An Empirical Comparison of Structural and Reduced-Form Credit Risk Frameworks: Evidence from the Credit Default Swap Market

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Abstract

Increasing interest in credit risk modeling necessitates empirical validation of the numerous theoretical alternatives. However, the empirical literature on credit risk has so far yielded mixed results. The aim of this paper is three-fold: First, it compares the basic forms of structural (the Merton model) and reduced-form (constant intensity) models in a cross-sectional and time series setup. Second, it utilizes a credit default swap dataset exclusively for both estimation and out-of-sample prediction. Finally, it contrasts the results to the performance of a machine learning algorithm, Support Vector Machines Regression, to compare prediction capability. We show that although the Merton and the constant intensity models handle default timing and interest rates differently, the prediction performance in cross-sectional and time series analyses is, on average, similar. In one-, five-, and ten-step-ahead predictions of time series, the machine learning algorithm significantly outperformed financial models.

Keywords: Credit Risk, Structural Models, Reduced-Form Models, Credit Default Swaps, Support Vector Machines Regression.

JEL Classificiation: G13

1. Introduction

In the last decade, credit risk modeling has received increasing attention within academia and practice. On the "structural" modeling side, various extensions have been made to the early Merton model (1974), whereas on the "reduced-form" side, alternative variations for the intensity process are proposed in modeling. The literature is continuously renewed by new approaches, but there is no dominant framework capable of achieving "a shift of a paradigm" in the field in the Kuhnian sense. So far, there is no consensus on a model that could serve as a benchmark on a par with the Black/Scholes framework in equity and foreign exchange derivatives. One of the main reasons for this deficit is the fact that the sources of validation for theoretical approaches, the empirical studies, have yielded controversial results, leaving the theory adrift. At this stage, it is necessary to re-evaluate what the frameworks have put forward, and thereby undertake a first step towards comparing the main structures.

The rapid expansion of the credit derivatives market has in turn placed increased demands on credit risk analysis. These contracts, whose payoffs depend on the creditworthiness of corporations, banks, or sovereign entities, are expected to reach a global market of about USD 8.2 trillion by the end of 2006, according to British Bankers' Association's Credit Derivatives Report (BBA, 2004). With 51 per cent of the market share, credit default swaps are by far the most frequently traded type of credit derivatives (BBA, 2004; p. 21). This popularity has generated interest and launched efforts for adapting theoretical pricing models. By its nature, the price of a credit default swap (CDS) represents a near-ideal measure of credit risk. By virtue of being almost unconstrained by liquidity effects, CDSs provide an indispensable media for credit risk analysis.

Within this evolving scene in the field of credit risk, the contributions of this study are three-fold. Firstly, the same dataset is applied to structural and reduced-form approaches. So far, the credit risk literature has analyzed the empirical fit to bond or CDS prices only within a certain framework of models. The empirical performance of the two major approaches to model credit risk, structural and reduced-form, have performed variably in different studies. When the dataset characteristics and the time frame involved were altered, there was no means of comparison among alternative models. Our study overcomes this difficulty by applying a CDS dataset to both model types, and compares the out-of-sample prediction errors. In addition, our study fills the gap in the literature on empirical tests that depend solely on CDS data. To date, there has been no effort using only CDS data for the estimation and subsequent testing of the out-of-sample prediction ability of credit risk models. Comparable studies have either worked only with bond data[1], or utilized bond data in estimation and predicted CDS prices[2], or, conversely, made use of CDS data in estimation, and predicted bond prices.[3] Moreover, our study distinguishes between the results of cross-sectional and time series out-of-sample predictions, with the latter achieving far better results than the former. The third contribution of the study is to apply a machine learning algorithm whose recent empirical results have been promising. The Support Vector Machines Regression method has been utilized as a possible alternative to financial approaches. The prediction errors of the machine learning algorithm, which has no financially backed structure at all, is compared to structural and reduced-form frameworks in a cross-sectional and time series setup. In the cross-sectional setup, our results indicate an overall poor fit with close prediction performance of financial models. We attribute this closeness to the similarity of the model settings, which is due to not having a breakdown into asset value parameters for the Merton model. Still, both financial models are superior to SVM methods, whose errors are mostly out of the reasonable range. Interestingly, the one-, five- and ten-day-ahead predictions of the SVM method dominate the financial methods in time series setups.

The remaining sections of the study are organized as follows: Section 2 provides a review of the literature on credit risk. Section 3 introduces the credit default swap dataset used in the analysis. In Section 4, the three modeling approaches, (i) Merton, (ii) constant intensity, and (iii) Support Vector Machine Regression are explained, and the pricing of CDSs with these models is discussed. Sections 5 and 6 present the results with cross-sectional and time series analyses, respectively. The last section concludes with remarks, providing implications on the path towards a widely accepted credit risk modeling framework.

2. Review of Literature and Purpose of the Study

The history of credit risk modeling dates back to the 1970s. The introduction of the Black and Scholes (1973) and Merton (1973) valuation framework eventually led to the development of a new branch of finance. Extending this framework to include corporate bonds, Merton’s (1974) methodology was based on the central point that debt and equity can be interpreted as options on the firm value of a corporation. Over time, different approaches to modeling credit risk have been developed, resulting in two main branches of research in the current academic literature. Following Merton's (1974) idea, the *structural* approach is based on modeling the evolution of issuer balance sheets. Default occurs when the value of assets falls below a certain level and the issuer is unable or unwilling to meet its obligations. There have been various structural modeling extensions of Merton's approach (1974), most significantly in terms of (i) allowing default at any time during maturity, (ii) endogenously deriving the level of the default barrier, and (iii) introducing stochastic interest rates. Black and Cox (1976) have provided a closed form solution for the "first-passage time" models. In addition, their study was important for its derivation of an endogenous default barrier, which has since been extended by Leland (1994) and many others. Longstaff and Schwartz (1995) carried the debate to include stochastic interest rates.

In contrast to structural models, *reduced-form* models specify the default probabilities exogenously. According to these models, default time is unpredictable and is calculated by means of a default intensity function. Instead of relying upon the diffusion process inherent in structural models, reduced-form approaches model the default time as the first occurrence of an event in a jump process. The simplest type of reduced-form models is one in which default intensity is constant, as put forward by Jarrow and Turnbull (1995). Many variations of this model have been developed. Important contributions among them include Jarrow et al.'s version (1997) with rating-dependent intensities in a Markov chain setup, as well as the Cox processes used by Lando (1998) and Duffie and Singleton (1999) for default intensity modeling. A comprehensive review on both structural and reduced-form credit risk models can be found in Uhrig-Homburg (2002).

With all these different approaches available, the question becomes: How well do they represent a good benchmark for real prices? In the end, all the above models have arisen to serve the need of reaching consensus on a single approach. To date, there has been no common agreement in academia or practice as to which model framework better represents default risk. One main reason for the lack of consensus is that empirical studies have provided controversial guidance in the validation process for theoretical models. The unevenness of the studies can be attributed to three factors: (i) When testing a given model empirically, the usage of different datasets produces widely varying prediction results. For instance, structural models were often criticized by early empirical studies as under-predicting credit spreads (Jones et al., 1984; Ogden, 1987; Lyden and Saraniti, 2000), whereas more recent studies utilizing the same models suggest that this is not a consistent occurrence (Eom et al., 2004). It is unclear, however, whether this is due to the models or the datasets used. (ii) Even though the prediction performances of structural and reduced-form models have been compared within each framework, there have been no empirical studies examining the results of studies in which the same dataset and methodology were applied to both frameworks. For instance, although Eom et al.'s (2004) study is the most comprehensive study to date in which several structural models are compared in one setting, it does not address the results acquired with reduced-form approaches. Similarly, empirical studies conducted by Anderson and Sunderasan (2000) or Bakshi et al. (2006) have approved a special model setup without any basis of comparison across frameworks. (iii) Moreover, although the error results between the compared models might turn out to be similar, the estimation technique and the sampling setup for prediction highly influences the forecasting ability. As an example, Ericsson and Reneby's (2004) out-of-sample prediction results, obtained by using an extension of Leland's (1994) endogenous structural model and employing an innovative estimation technique in Duan (1994), seem well comparable to Duffee's (1999) in-sample results with a reduced-form model utilizing Kalman filter estimation, both having a root mean squared error of around 10 bps. Apparently, looking at the prediction results alone would be misleading, since these do not express the detailed aspects of both settings. The presence of all these issues therefore necessitates that further efforts be undertaken. Ideally, this would be accomplished by testing structural and reduced-form models via the application of the same methodology to the same dataset, as will be presented.

In addition to comparing the two financial credit risk frameworks, we employ a third alternative method in this study. The recent developments in machine learning have opened a new pathway for computing empirical predictions: Support Vector Machines (SVM) is an innovative technique for data classification and regression. As an alternative to traditional neural network approaches, SVM, whose fundamentals were developed by Vapnik (1995), have become popular due to their promising empirical performance. Specifically, the SVM regression method proposes alternative kernel functions to be used in mapping into a high dimensional feature space. Literature on SVM regression applications on finance is sparse; there has been coverage especially on financial time series forecasting (Cao and Tay, 2001; Müller et al., 1997). To our knowledge, SVM has not been applied to credit derivatives pricing, and its results have accordingly not yet been compared with financial methods.

