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On the consistency of ratings and bond market yields

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Abstract

We study the consistency of the credit-risk orderings implicit in ratings and bond market yields. By analyzing errors in term structure estimates for bonds with particular ratings, we show that for significant periods, a quarter of some categories of high credit quality bonds are rated in a manner that is inconsistent with their pricing. Adjusting for economic determinants of spreads (tax, liquidity and risk premiums) and allowing for the dynamic adjustment of ratings and spreads largely eliminates the inconsistencies, however.

JEL classification: C25; G21; G33
Keywords: Credit spreads; Risky debt yields; Term structure

1. Introduction

Long-term bond ratings produced by agencies like Moody's and Standard and Poor's provide financial market participants with judgments, of a standardized nature, on the likelihood that bond issues will be repaid in an orderly manner. The

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importance of ratings as a source of information to investors has increased in recent years as bond markets have grown more international and come to include a wider range of obligors. [1] Ratings have also acquired new roles, as supervisory authorities have made regulatory requirements for financial institutions contingent on ratings. [2] Recently, it has been suggested (see Basel Committee on Banking Supervision, 1999) that regulatory capital for G10 banks be based in part on the agency ratings of the bank's borrowers.

In view of the increasing reliance on bond ratings in credit risk markets, it is important to ask how reliable are ratings as indicators of credit standing, both in general and for particular types of obligor. In particular, are ratings consistent, cross-sectionally and over time, with other measures of credit risk? Two recent papers have critically examined ratings as measures of default risk in this way.

First, Blume et al. (1998) show that firms with given accounting ratios received a significantly lower rating in the early 1990s than firms with similar accounting ratios would have received in the late 1970s and early 1980s. [3] The implication is that rating agencies have changed the way in which they evaluate credit standing.

Second, Delianedis and Geske (1998), use equity and liability data for US firms, to construct alternative credit risk indicators and compare their forecasting performance to that of ratings. They conclude that the default probabilities generated by their models increase well in advance of ratings down-grades. They cite this as evidence of "rating stickiness", i.e., that rating agencies do not immediately change ratings when news affecting an obligor's credit quality is revealed.

In this paper, we study a third aspect of ratings, namely their consistency or otherwise with bond market prices. Altman (1989) shows that, for all years from 1973 to 1987, mean yields to maturity increase monotonically as one descends the ratings scale. However, Altman's finding only implies that *average* bond spreads and ratings are consistent. If individual spreads within a particular rating category vary substantially around their mean, it may be that the implicit credit quality ordering attributed to obligors by the rating agencies and the bond market are very different.

To investigate this empirically, we extract average yields for different rating categories using Nelson–Siegel techniques as described in Nelson and Siegel (1987). The data we employ consists of ratings and price histories in the period 1988–1998 for a large number of non-callable, dollar-denominated, international bonds, primarily Eurobonds. For each trading day, we calculate yields for different maturities for the three highest credit quality rating categories, AAA, AA, and A. We then compare the bonds' actual market values with the prices they would have if a claim to the bond's cash flows were priced with our estimated yields.

[1] In December 1970, 98.0%, 0.3%, and a negligible fraction of Moody's-rated obligors were domiciled, respectively, in the USA, Europe and Japan. By end-December 1989, issuers from the US, Japan, the UK and other European countries were 84.7%, 2.1%, 2.3% and 4.3%, respectively, while by December 1997, they were 66.0% 4.7%, 5.4% and 20.0%.

[2] See Cantor and Packer (1994).

[3] The basic approach of Blume et al. (1998) follows that of Kaplan and Urwitz (1979) who show that ratings may be reasonably well predicted using accounting information.

We say that a bond valuation is *inconsistent* with its rating if the market price is above (below) the price it would have if it were valued using average term structures corresponding to a higher (lower) rating category. Thus, the price of a AAA bond is inconsistent with its rating if it is lower than the value one obtains using the AA term structure. Similarly, an AA bond price is inconsistent with the bond's rating if it is higher than the price obtained using the AAA term structure or below that one obtains using the A term structure.

We find that, on average, between a fifth and a quarter of AA bonds are priced in a way that is inconsistent with their ratings. Smaller fractions of AAA- and A-rated bonds are inconsistent but only because these can only be reclassified in one direction (down for AAA and up for A since we only consider A and above rated bonds in our study).

Some fraction of bond price variation no doubt reflects liquidity, risk premiums and tax effects. To allow for these influences, we regress pricing errors from the Nelson–Siegel fits on variables designed to proxy for economic determinants of spreads, i.e., risk premiums, liquidity and tax. The risk premium variables are based on bond market factor "betas". Liquidity proxies include the age and face value of the bond issue and the frequency with which it is quoted. The proxy for tax effects is the coupon rate.

After subtracting the fitted value of these effects (the regression coefficient times the regressor) from the market price, we once again compare the adjusted market prices with the prices obtained using estimated yields for superior and inferior ratings categories. About a third of the inconsistencies are eliminated by adjusting this way for tax, liquidity and risk premiums. After six months, during which time spreads and ratings have had time to adjust dynamically, around a half of the remaining inconsistencies disappear. Hence, we conclude that ratings and bond market yields suitably adjusted are reasonably consistent, contrary to what one might believe if one looked at the unadjusted data alone.

A substantial number of earlier studies have looked at the relationship between ratings and bond prices. West (1973), Liu and Thakor (1984), Kao and Wu (1990) and Ederington et al. (1987) find that, conditional on economic and firm specific variables, ratings do have explanatory power for bond yields. In these studies, the ratings may proxy for (publicly known) omitted variables which affect yield spreads. To avoid this problem of firm-specific omitted variables, several studies have examined whether rating *changes* coincide with excess returns on either the obligor's equity or debt values (see Katz, 1974; Weinstein, 1977; Griffin and Sanvicente, 1982; Ingram et al., 1983; Hand et al., 1992; Goh and Ederington, 1993; Kliger and Sarig, 2000). While evidence from the earlier studies was mixed, the more recent contributions suggest that rating changes do impart some new information, not publicly available to the investor.

