Yale ICF Working Paper No. 04-14
December 2004

# INDIVIDUAL STOCK-OPTION PRICES AND CREDIT SPREADS

Martijn Cremers
Yale School of Management
Joost Driessen
University of Amsterdam
Pascal Maenhout
INSEAD
David Weinbaum
Cornell University

# Individual Stock-Option Prices and Credit Spreads*

Martijn Cremers[†] Joost Driessen[‡] Pascal Maenhout[§] David Weinbaum[¶]

December 2004

**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 important information for credit spreads and improve on both implied volatilities of index options and 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 the implied-volatility skew matter for credit spreads. The empirical estimates are in line with the coefficients predicted by a theoretical structural firm value model. Importantly, detailed principal component analysis shows that our newly constructed determinants of credit spreads reverse the finding in the literature that structural models leave a large part of the variation in credit spreads unexplained. Furthermore, our results indicate that option-market liquidity has a spillover effect on the short-maturity corporate bond market, and we show that individual option prices contain information on the likelihood of rating migrations.

*We would like to thank 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 Day (Rochester), 2004 WFA (Vancouver) and EFA (Maastricht) meetings, the 2004 CEPR Summer Symposium in Financial Markets (Gerzensee) and the University of Amsterdam for their comments.

[†]Yale School of Management, International Center for Finance, Box 20820, 135 Prospect Street, New Haven, CT 06520. Email: martijn.cremers@yale.edu.

[‡]University of Amsterdam, Finance Group, Faculty of Economics and Econometrics, Roetersstraat 11, 1018 WB Amsterdam, the Netherlands. Email: J.J.A.G.Driessen@uva.nl.

[§]INSEAD, Finance Department, Boulevard de Constance, 77305 Fontainebleau Cedex, France. Email: pascal.maenhout@insead.edu.

[¶]Cornell University, Johnson Graduate School of Management, 375 Sage Hall, Ithaca NY 14853-6201. Email: dw85@cornell.edu.

# Individual Stock-Option Prices and Credit Spreads

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 important information for credit spreads and improve on both implied volatilities of index options and 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 the implied-volatility skew matter for credit spreads. The empirical estimates are in line with the coefficients predicted by a theoretical structural firm value model. Importantly, detailed principal component analysis shows that our newly constructed determinants of credit spreads reverse the finding in the literature that structural models leave a large part of the variation in credit spreads unexplained. Furthermore, our results indicate that option-market liquidity has a spillover effect on the short-maturity corporate bond market, and we show that individual option prices contain information on the likelihood of rating migrations.

In a seminal contribution, Merton (1974) developed the structural firm-value approach to the valuation of corporate bonds. According to 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 the structural firm-value approach to credit risk (see for instance Eom, Helwege and Huang (2003), or Duffie and Singleton (2003) for a textbook treatment). An important finding in this work 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).

In this paper, we propose to consider market-based proxies for two fundamental theoretical determinants of credit spreads, volatility and jump risk, that are directly 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 highly relevant for credit risk. In particular, 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 very natural to consider the market for out-of-the-money puts. Because the prices of these puts are particularly sensitive to jump intensity risk, they enable us to construct a market-based proxy, namely the option-implied volatility skew, for this determinant of credit spreads.

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 are indeed non-redundant securities. However, there is ample evidence in the option-pricing literature for violations of the complete-market assumption of the Black-Scholes model, and of priced jump and volatility risk (see Bakshi and Kapadia (2003b) and Bakshi, Kapadia and Madan (2003) for individual options).[1] Both at-the-money options as well as out-of-the-money put options are needed to fully capture and disentangle the respective effects of these two factors. Whether individual stock options do indeed add relevant and quantitatively important

[1]The importance of jumps and stochastic volatility in the equity index is studied in Andersen, Benzoni and Lund (2002) and Eraker, Johannes and Polson (2003). Evidence of priced jump and/or volatility risk in index options is presented in Ait-Sahalia, Wang and Yared (2001), Bakshi, Cao and Chen (1997), Bakshi and Kapadia (2003a), Buraschi and Jackwerth (2001), Coval and Shumway (2001), Pan (2002) and Rosenberg and Engle (2002), among others. See also Bates (2002) for an excellent survey.

information for credit risk is ultimately an empirical question and this constitutes the main focus of our paper.

We should also emphasize upfront that any evidence of a strong relationship between credit spread levels and implied volatility levels and skews is not simply reflecting the so-called 'leverage effect'. According to the leverage effect (Black (1976)), equity returns and volatility are negatively correlated because a decrease in the value of the firm lowers the value of equity and increases financial leverage, which in turn makes equity more volatile. We control for this leverage effect by including the firm's stock return in our regressions of credit spreads on implied volatilities and implied-volatility skews.

While prices (or equivalently, implied volatilities) of individual options have not previously been suggested as potential determinants of credit spreads on corporate bonds, CGM used information in index options in their analysis of the determinants of credit spread changes. However, by definition, index options cannot capture firm-specific information and are therefore unable to explain cross-sectional differences in credit spreads across issuers.

We therefore propose to explain credit spreads over time and across issuing firms based on implied volatilities and implied-volatility skews of the individual options on the issuers' equity. In recent work, Campbell and Taksler (2003) document a very strong relationship between the historical volatility of equity returns and bond yields. Individual options may provide us with a superior proxy of the volatility of the issuer since the measure is forward-looking rather than historical in nature. Furthermore, to the extent that volatility risk matters and is priced, this would be captured by implied volatilities, but never by a historical measure. As a second important explanatory variable we suggest the implied-volatility skew, which is interpreted as measuring the firm's jump risk, stemming from time-variation in the likelihood and severity of a downward jump in firm value.

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 on a number of explanatory variables. Because we regress credit spread levels, we can investigate the determinants of both the time-series variation and the cross-sectional variation in credit risk.

As our first contribution, we show that option-implied volatilities are extremely successful in explaining credit spreads, both over time and across firms. In particular, even though we impose a tight panel structure on the coefficients (using a pooled regression), implied volatilities alone can explain close to one third of the total variation in credit spreads. The coefficients on at-the-money implied volatility are highly significant both economically and statistically. Unlike alternative measures of volatility, our proxy is very robust to the inclusion of a large number of control variables. The implied volatility skew also manifests itself as a significant explanatory variable, especially for lower-rated firms. We provide further empirical support for our claim that individual options are relevant for understanding credit risk by showing the impact of option-market liquidity on the credit spreads of short-maturity bonds, and by documenting that option-implied volatilities anticipate downward credit rating migrations.

Importantly, option prices are shown to contain substantially more information about credit spreads than do credit ratings. The explanatory power in a pooled regression of credit spreads is 5 to 15 percentage points higher (depending on the maturity of the bonds) when regressing on option-based information than when using credit ratings as an explanatory variable.

As a second contribution, we calibrate a theoretical extension of the structural firm value model of Longstaff and Schwartz (1995) that allows for priced jump and volatility risk. We show that our empirical estimates are qualitatively in line with this model. For example, we find that the sensitivity of credit spreads to volatility and crash imminence is much larger for poorly rated debt (BBB+ or worse) than for bonds with strong credit ratings (A- or better).

Finally, we show as a third contribution that structural firm value models extended in this way can in fact explain the time-series variation in credit spreads adequately, contrary to what earlier work has suggested. Two important empirical findings substantiate this claim. First, adding time-dummies to the regressions has no impact whatsoever on the results. Secondly, detailed principal component analysis shows that our option-implied determinants of credit risk do explain the variation in credit spreads 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 spreads, as reported by CGM. If anything, our results may on the contrary be interpreted as showing 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 a role in our regressions.

The rest of the paper is structured as follows. Section 1 describes the bond and option data we use and presents summary statistics. The benchmark regressions explaining credit spreads are reported in section 2. Section 3 considers a number of extensions and additional control variables, as well as firm fixed effects and time dummies, and studies the effect of option-market liquidity on credit spreads. Credit ratings are introduced in section 4. The theoretical coefficients predicted by a structural firm value model with jump-diffusions are presented in section 5. As an application of our main results, section 6 documents patterns in implied volatilities around rating migrations. Section 7 uses principal component analysis to analyze whether our option-based variables explain all systematic variation in credit spreads. Finally section 8 concludes.

# 1 Data Description

## 1.1 Corporate Bond Prices

The data on US-dollar corporate bond prices are taken from the Bloomberg Corporate Bonds Database (BCBD), which contains mid-quotes for corporate bond prices. Besides these mid-quotes, the dataset contains for each bond the maturity date, the coupon size and frequency, the 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 a set of 69 firms for which both corporate bond data and equity option price data are available. This is a subset of the set of 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), observations on bond prices with remaining maturity less than one year are dropped. Most bonds are senior unsecured. We only include other bonds, such as subordinated bonds, if a bond has the same rating as the senior unsecured bonds of the particular firm. Most firms are rated investment grade throughout the sample period, but some firms become speculative grade in the last three years of the sample period. Two firms in our sample default, Comdisco and Enron.[2]

In total, we end up with 524 corporate bonds. There are several missing observations in the data, which is typical for corporate bond price datasets. Besides corporate bond price data,

[2] The default events however occur after the firms leave the sample and are therefore not driving the results.

we also use Bloomberg data on the 6-month US Treasury bill, and the most recently issued US Treasury bonds with maturities closest to 2, 3, 5, 7, 10, and 30 years.

For our empirical analysis, we use credit spreads of these coupon-paying corporate bonds, defined as the difference between the corporate bond yield and the yield on a government bond with exactly the same maturity and coupon size. Since we do not observe government bond yields for all relevant coupon sizes and maturities, we first estimate the term structure of default-free zero-coupon interest rates. We use the following extended Nelson-Siegel (1987) specification for these zero rates $R(t,T)$:

$$R(t,T) = \delta_{1,t} + \delta_{2,t}\frac{1-e^{-\delta_{3,t}(T-t)}}{\delta_{3,t}(T-t)} + \delta_{4,t}e^{-\delta_{3,t}(T-t)} + \delta_{5,t}\frac{1-e^{-\delta_{6,t}(T-t)}}{\delta_{6,t}(T-t)} \tag{1}$$

Each week, we estimate the parameters $\delta_{1,t},...,\delta_{6,t}$ by minimizing the sum of squared bond pricing errors for the Treasury bills and Treasury bonds over these parameters. To account for the fact that long-maturity bond prices are more sensitive to interest rates, we weight each pricing error by the inverse of the duration of the bond. Given this term structure of default-free zero-coupon rates, credit spreads on corporate bonds can readily be calculated. Finally, 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.

## 1.2 Options

The options data originate from OptionMetrics, LLC. This is a comprehensive dataset, covering all exchange listed call and put options on the entire universe of US equities. The data consist of end-of-day bid and ask quotes, open interest and volume, and cover the period January 1996 to September 2002; there are over 3 million option observations per month in the later part of the sample. In addition, with each option price quote OptionMetrics reports the option's implied volatility (calculated using American or European models, as appropriate). Implied volatility calculations use historical LIBOR/Eurodollar rates for interest rate inputs, and incorporate discrete dividend payments. At any given point in time, exchange traded options on US equities have four distinct expiration dates: there are options expiring over the nearest two months and the next two months of the underlying stock's expiration cycle. So as 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.

The implied volatility skew is calculated as the (left) slope of the implied volatility smirk: it 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.

