Explaining the Level of Credit Spreads: Option-Implied Jump Risk Premia in a Firm Value Model*

Martijn Cremers† Joost Driessen‡ Pascal Maenhout§

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†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.

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Abstract: This paper investigates whether option-implied jump risk premia can explain the high observed level of credit spreads (the 'credit spread puzzle'). Prices of equity index put options provide information on the price of systematic downward jump risk. We use a structural jump-diffusion firm value model with systematic and firm-specific jumps to assess the level of credit spreads that is generated by option-implied jump risk premia. In our compound option pricing model, an equity index option is an option on a portfolio of call options on the underlying firm values. We calibrate the model parameters to historical information on default risk, the equity premium, equity option prices and returns. Our results show that incorporating option-implied jump risk premia brings predicted credit spread levels much closer to observed levels. We also evaluate the implications of the jump-diffusion model along other dimensions. The introduction of jumps produces model predictions for the volatility of credit spread changes and equity returns that are closer to the empirically observed values and generates a reasonable fit of observed default correlations.

1 Introduction

Corporate bonds are defaultable and thus trade at higher yields than default-free government bonds. However, it has been difficult to reconcile this observed difference in yields (the credit spread level) with the historically observed default losses of corporate bonds, especially for investment-grade firms (Elton et al. (2001)). In particular, Huang and Huang (2003, henceforth HH) analyze a wide range of structural firm value models that build on the seminal contingent-claims analysis of Black and Scholes (1973) and Merton (1974). HH show that these models typically explain only 20% to 30% of observed credit spreads for these firms. In response to what has emerged as the credit spread 'puzzle' (Amato and Remolona (2003)), a number of authors have most recently incorporated jump risk premia into the analysis. As discussed below, the existing evidence on the relevance of jump risk premia is inconclusive.

The contribution of this paper is to use information on the market price of downward jump risk embedded in index put options to estimate a structural jump-diffusion firm value model. We investigate the out-of-sample predictions of the estimated model for credit spreads. As a result, the main contribution of our work is to study whether the price of jump risk embedded in corporate bonds is consistent with the price of jump risk in index options. This is a natural question since index put options constitute the prime liquid market for insurance against systematic jumps, i.e., precisely the type of jumps that corporate bond investors may be exposed to. A short index put option tends to pay off particularly badly in the most expensive states of the world (i.e., where the stochastic discount factor is extremely high) and therefore commands a large risk premium. Furthermore, interpreting a corporate bond as a default-free bond plus a short position in a put option on the firm value (Merton (1974)), we effectively test empirically whether the jump risk premium embedded in this firm value put is in line with the jump risk premium embedded in equity index put options.

There are several reasons why the relationship between the prices of the firm value put and equity index put is not obvious. First, equity index put options have much shorter maturities and are less 'out-of-the-money' than the firm value put. Second, equity index put options have the equity index as underlying asset, while the embedded corporate bond put option has the firm value as underlying. Third, there is a debate on whether corporate bond and equity (option) markets are integrated (Collin-Dufresne, Goldstein, and Martin (2001), Cremers et al. (2005) and Ericsson, Jacobs, and Oviedo (2005)).

Recent empirical work has revealed a number of intriguing stylized facts about the prices of equity index options (see e.g. Bates (2003) for a survey). It is now well accepted that the underlying index is subject to jumps to returns and volatility[1], generating market incompleteness. Moreover, this incompleteness seems to be priced (Buraschi and Jackwerth (2001)).[2] The goal of our paper is not to explain the source and nature of the jump risk premium. Instead, we examine the implications of the observed size of this option-implied jump risk premium for the level of credit spreads.

Our model has the following structure. The asset value of each firm in the S&P 100 follows a jump-diffusion process. Allowing for common and firm-specific jumps, the jump sizes are drawn from a double-exponential distribution. We incorporate a risk premium for the common, but not for the firm-specific jumps: only the common jumps are systematic and should be priced in equilibrium. Given assumptions about the debt structure, default boundary and recovery rule, the corporate bond and equity can be priced under the risk-neutral measure. Pricing the equity of all firms in the index in this way and aggregating constructs the S&P 100 index, so that in the final step index put options can be priced. As a result, S&P 100 index options are viewed as options on a portfolio of 100 firm value call options, i.e., as compound options.

The parameters of the model (e.g. governing the recovery rule, the default boundary, the asset risk premium and diffusion volatility, the cross-firm diffusion correlation, the jump processes, etc.) are calibrated to the following moment conditions: the default probability (per rating category), the average par recovery rate, the equity risk premium, the leverage ratio, equity correlations, equity option prices and expected option returns. This ensures that the model matches estimates for the expected loss and the equity premium. By calibrating to both the equity premium and the expected option returns, we can disentangle

[1] See Aït-Sahalia (2002), Andersen, Benzoni and Lund (2002) and Eraker, Johannes and Polson (2003) for recent contributions to this literature.

[2] Evidence of priced jump risk in index options is presented in Aït-Sahalia, Wang and Yared (2001), Bakshi, Cao and Chen (1997), Bates (2002), Pan (2002) and Rosenberg and Engle (2002), among others.

the diffusion risk premium from the jump risk premium. Data on S&P 100 options and stock options for 69 firms (January 1996 until September 2002) are used to identify the parameters related to the common and firm-specific jump processes. Importantly, the model is not calibrated to credit spread data. Once the model is estimated, the model-implied credit spread is calculated and compared to the observed average credit spread level, for either corporate bonds or credit default swaps.

Our estimates show that both common and firm-specific jumps are relevant. While firm-specific jumps are relatively large and occur quite often, common jumps are less frequent and somewhat smaller: the annualized common jump intensity equals 5.7% per year with an expected jump size of -7.4%. Consistent with the option pricing literature (e.g. Pan (2002)), we find a large risk premium on the common jump risk. Under the risk-neutral measure, the annualized jump intensity equals 20.5% and the expected jump size equals -23.4%. This jump risk premium reflects the strongly negative average return on equity index put options. Relative to a model without jumps, the addition of priced jumps enables the model to price options much better and to obtain a closer fit of the distribution of index returns. Furthermore, the model predicts that individual stock-option prices should be higher for lower-rated firms, as observed in our sample.

Most importantly, the jump-diffusion model generates an out-of-sample prediction of 66 basis points for the credit spread on a 10-year bond of a typical A-rated firm. Across ratings, we obtain credit spreads ranging from 44 basis points for AAA to 492 basis points for B. The jump-diffusion model explains a reasonably large fraction of the observed corporate bond credit spreads. After correcting for a tax effect in corporate bonds (Elton et al. (2001)), we do not find significant differences between the model-implied and observed credit spread levels. Furthermore, the credit spreads predicted by the model also come close to estimates of default risk based on credit default swaps (CDS). In line with HH, we show that a model without jumps predicts much lower credit spreads. Using individual corporate bond price data, we study the term structure implications and find that the jump-diffusion model generates term structure shapes that are similar to observed shapes.

Besides the out-of-sample prediction of credit spread levels, we test the model also along other dimensions. First of all, we use bootstrap techniques to show that the common jump process does not generate too much negative skewness in the actual distribution of the equity index return. Instead, the model somewhat underestimates both the volatility of equity returns (under the actual and risk-neutral measures) and of credit spread changes. This is caused by our matching of the historical default rates, which constrains the level of volatility in the model. As argued by HH, excessive volatility in financial markets may be an explanation for this result. Finally, the amount of default correlation generated by the model is quite similar to empirical estimates of default correlations.

In sum, our analysis leads to two novel findings. First of all, the results indicate that structural models *are* useful for the analysis and pricing of credit risk, in contrast to the conclusions of previous work. Second, we relate the credit spread puzzle to the puzzling level of average index option returns, and provide evidence that option-implied jump risk premia generate credit spread levels that are quite close to observed spreads.

The remainder of the paper is structured as follows. Section 2 discusses the contribution of our paper to the existing literature. Section 3 presents the theoretical model used for the calibration and estimation. The calibration methodology we follow is explained in section 4. Section 5 describes the options data that we use in the calibration and discusses the parameter estimates. In section 6 we compare the model-implied credit spreads with observed levels of credit spreads and credit default swap spreads. Section 7 studies default correlations, the volatility of credit spreads and equity returns, and other out-of-sample predictions. The conclusion follows in section 8.

2 Related Literature

This paper is closely related to the work of HH: our specification for the firm value process is the same as in HH, except that we distinguish between common and firm-specific jumps. However, our paper differs from HH in several major ways. First and most importantly, an essential part of our analysis is to estimate both the jump process and the jump risk premium from data on equity returns and option prices. To this end, we model the joint behavior of all firms in the equity index. In contrast, HH do not model this joint process and mostly focus on pure diffusion models. They do consider a jump-diffusion model, but do not estimate or calibrate the parameters associated with the jump process. In section 5.2 we discuss this in more detail. Second, HH only focus on credit spread implications and do not assess the model implications for equity and option prices. Our results show that allowing for jumps improves the fit not only for credit spread levels, but also for equity returns and option prices. Third, we provide results for the entire term structure of credit spreads. Finally, we study the implications for the volatility of credit spreads and perform a comparison of empirical versus model-implied default correlations.

Our paper is also related to recent work that studies the role of jump risk premia in explaining credit spread levels. Collin-Dufresne, Goldstein and Helwege (2003) argue that jump risk premia are unlikely to explain the level of credit spreads. However, in their paper the jump risk premium is not estimated, so that the empirical relevance of jump risk remains unclear. Berndt et al. (2004) and Driessen (2005) estimate a jump risk premium from corporate bond spreads and CDS spreads, respectively. Their results suggest that large jump risk premia are needed to explain the level of credit spreads. However, their jump risk premia are essentially fitted to the spread level. Instead, we provide an out-of-sample test of the importance of the jump risk premium. This has the advantage that our estimates are not affected by tax effects that impact corporate credit spreads and liquidity premia that may be relevant for both corporate and CDS spreads. Also, in contrast to Driessen and Berndt et al., our firm value model does not necessarily have jumps directly to default. In particular, both the jump intensity and the jump size are estimated from equity and option data.

Eom, Helwege, and Huang (2004) and Ericsson, Reneby, and Wang (2005) perform an analysis of structural firm value models using data at the firm level. However, they do not incorporate jump risk and jump risk premia. In addition, their estimation methodology does not impose that the expected loss is matched to the data (as is done in HH and in this paper). Carr and Wu (2005) use data on credit default swaps and equity options to estimate a jump-diffusion model where stock prices can jump to zero in case of default. They find evidence for a risk premium associated with the time variation in the jump intensity.

