Pricing the Risk of Default: Are Bonds Enough?[1]

Daniel Gomez and Boris Nikolov [2]

October 19, 2003

[1]Acknowledgments: we thank Didier Cossin for accepting to supervise our research and helping us both with timely comments and valuable contacts with financial practitioners. We thank Philippe Graeub, Sebastian Eisinger and Rajeev de Mello from Picet & Cie for their availability and providing us with data. Special thanks to Henri Schellhorn for his comments and suggestions and to Hongze Lu for his support. All the usual disclaimers apply. Last but not least, we would like to thank our families for continuous support throughout the project.

[2]Thesis, Master of Science in Banking and Finance, University of Lausanne, 2002-2003

Abstract

This paper implements a reduced form credit default swap (CDS) pricing model. Theoretical prices found are compared with market prices to evaluate the goodness of fit. Theoretical prices and pricing errors are inspected by rating classes, sectors of economic activity and currency denomination of CDS. Pricing errors are analyzed through panel data estimation techniques, to find determinants of pricing errors. These determinants could be used in theoretical pricing models as well as by practitioners when evaluating credit risk. Results suggest that debt market information is not enough for pricing credit risk and that equity markets have the potential for complementing credit pricing techniques.

JEL Classification: C23, G12, G13

Key Words: Credit Derivatives,Credit Spreads, Credit Risk Pricing, Default Probability, Equity Markets

Executive Summary

Although the credit derivatives market dates back to no longer than the early 1990's, it has been one of the fastest growing with a notional outstanding of US$ 1398 billion by the end of 2001 (British Bankers Association, BBA Credit Derivatives Report, 2002). The increased interest in these type of instruments comes from the possibilities they offer for pricing and trading credit risk isolated from other sources of risk. We can in fact be short credit risk and manage credit risk much more accurately and dynamically than with the traditionally used credit lines.

The economic downturn seen from 2000, together with both sovereign and corporate financial distress have constituted an ideal environment for putting credit derivatives at test . The last couple of years have seen the plummeting of stock markets following the burst of the high tech bubble, an increase in uncertainty and increased event sensitivity. Corporations have been subject to increased scrutiny from investors and in general from market participants who are closely analyzing fundamental company performance measures and corporate governance issues.

The circumstances described above make the availability of sophisticated instruments such as credit derivatives ever more useful. Market participants with the skills to use them appropriately will certainly have an important competitive edge. This requires the ability to correctly price and extract information from derivatives written on credit risk.

Despite the existence of several credit derivatives pricing models, no consensus exists as to which approach is most adequate. Furthermore, empirical testing of the models is still scarce. This paper both implements and tests the goodness of fit of one of the latest CDS pricing models. The model relies on information from the bonds market for extracting implied probabilities of default that will be used as inputs for the pricing of CDS. The simplifying assumptions of the model make it both implementable and intuitive, two characteristics dear to practitioners. Besides the theoretical prices of CDS obtained, the model provides estimates of the probability of default of bond

issuers. This in itself is a very valuable output from the perspective of risk and portfolio management.

The data used for implementation is particularly rich in terms of issuers, currencies, ratings and sectors of industrial activity. We have two large subsamples of dollar and euro denominated CDS quotes. The performance of the model was analyzed for each subsample grouping by sector and rating. The model replicates the main trends in the CDS market as well as jumps in CDS prices. Goodness of fit increases for investment grade issuers and is best for the dollar denominated sample. By implementing the model with treasury rates and swap rates as reference risk free rates, we tested the hypothesis that the swap rate has displaced treasuries as the benchmark risk free rate. We find no evidence of this in the CDS market. Finally, we search for determinants of pricing errors in equity markets. We find evidence that variables such as stock prices, implied volatilities and earnings per share should also be monitored when analyzing credit risk.

1 Introduction

During the last decade the market for credit derivatives has grown at an exponential rate. Even though they still represent a small fraction of the derivatives market, they have gained in importance and will apparently continue to expand as further research allows for more accurate pricing. Furthermore, the current slump in economic activity and the increased risks of default have highlighted the potential value-added of being able to price and trade credit risk separately. The last two years have seen particular upheaval in credit markets. After several years of market build up, the test time seems to have come for credit derivatives as effective instruments of credit management.

The development of credit derivatives, especially credit default swaps (CDS), has been paralleled by theoretical developments in academia. However, empirical work has been less abundant and testing of the various pricing models is a fertile area of research. To our knowledge, only four attempts of implementation have been published (Houweling and Vorst (2002), Aunon-Nerin, Cossin, Hricko and Huang (2002), Longstaff, Mihal and Neis (2003) and Zhang (2003)).

In this paper we aim to implement one of the latest CDS pricing models, the Hull and White 2000. Additionally, we will test whether swap rates or treasury rates are the relevant risk free rate in the CDS market as reflected by the goodness of fit.

CDS are instruments that allow for the pricing and trading of credit risk independently of market risk. It involves three parties: the protection seller, the protection buyer and a reference entity. This last is the issuer of defaultable bonds, denominated reference bonds in the CDS contract. The protection buyer pays regular fees, called the CDS spread. In case of default, the protection seller will cover the losses on the defaulted reference bond. Although these instruments are OTC, their trading has been largely facilitated by standardization by the ISDA Master Agreement of 1999.

The data used was taken from Bloomberg and Datastream. In particular, CDS quotes were taken from Morgan Stanley. The sample is particularly rich both in terms of number of names and in historical observations by name. It is divided in two large subsamples of euro and dollar denominated CDS's. The model provides three interesting outputs: yield spreads, implied probabilities of default and theoretical CDS spreads. Each of these will be analyzed in detail.

The paper consists of 8 parts including this introduction. The second section presents a short survey of the literature on credit derivative pricing models. Section 3 introduces the model and section 4 describes the implementation. Section 5 describes our data set. Results of the model implementation and the analysis of pricing errors are presented in sections 6 and 7 respectively. Finally, section 8 summarizes our findings and concludes.

2 Literature Review

During the last years there has been increased interest from academics as well as practitioners in modelling credit risk, pricing it and developing instruments useful for trading and isolating it from other sources of risk such as market risk. Most models can be classified in one of two approaches: structural models and reduced form models. The former can be subdivided in several subgroups depending on how they model default risk, recovery risk and interest rate risk.

