Extracting the Expected Equity Premium from Credit Spreads*

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Abstract

We propose an approach based on structural models of default to extract investors' point-in-time equity premium expectations from CDS spreads. Our model is based on the simple observation that the difference between physical and risk-neutral default probabilities depends on the Sharpe ratio of the companies' assets. Our methodology thereby benefits from the fact that good estimates for physical probabilities are available for credit instruments. The estimator yields an average equity premium of 6.50% for the U.S., 5.44% for Europe and 6.21% for Asia based on 5-year CDS spreads over the period 2003-2007. Using different maturities yields similar results. Although we develop the estimator in a Merton framework, we find the results to be robust in more advanced structural models of default, like first passage time models or models with unobservable asset values.

Keywords: expected returns, expected equity premium, Sharpe ratio, credit risk, structural models of default, term structure of risk premia
JEL classification codes: G12, G13, G31

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Abstract

We propose an approach based on structural models of default to extract investors' point-in-time equity premium expectations from CDS spreads. Our model is based on the simple observation that the difference between physical and risk-neutral default probabilities depends on the Sharpe ratio of the companies' assets. Our methodology thereby benefits from the fact that good estimates for physical probabilities are available for credit instruments. The estimator yields an average equity premium of 6.50% for the U.S., 5.44% for Europe and 6.21% for Asia based on 5-year CDS spreads over the period 2003-2007. Using different maturities yields similar results. Although we develop the estimator in a Merton framework, we find the results to be robust in more advanced structural models of default, like first passage time models or models with unobservable asset values.

1 Introduction

The equity premium is one of the central parameters in finance. Its estimation is, however, difficult. An accurate estimation from historical averages is hardly possible even under a simplified assumption of constant risk premia. Since the volatility of stocks is a magnitude higher than equity premia, historical estimates will always be noisy even over very long periods (Lundblatt (2005)).[1] Problems are aggravated if equity premia are time-varying. Using implied estimates from stock prices by-passes many of the inherent problems of historical equity premia. However, it requires good estimates for future expected dividends, earnings or cash-flows over the entire life of a stock. Stocks have an infinite life-span, a rather daunting feature which requires subjective estimates for long-run growth rates and renders implied equity premia imprecise. We contribute to this discussion by proposing a new method for estimating equity premia. Our estimator uses credit spreads to measure risk aversion on the credit markets and transforms these into equivalent equity premia.

Our method is based on a simple observation: The difference between the physical and risk-neutral default probability in structural models of default depends on the Sharpe ratio of the companies' assets. The basic intuition is that credit risk constitutes systematic risk. Therefore, physical default probabilies are lower than risk-neutral default probabilities. The difference between risk-neutral and physical default probabilities will depend on the additional drift in the physical world scaled by the standard deviation of the asset returns.[2] Therefore, the companies' Sharpe ratio can be backed out from the physical and the risk-neutral default probability. This theoretical finding is supported by evidence that credit spreads predict future realized equity returns (Chen, Roll and

[1] E.g. with a volatility of 20%, even 100 independent yearly observations result in a standard error of 2%.

[2] In structural models of default, systematic default risk is driven solely by the systematic risk of the companies' assets. Intuitively, the asset value of a company has to fall by an additional $(\mu - r) \cdot T$ compared to the risk-neutral world in order to hit the default barrier in a simple Merton framework. Here, μ and r denote the physical and risk-neutral drift respectively and T denotes the maturity.

Ross (1986), Fama and French (1993)). Using credit spreads from credit default swaps (CDS), we are therefore able to back out the Sharpe ratio and derive an equivalent equity premium. Our approach offers some distinct advantages: First, there exist good estimates for physical default probabilities on the credit markets. This statement is supported by two arguments: Available methodologies and limited maturities. Indeed, much of the literature in credit risk focusses on an estimation of physical probabilities of default.[3] Such an extensive research on physical probabilities would not be available e.g. on the equity options market. In addition, instruments on credit markets have - in contrast to stocks - limited maturities.[4] Physical probabilities therefore only have to be estimated for a fixed horizon. Second, our framework is quite stable with respect to model changes. In particular, the difference between physical and risk-neutral default probabilities turns out to be amazingly stable across all the major structural models of default used so far in the literature.[5] Third, our model is robust with respect to sensitivities in the estimation of the physical expected loss. On average, physical expected loss only accounts for 1/3 of the credit spread while risk premia account for 2/3 of the credit spread. Therefore, inaccuracies in the estimation of the expected loss portion do not transform one to one into inaccuracies in the estimation of the risk premium portion.

A natural candidate for estimating expected equity premia is the historical average. Estimates from Ibbotson (2007) are the standard source of historical equity premium estimates on the U.S. market. Dimson, Marsh and Staunton (2003, 2006) provide an estimation of historical equity premia over more than 100 years for 17 countries. For the U.S. they report an average of 7.41% with a standard error of 1.91%. Historical equity premia have some limitations: First, their standard errors are quite large and

[3] Altmann (1968) published his seminal paper in this field already in 1968, using discriminant analysis to predict corporate bankruptcy. More recent models include Zmijewski (1984), Shumway (2001), Hillegeist, Keating, Cram and Lundstedt (2004), Chava and Jarrow (2004) and Duffie, Saita and Wang (2007).

[4] This advantage is shared by models using option prices to derive risk premia (Bliss and Panigirtzoglou (2004)).

[5] Cf. Huang and Huang (2005) for a theoretical analysis of the relationship between risk-neutral and physical default probabilities.

realized returns converge to expected returns only over a very long time horizon (Lundblad (2005)). Second, historical equity premia are biased estimators if equity premia themselves are time-varying. E.g. if equity premia increase this will result in a decrease in stock prices thereby decreasing historical equity premium estimates.

Implied equity premium estimates have been proposed as an alternative. These approaches use today's market prices of stocks together with analyst forecasts to derive equity premium estimates. Claus and Thomas (2001) have used a residual income model combined with analyst forecasts to contest the equity premium levels used so far in the literature. They derive implied equity peremia as low as 3%. Similar approaches have been developed using earnings discount and cash-flow discount models (Gebhardt, Lee and Swaminathan (2001), Easton, Taylor, Shroff and Sougiannis (2002), Fama and French (2002), Brav, Lehay and Michaely (2005), Campello, Chen and Zhang (2008), Pastor, Sinha and Swaminathan (2008)). These models rely on good estimates for future expected dividends, earnings or cash-flows and long-run growth rates. Therefore, the results of these models will be inaccurate if either estimates are biased[6] or if the terminal value adds a significant portion to today's value.

The use of the difference between physical and risk-neutral return densities to estimate equity premia has already been used in a different context. Authors have used this idea to estimate risk aversion from equity option prices (Bliss and Panigirtzoglou (2004), Ait-Sahalia and Lo (2000), Ait-Sahalia, Wang and Yared (2001), Jackwerth (2000), Weinberg (2001), Pérignon and Villa (2002) and Rosenberg and Engle (2002)). These papers estimate risk aversion based on the difference between physical densities derived from historical data and risk-neutral densities derived from option prices. One of the key challenges is to obtain good estimates of the physical return densities. Generally accepted estimates for physical probabilities are not available for equity options. Therefore, these papers usually perform extensive GARCH-type modeling of the underlying return process.

[6]E.g. Easton and Summers (2007) show that analyst's forecasts are systematically upward biased leading to an upward bias in the estimates for the implied cost of capital.

Our work also builds upon the empirical literature that relates credit spreads to expected equity returns. Keim and Staumbaugh (1986), Jagannathan and Wang (1996), Chen, Roll and Ross (1986), Cornell and Greene (1991), and Fama and French (1993) use simple regression-based links to show that credit spreads predict future realized equity returns. Huang and Huang (2003), Baele, Bekaert and Ingelbrecht (2009) and Bekaert, Engstrom, and Grenadier (2010) all establish theoretical links between credit and equity pricing, although they do not aim to estimate implied risk premia. Similar to Campello, Chen and Zhang (2008), we use a Merton framework to derive the relationship between credit spreads and equity returns. While they analyze the cross-section of expected returns, we focus on the aggregate equity premium. Chen, Collin-Dufresne and Goldstein (2009) also use structural models of default to derive a link between physical default probabilities, credit spreads and market Sharpe ratios. They focus on deriving credit spreads from physical default probabilities and risk aversion parameters while we estimate CDS-implied equity premia from physical default probabilities and CDS spreads.

This paper develops a tractable formula based on a simple Merton model to extract equity premia from CDS spreads. We thereby benefit from the fact that generally accepted estimates for physical probabilities are available on the credit markets. In addition, with the rise of CDS markets over the last 10 years, pure credit spreads are now also available.[7]

We estimate an average CDS-implied equity premium of 6.50% for the U.S. using 5-year CDS from 2003-2007 and EDFs as a proxy for the physical default probability.[8] Estimates for Europe (5.44%) and Asia (6.21%) are similar but slightly lower. We perform several robustness tests: First, the estimation of physical default probabilities is

[7] CDS spreads are widely seen as being rather unaffected by liquidity issues, cf. Longstaff, Mithal and Neis (2005) and Ericsson, Reneby and Wang (2005). Although counterparty risk may be an issue, it should have a limited effect on our results due to two reasons: First, we only look at the period from 2003-2007, where counterparty risk was lower than in the recent financial crisis. Second, we use standardized CDS which are usually collateralized with daily margining processes. A yearly survey of the use of collateral agreements for certain OTC derivatives types can be found on http://www.isda.org/.

[8] EDFs have also been used by Garlappi, Shu and Yan (2008) in a recent paper as market-based, forward-looking estimates of default probabilities.

obviously a central challenge. Therefore, we use a hazard rate model and agencies' ratings to confirm the robustness of our results using the distance-to-default-based EDFs. This robustness is facilitated by two key characteristics: First, approximately 2/3 of the CDS spread are due to a risk premium while only 1/3 is due to the physical expected loss.[9] Therefore, a 10% uncertainty in the estimation of the physical expected loss translates only into a 5% uncertainty of the risk premium portion of CDS spreads. Second, generally accepted methodologies for physical default probabilities exist based on intensive academic research in this area.[10] We also test the robustness of our results using several key structural models of default including a first-passage time framework and a model with incomplete information (Duffie and Lando (2001)). Again, our results are robust. This is due to the observation that the *difference* between risk-neutral and physical default probabilities is almost unaffected by the choice of model - which has also been observed by Huang and Huang (2003).

