Individual stock-option prices and credit spreads

Cremers, M.; Driessen, J.; Maenhout, P.; Weinbaum, D.

DOI
10.1016/j.jbankfin.2008.07.005

Publication date
2008

Published in
Journal of Banking & Finance

Individual stock-option prices and credit spreads*

Martijn Cremers,[a] Joost Driessen,[b,**] Pascal Maenhout,[c] David Weinbaum[d]

[a] *Yale School of Management, International Center for Finance, Box 20820, 135 Prospect Street, New Haven, CT 06520*
[b] *University of Amsterdam, Finance Group, Faculty of Economics and Econometrics, Roetersstraat 11, 1018 WB Amsterdam, the Netherlands*
[c] *INSEAD, Finance Department, Boulevard de Constance, 77305 Fontainebleau Cedex, France*
[d] *Cornell University, Johnson Graduate School of Management, 375 Sage Hall, Ithaca, NY 14853-6201*

This version: July 2008

Abstract

This paper introduces measures of volatility and jump risk that are based on individual stock options to explain credit spreads on corporate bonds. Implied volatilities of individual options are shown to contain useful information for credit spreads and improve on historical volatilities when explaining the cross-sectional and time-series variation in a panel of corporate bond spreads. Both the level of individual implied volatilities and (to a lesser extent) the implied-volatility skew matter for credit spreads. Detailed principal component analysis shows that a large part of the time-series variation in credit spreads can be explained in this way.

JEL Classification: G12 ; G13
Keywords: Credit spreads; Options; Implied volatility; Skew

**Corresponding author. Tel.: +31 20 525 5263; fax: +31 20 525 5285.
E-mail addresses: martijn.cremers@yale.edu (M. Cremers), j.j.a.g.driessen@uva.nl (J. Driessen), pascal.maenhout@insead.edu (P. Maenhout), dw85@cornell.edu (D. Weinbaum).

*This paper was originally submitted to Professor Giorgio Szego on June 21, 2006 and was revised twice prior to this submission through EES. We thank Ike Mathur (the Editor), two anonymous referees, Ed Altman, Warren Bailey, Antje Berndt, Pierre Collin-Dufresne, Ludger Hentschel, Michael Johannes, David Lando, and seminar participants at Copenhagen Business School, the Second International Conference on Credit Risk (Montreal), the Johnson-Simon Finance Conference (Rochester), the 2004 WFA (Vancouver) and EFA (Maastricht) meetings, the 2004 CEPR Summer Symposium in Financial Markets (Gerzensee), and the University of Amsterdam for their comments.

1. Introduction

Merton (1974) developed the structural firm value approach to the valuation of corporate bonds. In this model, corporate debt is simply riskless debt combined with a short position in a credit put option, struck at the face value of the debt. A number of papers have studied the empirical implications of this approach to credit risk. An important finding is that it is challenging to explain variation in credit spreads based solely on credit-risk factors, even when accounting for liquidity proxies (Collin-Dufresne, Goldstein and Martin (2001, henceforth CGM)).

We consider market-based proxies for two fundamental theoretical determinants of credit spreads, volatility and jump risk, that are observed in the market for individual options on the equity of the issuing firms. Traded individual options encode the assessment of market participants of the volatility risk that the firm value is subject to and would therefore be expected to contain forward-looking information that is relevant for credit risk. We suggest at-the-money implied volatilities of individual equity options as a useful proxy of volatility risk. Second, since corporate bonds embed a short position in out-of-the-money puts, it is natural to consider the market for out-of-the-money puts. Because the prices of these puts are particularly sensitive to jump risk, they enable us to construct a market-based proxy, namely the option-implied volatility skew, for this determinant of credit spreads.

We analyze to what extent variation in credit spreads can be explained by implied volatilities and implied-volatility skews of individual options on the issuers' equity. Campbell and Taksler (2003, henceforth CT) document a strong relation between historical equity volatility and bond yields. Taking their regressions as our benchmark, we examine the incremental explanatory power of option-implied volatilities and volatility skews.

It is important to point out that traded individual options should only add additional information about credit risk not already captured by equity and riskless debt if the options indeed are not redundant. However, there is ample evidence in the option-pricing literature of violations of the complete-market assumption and of priced jump and volatility risk.[1] Both at-the-money and out-of-the-money put options are needed to fully capture and disentangle the respective effects of these two factors. Even in the case of market incompleteness due to jumps and/or stochastic volatility, historical volatility and skew measures could capture their effects on credit spreads. However, given their backward-looking nature, historical measures may have difficulty picking up time-variation in volatility and jump risk, unlike forward-looking option-implied measures. Christensen and Prabhala (1998) show that option-implied volatility predicts future volatility better than historical measures, and we examine whether this predictive information helps explain credit risk, as would be expected in a structural firm value model. Another reason why option-based information may improve over historical measures is related to the empirical finding in the option-pricing literature of priced volatility and jump risk. To the extent that these risks matter and are priced, this would be captured by implied volatilities and skews, but not necessarily by historical measures. For instance, an increase in the volatility risk premium leads to higher option prices, which directly affects the implied volatilities, without changing historical stock-return volatilities. Finally, although equity is itself an option in the firm value framework, it is not trivial to back out a forward-looking volatility or jump measure from its price, because this requires a specific model along with assumptions about the default boundary to back out for example the implied asset volatility. Using option-implied volatilities is empirically more straightforward.

Whether option-based measures add relevant and quantitatively important information

[1] Evidence of priced jump and/or volatility risk is presented in, e.g., Ait-Sahalia, Wang and Yared (2001), Bakshi, Cao and Chen (1997), Bakshi and Kapadia (2003a, 2003b), Bakshi, Kapadia and Madan (2003), Bates (2003), Buraschi and Jackwerth (2001), Pan (2002), Topaloglou, Vladimirou and Zenios (2008). See, e.g., Chern, Tandon, Yu and Webb (2008) for evidence on the informational role of options.

for credit risk compared to historical information is ultimately an empirical question and this constitutes the main focus of our paper. We use a panel of weekly data on US corporate bond prices and individual option prices of 69 firms for the 1996-2002 period. In our benchmark analysis, we perform a panel regression of the level of credit spreads and investigate the determinants of both the time-series and cross-sectional variation in credit risk.

We show that option-based information is useful for explaining credit spreads, both over time and across firms, and adds explanatory power beyond the information in historical measures of volatility and jump risk, especially for long-maturity credit spreads. The coefficient on implied volatility is highly economically and statistically significant, unlike historical volatility, which becomes insignificant in some regressions for long-maturity bonds. In most (but not all) regression specifications, the implied volatility skew also manifests itself as a significant explanatory variable, especially for lower-rated firms. Consistent with a structural firm value model, we allow for non-linearities in the relationship between equity volatilities and credit spreads and find that the sensitivity of credit spreads to volatility and crash imminence is much larger for poorly rated debt than for bonds with strong credit ratings. A one-standard-deviation weekly shock in implied volatility changes the long-maturity credit spread by 5 basis points for an A-rated issuer and by 16 basis points for a BBB firm. We find that historical and implied individual volatility measures often both have a significant impact on credit spreads. This may suggest that both measures are imperfect proxies (subject to independent measurement errors) of the true volatility measure that drives credit spreads. We also obtain results that are difficult to explain and would be interesting to analyze in future research. Implied market volatility has a significantly negative impact on credit spreads, which seems anomalous. Similarly, the estimated coefficient on historical skewness has the 'wrong' sign: a more negatively skewed equity return distribution is associated with lower credit spreads.