Structural models are based on the seminal work by Merton (1974)[1] The underlying idea of these models is to endogenously determine the probability of default from fundamental measures of firm value and definition of bankruptcy. We may view the claimholders as possessing contingent claims on the assets of the firm. Seniority and bankruptcy rules will determine the order in which claimholders will be retributed. The value of each claim may be determined by modelling the dynamics of the underlying value of the firm. Once a default barrier is specified, the event of default and the probability

[1] In all rights, Black & Scholes (1973) should be regarded as the seminal work on credit risk as evidenced in the title: “The Pricing of Options and Corporate Liabilities”.

of this occurring can be determined through the distribution of firm values. The dynamics of firm value are described as a Geometric Brownian motion fully specified by a trend and volatility parameter. Given that firm value is not directly observable, parameters must be estimated through indirect methods coming from the link between equity and firm assets. Although this type of models give great insight into the issues related to credit risk, their implementation is hard because of complications such as diverse capital structures, coupons, convertible securities, diverse seniorities and more complicated bankruptcy procedures. Another set of problems are related to the results implied such as too low credit spreads for short maturities arising from the continuous path firm value follows, which precludes jumps to default (Schonbucher (2003)).

Among the models in the spirit of Merton (1974) are those by Ingersoll (1987) who proposes extensions to the basic model and allows for coupon bearing bonds, subordinated bonds, convertibles and stochastic interest rates. Posterior to this, are Brennan and Schwartz (1980), Leland (1994), Leland and Toft (1996), Hull and White (1995) and Longstaff and Schwartz (1995).

To circumvent some of the problems encountered in the structural form modelling approach, another approach to credit risk modelling, the so-called reduced form or intensity-based models, has been developed. There are three elements to be modelled in this strand of the literature: the probability of default, the recovery rate and risk-free interest rates. The probability of default, together with the recovery rate, determines the yield spread of bonds over a risk free benchmark. Since spreads are observed in the market, once any of the two elements that compose it is found, the third can be determined. This definition does not account for liquidity and tax effects. Given the above, we see that credit spread is only a fraction of the observed market spread. Research by Das, Sundaram and Sundaresan (2002) and Perraudin and Taylor (2003) has attempted either modelling directly the dynamics of credit spread or modelling its components separately.

The specification of the model must take into account the correlation between the different processes. The positive correlation between default processes and interest rates is usually accounted for, whereas, the correlation between recovery rates and other variables is rarely included.[2] Recovery rates are frequently taken as constant allowing intensity to adjust so as to arrive at the observed market spread. In this way, this simplifying assumption is not a source of bias in the application of credit models to pricing or calibration exercises.

The first issue to tackle in reduced form models is the modelling of risk-free interest rates. Two broad families of models are the equilibrium models and the no-arbitrage models. In the first family we can mention Vasicek (1977) and Cox, Ingersoll, Ross (1985) (CIR in what follows). The second family of models, no arbitrage models, includes Ho and Lee (1986) and Hull and White (1990). Within the no-arbitrage models we also have two factor models such as Hull and White (1994), Heath, Jarrow and Morton (HJM) (1992) and the Libor Market Model or BGM (1997).[3] All these models for risk-free rates can be adapted to incorporate default features while keeping the same structure and type of solutions.

The default intensity can be derived from transition matrices or modelled as a deterministic or stochastic process. The first method relies on data provided by rating agencies such as Moody's, Standard and Poor's and Fitch. These matrices are constructed to reflect business cycles and industrial sectors. Examples of this type of modelling are Jarrow and Turnbull (1995) and Jarrow, Lando and Turnbull (1997).[4] The second method requires specifying the form of the process. It could be either a deterministic process, a gaussian process, a CIR process or a mean reverting process. The modelling techniques are borrowed from the fixed income literature such as the risk-free

[2]The correlation between default probabilities and the business cycle have been studied empirically by Duffee (1996) and Alessandrini (1998)

[3]All these models are described in Hull (2000)

[4]a common critique to this approach is that ratings react with a lag to changing credit quality of issuers. Never the less, new techniques are being developed to improve this approach (Couderc, Renault and Scaillet (2002))

rate models mentioned above.

There are five different type of recovery specifications: Recovery of Treasury (RT), Multiple defaults (MD), Recovery of Market Value (RMV) or fractional recovery, Recovery of Par (RP) and Zero Recovery (ZR)(Schonbucher (2003)). These strategies aim at modelling the value of recovery and not necessarily the specific bankruptcy process or percentage of liability that is actually redeemed to the creditor given default. RT defines recovery as a fraction of an equivalent treasury bond. MD and RMV lead to the same type of solution: at each default time, which can be followed by a renegotiation, the claim holder looses a fraction u of the value of his claim. Alternatively, given default he is paid a proportion $1 - u$ of a non-defaulted but otherwise identical security. This corresponds to a proportion of the value of the defaulted security just before default. RP pays a fraction of the notional. Whereas RMV and MD are based on the idea of renegotiation of debt, RP is based on the idea of liquidation. ZR means that nothing at all is redeemed after a default event.

An example of a spread based model is Das and Sundaram (1998) who extend the HJM framework to allow for defaultable debt, model directly the spread dynamics and use RMV as recovery model. They propose a tree structure to implement their model. A full implementation using CDS transaction data was done by Aunon-Nerin, Cossin, Hricho and Huang (2002). Using the same data set, they analyze the factors influencing CDS spreads for the whole sample and by subsamples of rating classes, industries and countries. Examples of intensity based models follow. The first model to consider stochastic default intensities was proposed by Madan and Unal (1998). The development of a tree model based on the Hull and White trinomial tree in a Gaussian set up for the risk free and intensity rates, was developed by Schonbucher (1998). Duffee (1999) models interest rates and intensities of default as CIR two factor processes, allowing for correlation between the processes and assumes RP. Duffie and Singleton (1999) introduce the concept of RMV as recovery model and develop several cases: an HJM framework and a

CIR framework. A simplified model in the spirit of Duffie and Singleton was implemented by Houweling and Vorst (2002). They also analyze in detail the choice of the risk free term structure between treasury, swap and repo rates. Finally, a model proposed by Hull and White (2000) simplifies in many ways the specification of the variables of the reduced type model framework. They consider default intensities, interest rates and recovery rates to be independent and rely on default probability densities rather than the default intensity directly.

3 The Model

The model proposed by Hull and White (2000) is the first of two papers, one not considering counterparty default risk and the other considering this source of risk. We will describe the model with no counterparty default risk.

Hull and White "Valuing Credit Default Swaps I: No Counterparty Default Risk" is a model of the intensity or reduced form type. Whereas most of the models of this family rely on modelling the hazard rate, this model relies on a related variable defined as the density of the probability of default, which is a function of the hazard rate. The model arrives to closed form solutions for the CDS spread, and unlike many of its predecessors, which use intensively the mathematics of stochastic processes, it stands out for its intuitive construction and interpretation. It is probably this last feature, which has rendered it popular among practitioners.

The hypotheses of the model are the following:

H1 Probability of default, risk free interest rate and recovery rates are mutually independent.

H2 Claim given default is face value plus accrued interest.

H3 Recovery rate is independent of time and maturity of reference bond.