Our methodology seems to perform best when three conditions are met: First, reliable estimates for pure credit spreads and physical default probabilities must exist. This is usually the case for larger companies.[11] Second, our model is based on the assumption of a continuous asset value process. We do not capture models with jumps. Therefore, if asset value jumps significantly contribute to the credit risk of a company, our model will not perform as expected. Third, our estimator seems to be better suited to estimate implied risk premia from companies with a good credit quality. For companies with a bad credit quality, the relative importance of physical expected loss increases and risk premia are therefore harder to extract. In effect, credit spreads for

[9]The numbers given here are averages over our sample and differ by maturity and credit quality.

[10]We require a good estimate of the default probabilities used by the marginal investor. There are three main methodologies used in the literature for estimating default probabilities: Distance-to-Default based models (e.g. KMV EDFs), discriminant/hazard rate models (e.g. Altman (1968), Shumway (2001)) and default probabilities derived from agencies' ratings. It is hard to tell which of these methodologies is predominantly used by the marginal investor. Therefore, we cover all of these three major methodologies in our paper.

[11]CDS quotes are most widely available for larger companies. In addition, larger companies have lower bid/ask spreads and higher trade volume on the CDS markets. The applicability of certain estimates of the probability of default also depends on the availability of certain accounting and market variables - which are more likely available for larger companies.

companies with a good credit quality almost entirely reflect risk premia and therefore offer a good chance to estimate risk aversion of market participants.

The remainder of the paper is structured as follows. Section 2 describes the theoretical framework for extracting equity premia from credit spreads. Section 3 describes our data and provides descriptive statistics. The equity premium estimates for the U.S. based on 5-year CDS are reported in section 4, results for other maturities (3-, 7- and 10-year) and other markets (Europe and Asia) are reported in section 5. To confirm the robustness of our results, we conduct extensive sensitivity analysis which we report in section 6. Section 7 concludes.

2 Model setup

The basic idea of our approach is to measure the excess return on debt and postulate a model linking debt valuation to asset valuation and asset valuation to equity valuation. Expected returns on debt instruments can then be transformed into expected returns on equity instruments. Technically, we use structural models of default to derive a relationship between risk neutral and actual default probabilities. Our approach is probably most similar to Chen, Collin-Dufresne and Goldstein (2009), Huang and Huang (2005) and Bohn (2000). Our approach differs though in at last three ways: First, we use the Merton (1974) model just as a starting point and then pass to structural models of default by explicitly integrating time patterns (first passage time model) and information uncertainty (Duffie/Lando (2001) model). Second, we use CDS spreads instead of bond spreads. As has already been mentioned, there is evidence that the former should be less sensitive to liquidity distortions than the latter. Third, to our best knowledge, this is the first paper that directly extracts the expected equity premium out of credit prices.

2.1 Equity Premium Estimation in the Merton Framework

The Merton framework presented in this subsection is based on Merton (1974), who explicitely focusses on the pricing of corporate debt. In this perspective a company's debt consists of one zero-bond. Default occurs if the asset value of the company falls below the nominal value N of the zero bond at maturity of the bond. A company can therefore only default at one point in time, which obviously poses a simplification of the real world. The asset value V_t is modelled as a geometric Brownian motion with volatility $\sigma = \sigma_V$ and drift $\mu = \mu_V$ (actual drift), i.e. under the actual probability measure P the asset value dynamic is given as $dV_t^P = \mu V_t dt + \sigma V_t dB_t$, where B_t denotes a standard Wiener process. By applying the usual martingale arguments, under the risk neutral measure Q the asset value dynamic obeys to $dV_t^Q = rV_t dt + \sigma V_t dB_t$.

In this framework, the real world (actual) default probability $P^{def}(t,T)$ between t and T can be calculated as follows:

$$\begin{aligned} P^{def}(t,T) = P[\, V_T < N \,] &= P[\, V_t \cdot e^{(\mu - \frac{1}{2}\sigma^2)\cdot(T-t) + \sigma\cdot(B_T - B_t)} < N \,] \\ &= \Phi\left[\frac{ln\frac{N}{V_t} - (\mu - \frac{1}{2}\sigma^2)\cdot(T-t)}{\sigma\cdot\sqrt{T-t}} \right] \end{aligned} \tag{1}$$

Here, Φ denotes the cumulative standard normal distribution function. The default probability under the risk neutral measure Q can be determined accordingly as

$$Q^{def}(t,T) = Q[\, V_T < N \,] = \Phi\left[\frac{ln\frac{N}{V_t} - (r - \frac{1}{2}\sigma^2)\cdot(T-t)}{\sigma\cdot\sqrt{T-t}} \right] \tag{2}$$

Combining (1) and (2) yields (cf. Duffie and Singleton (2003))

$$Q^{def}(t,T) = \Phi\left[\Phi^{-1}(P^{def}(t,T)) + \frac{\mu - r}{\sigma}\cdot\sqrt{T-t} \right] \tag{3}$$

Note that the right hand side of this equation contains the Sharpe ratio of the companies assets (SR_V). Hence, by solving (3) for this Sharpe ratio the following expression results:[12]

$$SR_V := \frac{\mu - r}{\sigma} = \frac{\Phi^{-1}(Q^{def}(t,T)) - \Phi^{-1}(P^{def}(t,T))}{\sqrt{T-t}}, \tag{4}$$

It should be noted, that the formula is still correct if a non-stochastic, constant payout ratio δ is introduced. Relationship (4) is a central formula in our paper. It has two main advantages that make it convenient for our purpose: First, it directly yields the Sharpe ratio of the assets, i.e. neither the real wordl drift (μ_V), nor the asset volatility (σ_V), the asset value (V_t), the face value of debt (N) or the risk fre rate of return (r) have to be estimated. In contrast to other applications of structural models we do not have to calibrate any parameter of the asset value process. In order to estimate the company's Sharpe ratio we simply need the actual and risk neutral default probabilities and the maturity. Second, as we will show in the next subsection the Sharpe ratio estimator derived in (4) is robust with respect to model changes.

If we would like to extract the market Sharpe ratio out of (4), we face the following problem: The Sharpe ratio of the assets will usually differ from the market Sharpe ratio, since a single asset V_t will most probably not be on the risk efficient frontier. Therefore, we refer to the continuous time CAPM in order to derive the following relationship between the Sharpe ratio of the assets $\frac{\mu_V - r}{\sigma_V}$ and the market Sharpe $\frac{\mu_M - r}{\sigma_M}$:

$$\mu_V = r + \frac{\mu_M - r}{\sigma_M} \cdot \rho_{V,M} \cdot \sigma_V \quad \Leftrightarrow \quad \frac{\mu_M - r}{\sigma_M} = \frac{\mu_V - r}{\sigma_V} \cdot \frac{1}{\rho_{V,M}} \tag{5}$$

where $\rho_{V,M}$ denotes the correlation coefficient between the asset returns and the market returns.

Hence, in order to get an estimation for the market Sharpe ratio we need to estimate the correlation coefficient between the asset value and the market portfolio. In the

[12] In a CAPM setting the Sharpe ratio of the companies assets depends on the firm's assets beta. Consequently, the risk neutral default probability and the credit spread also depend on the firm's assets beta in our setting. This is in line with the results of Demchuk and Gibson (2006).

Merton framework, asset and equity values have the same instantaneous Sharpe ratios and the same instantaneous correlation with the market portfolio. Hence, we assume that $\rho_{V,M}$ can be proxied by the correlation between the corresponding equity return and the market return (denotet by $\rho_{E,M}$), i.e. we assume $\rho_{V,M} \approx \rho_{E,M}$.[13] Hence, the following approximation holds:

$$\frac{\mu_M - r}{\sigma_M} \approx \frac{\Phi^{-1}(Q^{def}(t,T)) - \Phi^{-1}(P^{def}(t,T))}{\sqrt{T-t}} \cdot \frac{1}{\rho_{E,M}}.$$

Therefore, we define the Merton estimator of the market Sharpe ratio as:

$$\widehat{\gamma}_{\mathrm{SR_M,Merton}} := \frac{\Phi^{-1}(Q^{def}(t,T)) - \Phi^{-1}(P^{def}(t,T))}{\sqrt{T-t}} \frac{1}{\rho_{E,M}} \tag{6}$$

Including the volatility of the market portfolio σ_M yields an estimator for the equity premium:

$$\widehat{\gamma}_{\mathrm{EP,Merton}} := \frac{\Phi^{-1}(Q^{def}(t,T)) - \Phi^{-1}(P^{def}(t,T))}{\sqrt{T-t}} \frac{\sigma_M}{\rho_{E,M}} \tag{7}$$

It should be noted that this method can also easily be used to extract the market return expectation with respect to any single stock. In fact, by using (4) and the assumption that the equity Sharpe ratio equals the asset Sharpe ratio, it follows that the expected risk premium on a single stock, i.e. $\mu_E - r$, can be written as follows:

$$\mu_E - r = \frac{\Phi^{-1}(Q^{def}(t,T)) - \Phi^{-1}(P^{def}(t,T))}{\sqrt{T-t}} \sigma_E \tag{8}$$

where σ_E denotes the equity volatility of the respective company. Extracting single stock's expected returns is not in the focus of this paper. However, by calculating the

[13] The approximation is also valid in an non-instantaneous setting. Within the Merton framework the equity value of an investment grade company equals a deep-in-the-money call option on the assets. The option is deep-in-the-money, since annual default probabilities are less than 0.4% for these companies. And even for all obligors rated B and above, the annual default probability is less than 10%. It should be noted that for deep-in-the-money options gamma is approximately zero, i.e. we have an almost affine linear relationship between asset and equity value, cf. Hull (2009). We have also performed robustness tests for other structural models of default (first-passage time and Duffie/Lando model). For reasonable parameter choices, the approximation error is less than 4%, detailed results are available on request.

expected risk premium for any single stock according to (8) an alternative estimator for the equity premium can be derived. Defining an appropriate vector of weights w_i to be assigned to any single stock, e.g. market capitalization weights, the equity premium would be given by the following estimator:

$$\widetilde{\gamma}_{\text{EP,Merton}} := \sum_i w_i(\mu_E - r) \tag{9}$$

From an empirical perspective, this second estimator for the equity premium offers an advantage with respect to the estimator proposed in (7). It should be noted that $\widehat{\gamma}_{\text{EP,Merton}}$ would be upward biased even if the estimation for the correlation coefficient is unbiased. This is due to the fact the correlation coefficient appears in the denominator. Therefore, an underestimation of the coefficient of correlation has a stronger impact on the estimator than an overestimation by the same relative amount. Therefore, we report also the results generated according to the estimator in (8).