### 1.3 Summary Statistics

We now turn to the summary statistics in Table 1 for the dependent variable and for the explanatory variables used in the benchmark analysis. The average credit spread in our sample is 103.1 basis points for short-maturity bonds and 110.9 basis points for long-term bonds. Credit spreads are highly volatile and exhibit substantial cross-sectional variation. While credit spreads are expressed in basis points, all other variables are expressed in their actual units. Therefore, the average implied volatility for individual options is 34.8% in our sample. Implied volatilities are also highly volatile, both in levels and in first differences, but exhibit somewhat less cross-sectional variation. Interestingly, the individual implied volatility exceeds on average the individual historical volatility, which can be interpreted as evidence of a volatility risk premium. The same is true for the S&P index. Not surprisingly, the volatility of the S&P index (both implied and historical) is substantially smaller than the average individual volatility. Another important finding is that the individual option-implied skew is extremely volatile, both in the time-series dimension and cross-sectionally.

In terms of correlations with credit spreads, individual volatility stands out. While the historical measure has a somewhat higher time-series correlation with credit spreads (averaged across bonds and firms), the cross-sectional correlation is most pronounced for option-implied volatility. The time-series and cross-sectional relation between credit spreads and the option-based volatility measure is presented graphically in Figures 1 and 3, respectively. The relation between the implied volatility skew and credit spreads is plotted in Figures 2 (average time-series) and 4 (cross-section). While the average time-series correlation is 25.8%, the (univariate) cross-sectional correlation is rather small. Finally, Table 1 shows that the historical measure of S&P volatility is highly correlated with the cross-firm average of the credit spread during our sample (82.2%).

## 2 Benchmark Results

We first turn to the benchmark regressions, where credit spreads are explained by alternative measures of volatility and jump risk. Based on the insights of a structural firm-value model (as explored in more detail in section 5) with jump-diffusions and stochastic volatility, the effect of volatility on credit spreads is expected to be positive. Option-implied skews can be interpreted as measuring jump risk, i.e. the severity and likelihood (or intensity) of a downward jump in firm value, and should therefore have a positive coefficient.

We only retain bonds for which at least 25 observations are available. The regressions are pooled, imposing the same coefficients over time and on different bonds and firms. We distinguish however between short-maturity bonds (between 1 and 5 years) and long-maturity bonds (at least 7 years to maturity), since the results are sufficiently different, as would be expected economically, to warrant separate regressions.

The regression coefficients are consistently estimated with OLS, but the standard errors we use to compute $t$-statistics are corrected for heteroskedasticity, autocorrelation as well as 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 the error term of each bond.

Another important feature of our empirical strategy is that we regress credit spread levels, rather than credit spread changes. We choose this specification for the following reasons. First, credit spreads are, economically speaking, not expected to be non-stationary, since they are ex ante expected return differentials. Second, there is no econometric evidence for non-stationarity, i.e. for a unit root in credit spreads. Furthermore, it is well known that first-differencing a stationary time-series and regressing changes rather than levels introduces noise into the estimation. Importantly, running the regressions in levels allows us to empirically 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, the focus would be on time-series variation only. Our results below indicate that this misses an important part of the analysis. While CGM limit their attention to credit spread changes, Campbell and Taksler (2003), among other papers in the literature, consider credit spread levels. Finally, the new determinants of credit spreads that we suggest in this paper require detailed data on individual stock options. While the OptionMetrics database we use for this is very extensive, the data does have some missing observations, which renders first-differencing less suitable.

Table 2 reports the benchmark regression results for weekly credit spreads of short- and long-maturity bonds. All regressions are contemporaneous. Results are reported for 3 sets of explanatory variables, where each set includes a measure of volatility and of downward jump risk. The first set considers individual implied volatility and the implied-volatility skew of the issuing firm. As a second set we use the option-implied volatility and implied-volatility skew of the S&P index. Finally, the third set contains all these explanatory variables simultaneously, along with the historical volatility of both the issuing firm and the S&P index, as a first step towards assessing the robustness of the different proxies. We consider these different sets of regressors because it allows a first exploration of the extent to which option-based information is useful in explaining credit spreads, both in absolute terms and in comparison with regressors previously used in the literature. Bakshi, Madan and Zhang (2003) and Campbell and Taksler (2003) investigate historical individual volatilities, CGM include implied volatility and skew for index options, and Campbell and Taksler (2003) and Huang and Kong (2003) use historical index volatility.

## 2.1 Individual Option-Implied Measures

When regressing weekly credit spreads on individual implied volatility, the individual implied-volatility skew and a constant (regression 1), both option-based measures are extremely statistically significant, for short- as well as long-maturity bonds. The coefficients are large and have the expected sign: an increase in implied volatility and in implied-volatility skew both widen the credit spread, reflecting the rise in the market's assessment of the firm's volatility and jump risk, respectively.

To gauge the economic significance more systematically, 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 according to the estimated coefficient, a one-standard-deviation weekly shock in implied volatility leads to a widening of the credit spread by almost 12 basis points for short-maturity bonds and by 20 basis points for long-maturity debt. The implied-volatility skew has a smaller coefficient, but is much more volatile. A typical weekly one-standard-deviation shock in the implied-volatility skew increases the credit spread of that issuer by slightly less than 10 basis points, for both maturities.

Finally, the $R^2$ of the regression for short-maturity bonds is 14%. Option-implied volatility and skew alone explain more than one seventh of the cross-sectional and time-series variation in credit spreads, even though short-maturity bonds are used (which are typically harder to explain, see for instance the structural-model approach of Huang and Huang (2003)) and even though the pooled regression imposes identical coefficients across all bonds, across all firms and throughout the sample period. For long maturities however, the $R^2$ of the regression more than doubles: measures of volatility and jump risk based on individual stock-option prices explain roughly one third of the variation across firms and over time in credit spreads, without the inclusion of any other explanatory variables.

## 2.2 Aggregate Option-Implied Measures

In order to compare our results with CGM, we now regress credit spreads on option-implied measures of volatility and jump risk based on S&P index options.

The aggregate implied-volatility measure is statistically significant, but seems to have less economic impact on credit spreads than individual options. A weekly one-standard-deviation shock in the S&P implied volatility changes credit spreads by almost 6 (short-maturity) to 10 (long-maturity) basis points. While this is about half the economic impact of the individual implied-volatility, it is clear that this shock actually affects credit spreads of all bonds simultaneously and is therefore far from negligible. The S&P implied skew does not matter for short-maturity issues, but comes in with the wrong sign for long-maturity debt. However, we will show that this counter-intuitive effect is not robust to the inclusion of various control variables. S&P-based variables cannot explain any cross-sectional variation in credit spreads and only pick up time-series variation. This is reflected in the very low $R^2$ (2% and 5%). CGM obtained similar results, but using a different methodology: they run bond-by-bond regressions and report average results, while we impose constant coefficients in a pooled regression. Also, they analyze the determinants of credit spread changes, and not of credit spread levels as we do here. The results are therefore not fully comparable, although one would certainly expect a much higher average $R^2$ in bond-by-bond regressions for our sample. Section 7 (principal component analysis) will show that this is indeed the case.

### 2.3 Individual and Aggregate Measures

Combining both sets of regressors, along with historical measures of individual and index volatility gives a first indication about the robustness of the results. As can be seen from regressions 3 in Table 2, the individual option-based measures remain very significant. The point estimates are naturally somewhat smaller, but the economic impact of these variables on credit spreads continues to be nontrivial: a weekly one-standard-deviation shock to either variable moves short-maturity credit spreads by 5 to 6 basis points. For long-maturity bonds, the results are particularly striking: individual option-implied volatility emerges as the most important firm-specific determinant of credit spreads. Despite the inclusion of other proxies for volatility among the set of regressors, individual implied-volatility has now the most significant coefficient ($t$-statistic of 23.13). Its economic impact is substantial: a one-standard-deviation weekly increase in the implied volatility of an issuer widens its credit spread by 13 basis points. An equivalent increase in the implied-volatility skew induces a 7 basis point increase, with a $t$-statistic of 11.95.

Turning now to the historical measure of the volatility of an issuer's stock return, we first of all replicate Campbell and Taksler's finding of a very significant coefficient on historical stock return volatility, especially for short-maturity bonds. Assessing the economic importance is less straightforward than for option-based measures. Since historical volatility is calculated using the past 180 return observations, the weekly change in the measure is by construction bound to be small. This is in fact a major disadvantage over option-based measures, which are more forward-looking and which can and do change substantially from week to week. This is clear for instance when comparing the standard deviations of weekly changes for implied and historical volatility in Table 1 (0.046 versus 0.012). Therefore, in order to interpret the economic significance of historical proxies more directly, the historical volatility variable is rescaled for all regressions so that it has the same time-series standard deviation (on average across all bonds) as the corresponding implied measures. That way, we can directly compare the estimated coefficients. Doing this reveals that historical volatility has a slightly larger economic effect on short-maturity bonds than does option-implied volatility. However for long-maturity credit spreads, it is clear that the economic impact is much smaller for the historical proxy than for the option-implied measure of volatility.

Interestingly, the sign of the S&P implied volatility flips for both maturities due to the correlation structure of the variables included in the regression. In contrast, our individual measures seem much more robust to these correlation effects. Also, both index-based implied measures become statistically insignificant for short-maturity bonds. Notice also that the S&P implied skew continues to have the 'wrong' sign for long-maturity credit spreads.

Finally, moving to the historical aggregate measure of volatility (as used also in Campbell and Taksler (2003) and in Huang and Kong (2003)) we obtain rather surprising results. The coefficient on historical S&P volatility is very large and statistically significant. This may raise the suspicion that the historical S&P volatility is simply picking up the economic effect of other economy-wide determinants of credit spreads, such as the business cycle and interest rates. We will address this issue in the next section, where we show that these findings are not robust to the inclusion of additional economic control variables.

Even though we impose a tight structure on the coefficients through the use of a panel and even though any other explanatory variables are lacking, the pooled panel regression explains 22% of the cross-sectional and time-series variation in credit spreads of short-maturity bonds. For long-maturity debt, the $R^2$ of the regression is 40%. Since implied volatility and the implied-volatility skew (based on individual options) alone had $R^{2\prime}s$ of 14% and 32%, for short- and long-maturity respectively, adding 4 more explanatory variables increases the explanatory power of the regressions somewhat, but not by much. In fact, in section 4.2 we will show that our two option-implied measures alone can do at least as well by specifying the regression differently.

# 3 Robustness and Sensitivity Analysis

To analyze the robustness of the benchmark results, we now consider a variety of extensions. First, we add a number of regressors that have been shown in the literature to have explanatory power for credit spreads. Second, we introduce year dummies and firm fixed effects to explore to what extent our option-based measures explain cross-sectional versus time-series variation. Finally, we present some evidence of liquidity spillovers between the options market and the corporate bond market, by showing that simple proxies for liquidity in the options market affect credit spreads.

## 3.1 Control variables

A number of papers have examined the determinants of credit spreads. It is therefore important to investigate whether our option-based variables are just proxying for these determinants or whether they provide indeed additional explanatory power.

A first natural control variable is the firm's past stock return. Kwan (1996), CGM and Campbell and Taksler (2003) 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 alternatively, as being a high-frequency proxy for leverage. The latter interpretation is important since one may think that our results reflect the so-called leverage effect (the negative correlation between equity returns and equity volatility) combined with the empirical finding that equity returns and yield changes are negatively correlated. To control for this, we now simply include the firm's past stock return. 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, Campbell and Taksler (2003) 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 Duffee (1998 and 1999), CGM, Campbell and Taksler (2003), Driessen (2003), Elton, Gruber, Agrawal and Mann (2004) and Huang and Kong (2003), among others. The general empirical finding is a negative relationship between default-free rates and credit spreads. One explanation for this effect 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 as well as 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.