H4 There is no systematic risk in recovery rates so that risk neutral recovery is equal to real world recovery.

H5 Default can arrive at any time and time is measured continuously.

H6 The default probability density, $q(t)$, is piecewise constant for any interval $t_{i-1} < t < t_i$.

H7 The risk free rate is given by treasury rates.

The valuation of a credit default swap is modelled in two steps: first, the estimation of the risk neutral probability of default using information in bond prices; second, the estimation of the CDS spread defined as the fee that makes the value of the contract zero at issuance.

3.1 Estimation of default probabilities

The variables required for the estimation of default probabilities are:

B_j price of a defaultable bond maturing at time j.

G_j price of a default free bond maturing at time j.

$F_j(t)$ forward price of a forward contract maturing at time t on a default free bond maturing at time j.

$v(t)$ present value of 1 monetary unit received at time t with certainty.

$C_j(t)$ claim amount given default at time t of a bond maturing at time j. $C_j(t) = 1 + A(t)$.

$R_j(t)$ recovery rate on the bond maturing at time j if default occurs at time t. $R_j(t) = \hat{R}$.

β_{ij} present value of the loss, relative to the value the bond with maturity j would have if there were no possibility of default, after a default at time t_i.

q_i default probability density for period i such that $q_i\Delta(t)$ is the probability of default between times t and t+$\Delta(t)$ as seen from time $t = 0$.

β_{ij} is given by:

$$\beta_{ij} = \int_{t_{i-1}}^{t_i} v(t)[F_j(t) - \hat{R}C_j(t)]dt \quad (1)$$

The integral may be approached by Simpson's rule.

Default probability density and hazard rates are related by the following equation:

$$q(t) = h(t)\exp^{-\int_0^t h(\tau)d\tau} \quad (2)$$

Hazard rates $h(t)$ are defined such that $h(t)\Delta(t)$ is the probability of default between t and $t + \Delta(t)$ as seen from time t. It is also the intensity of the poisson process driving the arrivals of default.[5]

The present value of the losses on the defaultable bond B_j, is given by:

$$G_j - B_j = \sum_{i=1}^{j} q_i\beta_{ij} \quad (3)$$

By induction, we can find any one q_j. This gives:

$$q_j = \frac{G_j - B_j - \sum_{i=1}^{j-1} q_i\beta_{ij}}{\beta_{ij}} \quad (4)$$

3.2 Valuation of Credit Default Swap

The variables used in the valuation are the following:

T maturity of credit default swap.

$u(t)$ present value of an annuity of 1 between times $t = 0$ and t.

$e(t)$ present value of the accrual fee payment between times t^* and t where t^* is the last payment date.

[5]for a detailed discussion of default process modelling see Schonbucher (2003)

w total payments per year, or fees, paid by the CDS buyer.

s CDS spread, given by the value of w that makes the value of the CDS contract zero at issuance.

π survival probability or risk neutral probability of no credit event during the life time of the swap.

$A(t)$ accrued interest on the reference obligation as a percent of face value

The value of π is given by:

$$\pi = 1 - \int_0^T q(t)dt \tag{5}$$

The CDS is composed of two legs: the fee payment leg and the payment at default leg. The expected present value of the first leg is:

$$w \int_0^T q(t)[u(t) + e(t)]dt + w\pi u(T)$$

The first term in this expression is the expected present value of the fee payments if default occurs at any time between zero and T. The second term is the expected present value of payments if no default occurs.

The expected present value of the second leg is

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt$$

The term in brackets reflects the assumption on the claim amount. This term for each time t is discounted by $v(t)$ and weighted by the probability of default at each instant between $t = 0$ and T.

The CDS spread is the value of w such that the values of the two legs defined above are equal. After some manipulation, the following solution is found:

$$s = \frac{\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt}{\int_0^T q(t)[u(t) + e(t)]dt + \pi u(T)} \tag{6}$$

3.3 Model Implications

The model presented above is based on the idea that the difference in value between a treasury, risk-free bond and a defaultable bond, is due entirely to the expected present value of the costs of default. Although it is likely that the spread between treasuries and corporates is mainly determined by credit risk, there are other sources of risk, such as liquidity risk and tax effects, which could command a premium.

With either of the two assumptions on claims proposed, i.e. face value plus accrued interest or no-default value of the bond, the equations presented for estimating probability of default hold both for deterministic and stochastic interest rates, default probabilities and recovery rates provided they are mutually independent.[6] A second implication of the assumption on claims is related to the value additivity of coupon bearing bonds. This property states that the value of a coupon-bearing bond can be decomposed into underlying zero coupon bonds, and therefore the price of the bond can be found by discounting its cashflows with the relevant zero-rates. As showed by Jarrow and Turnbull (2000) this property does not hold when the claim is assumed to be face value plus accrued interest. This would imply that the zero rates found from bonds using the bootstrapping procedure cannot be used for pricing coupon bonds. Finally, it is found that the implied probability densities found using either definition of claim amount are very similar. They would diverge only if coupon rates and risk free rates are significantly different.

In order to test whether the assumed recovery rate is consistent with observed bond prices, the paper derives from the default probability density equations an interval in which bond prices must be found. These bounds are given below:

$$G_j - \sum_{i=1}^{j-1} q_i \beta_{ij} - \frac{\beta_{ij}}{t_j - t_{j-1}}[1 - \sum_{i=1}^{j-1} q_i (t_i - t_{i-1})] \leq B_j \tag{7}$$

[6] Although there is evidence of correlation between these three variables, Hull and White argue that the effects on CDS pricing tend to cancel out.

$$B_j \leq G_j - \sum_{i=1}^{j-1} q_i \beta_{ij} \tag{8}$$

Following the initial interpretation of the spread between defaultable bond prices and treasuries, we can also arrive through no-arbitrage arguments to a relationship between bond par yields, treasury yields and CDS spreads. The spread s^* is equal to the difference between the yields. This, however, is only an approximate or benchmark relationship. Hull and White show that with flat treasury yield curves and constant interest rates, together with a claim amount of $L(1 + A^*(t)))(1 - R)$, this approximation holds exactly. This last definition of the claim amount defines A^* in terms of the underlying par yield corporate bond. The spread described above will overestimate the spread found using the definition of claim as face value plus accrued interest. The two are linked by the following approximate relationship:

$$s = \frac{s^*(1 - \hat{R} - a\hat{R})}{(1 - \hat{R})(1 + a^*)} \tag{9}$$

Where a and a^* are average values of accrued interest.

If yield curves are not flat but rather upward sloping, then s^* will underestimate the spread on the idealized CDS. This is because the upward sloping yield curve causes the par treasury to be, on average, worth less than the face value plus accrued interest. In the same way, a downward sloping yield curve will cause s^* to overestimate the idealized CDS spread. Another source of error is to assume that the yield on all corporate bonds is the same as that of bonds selling at par.