From an empirical perspective, it should be emphasized that we need a sufficient sensitivity of the risk neutral default probability $Q^{def}(t,T)$ with respect to the Sharpe ratio. Otherwise noise in the data (e.g. bid-ask-spreads, inaccuracies in determining correlations and actual default probailities) will result in a very inaccurate estimation. If we look, for example, at a BBB-rated obligor with a 5-year cumulative actual default probability of 2.17%, the resulting model-based risk neutral default probability should be either 3.6% (for an asset Sharpe ratio of 10%) or 13% (for an asset Sharpe ratio of 40%) respectively. Assuming a recovery rate (RR) of 50% transforms this into a CDS spread of either 37 bp or 140 bp.[14] This large difference indicates that noise in the input parameters will only have a minor effect on our Sharpe ratio estimation. The sensitivity with respect to noise in different input parameters is analyzed in more detail in section 6.

[14] Here we are using the approximation CDS-spread $= \frac{\lambda^Q}{1-RR}$. The risk neutral default intensity λ^Q is derived from the risk neutral cumulative default probability via the relationship $Q^{def}(t,T) = 1 - e^{-\lambda^Q \cdot (T-t)}$. Cf. Duffie and Singleton (2003)

2.2 Equity premium estimation in other frameworks

Of course, our estimator $\widehat{\gamma}_{\text{EP,Merton}}$ for the equity premium is formally only justified in a Merton framework. Moving to more elaborated structural models of default usually has a significant impact on actual and risk neutral default probabilities. E.g. in a first-passage-time framework with zero drift in the real world, actual default probabilities are twice as high as actual default probabilities in the Merton framework for the same parametrisation because of the 'reflection principle'.

Fortunately, our estimator does not only include the actual default probability but the difference between the inverse of the cumulative normal distribution function of the risk neutral and the inverse of the cumulative normal distribution function of the actual default probability. This difference can be shown to be very robust with respect to model changes. Intuitively, most models introduce features, e.g. first-passage mechanism, unobservable asset values, that have an effect on both the actual and risk neutral default probability which goes in the same direction. Therefore, it may well happen that the overall impact on the nominator in (7) is small. And in fact, we will show that this is going to happen for a large set of empirical constellations.

The robustness with respect to model changes is analyzed in more detail in appendix A based on a first-passage-time framework, strategic default frameworks and the Duffie and Lando (2001) framework with unobservable asset values. In a similar analysis, Huang and Huang (2005) have also shown that the difference between real-world and risk-neutral default probabilities is almost unaffected by the choice of model. They also include a model with time-varying risk premia, stochastic interest rates and a strategic default model.

3 Data sources and descriptive statistics

In each week our sample consists of the intersection of a) on-the-run companies in the CDX.NA.IG index[15], b) the credit default swap (CDS) database of CMA (credit markets association) and c) the KMV EDF database. The Dow Jones CDX.NA.IG-index is the main CDS index in North America. It covers the 125 most liquid North American investment grade CDS. [16] We used 5-year CDS spreads to derive risk neutral default probabilities because the 5-year maturity is the most liquid one. Expected default probabilities (EDFs) from Moody's KMV data base were used as a proxy for the actual default probabilities and correlations with the S&P500-index as a proxy for the correlations with the market portfolio. For all parameters, we used weekly data from the period from April 2003 until June 2007.[17]

The 5-year CDS spreads (bid/ask/mid) used in our analysis were taken from Datastream. These data is compiled and provided by Credit Market Analysis (CMA) who collects CDS data from a range of market contributors from both buy- and sell-side institutions. Only dates with at least one trade or firm bid for the respective CDS are used to avoid potential errors from pure market maker data. We used CDS mid spreads for our analysis.

The risk neutral default probability Q^{def} was derived by the approximation $Q^{def} = 1 - exp\left(-\frac{s}{LGD} \cdot T\right)$ out of the CDS spread s with maturity T and the risk neutral loss given default LGD (cf. Duffie and Singleton (2003)). A recovery rate $(1 - LGD)$ of 45% was used and robustness tests were conducted.

We used EDFs from Moody's KMV data base as our primary proxy for the actual default probabilities. Robustness tests based on agencies ratings and hazard rate models

[15]Our data sample starts in 04/2003 whereas the first CDX.NA.IG index starts in 10/2003. For the dates before 10/2003 we used the constituents of the CDX.NA.IG 1 index. The results do not materially differ if we start our sample period in 10/2003.

[16]Although the CDX.NA.IG index is a North American index we will frequently refer to 'U.S.' since the vast majority of constituents is based in the U.S. Only two non-U.S.-based companies are in our sample (Bombardier and Alcan (both from Canada)).

[17]EDFs from KMV are only available on a monthly basis. We assumed EDFs to be constant within each month.

are provided in the robustness section. EDFs are default probabilities, which are based on a Merton-style structural framework, cf. Moody's KMV (2007). The calibration is, however, done more pragmatically based on a large set of historical data and on discriminant analysis.[18] EDFs are widely used in the banking industry and also constitute a part of some of the internal rating systems of large banks. They have also been used in academic studies such as in Berndt, Douglas, Duffie, Ferguson and Schranz (2005) or Garlappi, Shu and Yan (2008) . We used 1-year EDFs (and the respective equivalent rating grades from Aaa to B3) and derived multi-year EDFs by Moody's cumulative default probabilities per rating grade. [19] The cumulative default probabilities were determined via a logarithmic approach based on raw data from Moody's (2007). The resulting table of cumulative default probabilities can be found in Appendix B. The main advantage of EDFs compared to other ratings for our purpose is its link to market data: The current asset volatility and equity value are direct input parameters, therefore EDFs constitute a 'point-in-time' estimation of the current default probability. In contrast to EDFs, the ratings of the large rating agencies are defined as 'through-the-cycle'-ratings, which - in effect - results in different default probabilities for a specific rating grade dependent on the current overall economic outlook.

We used 2-year weekly[20] correlations between the reference entities share price returns and the S&P-500 index. The share prices were taken from Datastream. We used median industry correlations since industry wide estimations of correlations have lower standard errors than a company by company estimation. This procedure also allowed to include companies without a 2-year equity price history. The industry sector classification was based on the sub-indices of the CDX.NA.IG index.

[18] As Moody's KMV does not use its own estimate for the drift parameter but rather uses a calibration procedure based on the distance-to-default there is no circular statement in our arguments, cf. Moody's KMV (2007).

[19] Cf. Appendix B for details. Elton, Gruber, Agrwal and Mann (2001) use a similar approach based on transition matrices. We have opted for a direct cumulative estimation because of indications that rating migrations are non-Markovian and cannot be explained by constant transition probabilities; cf. Farnsworth and Li (2007). The differences are though minimial, robustness tests based on migration matrices are available on request.

[20] The calibration of correlations has a minor effect on the overall result, using 3-year or 1-year correlations did not alter results significantly.

Expected volatilities for the market portfolio were approximated by implied volatilities from the VIX term structure. Data was collected directly from the CBOE webpage[21]. We used implied volatilities based on mid options prices for maturities from 18-23 months which was the longest maturity bucket that was consistently available.

Our final data set consists of 24,785 date/firm-observations for which 5-year CDS spreads and EDFs were available. Table I gives an overview of data.[22]

Insert Table I about here

4 Results

Based on the data described in section 3 and the Merton estimator for the equity premium according to (7) and (8), the company Sharpe ratio (4) and the market Sharpe ratio (6) derived in section 2, we estimate the implicit equity premium and company and market Sharpe ratios for each of the 24,785 observations. Table II provides the results on a yearly, equally-weighted basis.[23]

Insert Table II about here

Our estimation yields an average equity premium of 6.50% for the U.S. market based on (7) and 4.73% based on (8).[24] The average company Sharpe ratio is 19.33% and the average market Sharpe ratio is 38.77%. The median values are even lower with 5.95% for the equity premium based on (7), 4.30% for the equity premium based on (8) and 18.17% and 35.30% for the company and market Sharpe ratio. We would already like to mention here that all these values are upper limits for the equity premium. This is

[21] Chicago Board Option Exchange, www.cboe.com/publish/vixtermstructure/ vixtermstructure.xls.

[22] Based on 222 weeks in our sample period and 125 on-the-run constituents in the CDX.NA.IG index the theoretical maximum is 27,750 date/firm-observations. Therefore, we have data available for approximately 90% of the theoretical maximum. This is probably also due to the fact that we used constituents of the most liquid CDS index and our sample period starts approximately at the same time when index trading - and therefore also liquidity - took off in the CDS markets.

[23] We report all results - including the equity premium based on (8) - on an equally weighted basis to allow for a better comparison. The value-weighted means are even lower, results are available on request.

[24] The lower results based on (8) are not surprising given the theoretical discussions about an upward bias of (7), cf. section 2.

due to some implicit conservative assumptions, especially concerning the fact that we assume the CDS spread to be totally due to credit risk; cf. also section 6 for details in this regard.