A significant part of our study involves estimation of term structures for corporate bonds. Earlier papers which have extracted such term structure estimates include Sarig and Warga (1989), Schwartz (1998) and Dullmann et al. (2000). None of these has examined bond-spread/rating inconsistencies of the kind we analyze here, however, although both Schwartz (1998) and Dullmann et al.

(2000) observe crossings in the mean spreads for different rating categories and Schwartz (1998) discusses trading strategies based on these inconsistencies.

Finally, note that an important literature has recently emerged on the determinants of bond market spreads. Notable contributions to this literature include Delianedis and Geske (1999), Elton et al. (2001), Elton et al. (2000), Huang and Huang (2002) and Houweling et al. (2003). These papers model determinants of spreads as we do when we adjust spreads for non-credit pricing factors. [4] But they do not share our focus on a comparison of credit risk orderings implicit in ratings.

The structure of the paper is as follows. Section 2 describes our bond data set and the Nelson–Siegel techniques we use to extract estimates of average yield curves for different rating categories. Section 3 defines two notions of rating/spread consistency and inconsistency. Section 4 discusses adjustments for tax, liquidity and risk premiums and dynamic effects. Section 5 concludes.

2. Data and curve fitting techniques

2.1. The bond price data set

The bond price data set, from which we calculate daily term structure estimates, is the same as that employed in Nickell et al. (2000). It consists of 1430 US dollar-denominated bonds [5] selected from the much larger number of dollar-denominated bonds listed on the Reuters 3000 price service. The bonds are selected using the criteria (i) that they are straight bonds (not floaters), (ii) that they are neither callable nor convertible, (iii) that a rating history is available, (iv) that the coupons are constant with a fixed frequency, (v) that repayment is at par, and (vi) that the bond does not possess a sinking fund. To arrive at the 1430, we further eliminate bonds for which the price and rating histories do not overlap for more than a year, and very illiquid bonds with price histories which contain at least one gap of more than 100 days.

The prices we use are Reuters composite bids, i.e., the best bid reported at close of trading by a market-maker from which Reuters has a data feed. The data includes comprehensive information on the cash flows, ratings and price histories of the bonds, and the name, domicile and industry code of the obligor. The price data stretches from April 1991 to March 1998. The break-down of bonds by industry and domicile of the obligor is given in detail in Nickell et al. (2000). 45%, 9% and 23% of obligors are domiciled, respectively, in the US, Japan and in one of the four largest European countries. 24% and 42% of obligors are commercial banks or other financial services, respectively, with the remainder coming from a wide range of non-

[4] Here and elsewhere in the paper, we use the term "non-credit effects" to refer to determinants of spreads apart from expected losses.

[5] Of which 90% are Eurobonds.

financial industries. 58%, 19% and 14% of bonds are categorized as unsecured, guaranteed and senior.

The data set includes a rating history for each bond, the majority coming from Moody's or Standard and Poor's. To obtain a rating history for a particular bond, we observed which rating agency first rated the bond issue (usually either Moody's or Standard and Poors) and continued to use ratings only from that agency.

2.2. Curve fitting techniques

In this section, we briefly describe the Nelson–Siegel techniques we employ to estimate term structure for bonds in specific rating categories. This method fits the term structure to a parametric form that is flexible enough to fit most shapes observed in yield curves. The method performs well against other competing methods such as spline fitting techniques. [6]

Suppose we have N bonds with prices P_i and cashflows c_{ij} for $i=1,2,\dots,N$ and $j=1,2,\dots,J_i$ paid on dates t_{ij} for $i=1,2,\dots,N$ and $j=1,2,\dots,J_i$. Suppose N is large so the parsimoniously parameterized interpolation fits each bond with error:

$$P_i = \sum_{j=1}^{J_i} c_{ij} \exp\left[-h(t_{ij})t_{ij}\right] + \epsilon_i, \tag{1}$$

$$h(t_{ij}) \equiv a_1 + a_2[1 - \exp(-t_{ij}/a_4)]/(t_{ij}/a_4) - a_3 \exp(-t_{ij}/a_4). \tag{2}$$

It is assumed that $\text{Variance}(\epsilon_i) = w_i^2\sigma^2$, i.e., the errors terms are heteroskedastic. A common approach [7] is to suppose that, for a given bond, the parameter w_i is closely related to the bond's duration. I.e., if Y_i is defined implicitly by $P_i = \sum_{j=1}^{J_i} c_{ij}/(1+Y_i)^{t_{ij}}$, then $w_i = \mathrm{d}P_i/\mathrm{d}Y_i$.

The coefficients a_1, a_2, a_3 and a_4 are found by minimizing the sum of squared weighted error terms $\tilde{\epsilon}_i \equiv \epsilon_i/w_i$. For each day in our sample period, we select bonds that have both a price quote and a current rating and perform a separate term structure fit for the bonds in each rating category. We omit bonds with maturities under 1 year since they are likely to be illiquid. To prevent grossly mis-priced bonds from unduly affecting the results, we run regressions repeatedly, dropping any bond prices which, in the previous regression, were more than four standard deviations from the fitted price. We ceased iterating when all bond prices satisfied this condition.

[6] Bliss (1997) compares four different techniques to fitting government bond term structures: cubic splines (McCulloch, 1975), smoothing splines (Fisher et al., 1995), parametric fitting function (Nelson and Siegel, 1987), bootstrap method (Fama and Bliss, 1987) and finds that Nelson–Siegel perform reasonably well. In any case, our results are not sensitive to the method of fitting the yield curve in that we obtain qualitatively the same results using cubic spline fitting as described in McCulloch (1975).

[7] See, for example, McCulloch (1975).

3. Rating and valuation (in)-consistency

3.1. Yield estimates

Implementing the Nelson–Siegel fitting techniques described above, we obtain term structures for each day in our sample period for AAA-, AA- and A-rated bonds. Since our conclusions depend on the accuracy of our term structure estimates, we restrict our attention to the three coarse rating categories for which we have a substantial amount of information; even though it would have been possible to estimate term structures for BBB bonds for the latter part of the sample period, or for finer rating categories such as AA− and AA+. The average number of bonds we employed on the days for which we performed term structure spline fits was 161, 125, and 136 for the three categories AAA, AA and A, respectively.