Finally, the impact of the assumed recovery rate will be negligible as long as the assumption lies within reasonable bounds. However, an upward sloping yield curve makes the CDS spread an increasing function of expected recovery rates.

To support the hypothesis of independent default probabilities, interest rates and recoveries, Hull and White argue that the effect of positive correlation between interest rates and default probabilities has two opposite effects that tend to cancel out. It also seems to be that this correlation is negligible as found empirically by Moody's Investors Services. Although recoveries and default probabilities could be thought to be negatively correlated, they believe this correlation is small enough to be ignored. [7]

4 Implementation

As outlined in the model description, the Hull and White (2000) model is built on three equations: one for the present value of losses at default, one for the default probabilities and finally the CDS spread equation. Since the model is defined in continuous time which implies that default can arrive at any moment, implementation requires the choice of discrete time intervals. All outputs, probability of default, expected losses given default, and so on will be given for each one of these intervals. We chose time intervals of three months to allow for default at least at all CDS fee payment dates, which are paid quarterly.The data required to implement these equations for each date in the study period are:

1. Risk free zero yield rates for each possible date of default.
2. Corporate zero rates for each possible date of default
3. Forward price of risk free bonds for each possible date of default
4. Information on reference bond for each CDS: date of maturity, coupon rates and frequency of coupon payments
5. Characteristics of CDS contract: frequency of fee payments, maturity of contract
6. Recovery rates for each reference entity

This data is rarely directly available. The raw data used to derive the above inputs is the following:

[7] More recent studies suggest that negative correlation between recoveries and default probabilities is significant and could affect pricing.

1. Treasury or swap yield curves
2. Corporate bond prices for different maturities, their coupon rates and frequency of coupon payments
3. Information on reference bonds and CDS contracts are readily available.
4. Recovery rates are estimated through different methods. We use estimates by Altman, Kishor and Vellor (1996).

The implementation of the model was done on Matlab 6. It consists of two main sections: construction of input variables from raw data, and the implementation of the model itself. The procedure is composed of two steps: construction of input variables and model implementation.

4.1 Construction of input variables

1. Derivation of corporate zero rates by bootstrapping: For each reference entity a set of at least 4 bonds with well spaced maturities between 2003 and 2008 were used. This covers a five year period starting from the last date of the CDS spread sample and allows for smooth interpolated yield curves. All bonds are straight bonds with no embedded options, such as convertibility and callability. In this way, bond prices correctly account for risk perception and we are certain that the maturity date is meaningful. Otherwise, the value of the embedded option would have to be accounted for (Duffee (1998)). The second criteria in the choice of bonds was their liquidity. The most liquid bonds for each company were chosen so as to guarantee that their quoted prices reflect market perception. The volume of the issue was taken as an indication of liquidity.

   The bootstrapping procedure is done using a Matlab Financial Toolbox function that takes as inputs bond prices, coupon rates, maturities and coupon frequencies. The procedure is described in Hull (1999). Using this procedure we obtain equally spaced zero rates comprised between the earliest and latest maturity of the bonds used as inputs. We obtain at least a number of rates equal to the number of bonds used and at most 8 rates.This justifies the choice of at least 4 bonds and the corresponding maturities which determine the precision of the interpolated zero curve.

2. Interpolation of corporate and risk free zero curves to obtain zero rates every three months: The three month time step measured from each date for which CDS quotes are available determine the dates of possible default, and hence, the dates for which zero rates are needed. We linearly interpolate zero curves from the bootstrapped rates. The procedure is defined as a Matlab function. For very short maturities, specially the first three months, where we frequently did not have bootstrapped rates, we linearly extrapolated the corresponding zero curve[8]. Finally, all rates are expressed as continuously compounded rates.

3. Bond prices: Corporate and treasury bond prices are calculated from the zero curves above. These will be used to calculate the bond spread which is assumed to reflect the present value of expected losses due to credit risk[9]

4. Forward price of risk free bonds using standard cash-and-carry formula: forward prices are derived through no arbitrage arguments from the relevant bond prices.

4.2 Model implementation

Three variables constitute the model output:

β: For every maturity we obtain a vector of expected losses corresponding to the time interval between time $t = 0$ and the maturity date. The model

[8]An application of different yield curve building methods using splines can be found in Houweling (2001)

[9]Houweling (2001) argues in favor of joint estimation of risk free and risky yield curves for calculation of spreads.

in continuous time defines β as an integral over time since default can occur at any point in time. Since we consider time steps of three months, our β's are defined only every three months.

q: The default probability intensities are calculated recursively from bond spreads and β's.

s: The CDS spread is calculated as the ratio between two expressions involving integrals. As mentioned above, we discretize the integrals in time steps of three months. All integrals are approximated using Simpson's Rule.

The main issues to deal with during the process of implementation arise from data problems such as missing data either for some dates or for some maturities. When calculating the zero curves, bonds of short maturity were scarcer than bonds with long maturities. This meant that zero rates for less than one year maturities had to be extrapolated. If the slope of the curve was steep for long maturities, we ended up with either very low, or even negative risky rates. To avoid negative yield spreads, we replaced these cases with the corresponding yield curve of a company with the same risk profile. We consider companies in the same rating class and same sector of industrial activity to have comparable credit risk. If no such company existed, we searched for a company in the same sector and same rating class but different notch. For cases where negative spreads are only due to extrapolation and hence correspond to very short maturities, we only replace the first four rates. For the very rare cases where negative spreads happen after the first year, we replace the entire curve. If no sensible replacement could be done, we dropped the observation.

5 Data Description

The data set consists of data for the model implementation as described in the preceding section, and of data on actual CDS spreads which will be used to test the model prices. Data was provided by Pictet & Cie. The data set consists of daily last price quotes for CDS's denominated in both euros and dollars from Morgan Stanley. The time period goes from 06/06/2001 to 23/07/2003. The whole data set consists of 204 names for US denominated CDS and 184 for Euro denominated CDS.

The period of study is particularly interesting as it covers two years of recession in many industrialized countries and includes mayor credit blow ups such as Ahold, Fiat, Ford, France Telecom and Alcatel.[10] It also covers a period of mayor accounting and corporate governance scandals such as Enron and WorldCom. The main features of the period are falling equity markets, high corporate leverage and an increased sensitivity to event risk. All these factors significantly affected perception of credit risk and delivered the conditions for credit derivatives trading in the credit market.

As outlined in the section on model implementation, the choice of companies was determined by the availability of liquid, straight bonds that could be used to derive probabilities of default as reflected in bond spreads. Additionally, we required bonds to be denominated in the same currency, either dollars or euros so as to avoid including exchange rate risks. We required each firm to have a minimum of 4 bonds with these characteristics to be included in our data set. The highest number of bonds available was of 12. Finally, we redefined some of the sectors in more disaggregated groups. The final data set is presented in Table 9 and Table 10 in the appendix.