We show that the time-series variation in credit spreads can be explained rather well. Two empirical findings substantiate this claim. First, adding time-dummies to the regressions has little impact on the results. Second, detailed principal component analysis shows that our option-implied determinants of credit risk do explain the systematic variation in credit spread levels rather exhaustively. There is no evidence of a large unidentified factor that would be unrelated to credit risk and that would be driving the common variation in credit spread levels. Instead, our results show that the *cross-sectional* variation is less exhaustively explained by individual credit risk factors, since credit ratings or issuer-specific fixed effects continue to play an important role in our regressions.

Our paper is related to the recent work of Cao, Yu and Zhong (2006), who study the impact of stock-option prices on credit default swap spreads. Their results are consistent with ours. They also find that option-implied volatilities dominate historical volatilities in explaining spreads on credit default swaps and that implied volatilities matter most for firms with lower ratings. Hilscher (2007) uses the structural firm value model to infer a bond-implied volatility measure from corporate bond spreads and shows that this measure has predictive power for future volatility, beyond the information in historical volatility, consistent with our findings.

This paper aims to explain the cross-sectional and time-series *variation* in credit spreads. A parallel literature focuses instead on explaining the high *average* level of credit spreads (the 'credit spread puzzle'). Cremers, Driessen and Maenhout (2006) show that incorporating information embedded in option prices helps to explain this puzzle. We complement this work by showing that option prices also help to explain credit spread variation.

The rest of the paper is structured as follows. Section 2 describes the bond and option data and presents summary statistics. The benchmark regressions explaining credit spreads are reported in section 3, as well as extensions with firm fixed effects and time dummies. Credit ratings are introduced in section 4. Section 5 uses principal component analysis to study whether our option-based variables explain all systematic variation in credit spreads. Section 6 concludes.

2. Data description

2.1. Sources

The data on US-dollar corporate bond prices are from the Bloomberg Corporate Bonds Database, which contains mid-quotes for corporate bonds, as well the bond's maturity date, coupon size and frequency, S&P credit rating, the firm's industry sector, and the amount issued. We collect data from January 1996 until September 2002, for a total of 351 weeks. We restrict ourselves to 69 firms for which both corporate bond and equity option price data are available. This is a subset of the firms analyzed by Duffee (1999). We only use bonds with constant, semiannual coupon payments, and no embedded put or call options or sinking fund provisions. As in Duffee (1999), bonds with remaining maturity less than one year are dropped. Most bonds are senior unsecured. We only include other bonds (e.g. subordinated bonds) if they have the same rating as the senior unsecured bonds. Most firms are investment grade throughout the sample period, but some firms become speculative grade in the last three years of the sample. Two firms in our sample default, Comdisco and Enron.[2]

In total, we have 524 corporate bonds. We use Bloomberg data on 6-month Treasury bills and the most recently issued Treasury bonds with maturities closest to 2, 3, 5, 7, 10, and 30 years to calculate the credit spreads of the corporate bonds, defined as the difference between

[2] The defaults occur after the firms leave the sample and are therefore not driving the results. Our dataset may include some matrix prices, which would make it more difficult to find an effect of individual stock-option prices on credit spreads, as matrix prices are not based on firm-specific information. However, since we look at large companies with relatively liquid corporate bonds, we expect few matrix prices in our sample.

the corporate bond yield and the yield on a government bond with the same maturity and coupon size. Since government bond yields are not observed for all relevant coupon sizes and maturities, we first estimate the term structure of default-free zero-coupon interest rates, using an extended Nelson-Siegel (1987) specification for these zero rates. Given this term structure of default-free zero-coupon rates, credit spreads on corporate bonds can readily be calculated.[3]

The option data originate from OptionMetrics. OptionMetrics reports each option's implied volatility, calculated with American or European models (as appropriate) and using historical LIBOR/Eurodollar rates as well as incorporating discrete dividend payments. To keep expiration dates the same across stocks, we only use the prices of options that expire in the month immediately following the current month.

We calculate the implied volatility skew as the difference between the implied volatility of the put with strike-to-spot ratio closest to 0.92 and the implied volatility of an at-the-money put, divided by the difference in strike-to-spot ratios. The raw time-series for this variable contains a mechanical and periodic pattern that is simply due to the fact the options get closer to maturity. Since we fix the strike-to-spot ratio for the implied skew at 92%, as we get closer to maturity the 92% OTM put becomes relatively more out-of-the-money because the uncertainty about the stock price at maturity is decreasing, leading to steeper skews for shorter maturities. We therefore remove the cyclical pattern in the individual option-implied skew in a model-free fashion by dividing each weekly observation for the skew of an issuer by the ratio of the time-series average of the skews of options with the same time to maturity to the overall time-series average across options.

[3] Some bond prices very likely contain data errors. We eliminate observations for which the credit spread is below -50 basis points. Also, we delete the 'middle' observation if the credit spread moves more than 50 basis points in one week, and again more than 50 basis points in the opposite direction in the next week.

2.2. Summary statistics

Table 1 reports summary statistics for the dependent and the main explanatory variables. The average credit spreads in our sample are 103.1 (short-maturity bonds with 1 to 5 years to maturity) and 110.9 basis points (long-term bonds with at least 7 years to maturity). Credit spreads are highly volatile and exhibit substantial cross-sectional variation. Implied volatilities are also highly volatile, both in levels and in changes, but exhibit somewhat less cross-sectional variation. Not surprisingly, the volatility of the S&P500 index is substantially smaller than the average individual volatility. Interestingly, the individual option-implied skew is extremely volatile, both in the time-series dimension and cross-sectionally.

Following CT, we consider both idiosyncratic and market-wide historical volatility, and calculate idiosyncratic volatility as the second moment of equity returns in excess of the CRSP value-weighted index over a 180-day window. We also consider historical measures of skewness to complement the option-implied skew (calculating idiosyncratic historical skewness in the same way as idiosyncratic historical volatility). As the correlation across all observations between idiosyncratic and individual (total) volatility is 96.8% (89.8% between the two measures of individual historical skewness), we refer to these variables as historical individual volatility and skewness. In terms of correlations with credit spreads, individual volatility stands out. Finally, Table 1 shows that the historical measure of S&P volatility is highly correlated with the average credit spread during our sample.

3. Benchmark regressions

3.1. Empirical methodology

To gauge the incremental explanatory power of option-based volatility and skewness measures for credit spreads, we take the regressions of CT as our benchmark. CT consider historical individual and market volatility as well as a number of control variables that have been shown in the literature to have explanatory power for credit spreads. We add historical measures of skewness for completeness.[4] Market volatility is included in our regressions because we take the CT specification as a benchmark. However, in a structural model credit spreads are driven by individual volatility, not market volatility. An empirical motivation for nevertheless adding market volatility as an explanatory variable may be based on concerns of measurement error in firm-level volatility.

A structural firm value model with jump-diffusions and stochastic volatility would suggest that the effect of volatility on credit spreads should be positive. Option-implied skews can be interpreted as measuring downward jump risk and should therefore have a positive coefficient. Historical measures of skewness are expected to affect credit spreads negatively, since credit spreads should widen as the return distribution becomes more negatively skewed.

We only retain bonds with at least 25 weekly observations. The regressions are contemporaneous and pooled, and we distinguish between short-maturity (1 to 5 years) and long-maturity bonds (at least 7 years to maturity), since the results are sufficiently different to warrant separate regressions. The regression coefficients are consistently estimated with OLS, and standard errors (and t-statistics) are corrected for heteroskedasticity, autocorrelation and cross-correlations across all bonds. We do this by estimating a full bond-by-bond covariance matrix for the residuals. To correct for serial correlation, we estimate an AR(1) specification for each bond's error term.