The general trend in the level of credit spreads over time is controlled for by including the BAA rate. CGM show it has explanatory power on top of many other variables. 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 Campbell and Taksler (2003)). All these data are obtained from Datastream.

The introduction of these additional economically motivated control variables has a number of interesting implications in Table 3. First, the individual option-based measures turn out to be very robust. Although the coefficients on the implied volatility and implied-volatility skew of the issuing firm shrink, they remain statistically and economically significant. Individual implied volatility comes out as a very important determinant of credit spreads on long-maturity bonds: the coefficient of 2.38 means that a weekly one-standard-deviation shock to implied volatility moves credit spreads for long-maturity bonds by 11 basis points. Statistically, it is the single most significant regressor with a $t$-statistic of 21. Interestingly, the skew variable now matters most for short-maturity credit spreads. It should not come as a surprise though that the coefficients become smaller. The controls include for instance the BAA rate, which captures the overall trend in credit spreads. To the extent that the option-implied variables measure this trend as well, it is to be expected that their coefficients become smaller. The fact that they remain important highlights that the measures capture more than just the overall trend, i.e. they carry relevant information beyond the BAA rate.

Individual historical estimates of volatility continue to play an important role, but mainly for short-maturity credit spreads. The introduction of other macroeconomic and market-wide variables clearly matters for the aggregate S&P-based measures. These are not robust to the inclusion of additional controls and have in fact the wrong sign in many cases. For instance the coefficient on S&P historical volatility drops from 5 in Table 2 (long-maturity bonds, regression

3) to essentially zero in the last column of Table 3. This suggests that the earlier results simply reflected to a large extent the correlation of the S&P-based measures with other market-wide variables: for instance both the S&P implied volatility and the S&P historical volatility are highly correlated with the 10-year yield (correlation of -56% and -70%, respectively) and with the market return (-44% and -64%, respectively).

Consistent with earlier work, we find significant and robust coefficients for the interest rate variables considered: the 2-year yield, 10-year yield, BAA rate and to a lesser extent also the (10-year) swap rate emerge as relevant explanatory variables for credit spreads. The firm and market return only matter for long-term bonds, but have rather small effects economically speaking. This may of course also 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 for instance Janosi, Jarrow and Yildirim (2002) and Driessen (2003). Finally, the $R^2$ increases by 8 to 15% for long-maturity bonds and by 6 to 12% for short-term corporate debt.

### 3.2 Year Dummies and Firm Fixed Effects

As a next robustness check, we introduce year dummies in the regression with all other controls of Table 3. Two conclusions can be drawn from this exercise.

First, individual implied volatilities and implied skews pick up more than just time-variation in credit spreads, both for short- and long-maturity bonds. This can be seen in Table 4, since year dummies have very little impact on the effect of these variables. If anything, the coefficients become actually slightly larger and more significant. The coefficients on the S&P-based measures however, as well as on some of the control variables (e.g. the market return), shrink substantially with the inclusion of year dummies, since they only pick up time-series variation. Second, the fact that the $R^2$ is essentially unchanged means that our explanatory variables already account for all low-frequency time-variation.

To understand how much cross-sectional variation in credit spreads is left unaccounted for, we augment the regression to include firm dummies or firm fixed effects. Unlike year dummies, issuer fixed effects do change the results somewhat. The coefficient on individual implied-volatility increases from 0.87 to 1.32 for short-maturity bonds and drops from 2.38 to 1.69 for long-term bonds. In both cases the coefficients remain very statistically significant, with $t$-statistics of 10.3 and 17, respectively. The biggest change can be observed for the coefficient on the individual option-implied skew for long-term bonds, which increases from 0.04 to 0.096 and now has a $t$-statistic of 7.58. 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 (or at least with a smaller coefficient): 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. When going back to the simple descriptive statistics studied in the previous section (Table 1 and Figure 4), this is not too surprising, since the cross-sectional relation between option-implied skews and credit spreads was considerably less strong.

Another important finding in Table 4 is that the $R^2$ 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% (short-maturity) and 48% (long-maturity) without fixed effects suggests that individual options do not exhaustively explain the cross-section of credit spreads, even though they are very important determinants. Other issuer-specific factors seem to be reflected in credit spreads.

### 3.3 Option-Market Liquidity

As a final extension, we now consider the liquidity of the market for individual options. Although several articles have analyzed the liquidity of corporate bond markets, a study of the impact of option-market liquidity on credit spreads is lacking. A motivation for considering option-market liquidity is that it may have an effect on credit spreads beyond and in addition to the influence of implied volatilities and option-implied smirks. This may happen because of a liquidity-spillover effect: some corporate bonds may be rather illiquid and investors may require an additional premium as compensation for this illiquidity. If the liquidity of a corporate bond of an issuer is correlated with the liquidity of its traded options, then an issuer-specific measure of option-market liquidity should matter for the credit spreads of that issuer.[3] This relation between option-market illiquidity and credit spreads may also reflect hedging activities if issuer-specific credit risk as present in corporate bonds can to some extent be hedged by trading in individual options of that issuer. If these options are particularly illiquid, then hedging becomes more difficult and more costly. This cost may manifest itself in the discount at which the corporate bonds are trading, i.e. in the credit spread.

As a firm-specific measure of the liquidity of its traded options we use the bid-ask spreads on both out-of-the-money and at-the-money options. Table 5 shows the pooled regression results when adding these measures to all other controls. Two findings are noteworthy. First, the coefficients on implied volatility and on the implied-volatility skew change slightly, but mainly for short-maturity bonds. Second, the coefficients on the option-liquidity proxies are rather large and significant for short-maturity bonds, but zero in the last column (long-maturity bonds). This is quite sensible, since previous articles have shown that the liquidity spread is largest for short-term bonds (e.g., Janosi, Jarrow, and Yildirim (2002) and Driessen (2003)). Also, for short-maturity bonds, it is the effect of the bid-ask spread on out-of-the-money options that is most precisely estimated ($t$-statistic of 9.21), which is also reasonable since out-of-the-money options tend to be more illiquid than at-the-money ones.

# 4 Incorporating Credit Ratings

Credit ratings have been shown to have explanatory power for credit spreads, even when controling for economic determinants of spreads (e.g. Campbell and Taksler (2003)). We therefore include these ratings along with the other variables considered so far. We then proceed to study the interaction between credit ratings and our measures of the option-market assessment of the volatility and jump risk of a firm, in order 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 (presented in section 5).

[3] Since we do not have bid-ask spreads for corporate bond prices (only mid-quotes), we cannot directly relate option-market liquidity to bond-market liquidity.

### 4.1 Credit Ratings as a Control Variable

Standard and Poor's classify issuing firms into 26 different categories based on their risk of default. Even with our reasonably large sample, it is not meaningful to distinguish all 26 distinct groups. We therefore aggregate up the different ratings into 5 groups: AAA, AA, A, BBB, and finally BB and lower.

We first regress credit spreads for short- and long-maturity bonds on a constant and four rating dummies (Table 6). The rating dummies are highly statistically significant and have the expected sign: poorly rated bonds on average have higher credit spreads. The explanatory power of these regressions is quite limited however, with an $R^2$ of 9% for short-maturity bonds and 17% for long-maturity bonds. Interestingly, this is substantially less than when regressing credit spreads on the measures of volatility and of jump risk implied by individual option markets. In Table 2 we found that implied volatility and the option skew alone explain 14% of the variation in short-maturity credit spreads and 32% for long-maturity bonds, which is respectively 5 and 15 percentage points higher.

The arguments made by Campbell and Taksler (2003) to explain the relatively poor results with ratings apply here a fortiori. First, ratings are updated slowly and gradually, while our measures exhibit much more high-frequency variation. In addition, our option-based measures are forward-looking in nature. Second, credit ratings have less cross-sectional explanatory power by construction, due to the discreteness of the rating categories (which we exacerbated by further aggregation into just 5 categories): they cannot explain differences in credit spreads for bonds with the same rating, unlike our issuer-specific variables.

In spite of their rather limited explanatory power, the rating dummies remain statistically significant when all other control variables are added, especially the ones for the categories closest to default. The individual implied-volatility measure continues to be highly statistically and economically significant. In fact, the point estimate in the regression for short-maturity bonds increases slightly. The implied-volatility skew variable on the other hand shrinks when controling for ratings and becomes less statistically significant. Its economic significance also becomes quite small: a 1-standard-deviation weekly shock to the option-implied skew changes credit spreads by around 1 (long-maturity) to 2 basis points (short-maturity bonds). It seems that the skew variable, at least to some extent, picks up information that is also conveyed by credit ratings. Of course, the smaller coefficients on the skew variable may well be due to the large number of regressors and control variables included, so that disentangling the different effects becomes difficult.

Finally, it can be seen that credit ratings are quite complementary to the fundamental economic variables: the $R^2$ increases from 28.8% to 32.1% for credit spreads on short-maturity bonds and from 48% to 56% for long-term bonds, suggesting that ratings do convey additional information not already present in the economic variables we consider.

### 4.2 Interaction Terms

So far, we have found empirical support for the prediction of an extended 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 of the firm value of the issuer and of its jump risk. A further and more precise prediction that will be analyzed in the structural firm value model of Section 5 is that the sensitivity of credit spreads to volatility and jump risk typically increases as the firm gets closer to the default boundary. To test whether the impact of volatility and of jump risk on credit spreads is indeed different for lower-rated issuers than for investment-grade firms, we now interact the credit rating with our option-implied measures of the volatility of the firm value and of the jump risk of the issuer. Since the historical volatility of the return distribution is a potential alternative measure of volatility risk, we also interact the credit ratings with this historical proxy. Because some of the rating categories contain too few bonds, we pool the data for this purpose into 3 categories: AAA to A-, BBB+ to BBB-, and BB+ and lower.

The first regressions reported in Table 7 replicate the basic regressions of Table 2, where spreads are explained by individual implied volatility and the implied-volatility skew only (with a constant), but now allow for interaction with the credit rating, for short- and long-maturity bonds respectively. The sensitivity of credit spreads to implied volatilities increases significantly as the credit rating deteriorates from category 1 to category 2, in line with the prediction of the model. The reported coefficients are additive, so that (for instance) a BBB long-maturity issuer (category 2) faces a 4.7 total coefficient on its implied volatility, while the impact for investment-grade issuers in category 1 is given by the coefficient of 3.47. This means that a one-standard-deviation weekly shock in implied volatility changes the credit spread by 16 basis points for an A-rated issuer and by 22 basis points for a BBB firm (versus 20 basis points in the benchmark regression without credit-rating interaction terms). Long-maturity junk-bond issuers (category 3) also have significantly higher coefficients than investment-grade firms in category 1, but, surprisingly, somewhat less so than firms in category 2. Note that the incremental effect for short-maturity issuers in category 3 relative to category 1 is insignificant, because of the small number of observations in that cell.

The results of the interaction between the implied-volatility skew variable and credit ratings are also intuitive and actually stronger quantitatively than for the implied volatility level. For short-maturity bonds, an increase in the option-implied skew has more than twice as much impact for firms in category 2 than for issuers in category 1 (total coefficients of 0.32 and 0.15, respectively). The effect of the volatility skew on long-maturity credit spreads is almost 4 times larger for a junk-bond issuer than for an investment-grade firm in category 1 (total coefficients of 0.463 and 0.117, respectively). In particular, a one-standard-deviation weekly shock to the implied-volatility skew changes the long-maturity credit spread by only 4 basis points for category 1 firms, by 13 basis points for category 2 and by 17 basis points for high-yield issuers. Allowing for interaction increases the fit of the regression substantially: from 14% to 21.5% for short-maturity and from 32% to 42% for long-term bonds.