Most firms in our US sample are investment grade. Only 3 have credit ratings below BBB3. Out of 60 firms, 29 are rated BBB and 15 are BBB2.

Most well rated firms are in the Finance sector where all entities have ratings of at least A. One of the most homogenous sectors in terms of rating is Utilities where most firms are rated BBB. The lowest rating is BB3.

The EU sample as two firms rated B and one rated AAA. The distribution is in figure 1. As for the US sample, highest ratings are found in the Finance sector. For both sub samples, we must bare in mind that ratings correspond to the ratings of bonds taken for each firm at the end of the study period.

The two graphics below show a representative subsample of historical

[10]We thank Rajeev de Mello for pointing these cases out for us.

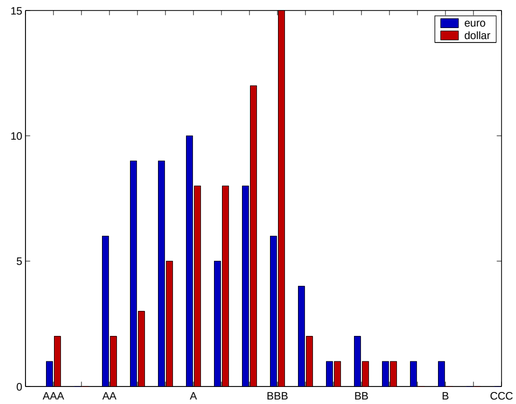


Figure 1: EU and US: Distribution of sample by Rating

CDS quotes for both the dollar and euro groups.

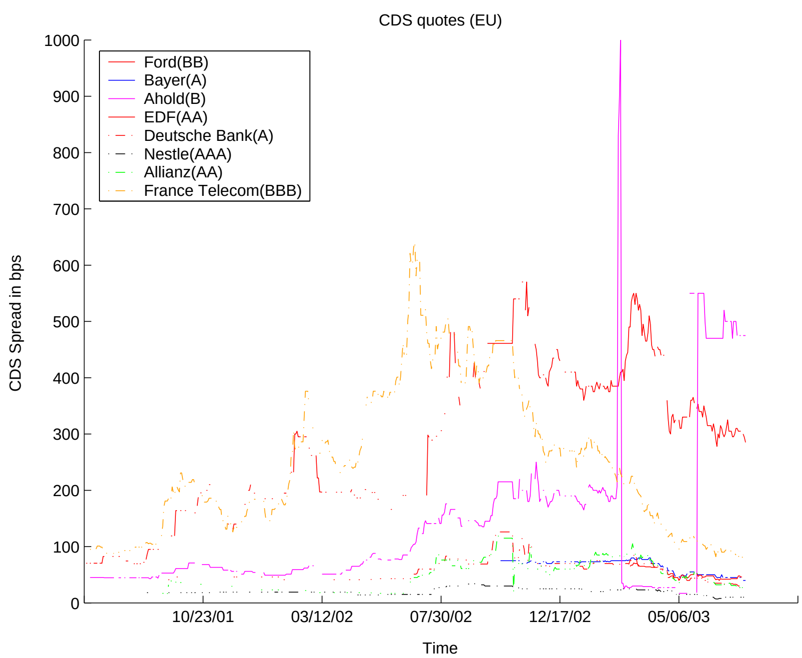


Figure 2: EU CDS Quotes (Representative Sample)

We have selected one firm from each industry or sector and, when possible, at least one firm per rating. In both subsamples we present blow up examples such as Ahold and France Telecom in the EU sample, and Ford in the US sample. In both cases, CDS quotes begin at low levels below 100bps and tend to peak during the second half of 2002 before coming back down towards the end of the period. In any case, it seems that CDS's have not returned to their pre 2002 levels. We verify that in general the best ratings, such as Nestle, Allianz, Deutsche Bank, Procter and Gamble, Deere and Merril Lynch, have both the lowest and the less volatile CDS quotes. The worst ratings in the sample, such as France Telecom and Georgia Pacific have the highest and most volatile CDS spreads.

A final set of data consists of daily equity market data for all firms taken from Datastream. The variables included are equity prices, market capitalization, turn over rate, price to earnings ratio and earnings per share. Implied volatilities from call options were taken from Bloomberg.

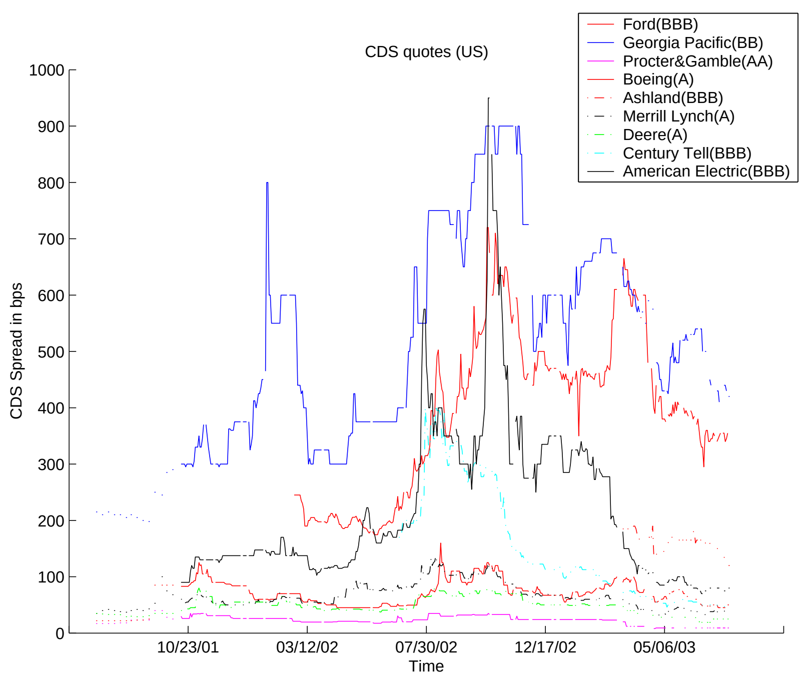


Figure 3: US CDS Quotes (Representative Sample)

6 Results

During the implementation procedure, several problems linked with data constraints had to be dealt with. In particular, we faced a problem of missing values for bootstrapping bond prices and of insufficient data for long and short maturities for the bootstrapping procedure. These two problems resulted in either negative spreads for very short maturities (3 and 6 months) or extremely high spreads for long maturities (5 years). The problem was solved by taking as proxy for the spread on these particular dates, the spread curve of a company with similar risk profile. That is, a company with the same rating and in the same sector.