Following CT and other papers in the literature, we regress credit spread levels, rather than changes. This specification has the following advantages. First, credit spreads are, economically speaking, not expected to be non-stationary, since they are ex ante expected

[4] Bakshi, Madan and Zhang (2006) also investigate historical individual volatilities, CGM include implied volatility and skew for index options, and Huang and Kong (2003) use historical index volatility. Berndt et al. (2005) use the VIX, which is highly correlated with implied index volatility, to explain credit default swap spreads.

return differentials. Second, there is no strong econometric evidence for non-stationarity, i.e. for a unit root in credit spreads.[5] First-differencing a stationary time-series and regressing changes rather than levels introduces noise into the estimation. Moreover, running the regressions in levels allows us to investigate the determinants of time-series variation as well as cross-sectional variation in credit spreads. If we were to analyze credit spread changes instead (as in CGM), the focus would be on time-series variation only. This misses an important part of the analysis, as our results below indicate.

Many papers have examined the determinants of credit spreads. To investigate whether our option-based variables provide additional explanatory power, it is important to control for these other determinants. A first natural control variable is the firm's leverage. As in CT and CGM, we expect a positive impact of book leverage (long-term debt over total assets, from Compustat) on credit spreads. Kwan (1996), CGM and CT document a negative relationship between the firm's past stock return and credit spreads. The equity return can be interpreted as reflecting the firm's health, or might alternatively be interpreted as being a high-frequency proxy for changes in leverage.[6] As a further control, the overall state of the economy may matter and can be captured by the market (S&P) return, as in Longstaff and Schwarz (1995), CGM, CT and Huang and Kong (2003). Both the firm and market return are calculated over the past 180 days and obtained from CRSP.

To control for the level and slope of the term structure of interest rates, we include the yield on 2- and 10-year Treasury bonds from Datastream, following, e.g., Duffee (1998, 1999), CGM, CT, Driessen (2005), Elton, Gruber, Agrawal and Mann (2004) and Huang and

[5] Estimating affine term structure models for firm-level credit spreads, Duffee (1999) finds mean-reversion for spreads with an average half life of about 3 years.

[6] Theoretically, a positive stock return implies a decrease in leverage; in the Merton model, an increase in the firm value affects the leverage ratio and at the same time leads to an increase in the equity price. Empirically, changes in equity returns may reflect many additional factors, making accounting leverage (included in our regressions) a more direct and cleaner measure.

Kong (2003). The general finding is a negative relation between default-free rates and credit spreads. One explanation for this is given by Longstaff and Schwartz (1995). In their model, a rise in the level of interest rates increases the drift of the risk-neutral process for the value of the firm, thus reducing the risk-neutral probability of default and credit spreads. CGM interpret the slope of the term structure as a proxy for the overall state of the economy, as well as a measure of expected future short rates. A negative sign is therefore expected.

Following CGM, we include the BAA rate to control for the general trend in the level of credit spreads. Finally, liquidity may be an important factor driving credit spreads. We use the 10-year swap rate as a first proxy for liquidity (as in CGM) and the difference between the 30-day Eurodollar and the Treasury yield as a second control (following CT). All these data are obtained from Datastream.

3.2. Benchmark results

Table 2 reports the benchmark results. Starting with historical measures of volatility and downward jump risk in regression 1, we replicate CT's finding of a very significant coefficient on historical volatility. The coefficients on historical individual skewness and S&P volatility are significant (the latter only marginally for long-term bonds), but do not have the expected sign. The positive coefficient on skewness suggests that, as the return distribution becomes more negatively skewed, credit spreads become smaller, not larger as would be expected economically. We conduct some additional analysis below in an attempt to understand this anomalous finding. The negative coefficient on historical S&P volatility is also surprising. As discussed above, S&P volatility should not have an effect on credit spreads if one controls for the correct measure of individual volatility. The significantly negative coefficient is therefore difficult to explain, but not robust to the inclusion of month dummies (section 3.3). Historical S&P skewness is insignificant.

Consistent with earlier work, we find significant coefficients for the 2-year and 10-year yield and BAA rate. Accounting leverage is only significant for short-term bonds. The firm and market return mainly matter for long-term bonds, but have rather small effects, which may of course be due to their correlations with other regressors, so that their effect on credit spreads becomes hard to disentangle. Liquidity as proxied by the difference between the 30-day Eurodollar and the Treasury yield matters only for short-term bonds, which is sensible and in line with e.g. Janosi, Jarrow and Yildirim (2002) and Driessen (2005).

The pooled panel regression explains 28% of the cross-sectional and time-series variation in credit spreads for short-maturity bonds and 45.5% for long-maturity debt.

Regression 2 considers individual and market-wide option-based measures of volatility and jump risk to explain credit spreads. Both individual option-based measures are highly statistically significant, for short- and long-maturity bonds. The coefficients have the expected sign: an increase in implied volatility and in implied-volatility skew both widen the credit spread. To gauge economic significance, it is useful to go back to the summary statistics of Table 1. The cross-firm average of the standard deviation of a weekly change in option-implied volatility is 0.046. Thus a one-standard-deviation weekly shock to implied volatility leads to a widening of credit spreads by 7 basis points for short-maturity bonds and 12 basis points for long-maturity debt. The implied-volatility skew has a much smaller coefficient, but is more volatile. A typical weekly one-standard-deviation shock in the implied-volatility skew increases the credit spread of that issuer by only 2 to 3 basis points.[7] S&P implied volatility is significant, but has a negative sign, for both maturities.[8] The

[7]We have also implemented a more formal measure for the skewness of the risk-neutral distribution, using the expressions of Bakshi, Kapadia and Madan (2003). In general, this does not lead to better results than our simple implied skew measure. This is likely due to the small number of strike prices available for individual options, which makes the construction of a formal risk-neutral skewness measure nontrivial.

[8]Univariately, S&P implied volatility has a positive sign, as would be expected and in line with Berndt et al. (2005), who show that the VIX has significant explanatory power for credit default swap spreads.

same finding obtains for the S&P implied skew for long-maturity bonds. However, neither of these counter-intuitive results survives the inclusion of month dummies. The results for the control variables remain largely as before, except for accounting leverage, which becomes insignificant for short-maturity debt, but significantly negative for long-maturity bonds. The positive coefficient on the swap rate is now significant, in line with the findings of CGM.

The R^2 of the regression for short-maturity bonds (27.2%) is actually marginally lower than for regression 1, suggesting that option-implied information may not be essential for short-maturity bonds. For long-maturity bonds, the option-based measures do perform better than the historical measures and explain, together with the control variables, roughly half the variation in credit spreads (R^2 of 48.1%), even though the pooled regression imposes identical coefficients across all bonds, across all firms and throughout the sample period.

Regression 3 adds the option-based measures to regression 1. When including both historical and option-implied measures of volatility and jump risk, multicollinearity between our four main variables may be problematic. However, pooling the individual measures across firms, the highest correlation between these variables is 64% (between implied and historical volatility), while all other correlations are below 20% (in absolute value). Several interesting findings emerge from regression 3. First, the coefficients on historical volatility remain significant, but shrink substantially, especially for long-maturity bonds. Second, while the coefficient on implied volatility becomes smaller for short-maturity bonds (but remains highly significant), we find that individual option-implied volatility emerges as the most important firm-specific determinant of long-maturity credit spreads. Its economic impact is substantial: a one-standard-deviation weekly increase in the implied volatility of an issuer widens its credit spread by 11 basis points.