When adding all the control variables, including alternative measures of volatility and jump risk, the same results obtain. Remarkably, the effect of the option-based volatility-risk measure on long-maturity credit spreads is now extremely precisely estimated, as is clear from the large $t$-statistics. While the coefficients are naturally smaller than without the control variables, adding the controls actually strengthens the relative effect of the rating interaction with option-implied volatility. This also happens for the implied skew. We now even find that highly-rated bonds have no (for short-maturity) or a slightly negative - but economically small - (for long-maturity) coefficient on this proxy for jump risk, while category 2 (both maturities) and 3 (long-maturity only, as before) have remarkably large sensitivities. This finding can explain why before, i.e. without allowing for the interaction with credit ratings, the implied volatility skew sometimes became less significant for long-maturity bonds. Notice that the interaction of historical volatility with credit ratings produces insignificant results for short-maturity spreads, while for long-maturity bonds the coefficient on the historical measure of volatility is significantly negative.

With the credit rating interaction and the controls, the $R^2$ grows to 34% for short-maturity bonds (from 29%) and to 57% for long-term bonds (from 49%). The high explanatory power of these regressions, combined with the finding that most coefficients are estimated extremely precisely (especially for long-maturity debt) may suggest that the rating interaction is in fact crucial for the correct specification of the empirical model, precisely in line with the theory, as will be clear from the next section.

# 5 Theoretical Coefficients in a Structural Firm Value Model

Our empirical results provide evidence that both the implied volatility and implied skew are important determinants of credit spreads. An obvious and important question is whether the empirical relationship is in line with the predictions of theoretical firm value models. In this section, we therefore explore the implications of a jump-diffusion firm value model. We incorporate both a jump and diffusion component in order to allow for a separate role of the volatility and skew effects. More precisely, we analyze the same jump-diffusion model and calibration procedure as Huang and Huang (2003). The firm value volatility and the jump intensity are constant in this jump-diffusion model, and the jump size follows a double-exponential distribution. The model has a constant and continuous default boundary, as in Longstaff and Schwartz (1995). Finally, the term structure of interest rates is modeled to be constant and flat, and the firm has a constant asset payout rate.

Before turning to the calibration details, two important remarks are in order. First, note that this model is clearly a simplified version of what we believe is captured by the empirical analysis. In the empirics, we interpret implied volatility and the implied-volatility skew as proxies for volatility risk and jump intensity risk, respectively. The theoretical model analyzed here has constant volatility and a constant jump intensity. Nonetheless, varying these fixed parameters allows us to compute the theoretical partial derivatives of credit spreads with respect to theoretically calculated proxies for these parameters, in exactly the same way as one can calculate the 'vega' or sensitivity of the value of a plain vanilla call option to a change in volatility in a Black-Scholes model, even though volatility is assumed to be constant in that model. Second, although both the volatility of the underlying firm value and the jump intensity are fixed, equity options are not redundant, but needed to complete the market because of the presence of jumps in the firm value process. Due to these jumps, the options are not priced by the Black-Scholes-Merton formula and an implied-volatility skew is obtained.[4]

The calibration procedure of Huang and Huang consists of three steps. In a first step, a particular choice for the parameters in the jump process is made. Since no direct estimates for these parameters are available, we will provide results for different sets of jump process parameters. Second, the default-free interest rate, the payout rate of the firm, and the default boundary are fixed at reasonable levels of, respectively, 8%, 6%, and 100%.[5] Third, the remaining four parameters in the model (the volatility of firm value, expected return on firm value, initial firm value, and recovery in case of default) are calibrated to match four historically estimated quantities: the average leverage ratio, average equity return, average recovery rate, and the 10-year cumulative default rate. Except for the recovery rate, Huang and Huang allow these target quantities to vary across rating categories. The calibration procedure thus matches historical losses on corporate bonds, as well as the historically observed equity premium. For further details on the model and calibration procedure we refer to Huang and Huang.

Given the results of the calibration, we calculate for each rating category the credit spread on a 10-year par coupon bond. We simulate under the risk-neutral measure to obtain prices for the bond, equity, and equity options in the firm value model. Next, we numerically calculate the partial derivatives of the credit spread with respect to the implied volatility and the implied skew, by appropriately varying the underlying firm value volatility and jump intensity parameters. For example, to calculate the partial derivative of the credit spread with respect to the implied skew, we first of all increase the jump intensity and assess the (positive) effect on the implied volatility, implied skew, and credit spread. Next, we appropriately decrease the firm value volatility such that the total effect on the IV is constant, and calculate the net effect of the implied skew on

[4] A second reason why Black-Scholes-Merton is invalidated is the leverage effect: options on the equity of the firm are compound options since equity is itself a call option on the underlying firm value. Even in a pure diffusion setting, implied volatilities of equity options exhibit a skew (Geske (1979) and Toft and Prucyk (1997)). The model we simulate here predicts a skew both because of the jump risk and because of the leverage effect.

[5] Huang and Huang (2003) mostly use a default boundary of 60% of the face value of the debt. Instead, we use a default boundary of 100%, which seems more sensible since we price both equity and debt.

the credit spread.

As mentioned above, appropriate estimates for the jump parameters are not available from the existing literature. We therefore analyze three sets of jump parameters that seem reasonable. To be conservative, we set the jump risk premium equal to zero. Also, we only allow for downward jumps, as these are most relevant for our analysis of the implied skew. In this case the jump size follows an exponential distribution. The two remaining parameters are the jump intensity and the exponential-distribution parameter. Our benchmark case has a jump intensity of 0.4 on an annual basis, which corresponds to 1 jump every 2.5 years, and an average jump size of 20%. We also consider two cases with more frequent jumps (0.8 and 1.6 intensity) of smaller size (10% and 5%, respectively). Finally, we also consider a different variation of the benchmark case: instead of a continuous default boundary, we consider the case with default at maturity only. This case is included to compare our results to those of Campbell and Taksler (2003). They analyze the relationship between volatility and credit spreads using the Merton firm value model, i.e. without jumps and with default at maturity only.

Table 8 reports the theoretical sensitivities of the credit spread with respect to the implied volatility and skew, according to these 4 different assumptions about jump size (and intensity) and default boundary. The coefficients are defined so that they are directly comparable to the empirical regression coefficients. Starting with implied volatility, we obtain theoretical coefficients that are large and increase monotonically as the rating worsens. The theoretical partial derivatives are not highly sensitive to the assumed jump intensity and mean jump size. The assumption about the default boundary does have a major impact however, especially for lower-rated firms. This can be understood by realizing that the poorly-rated firms are closer to the default boundary. An increase in the asset volatility for a firm that is close to the default boundary will affect its credit spread more if default is possible before maturity and not just in 10 years, as in the Merton model. Finally, it is interesting to note that the results for the last column (without a continuous default boundary) are similar to the ones presented in CT. This is not obvious however, since CT do not have jumps in their analysis.

These theoretical coefficients can be compared with the results from regression 1 (without other controls, as for the theoretical coefficients in Table 8) for long-term bonds in Table 7. The total coefficients for implied volatility are estimated to be 3.47 for category 1 (A- or better), 4.72

for category 2 (BBB+ to BBB-) and 4.45 for category 3 (BB+ and worse). Broadly speaking, it seems therefore that these estimates are not too far removed from the predictions of the theoretical model, for 'reasonable' sets of parameters.

Turning to the bottom panel of Table 8 with the theoretical partial derivatives of credit spreads with respect to the volatility skew, we also find fairly large coefficients. These vary more across columns however than do the coefficients on implied volatility, which is natural since the different columns represent alternative assumptions about the jump intensity and mean jump size and since the implied volatility skew proxies for jump risk. For the column with the smallest average jump size (5%) and highest intensity (1.6), the coefficients are remarkably smaller. This makes sense since having more frequent but smaller jumps in the limit approaches the limit case where very small, fixed-size jumps occur very frequently, in other words jump risk vanishes and skew has no impact that is not already captured by the implied volatility. Across rows, an interesting result is that the effect of the volatility skew on credit spreads first increases, but then decreases as the firm gets closer to the default boundary. Eventually the effect even becomes negative (except in column 2). This is due to the fact that we calculate partial derivatives, which means that when changing the jump intensity we lower the firm value volatility so as to keep the implied volatility constant. For B-rated firms, the negative effect on credit spreads of the decrease in the firm value volatility that needs to accompany the increase in jump intensity (which itself has a positive effect on the credit spread) actually dominates.

Comparing with our estimates in Table 7, where the total coefficients are 0.12 (category 1), 0.37 (category 2) and 0.46 (category 3), we see that the theoretical coefficients are in most cases in fact substantially larger than our empirical coefficients. Difficulties in measuring the empirically option-implied volatility skew precisely may be responsible for this. But it is comforting to know that the fairly large estimates we obtain are certainly not unreasonable.

Finally, the theoretical coefficients in Table 8 are typically larger for implied volatility than for the volatility skew. This prediction finds very strong support in our sample, since the empirical estimates for the skew effect are an order of magnitude smaller than they are for IV. Other empirical findings are less in line with the theoretical implications of Table 8: we obtain that the response to the implied skew increases dramatically as the rating worsens, while the sensitivity to IV is less dependent on the credit worthiness of the issuer, while in fact the opposite obtains in Table 8. By and large however, this section is meant as a first exploration and lots of interesting work in this area remains for future research. It is fair to say that our empirical estimates are in line with the predictions of a structural firm value model with jump-diffusions, for reasonable parameter choices.

# 6 Implied Volatility Patterns around Rating Migrations

In order to shed more light on applications of the relationship between credit markets and individual option markets, and in particular to understand to what extent individual stock-option prices carry information that is relevant for credit risk, we now study the dynamics of implied volatilities of individual options during periods of rating migrations. A number of papers have analyzed the impact of changes in credit ratings on stock and bond prices. The effect of rating migrations on option prices however has not been documented before. If prices of options already incorporate the information that triggers the change in credit rating, we would expect to observe different dynamics of option prices for migrating firms than for non-migrating firms before the announcement. If however the change in credit rating represents new information, not previously reflected in option prices, the main effect on the dynamics of option prices would be expected after the announcement. A detailed study could try to test whether option prices can be used to predict rating changes with a probit analysis or could use option information to model the dynamics of the migration probability matrix (extending for instance Kavvathas (2000)). Since our sample only contains a limited number of rating changes[6], we instead conduct an informal and purely exploratory analysis. We report the patterns in the implied volatilities of firms that migrate and compare with a control group of all non-migrating firms during the same time-period in order to correct for general trends. We distinguish between upgrades and downgrades, because the work on stock and bond price reactions to rating changes has found that the results depend on whether the change concerns an upward or a downward migration (see for instance Hand, Holthausen and Leftwich (1992), Hull, Predescu and White (2004) and Katz (1974)).

Figure 5A shows the average implied volatility for 4 groups of firms, computed as follows.

[6] The number of observations declines further if we insist on having data on implied-volatility skews of the migrating firms. For this reason, we are forced to focus on patterns in implied volatilities only.