Another strand in the literature estimates jump-diffusion models using option price data (e.g. Bakshi, Cao, and Chen (1997) and Pan (2002)). We extend this literature by studying a model for the firm value and assessing the implications of jump risk for credit spreads. Finally, several authors have empirically analyzed the determinants of credit spread variation, including, among other explanatory variables, implied volatilities of equity options (e.g. Collin-Dufresne, Goldstein and Martin (2001), Hull, Nelken and White (2004), and Cremers et al. (2005)). In general, these articles document a significant relationship between equity option prices and credit spreads. However, this work focuses on explaining the empirically observed variation in credit spreads and does not study the pricing of default risk through structural models nor the impact of jump risk premia on the level of credit spreads.

3 The Model

We model the dynamics of all N firms in the stock market index. The firm value is exposed to correlated diffusion shocks, common jumps, and firm-specific jumps. The dynamics of the asset value $V_{j,t}$ of a typical firm j, where $j \in \{1, ..., N\}$, under the physical measure are given by the following jump-diffusion with constant coefficients:

$$\frac{dV_{j,t}}{V_{j,t-}} = (\pi + r - \delta)\, dt + \sigma dW_{j,t} + dJ_t - \lambda\xi dt + dJ^f_{j,t} - \lambda_f \xi_f dt \tag{1}$$

where π is the total firm value risk premium, r is the risk-free rate and δ is the payout rate (resulting from both coupon payments and dividends). The loading on the standard Brownian motion $W_{j,t}$ is σ. This specification is also used by HH, except that we allow for firm-specific jumps as well. The Brownian motions affecting different firms j and k are assumed to be correlated according to a correlation parameter ρ:

$$E\left[dW_{j,t} dW_{k,t}\right] = \rho dt, \;\; \rho \in [-1, 1] \;\text{ for } j \neq k. \tag{2}$$

The common jump process J_t has the following structure:

$$J_t = \sum_{i=1}^{N_t} (Z_i - 1) \tag{3}$$

where N_t is a standard Poisson process with a jump intensity λ and $\ln(Z_i)$ has a double-exponential distribution with density given by

$$p_u \eta_u e^{-\eta_u \ln(z_i)} 1_{[\ln(z_i) \geq 0]} + (1 - p_u) \eta_d e^{\eta_d \ln(z_i)} 1_{[\ln(z_i) < 0]} \tag{4}$$

where $\eta_u, \eta_d > 0$ and $0 \leq p_u \leq 1$. Hence, any jump occurring is a downward jump with probability $(1-p_u)$, and the associated jump size distribution is exponential with parameter η_d. The mean jump size is $\xi \equiv E\left[Z_i - 1\right] = \frac{p_u \eta_u}{\eta_u - 1} + \frac{(1-p_u)\eta_d}{\eta_d + 1} - 1$. The processes $W_{j,t}$ and N_t as well as the random variables $\{Z_i\}$ are independent. The term $\lambda \xi dt$ de-means the jump term in (1) in the usual fashion, thus leaving the drift of $V_{j,t}$ unaffected by the introduction of the jump process. Zhou (2001) proposes a similar jump-diffusion model for the value of the firm using a lognormal distribution for the jump size. The firm-specific jump processes, denoted $J_{j,t}^f$for firm j, are modeled in exactly the same way as the common jump process. Both the jump sizes and the counting processes underlying the common and firm-specific jumps (across firms) are assumed to be independent.

As discussed below in more detail, we ensure that we do not overstate the jump risk in the model by imposing in the calibration that the historical default probability for each rating category is matched by the model. In addition, we also calibrate to the observed cross-firm correlation of equity returns which further limits the common jump component, since the equity correlation implied by the model depends on both the cross-firm diffusion correlation ρ as well as on the parameters of the jump processes.

All parameters are assumed to be identical across firms in the model, in order to maintain parsimony. The only ex-ante heterogeneity allowed for concerns the initial firm value $V_{j,0}$, which depends on the rating category.

We allow for risk premia on both the correlated diffusion shocks and the common jumps. We assume that the firm-specific jumps do not carry a risk premium, since these jumps are diversifiable. Then, under a risk-neutral measure Q, the asset value process is assumed to follow:

$$\frac{dV_{j,t}}{V_{j,t-}} = (r-\delta)\,dt + \sigma dW_{j,t}^{Q} + dJ_t^Q - \lambda^Q \xi^Q dt + dJ_{j,t}^f - \lambda_f \xi_f dt \tag{5}$$

where $J_t^Q = \sum_{i=1}^{N_t^Q}\left(Z_i^Q - 1\right)$ with N_t^Q having jump intensity λ^Q and $\ln(Z_i^Q)$ has a double-exponential distribution with parameters p_u^Q, η_u^Q, and η_d^Q. The mean jump size is now

$$\xi^Q \equiv E^Q\left[Z_i^Q - 1\right] = \frac{p_u^Q \eta_u^Q}{\eta_u^Q - 1} + \frac{(1-p_u^Q)\eta_d^Q}{\eta_d^Q + 1} - 1. \tag{6}$$

Therefore, the jump risk premium, an important economic parameter in our model, is given by $\lambda\xi - \lambda^Q\xi^Q$. The total firm value risk premium π is thus the sum of this jump risk premium and the diffusion risk premium π_d, so that we have $\pi = \pi_d + \lambda\xi - \lambda^Q\xi^Q$. HH invoke the equilibrium analysis of Kou (2002) to motivate the following transformation from the physical to the risk-neutral measure: $\lambda^Q = \lambda E\left[Z_i^{-\gamma}\right]$, where the risk premium parameter γ can be interpreted as the coefficient of relative risk aversion of the representative agent in an equilibrium model. The same risk premium parameter dictates the mapping of the jump size parameters p_u, η_u and η_d from the double-exponential distribution under the physical measure to the double-exponential distribution under the risk-neutral measure: $p_u^Q = \frac{p_u\eta_u/\eta_u^Q}{p_u\eta_u/\eta_u^Q + (1-p_u)\eta_d/\eta_d^Q}$, $\eta_u^Q = \eta_u + \gamma$, and $\eta_d^Q = \eta_d - \gamma$.

Each firm j has a single long-maturity coupon bond outstanding, maturing at T with face value F. This assumption is made for simplicity. The coupon rate is chosen so that the associated default-free bond trades at par. As is standard in structural firm value models, default occurs when the asset value V_t drops to, or below, the default boundary V_t^*. In our model, the default boundary process is exogenous. At maturity, for the default event to be well defined, we impose that $V_T^* = F$. Given that we only model a single bond, the default boundary would be 0 before maturity (since the coupon is automatically paid through the payout rate δ). However, to mimic a richer setting with multiple bond issues maturing at different points in time (where default can occur at these different points in time), we allow for a non-zero default boundary before maturity. We set the default boundary for times $t < T$ at $V_t^* = F$. This enables us to study the term structure of credit spreads up to the final maturity date T. Another important ingredient of the model is the recovery rule. At each point in time, we assume fixed fractional recovery of par, as in e.g. Longstaff and Schwartz (1995) and HH, according to a fractional recovery parameter R. That is, bondholders recover $R \times F$ upon default.

Given the asset value process, default boundary process and recovery rule, the model can be used in the standard fashion to price the corporate bond under the risk-neutral measure and to obtain the credit spread on the corporate bond. Relative to HH, a novelty of our paper is that we go further and also price the equity of each firm, which is effectively a call option on the asset value. The equity values for all firms are added up to obtain the stock market index, which is used to price options on the stock market index. Hence, the index option is priced under the risk-neutral measure as a compound option, namely an option on a portfolio of N call options. It is precisely from the prices of different index options that the crucial parameters concerning the common jump process and the jump risk premium are estimated, as is explained in detail in the next section.

4 Calibration Methodology

This section describes the calibration strategy for the two models we analyze. The first model is the jump-diffusion model, which is the main focus of the paper. Second, we also calibrate a diffusion-only model to highlight the relative importance of jumps. Table 1 summarizes the calibration setup and contains all target values. Generally speaking, the calibration methodology is designed to fit historical information in equity and option prices, as well as historical default and recovery rates. In all cases, we strive to obtain long-term averages for the relevant calibration inputs, as our goal is to analyze the unconditional implications of a jump risk premium for credit spread levels. Importantly, the historically observed level of credit spreads is not included as one of the calibration targets, allowing us to compare our model's out-of-sample forecast to observed credit spread levels.

We model the joint firm value process of 100 firms in order to construct an equity index that closely resembles the S&P 100 index. As discussed in the previous section, we restrict the parameters of the firm value process to be the same across firms with different ratings, except for the initial firm value, which we allow to depend on the rating of the firm. To this end, we use the rating distribution of all firms in the S&P 100 index as of February 2006, which is as follows: 5% (AAA), 16% (AA), 42% (A), 25% (BBB), 5% (BB), and 7% (B). The median and mode of this rating distribution are the A rating. Unreported results show that we obtain very similar results along all dimensions if we assume that all firms in the index are rated A.[3]

The calibration methodology consists of three steps. The first two steps apply to both the diffusion-only and jump-diffusion model, while the third step is only relevant for the jump-diffusion model. We now describe these three steps.

4.1 First two steps of the calibration methodology

In the first step, some parameters that are common to the two models considered, a diffusion-only model and a jump-diffusion model, are fixed at reasonable levels. Here we follow HH and fix the risk-free rate r and the payout rate δ at 8% and 6%, respectively. HH choose the risk-free rate level using historical data for Treasury yields and the payout rate as a weighted average of bond coupons and equity dividend rates. We focus on coupon-paying corporate bond issues that have 10 years to maturity. The face value F of the debt is normalized to 1.

In a second step we exactly match 10 moment restrictions. Of these 10 restrictions, 9 are the same as in HH. First of all, we calibrate to historical estimates of the cumulative 10-year default probability for all ratings from AAA to B, based on Moody's data for 1970-1998.[4] For example, for an A-rated firm the historical estimate for the 10-year default probability equals 1.55%. Second, we calibrate to a historical estimate for the par recovery rate of 51.31% (Keenan, Shtogrin, and Sobehart (1999)). The third calibration restriction involves an equity premium for A-rated firms of 5.99% per year (derived from results of Bhandari (1988)). Fourth, we calibrate to the firm leverage ratio, defined as the market

[3] Over time, the composition of firms in the S&P 100 index changes. For example, poorly performing firms (with decreasing firm value) drop out of the index. We neglect such changes in the composition of the S&P 100 index. To price options and assess the equity return distribution, we only need to simulate the behavior of the stock index one month ahead in our model, so that such composition changes are unlikely to seriously affect our results.