3. Data

A study that compares credit risk modeling approaches needs to make use of a pure instrument whose price fully reflects the credit risk premium. Until recent years, corporate and sovereign bonds were the only tools available for studies on credit risk. However, the utilization of bonds has so far yielded intricate results. In the early years, the credit risk analysis was complicated because the bond price often included a callable option (Jones et al., 1984; Ogden, 1987). Even though this difficulty was later overcome with the availability of non-callable bond data (Eom et al., 2004), the bond spreads have prompted arguments as to which proportion of the spread credit risk actually constitutes. In an in-depth analysis, Collin-Dufresne et al. (2001) have attributed the spread changes primarily to a non-credit risk related systematic factor, such as local supply-demand shocks. After dividing the risky portion of the bond premium into default and non-default components, the results of Longstaff et al. (2005) confirm that the non-default component in spreads are strongly related to a number of liquidity measures.

Over the last decade, the expansion of the credit default swap market has provided a good alternative for transferring credit risk. The buyer of the CDS is insured against the default of the underlying entity by the seller of the CDS, who in exchange receives periodic payments, the CDS premiums. Obviously, this premium should be driven only by the credit risk of the underlying entity; the higher the credit risk, the higher the CDS premium will be. Since CDSs are contracts but not securities, they are not subject to squeezing effects. They are also less likely to be under supply and demand pressures since they are not in fixed supply like securities are.[4] Blanco et al.'s results (2005) demonstrate that the CDS market leads the bond market in price discovery, and therefore suggest higher liquidity of CDSs. All these reasons imply that in relative terms, liquidity constraints are far less applicable to CDSs, hence leaving the CDS premium with only the credit risk component. With these facts in mind, our study utilizes a CDS dataset for credit risk modeling analysis.

Our dataset consists of over 235,000 daily quotes of the prices of liquid CDS contracts. CreditTrade's daily indicative bid-ask quotes[5] range over the period of January 2001 to December 2004. Figure 1 plots the CDS bid-ask midpoints as a function of credit ratings, which are a proxy for credit quality. The dataset is in line with the theoretical hypothesis that the higher the risk of default, the higher the premium will be. The full set of prices comes from interdealer voice brokerage, and the descriptive statistics can be found in Table 1. In Panel A, it can be observed that the number of observations increase from around 24,000 in 2001 to 76,000 in 2004, indicating an expanding market. One direct measure for liquidity of the market is the size of the bid-ask spread, which shows the tightness of orders to buy and sell.[6] The bid-ask spread is observed to decrease over time, attaining its lowest level in 2004. Due to the steady level of daily observations after December 2002, this period has been focused on to the exclusion of earlier intervals. There is a cut-off point in the dataset in December 2002 as well, occasioned by a shift from 10 million notionals to 5 million notionals. Moreover, as the dataset is mostly dominated by corporates and banks as the underlying entities; the sovereign entities are excluded due to (i) having too few data points, and (ii) for being mostly non-investment grade CDSs (as in the case of Latin America, which actually has higher number of observations). Panel B of Table 1 presents the descriptive data on rating classes across different maturities. The most liquid maturity is the 5-year CDS, followed by 10- and 3-year CDSs. For similar reasons as above, we focus on the liquid segments of Aa- and A-rated classes, senior and 5-year maturity CDSs.

[Figure 1 is presented here]

[Table 1 is presented here]

Table 2 provides the average spreads across ratings for the CDSs that are focused upon in the remainder of the study. The offer price minus the bid price for a given quote in our dataset has an average of 4.75 bps for the Aa-European class, whereas it is 6.81 bps for A-European CDSs. A similar rise is observed for North American CDSs. Notably, the average premiums and spreads are observed to steadily decrease over time.

[Table 2 is presented here]

In addition to the CDS dataset, riskless interest rates are required as a major variable in models. In doing this, USD- and Euro-denominated contracts have to be treated separately. The daily estimates of Svensson (1994) model are used as the rates for the European region. Deutsche Bundesbank has estimated these parameters from government bonds. For the North American region, US Treasury Constant Maturity rates were linearly interpolated for quarterly intervals. The data are directly available from the corresponding web sites.

4. Selected Approaches and CDS Valuation

In our attempt to compare financial modeling frameworks, we have chosen to work with the Merton model (1974), which has the simplest form that a structural model can have. Meanwhile, we employ the constant default intensity as outlined by Jarrow and Turnbull

(1995), which can be regarded as the simplest form in the reduced-form framework. Although there are many extensions that have developed on top of these structures, we concentrate initially on a comparison of the two basic models. The results of both approaches are contrasted with the prediction results of a machine learning approach. The analysis is therefore three-fold:

i. It applies the most financially structured models to a CDS dataset under the hypothesis that default is triggered by the asset value of the firm being below a certain threshold at maturity.
ii. It applies the intensity-based Poisson jump process setting to the same dataset under the hypothesis that default is defined as a surprise event that can occur at any time during the lifetime.
iii. It applies Support Vector Machines – a machine learning algorithm that does not have an economically-backed structure at all – under the hypothesis that whatever resides in the prices is the best source to train the function for predictions.

4.1 The Merton Model

We start by applying Merton's (1974) model to the CDS dataset. This model allows default only at maturity, and does not incorporate a stochastic process for the interest rate. In order to value a CDS, consider its two legs, the premium and the protection leg. The premium leg is the fee as a percentage of the contract amount that the buyer of the insurance has to pay to the seller until maturity or default, whichever comes first. The protection leg is the single payment that the seller of the contract is obliged to undertake in case of default of the entity upon which the contract is written. In Merton's setting, the premium leg is nothing but the discounting of each fair premium s^{theo} paid until maturity:

$$\text{Premium Leg} = s^{theo}\sum_{i=1}^{n} e^{-r(i)T(i)} \qquad (1)$$

where $T(i)$ is the time interval in yearly terms, and, as the usual practice is quarterly paid premiums, $T(1)$ is 0.25, $T(2)$ is 0.5, and so on; the maturity of the contract $T(n)$ is 5 years. $r(i)$ is the riskless interest rate for maturity $T(i)$ on the contract setup date. The protection leg constitutes the discounting of the probability of default at maturity, multiplied with the non-recoverable amount:

$$\text{Protection Leg} = (1-\omega)\Phi(-d_2)(e^{-r(n)T(n)}) \qquad (2)$$

where $\Phi(-d_2)$ is the risk-neutral default probability in the Merton setting. The recovery rate in case of default, ω, also enters the protection leg. It might have been a sound approach to estimate the recovery rate simultaneously with the default intensity; however, recent applications undertaken by Houweling and Vorst (2005) and Frühwirth and Sögner (2006) have shown the insensitivity of the results based upon the selection of this variable. To simplify methods, the recovery rate can be fixed to a value obtained in empirical studies based on historically defaulted bonds. Following the results produced by Altman and Kishore (1996) and recent practice, we use 0.5 for the senior class.[7] As a last step, the theoretically fair CDS premium is reached by equating the premium and protection legs at time zero:

$$\text{Fair (Theoretical) Premium of a CDS} = s^{theo} = \frac{(1-\omega)\,\Phi(-d_2)(e^{-r(n)T(n)})}{\sum_{i=1}^{n} e^{-r(i)T(i)}} \qquad (3)$$

This premium ensures that the CDS contract has zero value on initiation, which in turn guarantees that the buyer and the seller are even under no-arbitrage assumptions.

4.2 Default Intensity Model

The basic structure of a constant default intensity model was introduced by Jarrow and Turnbull (1995). This model has simplifying features: The default time is the first jump of a Poisson counting process, with the default intensity as the constant parameter. While Jarrow and Turnbull assume a constant intensity under the real world measure, the intensity becomes time-varying when they turn to the risk-neutral world. In our application, we start directly with a constant risk-neutral intensity. In contrast to more advanced intensity-based models, the stochastic process driving the riskless term structure and the default process is assumed to be independent in the Jarrow and Turnbull setting. Following Duffie and Singleton (2003), it can be shown that the pricing of CDS is composed of a premium and protection leg as below:

$$\text{Premium Leg} = s^{theo} \sum_{i=1}^{n} e^{-(\lambda + r(i))T(i)} \qquad (4)$$

$$\text{Protection Leg} = (1-\omega)\sum_{i=1}^{n} e^{-r(i)T(i)} (e^{-\lambda T(i-1)} - e^{-\lambda T(i)}) \qquad (5)$$

where λ is the constant default intensity parameter. Equating these two legs to extract the theoretically fair premium leads to:

Fair (Theoretical) Premium of a CDS = $s^{theo} = (1-\omega)(e^{\lambda\Delta t}-1)$ (6)

when intervals $T(i+1)$-$T(i)$ = Δt are constant between premiums. Thus, in our case of quarterly payments, the interest rate parameters cancel out, and the constant intensity case is insensitive to interest rates. This is the most significant difference in the constant intensity setting from the Merton model in our application. A second important distinguishing feature is that the Merton model allows default only at maturity, whereas our setup permits early default in the intensity setting.