A second issue that resulted was the estimation of negative q's. This should never be the case as theoretically q's are always bounded at zero. We can, never-the-less, point out that negative q's occur most frequently for firms with high ratings. There are two reasons for this problem: one is the overreaction of q's to changes in yield spreads, and the second is the overestimation of probabilities of default when other risk factors are included in the spread. [11]The second problem comes from the fact that the model assumes that the spread is due only to credit risk. However, if we recognize the spread to include a liquidity premium, then it is likely that high rated firm spreads have a higher proportion of liquidity premium than lower rated firms. This leads us to over estimate the default probability for well rated firms. This is eventually adjusted for by a negative q for a farther away maturity. To understand this possibility, we must recall that the difference between government and corporate bond prices is the expected value of losses over the life of the bonds. If the bond with maturity one year has a high component of liquidity risk, because say, the bond is off the run, then the probability of default for maturity one year will be overestimated. p_1 solves $G_1 - B_1 = p_1 * \beta_{11}$. If the illiquidity factor for the second year bond falls, that

[11]The problem could come from twisting spread curves that result from calculating the spread by subtracting independently estimated government and corporate term structures. Joint estimation as proposed by Houweling (2001) could limit this problem.

is, it is on the run, the q for this second year will tend to be underestimated to compensate for the artificially high q found for year 1, and in this way arrive at the year two bond spread. p_2 solves $G_2 - B_2 = p_1 * \beta_{21} + p_2 * \beta_{22}$.

The implementation of the model provides several variables of interest other than the model CDS spreads themselves. We will be particularly interested in the yield spreads and the default probability densities. Each variable will be analyzed by sector and rating for both euro and dollar denominated securities. The analysis by rating will be limited to rating classes abstracting from notches. The ratings are those corresponding to the end of the study period (July 2003). We do not account for rating transitions during the study period as no historical ratings were available. Since credit ratings adjust slower than market variables, we expect approximations from this source to be minor. The model was implemented both with treasury rates and swap rates as measures of the risk free rate. Finally, we will look in detail at the pricing errors both in absolute terms and as a percentage of the market CDS quotes.

The implementation of the model both with swap and treasury rates intends to find which specification matches best market data and in this way confirm or reject the belief that the swap rate has replaced in the last few years government rates as the risk free benchmark (Houweling and Vorst (2002)). However, we always take dollar or euro risk free rates for dollar and euro denominated bonds respectively. This in order to eliminate the portion of the spread that accounts for exchange rate risk. [12] In this way we search to be as close as possible to the hypothesis of the model by which spreads reflect only and exclusively credit risk. The effect of other sources of risk, such as liquidity, will be reflected on the estimation of default probability intensities.

[12] If we suppose one same entity issues both euro and dollar denominated bonds, we can expect the spread between the euro denominated bond yield and the dollar risk free rate to be larger(smaller) than the spread between the dollar denominated bond and the dollar risk free rate if the euro is expected to depreciate(appreciate) with respect to the dollar, and analogously when considering the euro risk free rate.

6.1 US denominated sample

We will first describe the results of the implementation with the treasury rates as benchmark risk free rate.[13] Risk free rates consistently fell during the study period 06/06/2001 to 23/07/2003. At the same time, the slope of the term structure fell reflecting negative expectations regarding the business cycle. In effect, the US was rapidly falling into recession during this period and the dollar was expected to depreciate responding to continued deficits in external balances. In what follows, we will analyze results by sector and by rating. These results reflect the average of all firms in the respective sector or rating class. Yield spreads and default probability densities, q's will be presented by maturity. Maturities are in quarterly intervals for 5 years, corresponding to the maturity of the credit derivatives studied. Results for the model CDS spreads reflect the average over time and across sectors or rating classes. As described in previews sections, the starting element of the model is corporate yield spreads. In fact, the underlying hypothesis is that CDS's can be correctly priced using only information from the bond market, and hence, that all information regarding credit risk and default probabilities is contained in bond spreads. Therefore, it is natural to begin by looking at yield spreads obtained through the bootstrapping and interpolation procedures.

We can see that yield spreads for all maturities and for all sectors are between 100bps and 200bps, except for Autos and Defense. In the Autos sector we have only Ford, which faced severe strain during this period. The upward sloping yield spread curve accounts for the perception of increased risk of default for further away periods. A similar explanation applies for the Defense sector. As it is composed of Boeing and Northrop Grumm, we can expect the yield spread curve to reflect conditions in the aerospace sector severely affected by economic downturn, uncertainty linked to deregulation and the effect of terrorist attacks and security problems in business conditions. The volatility of the yield spreads is a measure of the heterogeneity

[13] Figures not included in the text can be consulted in the appendix.

of the sector in terms of risks as reflected in the spread. We can therefore expect the sectors with most diverse ratings to have the highest volatility as is indeed the case. On the other hand, the different volatilities by maturity come from other sources of risk and idiosyncratic factors. This could be linked to company specific news. In this way, it seems that the long term performance and associated risks of the companies in the energy sector are more similar among them than those of the companies in the Defense sector.

The yield spreads by rating clearly correspond to the risks implied by the corresponding rating class with AAA spread being the lowest and BB the highest (no B firm was available in this subsample). Figures 4 and 5 illustrate these results. Furthermore, the difference between yield spreads for investment grade firms are smaller than between investment and non-investment grade firms as reflected in the large difference between BBB and BB. We can also highlight the fact that the volatility of yield spreads for investment grade ratings is smaller than for non-investment grade firms and that volatilities are higher for short maturities than for long maturities.

These results indicate that ratings are a better measure of risk for investment grades than for non investment grades where the spreads vary more widely reflecting more firm specific characteristics.

Yield spreads reflect the expected losses incurred due to default. They reflect probabilities of default over the life of the security together with a measure of losses given default. The model is formulated in terms of default probability densities, which in turn determine probabilities of default as seen from time $t = 0$. As is expected, q's increase as rating worsens. This holds for all ratings except for AAA for maturities longer than 1 year. This could reflect expectations of rating transition for Con Edison, only firm in this rating class. [14]

The results show that the q_i for all sectors are between 0% and 1%. Only Autos and Defense go beyond this and over 50%. It is worth pointing out the

[14] AIG , IBM and Bell South were not taken into account for these statistics due to poor information on long maturities. This resulted in excessively high extrapolated spreads.