[4] Throughout the paper we assume that Moody's and S&P ratings are the same.

price of the corporate bond divided by the firm value at time zero. Standard and Poor's (1999) report a leverage ratio of 31.98% for A-rated firms. The choice of these calibration restrictions is intuitively clear. For example, the leverage ratio is informative about the initial firm value, the jump and diffusion risk premia are related to the equity premium, and the observed par recovery rate can be used directly to calibrate the fractional recovery rate. The default probabilities depend strongly on the initial firm values and the firm value volatility. Importantly, the calibration approach ensures that both the expected loss on a corporate bond and the equity premium are matched to the data.

Since HH do not model the interaction between firms, they do not need to calibrate to cross-firm return dependence. We calibrate to the equity return correlation of S&P 100 firms. We estimate this correlation by calculating the full correlation matrix for S&P 100 stocks over the 1996-2002 period, using data on daily equity returns, and subsequently taking the average across all correlations. This average correlation equals 25.4%. To summarize, the model parameters are calibrated to exactly match the historical default and recovery rates, the equity premium, the leverage ratio, and the average equity return correlation.

As discussed above, to place the results for the jump-diffusion model in perspective, we will consider a pure diffusion model (which has no common or firm-specific jumps). For this model, the number of parameters[5] is equal to the number of moment restrictions discussed above, so that a perfect fit can be obtained.[6] The jump-diffusion model contains additional parameters and consequently its calibration approach involves a third step, which is described in the next subsection.

4.2 Third step of the calibration methodology

Compared to the diffusion-only model, the jump-diffusion model has nine additional parameters: the common and firm-specific jump intensities λ and λ_f, the probabilities p_u and p_u^f that the (common and firm-specific, respectively) jump is upward, the common and

[5] The parameters are the initial firm value for each rating category (6 parameters), the recovery rate R, the firm value volatility σ, the expected excess return on the firm value π, and the diffusion correlation ρ.

[6] In the diffusion model the firm value correlation is equal to the equity return correlation in continuous time. To speed up the calculations, we thus directly use a value for ρ of 25.4%. This procedure neglects a discretization error which is expected to be small.

firm-specific jump size parameters η_u, η_d, η_u^f, and η_d^f, and the common jump risk premium parameter γ. In addition to all calibration restrictions that are used for the diffusion-only model, we include 15 additional restrictions. First of all, we calibrate the model to prices of S&P 100 index options and individual equity options. For both the index and individual options, we use three strike levels and calibrate to out-of-the-money, at-the-money, and in-the-money (OTM/ATM/ITM) option prices. Again, we allow for rating heterogeneity at the firm level by calibrating to individual option prices across firms with different ratings. As discussed in the next section, we have sufficient individual stock-option data for three rating categories: AA, A, and BBB. We standardize for the level of the stock price by dividing the option prices by the price of the underlying stock (at each point in time). For each rating category, we average the standardized individual option prices across all firms in this rating category and over all weeks in our sample. In total, this gives 12 additional moment restrictions (3 index options, and 3 $\times$ 3 individual options). Clearly, the firm value volatility and the jump parameters are related to the option prices. In particular, the OTM, ATM and ITM index option prices capture the distribution of stock index returns, and are therefore informative about the common jump intensity and the common jump size. Similarly, the individual stock-option prices are informative about the firm-specific jump intensity and the firm-specific jump size.

Finally, we calibrate to the expected returns on S&P 100 equity index options for three moneyness levels. These expected returns on index options are particularly informative about the size of the diffusion and common jump risk premia, since the index options are mainly affected by the common jumps (besides the diffusion shocks). In the next section, we describe how these expected returns are estimated from historical data on S&P 100 index options and the index level. By including both option returns and option prices, we calibrate to information related to the actual as well as the risk-neutral behavior of equity prices. Moreover, by calibrating to both the equity premium and the expected option returns, we can disentangle the diffusion risk premium from the jump risk premium, since options generally have different loadings on diffusion and jump risk than equity. In our calibration, we will impose that the diffusion risk premium and the jump risk premium are both non-negative, consistent with risk-averse investors, by requiring $0 \leq \lambda\xi - \lambda^Q \xi^Q \leq \pi$.

For this jump-diffusion model, the number of parameters is lower than the number of restrictions. We impose that the jump-diffusion model perfectly fits the 10 moments that are used for the diffusion model: the default probability (for each rating category), the recovery rate, the leverage ratio, the equity premium, and the equity correlation. The remaining restrictions (the option prices and option returns) are fitted by minimizing the sum of squared percentage differences between the observed and model-implied restrictions (see Table 1 for an overview).

5 Estimation Results and Model Fit

This section presents the parameter estimates for the diffusion and jump-diffusion models, and discusses the fit of the moment restrictions in the calibration. First we discuss the option data.

5.1 Option data

We use option data from OptionMetrics, consisting of options on the S&P 100 index and individual stocks, which are traded on CBOE. The dataset contains daily end-of-day bid and ask quotes for options with various strike prices and maturities. The sample runs from January 1996 until September 2002.[7] In addition to index options, we use data on individual stock options for 69 different firms. These firms are chosen such that we have a matching sample of individual corporate bonds with available price data.

We focus on short-maturity put options that have on average one month to maturity. These options typically have the largest trading volume (Bondarenko (2003)). For each day in the sample period and for each stock (and for the S&P 100 index), we collect the price of a put option whose remaining maturity is closest to one month and whose strike price is closest to the ATM level. Similarly, we collect the prices of put options whose strike price is closest to 8% OTM and ITM levels for individual options, and closest to 4% OTM and ITM

[7] The equity premium estimate over the 1996-2002 period is 5.96% per year (using S&P 100 returns and the 3-month T-bill rate), which is extremely close to the equity premium of 5.99% (obtained from a longer sample) that we use in the simulation.

levels for index options. We divide each option price by the price of the underlying stock (or index) and take the average over the full sample period. This gives average ITM, ATM and OTM option prices (as a percentage of the underlying value), which we average across firms in the same rating category using the average rating of a firm over the 1996-2002 period. This way, we have individual option prices for 11 AA-rated, 36 A-rated firms, and 22 BBB-rated firms.[8]

Next, we construct estimates for the expected option returns. As mentioned above, we focus on options that have on average one month to maturity. On each day, we construct the return to holding the option to maturity. Using the S&P 100 index option prices and daily data for the value of the S&P 100 index, we construct a time-series of overlapping monthly option returns from which we obtain the average option return over the full sample.

The resulting estimates can be found in the 'target' column in Table 1. The OTM, ATM and ITM index option prices are equal to 0.85%, 2.07% and 4.39% of the underlying index value, respectively. The average monthly return equals about -15% for the ITM option, -25% for the ATM option and -47% for the OTM option. Even though we use a different sample period, these numbers are in line with average option returns reported in Bondarenko (2003) and Driessen and Maenhout (2003). Bondarenko constructs monthly S&P 100 option returns, holding the one-month options until expiration. Using a longer sample period, he reports an average monthly return of -58% for OTM options and -39% for ATM options. Driessen and Maenhout analyze returns on equity index options that are not held until expiration, and report an average monthly return on OTM put options of about -41%.

5.2 Parameter estimates

This subsection discusses the parameter estimates. First, we briefly discuss the estimates for the diffusion-only model. Next, we turn to the estimates for the jump-diffusion model. Finally, we compare the estimation results to findings in the existing literature.

[8] We could not obtain sufficient data for option prices on stocks with AAA ratings or below-BBB ratings.

5.2.1 Diffusion-only model

We start with the model without jumps, which is effectively a Longstaff-Schwartz (1995) model with constant interest rates. By construction, this model achieves a perfect fit for the following target values: the 10-year default probabilities (for all rating categories), the equity risk premium, the leverage ratio, the average par recovery rate and the stock return correlation. The perfect fit is possible because the number of parameters to be estimated equals the number of restrictions.

Turning to the estimated parameters in Table 2, the intuition for the estimates is straightforward. Given the 5.99% matched target value for the equity risk premium, combined with a leverage ratio of roughly 1/3, the firm or asset value risk premium π of 4.11% can be understood as follows. As a first-order approximation, the drift of the equity value process in a pure diffusion model can be written as the firm value drift $(\pi + r - \delta)$ multiplied by the firm-value-to-equity ratio (roughly 3/2) and the delta of equity (close to 1). This results in a equity value drift of roughly 9%. Given a risk-free rate r of 8%, this is consistent with an equity risk premium of 6% if the dividend rate is around 5%. A dividend rate of 5% is reasonable for our model since the coupon rate is 8% and the total payout rate of the firm (weighted sum of coupons and dividends) equals 6%. In fact, using weights of 1/3 and 2/3 for debt and equity, respectively, produces exactly a 5% dividend rate. The firm value volatility σ of 19.95% is consistent with an individual equity return volatility of around 30%, due to the leverage effect. Note that the individual firm value volatility σ is closely related to the default probability. The initial firm value $V_{A,0}$ of 3.072 is clearly driven by the leverage ratio of roughly 1/3, since the face value of the debt is normalized to 1 and the debt is not very risky. The fractional recovery parameter R equals 51.31%. Finally, as discussed before, the firm value diffusion correlation ρ equals the stock return correlation in this model, since jumps are absent.