4.3 Support Vector Machines Regression (SVM)

After introducing the finance-based models, we now turn to present a machine learning approach, the SVM regression method. SVM has proven to be a good alternative to traditional neural network applications: The problem of building architecture for neural networks is replaced by the problem of choosing a suitable kernel[8] for the SVM. In our study, the results of the financial models are compared to SVM regression models with linear, polynomial, Gaussian radial basis and exponential radial basis kernel functions. These four fundamental kernel functions are described below. The most basic kernel function is linear; it is simply the inner product of training points *u* and test points *v*:

$$K(u,v) = \langle u,v \rangle \quad (7)$$

An alternative approach would be to analyze polynomial kernel function with degree 2. This is a popular method for non-linear modeling:

$$K(u,v) = \left(\langle u,v \rangle + 1\right)^2 \quad (8)$$

The third type to have received significant attention in the literature is the Gaussian radial basis function, which is:

$$K(u,v) = \exp\left(-\frac{\|u - v\|^2}{2\sigma^2} \right) \quad (9)$$

where σ is taken to be 0.5 after observing fits of alternative parameter choices used in the literature (Müller et al., 1997; Gunn, 1998; Cao and Tay, 2001). A final choice would be exponential radial basis function, which is a similar alternative to Gaussian RBF.

$$K(u,v) = \exp\left(-\frac{\|u - v\|}{2\sigma^2} \right) \quad (10)$$

A parameter value C, which allows slack in the system that permits the samples to be on the wrong side of the decision boundary (a penalty parameter of the error term), is also taken as 10, in all runs, after a search for the best-fitting value. Similarly, the ε–insensitive band has been set to 10E-4.

5. Results of the Cross-Sectional Design

In order to pursue a cross-sectional analysis within a specific set of CDS prices, we divide our dataset into certain risk clusters that ought to exhibit identical risk characteristics. Thus the main hypothesis of the cross-sectional study is that within certain risk classes, the credit risk is priced the same. As outlined in Section 3, specific risk clusters were focused on, namely the contracts on Aa- and A-rated companies with 5-year maturity ranked senior. Although the literature does not distinguish between North American and European entities, this breakdown would enable us to analyze regional characteristics. An additional split according to the currency of the contract that the CDS is written on was not necessary, because European and North American entities had a natural breakdown into euros and US dollars, respectively. The number of price observations for each firm in the selected rating classes can be found in the appendix.

5.1 Credit Risk Models

5.1.1 Setting with Merton's Model

Our cross-sectional/out-of-sample prediction methodology is to first estimate the daily risk-neutral default probabilities for each firm in a "risk cluster" described above from the observed CDS premiums of the firms in the estimation sample. Individual default probabilities ($\Phi_j(-d_2)$) were estimated for each firm j each day using:

$$\Phi_j(-d_2) = \frac{s_j^{obs} \sum_{i=1}^{n} e^{-r(i)T(i)}}{(1-\omega)(e^{-r(n)T(n)})} \tag{11}$$

where s_j^{obs} is the observed CDS premium for firm j. Afterwards, the Black/Scholes parameter d_2 was averaged across the full set of companies in the estimation sample to reach a daily value. Our estimation therefore results in an aggregate default probability for each class and day.[9] Figure 2 plots the daily risk-neutral default probability estimates for the Aa-rated North American and European CDSs. Interestingly, the North American CDSs have a higher default probability throughout the time horizon, which justifies our inclusion of the regional breakdown when setting up risk classes.

[Figure 2 is presented here]

This daily value is used to predict the theoretical CDS premiums of a second set of firms in the prediction sample. Given the specific set of companies in the cluster (all with the same rating class, rank, currency and region), the division of the estimation sample and prediction sample are taken to be around the ratio of 2:1 – 4:1. Sample selection for estimation and prediction groups was fully random in order to preclude any biases due to sample choice.

5.1.2 Setting with the Constant Intensity Model

To ensure that the parameter estimates of the constant default intensity setting are comparable to the Merton model, the firms in the estimation and prediction samples are kept the same. Similar to the Merton setup, the default intensity is estimated for each firm *j* each day from the first sample of firms using Equation (6):

$$\lambda_j = \frac{\ln\left[\dfrac{s_j^{obs}}{(1-\omega)} + 1\right]}{\Delta t} \qquad (12)$$

Again, s_j^{obs} is the observed CDS premium for firm *j*. Next, we obtain an average daily default intensity for each risk class. This value is then plugged into Equation (6) to predict the fair value of the firms' CDS premium in the prediction sample.

At this point, it would be insightful to compare our estimates with a recent study. Table 3 compares the average default intensities with the results of Frühwirth and Sögner (2006), which is an application of the Jarrow and Turnbull model to European corporate/bank bonds. Our default intensity estimates from CDS prices and a larger dataset extend the estimates of this study. Moreover, some of the inconsistencies of their results have been overcome in our findings.[10]

[Table 3 is presented here]

5.1.3 Prediction Results with Cross-Sectional Design

Before comparing the out-of-sample prediction quality, we would first like to provide some insights on the parameter estimates of the two modeling approaches. In order to make the intensity estimates comparable to the estimates advanced in Merton's model, the intensity estimates are used to calculate the 5-year risk-neutral default probability:

$$p(T) = 1 - e^{-\lambda T} \tag{13}$$

This enables the direct comparison of the default probability estimates for the four risk classes. First, it is expected that the constant intensity model would yield lower default probability estimates than the Merton model, since it incorporates early default. Figure 3 provides the trajectories for the Aa-North American risk class. Table 4 provides the means, deviations and the number of days that the Merton default probability is higher than the 5-year estimate obtained with the intensity model. It is observed that the means are close, and except for a few weekly intervals, the Merton probability estimate is higher, in line with our expectations. However, note that a higher default probability does not directly translate into a higher CDS premium. In fact, although not tabulated explicitly, the Merton model prediction for the premium is significantly lower than the intensity prediction for three out of four risk classes. The reason for this is that the default payment of (1-ω) is made available only at T in the Merton setting, whereas in the intensity setting the same level of payment can be made earlier.

[Figure 3 is presented here]

[Table 4 is presented here]

The out-of-sample prediction errors are summarized in Table 5. Our results indicate a low fit in basis points for all classes, while Mean Absolute Percentage Errors (MAPE) are high. The best fit in terms of MAPE is around 23-25%. It can be observed that European/Euro-denominated CDSs have a better fit than North American/USD-denominated CDSs.

[Table 5 is presented here]

A comparison of the prediction errors produced by the Merton and the constant intensity models shows that the results are close. To test this observation statistically, we focus on the difference between the absolute prediction errors in order to determine whether the models have predicted significantly differently. Table 6 summarizes the t-statistic results of the significance tests with the Yule-Walker estimation method. By so doing, we were able to reach autocorrelation adjusted estimates of the time series for each rating class via backward elimination of insignificant autoregressive lags. In one out of four classes, the Merton model has lower average errors, while there is no statistical difference in the remaining three. This result is rather surprising; by allowing default only at maturity, the Merton model appears to be more restrictive. This may be due to the treatment of default probability as a single parameter rather than breaking it down into Black/Scholes parameters like asset value and asset volatility. Structural models have often been criticized for their weakness of lacking a robust estimation process in these parameters, which hinders their predictive performance. Our cross-sectional results signify that in the absence of an estimation process for the asset value and asset volatility parameters, Merton's model can perform at least as well as a reduced-form model.[11]

[Table 6 is presented here]

5.2 Setting and Prediction Results with SVM Regression Method

In order to design cross-sectional samples for SVM comparable to the Merton/Intensity setups, two datasets are required for training the SVM function, plus two additional datasets for test input and test output. Therefore, the firms in the estimation samples in the previous sections have also been selected for training input, training output and test input samples. For instance, if the estimation in the Merton/Intensity setups includes data from 23 firms (as in AA-North America), then these 23 firms were divided into 3 groups; the training input, the training output and the test input samples. Specifically, an out-of-sample SVM prediction is maintained as follows: First, within each risk class, the firms' CDS premiums within each of the four samples (three estimative and one predictive) are averaged to obtain a daily value. In order to train the function, the daily average of the training input sample is mapped to the average of the training output sample. Afterwards, the daily average of the premiums in the test input sample are used to predict a theoretical daily premium based on the SVM function. Finally, the predicted value is compared to the test output sample daily average values, so that the out-of-sample prediction errors can be computed.

The results from the cross-sectional approach can be found in Table 7. It can be observed that the SVM algorithm yields poor results in comparison to the financial models in most cases. Some kernels produce results that are too inaccurate to be considered an alternative, e.g. the polynomial kernel. Among all kernels, the linear kernel has the best MAPE in three out of four risk classes. In Table 8, the difference between the absolute errors of the Merton/Intensity models and the best performing linear kernel SVM is tabulated. The financial methods are a better predictor in two risk classes, whereas there is insignificance in the remaining two. For the indecisive risk classes, the linear kernel MAPE results come close to the financial methods, one being the A North American class, which produces the best result of all. Due to the overall poor fit of SVM kernels, we discontinue efforts with the full set of kernels, and focus instead on the linear kernel in the rest of the study.[12]

[Table 7 is presented here]

[Table 8 is presented here]

6. Results of the Time Series Design

6.1 Credit Risk Models

As an alternative to cross-sectional estimation and prediction, we analyze the models in a time series design. This effort hypothesizes that every firm in the sample has a constant default probability/intensity. In contrast to the cross-sectional design, in which the daily default probabilities/intensities are averaged, we now estimate the default probabilities/intensities from a fixed interval, and predict one-, five-, and ten-day-ahead default probabilities/intensities separately for each firm.