We calculate historical volatility using the past 180 return observations, thus its weekly change is small (see the standard deviations in Table 1, 0.046 for implied versus 0.012 for historical volatility). Therefore, in order to interpret the economic significance of historical proxies more directly, the historical volatility variable (as well as historical skewness) has been rescaled for all regressions so that it has the same time-series standard deviation (on average across all bonds) as the corresponding implied measure. That way, we can directly compare the estimated coefficients. Doing this reveals that historical volatility has a larger economic effect on short-maturity bonds than does option-implied volatility. However for long-maturity credit spreads, the economic impact is much smaller for the historical proxy than for the option-implied measure of volatility. Nevertheless, it may seem surprising that the historical volatility measure remains significant. One explanation for why both the historical and implied individual volatility measures have explanatory power may be that both measures are imperfect proxies for the 'true' unobserved volatility that drives credit spreads.[9]

The puzzling positive sign on historical skewness persists in regression 3. The implied skew continues to have the expected (positive) sign. It can be noted that the time-series correlation (averaged across all firms) between implied skew and historical skew is only -9%. A potential explanation for the difference between historical skewness and option-implied skew may be related to their respective time-series properties. The implied-volatility skew is not only highly volatile, but also mean-reverts much more quickly than the very persistent historical measure. The autocorrelation coefficient for the option-implied measure is 40%, while it is 96% for historical individual skewness. The fact that historical skewness is so highly persistent is quite natural as it is measured over a rolling horizon. But if the

[9] We have also analyzed a setup without overlapping historical measures, by using a monthly frequency and historical measures based on a window of 4 weeks. In this case, the historical measures are noisier and the option-implied measures perform substantially better.

'true' measure of crash imminence or of jump risk that matters for credit spreads exhibits less persistence and mean-reverts more quickly (like the implied skew), then the historical measure might simply be too slow to react to changes in jump risk and might in fact by construction be limited in its ability to pick up the dynamics that matter for credit spreads.

The adjusted R^2 indicates that the incremental explanatory power of option-implied volatility and skewness is limited for short-maturity bonds. Option-based information is more successful explaining credit spreads on long-maturity debt; the adjusted R^2 increases by more than 3 percentage points relative to regression 1.

3.3. Month dummies and firm fixed effects

As a robustness check and to explore to what extent option-based measures explain cross-sectional versus time-series variation, we introduce month dummies and firm fixed effects.

When adding month dummies in regression 4, several conclusions can be drawn. First, individual implied volatilities and implied skews pick up more than just time-variation in credit spreads, since month dummies have very little impact on these variables: the coefficients become slightly larger and more significant. In contrast, the coefficients on all S&P-based measures (historical and implied), many of which had counter-intuitive signs in the previous regressions, shrink substantially and become insignificant with the inclusion of month dummies, since they only pick up time-series variation, thus highlighting the importance of using firm-level measures. The same happens for some of the control variables (e.g. the market return and all interest rate variables). Interestingly, historical individual volatility now becomes economically and statistically insignificant for long-maturity bonds. We also note that historical individual skewness continues to have the 'wrong' sign. It is difficult to explain this sign, and while it may be the case that historical skewness proxies for other factors, we have no evidence to support this. Finally, the fact that the R^2 only increases slightly means that our explanatory variables already account for most time variation.

To understand how much cross-sectional variation in credit spreads is left unaccounted for, regression 5 includes firm fixed effects. Unlike month dummies, issuer fixed effects do change the results somewhat. The coefficient on individual implied-volatility increases from 0.78 to 1.28 for short-maturity bonds and drops from 2.33 to 1.66 for long-term bonds. Both coefficients remain very statistically significant, with t-statistics of 10 and 17, respectively. The biggest change can be observed for the coefficient on the individual implied skew for long-term bonds, which increases from 0.03 to 0.09 and now has a t-statistic of 7. This suggests that, for long-term bonds, the implied-volatility skew variable is more closely related to individual time-series variation in credit spreads, and less related to cross-sectional variation; introducing firm fixed effects allows the variables to 'focus' on individual time-series variation, since the firm dummies can take care of the cross-sectional variation. This is not too surprising given the descriptive statistics in Table 1, where the cross-sectional relation between option-implied skews and credit spreads is considerably less strong.

Another important finding for regression 5 is that the (adjusted) R^2 goes up substantially when issuer fixed effects are introduced. The explanatory variables explain almost half the variation in credit spreads on short-maturity bonds and more than two thirds of the variation for long-term bonds. Keeping in mind that we impose panel regressions, these numbers are quite remarkable. At the same time, the fact that the R^2 was 29.3% (short-maturity) and 48.7% (long-maturity) without fixed effects suggests that individual options do not exhaustively explain the cross-section of credit spreads, even though they are important determinants. Other issuer-specific factors seem to be reflected in credit spreads.[10]

[10] In untabulated robustness checks, we verify the results with Fama-MacBeth (1973) regressions and standard errors. This approach yields similar results. For short-maturity bonds, the coefficients on implied and historical volatility are highly significant (t-stats of 5.4 and 7.8, respectively). However, the implied-volatility skew becomes insignificant. For long-maturity bonds, implied volatility is extremely significant

4. Incorporating credit ratings

CT and others show that credit ratings have explanatory power for credit spreads, even when controlling for economic determinants of spreads. We therefore include ratings in the regressions. We also study the interaction between ratings and our measures of volatility and jump risk, to analyze whether these measures matter more for bonds of issuers that are closer to default, as would be predicted by a structural firm value model.

4.1. Credit ratings as a control variable

S&P classifies issuing firms into 26 different categories based on their default risk. We aggregate these different ratings into 5 groups: AAA, AA, A, BBB, and BB or lower.

As a starting point and to facilitate subsequent comparisons, regression 1 in Table 3 adds the rating dummies to regression 1 of Table 2, i.e., to the benchmark model of CT.[11] In line with CT, we find that rating dummies substantially improve the explanatory power of the regressions. The R^2 increases from 28.4% to 31.8% for short-maturity spreads and from 45.5% to 54.0% for long-maturity bonds. The rating dummies are highly statistically significant and generally have the expected sign: poorly rated bonds on average have higher credit spreads, except for rating group 2 (AA) for long-maturity bonds.[12]

Regression 2 in Table 3 demonstrates that our option-based variables add incremental explanatory power for long-maturity bonds (the R^2 grows from 54.0% to 56.2%), but very little for short-maturity spreads, in line with our earlier findings. The results also show

(t-stat of 13.5), unlike historical volatility (t-stat of 1.5), while the implied-volatility skew remains significant. In line with the results for the regressions with month dummies, the anomalous finding of a positive coefficient on historical skewness persists in the Fama-MacBeth regressions.

[11] While not reported to conserve space, all regressions in Table 3 include the control variables of Table 2.

[12] These regressions also put the success of option-implied measures in perspective: adding rating dummies to CT improves the explanatory power substantially more than adding option-implied volatility and skew. While other work has indicated that credit ratings do reflect highly relevant information, it is also interesting to analyze whether our option-implied measures can still add incremental explanatory power when added to the explanatory variables in regression 1 of Table 3.

that the significant effect of individual implied volatility on credit spreads is robust to the inclusion of rating dummies. In fact, the point estimate for short-maturity bonds increases slightly. The implied-volatility skew variable on the other hand shrinks when controlling for ratings and becomes statistically insignificant for long-maturity credit spreads. Its economic significance becomes very small and it seems difficult to disentangle the effect of the skew variable and the effect of credit ratings.