Looking at each year of our sample period separately shows a quite homogenous result: Based on (7), the implicit equity premium estimates range from 5.16% in 2003 to 7.18% in 2005. The year 2005 also exhibits the largest one-year increase in the equity premium up 23% from 5.84% in 2004. CDS premia were still as high in 2005 as in 2004 - especially due to an increase in spreads in the second quarter around the downgrades of Ford and General Motors - while EDFs were decreasing (2.37% vs. 1.54%) due to bullish equity markets and lower volatilities . Correlations were decreasing from 0.55 to 0.50 while implied volatilities decreased from 18.28% to 16.04% resulting in an almost unchanged term $\frac{\sigma_M}{\rho_{E,M}}$. It seems plausible to assume that these downgrades have led to an increase in risk aversion among market participants. We would like to point out that the implied equity premia also increased in the second quarter of 2007 at the beginning of the subprime crisis. Due to low CDS spreads in the first quarter of 2007, average estimates for the first half of 2007 are though almost the same than in 2006 (7.08% vs. 7.17%). The results based on (8) show a similar time-series behavior although the absolute level is 1.5-2PP lower.

We would also like to emphasize the fact that our results stem from very different conditions on the credit markets. Looking at CDS spreads, they averaged 75.10 bp in the year 2003. This was accompanied by large EDFs (3.72%), large correlations (0.57), a high implied market volatility (20.93%) and a high average company-specific volatility (32.06%). In the first half of 2007, spreads were less than half the spreads of 2003 (37.10 bp), EDFs were less than a fourth of their 2003 levels (0.82% vs. 3.71%), correlations were down to 0.50 and implied market and company-specific volatility was also significantly lower than in 2003 (15.39% vs. 20.93% and 25.44% vs. 32.06%). The fact that equity premium estimates were very similar throughout this time period indicates, that our estimates are not simply a result of a specific set of parameters but exhibit a certain robustness to changing market conditions. If at all, there seems to be a small tendency for equity premia to rise when credit markets are bullish (e.g. default rates and spreads decrease), although this is not or only partially true for the 2006 and 2007 period.

5 Equity premium estimates for further maturities and from other markets

We have expanded our analysis to maturities of 3, 7 and 10 years and to European and Asian reference entities, too. Maturities of 3, 5, 7 and 10 year are the standard maturities for which CDS indices are provided by 'markit'.

Using other maturities than 5 years offer a robustness check of our results from the previous section. On average, risk premia estimates based on 3, 7 and 10 year maturities should not largely deviate from the results of the respective 5-year maturities unless there is a term structure in the risk premium. Hence, the comparison of risk premia estimated on the basis of different CDS maturities could also be used as a staring point for investigating whether there is a term structure in the risk premium. We are not aware of any empirical analysis so far which has captured this topic.

Additionally, we extend our analysis to European and Asian markets. This also offers several perspectives. First, the results itself are of course interesting for an estimation of equity premia on these markets. Second, the results offer a good possibility to validate the robustness of the U.S.-results. If equity markets are globally integrated, investors should demand a similar risk premium across different countries/regions. We would therefore expect equity premium estimates in a similar magnitude than based on U.S. data. Third, U.S., Europe and Asia offer a certain diversity concerning the loss experience and credit quality over our sample period. While the U.S. market was still in the aftermath of the Enron and Worldcom defaults at the beginning of our sample period and suffered the downgrades of Ford and GM in 2005, Europe did not suffer any comparable big-scale losses and had, on average, a better credit quality than the

U.S. market. The Asian market did not suffer any unexpected large losses, too, but had on average a significantly lower credit quality than the U.S. market. These markets therefore offer a good opportunity to check if our estimator is robust with respect to these different credit market conditions.

Again, our data sample consists of the intersection of the KMV database, the main CDS index for the respective markets and the CMA CDS database. We used the iTraxx Europe index for Europe and the iTraxx Asia ex Japan index for the Asian market.[25] Only on-the-run companies were considered. The iTraxx Europe IG index consists of 125 investment grade constituents and is rolled over every 6 months. Index trading started in June 2004, actually some months later than in the U.S. The iTraxx Asia index started with 30 constituents in July 2004, it was later enlarged to 50 constituents in September 2005.[26] Due to the later start of index trading compared with the U.S. and data availability our sample period starts at the beginning of 2004, so our sample includes the time period from January 2004 until June 2007. Again, we used the first series of the respective index to define on-the-run companies before the effective date of the first series. CDS spreads were based on the CMA database. For comparability, we included only weeks where spreads for all maturities (3, 5, 7 and 10 years) were available. Actual default probabilities were determined via EDFs from KMV. We used the same methodology as for the U.S. to transfer 1-year EDFs to cumulative default probabilities.[27] The DJStoxx 600 (Europe) and the S&P Asia 50 (Asia) were used for an estimation of correlations. Median correlations per industry sector were again used for reasons of robustness. Implicit volatilities were calculated based on the VSTOXX

[25] There is also an iTraxx index covering Japan. We have choosen the iTraxx Asia ex Japan index to cover countries which seem to offer the best independent view compared with the U.S. and Europe. The biggest countries in the iTraxx Asia ex Japan are Korea, Hong Kong, Singapore, Malaysia, China and Taiwan. Together these countries offer a good perspective on a region where experience with corporate finance, derivative products and governance structures seem to be significantly different from the U.S. and Europe.

[26] After our sample period, in on September, 20, 2007, it was again enlarged to 70 constituents.

[27] Migration probababilities and cumulative loss rates are very similar for the U.S. and Europe, cf. Moody's 2008). Historical default data for the Asian market is rare. We are though not aware of any arguments why migration behaviour should be different in Asia and think that this pproach gives estimates which are as close as possible to what market participants would assume.

Volatility sub-index 24 months.[28] For the Asian market, implicit volatility indices are not available, therefore we used rolling 1-year historical volatilities of the S&P 50 Asia index.

Table III provides the results for the 3-, 5-, 7- and 10-year maturities for the U.S., Europe and Asia from 2004-2007. Please note that the 5-year results for the U.S. differ slightly from the previous section since only weeks where spreads for all maturities were available have been included in this data sample.

Insert Table III about here

For the U.S., results based on 3-, 7-, and 10-year maturities are similar - but slightly smaller - than for the 5-year maturities. For the 2004-2007 period the equity premium estimation based on 5-year maturities and (7) is 7.00% while the estimates for the 3-, 7- and 10-year maturities were 6.43%, 6.62% and 6.26% respectively. The estimates based on (8) are 4.87% for the 5-year maturities and 4.38%, 4.60% and 4.35% for the 3-, 7- and 10-year maturities. The market Sharpe ratio estimates range frome 39.32% (T=10) to 43.85% (T=5). All maturities show quite similar results for each year with equity premium estimates ranging from 4.80% (T=10, 2004) to 7.33% (T=5, 2005). Moreover, all maturities exhibit an increase in the implied equity premium from 2004 to 2005 while the effect for other years is quite small. These results confirm our analysis for the equity premium from the last section.

For Europe, implied equity premium estimates are lower than for the U.S. Based on (7), they range from 5.03% (T=3) to 5.44% (T=5). Again, estimates for the 7-year maturity (5.24%) and the 10-year maturity (5.06%) yield similar results. Results based on (8) are 2.5PP lower. Lower equity premia for Europe compared to the U.S. are consistent with both historical experience as well as evidence from other implied equity premium estimates.[29] Market Sharpe ratios for Europe are also lower than for the

[28] Implied volatiities for longer maturities are not available due to the lack of liquid option markets for longer maturities. Implied volatilities do though have the characteristic that they are less volatile for longer maturities. If at all, our results would therefore be even smoother if volatilities for longer maturities were available.

[29] For example, Claus and Thomas (2001) estimates an equity premium of 3.40% for the U.S. while estimates for the UK, France and Germany are 2.81%, 2.60% and 2.02%.

U.S., ranging from 26.33% (T=3) to 28.39% (T=10) compared to a range of 39.32% to 43.85% for the U.S. This is also consistent with the theoretical argument that - from a global perspective - the U.S. market should be closer to the global market portfolio and therefore closer to the capital market line. The difference between estimates for the U.S. and Europe is especially pronounced in 2004 where implied equity premia estimates for Europa are as low as 1.87% (T=3). Excluding 2004 from the analysis does, however, still result in lower estimates for Europe compared to the U.S.

Average equity premia estimates for Asia are between the estimates from the U.S. and Europe. Based on (7), the lowest average estimates comes from the 10-year maturity (5.60%) and the highest from the 3-year maturity (6.50%) with estimates for the 5- and 7-year maturities in between (6.21% and 5.84%). Estimates based on (8) are 1.5-2.0PP lower. The market Sharpe ratio estimates range from 35.54% to 41.40%. Again, all yearly estimates are quite similar with the lowest estimate of 4.98% (T=10, 2005) and the highest estimate of 7.63% (T=3, 2006). Interestingly, the increase in risk premia from 2004 to 2005 which occured both for the U.S. and for Europe was much less pronounced for Asia. Market Sharpe ratios in Asia were increasing from 2004 to 2005 - but significantly less than in the U.S. and Europe - while equity premia estimates were even decreasing due to decreasing volatilities.

All in all, the results based on 3-, 7- and 10-year maturities as well as the estimates for Europe and Asia confirm the results of the previous section and even lead to smaller equity premium estimates. Again, the resulting implicit equity premia are lower than based on historical estimates.

6 Sensitivity analysis and robustness checks

6.1 Sensitivity with respect to noise in input parameters

In subsection 22.2 and appendix A we have shown that the results are quite robust to model changes. Besides misspecifying the model, a wrong measurement of the input parameters poses another possible source of inaccuracy. In the following, we concentrate on robustness tests based on our equity premium estimator (7). The results are, however, usually also valid for the equity premium estimator (8) and the company and market Sharpe ratio estimators (4) and (6).