A rolling estimation and prediction is applied to both the Merton and intensity settings. Frühwirth and Sögner (2006) analyzed the impact of the length of the estimation period on the prediction errors. Within a 5-25 day period, the 14-day mark gave one of the best results. Parallel to these findings, our rolling estimation period is set at 14 days. In order to estimate the default probabilities and predict the CDS premium one day ahead, the approach below has been adapted. First, default probabilities are estimated by minimizing the sum of squared errors between the observed and theoretical CDS premiums:

$$\Phi(-\hat{d}_2)_{t+14} = \arg\min_{\Phi(-d_2)} \sum_{k=t}^{t+13} (s_k^{obs} - s_k^{theo}(\Phi(-d_2)))^2 , \qquad (14)$$

where s_k^{obs} is the observed CDS premium on the k^{th} day within the 14-day period, and s_k^{theo} is the theoretically fair price computed from Equation (3). For each firm's 14-day period, a default probability estimate is reached, and this figure is plugged into Equation (3) to obtain a theoretically fair CDS premium for the 15^{th} day. By comparing the observed and theoretical CDS premiums for one day ahead in a rolling procedure, out-of-sample prediction error statistics are computed.

In Table 9, Mean Errors (ME), Mean Absolute Errors (MAE) and Mean Absolute Percentage Errors (MAPE) for the prediction process are given.[13] As can be observed from Table 9, MAEs and MAPEs are significantly lower in the time series prediction in comparison to cross-sectioning. The Merton model predicted the four datasets with a MAPE of around 6 per cent. Furthermore, all the error statistics decline in increasing credit quality.

With the constant intensity model, a similar analysis is applied to the same dataset. The sum of squared errors was minimized in 14-day periods to reach an estimate of the default intensity, as can be seen in Equation (15), where s_k^{theo} corresponds to the theoretically fair price of the CDS premium from Equation (6).

$$\hat{\lambda}_{t+14} = \arg\min_{\lambda} \sum_{k=t}^{t+13} (s_k^{obs} - s_k^{theo}(\lambda))^2 \tag{15}$$

Again, Table 9 shows that a fit superior to cross-sectional estimation has been reached. A similar pattern of decreasing errors with increasing credit quality is also indicated by the figures. Moreover, the time series prediction results of the Merton and intensity settings appear even closer than in the cross-sectional setup. Nevertheless, a test for significance has revealed that the intensity model outperformed its counterpart in three out of four risk classes in absolute error terms. Panel A of Table 11 tabulates these results. Although the mean difference of absolute errors is close, low standard deviation and large sample size caused high significance.

[Table 9 is presented here]

A second step would be to look at further horizon out-of-sample results. In a similar setup, 14-day time series are utilized to predict five-day- and ten-day-ahead CDS premiums. These results can be found in Table 10. As expected, the prediction quality deteriorates stepwise, to a MAPE of around 7-9% for five-day-ahead and to around 9-11% for ten-day-ahead predictions. When viewed side by side, the differences between the models become less pronounced. The significance tests in Table 11 Panels B and C reveal that for five-day-ahead prediction, the intensity model outperforms the Merton model in only two cases now

(Aa-Europe, A-Europe), and in one (A-North America), the Merton model even provided smaller absolute errors. Turning to the ten-day-ahead prediction, there is a balance between the Merton and intensity models, with each proving superior for one class apiece (Aa-North America and AA-Europe, respectively), and the two remaining classes are indifferent for the models. Again, these results have mostly arisen from a very small mean difference, complemented by a very low standard error and large sample size.

[Table 10 is presented here]

[Table 11 is presented here]

Overall, the comparison shows that it is hard to distinguish between the Merton and intensity model in a time series setup as well. Nevertheless, the errors are much lower than in the cross-sectional analysis. This better fit in the time series analysis over cross-sectioning signifies that credit risk may not be uniformly priced in a given risk class. This result parallels the findings of Frühwirth and Sögner (2006), who have applied the constant intensity model to out-of-sample bond price prediction and concluded that any kind of cross-sectioning would provide poorer estimates than a bond-by-bond analysis.

6.2 SVM Regression Method

In a final step, we compare the machine learning approach to the financial models in a time series setup. To this end, we concentrate on the linear kernel due to its overall best performance in the cross-sectional setting. In order to use an analogous setup with the same number of observations as in the financial models, we divided the time series of prices of each firm into estimation and prediction samples. A ratio of 3:1 for estimation and prediction sample sizes was applied to each firm, which indicates that the first three quarters of the time series was used to train the SVM function. With a rolling time horizon in this estimation sample, the consecutive 14-day observations were used as the training input dataset, whereas the observation on the following day was used as the training output. After the function was trained, the unused last quarter of the time series was utilized for prediction. This time the remaining consecutive 14-day observations were used as test input to predict the observation on the following day as the test output. By virtue of such a setup, we were able to ensure the comparability of the out-of-sample design to the design used for the financial models.

Interestingly, the results presented in Panel A of Table 12 are very promising. For one-day-ahead prediction, the SVM method exhibited a surprisingly good fit in terms of mean absolute percentage errors, which are around 2-3%. Similar to financial models, as the prediction horizon extends, this figure worsens. Panels B and C present the five-day- and ten-day-ahead prediction errors; these deteriorate to 4-6% and 6-8%, respectively. Again, these figures indicate that the time series design achieved results superior to those of the cross-sectional design for SVM as well.

[Table 12 is presented here]

Furthermore, in comparison to the financial model results with the same setting, this time the SVM method also yielded very strong results. Each of the one-day-, five-day- and ten-day-ahead prediction results signifies a better fit than either of the financial models presented in Table 9. In all four risk classes, SVM errors were significantly lower than both the Merton and intensity one-day-ahead absolute prediction errors (Table 13).[14] This result is interesting and suggests that further work on the subject is warranted. However, it should be kept in mind that we chose to utilize the best performing case among different kernels, whereas structural and reduced-form models were presented in their simplest forms. It therefore remains to be seen if these results would vary if more sophisticated financial models were applied.

[Table 13 is presented here]

7. Conclusion and Outlook

This study compared basic versions of structural (Merton) and reduced-form (constant intensity) models as a first attempt. In this regard, four aspects of the study stand out: First, while cross-sectional results indicated a better fit of the Merton model in only one out of four cases, the one-day-ahead time series analysis revealed the significance of lower absolute prediction errors with the constant intensity model in three classes. Five-day- and ten-day-ahead predictions produced mixed results, signifying that one framework's performance does not significantly outperform the other. The most distinctive feature of the models is the default timing, which revealed in the cross-sectional setup that the Merton model estimated higher default probabilities on average, as the constant intensity model allows early default. The second major feature is the inclusion of interest rates in the Merton model, whereas the intensity model is insensitive to this parameter. Despite these factors, the error results are rather close. This could be attributable to treating the default probability in the Merton setting as the firm value variable on its own, rather than breaking it down into Black/Scholes parameters, such as asset value and volatility. An extension of this study should investigate whether the differences in prediction power between frameworks arises from this choice. Secondly, estimation and out-of-sample prediction using solely CDS data was unique to this study and requires special attention. The usage of CDS data enabled us to concentrate the prediction ability of credit models directly on the default risk premiums that constitute the prices. Without the presence of liquidity and other non-default premiums in CDS prices, the models could be applied to investigate the credit risk factors. Nevertheless, further efforts could include bond and stock price data to extend the estimation process for both modeling classes. Third, our results confirm recent results in the literature indicating that cross-sectioning is inferior to separate estimation. The high prediction errors from cross-sectional analysis in comparison to lower errors in the time series analysis revealed that credit risk is priced separately for each individual firm, rather than the joint classification provided by rating classes/regions. Fourth, although most of the cross-sectional predictions with SVM algorithms have ended in poor results, it is important to underline that one-day-, five-day-, and ten-day-ahead time series prediction results with the linear kernel SVM have achieved significantly lower error figures than financial methods. A thorough analysis for applying alternative kernel functions should be pursued that investigates cross-sectional and time series mappings of the data. Overall, our results should be extended by applying different versions of structural and reduced-form models. Introducing endogenous default barriers and stochastic interest rates for structural models while modeling intensity to be stochastically dependent on state variables for reduced-form models should be the next step in the comparison of both frameworks.

Notes

[1] These include Jones et al. (1984), Ogden (1987), Eom et al. (2004), Ericsson and Reneby (2004), Frühwirth and Sögner (2006), Bakshi et al. (2006).

[2] See Houweling and Vorst (2005).

[3] Longstaff et al. (2005). The study also incorporates bond data in the estimation process for the liquidity premium.

[4] A thorough discussion can be found in Longstaff et al. (2005).