4.2. Interaction terms

We have found empirical support for the prediction of a structural firm value model, augmented to allow for stochastic volatility and jumps, that credit spreads on corporate bonds are positively related to measures of the volatility and jump risk of the issuer. A further prediction that we analyze in Cremers et al. (2008) is that the sensitivity of credit spreads to volatility and jump risk increases as the firm gets closer to the default boundary. To test this, we now interact the credit rating with our option-implied measures of the volatility and jump risk of the issuer. Because some of the rating categories contain too few bonds, we pool the data for this purpose into 3 categories: AAA to A- ('I'), BBB+ to BBB- ('II'), and BB+ and lower ('III'), while keeping the same rating dummies as before.

Regression 3 in Table 3 replicates the basic regression of Table 2, where spreads are explained by (individual and index) implied volatility and implied-volatility skew and control variables (coefficients unreported), but now includes rating dummies, as well as interaction with the credit rating. The sensitivity of credit spreads to implied volatilities increases significantly as the rating deteriorates from category I to category II, in line with the prediction of the model. The reported coefficients are additive, so that a BBB long-maturity issuer (category II) faces a 3.4 total coefficient on its implied volatility, while the impact for investment-grade issuers in category I is given by the coefficient of 1.02. This means that a one-standard-deviation weekly shock in implied volatility changes the credit spread by 5 basis points for an A-rated issuer (having an average long-maturity credit spread of 92 basis points) and by 16 basis points for a BBB firm, which has an average credit spread of 168 basis points (versus 12 basis points in the benchmark regression without credit-rating interaction terms). Junk-bond issuers (category III) surprisingly have coefficients that are not significantly larger than investment-grade firms in category I. However, the lack of statistical significance can be attributed the small number of observations in that cell.

The results for the interaction between the implied-volatility skew and credit ratings are also interesting. Highly-rated bonds have a slightly negative, but economically small, coefficient on this proxy for jump risk, while category II has large sensitivities. For these firms, the impact of the option-implied skew on credit spreads is 3 to 4 times larger than without the rating interaction. In particular, a one-standard-deviation weekly shock in the implied-volatility skew changes the short-maturity credit spread by 13 basis points for a BBB firm, which has an average credit spread over our sample of 160 basis points (versus an effect of only 3 basis points in the benchmark regression). As for implied volatility, category III does not produce statistically significant results since we have only few speculative-grade issuers in the sample. The finding of a large difference between the first 2 rating categories can explain why previously, without the interaction with credit ratings, the implied volatility skew often had a small coefficient. Allowing for rating dummies and interaction terms increases the fit of the regression substantially: compared to regression 2 in Table 2, the R^2 increases from 27.2% to 34.6% for short-maturity and from 48.1% to 57.9% for long-term bonds.

When adding the historical proxies for volatility and jump risk in regression 4, the same results obtain. While the coefficients are naturally smaller than without the historical proxies, it is still the case that the economic impact of implied volatility and of the implied-volatility skew on credit spreads of short- and long-maturity bonds is much larger for category II issuers than for firms with the highest credit rating.

Relative to regression 2 in Table 3, the credit rating interaction terms increase the (adjusted) R^2 from 32.6% to 36.1% for short-maturity bonds and from 56.2% to 58.8% for long-term bonds. The high explanatory power of these regressions, combined with the finding that most coefficients (except for category III) are estimated very precisely (especially for long-maturity debt) may suggest that the rating interaction is in fact crucial for the correct specification of the empirical model, in line with the theory.

4.3. Theoretical coefficients in a structural firm value model

Our empirical results provide evidence that both the implied volatility and (to a lesser extent) implied skew are important determinants of credit spreads. An interesting question to examine is whether the empirical relationship is in line with the predictions of a theoretical firm value model. This analysis, which is ommitted here to conserve space, reveals that our empirical estimates are reasonably close to the predictions of a structural firm value model with jump-diffusions, especially for implied volatility and long-maturity bonds, where we also obtain the strongest and most robust empirical results. Please see Cremers et al. (2008).

5. Principal component analysis

We now study the extent to which our main variables and the controls capture systematic credit spread variation. In doing so, we revisit the claim in CGM that a large fraction (75%) of the residual variation is captured by the first principal component, which they interpret as evidence that credit spread changes "contain a large systematic component that lies outside the structural model framework." Further, they conclude that "this implies that the low average R^2 [in their paper] is likely not due to noisy data, but rather to a systematic effect." However, we reach different conclusions, as we find that essentially all systematic variation is captured by our variables.

First, we extract the first ten principal components (PCs) from the raw credit spreads. We create an unbalanced sample that combines the credit spreads of both short and long maturity bonds, and estimate the principal components using an EM-algorithm to deal with missing data.[13] Table 4 presents the average cumulative R^2 of regressing the credit spreads of each individual bond on an increasing set of PCs, the increase in the average R^2 from adding a PC, and the standard deviation of the cumulative R^2 across bonds. The first two PCs capture on average 87% of the weekly variation in credit spreads, and the next three an additional 7%. While the number of statistically significant factors in credit spreads is difficult to estimate, most papers find two or three factors.[14] To be conservative, we use the first five factors as capturing systematic variation in credit spreads with a total R^2 of 93.9%.

Next, we compare the residuals of our pooled panel regressions to these five PCs in order to find to what extent systematic variation is left by our variables. CGM did not conduct such comparison, as they extracted PCs only from the residuals, making it impossible to say to what extent their residuals indeed represent systematic variation in credit spread changes. For our main model (regression 3 in Table 2), Panel A of Table 5 reports the R^2 of pooled panel regressions of the residuals on the set of five PCs. For comparison, we also report the R^2 of the pooled panel regression of the credit spreads themselves on this set of five PCs.

Our model with volatility and jump risk measures captures a very large part of the systematic variation, as only 0.74% of the residual variation of the credit spreads of short-term bonds is systematic (0.63% for long-term bonds). We conclude that the structural model

[13] We only use bonds with at least 75 weekly observations (out of a total of 349 weeks). The EM-algorithm we repeatedly (1,000 times) run consists of two steps: the estimation step extracts principal components, and in each maximization step, missing values are set to the values fitted by a linear model including these principal components.

[14] For credit spreads, Driessen (2005) finds evidence of two common factors. Feldhutter and Lando (2004) work with two credit factors (in addition to riskfree rate factors) for the term structure of corporate bonds.

variables do a great job in capturing systematic variation, consistent with the findings in section 3.3 for month dummies. We also calculate the R^2 for residuals of pooled regressions on option-implied volatility and skew, and on historical proxies, in both cases without control variables. With the option-implied regressors, 10.3% of the residual variation can be explained by the 5 PCs for short-maturity bonds and 11.6% for long-maturity debt. Using instead historical measures, 13.0% (short-maturity) and 13.6% (long-maturity) of the residual variation is systematic. Therefore, option-implied information is useful in explaining systematic variation in credit spreads.

Next, we attempt to replicate the CGM results. As CGM employ per-bond regressions rather than pooled panel regressions, for comparison purposes we also regress the credit spread of each individual bond separately on the full model that includes all volatility, implied-skew and control variables (regression 3 in Table 2).[15] The average R^2 equals 85% for the short-maturity bonds and 83% for the long-maturity bonds. Then we extract the first five PCs from the residuals of these regressions, henceforth denoted as 'residual PCs'. Finally, we regress these residuals on the set of five PCs as used above, as well as on the set of five residual PCs, again using per-bond regressions.