Fig. 1 shows time series plots of our fitted spreads for 2, 5 and 7 year maturities. The default-free interest rates we used in calculating the spreads are Treasury strip yields obtained from Bloomberg. The general picture that emerges from the figure is one of a gradual decline in spreads from 1991 to the second half of 1997. It is noticeable that the spreads are highly correlated. Also, the spreads cross on very few occasions and by only marginal amounts. [8]

Fig. 2 shows estimated densities of the errors from the Nelson–Siegel fits for the three rating categories. [9] The errors correspond to $\tilde{\epsilon}_i$ in the notation employed above. Hence, they represent differences between Nelson–Siegel fit prices and market prices divided by $\mathrm{d}P_i/\mathrm{d}Y_i$. If $P_{i\mathrm{f}}$ is the fitted price, $\tilde{\epsilon}_i = ((P_{i\mathrm{f}} - P_i)/P_i)/(\|\mathrm{d}P_i/\mathrm{d}Y_i\|/P_i)$ and, thus, the errors are in units of *proportional* mis-pricings *divided by duration*. They are, therefore, approximately in units of per annum yields. Since we also multiply by 10,000, one may regard the horizontal axis in the figure as being expressed in annualized basis points.

A noticeable feature of the densities for the different rating categories is that they exhibit approximately the same variance. This despite the fact that the magnitude of spreads and the volatility of spread changes are distinctly smaller for the AAA category than for AA or A. It is striking that, for much of the sample period, AAA spreads are around 20 basis points, whereas the price errors for AAA bonds as shown in Fig. 2 exceed 20 basis points with a reasonably high probability.

Fig. 3 further illustrates the variation of prices around the fitted values by showing the standard deviation of the error distribution over time. The calculations are done on a weekly basis, pooling the errors from the daily Nelson–Siegel fits within each week. The standard errors fall sharply over time, in line with the declines in the levels of spreads evident in Fig. 1. The standard deviations, however, are large

[8] Schwartz (1998) found much larger numbers of "crossings" but he mostly employed fewer bonds and used finer rating categories. The only place in the paper in which we employ the Bloomberg Treasury yields is in calculating spreads for Fig. 1. So the fact that there are a few dates on which our AAA yields are apparently lower than the Treasury yields does not affect our analysis.

[9] The errors are pooled across the monthly Nelson–Siegel fits. Observations are "bucketed" in discrete ranges and then the fraction falling into each range is plotted.

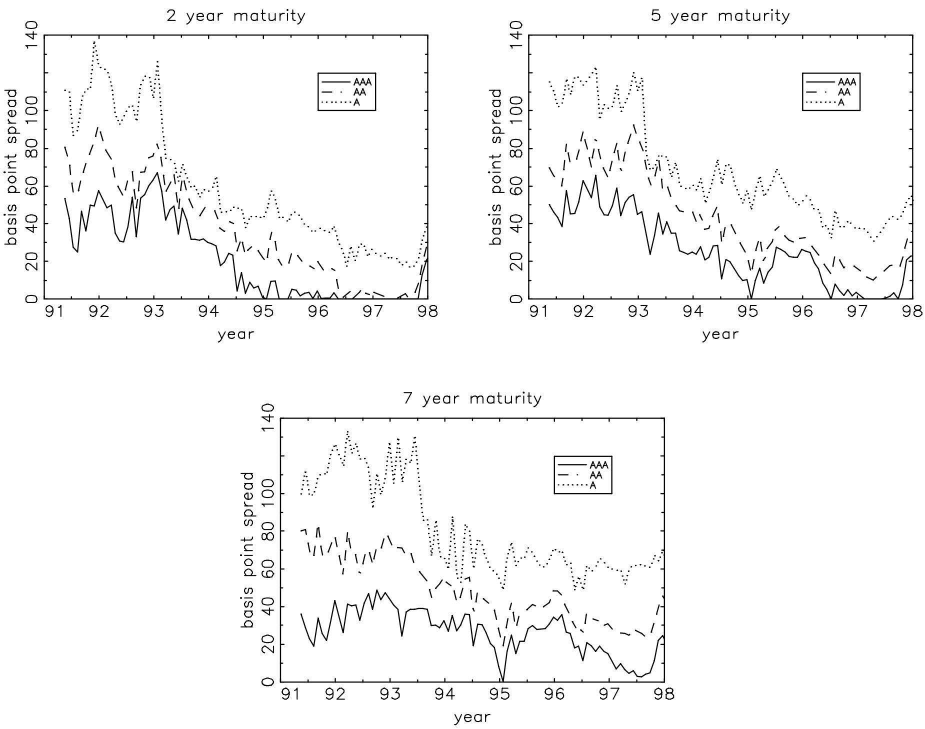

Fig. 1. Time evolution of the term structure.

relative to what one might expect given the magnitudes of the spreads between adjacent rating categories.

3.2. Weak reclassifications

For the first day of each month in the sample period, we calculate for each bond [10] the price the bond would have if its coupon and principal payments were discounted using the term structure implied by the Nelson–Siegel estimates. We do this not just using the term structure appropriate to the rating category that the bond has on the day in question, but also using term structures for other rating categories as well. For each bond, this yields three fitted prices

$$\hat{P}_i^r = \sum_{j=1}^{J_i} c_{ij} \exp[-h^{(r)}(t_{ij})t_{ij}] \quad \text{for } r = \text{AAA}, \text{AA}, \text{A}. \tag{3}$$

Here, $h^{(r)}$ is the Nelson–Siegel fit function estimated from data with rating r.

[10] Bonds with maturities between 1 and 10 years are selected for this analysis.