[5] Usage of actual transaction data would result in a rather small dataset with inferior time series. In order to pursue an empirical study with abundant data, the indicative prices are utilized.

[6] For a more in-depth study on the microstructural effects on credit default swap prices, Gündüz et al. (2006) analyzes the choice of trading venues with the same dataset.

[7] Although the 0.5 figure is derived from the US market, recent efforts with European data have also relied on this figure (Houweling and Vorst, 2005; Frühwirth and Sögner, 2006). Considering the fact that Basle 2 provisions accept a loss given default of 50% for bank loans independent of the country chosen, this is not an unrealistic assumption.

[8] Without the use of kernels, the problem of non-linear machine construction would have required two steps: First, a fixed non-linear mapping to transform the data into a “feature” space where the analysis is easier, and then a linear machine to classify/regress it in the feature space. Kernel theory stipulates that an inner product in feature space has an equivalent kernel in input space; utilizing kernel functions therefore simplifies the algorithm. There is no more need to think about the mapping and evaluation of the feature map, but only about the inner products of test and training variables (for details see Cristianini and Shawe-Taylor, 2000; Gunn, 1998).

[9] Minimizing the sum of squared differences was a possible alternative, which would have simply returned the default probability for the average of s^{obs} on any given day. The results from using this approach do not differ significantly.

[10] The authors utilized a period between January 1999 and July 2000. In their estimates, A-rated banks had a lower average intensity than Aa-rated banks, which should supposedly be higher.

[11] The traditional approach for estimating asset value and asset volatility is based on Jones et al.’s (1984) study. Here, the asset value is estimated as the sum of traded debt, non-traded debt and equity value. After an initial estimate for asset volatility is reached from the returns on asset value, this is refined through an equality reached from Ito’s Lemma, which

formulates asset volatility as a function of equity volatility. Alternative versions of this approach are followed by Lyden and Saraniti (2000), Anderson and Sunderasan (2000) and Eom et al. (2004). Ronn and Verma (1986) extended Jones et al.'s (1984) single equation to solve two simultaneous equations for two unknowns, asset value and volatility, where the second equation is simply used to view equity as the call option on asset value. A completely different alternative has arisen from the work of Duan (1994), who introduced an ML approach, proponed by Ericsson and Reneby (2004, 2005), with good prediction results. Overall, the estimation technique for structural models remains an open research question in the field.

[12] Alternative to the cross-sectional setup, a panel setting was analyzed as well. There are 2,650 data points in the training input and output sets from the data of five companies for each set, respectively; 2,120 data points in test input and output sets were used from the data of four companies for each set. This is a setting that is computationally more expensive, and whose prediction results are inferior to those yielded by the cross-sectional design. The results are therefore not presented.

[13] Only consecutive 14-day periods of observation were used to ensure the continuity of the time series. The estimation sample is simply 14 more for each firm in the risk class and have not been explicitly tabulated.

[14] The five-day- and ten-day-ahead prediction errors are also significantly better than the financial models, which have not been tabulated.

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Tables and Figures

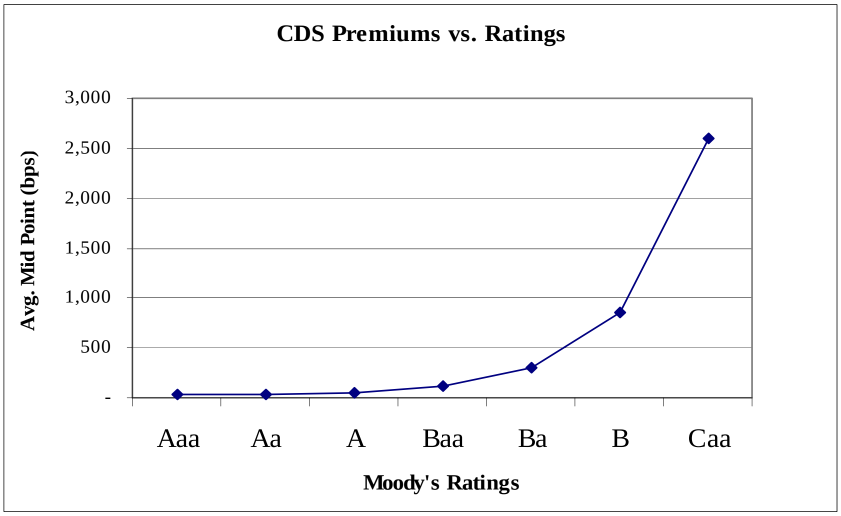

Figure 1. Average Bid-Ask Midpoints (bps) vs. Credit Quality (Moody's Ratings)

Panel A. Number of Observations and Bid-Ask Spreads across CDS Types and Regions.

			2001		2002		2003		2004		Full Horizon	
Type	***Region***	***Currency***	***Obs***	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***
Corporate	Europe	EUR	4409	21.38	26719	25.91	31890	13.21	33922	6.35	96940	14.68
	N. America	USD	8092	40.72	11749	44.81	15841	27.25	16286	17.10	51968	30.14
Bank	Europe	EUR	1917	9.90	10402	13.48	11262	8.00	11308	3.25	34889	8.20
	N. America	USD	3646	13.17	4056	18.62	4000	11.42	3780	9.99	15482	13.37
Sovereign	Europe	USD	777	2.86	1330	3.60	2530	2.80	2570	1.41	7207	2.46
	E. Europe	USD	1554	34.27	1746	25.10	3289	15.83	3341	10.82	9930	18.66
	L. America	USD	3369	77.70	4539	165.82	5252	72.21	5169	29.48	18329	84.35

Panel B. Number of Observations and Bid-Ask Spreads across Ratings, Ranks and Maturities.

		Maturity (Years)									
Moody's Rating	***Rank***	***3***		***5***		***10***		***Other***		***All Maturities***	
		Obs	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***	***Obs***	***Spread***
Aaa	Senior	-	-	3230	9.11	-	-	-	-	3230	9.11
Aa	Senior	767	8.07	25462	8.30	787	10.88	-	-	27016	8.37
	Subordinate	-	-	5457	8.90	-	-	-	-	5457	8.90
A	Senior	2534	9.93	55003	11.97	4649	9.25	717	38.73	62903	11.99
	Subordinate	-	-	6663	10.19	-	-	-	-	6663	10.19
Baa and Worse	Sen./Sub.	6821	47.21	62773	28.61	5546	46.65	5431	82.49	80571	35.06
Non-rated	Sen./Sub.	6529	32.73	31152	20.84	4299	29.08	7852	47.03	49832	27.23
Cross Sectional Total/Avg.		16651	34.06	189740	18.24	15281	28.49	14000	60.36	235672	22.53

Obs: Number of observations in the risk class
Spread (bps): Average of the difference of offer price - bid price in basis points

Table 1. Descriptive Statistics of the CDS Dataset.

		2002			2003			2004			TOTAL		
Rating	***Region***	***Mid***	***Spread***	***Obs***	***Mid***	***Spread***	***Obs***	***Mid***	***Spread***	***Obs***	***Mid***	***Spread***	***Obs***
Aa	Europe	30.83	9.17	400	22.06	6.06	5119	14.46	3.17	5382	18.63	4.75	**10901**
Aa	N. America	46.99	13.66	231	33.81	10.40	2374	26.45	10.03	2441	30.85	10.37	**5046**
A	Europe	65.06	13.18	858	48.91	8.69	10081	33.43	4.17	9273	42.49	6.81	**20212**
A	N. America	98.28	21.12	459	53.27	14.56	5493	34.82	9.96	5187	46.53	12.69	**11139**

Mid (bps): Average of the midpoint of each bid and offer price
Spread (bps): Average of the difference of offer price - bid price
Obs: Number of observations in the cluster

Table 2. Descriptive Statistics of CDS Dataset between December 2002-December 2004. Midpoints of Bid-Ask Prices, Average Bid-Ask Spreads and Number of Observations across Ratings and Regions for 5-year, Senior CDS.

