Note. Table 7 reports some statistics regarding the goodness of fit of our ordered probit model of credit ratings. The output in each panel reflects a comparison of actual credit ratings with the prediction of the given empirical specification. The top panel relates to the empirical specification including time dummies where the underlying coefficients are reported in Table 3. The middle panel corresponds to the coefficients in Table 4. The bottom panel relies on the coefficient estimates reported in Table 5.

second case, we only include observations of a firm's initial rating or a rating that has just been changed. As in the previous section, we estimate both Baseline 1 and 2 versions of the model.

6.1. Results for investment grade ratings

Traditional practice separates rated firms into two pools, investment grade and speculative grade. It is often assumed, either explicitly or implicitly, and in both the academic literature and amongst market participants, that a fundamental difference exists in the nature of firms of these two types. As such, lumping together both investment and speculative grade ratings, as in our baseline sample, may result in misspecification of our model if changes in financial and business risk have a differential impact on creditworthiness across the two groups. In this subsection, we investigate this possibility by repeating our empirical tests on the subset of investment grade firms only. [35] As noted earlier, our baseline ordered probit model already allows for the impact of a given change in any explanatory variable to differ quantitatively *across rating categories*. By contrast, differences in the results here compared to our baseline would indicate that the *relative marginal impact* of the explanatory variables on ratings differs across investment and speculative grade firms.

Estimates of the ordered probit model for this new sample are shown in Table 8. The first three columns report results for the three cyclical measures under the Baseline 1 specification; the last three columns under the Baseline 2 model. The coefficients on the cycle in the Baseline 1 estimates are all negative. Moreover, in contrast to Table 4, two of the three are statistically significant at the 1% level. Also, there is some evidence of excessive procyclicality in the Baseline 2 results: the estimate on the discrete growth indicator is negative and significant. The estimated coefficients on the other variables, the financial factors and trend, are largely the same as before.

From a statistical point of view, it appears that investment grade ratings are, on a conditional basis, more procyclical than speculative ratings. However, the economic importance of this result is difficult to discern from the coefficient estimates alone. One way to assess the economic significance of our findings is to compare ratings predictions by changing the state of the cyclical measure included in the model. The results from this exercise for the sample of investment grade ratings are shown in Table 9. Panel A pertains to the Baseline 1 specification, Panel B to Baseline 2. The cyclical measure used is the output growth gap. In each panel, the values given across the columns correspond to the number of predicted ratings in each category when the growth gap is set equal to -0.015 (a "downturn"), regardless of the actual state of the cycle corresponding to each observation. Similarly, the values across rows report predicted ratings when the growth gap is set equal to 0.015 (an "upturn").

From both panels it is apparent that a shift in the business cycle, all else equal, can induce a change in the predicted rating. [36] Consistent with the coefficient estimates discussed above, the economic impact of any procyclical behavior exhibited by the agencies is greater in the Baseline 1 case. For instance, in Panel A, of the 676 firms predicted to have a AA rating in an upturn, 127 of these would be downgraded to A

[35] As mentioned earlier, this particular sample selection might impose bias in our results since we observe better-than-expected ratings of would-be speculative firms but not lower-than-expected ratings of would-be investment grade firms.

[36] Note that we are restricted from assessing the effect of a switch in the business cycle on BBB rated firms because the threshold to the BB (and lower) rating categories is not identified in estimation of the ordered probit model.

Table 8
Estimates of ordered probit model with trend and cycle: investment grade only