For each downgraded firm, we first find the date of the rating change and the implied volatility of its traded at-the-money options during the 32 weeks around the event date. We then calculate the average implied volatility across all non-downgraded firms (the control group) over the same 32 weeks. Having done this for each migration event, we then average across all downgrades, to obtain the average implied volatility for downgraded firms and for the control group, as plotted in Figure 5A. The same is done for upgrades, where the control group consists of all non-upgraded issuers.

A number of interesting results emerge in Figure 5A. First, it is clear that downgrades tend to occur during volatile times, while upgrades happen in periods with lower implied volatilities, since the controls groups exhibit on average higher implied volatilities around downgrade events than around upward migrations. Second, the issuers that are downgraded have substantially higher implied volatilities. Focusing now on the time pattern of implied volatilities, we find for downgraded issuers that the option market's assessment of the volatility of firm value rises during the months preceding the migration and peaks 2 to 3 weeks before the rating change announcement. This suggests that option markets anticipate to a large extent the downgrade, or at least, that most of the information triggering the migration is already reflected in the option prices. Subsequent to the downgrade, the implied volatility of the affected firms tends to decrease, but only very gradually. The implied volatility remains well above the level for non-downgraded firms, even 16 weeks after the event. One reason for this could be that lower-rated firms tend to have higher implied volatilities. Upgraded firms on the other hand are less dramatically different from other firms. Although the implied volatility for issuers that are upgraded is typically lower than for all other firms, the difference is quite small. Furthermore, firms that experience upward migrations see essentially no change in their implied volatilities during the months preceding the rating change. Interestingly, their implied volatility fully reverts back to the mean for non-upgraded firms during the month subsequent to the rating change.

These findings are consistent with the results in the literature that downgrades have a larger effect on credit spreads and equity prices than do upgrades.[7] The fact that implied volatilities of downgraded issuers are substantially higher and remain high after the rating change is also

[7] As a caveat however, it should be pointed out that the lack of striking results for upgrades may also simply be due to the small number of upward migrations in the sample (34 upgrades versus 73 downgrades).

in line with Cantor and Hamilton (2004) who find that current rating practices attempt to limit rating reversals and rating change volatility, so that different issuers carrying the same rating may have vastly different risks of rating migration and default. Of particular interest to us, Cantor and Hamilton (2004) find that recently downgraded issuers have a greater likelihood of future rating downgrades and default. For example, issuers downgraded in the past twelve months are eight times more likely to be downgraded than upgraded in the next year.

As a next step, we classify firms into the 3 broad rating categories of the previous sections (AAA to A-, BBB+ to BBB-, and BB+ and lower), based on their pre-migration rating. However, we continue to identify all rating changes: for instance, a firm that is downgraded from AA to AA- is included in the group of downgrades (of rating category 1), even though it stays within the same category. The various control groups are also constructed using firms belonging to the respective rating category. A first finding is that within each pre-migration rating category, downgraded firms have substantially higher implied-volatilities. This lends further support to our claim that firm-specific option-implied volatility matters for credit risk, since within a given rating category the implied-volatility essentially provides information (on average) about subsequent downgrades, i.e. about increases in credit risk as perceived by the rating agency. Comparing Figures 5B, 5C and 5D, a striking result is that the strongest quantitative effect occurs for downgrades in categories 2 and 3. Firms that are already poorly rated and that experience a further downgrade, have extremely high implied volatilities that (on average) reach twice (category 2) or even three times (category 3) the implied volatility of firms in the corresponding control group. It is also noteworthy that the implied volatility of downgraded issuers in the weakest group (category 3) continues to increase after the downgrade and peaks roughly half a month later. As in Figure 5A, the difference between upgraded firms and other issuers is very small.

# 7 Principal Component Analysis

In this section, we investigate the extent to which our main variables of interest in conjunction with the control variables suffice in capturing systematic credit spread variation. In doing so, we revisit one of the most striking claims in CGM, namely that a large fraction (75%) of the residual variation is captured by the first principal component (PC). CGM interpret this 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 $R^2$ [found in their paper] is likely not due to noisy data, but rather to a systematic effect." However, our results reverse both conclusions, as we find that essentially all systematic variation is captured by our variables suggested by the structural model.

First, we extract the first ten principal components (PCs) from the raw - not residual - credit spreads. In particular, we create an unbalanced sample that combines the credit spread of both short and long maturity bonds, and estimate the principal components using a simple EM-algorithm to deal with the many missing data.[8] Table 9 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%. The number of statistically significant factors in credit spreads is difficult to estimate and outside the scope of this paper. However, most papers addressing this issue find two or three factors.[9] In order to be conservative, we use the first five factors as capturing systematic variation in credit spreads with a total $R^2$ of 94%.

Next, we compare the residuals from our various pooled panel regressions to these five PCs in order to find to what extent systematic variation is left by our variables from the structural model framework. CGM did not conduct such comparison, making it impossible to say to what extent their residuals indeed represent systematic variation in credit spread changes. For our two main models (including all implied/historical volatility and implied-skew variables, with and without the control variables), Panel A of Table 10 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.

[8] Only bonds with at least 75 weekly observations are used (out of a total of 349 weeks). The EM-algorithm we repeatedly (1,000 times) run consists of two steps: 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.

[9] For credit spreads, Driessen (2003) finds evidence of two common factors. Feldhutter and Lando (2004) also work with two credit factors (in addition to riskfree rate factors) for the term structure of corporate bonds.

The pooled panel restriction that all bonds have identical regression coefficients clearly significantly decreases the variation captured by the five PCs, e.g. compare $R^2$'s of 25% and 42% for short- and long-term bonds, respectively, in the pooled panel to the average $R^2$ of 94% for the per-bond regressions of credit spreads on the five PCs. Further, the individual and S&P volatility and volatility-skew measures clearly capture a large part of the systematic variation, as only 5.58% of its residual variation of the credit spreads of short-term bonds (itself being 75% of total variation) is systematic, versus 6.97% for long-term bonds (where the residual variation itself is 58% of total variation). After adding the control variables from Table 3, the five PCs capture almost no residual variation anymore. Therefore, we conclude that the structural model variables do a great job in capturing systematic variation.

Next, we attempt to replicate the CGM results.[10] 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 (model 3 in Table 3).[11] 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 both of these sets of residuals, 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 10 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% of the variation of the credit spreads themselves (21% of the residual variation, which is 15% of total credit spread variation). Further, looking at the residual PCs, we find that the first two residual PC factors explain about 28% of the variation in the credit spread residuals, and 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

[10] The main difference is that here, as throughout this paper, we use levels of credit spreads rather than changes. Given that there is no evidence for a unit root in credit spreads, differencing the credit spreads and variables can only introduce additional estimation noise.

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

due to estimation errors. Table 11 documents the extent to which these residual PCs contain systematic variation.

We find that only a small fraction of the variation in the residual PCs can actually be explained by the systematic factors, for example 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 credit spread changes relative to the 83% - 85% found here).

Finally, it is useful to consider the work by Brown (1989) in light of CGM's interpretation that a single systematic factor is driving their residual variation in credit spread changes. Even if all variation picked up by their first residual PC factor is systematic, Brown shows that such evidence is consistent with there being in fact $k$ 'equally important' factors, where the first PC factor is simply a weighted average of these $k$ factors.

# 8 Conclusion

We have demonstrated empirically that prices of traded individual equity-options contain important information about credit risk. In particular, volatilities implied by at-the-money and out-of-the-money options are very useful proxies for two fundamental theoretical determinants of credit spreads, namely volatility and jump risk, in an extended structural firm value model. The effect of at-the-money implied volatility on credit spreads is economically and statistically very significant, and robust to a number of extensions. Together with option-implied skews, but without any other explanatory variables, 32% of the variation in long-term credit spreads can be explained, even though the pooled regression imposes constant coefficients over time and across issuers. This is almost twice the explanatory power that can be achieved by credit ratings. Importantly, interacting our measures of volatility and jump risk with credit ratings, we find the economically meaningful result that the credit spreads of poorly rated bonds are more sensitive to these determinants.

Further empirical evidence for the interaction between the individual equity-option market and the market for corporate bonds is provided by the following findings. Short-maturity credit spreads are significantly affected by measures of firm-specific option-market liquidity, suggesting the existence of a liquidity-spillover effect. Furthermore, option-implied volatilities anticipate downward credit rating migrations in a striking way, especially for issuers that already have a low credit rating.

As an important contribution, we show that the structural firm value model extended to allow for volatility and jump risk can explain the time-series variation in credit spreads rather well. In contrast to existing work, we find that essentially all systematic variation is captured by our variables suggested by the structural model. 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. Since both firm-specific fixed effects and credit ratings do improve the explanatory power of our regressions substantially, we conclude that explaining the cross-section is in fact more challenging than explaining the time-series variation.

## References


[1] Ait-Sahalia, Y., Y. Wang and F. Yared, 2001, "Do Options Markets Correctly Price the Probabilities of Movement of the Underlying Asset?," *Journal of Econometrics* 102, 67-110.

[2] Andersen, T., L. Benzoni and J. Lund, 2002, "An Empirical Investigation of Continuous-Time Models for Equity Returns," *Journal of Finance* 57, 1239-1284.

[3] Bakshi, G., C. Cao and Z. Chen, 1997, "Empirical Performance of Alternative Option Pricing Models," *Journal of Finance* 52, 2003-2049.

[4] Bakshi, G. and N. Kapadia, 2003a, "Delta-Hedged Gains and the Negative Market Volatility Risk Premium," *Review of Financial Studies* 16, 527-566.

[5] Bakshi, G. and N. Kapadia, 2003b, "Volatility Risk Premium Embedded in Individual Equity Options: Some New Insights," *Journal of Derivatives*, 45-54.

[6] Bakshi, G., N. Kapadia and D. Madan, 2003, "Stock Return Characteristics, Skew Laws, and Differential Pricing of Individual Equity Options," *Review of Financial Studies* 16, 101-143.

[7] Bakshi, G., D. Madan and F. Zhang, 2003, "Investigating the Role of Systematic and Firm-Specific Factors in Default Risk: Lessons from Empirically Evaluating Credit Risk Models," forthcoming in *Journal of Business*.

[8] Bates, D., 2002, "Empirical Option Pricing: A Retrospection," forthcoming in *Journal of Econometrics*.

[9] Black, F. and M. Scholes, 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] Bollen, N. and R. Whaley, 2003, "Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?," forthcoming in *Journal of Finance*.

[12] Bondarenko, O., 2003a, "Statistical Arbitrage and Securities Prices," forthcoming in *Review of Financial Studies*.

[13] Bondarenko, O., 2003b, "Why are Puts So Expensive?," working paper, University of Illinois, Chicago.

[14] Brown, S., 1989, "The Number of Factors in Security Returns," *Journal of Finance* 44, 1247-1262.

[15] Buraschi, A., and J. Jackwerth, 2001, "The Price of a Smile: Hedging and Spanning in Option Markets," *Review of Financial Studies* 14, 495-527.

[16] Campbell, J.Y. and G. Taksler, 2003, "Equity Volatility and Corporate Bond Yields", forthcoming in *Journal of Finance*.

[17] Cantor, R. and D. Hamilton, 2004, "Rating Transitions and Defaults Conditional on Watchlist, Outlook and Rating History," *Moody's Investors Service*, Special Comment, February.

[18] Collin-Dufresne, P., R. Goldstein and S. Martin, 2001, "The Determinants of Credit Spread Changes", *Journal of Finance* 56, 2177-2207.

[19] Coval, J., and T. Shumway, 2001, "Expected Option Returns," *Journal of Finance* 56, 983-1009.