Panel B of Table 5 reports the average cumulative R^2 of regressing these residuals, per bond, on both sets of five PCs. For the per-bond regressions, we conclude that here a higher percentage of residual variance is captured by the systematic PCs, of about 8% assuming two factors and up to 21% assuming five factors. However, even this latter fraction would translate into only 3% (= 21% $\times$ 15%) of the variation of the credit spreads themselves (21% of the residual variation, which is 15% of total credit spread variation). Further, the first two residual PCs explain about 28% of the variation in the credit spread residuals, and

[15] We require at least 75 weekly observations to be available, giving 407 bonds with sufficient data.

the first five about 48%. The difference in R^2 captured by the systematic versus residual PCs is driven by the inclusion of non-systematic variation in the residual PCs likely due to estimation error. Even if asymptotically the cross-correlations of residuals are equal to zero, in a small sample these correlations will differ from zero and PCA will then use these residual correlations to construct factors that are asymptotically not systematic. Table 6 documents the extent to which these residual PCs contain such factors.

We find that only a small fraction of the variation in the residual PCs can actually be explained by the systematic factors, about 24% and 23% of the first residual PC for short and long-maturity bonds, respectively. Thus CGM's finding that their first residual factor explains 75% of the remaining variation after incorporating all structural firm value variables may not say much about the remaining systematic variation, particularly in light of the apparent general lower level of systematic variation in credit spread changes rather than levels (as evidence by the much lower average R^2 of the per-bond regressions in CGM for changes relative to the 83% - 85% here).

6. Conclusion

Prices of individual equity-options contain information about credit risk. Interacting our measures of volatility and jump risk with credit ratings, we find the economically meaningful result that the credit spreads of lower rated bonds are more sensitive to these determinants. There is no evidence that credit spread residuals contain a large systematic component outside the structural firm value model. Because we focus on credit spread levels rather than changes, we can also examine the extent to which the structural firm value model is able to explain cross-sectional credit-spread variation. We find that explaining the cross-section is in fact more challenging than explaining the time-series variation.

References

[1] Ait-Sahalia, Y., Wang Y., Yared, F., 2001. Do options markets correctly price the probabilities of movement of the underlying asset? Journal of Econometrics 102, 67-110.

[2] Bakshi, G., Cao, C., Chen, Z., 1997. Empirical performance of alternative option pricing models. Journal of Finance 52, 2003-2049.

[3] Bakshi, G., Kapadia, N., 2003a. Delta-hedged gains and the negative market volatility risk premium. Review of Financial Studies 16, 527-566.

[4] Bakshi, G., Kapadia, N., 2003b. Volatility risk premium embedded in individual equity options: Some new insights. Journal of Derivatives, 45-54.

[5] Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and differential pricing of individual equity options. Review of Financial Studies 16, 101-143.

[6] Bakshi, G., Madan, D., Zhang, F., 2006. Investigating the role of systematic and firm-specific factors in default risk: Lessons from empirically evaluating credit risk models. Journal of Business 79, 1955-1988.

[7] Bates, D., 2003. Empirical option pricing: A retrospection. Journal of Econometrics 116, 387-404.

[8] Berndt, A., Douglas, R., Duffie, D., Ferguson, M., Schranz, D., 2005. Measuring default risk premia from default swap rates and EDFs. Working paper, Stanford University.

[9] Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81, 637-654.

[10] Black, F., 1976. Studies of stock price volatility changes. Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economics Statistics Section, 177-181.

[11] Buraschi, A., Jackwerth, J., 2001. The price of a smile: Hedging and spanning in option markets. Review of Financial Studies 14, 495-527.

[12] Campbell, J., Taksler, G., 2003. Equity volatility and corporate bond yields. Journal of Finance 58, 2321-2349.

[13] Cao, C., Yu, F., Zhong, Z., 2006. How important is option-implied volatility for pricing credit default swaps? Working paper, Pennsylvania State University.

[14] Chern, K., Tandon, K., Yu, S., Webb, G., 2008. The information content of stock split announcements: Do options matter? Journal of Banking and Finance 32, 930-946.

[15] Christensen, B., Prabhala, N., 1998. The relation between implied and realized volatility. Journal of Financial Economics 50, 125-150.

[16] Collin-Dufresne, P., Goldstein, R., Martin, S., 2001. The determinants of credit spread changes. Journal of Finance 56, 2177-2207.

[17] Cremers, M., Driessen, J., Maenhout, P., 2006. Explaining the level of credit spreads: Option-implied jump risk premia in a firm value model. Forthcoming in Review of Financial Studies.

[18] Cremers, M., Driessen, J., Maenhout, P., Weinbaum, D., 2008. Individual stock option prices and credit spreads. Working paper, Yale University.

[19] Driessen, J., 2005. Is default event risk priced in corporate bonds? Review of Financial Studies, 18, 165-195.

[20] Duffee, G., 1998. The relation between Treasury yields and corporate bond yield spreads. Journal of Finance 53, 2225-2241.

[21] Duffee, G., 1999. Estimating the price of default risk. Review of Financial Studies 12, 197-226.

[22] Elton, E., Gruber, M., Agrawal, D., Mann, C., 2004. Factors affecting the valuation of corporate bonds. Journal of Banking and Finance 28, 2747-2767.

[23] Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: Empirical tests. Journal of Political Economy 71, 607-636.

[24] Feldhutter, P., Lando, D., 2004. The credit risk component in corporate spreads and swap spreads. Working paper, Copenhagen Business School.

[25] Hilscher, J., 2007. Is the corporate bond market forward looking? Working paper, Brandeis University.

[26] Huang, J., Kong, W., 2003. Explaining credit spread changes: Some new evidence from option-adjusted spreads of bond indices. Working paper, Pennsylvania State University.

[27] Janosi, T., Jarrow, R., Yildirim, Y., 2002. Estimating expected losses and liquidity discounts implicit in debt prices. Journal of Risk 5, 1-38.

[28] Kwan, S., 1996. Firm-specific information and the correlation between individual stocks and bonds. Journal of Financial Economics 40, 63-80.

[29] Longstaff, F., Schwartz, E., 1995. A simple approach to valuing risky and floating rate debt. Journal of Finance 50, 789-819.

[30] Merton, R., 1973. Theory of rational option pricing. Bell Journal of Economics 4, 141-183.

[31] Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates. Journal of Finance 29, 449-470.

[32] Nelson, C., Siegel, A., 1987. Parsimonious modeling of yield curves. Journal of Business 60, 473-489.

[33] Pan, J., 2002. The jump-risk premia implicit in options: Evidence from an integrated time-series study. Journal of Financial Economics 63, 3-50.

[34] Topaloglou, N., Vladimirou, H, Zenios, S., 2008. Pricing options on scenario trees. Journal of Banking and Finance 32, 283-298.

Table 1: Summary Statistics

We report summary statistics on the main variables (listed in rows) used in the analysis for the sample period of January 1996 until September 2002 with weekly frequency: corporate bond credit spreads (short-maturity and long-maturity) and measures of volatility and skewness (both option-implied and historical, both individual (69 issuing firms) and market-wide (S&P)). Credit spreads are expressed in percentage points and calculated over government bonds with identical maturity and coupon (computed based on a Nelson-Siegel term structure of default-free zero-coupon interest rates) for US-dollar bonds with constant, semiannual coupon payments and without embedded options or sinking fund provisions. Short-maturity credit spreads are for bonds with maturity between 1 and 5 years and long-maturity means a least 7 years. The implied volatility (for individual options as well as for S&P index options) is for at-the-money options. The implied-volatility skew is the difference between the implied volatility of a put with 0.92 strike-to-spot ratio (or the closest available) and the implied volatility of an at-the-money put, divided by the difference in strike-to-spot ratios. The cyclical variation in the individual option-implied skew is corrected for by dividing each weekly observation for the skew of an issuer by the ratio of the time-series average of the skews of options with the same time to maturity to the overall time-series average across options. Historical measures of volatility and skewness are calculated as second and third moments, respectively, of the corresponding equity returns in excess of the CRSP value-weighted index, over the past 180 days. Columns 2 through 7 list the global mean of each variable (computed as the average across bonds and firms of the time-series averages), the average time-series standard deviation of the levels of the variables, the average time-series standard deviation of the weekly change of the variables, the cross-sectional standard deviation (across bonds) in the time-series averages, and the correlations with credit spreads, both in the time-series (averaged across bonds and firms) and cross-sectionally (for the time-series averages of firm-specific variables).