5.2.2 Jump-diffusion model

Next, we add priced systematic jumps and firm-specific jumps to the model. As before, we constrain the estimation to perfectly fit the expected loss target (i.e., both the historical default probability and the recovery rate), ensuring that the amount of credit risk in the estimated model is not inflated. The parameter estimates, reported in Table 2, reveal an important role for jumps and jump risk premia. We first discuss the parameters of the common jump process. The jump intensity of 0.057 translates to a common jump hitting the economy every 17.5 years. The estimate of the probability that a jump is upward equals 0, so that the model only generates downward jumps. Intuitively, this is because the most important mismatch in the diffusion model is in the left tail of the equity index return distribution, both under the risk-neutral and actual probability measure (as discussed below in more detail). It thus turns out to be optimal to only incorporate downward common jumps in the model, in order to maximize the amount of negative skewness in the equity index return distribution. Note that the amount of negative skewness that can be incorporated is limited by fitting the actual default probability. The estimate for the downward jump size parameter η_d of 12.51 corresponds to a mean jump size ξ of -7.4%. Based on the equilibrium analysis of Kou (2002), the risk premium parameter γ is interpreted by HH as the relative risk aversion parameter of a representative agent. A coefficient of relative risk aversion of 9.24 reflects the high jump risk premium embedded in index option prices. Further, judging from the jump intensity and mean jump size under the risk-neutral measure implied by γ, it is clear that $\gamma = 9.24$ is nontrivial. Under the risk-neutral measure, common jumps with mean size -23.4% hit the economy every 5 years ($\lambda^Q = 0.205$). The effect of γ is summarized by the jump risk premium $\lambda\xi - \lambda^Q\xi^Q$ of 4.36%. Given that the total firm value risk premium π equals 4.36%, the estimate for the jump risk premium implies that the estimated diffusion risk premium equals 0%. That is, the restriction imposed in the calibration that the diffusion risk premium be non-negative is binding. Without this restriction, the diffusion risk premium estimate would be negative at -0.54%. These results illustrate the well-documented and very considerable degree of crash risk aversion embedded in the prices of traded index options.

Finally, we turn to the estimates for the firm-specific jump parameters (Table 2). We find that both upward and downward jumps are relevant for explaining the individual stock-option prices across strikes: conditional upon a jump occurring, the probability that the jump is upward is about 40%. Relative to common jumps, firm-specific jumps occur more often (once every 5 years), and are slightly larger. The expected downward jump size equals about -9%, while the expected upward jump size is 7.7%.

5.2.3 Comparison to previous work

In this subsection we compare the common jump parameter estimates with results from previous work. This comparison is not straightforward, since we model jumps in the firm value, whereas existing work has focused on jumps in equity prices. However, as argued above, given the leverage ratio and delta of equity, we can multiply firm value shocks with a ratio of roughly 1.5 to obtain shocks in the equity price of A-rated firms. This would generate a mean equity jump size of about -11% under the actual measure, and of about -35% under the risk-neutral measure. This can be compared with recent work of Pan (2002) and Eraker (2004), who both estimate a jump-diffusion model with stochastic volatility from equity index returns and prices of equity index options. They restrict the jump intensity to be the same under the actual and the risk-neutral measures, and report an average jump intensity of about 0.36 (Pan) and 0.50 (Eraker) per year,[9] which is much larger than our estimates. Pan reports mean jump sizes of -0.3% and -18% under the actual (P) and the risk-neutral (Q) measures, while Eraker reports mean jump sizes of -0.38% (P) and -2.00% (Q), respectively. These values are somewhat smaller than our estimates. One reason for this difference may be that Pan and Eraker also include stochastic volatility, which is negatively correlated with equity returns. This already captures some of the negative skewness in the return distribution. However, most important for our purpose is the total jump risk premium. The estimates of Pan imply a jump risk premium of 6.39% per year, while our firm value jump risk premium of 4.36% generates an equity jump risk premium of 5.99%. Without the non-negativity restriction on the diffusion risk premium, the model would generate an equity jump risk premium of 6.73%. Thus, our estimate for the jump risk premium is very much in line with Pan's estimate. Comparing with Eraker is more difficult, since he also includes a volatility risk premium. His estimates imply a jump

[9] These values are obtained by multiplying the parameter λ with $\overline{v}$ in Pan (2002), and by multiplying the parameter λ_0 in Eraker (2004) with 252 (the number of trading days).

risk premium of 0.85%.

Next, we compare our jump parameter estimates with Aït-Sahalia, Wang, and Yared (2001). They propose a peso-problem interpretation for the difference between the option-implied stock price distribution and the probability distribution generated by a one-factor diffusion model with time-varying volatility. Fixing the jump size at -10%, they show that a risk-neutral intensity of 1/3 per year generates the smallest difference between the option-implied and model-implied risk-neutral probability distributions. These numbers can directly be interpreted as estimates for risk-neutral jump parameters. Our jump estimates under the risk-neutral measure are somewhat different, since they generate jumps that are more negative, but occur less often. This could be due to a difference in modeling approach (our model does not have a fixed jump size) or sample period, but also due to a difference in calibration methodology: Aït-Sahalia, Wang, and Yared (2001) focus on fitting the skewness and kurtosis of the stock price distribution, while we calibrate to option prices and returns.

It is also insightful to compare our common jump estimates to the jump parameters employed by HH. As discussed above, HH do not estimate the common jump parameters, but calculate the credit spreads that obtain in a jump-diffusion model for two examples. The first example has a common jump intensity of $\lambda = 3$, and symmetric and small jumps: $p_u = p_d = 0.5$ and $\eta_u = \eta_d = 30$. Imposing that the total risk premium equals the jump risk premium, HH show that this model generates low credit spreads, similar to the diffusion-only model. The second example has less frequent but very large jumps, which are still symmetric: $\lambda = 0.1$, $p_u = p_d = 0.5$ and $\eta_u = \eta_d = 5$. This model generates credit spreads that are much higher than the credit spreads generated by our estimates. This shows that the two examples presented by HH are quite extreme and very different from our estimates. In particular, our estimates imply more downward than upward jumps (generating negative skewness), and jump sizes that are in between the two extremes presented by HH.

5.3 Fit of moment restrictions

In this subsection we analyze the calibration fit of option prices and returns. For the diffusion model, this is a direct out-of-sample test of the model, since the model parameters are not calibrated to option prices and returns. Table 3A shows that this model generates expected option returns that are much less negative than the observed average option returns. For example, the OTM expected option return predicted by the model equals −19.9%, while the empirical average is −46.5%. Therefore, the model does not capture the risk premia embedded in observed option returns, in line with evidence in the option pricing literature that additional risk factors are priced.

The diffusion-only model also generates option prices that are well below the observed option prices. For example, over our 1996-2002 sample the average ATM index option price equals 2.07%, as a fraction of the underlying value. The diffusion-only model generates a price of 1.48%. Similarly, the model underprices individual options: for A-rated firms, the average ATM option price is 3.50%, while the model predicts 3.01% (Table 3B).

Table 3 further shows that, in relative terms, the underpricing is most severe for OTM options. Because we consider put options, this means that the pure diffusion model generates an index return distribution that lacks the very considerable degree of negative skewness that is embedded in the observed option prices (i.e., the volatility skew). It is worth pointing out that this apparent mispricing of index options occurs even though the pure diffusion model endogenously produces stochastic volatility for the S&P index return and therefore moves beyond Black-Scholes pricing. Indeed, the well-known leverage effect makes equity volatilities stochastic since equity is a call option on the firm value, so that index puts become compound options. As an intuitive illustration of the index option prices in Table 3A, we calculate the Black-Scholes implied volatilities, both from observed put prices and from the put prices generated by the model. For the latter, the implied volatilities are 13.7% (ATM) and 14.5% (OTM), exhibiting a very slight implied-volatility skew. This finding of a very slight skew is quantitatively consistent with the work of Toft and Prucyk (1997), who only find some implied skew when firms have high leverage. However, the implied volatilities for observed ATM and OTM index option prices are 19.1% and 21.6%, respectively.[10] The observed option prices thus exhibit the well-known implied-volatility skew. This directly illustrates that the diffusion-only model misses both the overall level of option prices and

[10] These implied volatilities are calculated by inverting the average observed option prices, assuming an annual interest rate of 3.5% and dividend rate of 2.5%.

the volatility skew.

Compared to the diffusion model, the model with jumps fits expected index option returns and option prices much better (Table 3). The most important improvement of the jump-diffusion model over the diffusion model is in fitting the expected option returns. Due to the jump risk premium, the model predicts an expected return on OTM puts of -50.1%, which is close to the empirical counterpart of -46.5%. For ATM and ITM options, there is also a large improvement in the fit of option returns. Thus, allowing for a jump risk premium helps considerably in fitting expected option returns. Note that this is achieved without increasing the total equity premium.

Due to the jump risk premium, the jump-diffusion model also generates option prices that are much closer to observed prices than the diffusion-only model. Still, the observed option prices are even higher. Translating the prices in Table 3A into implied volatilities, the model generates 16.5% (ATM) and 18.0% (OTM), versus 13.7% and 14.5%, respectively, for the diffusion-only model, compared to observed implied volatilities of 19.1% and 21.6%, respectively. Importantly, the jump-diffusion model generates an implied skew that is much larger than the diffusion model, and closer to the observed implied skew. Turning to individual options, Table 3B shows that adding both systematic and firm-specific jumps also considerably helps to improve the fit of option price levels. As for index options, the model still underestimates the level of option prices to some extent.

In sum, the jump-diffusion model fits option prices and returns much better than the diffusion model. In particular, the fit of average index option returns is very good, while the jump-diffusion model somewhat underprices options. In other words, the model provides a very good description of the difference between the risk-neutral and actual equity index return distributions, while underestimating the dispersion of the risk-neutral distribution. In section 7.3 we will see that the model also underestimates the dispersion of the actual equity index return distribution, and we will discuss this result in more detail. For our purpose, the very good fit of option returns is most important, since the associated jump risk premium is a key determinant of credit spread levels.

A final interesting aspect of the model fit in terms of option prices concerns the variation of individual option prices across ratings. Empirically, Table 3B shows that lower-rated firms have higher option prices. Even though we restrict all parameters to be the same across ratings, our firm-value model also generates variation of option prices across ratings. This is because we allow the current firm value (and thus the leverage ratio) to vary across ratings. The results in Table 3B show that the model indeed generates higher option prices for lower-rated firms. Still, the empirically observed variation across ratings is slightly larger, suggesting that the parameters of the firm value processes may actually differ across ratings. A model with for example firm-specific regime switches in some of the parameters may help to explain this variation better. We leave this for future research.

6 Implications for Credit Spread Levels

We now turn to the main results of the paper, namely the out-of-sample implications of the models for the credit spread level. We first discuss the credit spread data that we use for this analysis, and then present the results for credit spread levels in section 6.2 and for credit spread term structures in section 6.3.

6.1 Credit spread data

In Table 4 we report the average credit spread levels for 10-year bonds as used by HH, based on Lehman data for 1973-1993. For comparison, we also consider a different sample of Datastream data on Lehman corporate bond indices, which runs from 1983 until 2002.[11] The second column of Table 4 contains the time series averages for these credit spreads, which are very similar to the levels reported by HH.