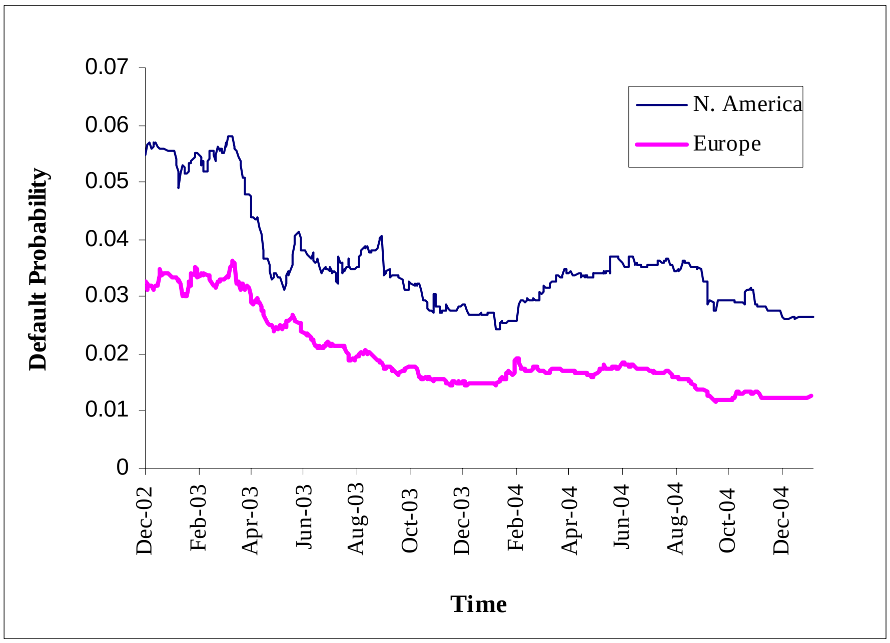

Figure 2. Default Probability Estimates with the Merton Model
AA-rated North American vs. European Contracts

European, Senior Risk Class	***Our Estimation of Intensity***		***Frühwirth/Sögner Estimation of Intensity with Bonds***
	No. of Obs	***Results with CDS***	
AA-rated Banks	4584	0.0036	0.0041
AA-rated Corporates	3037	0.0041	0.0085
A- rated Banks	3366	0.0069	0.0035
A- rated Corporates	11179	0.0090	0.0116

Table 3. Comparison of Two Studies with Constant Default Intensity

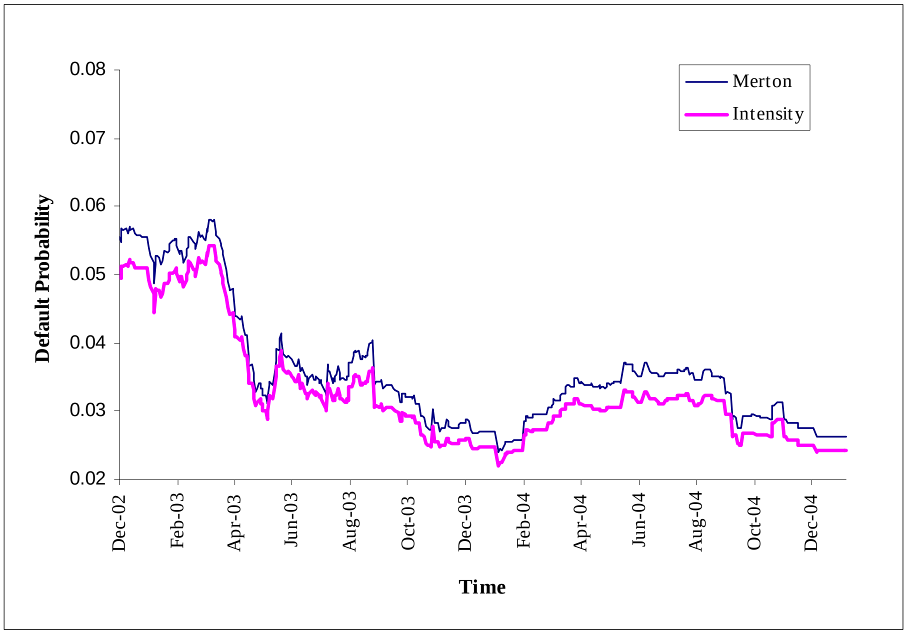

Figure 3. Default Probability Estimates with the Merton and the Constant Intensity Models Aa-rated North American Contracts

	Mean DP (bps)	*Std Dev DP (bps)*	*Obs*	*Merton DP > Intensity DP (%)*
Aa Europe				
Merton	197	67	523	97.1%
Intensity	188	66		
Aa N. America				
Merton	358	90	524	100%
Intensity	328	83		
A Europe				
Merton	422	148	526	93.2%
Intensity	408	146		
A N. America				
Merton	479	198	524	100%
Intensity	452	196		

Mean DP (bps): Average default probability in basis point

Std Dev DP (bps): Standard deviation of the default probability in basis points

Obs: Number of observation days

Merton DP > Intensity DP (%): Percentage of the total sample where Merton default probability is higher than 5-year constant intensity default probability.

Table 4. 5-year Default Probability Estimates of the Merton and Intensity Models

	Mean Error (bps)	*Mean Abs Error (bps)*	*Mean Abs Perc Error (%)*	*Total Sample Size Estimation*	*Total Sample Size Prediction*
Aa Europe					
Merton	-0.13	4.82	23.82%	7621	3135
Intensity	0.90	5.36	27.64%	7621	3135
Aa N. America					
Merton	9.13	9.30	43.16%	3475	1571
Intensity	9.87	10.01	46.16%	3475	1571
A Europe					
Merton	-2.92	10.18	25.57%	14545	5393
Intensity	0.46	10.20	27.49%	14545	5393
A N. America					
Merton	2.00	10.69	25.61%	9046	2093
Intensity	1.98	10.68	25.60%	9046	2093

Mean Error (bps) $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} s_f^{theo} - s_{f,h}^{obs}}{F*H}$ **Mean Abs Error (bps)** $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} \left| s_f^{theo} - s_{f,h}^{obs} \right|}{F*H}$

Mean Abs Perc Error (%) $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} \left| \dfrac{s_f^{theo} - s_{f,h}^{obs}}{s_{f,h}^{obs}} \right| \times 100}{F*H}$

s^{theo} is the theoretical CDS premium predicted by the Merton and Intensity models on day *f*, where *F* is the number of available days in the time series. s^{obs} is the observed CDS premium on day *f* for firm *h*, where *h*=1..*H* represents the number of firms in the prediction sample.

Table 5. Out-of-sample Prediction Errors of the Merton and the Constant Intensity Models in Cross-Sectional Design

	Mean Difference	*t-statistic*	*p-value*	
Aa Europe	-0.54	-1.64	0.1011	
Aa N. America	-0.72	-4.68	< 0.0001	***
A Europe	0.02	0.04	0.9713	
A N. America	0.01	0.41	0.6816	

Mean Difference (bps): Difference of **Absolute Errors** for prediction (Merton - Intensity) computed per day per firm for risk class

Absolute Error on day *f*, for firm *h* = $\left| s_f^{theo} - s_{f,h}^{obs} \right|$

******* Significance at 95% level

Table 6. Significance Tests for the Difference of Absolute Errors with the Merton and the Constant Intensity Models in Cross-Sectional Design

	Mean Error (bps)	*Mean Abs Error (bps)*	*Mean Abs Perc Error (%)*	*Total Sample Size Estimation*	*Total Sample Size Prediction*
Aa Europe					
Linear	-0.55	5.60	26.77%	7621	3135
Polynomial (Deg:2)	-1.05	5.25	24.69%	7621	3135
Gaussian RBF	-6.87	9.31	41.04%	7621	3135
Exponential RBF	-7.21	9.45	42.57%	7621	3135
Aa N. America					
Linear	3.14	17.75	81.18%	3475	1571
Polynomial (Deg:2)	49.85	157.68	657.85%	3475	1571
Gaussian RBF	-3.33	15.72	68.55%	3475	1571
Exponential RBF	-4.01	14.44	61.89%	3475	1571
A Europe					
Linear	6.82	12.57	37.17%	14545	5393
Polynomial (Deg:2)	6.57	12.51	37.30%	14545	5393
Gaussian RBF	-0.59	1.15	166.51%	14545	5393
Exponential RBF	-9.51	18.22	41.49%	14545	5393
A N. America					
Linear	-9.70	12.07	23.11%	9046	2093
Polynomial (Deg:2)	152.67	152.67	310.13%	9046	2093
Gaussian RBF	-17.10	18.02	35.06%	9046	2093
Exponential RBF	-4.01	14.44	61.89%	9046	2093

Mean Error (bps) $= \frac{\sum_{f=1}^{F} \sum_{h=1}^{H} s_f^{theo} - s_{f,h}^{obs}}{F * H}$ **Mean Abs Error (bps)** $= \frac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| s_f^{theo} - s_{f,h}^{obs} \right|}{F * H}$

Mean Abs Perc Error (%) $= \frac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| \frac{s_f^{theo} - s_{f,h}^{obs}}{s_{f,h}^{obs}} \right| \times 100}{F * H}$

s^{theo} is the theoretical CDS premium predicted by SVM algorithms on day *f*, where *F* is the number of available days in the time series. s^{obs} is the observed CDS premium on day *f* for firm *h*, where *h*=1..*H* represents the number of firms in the prediction (test output) sample.

Table 7. Out-of-sample Prediction Errors of SVM Algorithms in Cross-Sectional Design

	Mean Difference	*t-statistic*	*p-value*	
Aa Europe				
Merton - SVM	-0.85	-1.65	0.0998	
Intensity - SVM	-0.28	-0.6	0.5494	
Aa N. America				
Merton - SVM	-8.46	-19.25	< 0.0001	***
Intensity - SVM	-7.75	-24.29	< 0.0001	***
A Europe				
Merton - SVM	-2.32	-2.03	0.0426	***
Intensity - SVM	-2.30	-3.01	0.0026	***
A N. America				
Merton - SVM	-0.49	-0.14	0.8897	
Intensity - SVM	-0.49	-0.14	0.8892	

Mean Difference (bps): Difference of **Absolute Errors** for prediction (Merton - SVM) and (Intensity - SVM) computed per day per firm.