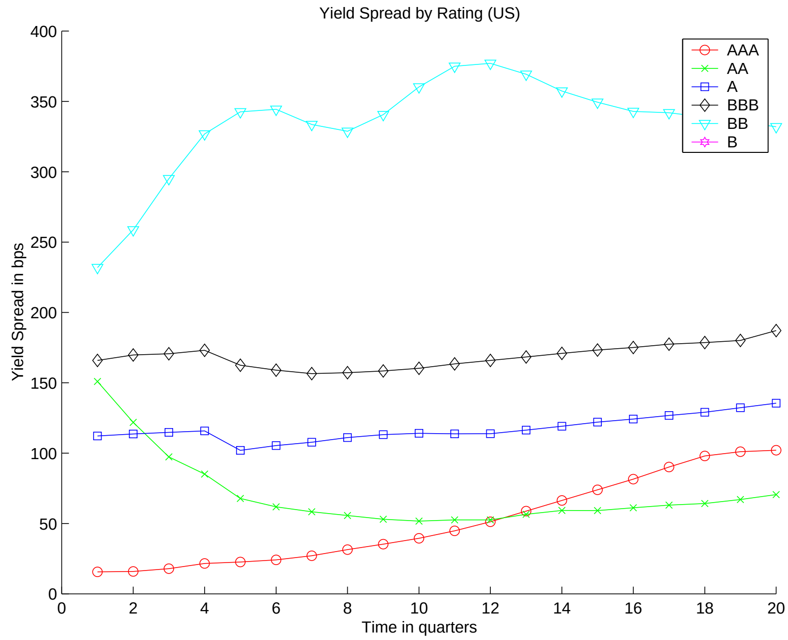


Figure 4: US Yield Spread by Rating (treasury rates)

overreaction of q's to changes in yield spreads. This explains the negative q's for Autos and could be an indication of stickiness of claim amounts, which forces all the adjustment to occur via q. A second interesting feature is the hump shape for Autos. This could result as the market identifies a particularly difficult period of strain. Default probabilities increase and reach a maximum at this date. If the firm manages to surpass this date, the probability of default once again falls (Schonbucher (2003)). In the case of Ford, this corresponds with the firms prospects during the sample period.

The volatility of q is highest in TMT and presents a hump shape in the Finance sector. Otherwise, volatility is always in the range 0.2% and 1.4%. The increasing trend in volatility for the Utilities sector matches the increased volatility in yield spreads and the disparity in long term prospects as perceived in the bonds market.

More interestingly, the q's by rating again show how perceived default probabilities for poorly rated firms are higher than for better rated firms.

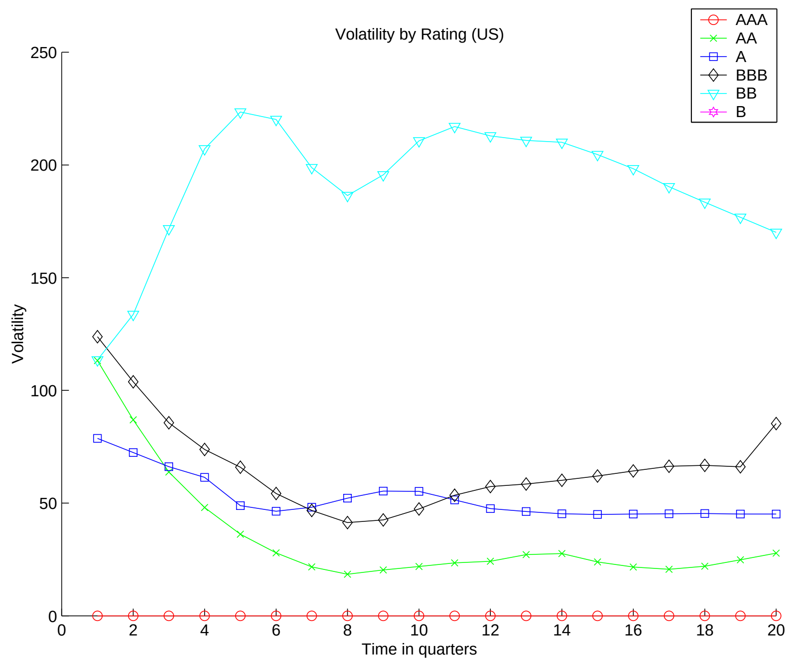


Figure 5: US Volatility of Yield Spread by Rating (treasury rates)

Volatility of q by rating is proportional to the level. The only case that does not exactly fit the expected pattern is the AAA rating. This again can reflect future rating transitions. q's by rating and volatility are presented in figure 6 and 7.

Finally, we turn to model CDS spreads by rating and by sector presented in figure 8. We see again that they are increasing for lower ratings. The only case where the ranking does not hold is the AAA rating for which the model CDS spread is higher than that of AA ratings. This could be because even if we choose AAA rated bonds from Con Edison, the spreads reflect expectations not yet accounted for by the rating, which is a backward looking measure. The model CDS spreads range from 20bps to 100bps and the standard deviation of model CDS spreads by rating increases for poorer ratings. This reflects the fact that better rated firms are more homogenous than poorly rated firms in our sample. In terms of sectors, the lowest model CDS spreads are in the Finance sector were the better ratings are, and the

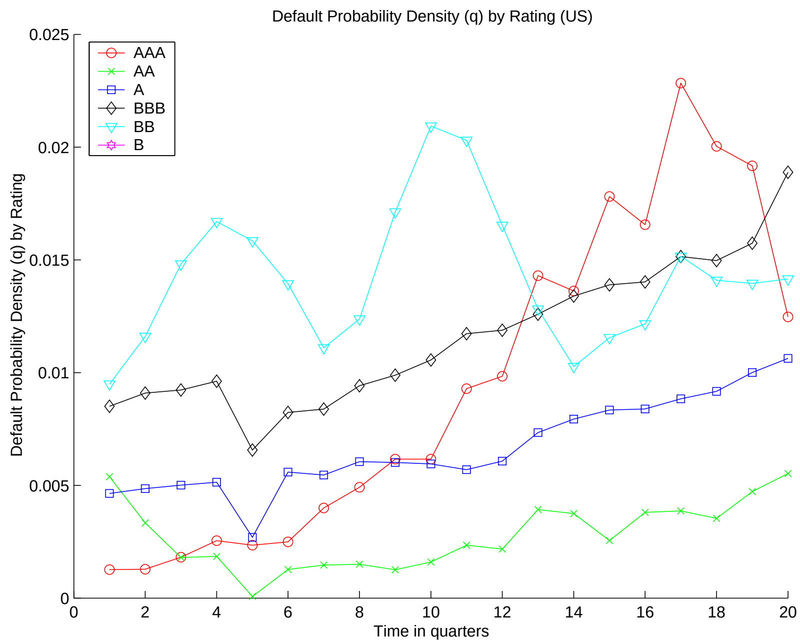


Figure 6: US Default Probability Density (q) by Rating (treasury rates)