We further validate our results using a different sample of corporate bond prices from Bloomberg for 1996-2002 for those 69 firms for which we have individual stock option data available. This allows a detailed study of the implications for the term structure of credit spreads. In total, we end up with 524 corporate bonds issued by these 69 firms.[12] Besides

[11] Datastream reports (average) yields for both intermediate and long-maturity government and corporate bond indices, as well as the average maturity for each index. We first subtract the appropriate Treasury yield from the yield of each corporate index to obtain credit spreads. Subsequently we interpolate between the intermediate and long-maturity credit spreads to obtain 10-year maturity credit spreads.

[12] We only use bonds with constant, semi-annual coupon payments, and no embedded put or call options or

corporate bond price data, 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 and 10 years.

We extract a term structure of zero-coupon credit spreads using these bond prices at the rating level, as in Elton et al. (2001). Each week, we assign the corporate bonds to rating-maturity buckets, with maturity intervals of 1 to 3 years, 3 to 5 years, 5 to 7 years, 7 to 9 years, and 9 to 11 years. We then assume that the term structure of zero-coupon corporate rates is flat within each maturity interval, allowing the estimation of the term structure for each rating category. The term structure of default-free zero-coupon interest rates is estimated in the same way, so that par-coupon credit spreads per rating category can readily be calculated. We only have sufficient data for AA, A, and BBB ratings. Figures 1 through 3 depict the observed par-coupon credit spread term structures. In line with several other papers (for example, Bohn (1999), Duffee (1999), and Elton et al. (2001)), we find upward sloping credit spread term structures for these investment-grade firms.

Finally, we also corroborate our results using data on credit default swaps (CDS). Recently, several articles have analyzed spreads on credit default swaps, e.g. Longstaff, Mithal, and Neis (LMN, 2005) and Blanco, Brennan, and Marsh (2005). These CDS spreads may provide a better measure of default risk than spreads on corporate bonds, since CDS spreads are not influenced by tax effects and have become more liquid than corporate bonds. Unfortunately, only recent data for CDS spreads are available. LMN report average corporate bond and CDS spread levels for the period March 2001 until October 2002, presented in the third and fourth column of Table 4.[13] These CDS spreads are clearly much lower than corporate bond credit spreads, and LMN attribute the difference to tax and liquidity effects. Because credit spreads on corporate bonds were historically high during the 2001-2002 sample period, we also provide extrapolated CDS spreads for the full 1973-1993 period of HH in Table 4.[14] In the next subsection we compare these spread levels with

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 they have the same rating as the senior unsecured bonds of the particular firm.

[13] LMN report results for different default-free term structures. We use the results that are based on the Treasury yield curve, for contracts with 5 years to maturity (see their Table 2).

[14] We attempt to correct for this by assuming that the ratio of CDS to corporate spreads is constant. We

the model-implied credit spreads.

6.2 Credit spread levels

We first briefly discuss the results for the diffusion-only model. This model generates very low credit spreads. The 10-year credit spread equals 27 basis points for A-rated debt (Table 5A). This number is similar to what HH report, across different structural firm value models and across a variety of different parameterizations. Empirically, the credit spread for 10-year debt of this rating is at least 4 times as large (depending on the sample period). For other ratings, the model-implied credit spreads are also well below the observed spreads (Table 5A). Especially for investment-grade firms the relative difference between model-implied and observed credit spreads is large. Even when looking at CDS data, Table 4 shows that the observed 5-year spreads range from 45 basis points (AA) to 132 basis points (BBB), while the model (unreported) generates 5-year par-coupon spreads between 4 basis points (AA) and 37 basis points (BBB).

Next, we turn to the results for the jump-diffusion model. The option-implied jump risk premium brings the 10-year credit spread level from 27 basis points to 65.6 basis points for A-rated firms (Table 5A). Given that the 10-year default rate equals 1.55% for A-rated firms, the result is rather encouraging. Similarly, for other rating categories a large increase in the credit spread is obtained. In order to directly test whether our model predictions are compatible statistically with the average credit spread in our 1983-2002 sample, we compute the 95% confidence interval (using Newey-West) for the estimated average credit spread (Table 5). For investment-grade ratings, the model-implied spread is outside this 95% confidence interval, showing that in our model credit risk does not fully explain observed credit spreads on corporate bonds. However, many authors have demonstrated the presence of non-default related factors in credit spreads, like taxes and liquidity. To illustrate this, we also calculate the model-implied credit spreads including the tax effect of Elton et al. (2001), which involves a state tax on corporate bond coupons that does not apply to Treasury bond coupons. Using a tax rate of 4.875% (as reported by

scale the CDS spreads by the ratio of the corporate bond spreads reported by HH to the corporate bond spreads reported by LMN.

Elton et al. (2001)) and following their procedure, Table 5 reports the tax-corrected model-implied credit spreads. Interestingly, in this case the spreads implied by the jump-diffusion model are inside the 95% confidence interval for 4 out of 6 rating categories.[15] Also note that the spreads implied by the diffusion-only model are still outside the confidence interval for 5 out of 6 ratings. These results illustrate that the tax effect is a potential candidate for explaining the residual error, but we do not want to claim here that the tax rate of 4.875% is the appropriate marginal tax rate faced by the marginal investor. In fact, the size of the tax effect is debated (see Amato and Remolona (2005)). As an alternative or complement to the tax effect, liquidity effects may well explain (part of) the residual difference between observed and model-implied credit spreads.[16]

Finally, we compare the model-implied 5-year spreads with the observed 5-year credit default swap spreads. The model generates 5-year spreads between 29 basis points (AA) and 89 basis points (BBB). Comparing this with the last column of Table 4, we see that our model still underestimates CDS spreads, but much less so than the pure diffusion model. Of course, CDS spreads may contain a liquidity premium, so that it is not clear that the firm value model should fully match the observed CDS levels. In addition, the CDS spread averages are estimated using a short sample period.

These results provide evidence that the severe mispricing of corporate bonds by existing structural models can be remedied to a large extent by introducing priced jump risk. Intuitively, having jumps allows the model to generate more negative skewness in the firm value return distribution. Furthermore, having jump risk premia enables the model to generate higher credit spread levels.

6.3 Term structure of credit spreads

So far, we have mainly focused on explaining the 10-year credit spread level. However, previous work has shown that short-maturity credit spreads are even harder to explain using structural firm value models. Given that we have incorporated a default boundary

[15] Note that the model-implied credit spreads are based on parameter estimates, which contain estimation error. Our procedure of comparing the model-implied spread with the empirical confidence interval is thus conservative in the sense that we reject the jump-diffusion model too often.

[16] See for instance Chen, Lesmond, and Wei (2005) and De Jong and Driessen (2005).

that equals the face value of the debt during the 10-year maturity period, we can directly value (hypothetical) bonds with shorter maturities. For each maturity, we choose a coupon rate such that the associated default-free bond trades at par, and calculate the credit spread relative to a default-free bond with the same maturity and coupon.

The results in Figures 1 through 3 show that incorporating jumps and a jump risk premium helps to generate larger short-maturity credit spreads. While the model without jumps generates short-maturity credit spreads that are in most cases essentially zero (not reported), the jump-diffusion model generates nonzero credit spreads. We compare these with observed term structures of credit spreads, constructed using Bloomberg data on individual corporate bonds of different maturities (see section 6.1). The figures show first of all that the empirically observed shapes of the credit spread term structure are very similar to the model-implied shapes. Further, using again the tax correction of Elton et al. (2001), both the level and shape of the observed and model-generated term structures are very similar.

7 Tests of Other Out-of-sample Implications

In this section we perform several additional out-of-sample analyses to examine the implications of the jump-diffusion model. We assess its implications for (i) the term structure of default probabilities, (ii) the volatility of credit spread changes, (iii) the distribution of equity index returns, (iv) default correlations, and (v) the behavior of credit spreads before and after the 1987 crash.

7.1 Term structure of default probabilities

In this subsection we study the term structure of default probabilities generated by the model. In particular, we analyze the relative importance of jumps versus diffusion shocks for generating default events.[17] We want to make sure that default events are not only the result of jumps, since in that case the model would generate a very irregular time

[17] Leland (2004) argues that including jump risk is important to generate a realistic term structure of default probabilities.

series of default rates. Therefore, we generate two term structures of default probabilities for each rating category: the 'total' default probability generated by the jump-diffusion model and the term structure of default probabilities that is obtained when we set all jump intensities (both common and firm-specific) equal to zero in the jump-diffusion model (without changing the other parameter values in the model).

Figures 4 and 5 depict the results for investment-grade firms. We obtain similar results for speculative-grade firms. Not surprisingly, the graphs show that the model generates rather low default probabilities for short horizons and high-rated firms. Most importantly, the results indicate that a considerable part of the default probability is generated by diffusion shocks. Even for AAA-rated firms, about half of the default probability is due to diffusion shocks. The main reason for the moderate impact of jumps is that the jump intensities under the actual measure are modest. For lower ratings, diffusion shocks account for an even larger fraction of the total default probability. These results show that even though our model contains large jumps, diffusion shocks and jumps both play an important role in the model.

7.2 Volatility of credit spread changes

Another way to assess the performance of the jump-diffusion model is to analyze to what extent the model fits the observed variation of credit spreads. This is particularly interesting since we also study how the model fits the variation of equity returns.

Similar to our analysis for stock returns, we focus on the systematic variation in credit spreads. Empirically, we measure this using the Lehman corporate bond index data for 1983 - 2002, discussed in section 6.1. For each rating category, we calculate the standard deviation of the monthly change in the average credit spread of all bonds in the appropriate corporate bond index. Table 5B contains these numbers. For example, for the A-rated index we find a monthly standard deviation of the credit spread change of 11.5 basis points. We also calculate a confidence interval for the estimated standard deviations, using the central limit theorem for the variance estimator and subsequently applying the delta-method. Table 5B reports the 2.5% lower bound of the 95% confidence interval. For the A-rated index, this lower bound is 6.9 basis points.

To compare these results with the model-implied standard deviations, we simulate monthly changes in the firm values for the jump-diffusion and diffusion model (given the initial levels of the firm values), from which we obtain monthly changes in the credit spreads. Given that we focus on the systematic variation of corporate bond indices, we simulate for each rating category credit spread changes for 100 firms, and calculate the monthly standard deviation of the average credit spread change across these 100 firms.