Absolute Error on day f, for firm h = $\left| S_f^{theo} - S_{f,h}^{obs} \right|$

******* Significance at 95% level

Table 8. Significance Tests for the Difference of Absolute Errors between the Merton/Intensity models and Linear Kernel SVM in Cross-Sectional Design

	Mean Error (bps)	Mean Abs Error (bps)	Mean Abs Perc Error (%)	Total Sample Size Prediction
Aa Europe				
Merton	0.30	1.06	5.71%	10373
Intensity	0.28	1.00	5.25%	10373
Aa N. America				
Merton	0.33	1.56	5.30%	4850
Intensity	0.33	1.54	5.17%	4850
A Europe				
Merton	0.49	2.78	6.15%	19200
Intensity	0.46	2.75	6.04%	19200
A N. America				
Merton	0.93	2.97	6.61%	10672
Intensity	0.93	2.98	6.59%	10672

Mean Error (bps) $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} s_{f,h}^{theo} - s_{f,h}^{obs}}{F * H}$ **Mean Abs Error (bps)** $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| s_{f,h}^{theo} - s_{f,h}^{obs} \right|}{F * H}$

Mean Abs Perc Error (%) $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| \dfrac{s_{f,h}^{theo} - s_{f,h}^{obs}}{s_{f,h}^{obs}} \right| \times 100}{F * H}$

s^{theo} is the theoretical CDS premium predicted by the Merton and Intensity models on day *f* for firm *h*, where *f* =1..*F* is the number of available days for prediction (preceded by 14 consecutive days of CDS premiums for estimation), with *h*=1..*H* being the number of firms in the risk class. s^{obs} is the observed CDS premium on day *f* for firm *h*.

Table 9. One-Day-Ahead Out-of-sample Prediction Errors of the Merton and the Constant Intensity Models in Time Series Design

Panel A. Five-Day-Ahead Out-of-Sample Prediction Errors	*Mean Error (bps)*	*Mean Abs Error (bps)*	*Mean Abs Perc Error (%)*	*Total Sample Size Prediction*
Aa Europe				
Merton	0.47	1.39	7.51%	10270
Intensity	0.44	1.34	7.11%	10270
Aa N. America				
Merton	0.50	2.09	7.13%	4798
Intensity	0.50	2.09	7.08%	4798
A Europe				
Merton	0.76	3.73	8.32%	19004
Intensity	0.72	3.71	8.23%	19004
A N. America				
Merton	1.41	4.00	9.02%	10567
Intensity	1.42	4.02	9.04%	10567

Panel B. Ten-Day-Ahead Out-of-Sample Prediction Errors	*Mean Error (bps)*	*Mean Abs Error (bps)*	*Perc Error Perc Error (%)*	*Sample Size Sample Size Prediction*
Aa Europe				
Merton	0.67	1.71	9.30%	10150
Intensity	0.64	1.67	8.96%	10150
Aa N. America				
Merton	0.69	2.62	9.02%	4733
Intensity	0.70	2.61	9.00%	4733
A Europe				
Merton	1.10	4.69	10.64%	18768
Intensity	1.05	4.67	10.54%	18768
A N. America				
Merton	2.00	4.99	11.47%	10437
Intensity	2.01	5.01	11.51%	10437

Mean Error (bps) $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} s_{f,h}^{theo} - s_{f,h}^{obs}}{F*H}$ **Mean Abs Error (bps)** $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} \left| s_{f,h}^{theo} - s_{f,h}^{obs} \right|}{F*H}$

Mean Abs Perc Error (%) $= \dfrac{\sum_{f=1}^{F}\sum_{h=1}^{H} \left| \dfrac{s_{f,h}^{theo} - s_{f,h}^{obs}}{s_{f,h}^{obs}} \right| \times 100}{F*H}$

s^{theo} is the theoretical CDS premium predicted by the Merton and Intensity models on day f for firm h, where f =1..F is the number of available days for prediction (preceded by 18 consecutive days, with the first 14 consisting of the CDS premiums for estimation) and h=1..H representing the number of firms in the risk class. s^{obs} is the observed CDS premium on day f for firm h.

Table 10. Five- and Ten-Day-Ahead Out-of-sample Prediction Errors of the Merton and the Constant Intensity Models in Time Series Design

Panel A. Significance Tests for the Difference of One-Day-Ahead Absolute Prediction Errors				
	Mean Difference	***t-statistic***	***p-value***	
Aa Europe	0.06	11.67	< 0.0001	***
Aa N. America	0.03	3.23	0.0012	***
A Europe	0.03	5.09	< 0.0001	***
A N. America	-0.01	-0.94	0.3488	

Panel B. Significance Tests for the Difference of Five-Day-Ahead Absolute Prediction Errors				
	Mean Difference	***t-statistic***	***p-value***	
Aa Europe	0.05	8.45	< 0.0001	***
Aa N. America	0.01	1.28	0.2010	
A Europe	0.02	3.32	0.0009	***
A N. America	-0.02	-2.49	0.0128	***

Panel C. Significance Tests for the Difference of Ten-Day-Ahead Absolute Prediction Errors				
	Mean Difference	***t-statistic***	***p-value***	
Aa Europe	0.04	6.62	<0.0001	***
Aa N. America	0.01	0.97	0.3297	
A Europe	-0.01	-0.96	0.3348	
A N. America	-0.02	-2.78	0.0054	***

Mean Difference (bps): Difference of **Absolute Errors** for prediction (Merton - Intensity) computed per day per firm.

Absolute Error on day f, for firm h = $\left| S_{f,h}^{theo} - S_{f,h}^{obs} \right|$

******* Significance at 95%level

Table 11. Significance Tests for the Difference of One-Day-Ahead Absolute Prediction Errors with the Merton and the Constant Intensity Models in Time Series Design

Panel A. One-Day-Ahead SVM Out-of-Sample Prediction Errors	Mean Error (bps)	Mean Abs Error (bps)	Mean Abs Perc Error (%)	Total Sample Size
Aa Europe	0.09	0.32	2.48%	10373
Aa N. America	0.34	0.87	3.18%	4850
A Europe	0.005	0.90	2.32%	19200
A N. America	-0.02	1.02	2.88%	10672

Panel B. Five-Day-Ahead SVM Out-of-Sample Prediction Errors	Mean Error (bps)	Mean Abs Error (bps)	Mean Abs Perc Error (%)	Total Sample Size
Aa Europe	0.25	0.60	4.65%	10270
Aa N. America	0.62	1.38	5.14%	4798
A Europe	0.85	2.52	6.23%	19004
A N. America	0.35	1.96	5.84%	10567

Panel C. Ten-Day-Ahead SVM Out-of-Sample Prediction Errors	Mean Error (bps)	Mean Abs Error (bps)	Mean Abs Perc Error (%)	Total Sample Size
Aa Europe	0.47	0.92	7.12%	10150
Aa N. America	0.99	1.86	7.15%	4733
A Europe	0.83	3.17	8.61%	18768
A N. America	0.97	2.73	8.68%	10437

Mean Error (bps) $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} s_{f,h}^{theo} - s_{f,h}^{obs}}{F*H}$ **Mean Abs Error (bps)** $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| s_{f,h}^{theo} - s_{f,h}^{obs} \right|}{F*H}$

Mean Abs Perc Error (%) $= \dfrac{\sum_{f=1}^{F} \sum_{h=1}^{H} \left| \dfrac{s_{f,h}^{theo} - s_{f,h}^{obs}}{s_{f,h}^{obs}} \right| \times 100}{F*H}$

s^{theo} is the theoretical CDS premium predicted by the SVM algorithm with a linear kernel on day *f* for firm *h*, where *f* =1..*F* is the number of available days for test output (approximately 1/4th of the full sample) and *h*=1..*H* representing the number of firms in the risk class. s^{obs} is the observed CDS premium on day *f* for firm *h*.

Table 12. One-Day-, Five-Day-, and Ten-Day-Ahead Out-of-sample Prediction Errors with Linear Kernel SVM in Time Series Design

	Mean Difference	*t-statistic*	*p-value*	
Aa Europe				
Merton - SVM	0.31	4.36	< 0.0001	***
Intensity - SVM	0.21	2.85	0.0044	***
Aa N. America				
Merton - SVM	0.30	2.20	0.0277	***
Intensity - SVM	0.26	1.88	0.0607	*
A Europe				
Merton - SVM	0.91	3.56	0.0004	***
Intensity - SVM	0.84	3.30	0.0010	***
A N. America				
Merton - SVM	0.91	7.58	< 0.0001	***
Intensity - SVM	0.88	7.31	< 0.0001	***

Mean Difference (bps): Difference of **Absolute Errors** for prediction (Merton - SVM) and (Intensity - SVM) computed per day per firm.