Variable	Baseline 1: Weak test of procyclicality			Baseline 2: Strong test of procyclicality		
	NBER recession	Output growth gap	Discrete growth indicator	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	−0.4119	−0.4131	−0.4133	−0.4171	−0.4171	−0.4176
	(0.0244)**	(0.0244)**	(0.0244)**	(0.0245)**	(0.0245)**	(0.0245)*
Interest coverage (C_2)	−0.0169	−0.0168	−0.0166	−0.0167	−0.0170	−0.0171
	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0123)	(0.0123)
Interest coverage (C_3)	−0.0617	−0.0618	−0.0620	−0.0614	−0.0612	−0.0613
	(0.0081)**	(0.0081)**	(0.0081)**	(0.0081)**	(0.0081)**	(0.0081)**
Interest coverage (C_4)	0.0130	0.0130	0.0130	0.0129	0.0129	0.0129
	(0.0020)**	(0.0020)**	(0.0020)**	(0.0020)**	(0.0020)**	(0.0020)**
Operating margin	−2.0470	−2.0477	−2.0433	−2.0294	−2.0284	−2.0214
	(0.1396)**	(0.1396)**	(0.1396)**	(0.1412)**	(0.1412)**	(0.1412)**
Long-term debt	4.9391	4.9401	4.9394	4.9768	4.9826	4.9883
	(0.2275)**	(0.2276)**	(0.2276)**	(0.2282)**	(0.2282)**	(0.2282)**
Total debt	−1.9241	−1.9258	−1.9311	−1.9527	−1.9587	−1.9965
	(0.2135)**	(0.2135)**	(0.2135)**	(0.2144)**	(0.2143)**	(0.2144)**
Market value	−0.3708	−0.3719	−0.3716	−0.3708	−0.3710	−0.3710
	(0.0125)**	(0.0125)**	(0.0125)**	(0.0125)**	(0.0125)**	(0.0125)**
Market-model beta	0.4327	0.4349	0.4359	0.4265	0.4281	0.4291
	(0.0312)**	(0.0312)**	(0.0312)**	(0.0315)**	(0.0316)**	(0.0316)**
Market-model standard error	1.2885	1.2968	1.2944	1.3159	1.3187	1.3195
	(0.0756)**	(0.0757)**	(0.0757)**	(0.0774)**	(0.0774)**	(0.0774)**
Linear trend	0.0275	0.0272	0.0276	0.0169	0.0152	0.0135
	(0.0009)**	(0.0009)**	(0.0009)**	(0.0093)	(0.0089)	(0.0089)

Cycle	−0.1206	−3.8543	−0.0487	0.0780	−2.3509	−0.0445
	(0.0634)	(1.1598)**	(0.0175)**	(0.1082)	(1.5609)	(0.0220)*
C_1 – yearly mean				−2.3029	−1.7426	−1.7553
				(0.9439)*	(0.9362)	(0.9209)
C_2 – yearly mean				2.0785	1.5339	1.4119
				(1.2517)	(1.3044)	(1.2954)
C_3 – yearly mean				−1.3213	−0.8933	−0.8944
				(1.7544)	(1.7755)	(1.7661)
C_4 – yearly mean				0.0923	0.0664	0.0551
				(0.1460)	(0.1463)	(0.1465)
Operating margin – yearly mean				−10.7782	−9.4098	−10.4164
				(6.9695)	(7.0358)	(6.9212)
Long-term debt – yearly mean				32.1300	25.0318	34.1815
				(20.4894)	(18.4291)	(18.8999)
Total debt – yearly mean				−22.6370	−16.0876	−22.9199
				(19.3832)	(17.1595)	(17.4830)
Market value – yearly mean				−0.2107	0.0173	0.0007
				(0.4784)	(0.3753)	(0.3752)
Market-model beta – yearly mean				1.0514	0.7486	1.1652
				(0.9887)	(0.8389)	(0.8722)
Market-model standard error – yearly mean				−2.1894	−0.4669	−1.2183
				(2.4994)	(2.1331)	(2.0790)

Note. Standard errors in parentheses; *significant at 5%; **significant at 1%. The first three columns of Table 8 reports the estimates of our ordered probit estimation of credit ratings on measures of business and financial risk, a linear trend, and three measures of business cycles. The second three columns also include the time series average value of our independent risk measures. For these results, we have restricted the sample to include only ratings that are BBB or above.

Table 9
Effect of cycle on predicted ratings: investment grade only

Predicted rating during upturn	Predicted rating during downturn				
	AAA	AA	A	BBB	Total
Panel A: Baseline 1					
AAA	50	29	0	0	79
AA	0	549	127	0	676
A	0	0	3340	273	3613
BBB	0	0	0	2356	2356
Total	50	578	3467	2629	6724
Panel B: Baseline 2					
AAA	62	15	0	0	77
AA	0	593	64	0	657
A	0	0	3430	154	3584
BBB	0	0	0	2406	2406
Total	62	608	3494	2560	6724

Note. Table 9 estimates the impact of the state of the business cycle on the assigned rating of an investment grade firm. The top panel reports the predicted rating of such a firm using the coefficients from the model that includes measures of business and financial risk, a linear trend, and three measures of business cycles as a function of the state of the business cycle. The bottom panel repeats this exercise, but relies on the coefficients estimated from a model that also includes the time series average value of our independent risk measures. For these results, we have restricted the sample to include only ratings that are BBB or above. Both panels are created using the output growth gap as the measure of the business cycle.

with the onset of a major growth slowdown, a ratio of 19%; in Panel B, this ratio drops to 10%. These values are comparable to the actual percentage of downgrades during the past two recessions: for example, the 12-months transition rates from AA to A in 1990 and 2000 were 13.7% and 12.6%, respectively.