The estimation of the input parameter may distort our results in two ways. First, parameters might have been estimated with noise. Our estimator (7) is convex in P^{def}, and $\rho_{E,M}$ and concave in the CDS spread s. Therefore, noise in the measurement of the CDS spread causes our estimator to be downward biased, noise in P^{def} and $\rho_{E,M}$ to be upward biased. The net effect is likely to be small and lead to an upward bias. Second, we may have systematically under- or overestimated any of the input parameters. We therefore tested the sensitivity of our results with respect to all input parameters. Parameter changes of 10% relative to its original value result in an equity premium of approximately 10%/0.6 percentage points higher/lower for all parameters in our model. In addition, the sensitivity is decreasing with increasing maturity. I.e., if input parameters have the same noise for all maturities then estimates based on 10-year maturities will be more accurate than estimates based on 3-year maturities.[30] Of course, these sensitivities must be analyzed in combination with the accuracy of the respective input parameters. I.e. a high sensitivity is worse if the respective input parameter can not be accurately determined, it is less harmful if the respective input parameter can be determined with very little noise. We will perform various robustness tests in the following subsections.

6.2 Robustness with respect to CDS spreads

We have used several measures to ensure that our CDS data is not significantly biased in any direction. First, our datasource (CMA) is not based on a single market participant but based on data from several buy and sell side contributors. Second, we have compared our spreads to data from Bloomberg with no significant differences. Third, we have used constituents of the most liquid indices, which should enhance liquidity and data quality

[30]Detailled results are available on request.

for the respective constituents. In addition our data sample should be easily comparable and reproducable and is not biased towards more recent dates.

Besides specific shortcomings of OTC markets, bid/ask spreads pose a natural noise in our data. We have used mean CDS spreads in our analysis. The average bid/ask-spread is only 4 bp in our sample which is probably also due to the fact that - in each week - we have only used the 125 most liquid companies in the market. Using bid or ask quotes changes our average equity premium by less than 5%/0.3 percentage points. Of course, some part of the CDS spread may not be attributable to credit risk. In contrast to bonds CDS are, however, seen as a rather pure measure of credit risk. Interestingly, Bühler and Trapp (2008) find based on a reduced-form credit risk model that the liquidity risk portions accounts for only about 5% of the spread.[31]

One indication that the CDS spread may not totally be due to credit risk is the compare Sharpe ratio estimates on the basis of different rating classes. If the CDS spread reflects only credit risk, Sharpe ratios should be independent of the credit quality. We have compared minimum and maximum Sharpe ratio estimates based on the adjustment factors derived in appendix A for different rating classes. It find Sharpe ratio estimates for higher rating grades to be higher compared to estimates on the basis of lower rating grades. In some cases these difference is statistically significant.[32] However, as we base our findings on a sample spread over different rating classes, it is unlikely that the results are heavily influenced by this effect. The problem might be relevant, however, if the method is used for extracting expected returns on an individual firm basis.

6.3 Robustness with respect to the recovery rate

Based on Moody's (2007), the average recovery rate from 1982-2006 on senior unsecured bonds was 38% on an issuer-weighted basis, 37% on a value-weighted basis and 46% if

[31] There is a growing literature on common factors in either bond or CDS spreads, cf. Elton, Gruber, Agrwal and Mann (2001), Colin-Dufresne, Goldstein and Martin (2001), Longstaff, Mithal and Neis (2005) and Martell (2008). If part of the CDS spread is not due to credit risk but to other factors, than our estimator is biased. While some of these common factos seem to be related to liquidity, Colin-Dufresne, Goldstein and Martin (2001) also argue that CDS spreads are a purer measure of default risk than bond spreads. In any case, our estimate is still valid as an upper bound for the equity premium.

[32] Details can be provided on request.

each year's issuer-weighted average is given the same weight. The recovery rate volatility is significantly smaller than the default rate volatility, with a coefficient of variation of about 25% on a 1-year basis compared to about 60% for the default probability. The interquartile range for a yearly issuer-weighted recovery rate is 39% to 54% on a 1-year basis and 43% to 51% on a 5-year average basis. Altman and Kishore (1996) also estimate an average recovery rate of 48% for senior unsecured bonds. Duffee (1999) and Driessen (2003) use a recovery rate of 44%.[33]

Research on the recovery rates has soared over the last years, indicating that recovery rates vary by industry sector and through the business cycle. E.g., Sironi, Altman, Brady and Resti (2008) find a significant negative correlation between the realized recovery rate and the realized default rate. In out-of-sample tests Chava, Stefanescu and Turnbull (2006) also find indications that this relationship holds true for expected recovery rates as well. These findings may affect our results in three ways: First, some of the Sharpe ratio variation over time may also be due to time-varying recovery rates.Second, the overall level of the market Sharpe ratio may be biased if the average expected recovery rate for our time period was significantly different from historical averages. Chava, Stefanescu and Turnbull (2006) set up a model where the expected recovery rate can be explained by the coupon rate, the 3-month Treasury yield, the issue size and the seniority. Other covariates analyzed by Chava/Stefanescu/Turnbull do not improve out-of-sample performance. Using their regression results for the expected actual recovery rate indicates again, that our recovery rate of 45% is an upper limit for the expected recovery rate.[34] In addition, our sample consists of CDS' with maturities up to 10 years from 2003-2007 which effectively means that recovery rates from 2003-

[33]Discussions with market participants indicated that a value of 40% for the risk neutral recovery rate is frequently used in practical applications.

[34]Based on Chava, Stefanescu and Turnbull (2006), the expected recovery rate for senior unsecured bonds can be estimated as $0.5183 + 0.0182 \cdot couponrate - 0.0319 \cdot 3_{m}onth_{T}reasury_{y}ield - 0.0332 \cdot log(issuesize)$, where coupon rate and Treasury yield are measured in percentage and the issue size is measured in \$'000. Even a very conservative calibration ($couponrate = 6$, $3_{m}onth_{T}reasury_{y}ield = 1$, $issuesize = \$10m$) results in an expected recovery rate of about 45%. Certainly, average coupon rates have been lower than 6%, the average 3-month Treasury yield has been higher than 1% and the average issue size for our sample has been higher than 10m, therefore the above mentioned calibration is conservative for our purpose.

2017 - e.g. a 15-year-horizon - are relevant for our averages. On the aggregate level, this should also help to mitigate some of the effects induced by time-varying recovery rates. Third, a countercyclical time-varying recovery rate results in risk neutral recovery rates which are lower than actual recovery rates. All of this makes us confident that the recovery rate of 45% used in this study can be regarded is an upper limit.

6.4 Robustness with respect to actual default probabilities

It is very important to note that our main target is to determine the PD estimates that are used by market participants. E.g. if there was a better estimate for the real world default probability than that used by market participants, it could be used to exploit arbitrage opportunities but it could not be used to gauge market participants risk aversion. Market participants rely almost entirely on three types of PD estimates: agencies ratings, distance-to-default-based measures such as KMV EDFs and hazard rate models. So far we have used EDFs as our primary source for the actual default probabilty. Here, we will perform robustness tests based on agencies ratings and a hazard rate model.

First, we have used agencies ratings with the corresponding cumulative default probabilities as a robustness check. Unfortunately, these ratings are through-the-cylce estimates of the default probability. Using agencies ratings therefore requires the assumption that we cover a whole economic cylce.[35] This assumption is probably most realistic for 5-year CDS - where we have covered the longest period from 2003-2007 including the high-expected default year 2003 - and 10-year CDS. We have averaged the ratings of Moody's, S&P and Fitch in our calculation and determined multi-period default probabilities based on appendix B. Because agencies ratings were not available for all the firms in our sample, we had to slighty decrease the data set for this type of robustness analysis. Results are reported in Table IV. For the 5-year CDS sample from 2003-2007 we estimate very similar default probabilities (1.77% vs. 1.65%) and equity premia

[35] More exactly, it requires the assumption, that investors average expectations over our sample period correctly mirror an economic cycle.

(6.70% vs. 6.66%). The estimated equity premium based on 10-year CDS spread are clearly lower (6.35% vs. 5.08%), but this may be due to a good credit environment from 2004-2007 - an effect which is certainly even more pronounced for shorter maturities.

Insert Table IV about here

Hazard rate models provide another robustness check for both 1-year and mulit-year default probabilities. There is a large literature on hazard rate models for the U.S. market, e.g. Shumway (2001) and Chava and Jarrow (2004). Unfortunately, most of these models only estimate one-year ahead default probabilities and can therefore only be used as a robustness check for one-year default probabilities. Löffler and Maurer (2008) estimate a discrete duration model for conditional default probabilities up to 5 years ahead. They use accounting covariates (e.g. EBIT, total assets) as well as market variables (e.g. return, volatility) similar to Shumway (2001) for default prediction. For the estimates based on Löffler and Maurer (2008) we had to exclude financial services companies, as they did in their analysis, and all companies where Compustat data was not available. The results are reported in Table IV. The estimates for the cumulative default probability are slightly higher resulting in slightly lower equity premia estimates, but both are very similar to the EDF model. Five (three) year cumulative default probabilities are 1.89% (0.72%) for the Löffler/Maurer model compared to 1.79% (0.59%) for the EDF model. The resulting equity premia are 6.74% (5-year) and 6.11% (3-year) compared to 6.96% (5-year) and 6.61% (3-year) for the EDF model.

Of course, accuracies for estimating equity premia in our model should always be interpreted compared to alternative techniques for estimating equity premia. An inaccuracy of 10% in the average default probability results in an increase/decrease of our equity premium estimate by about 10%/0.6 percentage points. This sensitivity is comparable to the sensitivity of the long-run growth rate in dividend discount models.[36] In contrast to long-run growth rates we do though have (partially) objective criteria for

[36]Based on a Gordon model the equity premium estimate in a dividend discount model is $EP = g + d - r_f$ where EP is the equity premium estimate, g the growth rate of dividends, d the dividend yield and r_f the risk-free rate. If $d \approx r_f$ then the sensitivity with respect to g is approx. 1.

default prediction. In addition - in contrast to dividend/earnings forecasts - default predictions are not systematically biased.