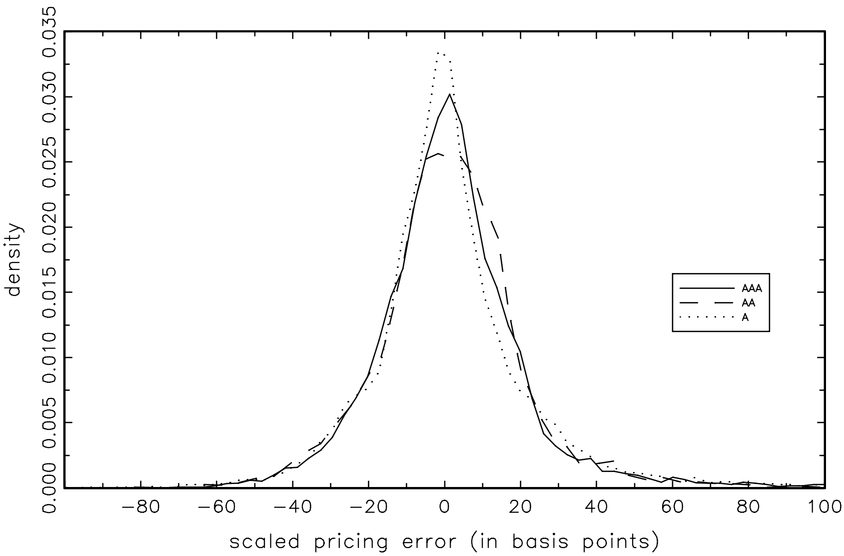

Fig. 2. Pricing error distributions.

We say an r-rated bond is weakly reclassified if its market price is closer to a fitted bond price based on a term structure other than r than it is to P_i^r. In other words, an r-rated bond is weakly reclassified if

$$\|P_i - \hat{P}_i^m\|\|P_i - \hat{P}_i^r\| \quad \text{for some } m \neq r. \tag{4}$$

For the first day of each month in the sample period, we calculate what fraction of the market prices available on that day are closest in value to each of the three fitted prices based on AAA, AA and A term structures. The results of these calculations are reported in Table 1. [11]

For AAA-rated bonds, on average, 72% have market prices closest to the prices based on the AAA term structures. As one might expect, very few AAA bonds are most closely priced using single A term structures. The fraction of AA bonds which are weakly reclassified is much larger. On average, 33% have market prices closer to the prices based on AAA term structures and a further 24%, on average, have prices closer to the A term structure prices. Of A-rated bonds, 29% are weakly reclassified on average across the sample period.

[11] As mentioned above, there are a few occasions in our sample period when the term structures for different rating categories cross. To prevent such crossings influencing our results, we replace any yield that is below the yield for a superior rating category with the latter yield for the day in question. Hence, in our adjusted term structure data, any crossings are replaced with zero yield spreads. We find that the over all results are qualitatively the same with or without this correction.

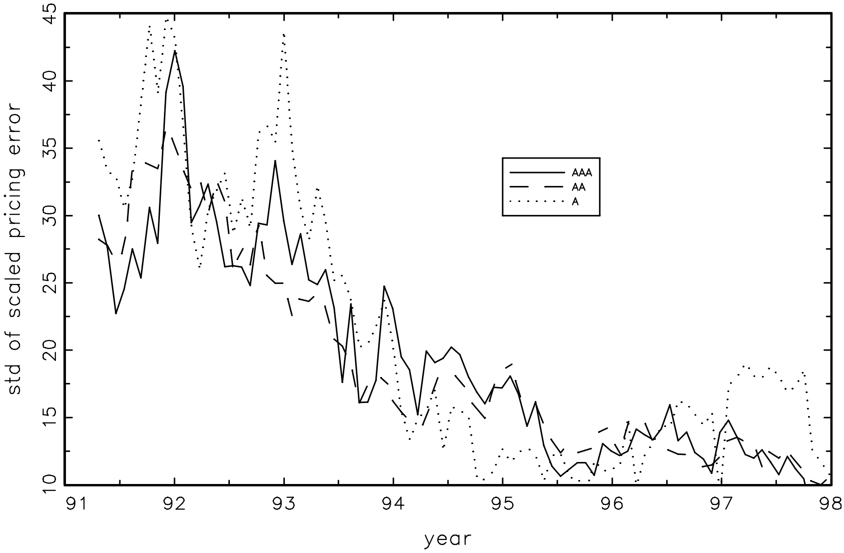

Fig. 3. Time series of error distributions.

Table 1
Reclassification results

Reclassifications based on unadjusted spreads						
Agency rating	% weakly reclassified			% strongly reclassified		
	AAA	AA	A	AAA	AA	A
AAA	72.35	20.91	6.75	83.53	12.95	3.52
AA	32.69	43.03	24.28	18.25	72.00	9.75
A	6.56	22.51	70.92	2.95	10.77	86.28

A bond with a particular rating is "weakly reclassified" if its market price, P_i, is closer in absolute magnitude to the price implied by average spreads associated with a different rating than it is to the price implied by average spreads of bonds with the same rating. A bond is "strongly reclassified up (down)" if P_i is greater (less) than the price implied by spreads for a superior (inferior) rating. The left hand column is the actual rating of the bond and row entries give the percentage in each rating category after reclassification averaged over the months in the sample period.

3.3. Strong reclassifications

The fact that bonds are weakly reclassified as defined above does not imply that ratings and bond market pricing are strictly speaking inconsistent. Even if ratings and yields reflect the same ranking of credit standing, an AA-rated bond which is close to the "frontier" between AA-rated and A-rated bonds, may have a market price which is closer to the price one obtains using A rating yields than to the price based on the AA term structure.

However, if the market price of a bond is above (below) the price one obtains if one values the bond's cash flows using the term structure for the rating above (below) the bond's current rating, the ordinal ranking of credit quality implicit in the ratings and in bond market yields must necessarily be different. If a bond has a market price which is "too high" or "too low" in this sense, we say it is strongly reclassified. More formally, an r-rated bond with market price P_i is strongly reclassified if

$$P_i > \hat{P}_i^m \quad \text{where } m \text{ is a superior rating category than } r \tag{5}$$

$$\text{or if} \quad P_i \hat{P}_i^m \quad \text{where } m \text{ is an inferior rating category to } r. \tag{6}$$

Table 1 shows the fractions of bonds on average on the first day of each month in the sample period which are strongly reclassified. On average, over the sample period, 16% of AAA bonds are reclassified down, 14% of A bonds are reclassified up, and 28% AA-rated bonds are either reclassified up or down.