6.2. Results for initial ratings and rating changes

One assumption implicit in the analysis so far 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; namely, we only include ratings in the sample that have either just been issued or changed. Even if staleness were a minor issue in reality, the examination of rating changes is of independent interest. Such analysis will indicate whether rating agencies overreact, possibly in a procyclical manner, when a decision to change a rating is made.

Estimates of the ordered probit model in this case are presented in Table 10, which has a similar structure to Table 8 that was discussed in the previous subsection. [37] For this sample, evidence of procyclicality is even stronger. In the Baseline 1 specification, all three cyclical measures enter with a negative sign, are statistically significant at the 1% level and the coefficient values are almost an order of magnitude greater than the previous estimates. In two of the three Baseline 2 regressions, the cycle enters with a negative and significant coefficient. Thus, the evidence is consistent with ratings agencies acting in an excessively procyclical manner when they apply new ratings or change ratings, relative to their treatment of the whole universe of rated firms.

The second noteworthy result from this sample concerns the trend in ratings. In the Baseline 1 case, the average ratings drift is estimated to be smaller. In the Baseline 2 case, the trend coefficients even change sign and are statistically significant at the 1% level. The Baseline 2 results show that, after conditioning on trend movements in the risk factors, the agencies' standards appear to have become more lenient over time. This mirrors the conclusion of Zhou (2001), whose findings are based on realized default rates.

Finally, to assess economic significance, we once again look at the impact on predictions from our model by changing the state of the cycle but holding the other variables constant. The results for this sample are shown in Table 11. Compared to the investment grade only sample (Table 9), a much greater effect is detected here from changing the state of the cycle. It is still true that ratings change by at most one category, but the percentage is now much higher. Further, changes in ratings are more pronounced for the higher and lower categories. For example, out of the 20 firms predicted to receive a AA rating when the output growth gap indicates an upturn in the Baseline 2 model, 16 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, 235 out of 855 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 615 out of 2268 (27%).

Taken at face value, these effects could have strong implications for both access to and the cost of capital. However, their importance for the macroeconomy should be downplayed because these predictions are based on a sample of ratings that have actually changed, which is only a small fraction of the entire ratings universe. As noted earlier, the 12-months transition rate from AA to A was only 13.7% in 1990. Even at a longer horizon of 36 months, the transition rate from AA to lower ratings categories only increased to 25.7%. Moreover, as argued by Cantor and Mann (2003b) on the basis of data from Moody's, the fact that ratings typically change by only a small fraction of one notch per year, and rarely by more than two notches in a given year, suggests that changes in funding costs for issuers may not be economically significant.

[37] 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 (see Appendix A). To conserve space, estimates of these parameters are not reported.

Table 10
Estimates of ordered probit model with trend and cycle: ratings changes and initial ratings only