[20] Driessen, J., 2003, "Is Default Event Risk Priced in Corporate Bonds?", forthcoming in *Review of Financial Studies*.

[21] Duffee, G., 1998, "The Relation Between Treasury Yields and Corporate Bond Yield Spreads," *Journal of Finance* 53, 2225-2241.

[22] Duffee, G., 1999, "Estimating the Price of Default Risk," *Review of Financial Studies* 12, 197-226.

[23] Duffie, D. and K. Singleton, 2003, *Credit Risk*, Princeton University Press.

[24] Elton, E., M. Gruber, D. Agrawal and C. Mann, 2004, "Factors Affecting the Valuation of Corporate Bonds," *Journal of Banking and Finance* 28, 2747-2767.

[25] Eom, Y., J. Helwege and J. Huang, 2003, "Structural Model of Corporate Bond Pricing: An Empirical Analysis," forthcoming in *Review of Financial Studies.*

[26] Eraker, B., M. Johannes and N. Polson, 2003, "The Impact of Jumps in Volatility and Returns," *Journal of Finance* 58, 1269-1300.

[27] Feldhutter, P. and D. Lando, 2004, "The Credit Risk Component in Corporate Spreads and Swap Spreads," working paper, Copenhagen Business School.

[28] Geske, R., 1979, "The Valuation of Compound Options," *Journal of Financial Economics* 7, 63-81.

[29] Hand, J., R. Holthausen and R. Leftwich, 1992, "The Effect of Bond Rating Changes Announcements on Bond and Stock Prices," *Journal of Finance* 47, 733-752.

[30] Huang, J. and M. Huang, 2003, "How Much of the Corporate-Treasury Yield Spread is Due to Credit Risk?," working paper, Stanford University.

[31] Huang, J. and W. Kong, 2003, "Explaining Credit Spread Changes: Some New Evidence from Option-Adjusted Spreads of Bond Indices," working paper, Pennsylvania State University.

[32] Hull, J., M. Predescu and A. White, 2004, "The Relationship Between Credit Default Swap Spreads, Bond Yields, and Credit Rating Announcements," *Journal of Banking and Finance* 28, 2789-2811.

[33] Janosi, T., R. Jarrow and Y. Yildirim, 2002, "Estimating Expected Losses and Liquidity Discounts Implicit in Debt Prices," *Journal of Risk* 5, 1-38.

[34] Katz, S., 1974, "The Price and Adjustment Process of Bonds to Rating Reclassifications: A Test of Bond Market Efficiency," *Journal of Finance* 29, 551-559.

[35] Kavvathas, D., 2000, "Estimating Credit Rating Transition Probabilities for Corporate Bonds," working paper, University of Chicago.

[36] Kwan, S., 1996, "Firm-Specific Information and the Correlation between Individual Stocks and Bonds," *Journal of Financial Economics* 40, 63-80.

[37] Longstaff, F. and E. Schwartz, 1995, "A Simple Approach to Valuing Risky and Floating Rate Debt," *Journal of Finance* 50, 789-819.

[38] Merton, R., 1973, "Theory of Rational Option Pricing," *Bell Journal of Economics* 4, 141-183.

[39] Merton, R., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29, 449-470.

[40] Nelson, C. and A. Siegel, 1987, "Parsimonious Modeling of Yield Curves," *Journal of Business* 60, 473-489.

[41] Pan, J., 2002, "The Jump-Risk Premia Implicit in Options: Evidence from an Integrated Time-Series Study," *Journal of Financial Economics* 63, 3-50.

[42] Rosenberg, J. and R. Engle, 2002, "Empirical Pricing Kernels," *Journal of Financial Economics* 64, 341-372.

[43] Toft, K. and B. Prucyk, 1997, "Options on Leveraged Equity: Theory and Empirical Tests," *Journal of Finance* 52, 1151-1180.

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 are calculated as second moments of the corresponding equity returns, 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 |
| 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 | |

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

This table reports the pooled panel results of regressing weekly corporate bond spreads on our measures of volatility and jump risk. We consider the implied volatility (IV) of both individual and market-wide (S&P) at-the-money options, and the individual and market-wide implied skew. Table 1 describes the construction of these variables. In addition, the set of independent variables includes historical estimates of the individual and market-wide volatility (see Table 1). The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | | | Long-Maturity | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 1 | 2 | 3 |
| Ind. IV | 2.5269 | | 1.1233 | 4.4642 | | 2.9084 |
| | (15.83) | | (6.93) | (32.59) | | (23.13) |
| Ind. Skew | 0.2429 | | 0.1800 | 0.2574 | | 0.1996 |
| | (15.56) | | (12.40) | (13.23) | | (11.95) |
| Ind. Hist. Vol. | | | 1.2816 | | | 0.6077 |
| | | | (11.74) | | | (6.16) |
| S&P IV | | 1.9370 | -0.2346 | | 3.4437 | -1.5284 |
| | | (4.99) | (-1.18) | | (5.72) | (-7.07) |
| S&P Skew | | -0.0328 | 0.0811 | | -0.4868 | -0.2371 |
| | | (-0.42) | (1.85) | | (-3.67) | (-4.87) |
| S&P Hist. Vol. | | | 2.6079 | | | 5.0158 |
| | | | (12.86) | | | (20.05) |
| Constant | 0.0014 | 0.5438 | -0.5033 | -0.3627 | 0.9076 | -0.5520 |
| | (0.11) | (8.69) | (-8.69) | (-25.27) | (8.45) | (-8.69) |
| $R^2$ | 0.143 | 0.022 | 0.221 | 0.322 | 0.056 | 0.406 |
| Adjusted $R^2$ | 0.143 | 0.022 | 0.221 | 0.322 | 0.056 | 0.406 |
| Number of bonds | 334 | 334 | 334 | 189 | 189 | 189 |
| Number of firms | 66 | 66 | 66 | 56 | 56 | 56 |
| Total number of bond-weeks | 34419 | 34419 | 34419 | 24261 | 24261 | 24261 |

Table 3: Regressions with Additional Control Variables

This table reports the pooled panel results of regressing weekly corporate bond spreads on our measures of volatility and jump risk (for descriptions, see Table 1 and 2), with a set of additional control variables: the market and firm stock return are the weekly excess returns on the S&P 500 and the firm issuing the relevant bond, respectively. 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. The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | 1 | 3 | 1 | 3 |
| Ind. IV | 1.3155 | 0.8705 | 2.2586 | 2.3782 |
| | (9.18) | (6.18) | (18.57) | (21.09) |
| Ind. Skew | 0.0825 | 0.0771 | 0.0338 | 0.0429 |
| | (7.17) | (6.40) | (2.30) | (2.92) |
| Ind. Hist. Vol. | | 1.4651 | | 0.3686 |
| | | (11.87) | | (4.04) |
| S&P IV | | -0.8463 | | -2.1028 |
| | | (-3.78) | | (-8.72) |
| S&P Skew | | 0.1216 | | -0.1411 |
| | | (2.36) | | (-2.52) |
| S&P Hist. Vol. | | -1.5297 | | -0.0201 |
| | | (-3.73) | | (-0.04) |
| Market Return | 0.0324 | -0.0638 | -0.3033 | -0.4065 |
| | (0.42) | (-0.77) | (-3.31) | (-4.50) |
| Firm Stock Return | -0.0253 | 0.0008 | -0.118 | -0.1372 |
| | (-1.08) | (0.03) | (-6.10) | (-7.18) |
| Two-year Yield | -0.159 | -0.1799 | -0.1781 | -0.1626 |
| | (-6.10) | (-6.38) | (-5.76) | (-5.39) |
| Ten-year Yield | -0.3117 | -0.3102 | -0.4512 | -0.4687 |
| | (-6.41) | (-3.97) | (-8.16) | (-5.71) |

Table 3 (continued): Regressions with Additional Control Variables

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | 1 | 3 | 1 | 3 |
| BAA Rate | 0.3290 | 0.2837 | 0.3795 | 0.3127 |
| | (7.30) | (6.10) | (7.42) | (6.42) |
| Swap Rate | 0.1720 | 0.1533 | 0.3222 | 0.2997 |
| | (1.96) | (1.58) | (3.22) | (2.94) |
| Liquidity | 0.1288 | 0.1594 | 0.0019 | 0.0836 |
| | (3.30) | (3.60) | (0.04) | (1.72) |
| Constant | -0.4768 | 0.1286 | -0.787 | 0.2275 |
| | (-3.32) | (0.50) | (-4.53) | (0.82) |
| $R^2$ | 0.265 | 0.288 | 0.468 | 0.481 |
| Adjusted $R^2$ | 0.265 | 0.288 | 0.468 | 0.481 |
| Number of bonds | 334 | 334 | 189 | 189 |
| Number of firms | 66 | 66 | 56 | 56 |
| Total number of bond-weeks | 34419 | 34419 | 24261 | 24261 |

Table 4: Regressions with Year Dummies and Firm Fixed Effects

We report the pooled panel results of regressing weekly corporate bond spreads on measures of volatility and jump risk and a set of controls (see Tables 2 and 3 for a description of the variables), with in addition either a set of year dummies or firm fixed effects, whose coefficients are not reported. The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | Year Dummies | Fixed Effects | Year Dummies | Fixed Effects |
| Ind. IV | 0.8948 | 1.3233 | 2.4518 | 1.6879 |
| | (6.27) | (10.30) | (21.41) | (17.08) |
| Ind. Skew | 0.0796 | 0.0663 | 0.0469 | 0.0955 |
| | (6.66) | (5.37) | (3.18) | (7.58) |
| Ind. Hist. Vol. | 1.4355 | 1.6946 | 0.2828 | 0.9194 |
| | (11.43) | (10.35) | (3.17) | (8.17) |
| S&P IV | -0.8950 | -0.9653 | -1.8871 | -1.5519 |
| | (-3.56) | (-4.84) | (-6.91) | (-8.29) |
| S&P Skew | 0.0845 | 0.1666 | -0.1500 | -0.0924 |
| | (1.50) | (3.63) | (-2.42) | (-2.15) |
| S&P Hist. Vol. | -1.2957 | -2.0087 | 0.7764 | -0.1224 |
| | (-2.50) | (-5.35) | (1.31) | (-0.33) |
| Market Return | -0.0448 | -0.0945 | -0.1240 | -0.3700 |
| | (-0.43) | (-1.31) | (-1.10) | (-5.17) |
| Firm Stock Return | -0.0054 | 0.1143 | -0.1538 | -0.0543 |
| | (-0.22) | (4.89) | (-8.21) | (-3.23) |
| Two-year Yield | -0.2281 | -0.1749 | -0.1390 | -0.1582 |
| | (-5.07) | (-7.08) | (-2.92) | (-6.49) |
| Ten-year Yield | -0.3467 | -0.2955 | -0.6921 | -0.5072 |
| | (-3.53) | (-4.26) | (-6.52) | (-7.83) |
| BAA Rate | 0.3696 | 0.2191 | 0.3686 | 0.3591 |
| | (6.40) | (5.47) | (6.02) | (9.08) |