7 Conclusion

In this paper, we have introduced a new framework for extracting expected equity returns from credit prices. We hereby contribute to a growing strand of the asset pricing literature focussing on how to test return generating models on the basis of expected returns and not on the basis of realized returns, as has been done over the last 30 years or so. As more and more evidence is emerging that except for very long price histories expected returns do systematically differ from realized returns, the development of reliable methods on how to extract expected returns is increasing in important.

We develop a framework based on structural models of default how to transform credit valuations into expected equity returns. The credit valuation information we use is the CDS spread. Intuitively, the CDS spread can be decomposed into a part which compensates for the expected loss and a part which covers the risk premium demanded by investors. By separating these two parts we can convert the credit risk premium into an equivalent equity risk premium.

Hitherto, in the literature have been used two methods for extracting expected returns. The first method is based on the implied cost of capital method (ICC) developed by Claus and Thomas (2001) and Gebhardt, Lee and Swaminathan (2001). With respect to this method our approach offers some decisive advantages. In fact, instead of having to estimate long-run growth rates, we only need actual default probabilities up to the maturity of the respective CDS. Moreover, there are (at least partially) objective criteria for estimating default probabilities, while expected long-run growth rates are hard to capture. And finally, we have not to rely on potentially upward biased analysts' earnings forecasts, but on quoted CDS spreads.

A second approach used in the literature is much closer to the idea developed in this paper. Campello, Chen and Zhang (2008) develop a framework where expected equity returns are extracted from bond prices. Though this is a quite similar idea, the most important difference to our paper rests on the fact that they use bond prices. It is well known, however, that bond prices do not only reflect credit risk but also other factors, like liquidity or tax issues. Moroever, while the paper of Campello, Chen and Zhang (2008) is completely related to a Merton framework, we can extend our approach to more general structural models of default.

We apply our approach to the question how to estimate the market's equity premium. We hereby offer a new line of thought for estimating the equity premium that is not directly linked to current methods, as the historical equity premium method or the implied cost of capital method. The paper develops an estimator for the equity premium based on a simple Merton structural model. This estimator only uses actual and risk neutral default probabilities, the recovery rate, the maturity and equity correlations. We do neither have to calibrate a structural model nor do we have to estimate earnings or dividend growth.

The estimator can also be derived in the context of more sophisticated structural models, like a first passage time model or a model with incomplete information based on Duffie and Lando (2001). A simulation analysis shows an astonishing robustness of this simple estimator with respect to these different models. Although actual and risk neutral default probabilities are largely affected by model changes, the Merton estimator for the Sharpe ratio is only marginally affected.

By applying our method to 5-year CDS spreads from 2003-2007 of the constituents of the main CDS indices in North America, Europa and Asia yielded upper limits for the equity premium of 6.50% for North America, 5.44% for Europe and 6.21% for Asia. Different CDS maturities (3-, 7-, 10-year) yield similar, but slightly lower, estimates for the equity premium and could provide an interesting insight into the potential term structure of risk premia.

Although we have performed several robustness checks, our approach will have to be challenged in several ways by future research. First, because of data limitations for the CDS market we have been able to analyze only a rather limited period of time and a restricted number of companies. It will be interesting to see whether the approach remains robust as presumed, if a whole economic cycle as well as a larger cross-section of firms can be integrated in the analysis. Second, the literature on the estimation of expected actual default probabilities is still evolving, especially concerning multi-year default prediction. Hence, it has to be seen whether our approach will remain robust with respect to future calibrations. In this context it should also be mentioned that while we use a constant recover rate, a time-varying estimation of the risk neutral recovery rate would improve the reliability of our approach. Third, our approach still suffers from the presumption that the observed CDS spread is totally due to credit risk. To the extent that this is not the case, we are overestimating the equity premium. Hence, more research is needed in order to be able to split-up the CDS spread in a part due to credit risk and a part due to other factors (e.g. liquidity). This could render the equity premium estimates more precise.

A Robustness of Sharpe ratio estimator with respect to model changes

In this section we will show that the Merton estimator for the Sharpe ratio is robust with respect to model changes. We will analyze the following frameworks: a first-passage-time framework based on Black and Cox (1976), a framework with unobservable asset values based on Duffie and Lando (2001) and - implicitly - all default frameworks that yield a constant default barrier (e.g. Leland (1994), Leland and Toft (1996)). In addition, Huang and Huang (2005) show in a similar analysis that the difference between real-world and risk-neutral default probabilities is almost unaffected by the choice of model. They also include models with stochstic interest rates, strategic default models and a model with time-varying risk premia in their analysis.

First-passage-time framework: In a first-passage-time framework default occurs as soon as the asset value falls below the (non-stochastic, constant) default threshold. As in the Merton framework asset values V_t are assumed to follow a geometric Brownian motion but default is now modelled as the stopping time $\tau := \inf\{s > t; V_s \leq L\}$, where $L \in \mathbb{R}$ denotes the default threshold. The actual ($P^{def}(t,T)$) and risk neutral ($Q^{def}(t,T)$) default probability can be calculated as

$$P_{FP}^{def}(t,T) = \Phi\left(\frac{b - m^P(T-t)}{\sigma\sqrt{T-t}}\right) - e^{\frac{2m^P b}{\sigma^2}}\Phi\left(\frac{b + m^P(T-t)}{\sigma\sqrt{T-t}}\right) \quad (10)$$

$$Q_{FP}^{def}(t,T) = \Phi\left(\frac{b - m^Q(T-t)}{\sigma\sqrt{T-t}}\right) - e^{\frac{2m^Q b}{\sigma^2}}\Phi\left(\frac{b + m^Q(T-t)}{\sigma\sqrt{T-t}}\right) \quad (11)$$

with $b = ln(\frac{L}{V_t})$, $m^P = \mu - \frac{1}{2}\sigma^2$, $m^Q = r - \frac{1}{2}\sigma^2$ and $\sigma = \sigma_V$. If either the actual or the risk neutral drift is zero, then - based on the reflection principle - the respective default probability simply equals twice the default probability of the Merton framework.

Framework with unobservable asset values (Duffie and Lando (2001): The first-passage-time framework has been extended in numerous ways to better reflect the default term structure observed in the markets. These extensions include jumps in the asset value process (Zhou (1997)), an unobservable default barrier (Finger, Finkelstein, Pan, Lardy, Ta and Tierney (2002)) and unobservable asset values (Duffie and Lando (2001)). We choose the Duffie/Lando model for our analysis as it is the only structural model consistent with reduced form credit pricing.[37] In addition, the Duffie and Lando (2001) model incorporates a sophisticated structural model of default (i.e. a strategic setting of the default barrier based on the asset value process, tax shield and insolvency costs) and - given an appropriate calibration - results in realistic default intensities for short and long term maturities.

The calculation of the cumulative default probabilities in the Duffie/Lando framework requires a weighted application of (10) and (11) over all possible asset values V_t, where the weight is - roughly speaking - the probability of the asset value V_t[38]

$$P_{DL}^{def}(t,T) = \int_L^\infty \underbrace{P_{FP}^{def}(t,T,x)}_{\text{PD(first passage time) if } V_t = x} \quad \underbrace{g^P(x|Y_t,z_0,t)}_{\text{Prob., that } V_t = x}\, dx \qquad (12)$$

$$Q_{DL}^{def}(t,T) = \int_L^\infty Q_{FP}^{def}(t,T,x) g^Q(x|Y_t,z_0,t) dx \qquad (13)$$

where $P_{FP}^{def}(t,T,x)$ resp. $Q_{FP}^{def}(t,T,x)$ denotes the actual resp. risk neutral probability that an asset value process starting in t at $V_t = x$ will fall below the default

[37] The Duffie and Lando (2001) model is the only structural model so far that yields a default intensity. Defaults in a Merton framework cannot be described by default intensity processes, since the probability of a default from t (today) until $t + \delta t$ is always zero or one for a sufficient small δt. A default intensity does also not exist in the Zhou (1997) framework, since the default time cannot be represented by a totally inaccessible stopping time (which is a consequence of the fact, that the default barrier may be hit/crossed by the normal diffusion process with positive probability), cf. Duffie and Lando (2001) for details.

[38] Of course the probability of a single value V_t will be zero for non-degenerated parameter choices, since we operate in a continuous setting. We will still use this informal notation to allow for a better understanding. A detailed derivation can be found in Duffie and Lando (2001).

barrier up to time T (cf. (10)and (11)) and g^P resp. g^Q is the actual resp. risk neutral conditional density of the asset value at t given the filtration $\mathcal{H}_t$.[39]

We will now introduce an adjustment factor which captures the difference between the Merton estimator for the Sharpe ratio and the 'true' Sharpe ratio. This adjustment factor will be defined by

$$\frac{\mu_M - r}{\sigma_M} = \gamma_{Merton} \cdot AF \tag{14}$$

where

$$\gamma_{Merton} = \frac{\Phi^{-1}(Q_{DL}^{def}(t,T)) - \Phi^{-1}(P_{DL}^{def}(t,T))}{\sqrt{T}} \cdot \frac{1}{\rho_{V,M}} = \gamma(V_t/L, \mu, r, \delta, \sigma, \alpha, t, T) \tag{15}$$

is a function of all parameters in the Duffie/Lando framework and therefore $AF = AF(V_t/L, \mu, r, \delta, \sigma, \alpha, t, T)$ is also a function of the same parameters. The basic idea is now to substitute V_t/L by the actual default probability PD^P. Fixing all other parameters except V_t/L, different values for V_t/L simply result in different actual default probabilities PD^P, i.e. we can write our adjustment factor as

$$AF = AF(PD^P, \mu, r, \delta, \sigma, \alpha, t, T). \tag{16}$$

As a special case, $\alpha = 0\%, \delta = 0\%$ yields the classic first-passage time framework. Strategic default frameworks where the default barrier is endogeneously determined but constant are also captured since we will simply cover any reasonable parameter combinations. I.e., for any default barrier L, we will cover all combinations which result in a rating between Aa and B and where the other parameters are within a reasonable range.