Variable	Baseline 1: Weak test of procyclicality			Baseline 2: Strong test of procyclicality		
	NBER recession	Output growth gap	Discrete growth indicator	NBER recession	Output growth gap	Discrete growth indicator
Interest coverage (C_1)	−0.2286	−0.2275	−0.2178	−0.2520	−0.2504	−0.2735
	(0.0293)**	(0.0292)**	(0.0293)**	(0.0305)**	(0.0305)**	(0.0307)**
Interest coverage (C_2)	−0.0606	−0.0640	−0.0610	−0.0463	−0.0525	−0.0677
	(0.0225)**	(0.0228)**	(0.0228)**	(0.0228)*	(0.0229)*	(0.0228)**
Interest coverage (C_3)	−0.0118	−0.0078	−0.0091	−0.0301	−0.0254	−0.0228
	(0.0174)	(0.0172)	(0.0173)	(0.0173)	(0.0175)	(0.0172)
Interest coverage (C_4)	−0.0019	−0.0028	−0.0028	0.0002	0.0002	0.0036
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0046)
Operating margin	−0.9193	−0.9218	−0.8614	−1.0856	−1.0954	−1.1087
	(0.2063)**	(0.2060)**	(0.2052)**	(0.2108)**	(0.2110)**	(0.2191)**
Long-term debt	2.1233	2.0132	2.0052	2.7752	2.7413	2.8416
	(0.3847)**	(0.3847)**	(0.3824)**	(0.3988)**	(0.4008)**	(0.4148)**
Total debt	−1.2717	−1.2232	−1.2162	−1.6872	−1.6482	−1.6721
	(0.3852)**	(0.3841)**	(0.3823)**	(0.3988)**	(0.4016)**	(0.4052)**
Market value	−0.4030	−0.4081	−0.4057	−0.4036	−0.4062	−0.4141
	(0.0211)**	(0.0212)**	(0.0211)**	(0.0220)**	(0.0220)**	(0.0220)**
Market-model beta	0.1944	0.2009	0.1961	0.2055	0.2088	0.1917
	(0.0438)**	(0.0438)**	(0.0436)**	(0.0454)**	(0.0453)**	(0.0466)**
Market-model standard error	1.6007	1.6029	1.5467	1.7693	1.7747	2.0426
	(0.0989)**	(0.1011)**	(0.1001)**	(0.1045)**	(0.1035)**	(0.1185)**

Linear trend	0.0071	0.0068	0.0084	−0.0092	−0.0093	−0.0086
	(0.0024)**	(0.0023)**	(0.0023)**	(0.0030)**	(0.0031)**	(0.0028)*
Cycle	−0.5896	−14.7066	−0.1386	−0.1414	−14.2007	−0.1020
	(0.0783)**	(1.6913)**	(0.0307)**	(0.1164)	(3.5485)**	(0.0464)*
C_1 – yearly mean				1.9463	1.8404	1.0789
				(1.0122)	(1.0035)	(1.0113)
C_2 – yearly mean				−0.6655	−1.3718	−0.1633
				(0.7507)	(0.7652)	(0.7351)
C_3 – yearly mean				0.0598	0.5004	−0.1277
				(0.4045)	(0.4075)	(0.3782)
C_4 – yearly mean				−0.0152	−0.0943	0.0695
				(0.1090)	(0.1101)	(0.1061)
Operating margin – yearly mean				−13.0557	−7.4890	−11.6360
				(3.3102)**	(3.5291)*	(3.3228)**
Long-term debt – yearly mean				28.6027	39.9741	34.4314
				(8.4186)**	(9.0020)*	(8.6037)**
Total debt – yearly mean				−10.2120	−25.5164	−15.7929
				(7.7224)	(8.8106)	(8.0126)
Market value – yearly mean				−0.6841	−0.1575	−0.8462
				(0.2943)*	(0.3031)	(0.2474)**
Market-model beta – yearly mean				0.1456	−0.1588	0.0763
				(1.0469)	(1.0477)	(1.0405)
Market-model standard error – yearly mean				2.9729	2.8574	3.5550
				(1.4682)*	(1.3916)*	(1.3628)**

Note. Standard errors in parentheses; *significant at 5%; **significant at 1%. The first three columns of Table 10 reports the estimates of our ordered probit estimation of credit ratings on measures of business and financial risk, a linear trend, and three measures of business cycles. The second three columns also include the time series average value of our independent risk measures. For these results, we have restricted the sample to include only first-time ratings or ratings that have recently been changed.

Table 11
Effect of cycle on predicted ratings: ratings changes and initial ratings only

Predicted rating during upturn	Predicted rating during downturn								
	AAA	AA	A	BBB	BB	B	CCC	CC	Total
Panel A: Baseline 1									
AAA	0	0	0	0	0	0	0	0	0
AA	0	9	20	0	0	0	0	0	29
A	0	0	228	223	0	0	0	0	451
BBB	0	0	0	624	236	0	0	0	860
BB	0	0	0	0	443	112	0	0	555
B	0	0	0	0	0	211	59	0	270
CCC	0	0	0	0	0	0	21	27	48
CC	0	0	0	0	0	0	0	55	55
Total	0	9	248	847	679	323	80	82	2268
Panel B: Baseline 2									
AAA	0	0	0	0	0	0	0	0	0
AA	0	4	16	0	0	0	0	0	20
A	0	0	276	213	0	0	0	0	489
BBB	0	0	0	620	235	0	0	0	855
BB	0	0	0	0	404	95	0	0	499
B	0	0	0	0	0	234	35	0	269
CCC	0	0	0	0	0	0	16	21	37
CC	0	0	0	0	0	0	0	99	99
Total	0	4	292	833	639	329	51	120	2268