Table 4 (continued): Regressions with Year Dummies and Firm Fixed Effects

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | Year Dummies | Fixed Effects | Year Dummies | Fixed Effects |
| Swap Rate | 0.1867 | 0.1717 | 0.4526 | 0.3007 |
| | (1.74) | (2.03) | (3.91) | (3.68) |
| Liquidity | 0.0976 | 0.1485 | 0.0357 | 0.0924 |
| | (1.98) | (3.81) | (0.66) | (2.49) |
| Constant | -0.4144 | 0.2219 | -0.2176 | -0.1209 |
| | (-1.18) | (0.98) | (-0.60) | (-0.57) |
| $R^2$ | 0.290 | 0.482 | 0.485 | 0.672 |
| Adjusted $R^2$ | 0.289 | 0.481 | 0.484 | 0.671 |
| Number of bonds | 334 | 334 | 189 | 189 |
| Number of firms | 66 | 66 | 56 | 56 |
| Total number of bond-weeks | 34419 | 34419 | 24261 | 24261 |

Table 5: The Effect of Option-Market Liquidity

This table reports the pooled panel results of regressing weekly corporate bond spreads on measures of volatility and jump risk and a set of controls (see Tables 2 and 3 for a description of the variables), plus two additional variables measuring the effect of option market liquidity, namely the bid-ask spreads of the put options on the firm that are closest to 92% moneyness (OTM) and closest to 100% moneyness (ATM). The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | Long-Maturity |
|---|---|---|
| Ind. IV | 1.0284 | 2.3764 |
| | (8.01) | (21.09) |
| Ind. Skew | 0.0594 | 0.0372 |
| | (4.59) | (2.31) |
| Ind. Hist. Vol. | 1.4579 | 0.3663 |
| | (11.68) | (4.03) |
| S&P IV | -0.8176 | -2.1025 |
| | (-3.70) | (-8.72) |
| S&P Skew | 0.1353 | -0.1418 |
| | (2.67) | (-2.54) |
| S&P Hist. Vol. | -1.4960 | -0.0182 |
| | (-3.71) | (-0.04) |
| Market Return | -0.0496 | -0.4079 |
| | (-0.61) | (-4.53) |
| Firm Stock Return | 0.0193 | -0.1367 |
| | (0.80) | (-7.10) |
| Two-year Yield | -0.1873 | -0.1646 |
| | (-6.75) | (-5.45) |
| Ten-year Yield | -0.3114 | -0.4694 |
| | (-4.07) | (-5.72) |
| BAA Rate | 0.2965 | 0.3141 |
| | (6.49) | (6.44) |

Table 5 (continued): The Effect of Option-Market Liquidity

| Regression | Short-Maturity | Long-Maturity |
|---|---|---|
| Swap Rate | 0.1539 | 0.3017 |
| | (1.62) | (2.96) |
| Bond Liquidity | 0.1602 | 0.0833 |
| | (3.69) | (1.72) |
| OTM bid-ask spread | 0.1469 | -0.0124 |
| | (9.21) | (-0.62) |
| ATM bid-ask spread | 0.3683 | 0.2003 |
| | (3.58) | (1.36) |
| Constant | -0.0619 | 0.2136 |
| | (-0.24) | (0.77) |
| $R^2$ | 0.293 | 0.481 |
| Adjusted $R^2$ | 0.293 | 0.481 |
| Number of bonds | 333 | 189 |
| Number of firms | 66 | 56 |
| Total number of bond-weeks | 33692 | 23885 |

Table 6: Controlling for Credit Ratings

We report the pooled panel results of regressing weekly corporate bond spreads on credit rating dummies only (model A) and on measures of volatility and jump risk with a set of controls (see Tables 2 and 3 for a description of the variables) as well as a set of credit rating dummies (model B). Five S&P credit rating groups are used: AAA, AA, A, BBB, and finally BB and lower. The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | A | B | A | B |
| Ind. IV | | 0.9243 | | 2.0447 |
| | | (6.27) | | (17.91) |
| Ind. Skew | | 0.0496 | | 0.0297 |
| | | (4.06) | | (2.04) |
| Ind. Hist. Vol. | | 1.1212 | | 0.1525 |
| | | (8.04) | | (1.54) |
| S&P IV | | -0.8805 | | -1.9745 |
| | | (-3.93) | | (-8.50) |
| S&P Skew | | 0.1238 | | -0.1456 |
| | | (2.40) | | (-2.68) |
| S&P Hist. Vol. | | -1.1800 | | 0.2836 |
| | | (-2.85) | | (0.64) |
| Constant | 0.6406 | -0.0932 | 0.7010 | 0.0487 |
| | (4.13) | (-0.36) | (7.81) | (0.18) |
| Rating Group 2 | 0.2704 | 0.1770 | 0.1135 | -0.0601 |
| | (16.95) | (10.22) | (8.77) | (-3.96) |
| Rating Group 3 | 0.2102 | 0.1469 | 0.3562 | 0.1267 |
| | (15.63) | (9.78) | (30.98) | (10.02) |
| Rating Group 4 | 0.7049 | 0.4811 | 0.9911 | 0.5508 |
| | (31.63) | (26.12) | (60.35) | (35.27) |
| Rating Group 5 | 0.1614 | 0.3285 | 0.7339 | 0.8292 |
| | (3.63) | (11.70) | (18.74) | (24.85) |

Table 6 (continued): Controlling for Credit Ratings

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | A | B | A | B |
| Market Return | | -0.0959 | | -0.4916 |
| | | (-1.15) | | (-5.69) |
| Firm Stock Return | | -0.0079 | | -0.1184 |
| | | (-0.31) | | (-6.20) |
| Two-year Yield | | -0.1597 | | -0.1178 |
| | | (-5.75) | | (-4.10) |
| Ten-year Yield | | -0.3022 | | -0.5253 |
| | | (-3.86) | | (-6.72) |
| BAA Rate | | 0.2635 | | 0.2914 |
| | | (5.71) | | (6.35) |
| Swap Rate | | 0.1611 | | 0.3418 |
| | | (1.67) | | (3.56) |
| Bond Liquidity | | 0.1818 | | 0.0982 |
| | | (4.11) | | (2.12) |
| $R^2$ | 0.094 | 0.321 | 0.171 | 0.558 |
| Adjusted $R^2$ | 0.094 | 0.321 | 0.170 | 0.558 |
| Number of bonds | 308 | 308 | 168 | 168 |
| Number of firms | 61 | 61 | 48 | 48 |
| Total number of bond-weeks | 30507 | 30507 | 22792 | 22792 |

Table 7: Interaction with Credit Ratings

This table reports the pooled panel results of regressing weekly corporate bond spreads on measures of volatility and jump risk without (model 1) and with (model 3) a set of controls (see Tables 2 and 3 for a description of the variables), where the volatility and jump risk variables for individual firms are interacted with rating dummies. Three S&P credit rating groups are used: AAA to A-, BBB+ to BBB- ('Rating2'), and BB+ and lower ('Rating3'). The $t$-stats in parentheses are computed with standard errors that are corrected for heteroskedasticity, autocorrelation and cross-correlations. Short maturity is between 1 and 5 years, and long maturity at least 7 years.

| Regression | Short-Maturity | | Long-Maturity | |
|---|---|---|---|---|
| | 1 | 3 | 1 | 3 |
| Ind. IV | 2.0575 | 0.6501 | 3.4733 | 1.6819 |
| | (13.04) | (6.37) | (28.07) | (40.30) |
| Ind. IV × Rating2 | 1.0958 | 0.7911 | 1.2464 | 0.6032 |
| | (15.66) | (6.70) | (23.97) | (9.86) |
| Ind. IV × Rating3 | 0.1873 | -0.0510 | 0.9783 | 1.0472 |
| | (1.07) | (-0.19) | (6.45) | (3.60) |
| Ind. Skew | 0.1528 | 0.0140 | 0.1168 | -0.0213 |
| | (9.97) | (2.25) | (6.76) | (-3.77) |
| Ind. Skew × Rating2 | 0.1687 | 0.1413 | 0.2508 | 0.0857 |
| | (5.20) | (10.75) | (6.78) | (7.41) |
| Ind. Skew × Rating3 | -0.1049 | -0.0341 | 0.3461 | 0.4044 |
| | (-1.04) | (-1.17) | (3.26) | (9.62) |
| Ind. Hist. Vol. | | 0.9729 | | -0.2371 |
| | | (15.16) | | (-7.47) |
| Ind. Hist. Vol.×Rating2 | | 0.1453 | | 0.6762 |
| | | (1.23) | | (10.82) |
| Ind. Hist. Vol.×Rating3 | | 0.7682 | | 0.5026 |
| | | (2.61) | | (1.69) |

Table 7 (continued): Interaction with Credit Ratings

| Regression | Short-Maturity 1 | Short-Maturity 3 | Long-Maturity 1 | Long-Maturity 3 |
|---|---|---|---|---|
| S&P IV | | -0.8031 | | -1.8742 |
| | | (-8.51) | | (-20.94) |
| S&P Skew | | 0.1254 | | -0.1461 |
| | | (5.71) | | (-6.98) |
| S&P Hist. Vol. | | -1.1593 | | 0.4253 |
| | | (-6.77) | | (2.51) |
| Market Return | | -0.1021 | | -0.5250 |
| | | (-3.07) | | (-15.97) |
| Firm Stock Return | | 0.0199 | | -0.1240 |
| | | (1.88) | | (-18.10) |
| Two-year Yield | | -0.1354 | | -0.0915 |
| | | (-12.12) | | (-8.31) |
| Ten-year Yield | | -0.3737 | | -0.5439 |
| | | (-11.59) | | (-18.25) |
| BAA Rate | | 0.2820 | | 0.3147 |
| | | (15.61) | | (17.87) |
| Swap Rate | | 0.1966 | | 0.3173 |
| | | (5.00) | | (8.65) |
| Bond Liquidity | | 0.1769 | | 0.0939 |
| | | (9.83) | | (5.30) |
| Constant | 0.1171 | 0.0934 | -0.1677 | 0.3179 |
| | (9.76) | (0.87) | (-13.44) | (3.16) |
| $R^2$ | 0.215 | 0.337 | 0.422 | 0.571 |
| Adjusted $R^2$ | 0.215 | 0.337 | 0.422 | 0.571 |
| Number of bonds/firms | 334/66 | 334/66 | 189/56 | 189/56 |
| Total number of bond-weeks | 34419 | 34419 | 24261 | 24261 |

Table 8: Theoretical coefficients in a structural firm value model

This table contains partial derivatives of the credit spread with respect to the individual implied volatility and individual implied skew, calculated from a firm-value jump-diffusion model. Three sets of parameters are considered for the jump process: a mean jump size of 5%, 10%, and 20%, and a corresponding jump intensity of 1.6, 0.8, and 0.4, respectively. The remaining parameters of the model are calibrated to fit the historical default and loss rates, the equity premium, and the leverage rate (per rating category). The credit spread is calculated for a 10-year par-coupon bond. The partial derivatives of the implied volatility and implied-volatility skew are calculated by appropriately varying the underlying firm value volatility and jump intensity. Results are presented for a continuous default boundary (for all 3 parameter sets) and in case of default at maturity only (for the first parameter set).

| Default boundary | | Continuous | | | Default at $T$ only |
|---|---|---|---|---|---|
| Mean jump size | | 20% | 10% | 5% | 20% |
| Implied Volatility | AAA | 0.8401 | 1.0561 | 0.9214 | 1.6686 |
| | AA | 1.1194 | 1.9545 | 1.5865 | 2.8707 |
| | A | 1.2672 | 2.2608 | 1.8009 | 3.2986 |
| | BBB | 4.6048 | 4.8823 | 5.1600 | 3.3104 |
| | BB | 13.4888 | 16.9994 | 14.5403 | 5.3813 |
| | B | 16.4485 | 17.5003 | 19.7054 | 1.5063 |
| Implied-Vol Skew | AAA | 1.0006 | 0.2474 | -0.0880 | 1.9791 |
| | AA | 1.7098 | 0.4657 | -0.0274 | 2.4501 |
| | A | 2.7242 | 0.7427 | 0.2006 | 3.4088 |
| | BBB | 4.4437 | 2.0125 | 0.6971 | 3.4150 |
| | BB | 4.4184 | 3.7613 | 0.2928 | 1.5195 |
| | B | -0.0849 | 0.4106 | -0.0319 | -0.8333 |

Table 9: 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 10, 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 two main models (including all implied measures and historical volatilities, with and without the control variables) 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) | Table 3 (3) | Constant | Table 2 (3) | Table 3 (3) |
| Res. on 5 PCs: $R^2$ | 0.2538 | 0.0558 | 0.0074 | 0.4243 | 0.0697 | 0.0063 |

Table 10, 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 (model 3 in Table 3). 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 11: $R^2$ when Regressing Residual PCs on the Set of Five PCs

This table reports the $R^2$ when regressing the residual PCs (defined in Table 10B) 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 |

## Figures 1 and 2

Figure 1 plots the weekly time series of the credit spread and the individual firm implied volatility (IV) of an at-the-money put option on the equity of the firm, averaged across all 524 bonds and 69 issuing firms, respectively. In the figure, the IV is scaled by multiplication by 0.1. Figure 2 plots the weekly time series of the credit spread and the individual firm implied skew, averaged across all 524 bonds and 69 issuing firms, respectively. The implied-volatility skew is the difference between the implied volatility of a put with 0.92 strike-to-spot ratio and an at-the-money put, divided by the difference in the respective strike-to-spot ratios. Our data set consists of 351 weekly observations, from January 1996 to September 2002. For a precise description of these variables, see Table 1.