Fig. 4 shows the behavior over time of the percentages of reclassified bonds. The percentages reclassified fluctuate considerably and are large in periods in which average spread levels are low.

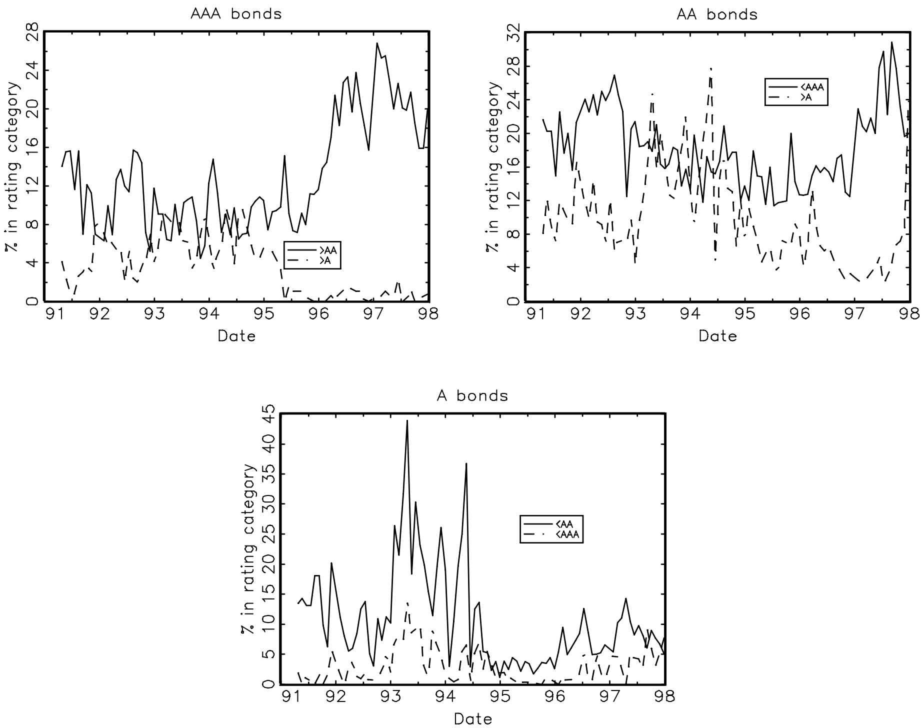

Fig. 4. Ratings after strict reclassification.

4. Risk premiums, tax and liquidity

It is clearly possible that the large number of strong reclassifications in our sample reflects non-credit related pricing factors such as risk premiums, liquidity or tax effects. To control for these non-credit-related factors, we perform the strong reclassification calculations described above but *adjusting for risk premiums, tax and liquidity effects*.

The first step in making these adjustments is, for the first day of each month in our sample period, to regress the fitted, weighted residuals from the Nelson–Siegel fit, denoted $\tilde{\epsilon}_i$, on a set of explanatory variables. These variables include the coupon rate of the bond as a proxy for tax effects, and the issue-size, age of the issue and the quote frequency as proxies for liquidity effects. The quote frequency is defined as the fraction of days on which the bond issue is quoted from the current date to the maturity date of the bond or the end of the sample, whichever occurs first.

To allow for risk premiums, betas from time series regressions of spreads on widely used bond market risk factors were included in the set of explanatory variables. The factors we employ are (i) the difference between the yields on 5 year BBB2-rated corporate bonds and the 5 year pure discount Treasury rate and (ii) the difference between the 1 and the 10 year pure discount Treasury rates. The source for these is Bloomberg. These factors closely resemble the bond market factors employed by Fama and French (1993).

Our basic cross-sectional regression equation may be summarized as

$$\tilde{\epsilon}_i = \sum_k^K \lambda_{1,k}\beta_{ki} + \sum_j^J \lambda_{2,j}x_{ji} + \eta_i \tag{7}$$

where x_{ji} are the liquidity and tax variables and the β_{ki} are time-series betas with respect to the bond market factors. Running this regressions yields estimates of the prices of risk λ_{rk} and the sensitivities λ_{cj} of spreads to the liquidity and tax variables.

Because many of the bonds in our sample have relatively short price times series, one must use daily data to estimate the betas with respect to the bond market factors. Estimating the betas is complicated by noise in the estimated spreads (attributable either to errors in the Nelson–Siegel fit or to underlying noise in the quote data). Regressing the daily bond returns on factor returns yields beta estimates that contain considerable estimation error and have low significance in the cross sectional regressions.

To overcome this we estimate the time series betas by regressing the individual bond spreads on factor yields as follows:

$$\tilde{\epsilon}_{it} = \mathrm{const}_i + \beta_i y_{\mathrm{c},t} + \beta_i y_{\mathrm{s},t} + \eta_{i,t}, \tag{8}$$

where $y_{\mathrm{c},t}$ and $y_{\mathrm{s},t}$ are, respectively, the credit and slope bond market factor yields. This approach of running regressions in levels rather than differences is suggested by Cochrane (2003) (see his p. 296 and his discussion of Lucas (1988)) as a way of coping with noisy observations. It is also the approach followed by Houweling et al. (2003), although they do not comment on the fact that it is in some ways non-standard.

Warga (1992) has shown that there is a significant age premium in bond returns, and previous studies, including Vasicek and Fong (1982), Bliss (1997), Schwartz (1998) and Dullmann et al. (2000) suggest that variables such as age, coupon and issue size have important explanatory power in explaining errors in risk-free and defaultable term structure fits. Crabbe and Turner (1995) argue that size of issue does not affect spreads and we shall return to a discussion of this point below. The relative quote frequency, as we define it, resembles variables found to be significant by Clare et al. (2000) and Elton et al. (2001).