The results in Table 5B show that both the diffusion and jump-diffusion model significantly underestimate the variability of credit spreads, except for the B rating category. Even though the jump-diffusion model underestimates volatility, Table 5B also shows that this model does much better than the diffusion model. For example, for the A rating, the diffusion model generates a monthly standard deviation of 2.8 basis points, while the jump-diffusion model predicts 5.9 basis points. In the next subsection, we will see that the jump-diffusion model also underestimates the equity volatility and discuss this in more detail.

7.3 Equity return distribution

In this subsection we study the model implications for the equity index return distribution, focusing on the stock index since, for our purpose, modeling the systematic variation (and the associated risk premium) is most important.

We first calculate the stock-index return distribution implied by the jump-diffusion model by simulating weekly changes in the firm value and the corresponding equity value. We focus on a weekly frequency using 250,000 simulations, since for daily returns one would need even more simulations to reliably estimate the impact of jumps on the distribution. We compare this with the empirical distribution of the S&P 100 index return. We estimate this empirical distribution from daily data for the 1996-2002 period, using overlapping weekly returns.

Figure 6 presents both the empirical and model-implied distribution of index returns. The graph shows that the empirical distribution has clearly more dispersion than the model-implied counterpart. Both the left and right tail are fatter for the empirical distribution, as evidenced by the annualized standard deviation, which equals 19.3% empirically as compared to 15.5% for the model.

Next we focus on the left tail of the distribution, since this is the most relevant part of the distribution for modeling default risk. We want to make sure that even deep in the left tail the jump-diffusion model does not generate 'too much' risk. Table 6 reports empirical and model-implied cumulative probabilities, as well as confidence intervals for the empirical cumulative probabilities. These are calculated by bootstrapping the daily observed returns and reconstructing a series of overlapping weekly returns in each bootstrap simulation. Table 6 shows that even for a weekly return of –10% the jump-diffusion model does not overstate the observed risk. In fact, the model predicts a left tail that is thinner than the observed left tail, although for the -10% to -8% return levels the difference is not significant.

In section 5.3 we already saw that the jump-diffusion model somewhat underestimates equity option prices, or equivalently, that the model underestimates the dispersion of the equity return distribution under the risk-neutral measure Q. In this section we have found the same result for the distribution under the actual measure P. This is consistent with the result that the jump-diffusion model gives a very accurate description of expected equity index option returns, which describe the transformation from P to Q. We observe a similar result for corporate bonds: the jump-diffusion model generates credit spread levels that are close to observed levels, but underestimates the volatility of credit spread changes.

The restriction to match the default probability is the main reason for the underestimation of volatilities. This highlights a tension between the observed level of default rates and the observed volatility of equity and corporate bond prices. As pointed out by HH, one interpretation of this result is that asset prices exhibit excessive volatility (Shiller (1981)). Such excessive volatility could for example be caused by liquidity-related shocks. Collin-Dufresne, Goldstein, and Martin (2001) argue that corporate bond prices are partially driven by local demand/supply shocks, while Chordia, Roll, and Subrahmanyam (2000) show that equity prices are exposed to systematic liquidity shocks. We leave a detailed analysis of excessive volatility for further research.

7.4 Default correlations

In this subsection we perform an explorative analysis of default correlations. This is interesting since the inclusion of common jumps could have a significant effect on default correlations. In fact, HH argue that such common jumps may cause defaults to be extremely highly clustered. To analyze this, we compare empirical estimates of default correlations, obtained by Lucas (1995), with the default correlations that are implied by the diffusion and jump-diffusion models analyzed in this paper. Lucas uses Moody's default data on more than 4,000 issues for 1970-1993. To obtain the model-implied correlations, we use simulations and calculate default correlations under the actual probability measure.

Before we present the results, it is important to emphasize that this is merely an explorative analysis. Our model setup explicitly focuses on the correlation structure of S&P 100 firms, while the empirical estimates of Lucas (1995) are based on a much larger sample of firms. It is likely that the cross-firm correlations of S&P 100 firms are higher than the correlations of other typically smaller firms. In addition, even though Lucas uses more than 4,000 issuers in his analysis, there is obviously estimation error present in his estimates of default correlations. As noted by Lucas, default rates are close to zero especially for short horizons, so that few default observations are available. For this reason, we focus on a 10-year horizon for our analysis of default correlations.

Table 7 reports the 10-year default correlations implied by the diffusion and jump-diffusion models, as well as the estimates reported by Lucas. Default correlations are presented for pairs of firms in different rating categories. Focusing on the diffusion-only model first, the model overestimates default correlations for high-rated firms. For example, the AAA-AAA default correlation is estimated at 1% by Lucas, while the diffusion model generates a default correlation of 3.2%. For low-rated firms, the diffusion model actually generates default correlations that are too low. The most extreme case is the B-B default correlation, for which the model generates a value of 14.5%, while the empirical estimate equals 38%.

Turning to the jump-diffusion model, incorporating common downward jumps clearly increases default correlations relative to the diffusion-only model. Quantitatively however, the effect is relatively small. For example, the AAA-AAA correlation increases from 3.2% to 3.4% when jumps are added, while the B-B correlation increases from 14.5% to 15.2%. Comparing the results with the empirical estimates, the model overestimates default correlations for high ratings (and more so than the diffusion model), and underestimates default correlations for low ratings (but less so than the diffusion model). In sum, we conclude that, although the models do not generate a perfect fit, the default correlations implied by both the diffusion and jump-diffusion models do not seem excessively high, especially given the limited empirical evidence and the caveats discussed above.

7.5 Credit spreads and the crash of 1987

As a final additional test of the jump-diffusion model, we examine a subtle implication stemming from a structural break in option prices around the stock market crash of 1987 (Rubinstein (1994)). Remarkably, before the crash, the implied volatilities of stock index options reflected a volatility smile, which changed into a volatility skew after the crash. This skew has not disappeared to date. If this change in option prices reflects a structural increase in risk premia, credit spreads would be systematically higher after the 1987 crash. However, we cannot rule out a different explanation for the systematic change in option prices. Before 1987, option markets were young and quite illiquid. Since the crash, options became more popular, in part perhaps due to the limited success of dynamic portfolio insurance schemes that were popular before the crash. It is therefore possible that option markets were not mature and liquid enough to properly reflect the distribution of the underlying asset prices.

To test for a systematic change in credit spreads after the crash, we again use the Lehman corporate bond index data, in this case an all-maturity index incorporating all investment-grade bonds, starting in 1973. We find that the average spread from 1973 to October 1987 equals 94.0 basis points, while the average spread from November 1987 to December 2005 equals 106.1 basis points. Even though the average spread is higher after the crash by about 12 basis points, this difference is not significant with a t-statistic of 0.86.[18] Changing the sample periods by deleting the first and last few years of data does

[18] This t-statistic is calculated using Newey-West with 12 monthly lags for both subsamples.

not change this result.

These results show that it is not clear whether credit spreads have increased since 1987. As discussed above, a possible explanation for this result is the limited liquidity and maturity of option markets before 1987.

8 Conclusion

We calibrate a structural firm value model with priced jump risk to information in equity and option prices. The estimated model with priced jump risk explains a significant part of observed credit spread levels, and much of the remaining error may be attributed to tax and liquidity effects. In line with existing work, we find that a model without jumps generates much lower credit spreads. We show that such a model also has a worse fit of equity and option prices. Most importantly, our results suggest that prices of jump risk embedded in corporate bonds and credit default swaps on the one hand, and in equity and equity options on the other hand, are close to each other.

Obviously, understanding the size and source of the jump risk premium is an interesting topic for further research. This is challenging since recent work has argued that rational pricing models may have difficulties explaining the option-implied jump risk premia (Bondarenko (2003), Driessen and Maenhout (2003)).

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Table 1: Target Values in Calibration

The table contains target values used for the calibration of the diffusion and jump-diffusion model (see section 4). The table also summarizes the calibration strategy for each model. 'Perfect fit' means that the calibration procedure is designed to perfectly fit this calibration target. 'Imperfect fit' indicates that the calibration target is fitted by a nonlinear least-squares procedure. 'Out of sample' means that the calibration target is not included in the calibration procedure.

	Target	Model	
		Jump-diffusion model	Diffusion model
10-year default prob. (A)	1.55%	Perfect fit	Perfect fit
Equity risk premium (A)	5.99%	Perfect fit	Perfect fit
Leverage ratio (A)	31.98%	Perfect fit	Perfect fit
Average recovery rate	51.31%	Perfect fit	Perfect fit
Stock return correlation	25.39%	Perfect fit	Perfect fit
10-year default prob (AAA)	0.77%	Perfect fit	Perfect fit
10-year default prob (AA)	0.99%	Perfect fit	Perfect fit
10-year default prob (BBB)	4.39%	Perfect fit	Perfect fit
10-year default prob (BB)	20.63%	Perfect fit	Perfect fit
10-year default prob (B)	43.91%	Perfect fit	Perfect fit
OTM index option price ($\times 100$)	0.847	Imperfect fit	Out of sample
ATM index option price ($\times 100$)	2.073	Imperfect fit	Out of sample
ITM index option price ($\times 100$)	4.392	Imperfect fit	Out of sample
OTM expected option return	-46.52%	Imperfect fit	Out of sample
ATM expected option return	-24.78%	Imperfect fit	Out of sample
ITM expected option return	-14.81%	Imperfect fit	Out of sample
Individual option prices	Table 3B	Imperfect fit	Out of sample

Table 2: Parameter Estimates

The table reports estimates of the model parameters (obtained using the calibration procedure described in section 4) for the jump-diffusion model and the diffusion-only model.