Note. Table 11 estimates the impact of the state of the business cycle on the assigned rating of a firm. The top panel reports the predicted rating of such a firm using the coefficients from the model that includes measures of business and financial risk, a linear trend, and three measures of business cycles as a function of the state of the business cycle. The bottom panel repeats this exercise, but relies on the coefficients estimated from a model that also includes the time series average value of our independent risk measures. For these results, we have restricted the sample to include only first-time ratings or ratings that have recently been changed. Both panels are created using the output growth gap as the measure of the business cycle.

7. Summary

It is a fact that credit ratings vary according to the state of the business cycle. However, the evidence we present using our baseline data sample for a variety of cyclical measures and model specifications suggests that this fact is driven by cyclical changes to business and financial risks, and not to cycle-related changes to rating standards. By contrast, we detect procyclicality in ratings when we examine just investment grade firms or newly assigned ratings and ratings changes. The results for some specifications suggest that ratings might even exhibit excess sensitivity to the business cycle. Certain classes of investors are likely to find these special cases to be of interest. For instance, there tends to be a close link between credit spreads and ratings, and thus our results would imply that spreads may vary excessively across the cycle for investment grade credits. The results from our ratings changes sample also indicate that spreads may be overly volatile for firms that experience downgrades.

Even though our focus is on the cyclical properties of ratings, we also provide new evidence on trends in ratings. In particular, our results indicate that previous findings of a secular tightening of rating standards are not robust to including more complete measures of systematic changes to risk. In some specifications, we actually find that the standards of ratings agencies have become more lenient over our sample period. This finding is further supported by the recent experience during the years 2000–2002, when default rates associated with most ratings categories were at post-war highs.

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Appendix A. Likelihood function for sample with initial ratings and rating changes

One issue encountered in maximum likelihood estimation of the ordered probit model using the data sample with rating changes is censoring. 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 Eqs. (1) and (2)). Notice that this issue does not arise for initial ratings or our baseline sample 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

$$P(R_{it} = j \,|\, X_{it}; R_{it} \neq R_{it-1}). \tag{A.1}$$

Expanding (A.1) by conditioning on the value of the previous rating and summing over the range of possible previous ratings, gives

$$\begin{aligned} P(R_{it} = j \,|\, X_{it}; R_{it} \neq R_{it-1}) \\ &= \sum_k P(R_{it} = j \,|\, X_{it}; R_{it} \neq R_{it-1}; R_{it-1} = k) \cdot P(R_{it-1} = k \,|\, X_{it}; R_{it} \neq R_{it-1}) \\ &= \sum_k P(R_{it} = j \,|\, X_{it}; R_{it} \neq k) \cdot P(R_{it-1} = k \,|\, X_{it}) \\ &= \sum_{k \neq j} \frac{P(R_{it} = j \,|\, X_{it}) \cdot P(R_{it-1} = k \,|\, X_{it})}{1 - P(R_{it} = k \,|\, X_{it})}. \end{aligned} \tag{A.2}$$

In the third line of (A.2) 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 (i.e. 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) and (2), to differ from β. Denote the normal distribution function evaluated at x by $\Phi(x)$. The likelihood for each observation R_{it} ($i=1,2,\ldots,I$; $t=t_{2,i},t_{3,i},\ldots,t_{T(i),i}$), 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

$$\sum_j \sum_{k\neq j} \frac{[\Phi(\mu_j-\beta X_{it})-\Phi(\mu_{j-1}-\beta X_{it})]\cdot[\Phi(\mu_k-\tilde{\beta}X_{it})-\Phi(\mu_{k-1}-\tilde{\beta}X_{it})]}{1-[\Phi(\mu_k-\beta X_{it})-\Phi(\mu_{k-1}-\beta X_{it})]} \cdot \chi(R_{it}=j), \tag{A.3}$$

where $\mu_0\equiv 0$, $\mu_8\equiv\infty$ 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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