To obtain an idea of a sensible specification for the liquidity proxies (the relations might, after all, be significantly non-linear), we plotted the Nelson–Siegel fit residuals against these variables. The plots (which we do not exhibit here) suggest that the coupon variable affects the Nelson–Siegel fit residuals in a linear way, while the dependency on age appears to be exponential. The nature of the issue size and quote frequency effects are less obvious but we take them to be linear. The age variable is, therefore, included as $\exp(-age)$ where *age* is in years from the issue date. The issue size variable is expressed is the face value of the issue measured in hundreds of millions of dollars, [12] while the coupon rate is expressed in percent.

Finally, note that we decided not to include other bond or issuer characteristics in the regression since our aim was to fit economic determinants of the spread, not to describe the spread data set.

4.1. Regression results

Performing the monthly regressions described above of Nelson–Siegel residuals on risk premium, tax and liquidity proxies, we obtained monthly time series of regression parameters. Tables 2 and 3 contain parameter estimates, t-statistics, R^2's and number of observations, all averaged across the monthly regressions. To understand the magnitude of the effects, note that the dependent variable is in units of basis points. The coupon rate is in percent, the age effect is included as an exponentials (and hence range from 1 for zero age to 0 for very old issues) and the quote frequency variable is in natural units (i.e., between zero and unity).

The magnitudes of tax and liquidity effects are economically substantial and statistically significant. For example, the coupon parameters are significant at a 5% level 81%, 67% and 63% of the time for the AAA-, AA- and A-rated bond regressions. All the liquidity variables are significant more than 50% of the time but quote frequency is most statistically significant, being significant at a 5% level 75%, 76% and 52% of the time for the AAA-, AA- and A-rated bond regressions. Issue size is the least significant variable, being significant at a 5% level 41%, 16% and 28% of the time. The most significant variable of all is the credit factor which is significant 84%, 81% and 63% of the time.

[12] The average bond issue size in the sample is $250 million.

Table 2
Bond spread regressions on bond characteristics and risk factors

Average regression coefficients and t-statistics

Independent variables	AAA-rated	AA-rated	A-rated
Const.	−0.07	−0.23	−0.36
	(−0.02)	(−0.13)	(−0.15)
Coupon	3.72	3.19	2.64
	(4.67)	(2.30)	(2.18)
Exp(−*age*)	−9.66	−15.43	−14.01
	(−1.98)	(−1.98)	(−2.02)
Quote freq.	−125.60	−140.17	−90.06
	(−3.13)	(−2.63)	(−1.51)
Credit factor	11.66	9.11	7.06
	(1.72)	(1.53)	(1.29)
Slope factor	47.68	43.09	29.08
	(3.58)	(2.62)	(2.65)
Issue	8.46	−13.12	−2.24
	(1.09)	(−0.81)	(−0.80)
Adj-R^2	0.49	0.36	0.28
Num. of obs.	158.99	123.80	143.66

Each month in our sample the spread deviations for each category are separately regressed on obligor and bond characteristics. The dependent variable in these regressions is spread deviations expressed in basis points. The results presented are the average regressions coefficients and t-statistics where the average is taken over each monthly regression in our sample. Regressors except for the constant are demeaned. The coupon rate measured in percent per annum, the issue size is measured in millions of dollars. The age regressor is exp(−*age*) where age is the time since first issue in years.

Table 3
Significance of parameters in bond spread regressions

Independent variables	AAA-rated	AA-rated	A-rated
Coupon	80.68	67.05	62.50
Exp(−*age*)	65.91	67.05	51.14
Quote freq.	75.00	76.14	52.27
Credit factor	84.09	80.68	62.50
Slope factor	79.55	70.45	72.73
Issue	40.91	15.91	28.41

The results presented are the percentage of monthly regressions (described in Table 1) in which one can reject (at a 5% level) that the parameter in question is zero.

To see whether our strong reclassifications are the result of tax and liquidity effects, we use the monthly time series of regression coefficients for the tax, liquidity and risk premium variables to implement a time varying correction for the tax and liquidity effects. We adjust the bond price upwards by the part of the fitted regression corresponding to the non-credit-related pricing factors by adding to each bond's market price the regression coefficients times the relevant bond-specific regressors. We then repeat the comparisons described above between market prices

Table 4
Reclassification results

Reclassifications based on tax liquidity and risk-adjusted spreads						
Agency rating	% weakly reclassified			% strongly reclassified		
	AAA	AA	A	AAA	AA	A
AAA	78.58	18.67	2.76	90.81	7.97	1.22
AA	27.69	55.14	17.17	11.89	81.83	6.29
A	4.17	21.21	74.62	1.91	8.10	89.99

For each month in our sample the bonds in each agency rating category are reclassified on the basis of the bonds spread deviation after adjusting for tax, liquidity and risk premiums. We reclassify the bonds in two ways, "weakly reclassified ratings" being a weaker condition than "strongly reclassified ratings". The left-hand column is the actual rating of the bond and row entries give the percentage in each rating category after reclassification.

and prices calculated using yields for the different rating categories, except now we replace market prices with tax–liquidity–risk-premium-adjusted market prices.

The results we obtain for strong reclassifications are shown in Table 4 and Fig. 5. On average over the sample period, the strong reclassifications equal 9% of AAA-rated bonds, 18% of AA bonds and 10% of A-rated bonds. As before, we regard the AA percentage as giving a better idea of the proportion of reclassified bonds since AA bonds can be reclassified up or down. We conclude that the fraction of reclassified bonds is substantially reduced by risk premium, tax and liquidity adjustments.

4.2. *Dynamic adjustment to strongly reclassified*

Having adjusted for risk premiums and liquidity and tax effects, we still find that 18% of AA-rated bonds and around 10% of AAA- and A-rated bonds are reclassified. We wish to examine whether this reflects lags in spread and ratings changes. It is acknowledged by the rating agencies that ratings changes may be delayed as the process of adjusting ratings entails a time-consuming, bureaucratic process within the agency involved. Equally, spreads may experience temporary fluctuations that are subsequently reversed as aggregate bond market liquidity is squeezed.