	Mean	TS Std. Dev.		CS Std. Dev.	Correlation	
Variable		Levels	Change		TS	CS
Short-Mat. Credit Spread	1.031	0.352	0.097	0.663		
Long-Mat. Credit Spread	1.109	0.402	0.083	0.583		
Ind. Implied Volatility	0.348	0.098	0.046	0.062	0.752	0.400
Ind. Skew	0.314	0.330	0.361	0.129	0.258	-0.122
Ind. Historical Volatility	0.325	0.119	0.012	0.090	0.862	0.289
Ind. Historical Skewness	0.121	0.662	0.184	0.267	-0.566	0.059
S&P Implied Volatility	0.205	0.050	0.029		0.419	
S&P Skew	0.773	0.179	0.148		-0.220	
S&P Historical Volatility	0.183	0.053	0.004		0.822	
S&P Historical Skewness	-0.302	0.505	0.136		0.714	

Table 2: Benchmark Regressions for Short- and Long-Maturity Bonds

This table reports the pooled panel results of regressing weekly corporate bond spreads on measures of volatility and jump risk. We consider the implied volatility (IV) of individual and index (S&P) at-the-money options, and the individual and index implied skew. Table 1 describes the construction of these variables. The set of independent variables also includes historical estimates of the individual and index volatility and skewness (see Table 1) and additional control variables. The market and firm stock return are the excess returns on the S&P 500 and the issuing firm, respectively, over the past 180 days. The 2-year and 10-year yields are on Treasury bonds. The BAA rate is the average yield on bonds rated BAA by Moody's. The swap rate is for a 10-year maturity. The liquidity variable is measured as the difference between the 30-day Eurodollar and Treasury yields. Regressions in columns 4 and 5 include month dummies and firm fixed effects, respectively. The t-stats in parentheses are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

	Short-Maturity					Long-Maturity				
Regression	1	2	3	4	5	1	2	3	4	5
Ind. Hist. Vol.	2.05		1.60	1.59	1.81	2.24		0.55	0.08	1.06
	(7.43)		(12.48)	(12.24)	(10.58)	(13.78)		(6.06)	(0.93)	(9.45)
Ind. Hist. Skew	0.16		0.14	0.14	0.12	0.19		0.17	0.19	0.07
	(12.46)		(9.77)	(9.97)	(8.92)	(12.86)		(11.20)	(12.49)	(5.16)
S&P Hist. Vol.	-2.00		-1.58	1.69	-2.05	-0.95		-0.07	0.38	-0.09
	(-5.38)		(-3.77)	(0.75)	(-5.42)	(-2.08)		(-0.15)	(0.15)	(-0.23)
S&P Hist. Skew	-0.05		0.06	0.06	0.02	-0.13		-0.16	0.03	-0.16
	(-0.75)		(0.84)	(0.24)	(0.26)	(-1.86)		(-1.95)	(0.13)	(-2.53)
Ind. IV		1.52	0.78	0.81	1.28		2.58	2.33	2.74	1.66
		(11.67)	(5.50)	(5.87)	(9.99)		(22.89)	(20.30)	(25.83)	(16.53)
Ind. Skew		0.09	0.07	0.07	0.06		0.05	0.03	0.05	0.09
		(7.36)	(5.76)	(6.67)	(5.07)		(3.26)	(2.26)	(3.33)	(7.21)
S&P IV		-1.30	-0.82	-0.45	-0.96		-2.26	-2.06	-0.63	-1.47
		(-5.90)	(-3.54)	(-1.08)	(-4.72)		(-9.28)	(-8.33)	(-1.37)	(-7.69)
S&P Skew		0.06	0.14	-0.03	0.17		-0.17	-0.20	-0.08	-0.15
		(1.20)	(2.40)	(-0.36)	(3.31)		(-2.96)	(-3.11)	(-0.93)	(-3.04)

Table 2 (continued): Benchmark Regressions for Short- and Long-Maturity Bonds

Regression	Short-Maturity					Long-Maturity				
	1	2	3	4	5	1	2	3	4	5
Leverage	0.06	-0.00	0.01	0.00	-0.05	0.04	-0.09	-0.04	-0.06	0.71
	(4.00)	(-0.05)	(0.34)	(0.09)	(-0.74)	(1.74)	(-3.30)	(-1.62)	(-2.33)	(10.27)
Mkt Return	-0.03	-0.07	-0.09	-0.01	-0.11	-0.28	-0.42	-0.41	0.24	-0.37
	(-0.36)	(-0.81)	(-1.02)	(-0.04)	(-1.56)	(-3.18)	(-4.69)	(-4.46)	(0.89)	(-5.13)
Stock Return	-0.08	-0.02	-0.05	-0.05	0.07	-0.22	-0.13	-0.18	-0.25	-0.07
	(-3.10)	(-0.80)	(-2.03)	(-2.13)	(2.78)	(-11.12)	(-6.76)	(-8.78)	(-13.62)	(-3.94)
2-yr Yield	-0.19	-0.16	-0.18	-0.22	-0.18	-0.19	-0.16	-0.20	0.08	-0.17
	(-6.39)	(-5.90)	(-5.53)	(-1.17)	(-6.39)	(-5.79)	(-5.36)	(-5.95)	(0.45)	(-6.40)
10-yr Yield	-0.30	-0.35	-0.27	-0.03	-0.26	-0.43	-0.52	-0.44	-0.34	-0.51
	(-4.31)	(-6.62)	(-3.33)	(-0.10)	(-3.62)	(-5.51)	(-9.34)	(-5.17)	(-1.34)	(-7.69)
BAA Rate	0.32	0.29	0.27	0.14	0.21	0.45	0.32	0.33	0.21	0.36
	(6.86)	(6.20)	(5.74)	(0.96)	(5.17)	(9.23)	(6.43)	(6.65)	(1.42)	(8.80)
Swap Rate	0.12	0.22	0.12	-0.04	0.15	0.20	0.34	0.29	-0.00	0.32
	(1.26)	(2.43)	(1.18)	(-0.21)	(1.71)	(1.98)	(3.56)	(2.72)	(-0.01)	(3.82)
Liquidity	0.18	0.16	0.15	0.01	0.15	0.09	0.08	0.10	0.10	0.11
	(4.26)	(3.58)	(3.26)	(0.11)	(3.62)	(1.87)	(1.53)	(1.89)	(1.01)	(2.96)
Constant	0.24	-0.12	0.08	0.01	0.25	-0.37	0.32	0.22	0.54	-0.52
	(1.20)	(-0.58)	(0.31)	(0.01)	(1.10)	(-1.65)	(1.40)	(0.79)	(0.54)	(-2.32)
R^2	0.284	0.272	0.293	0.308	0.485	0.455	0.481	0.487	0.505	0.676
Adj. R^2	0.284	0.272	0.292	0.306	0.484	0.455	0.481	0.486	0.502	0.675
# bonds	334	334	334	334	334	189	189	189	189	189
# firms	66	66	66	66	66	56	56	56	56	56
# bond-weeks	34419	34419	34419	34419	34419	24261	24261	24261	24261	24261

Table 3: Credit Ratings

Pooled panel regressions of weekly bond spreads on credit rating dummies and on measures of volatility and jump risk with a set of controls (see Table 2 for a description of the variables). Five S&P credit rating groups are used: AAA, AA, A, BBB, and finally BB and lower. The control variables are the same as in Table 2, but their coefficients are not reported. Regressions 1 and 2 add rating dummies to regressions 1 and 3 of Table 2, respectively. Regressions 3 and 4 additionally interact the individual volatility and skewness measures (the ones of regressions 2 and 3 in Table 2, respectively) with rating dummies. Three S&P credit rating groups are used for the interaction: AAA to A-, BBB+ to BBB- ('II'), and BB+ and lower ('III'). The t-statistics in parentheses are corrected for heteroskedasticity, autocorrelation and cross-correlations.