Model	Jump-diffusion model	Diffusion model
Firm value risk premium π	4.36%	4.11%
Firm value volatility σ	19.90%	19.95%
Fractional recovery par. R	51.31%	51.31%
Diffusion correlation ρ	28.13%	25.39%
Initial firm value (AAA) $V_{AAA,0}$	3.715	3.523
Initial firm value (AA) $V_{AA,0}$	3.325	3.203
Initial firm value (A) $V_{A,0}$	3.079	3.072
Initial firm value (BBB) $V_{BBB,0}$	2.392	2.290
Initial firm value (BB) $V_{BB,0}$	1.588	1.561
Initial firm value (B) $V_{B,0}$	1.267	1.221
Jump intensity λ	0.057	-
Probability of upward jump p_u	0.00%	-
Upward jump size parameter η_u	-	-
Downward jump size parameter η_d	12.513	-
Risk premium par. γ	9.239	-
RN jump intensity λ^Q	0.205	-
Mean jump size ξ	-7.40%	-
RN mean jump size ξ^Q	-23.40%	-
Jump risk premium $\lambda\xi - \lambda^Q\xi^Q$	4.36%	-
Firm-specific jump intensity λ_f	0.218	-
Prob. of firm-specific upward jump $p_{u,f}$	0.408	-
Upward firm-specific jump size par. $\eta_{u,f}$	11.981	-
Downward firm-spec. jump size par. $\eta_{d,f}$	10.087	-

Table 3: Option Pricing Implications

This table reports empirical estimates and model implications for option prices and expected option returns. Panel A reports average option prices and average monthly option returns for S&P 100 index options, as observed over the 1996-2002 sample period and as implied by the jump-diffusion and the diffusion-only models. The OTM (ITM) index options are 4% out-of-the-money (in-the-money). Panel B reports the average prices of individual stock options over the 1996-2002 period and the model-implied prices. The observed option prices are averaged according to the rating category of the underlying stock. The OTM (ITM) stock options are 8% out-of-the-money (in-the-money). Option prices are expressed as a fraction of the price of the underlying asset.

Panel A

	Observed	Jump-diffusion model	Diffusion model
OTM Index option price (×100)	0.847	0.553	0.308
ATM Index option price (×100)	2.073	1.783	1.478
ITM Index option price (×100)	4.392	4.364	4.084
OTM Exp. index option return	-46.52%	-50.13%	-19.92%
ATM Exp. index option return	-24.78%	-23.98%	-14.11%
ITM Exp. index option return	-14.81%	-13.11%	-9.24%

Panel B

	Observed	Jump-diffusion model	Diffusion model
AA-rated firms: OTM option price (×100)	0.915	0.717	0.501
AA-rated firms: ATM option price (×100)	3.164	3.131	2.911
AA-rated firms: ITM option price (×100)	8.436	8.549	8.322
A-rated firms: OTM option price (×100)	1.086	0.751	0.567
A-rated firms: ATM option price (×100)	3.496	3.215	3.010
A-rated firms: ITM option price (×100)	8.694	8.610	8.395
BBB-rated firms: OTM option price (×100)	1.285	0.898	0.708
BBB-rated firms: ATM option price (×100)	3.742	3.452	3.277
BBB-rated firms: ITM option price (×100)	8.948	8.763	8.578

Table 4: Observed Corporate Bond and Credit Default Swap Spreads

The table contains average credit spread levels (in basis points) across rating categories, (i) as reported by Huang and Huang (2003), (ii) estimated using a 1983-2002 sample of credit spread data for Lehman indices, and (iii) as reported by Longstaff, Mithal, and Neis (LMN, 2005). In addition, the table reports average credit default swap spreads (in basis points), as reported by LMN, and an extrapolation of these spreads to the 1973-1993 sample period of HH (see section 6).

	Corporate Bond Spreads			Credit Default Swap Spreads	
Source	HH	Lehman index	LMN	LMN	LMN
Period	1973-1993	1983-2002	2001-2002	2001-2002	extrapolated
Maturity	10-year	10-year	5-year	5-year	5-year
AAA	63	66	-	-	-
AA	91	92	104	51	45
A	123	115	151	80	65
BBB	194	171	229	156	132
BB	320	332	428	358	268
B	470	548	-	-	-

Table 5: Model Implications for Credit Spread Levels and Volatility of Credit Spread Changes

Panel A reports model implications for the level of the credit spread on a 10-year par-coupon corporate bond, as well as the average credit spread of Lehman corporate bond indices over a 1983-2002 sample period. In brackets, we report the value for the 2.5% confidence level of the average credit spread, calculated using the standard error (based on Newey-West with 12 monthly lags). We also report tax-corrected credit spread levels, using the tax correction on corporate bond coupons of Elton et al. (2001), with their tax rate of 4.875%. Panel B reports the standard deviation of monthly changes in the credit spreads on Lehman corporate bond indices (1983-2002), and as implied by the models. The model-implied standard deviation is calculated by simulating credit spreads for 100 firms per rating category, and subsequently calculating the monthly variation of the average spread across firms. For the empirical standard deviation, we also calculate the standard error and the corresponding 2.5% confidence level value (using the delta-method).

Panel A: 10-year Corporate Bond Credit Spread Level (in basis points)

Rating	Lehman index data Avg. (2.5% LB)	Jump-diffusion model	Diffusion model	Jump-diffusion model *Tax corrected*	Diffusion model *Tax corrected*
AAA	66.3 bp (55.0 bp)	44.3 bp	11.7 bp	79.4 bp	46.9 bp
AA	91.9 bp (75.2 bp)	52.5 bp	19.4 bp	87.6 bp	54.6 bp
A	115.4 bp (97.4 bp)	65.6 bp	27.1 bp	100.6 bp	62.2 bp
BBB	171.0 bp (147.7 bp)	111.0 bp	68.4 bp	145.0 bp	102.7 bp
BB	332.6 bp (281.4 bp)	292.0 bp	247.9 bp	332.9 bp	280.4 bp
B	547.8 bp (475.6 bp)	491.8 bp	478.7 bp	515.4 bp	502.9 bp

Panel B: Standard Deviation of Monthly Credit Spread Changes (in basis points)

Rating	Lehman index data Avg. (2.5% LB)	Jump-diffusion model	Diffusion model
AAA	10.3 bp (7.2 bp)	3.8 bp	1.5 bp
AA	10.9 bp (6.6 bp)	4.1 bp	2.3 bp
A	11.5 bp (6.9 bp)	5.9 bp	2.8 bp
BBB	16.0 bp (10.6 bp)	10.5 bp	6.7 bp
BB	41.2 bp (30.4 bp)	23.1 bp	20.9 bp
B	58.8 bp (41.2 bp)	49.8 bp	37.6 bp

Table 6: Implications for Equity Index Return Distribution

This table reports cumulative probabilities of the weekly equity index return distribution, as implied by the jump-diffusion model. We also report empirical cumulative probabilities, using weekly overlapping returns constructed from daily data on S&P 100 returns for 1996-2002. We bootstrap the daily data to construct bootstrap series of overlapping weekly returns. Using 1000 bootstrap simulations, we then calculate the confidence interval for the empirical cumulative probabilities.

	Empirical	Empirical	Jump-diffusion model
Return	cumulative probability	95% conf. interval	cumulative probability
-10%	0.33%	(0.00%; 0.44%)	0.02%
-9%	0.38%	(0.00%; 0.55%)	0.02%
-8%	0.55%	(0.03%; 0.93%)	0.03%
-7%	1.04%	(0.27%; 1.65%)	0.07%
-6%	1.81%	(0.93%; 2.97%)	0.24%
-5%	3.35%	(2.42%; 5.38%)	0.95%

Table 7: Default Correlations

This table reports 10-year default correlations of firm-pairs in different rating categories, as estimated empirically by Lucas (1995) and as implied by the jump-diffusion model and the diffusion-only model.

Empirical estimates Lucas (1995)						
	AAA	AA	A	BBB	BB	B
AAA	1%					
AA	2%	1%				
A	2%	2%	2%			
BBB	2%	1%	1%	0%		
BB	4%	3%	4%	2%	8%	
B	9%	8%	9%	6%	17%	38%
Jump-diffusion model						
	AAA	AA	A	BBB	BB	B
AAA	3.4%					
AA	3.4%	3.0%				
A	4.3%	4.3%	4.5%			
BBB	4.6%	4.8%	5.7%	5.9%		
BB	4.9%	5.6%	6.9%	8.5%	12.3%	
B	4.3%	4.7%	6.2%	8.0%	13.2%	15.2%
Diffusion model						
	AAA	AA	A	BBB	BB	B
AAA	3.2%					
AA	3.3%	2.5%				
A	3.4%	3.2%	3.4%			
BBB	3.6%	4.1%	4.4%	5.0%		
BB	4.2%	4.9%	5.5%	7.5%	11.9%	
B	3.5%	4.1%	5.2%	7.3%	12.3%	14.5%

Figures 1-3: Term Structure of Credit Spreads

These figures depict observed term structures of par-coupon credit spreads, constructed using Bloomberg corporate bond price data from 1996 to 2002, for three rating categories, AA (Figure 1), A (Figure 2), and BBB (Figure 3). Section 6 describes how the par-coupon spreads are constructed. The figures also contain the par-coupon credit spreads implied by the jump-diffusion model, with and without a correction for a tax on corporate bond coupons using a tax rate of 4.875% (Elton et al. (2001)).