In Table 5, we report the percentages of bonds which, conditional on being strongly reclassified (after adjustment for risk premium, liquidity and tax effects) on a particular date, are still strongly reclassified some months later. The results suggest that reclassifications diminish over time. Between half and two-thirds of the strong reclassifications have been eliminated after six months, depending on the category.

Table 6 contains figures on the average change in spreads over different horizons of bonds that are strongly reclassified. The results demonstrate that the adjustment of credit spread and ratings orderings over time shown by the Table 5 results is in part attributable to movements in spreads. To take an example, AA-rated bonds that are strongly reclassified up represent cases in which the spreads suggest the bond is

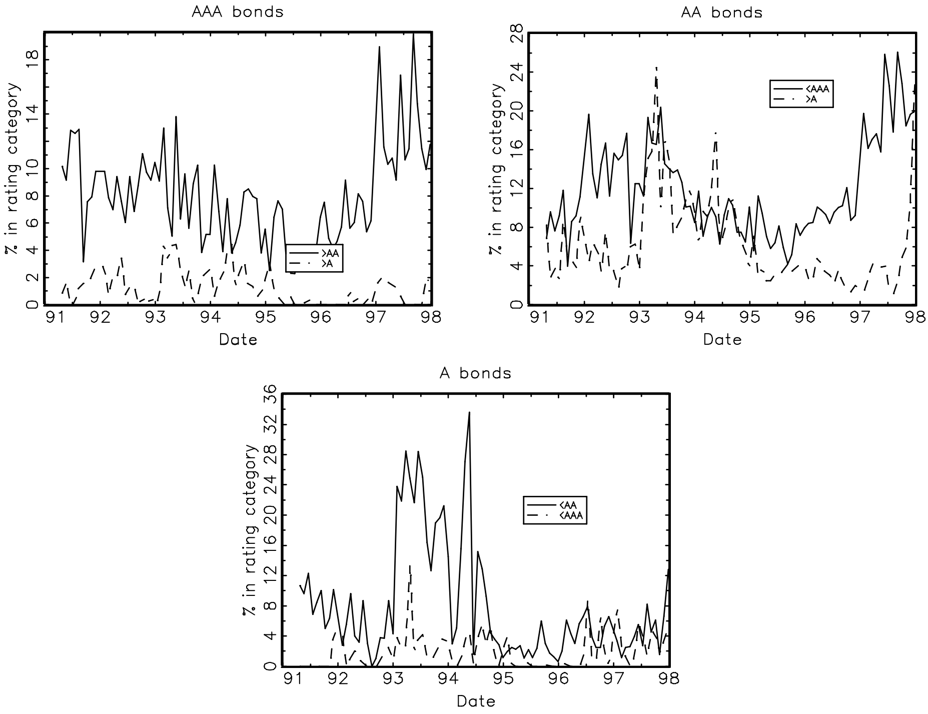

Fig. 5. Ratings after strict reclassification and correction for tax, liquidity and risk premiums.

Table 5
Persistence of reclassifications

Time period (months)	Percentage remaining strongly reclassified			
	AAA down	AA up	AA down	A up
1	64.90	65.22	62.72	62.35
3	54.86	58.08	53.29	50.73
6	50.34	55.64	36.23	32.41

The bonds that are strongly mis-rated after correction for tax, liquidity and risk premiums are tracked over time to see if they remain mis-rated. The table reports the percentage of bonds that remain mis-rated after various time horizons of 1, 3, and 6 months. AAA down are bonds with an agency rating of AAA that have been reclassified into a lower rating category.

AAA whereas the rating agency judges it AA. After 1, 3 and 6 months, spreads on average rise by 3.9, 7.2 and 10.0 basis points as the market revises down its evaluation of the credit quality of the borrower towards that of the rating agency.

On the other hand, as one may see from Table 7, the adjustment of the credit quality orderings in some cases also involves adjustments in the assessment of the rating agency that brings it closer to that of the bond market. The table shows transition probabilities between rating categories worked out for the bonds in our sample

Table 6
Change in spread conditional on reclassification

Time period (months)	Strong reclassification			
	AAA down	AA up	AA down	A up
1	−3.23	3.93	−3.50	4.18
	(−8.47)	(12.53)	(−6.27)	(13.98)
3	−5.32	7.17	−3.32	7.80
	(−6.68)	(9.29)	(−2.38)	(10.98)
6	−6.85	10.91	−3.68	10.21
	(−3.94)	(10.03)	(−1.51)	(7.50)

The bonds that are strongly mis-rated (after correction for tax,liquidity and risk premiums) are tracked over time to see how their spread deviation changes over time (measured in basis points). The table reports the average change in spread deviation (in basis points) over time horizons of 1, 3 and 6 months after being mis-rated. AAA down are bonds which have an agency rating of AAA but have been reclassified into a lower rating category. Standard errors are calculated under the assumption that spread changes are independent.

Table 7
Coarse-rated transition matrices over long horizons

Reclassification	Strong reclassification								
	1 year matrix			2 year matrix			3 year matrix		
	Up	Stay	Down	Up	Stay	Down	Up	Stay	Down
AAA	0.00	96.19	3.81	0.00	94.13	5.87	0.00	93.25	6.75
	(0.00)	(0.61)	(0.61)	(0.00)	(1.10)	(1.10)	(0.00)	(1.58)	(1.58)
AAA down	0.00	85.00	15.00	0.00	70.45	29.55	0.00	43.75	56.25
	(0.00)	(3.57)	(3.57)	(0.00)	(6.88)	(6.88)	(0.00)	(12.40)	(12.40)
AA up	4.55	81.82	13.64	6.25	75.00	18.75	20.00	50.00	30.00
	(2.22)	(4.11)	(3.66)	(4.28)	(7.65)	(6.90)	(12.65)	(15.81)	(14.49)
AA	1.47	82.67	15.86	0.94	75.55	23.51	1.69	72.32	25.99
	(0.46)	(1.45)	(1.40)	(0.54)	(2.41)	(2.37)	(0.97)	(3.36)	(3.30)
AA down	0.00	56.00	44.00	7.69	46.15	46.15	0.00	37.50	62.50
	(0.00)	(7.02)	(7.02)	(5.23)	(9.78)	(9.78)	(0.00)	(17.12)	(17.12)
A up	7.69	85.71	6.59	18.33	78.33	3.33	12.50	87.50	0.00
	(2.79)	(3.67)	(2.60)	(5.00)	(5.32)	(2.32)	(11.69)	(11.69)	(0.00)
A	7.47	84.20	8.32	13.26	71.55	15.19	14.01	64.97	21.02
	(0.86)	(1.19)	(0.90)	(1.78)	(2.37)	(1.89)	(2.77)	(3.81)	(3.25)