[39]Please note that the conditional density itself is dependent on the respective probability measure. Intuitively, the investor in the Duffie/Lando framework 'processes' two pieces of information: First, the noisy information about the asset value. Second, the fact that no default has occured up to time t. While the first piece of information is the same in both the actual and risk neutral world, the second differs.

We have numerically evaluated (16) for all reasonable combinations of input parameters.[40] The calculation was carried out in four steps: In the first step, a combination of a specific rating grade and all parameters from the Duffie/Lando framework excluding the asset value V_t was choosen. Please note, that this also involves the specification of the asset Sharpe ratio in order to determine the real world drift of the asset value process. Then, based on (12), the asset value V_t was numerically determined as to result in the cumulative actual default probability for the respective rating category. Given the asset value V_t and the other parameters choosen in the first step, a straight forward application of (13) based on risk neutral parameters was used to determine the risk neutral default probability. In the fourth step, the Merton estimator (15) was calcualted based on these model-based actual and risk neutral default probabilities. Comparison with the asset Sharpe ratio specified in step 1 yields the adjustment factor (based on (14)). These four steps were repeated for all reasonable parameter combinations.

The results are reported in table V based on three scenarios: Scenario 1 restricts the asset volatility to be larger or equal to 10%. Asset volatilities below 10% are usually only observed for financial services companies. Scenario 2 captures all parameter combinations where the average default time is larger than 0.5 time the maturity. This scenario is based on a usual assumption for investment grade entities, i.e. that real world annual conditional default probabilities are an increasing function of the maturity. Scenario 3 sets the risk neutral drift of the asset value relative to the default boundary to zero. This captures the assumption of constant expected leverage. These three scenarios were designed to capture realistic parameter combinations.

[40]Input parameters used were: $\sigma : 3\% to 30\%$ (the 5% and 95% quantile for the asset volatility from KMV was 6% and 25% respectively), Sharpe ratio of the asset value process: 10% to 40% (the market Sharpe ratio is usually assumed to be anywhere between 20% and 50%, due to a correlation of lower than 1, the asset Sharpe ratio should be smaller), $m : 0\% to 5\%$ ($m < 0$ would imply, that the payout rate is larger than the risk free rate, $m = 5\%$ was choosen as an upper limit to reflect (almost) zero payout at a risk free interest rate of 5%.), $\alpha : 0\% to 30\%$ ($\alpha = 0\%$ reflects the classical first passage model with observable asset values, Duffie/Lando use 10% as a standard value, the upper limit of 30% is also based on Duffie and Lando(2001)), $\widehat{V}_t = V_0$ was implicitly choosen to result in the desired rating grade from Aa to B. The case $\widehat{V}_t > V_0$ and $\widehat{V}_t < V_0$ was also analyzed, the results barely differ from the case $\widehat{V}_t = Z_0$ and are available upon request. The correlation coefficient $\rho_{V,M}$ is already captured by the asset Sharpe ratio, which is the product of market Sharpe ratio and $\rho_{V,M}$.

Insert Table V about here

Based on a 5-year maturity, the adjustment factor for investment grade entities is always between 0.85 and 1.27 in scenario 1, between 0.82 and 1.24 in scenario 2 and between 0.82 and 1.08 in scenario 3. If one does not restrict the parameter combination to one of these scenarios, very large adjustment factors may occur for some very rare parameter combinations, for instance if one combines a very high asset value drift with a low volatility. In these cases, default either happens 'very early' or never at all. Then, the difference between risk neutral and actual default probability is relatively small because the investor is only exposed to systematic risk for a very short time period, afterwards the large drift and low volatility result in very low default probabilities. Apart from these unrealistic cases, the adjustment factors are very close to one and the estimator is therefore robust with respect to model changes. The results are similar for maturities of 3, 7 and 10 years. Results can be provided on request.

B Mapping of Moody's rating grades to default probabilities

For the mapping of Moody's rating grades to default probabilities and one-year EDFs to mulit-year EDFs, we used the raw data provided by Moody's (2007). We used a log-linear relationship to calibrate the default probabilities, i.e. we performed the regression

$$ln(PD) = \beta_1 + \beta_2 \cdot NRG,$$

where NRG denotes the numerical rating grade ranging from 1 (Aaa) to 16 (B3) and PD denotes the historical default probabilities per rating grade.[41] The resulting cumulative default probabilities are shown in table VI.

Insert Table VI about here

[41] The log-approach is a common approach for the calibration of default probabilities (cf. for example Bluhm, Overbeck and Wagner (2003)).

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Variable	N	Mean	Median	Std. dev.	25th Perc	75th Perc
CDS mid	24,785	54.53	39.80	58.41	25.50	61.00
CDS offer	24,785	56.76	42.00	59.31	27.20	63.50
CDS bid	24,785	52.37	37.70	57.69	23.70	59.00
Δ(bid, offer)	24,785	4.40	4.00	3.02	3.00	5.00
EDF1	24,785	0.17%	0.07%	0.50%	0.04%	0.15%
EDF5	24,785	1.90%	1.26%	2.58%	0.85%	2.14%
ρ	24,785	0.52	0.53	0.08	0.46	0.59
Implied market volatility	24,785	17.14%	16.31%	2.36%	15.43%	18.80%

Table I:
Descriptive statistics

Descriptive statistics for input parameters. The sample consists of the intersection of the KMV database, the CDX.NA.IG on-the-run companies and the CMA CDS database (via datastream) from April 2003 to June 2007. *EDF1/EDF5* denote 1- and 5-year cumulative default probabilities based on KMV EDFs. ρ denotes the correlation between equity returns and S&P 500 returns. Implied market volatility is taken from the VIX term structure published by the CBOE based on mid option prices for maturities from 18-23 months.

Table II:

Company Sharpe Ratio, Market Sharpe Ratio and Equity Premium Estimates based on U.S. 5-year CDS spreads from April 2003 to June 2007

The sample consists of the intersection of the KMV database, the CDX.NA.IG on-the-run companies and the CMA CDS database (via datastream) from April 2003 to June 2007. For correlations, median industry correlations have been used based on 2-year weekly returns. Implied volatilities are based on maturities from 18-23 months from the VIX term structure (mid prices) of the CBOE. Company specific volatilities are based on 2-year weekly returns. N denotes the number of weekly company/date combinations. s denotes the CDS spread, *EDF5* denotes the 5-year cumulative default probability based on KMV EDFs, ρ denotes the Equity/Market-correlation and σ_M denotes the implied S&P 500 volatility. Averages are calculated as unweighted averages over all observations.

		Estimates						Mean of input parameters				
Parameter	Year	N	Mean	Median	Std. dev.	25th Perc	75th Perc	s	EDF5	ρ	σ_M	σ_i
Sharpe ratio	2003	4,235	13.44%	12.47%	14.18%	5.08%	20.68%	75.10	3.72%			
company	2004	5,916	16.77%	16.39%	11.52%	9.19%	23.57%	58.91	2.37%			
according to (4)	2005	5,860	21.62%	20.18%	13.13%	13.33%	28.15%	57.34	1.54%			
	2006	5,835	22.52%	21.25%	12.99%	13.36%	30.29%	41.12	1.00%			
	2007	2,939	22.07%	20.21%	14.16%	12.48%	30.07%	37.10	0.82%			
	2003-2007	24,785	19.33%	18.17%	13.50%	10.63%	26.59%	54.53	1.90%			
Sharpe ratio	2003	4,235	24.51%	21.80%	25.85%	8.36%	38.36%	75.10	3.72%	0.57		
market	2004	5,916	31.77%	30.06%	22.34%	16.44%	45.81%	58.91	2.37%	0.55		
according to (6)	2005	5,860	44.49%	40.83%	27.62%	25.45%	59.78%	57.34	1.54%	0.50		
	2006	5,835	46.88%	41.87%	29.49%	25.99%	63.11%	41.12	1.00%	0.50		
	2007	2,939	45.92%	40.82%	31.62%	24.72%	62.04%	37.10	0.82%	0.50		
	2003-2007	24,785	38.77%	35.30%	28.51%	19.31%	54.23%	54.53	1.90%	0.52		
Equity Premium	2003	4,235	5.16%	4.56%	5.49%	1.76%	8.02%	75.10	3.72%	0.57	20.93%	
according to (7)	2004	5,916	5.84%	5.53%	4.15%	2.97%	8.35%	58.91	2.37%	0.55	18.28%	
	2005	5,860	7.18%	6.55%	4.54%	4.03%	9.69%	57.34	1.54%	0.50	16.04%	
	2006	5,835	7.17%	6.46%	4.55%	3.91%	9.67%	41.12	1.00%	0.50	15.23%	
	2007	2,939	7.08%	6.25%	4.89%	3.77%	9.59%	37.10	0.82%	0.50	15.39%	
	2003-2007	24,785	6.50%	5.95%	4.74%	3.32%	9.10%	54.53	1.90%	0.52	17.14%	
Equity Premium	2003	4,235	4.28%	3.89%	4.86%	1.61%	6.34%	75.10	3.72%			32.06%
according to (8)	2004	5,916	4.76%	4.44%	3.60%	2.61%	6.39%	58.91	2.37%			28.65%
	2005	5,860	4.93%	4.41%	3.40%	2.81%	6.48%	57.34	1.54%			23.08%
	2006	5,835	4.84%	4.37%	2.96%	2.80%	6.53%	41.12	1.00%			21.90%
	2007	2,939	4.65%	4.12%	3.15%	2.39%	6.40%	37.10	0.82%			21.22%
	2003-2007	24,785	4.73%	4.30%	3.63%	2.58%	6.45%	54.53	1.90%			25.44%

Table III:

Company Sharpe Ratio, Market Sharpe Ratio and Equity Premium Estimates based on International 3-, 5-, 7-, 10-year CDS spreads from January 2004 to June 2007

The sample consists of the intersection of the KMV database and the major CDS indices for the U.S. (CDX.NA.IG), Europe (iTraxxEurope) and Asia (iTraxxAsia ex Japan) from January 2004 to June 2007. Only on-the-run companies are considered. CDS spreads are obtained from CMA through datastream where we included only company/date-combinations where spreads for all maturities (3-, 5-, 7- and 10-years) were available. For correlations, median industry correlations have been used based on 2-year weekly returns. Implied volatilities are based on maturities from 18-23 months from the VIX term structure (mid prices) of the CBOE for the U.S., the VSTOXX sub-index 24 months for Europe and 1-year historical volatilities for Asia. Company specific volatilities are based on 2-year weekly returns. N denotes the number of CDS spreads for each maturity, T denotes the CDS maturity. Averages are calculated as unweighted averages over all observations.