Figure 1

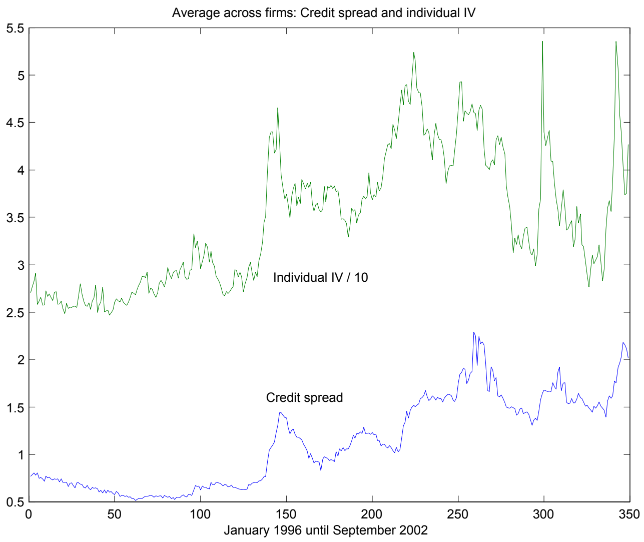
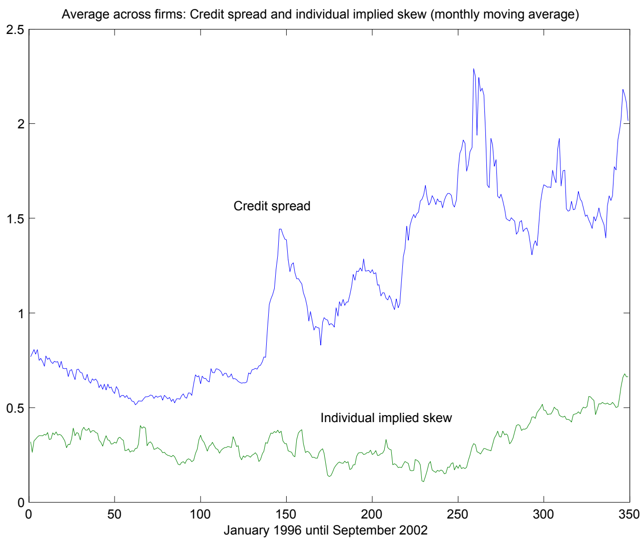



Figure 2



## Figures 3 and 4

Figure 3 depicts the cross-sectional relation between credit spreads and the individual firm implied volatility of an at-the-money put option of the 69 firms in our sample, each averaged over 351 weekly observations from January 1996 to September 2002. Figure 4 depicts the cross-sectional relation between credit spreads and the individual firm implied skew of an at-the-money put option of the 69 firms in the same sample. For a precise description of these variables, see Table 1.

Figure 3

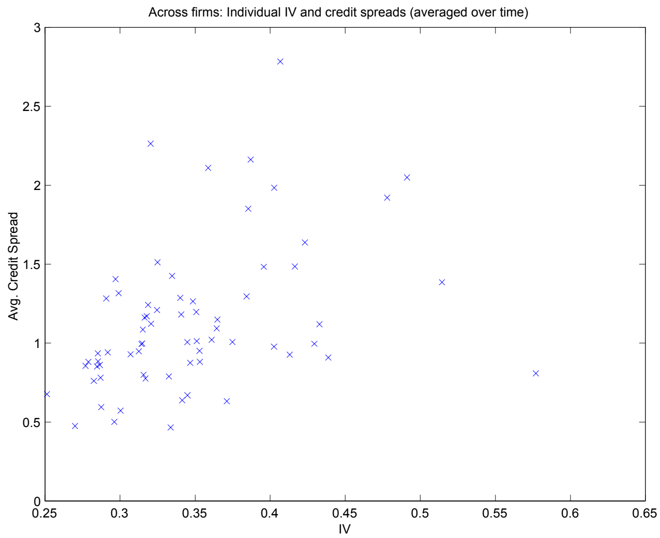
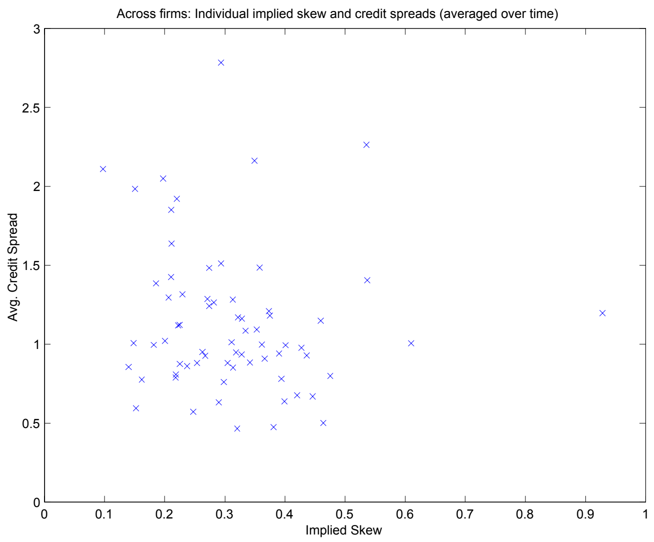



Figure 4



Figures 5

The following 4 figures contain the pattern of individual implied volatilities (IV) around rating migrations. Each graph contains (i) the time series of IVs of firms that are downgraded (averaged across all downgrades in our sample), (ii) the time series of IVs of all non-downgraded firms around a downgrade of a given firm (again averaged across all downgrades), and similar time series for upgrades. Figure 5A contains the averages of all firms, while Figures 5B-D contain the averages of firms that are initially in high, intermediate and low rating categories, respectively (AAA to A-, BBB+ to BBB-, and BB+ and lower).

Figure 5A

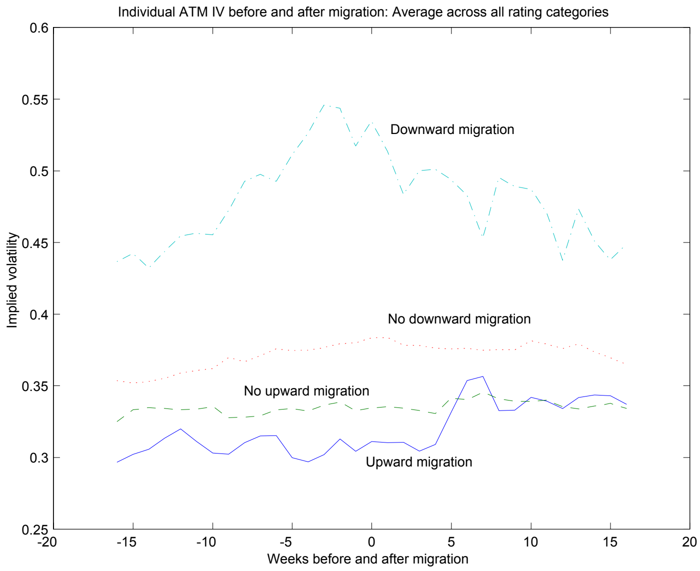
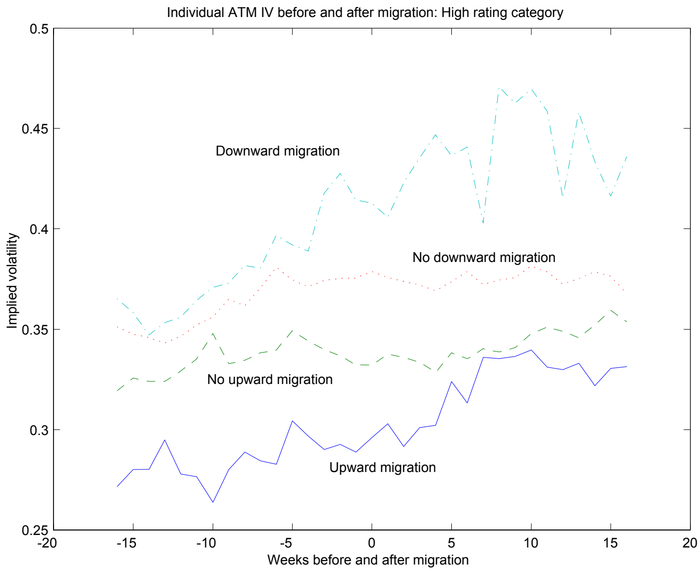
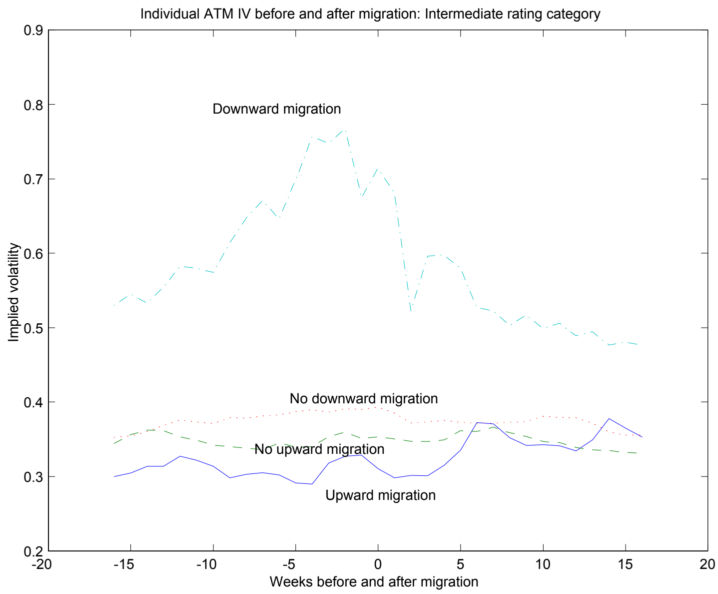



Figure 5B



Figures 5 (continued)

## Figure 5C




## Figure 5D