Regression	Short-Maturity				Long-Maturity			
	1	2	3	4	1	2	3	4
IV		0.84	0.43	0.25		1.98	1.02	1.19
		(5.59)	(4.45)	(2.47)		(17.06)	(21.92)	(27.14)
IV × 'II'			2.96	1.75			2.39	1.50
			(22.69)	(13.25)			(46.93)	(21.95)
IV × 'III'			0.04	0.28			0.21	-0.85
			(0.17)	(0.77)			(0.73)	(-2.15)
Skew		0.04	-0.04	-0.05		0.02	-0.05	-0.03
		(3.35)	(-6.71)	(-7.85)		(1.43)	(-7.70)	(-5.63)
Skew × 'II'			0.40	0.34			0.22	0.17
			(19.49)	(19.42)			(15.21)	(12.83)
Skew × 'III'			0.00	0.00			-0.07	-0.13
			(0.04)	(0.01)			(-1.44)	(-2.92)
Hist. Vol.	1.72	1.22		0.51	1.65	0.25		-0.09
	(5.81)	(8.30)		(8.05)	(11.10)	(2.51)		(-2.47)
Hist. Vol. × 'II'				1.56				1.12
				(10.72)				(16.59)
Hist. Vol. × 'III'				-1.34				0.34
				(-2.41)				(0.52)
Hist. Skewness	0.16	0.15		0.10	0.14	0.13		0.18
	(12.14)	(9.93)		(12.61)	(9.13)	(8.75)		(36.83)
Hist. Skew × 'II'				0.14				-0.25
				(8.16)				(-19.49)
Hist. Skew × 'III'				-0.46				-1.59
				(-4.07)				(-16.03)
S&P IV		-0.88	-0.81	-0.62		-1.96	-1.80	-1.70
		(-3.76)	(-8.27)	(-6.22)		(-8.25)	(-18.90)	(-18.74)
S&P Skew		0.15	0.11	0.18		-0.17	-0.17	-0.15
		(2.52)	(4.53)	(6.94)		(-2.69)	(-7.70)	(-6.35)
S&P Hist. Vol.	-1.64	-1.20		-0.65	-0.43	0.28		0.62
	(-4.38)	(-2.79)		(-3.64)	(-1.01)	(0.61)		(3.64)
S&P Hist. Skew	-0.01	0.11		0.16	-0.04	-0.06		-0.01
	(-0.16)	(1.36)		(4.61)	(-0.62)	(-0.75)		(-0.25)
AA rating	0.17	0.16	0.24	0.23	-0.05	-0.12	-0.02	-0.03
	(10.06)	(8.70)	(31.03)	(30.84)	(-3.26)	(-7.36)	(-3.20)	(-6.00)
A rating	0.14	0.12	0.20	0.18	0.12	0.04	0.15	0.14
	(9.19)	(7.18)	(21.42)	(21.05)	(6.84)	(2.79)	(25.84)	(23.68)
BBB rating	0.47	0.45	-0.62	-0.83	0.57	0.48	-0.32	-0.35
	(25.73)	(24.38)	(-12.55)	(-15.28)	(33.95)	(30.65)	(-16.07)	(-17.66)
BB and below	0.33	0.28	0.41	0.86	0.87	0.75	0.82	1.61
	(12.81)	(9.76)	(5.16)	(6.16)	(25.25)	(21.35)	(9.25)	(9.75)
R^2	0.318	0.327	0.346	0.361	0.540	0.562	0.579	0.588
Adjusted R^2	0.317	0.326	0.346	0.361	0.539	0.562	0.579	0.588
# bonds/firms	308/61	308/61	308/61	308/61	168/48	168/48	168/48	168/48
# bond-weeks	30507	30507	30507	30507	22792	22792	22792	22792

Table 4: Average R^2 when Regressing Credit Spreads on Principal Components

This table reports the average cumulative R^2, the increase in the average R^2 from adding a PC, and the standard deviation of the cumulative R^2 across bonds when regressing raw credit spreads on each bond with at least 75 observations (out of a total of 349 weeks) on an increasing set of principal components (PCs). The first ten PCs are estimated using an EM-algorithm, where in each estimation step principal components are extracted, and in each maximization step missing values are set equal to the values fitted by a linear model including these principal components.

PC#	Cumulative R^2	Increase in R^2	Std. dev. of Cum. R^2
1	0.6678	0.6678	0.2749
2	0.8677	0.1999	0.1227
3	0.8952	0.0275	0.0933
4	0.9238	0.0286	0.0680
5	0.9391	0.0153	0.0524
6	0.9511	0.0120	0.0462
7	0.9604	0.0093	0.0297
8	0.9654	0.0050	0.0271
9	0.9697	0.0043	0.0252
10	0.9724	0.0027	0.0234

Table 5, Panel A: Regression of Structural Model Residuals on Principal Components

This table reports the R^2 of pooled panel regressions of the residuals from our main model (regression 3 in Table 2) on the set of five PCs. For comparison, we also report the R^2 of the pooled panel regression of the credit spreads themselves on this set of five PCs (first column for each maturity).

Panel A: Pooled	Short Maturity		Long Maturity	
Model	Constant	Table 2 (3)	Constant	Table 2 (3)
Res. on 5 PCs: R^2	0.2538	0.0074	0.4243	0.0063

Table 5, Panel B: Average Cumulative R^2 when Regressing Credit Spread Residuals on PCs

This table reports the average cumulative R^2 when regressing residuals from bond-by-bond regressions on the 5 systematic PCs (first row) and on the residual PCs (second row). The residuals are taken from bond-by-bond regressions of the credit spread of each individual bond with at least 75 weekly observations on the full model, which includes all volatility, implied-skew and control variables (regression 3 in Table 2). The residual PCs are the first five PCs extracted from the residuals of these bond-by-bond regressions.

Panel B: Bond-per-bond	Short Maturity				
# of PCs	1	2	3	4	5
Systematic PCs	0.0340	0.0847	0.1331	0.1791	0.2078
Residual PCs	0.1545	0.2800	0.3841	0.4353	0.4801
	Long Maturity				
# of PCs	1	2	3	4	5
Systematic PCs	0.0322	0.0784	0.1269	0.1741	0.2017
Residual PCs	0.1548	0.2303	0.4039	0.4615	0.5136

Table 6: R^2 when Regressing Residual PCs on the Set of Five PCs

This table reports the R^2 when regressing the residual PCs (defined in Table 5B) on the set of 5 PCs in raw credit spreads.

Residual PC	1	2	3	4	5
Short Maturity	0.2402	0.0286	0.1146	0.0436	0.2135
Long Maturity	0.2321	0.0362	0.0975	0.0417	0.2225