		U.S. N=16,761				Europe N=17,786				Asia N=3,926			
Parameter	Year	T=3	T=5	T=7	T=10	T=3	T=5	T=7	T=10	T=3	T=5	T=7	T=10
Sharpe ratio company	2004	15.62%	16.70%	14.73%	13.79%	4.14%	6.70%	5.86%	5.54%	15.12%	15.09%	13.67%	13.13%
according to (4)	2005	19.86%	22.11%	20.79%	19.68%	12.36%	13.91%	13.43%	12.98%	17.59%	16.55%	15.64%	15.21%
	2006	20.75%	22.77%	21.78%	20.54%	15.61%	16.78%	16.41%	15.97%	20.65%	19.27%	17.72%	16.66%
	2007	20.67%	22.29%	22.09%	21.20%	17.00%	16.47%	16.34%	16.26%	15.38%	15.16%	15.39%	15.30%
	04-07	19.57%	21.44%	20.31%	19.22%	12.34%	13.65%	13.19%	12.83%	18.02%	17.16%	16.13%	15.50%
Sharpe ratio market	2004	29.91%	31.79%	28.08%	26.29%	8.20%	12.04%	10.57%	9.97%	31.49%	32.49%	29.69%	28.78%
according to (6)	2005	40.82%	45.36%	42.63%	40.35%	26.54%	29.09%	27.96%	26.83%	40.43%	38.05%	35.94%	34.93%
	2006	43.37%	47.30%	45.19%	42.57%	33.59%	35.64%	34.80%	33.68%	49.23%	45.79%	42.04%	39.45%
	2007	43.06%	46.32%	45.91%	44.02%	36.26%	35.08%	34.65%	34.10%	34.02%	33.40%	33.71%	33.45%
	04-07	40.20%	43.85%	41.56%	39.32%	26.33%	28.39%	27.40%	26.48%	41.40%	39.43%	37.03%	35.54%
Equity Premium	2004	5.51%	5.82%	5.13%	4.80%	1.87%	2.73%	2.38%	2.24%	5.65%	5.81%	5.31%	5.15%
according to (7)	2005	6.60%	7.33%	6.88%	6.51%	4.91%	5.37%	5.16%	4.94%	5.73%	5.42%	5.13%	4.98%
	2006	6.64%	7.23%	6.90%	6.50%	6.36%	6.75%	6.59%	6.37%	7.63%	7.10%	6.51%	6.10%
	2007	6.64%	7.14%	7.07%	6.78%	6.89%	6.66%	6.58%	6.48%	5.84%	5.73%	5.79%	5.74%
	04-07	6.43%	7.00%	6.62%	6.26%	5.03%	5.44%	5.24%	5.06%	6.50%	6.21%	5.84%	5.60%
Equity Premium	2004	4.31%	4.66%	4.09%	3.81%	0.37%	1.53%	1.32%	1.26%	3.91%	4.00%	3.62%	3.50%
according to (8)	2005	4.47%	5.05%	4.74%	4.49%	2.55%	3.01%	2.92%	2.85%	4.35%	4.16%	3.93%	3.83%
	2006	4.38%	4.89%	4.69%	4.43%	3.15%	3.43%	3.36%	3.27%	5.07%	4.78%	4.40%	4.14%
	2007	4.26%	4.69%	4.67%	4.49%	3.49%	3.41%	3.41%	3.40%	4.34%	4.35%	4.40%	4.35%
	04-07	4.38%	4.87%	4.60%	4.35%	2.41%	2.88%	2.78%	2.72%	4.57%	4.42%	4.16%	4.00%

		T=3 2004-2007		T=5 2003-2007		T=7 2004-2007		T=10 2004-2007	
		EDF Model	New Model	EDF Model	New Model	EDF Model	New Model	EDF Model	New Model
Agencies	N	16,032	16,032	23,100	23,100	16,032	16,032	16,032	16,032
Rating	PD	0.58%	0.78%	1.77%	1.65%	2.25%	2.89%	3.74%	4.78%
	EP	6.52%	4.29%	6.70%	6.66%	6.71%	5.26%	6.35%	5.08%
Discrete	N	10,078	10,078	14,700	14,700				
Duration	PD	0.59%	0.72%	1.79%	1.89%				
Model	EP	6.61%	6.11%	6.96%	6.74%				

Table IV:

Equity premium estimates based on different proxies for the real world default probability

This table shows equity premium estimates where agencies ratings and default probabilities based on a discrete duration model have been used as proxies for the real world default probability. Agencies ratings are based on average ratings of Moody's, S&P and Fitch with corresponding cumulative default probabilities based on appendix B. The discrete duration model is based on Löffler/Maurer (2008). *EDF Model* denotes the model with EDFs as proxies for the real world default probability. *New Model* denotes the model with either PDs based on agencies ratings or based on Löffler/Maurer (2008). *N* denotes the number of observations, *PD* the average cumulative default probability and *EP* the equity premium estimation. Equity premia estimations for the EDF model deviate from the previous sections due to a different sample size.

		$\sigma \geq 10\%$		Default Timing $\geq 50\% \cdot T$		Risk-neutral drift $= 0\%$	
Maturity	Rating	Min_{AF}	Max_{AF}	Min_{AF}	Max_{AF}	Min_{AF}	Max_{AF}
3	Aa	0.77	1.07	0.73	1.20	0.73	1.03
	A	0.78	1.10	0.73	1.23	0.73	1.04
	Baa	0.79	1.14	0.74	1.21	0.74	1.06
	IG (Total)	0.77	1.14	0.73	1.23	0.73	1.06
5	Aa	0.85	1.14	0.82	1.24	0.82	1.05
	A	0.86	1.19	0.82	1.23	0.82	1.06
	Baa	0.87	1.27	0.84	1.21	0.84	1.08
	IG (Total)	0.85	1.27	0.82	1.24	0.82	1.08
7	Aa	0.90	1.22	0.87	1.23	0.87	1.06
	A	0.90	1.29	0.87	1.20	0.87	1.07
	Baa	0.91	1.41	0.89	1.18	0.89	1.11
	IG (Total)	0.90	1.41	0.87	1.23	0.87	1.11
10	Aa	0.93	1.34	0.91	1.23	0.91	1.07
	A	0.94	1.45	0.92	1.22	0.92	1.10
	Baa	0.95	1.62	0.94	1.17	0.94	1.14
	IG (Total)	0.93	1.62	0.91	1.23	0.91	1.14
All	IG (Total)	0.77	1.62	0.73	1.24	0.73	1.14

Table V:

Adjustment factors in the Duffie/Lando framework

Minimum and maximum adjustment factors for investment grade (IG) ratings and maturities from 3 to 10 years. AF_{Min} and AF_{Max} denote minimum and maximum adjustment factors for the respective scenario. The scenario '$\sigma \geq 10\%$' represents non-financials since asset values below 10% are usually only observed for financial services companies. The scenario 'Default Timing $\geq 50\% \cdot T$' captures all parameter combinations where the average default time conditional on default up to time T ($\tilde{\tau} := E[\tau|\tau \leq T]$) was larger than $0.5 \cdot T$. This reflects the usual assumption that for investment grade entities the real world default probability is an increasing function of the maturity. The scenario 'Risk-neutral drift $= 0\%$' captures a frequent assumption of zero asset value drift in the risk neutral world, i.e. the expected leverage V_t/L is assumed to be constant. Rating categories and the respective mid-point PDs are from Moody's. *IG* includes all investment grade entities.

	Maturity									
Rating	1	2	3	4	5	6	7	8	9	10
Aaa	0.001	0.006	0.019	0.041	0.071	0.094	0.114	0.125	0.135	0.148
Aa1	0.002	0.011	0.032	0.065	0.108	0.143	0.173	0.190	0.205	0.224
Aa2	0.004	0.018	0.052	0.103	0.166	0.218	0.261	0.287	0.310	0.339
Aa3	0.007	0.032	0.085	0.163	0.255	0.331	0.394	0.434	0.470	0.512
A1	0.013	0.055	0.139	0.256	0.392	0.502	0.596	0.657	0.712	0.775
A2	0.024	0.095	0.228	0.404	0.601	0.763	0.900	0.995	1.078	1.173
A3	0.045	0.164	0.373	0.637	0.922	1.159	1.360	1.506	1.633	1.774
Baa1	0.083	0.285	0.611	1.004	1.416	1.760	2.056	2.278	2.475	2.683
Baa2	0.152	0.493	1.002	1.583	2.173	2.674	3.107	3.447	3.750	4.058
Baa3	0.279	0.855	1.642	2.496	3.335	4.063	4.695	5.217	5.681	6.139
Ba1	0.514	1.482	2.691	3.934	5.120	6.172	7.095	7.894	8.607	9.286
Ba2	0.946	2.569	4.411	6.202	7.858	9.376	10.722	11.946	13.041	14.046
Ba3	1.741	4.452	7.229	9.778	12.061	14.243	16.204	18.076	19.759	21.247
B1	3.204	7.716	11.847	15.414	18.512	21.638	24.488	27.354	29.936	32.139
B2	5.896	13.373	19.417	24.301	28.413	32.871	37.007	41.392	45.356	48.615
B3	10.850	23.178	31.823	38.310	43.611	49.936	55.926	62.635	68.719	73.538

Table VI:

Cumulative default probabilities for Moody's ratings in percent

Cumulative default probabilities based on Moody's (2007) and based on a log-approach $ln(PD) = \beta_1 + \beta_2 \cdot NRG$, where NRG denotes the numerical rating grade ranging from 1 (Aaa) to 16 (B3).