Absolute Error on day f, for firm h = $\left| s_{f,h}^{theo} - s_{f,h}^{obs} \right|$

******* Significance at 95% level
***** Significance at 90% level

Table 13. Significance Tests for the Difference of One-Day-Ahead Absolute Prediction Errors between the Merton/Intensity models and Linear Kernel SVM in Time Series Design

APPENDIX

Aa-Rated Issuers and Their Industry, Type, Region, Currency and Number of Quotes in the CDS Dataset

Issuer Name	Industry	Type	Region	Currency	Quotes
ABN AMRO BANK NV	Financial	Bank	Europe	EUR	520
ALLIANZ AG	Ins/Re-Ins	Corporate	Europe	EUR	427
ALLIED IRISH BANKS PLC	Financial	Bank	Europe	EUR	530
BANCO BILBAO VIZCAYA	Financial	Bank	Europe	EUR	530
BANCO SANTANDER CENTRAL	Financial	Bank	Europe	EUR	284
BANK OF AMERICA CORP	Financial	Bank	North America	USD	524
BANK OF IRELAND	Financial	Bank	Europe	EUR	105
BANK ONE CORP	Financial	Bank	North America	USD	474
BARCLAYS BANK PLC	Financial	Bank	Europe	EUR	530
BASF AG	Manufacturing	Corporate	Europe	EUR	530
BELLSOUTH CORPORATION	Telecommunications	Corporate	North America	USD	90
BNP PARIBAS SA	Financial	Bank	Europe	EUR	530
BP PLC	Energy	Corporate	Europe	EUR	530
CITIGROUP INC	Financial	Bank	North America	USD	524
CREDIT LYONNAIS	Financial	Bank	Europe	EUR	413
DEUTSCHE BANK AG	Financial	Bank	Europe	EUR	515
DRESDNER BANK AG	Financial	Bank	Europe	EUR	162
ELECTRICITE DE FRANCE	Utilities	Corporate	Europe	EUR	530
ENI SPA	Energy	Corporate	Europe	EUR	530
FLEETBOSTON FINANCIAL	Financial	Bank	North America	USD	84
GLAXOSMITHKLINE PLC	Pharms/Biotech	Corporate	Europe	EUR	530
GOLDMAN SACHS GROUP	Financial	Bank	North America	USD	524
JP MORGAN CHASE & CO	Financial	Bank	North America	USD	131
MERRILL LYNCH CO INC	Financial	Bank	North America	USD	524
MORGAN STANLEY	Financial	Bank	North America	USD	524
ROYAL BANK OF SCOTLAND	Financial	Bank	Europe	EUR	528
SANPAOLO IMI SPA	Financial	Bank	Europe	EUR	530
SBC COMMUNICATIONS INC	Telecommunications	Corporate	North America	USD	76
SIEMENS AG	Manufacturing	Corporate	Europe	EUR	530
SOCIETE GENERALE	Financial	Bank	Europe	EUR	530
TOTALFINAELF SA	Energy	Corporate	Europe	EUR	530
UBS AG	Financial	Bank	Europe	EUR	527
UNICREDITO ITALIANO SPA	Financial	Bank	Europe	EUR	530
WACHOVIA CORP	Financial	Bank	North America	USD	524
WAL-MART STORES INC	Retail	Corporate	North America	USD	523
WELLS FARGO AND CO	Financial	Bank	North America	USD	524
TOTAL					15947

A-Rated Issuers and Their Industry, Type, Region, Currency and Number of Quotes in the CDS Dataset

Issuer Name	Industry	Type	Region	Currency	Quotes
AKZO NOBEL NV	Chemicals	Corporate	Europe	EUR	530
AMERICAN EXPRESS CO	Financial	Bank	North America	USD	524
AVENTIS SA	Pharms/Biotech	Corporate	Europe	EUR	530
AXA SA	Ins/Re-Ins	Corporate	Europe	EUR	530
BAA (BRITISH AIRPORT AUTHORITY)	Transport	Corporate	Europe	EUR	530
BAE SYSTEMS PLC	Aerospace/Defense	Corporate	Europe	EUR	56
BANCA MONTE DEI PASCHI DI SIENA	Financial	Bank	Europe	EUR	530
BANCO COMERCIAL PORTUGUES SA	Financial	Bank	Europe	EUR	530
BANCO SANTANDER CENTRAL	Financial	Bank	Europe	EUR	246
BAYER AG	Chemicals	Corporate	Europe	EUR	530
BAYERISCHE HVBANK	Financial	Bank	Europe	EUR	507
BELLSOUTH CORPORATION	Telecommunications	Corporate	North America	USD	434
BOEING CO	Manufacturing	Corporate	North America	USD	524
BOOTS GROUP PLC	Retail	Corporate	Europe	EUR	530
CADBURY SCHWEPPES PLC	Food/Beverage	Corporate	Europe	EUR	11
CAMPBELL SOUP CO	Food/Beverage	Corporate	North America	USD	5
CARNIVAL CORP	Hospitality	Corporate	North America	USD	523
CARREFOUR SA	Retail	Corporate	Europe	EUR	530
CATERPILLAR INC	Manufacturing	Corporate	North America	USD	524
CINGULAR WIRELESS LLC	Telecommunications	Corporate	North America	USD	394
CIT GROUP INC	Financial	Bank	North America	USD	524
COMMERZBANK AG	Financial	Bank	Europe	EUR	530
COUNTRYWIDE HOME LOANS INC	Financial	Bank	North America	USD	524
CREDIT LYONNAIS	Financial	Bank	Europe	EUR	117
CVS CORP	Retail	Corporate	North America	USD	523
DAIMLERCHRYSLER AG	Auto	Corporate	Europe	EUR	530
DANONE	Food/Beverage	Corporate	Europe	EUR	530
DEERE AND CO	Manufacturing	Corporate	North America	USD	524
DELL INC	Technology	Corporate	North America	USD	521
DIAGEO PLC	Food/Beverage	Corporate	Europe	EUR	530
DOW CHEMICAL CO, THE	Chemicals	Corporate	North America	USD	524
DRESDNER BANK AG	Financial	Bank	Europe	EUR	358
DSM NV	Chemicals	Corporate	Europe	EUR	530
ELECTRICIDADE DE PORTUGAL SA	Utilities	Corporate	Europe	EUR	530
ELECTRONIC DATA SYSTEMS CORP	Technology	Corporate	North America	USD	48
ENDESA (SPAIN)	Utilities	Corporate	Europe	EUR	83
ENEL SPA	Utilities	Corporate	Europe	EUR	530
ERSTE BANK	Financial	Bank	Europe	EUR	65
FLEETBOSTON FINANCIAL CORP	Financial	Bank	North America	USD	331
GUS PLC	Retail	Corporate	Europe	EUR	7

(continued on next page)

A-Rated Issuers and Their Industry, Type, Region, Currency and Number of Quotes in the CDS Dataset (cont'd)

Issuer Name	Industry	Type	Region	Currency	Quotes
HEWLETT-PACKARD CO	Technology	Corporate	North America	USD	523
IBERDROLA SA	Utilities	Corporate	Europe	EUR	530
INTERNATIONAL BUSINESS MACHINES	Technology	Corporate	North America	USD	523
INTESABCI SPA	Financial	Bank	Europe	EUR	530
JP MORGAN CHASE & CO	Financial	Bank	North America	USD	393
LAND SECURITIES PLC	Property	Corporate	Europe	EUR	298
LEHMAN BROTHERS HOLDINGS INC	Financial	Bank	North America	USD	522
MARKS & SPENCER	Retail	Corporate	Europe	EUR	406
MAY DEPARTMENT STORES CO	Retail	Corporate	North America	USD	53
OMNICOM GROUP	Entertainment	Corporate	North America	USD	56
PHILIP MORRIS COS INC	Food/Beverage	Corporate	North America	USD	81
PHILIPS ELECTRONICS NV	Electronics	Corporate	Europe	EUR	530
REED ELSEVIER PLC	Publishing	Corporate	Europe	EUR	530
REUTERS GROUP PLC	Media	Corporate	Europe	EUR	455
RWE AG	Utilities	Corporate	Europe	EUR	530
SAFEWAY PLC	Retail	Corporate	Europe	EUR	41
SAINSBURY J PLC	Retail	Corporate	Europe	EUR	361
SAINT GOBAIN	Construction	Corporate	Europe	EUR	530
SBC COMMUNICATIONS INC	Telecommunications	Corporate	North America	USD	448
SIX CONTINENTS PLC	Hospitality	Corporate	Europe	EUR	77
TARGET CORP	Retail	Corporate	North America	USD	523
TELEFONICA SA	Telecommunications	Corporate	Europe	EUR	530
TELIASONERA AB	Telecommunications	Corporate	Europe	EUR	530
TESCO PLC	Retail	Corporate	Europe	EUR	530
THALES SA	Electronics	Corporate	Europe	EUR	530
UNILEVER PLC	Food/Beverage	Corporate	Europe	EUR	530
VALEO SA	Auto	Corporate	Europe	EUR	453
VATTENFALL AB	Utilities	Corporate	Europe	EUR	530
VERIZON GLOBAL FUNDING CORP	Telecommunications	Corporate	North America	USD	524
VERIZON WIRELESS CAPITAL LLC	Telecommunications	Corporate	North America	USD	522
VIACOM INC	Media	Corporate	North America	USD	524
VODAFONE GROUP PLC	Telecommunications	Corporate	Europe	EUR	530
VOLKSWAGEN AG	Auto	Corporate	Europe	EUR	530
VOLVO AB	Manufacturing	Corporate	Europe	EUR	530
WOLTERS KLUWER NV	Publishing	Corporate	Europe	EUR	241
TOTAL					31351