We calculate transition matrices conditional on the reclassified rating of the bonds (after correction for tax,liquidity and risk premiums). The table reports transition probabilities in percent for time horizons of 1, 2 and 3 years for strongly mis-rated bonds. For example, "AAA-down" are bonds which have an agency rating of AAA but have been reclassified into a lower rating category. Bonds with a reclassification of "AAA" are bonds which have an agency rating of AAA and have a reclassified rating of AAA. Standard errors in brackets are calculated under the assumption that rating transitions are independent.

for 1, 2 and 3 year time horizons. To take an example, for AAA-rated bonds that when reclassified are still AAA, the sample probability of remaining at AAA after 1 year is 96.2%. Conditional on being reclassified down (i.e., on the bond spread suggesting an AA rating or below) the probability of remaining at AAA is just 85.0%.

Over a 3 year horizon, the contrast is even greater with AAA downgrade probabilities being just 6.8% for AAA-grade bonds over all but 56.3% conditional on being strongly reclassified down. In general, the results in the table suggest that the "rating" suggested by the bond market spread systematically adds information to the agency rating in that it is useful in predicting changes in ratings.

It is possible that the differences between transition probabilities for bonds that are strongly reclassified up and down shown in Table 7 reflect the subdivision of rating categories into plus, minus and unqualified ratings grades, i.e., the sub-ratings categories. To examine this, Table 8 reports transition probabilities for the finer ratings grades when bonds are again sorted into strongly reclassified up or down or not strongly reclassified. Fewer observations are available to estimate the transition probabilities for these finer ratings grades but the effect evident in the results of Table 7 is clearly still present. Transition probabilities of downgrades (upgrades) are generally greater when the bonds are strongly reclassified down (up) than when they are strongly reclassified up (down).

Table 8
One year sub-rating transition matrices

	AAA	AA+	AA	AA−	A+	A	A−	BBB	# bonds
Panel A: Bonds not strongly reclassified									
AAA	96.64	2.56	0.71	0.09	0.00	0.00	0.00	0.00	1131.00
AA+	0.00	85.65	7.39	6.96	0.00	0.00	0.00	0.00	230.00
AA	0.75	1.13	82.26	11.70	2.64	1.13	0.38	0.00	265.00
AA−	0.99	0.00	0.66	86.14	8.58	2.97	0.66	0.00	303.00
A+	0.00	0.00	0.00	3.39	86.46	7.81	1.82	0.52	384.00
A	0.00	0.00	0.00	0.24	8.27	85.40	3.41	2.68	411.00
A−	0.00	0.00	0.00	0.00	0.50	11.50	79.50	8.50	200.00
Panel B: Bonds strongly reclassified down									
AAA	87.80	5.69	4.88	0.81	0.00	0.81	0.00	0.00	123.00
AA+	0.00	28.57	14.29	28.57	14.29	14.29	0.00	0.00	7.00
AA	0.00	0.00	85.71	14.29	0.00	0.00	0.00	0.00	7.00
AA−	0.00	0.00	0.00	63.64	22.73	11.36	2.27	0.00	44.00
A+	–	–	–	–	–	–	–	–	0.00
A	–	–	–	–	–	–	–	–	0.00
A−	–	–	–	–	–	–	–	–	0.00
Panel C: Bonds strongly reclassified up									
AAA	–	–	–	–	–	–	–	–	0.00
AA+	0.00	90.77	6.15	3.08	0.00	0.00	0.00	0.00	65.00
AA	2.44	4.88	78.05	12.20	0.00	2.44	0.00	0.00	41.00
AA−	0.00	0.00	5.26	84.21	10.53	0.00	0.00	0.00	19.00
A+	0.00	0.00	1.92	1.92	86.54	7.69	1.92	0.00	52.00
A	0.00	0.00	0.00	0.00	8.11	89.19	2.70	0.00	37.00
A−	0.00	0.00	0.00	0.00	0.00	22.22	77.78	0.00	9.00

We present 1 year ratings transition probabilities in percent similar to those shown in Table 7 but for fine rather than coarse ratings grades. The transition probabilities are calculated for bonds sorted into (A) not strongly reclassified, (B) strongly reclassified up, and (C) strongly reclassified down.

5. Conclusion

In this study, we identify and document substantial differences in the ordering of credit standing implicit in bond market yields and ratings. For example, one quarter of AA-rated bonds have inconsistent prices and ratings.

It is possible that the orderings implicit in yields and credit ratings differ even if ratings agencies and bond market participants are correctly evaluating credit quality. This will be the case if risk premiums, tax and liquidity effects are substantial. To adjust for these influences, we regress residuals from defaultable bond term structure fits on risk premium betas and proxies for tax and liquidity effects. Using the fitted part of the regressions to adjust for these effects, we reduce the number of reclassifications significantly.

It is also true that the credit quality orderings implicit in ratings and bond spreads are broadly consistent but that they adjust towards each other over time. We examine the rate at which inconsistencies between ratings and spreads are eliminated over time and find that after six months between half and two-thirds of inconsistencies have disappeared.

We conclude that allowing (i) for economic determinants of spreads and (ii) for dynamic adjustments, the apparent and very substantial discrepancies between ratings and bond market spreads can be accounted for.

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