Figure 1: Term structure of AA credit spreads

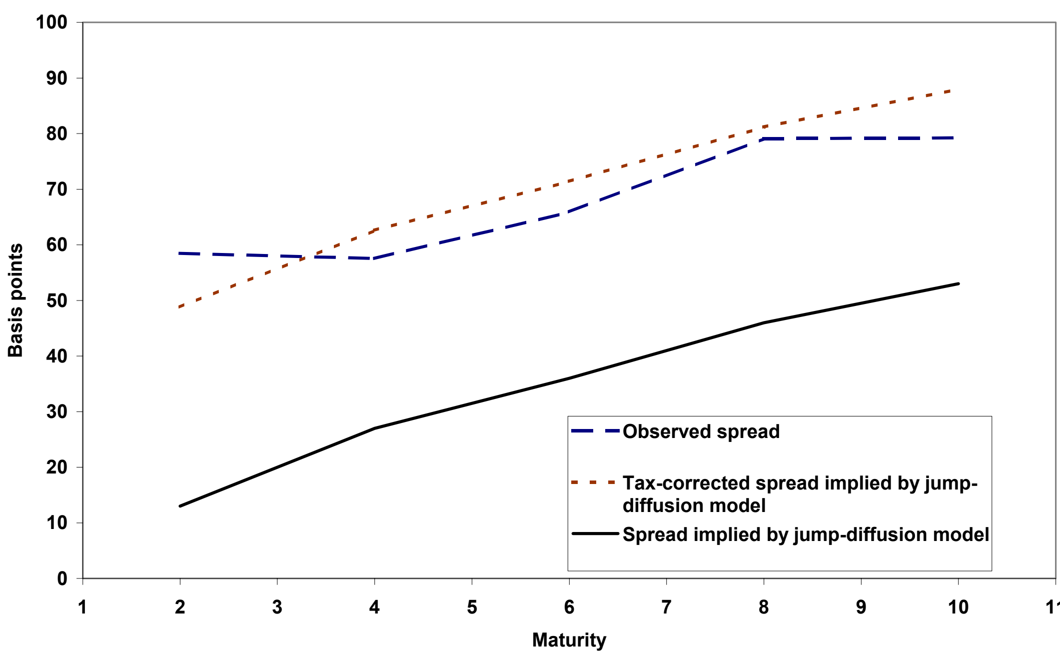


Figure 2: Term structure of A credit spreads

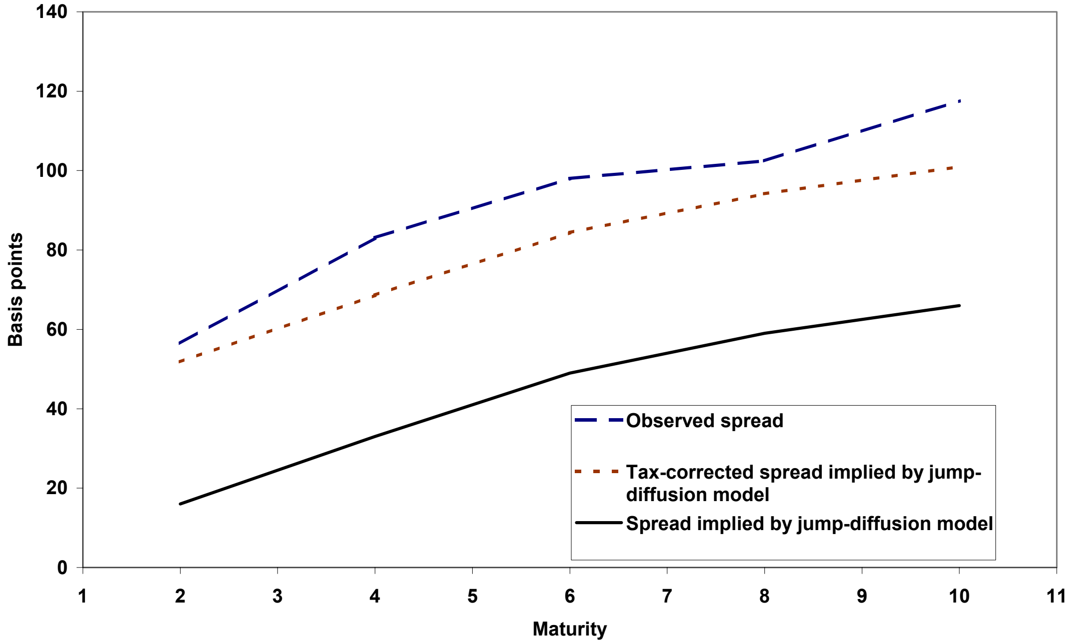
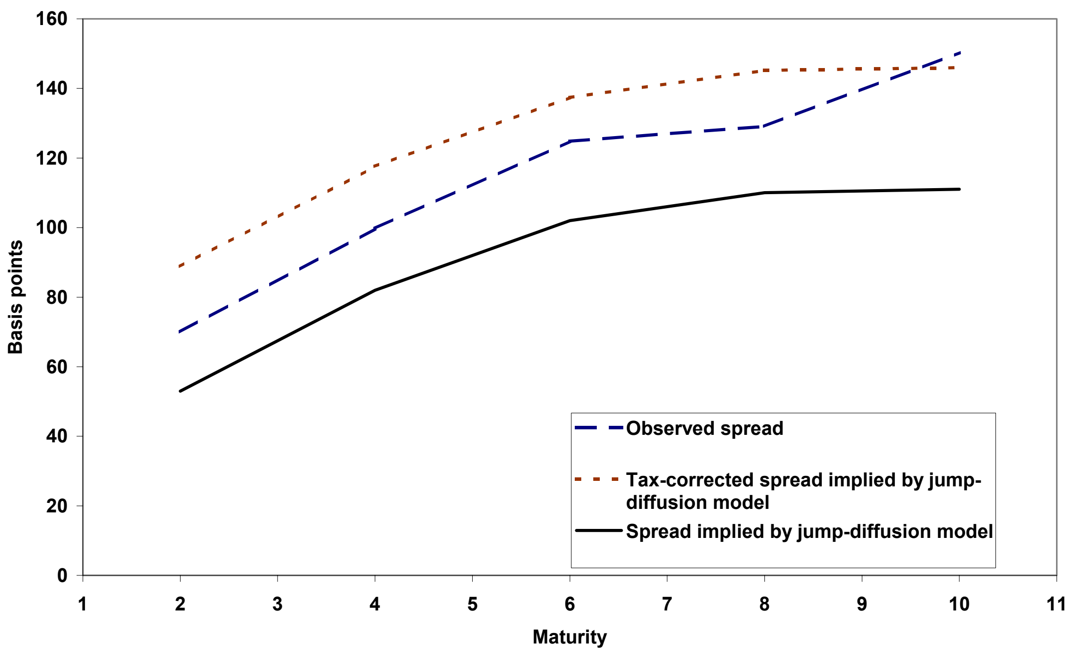


Figure 3: Term structure of BBB credit spreads



Figures 4 and 5: Cumulative Default Probabilities

Figures 4 and 5 depict cumulative default probabilities for four rating categories, AAA to BBB, as generated by the jump-diffusion model. The figures also contain the proportion of the cumulative default probability that is generated by diffusion shocks (denoted 'no jumps'). This is calculated by setting the jump intensities equal to zero in the jump-diffusion model, without changing the other parameter values.

Figure 4: Cumulative default probabilities

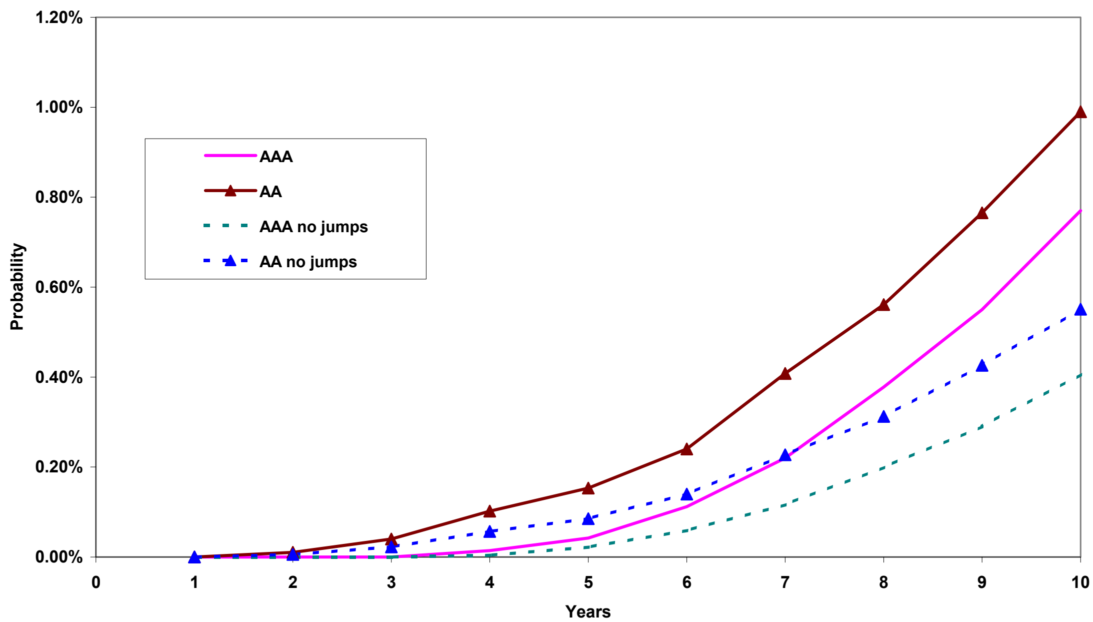


Figure 5: Cumulative default probabilities

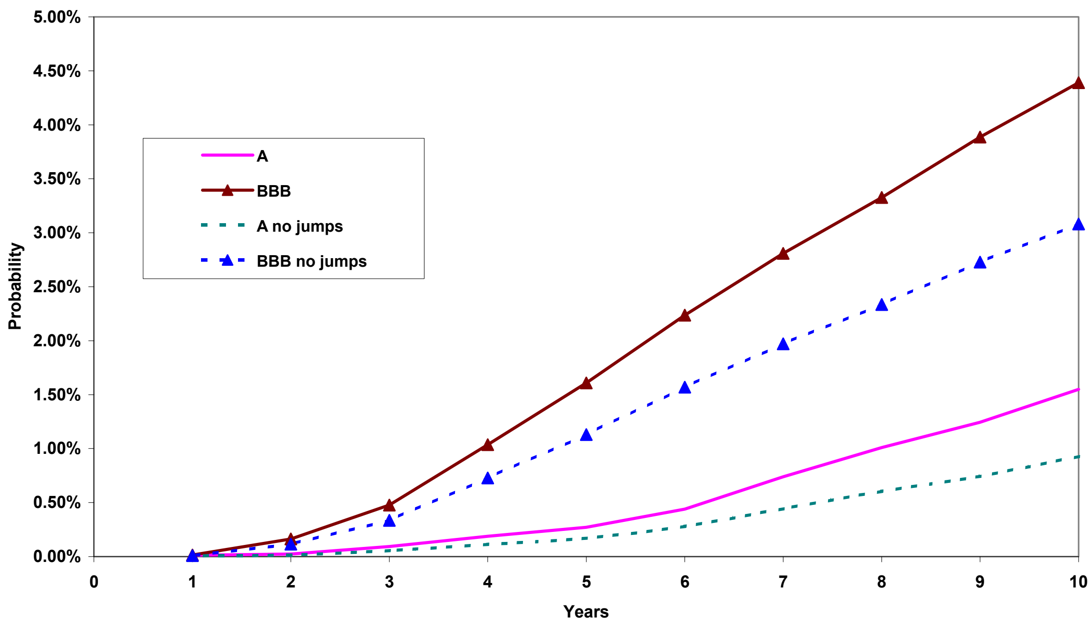


Figure 6: Probability Distribution of the Equity Index Return

The figure shows the probability distribution of the weekly return on the S&P 100 index, as generated by the jump-diffusion model (using 250,000 simulations). The figure also contains the empirical distribution of this return, calculated from daily S&P 100 return data for 1996-2002, using overlapping weekly returns.