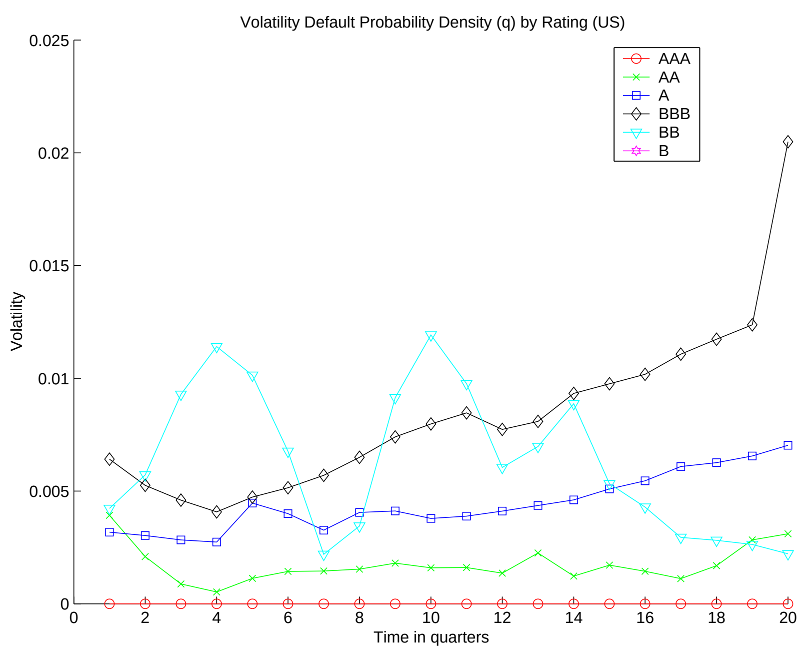
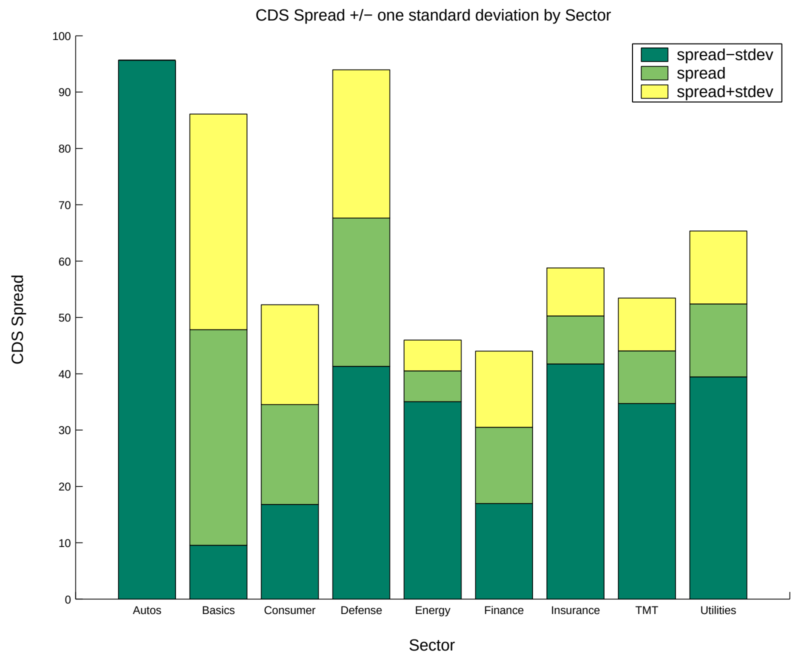


Figure 7: US Volatility of q by Rating (treasury rates)

highest spreads are in the Autos sector reflecting the credit blow up of Ford. The highest variability of these theoretical spreads is in the Basics sector and the lowest in the Energy sector.

The results for the yield spreads by sector with respect to the swap rate maintained the general trends but with a much higher spread for the Autos sector. When observing the yield spread by rating, we see that the shape for the AAA curve changes and slopes are inverted. The default probability density is the highest for Utiltities, Autos and Defense, and the volatility of q is highest for Utiltities. The ranking of default probabilities holds by rating. AAA q's are falling with maturities which can confirm our hypothesis of expectations of rating transitions in this sector. Again the volatility of q is higher for lower ratings.

The model CDS spreads by rating using swap rates keep the same ranking as with treasury rates. However, the standard deviation and means are smaller. Again lower ratings have much higher standard deviation than better ratings. The model CDS by sector are the lowest for the Finance sector (20bps) and the highest for the Autos sector (140bps). In general model CDS are lower and standard deviations are lower.



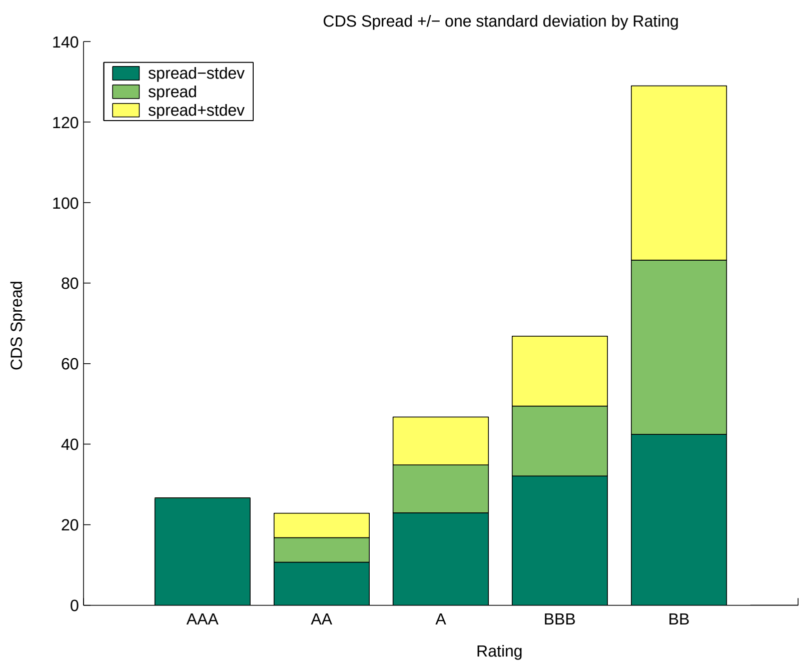


Figure 8: US Model CDS Spreads by Sector and Rating (treasury rates)

6.2 EU denominated sample

The same exercise was performed with the euro denominated CDS using a synthetic of the euro government rates provided by Bloomberg, and the euro swap rates. Using the treasury rates, we find that the highest spreads are in the consumer sector, which contains data for Ahold, one of the mayor credit blow-ups of the period. Other sectors are all below 200bps and have a slight hump shape increasing for short maturities and then falling for longer maturities. This is in line with market expectations of hard periods followed by smoother periods. Volatilities are also below 200bps, except for Finance where the volatility of yield spreads explodes for long maturities (figure 9).

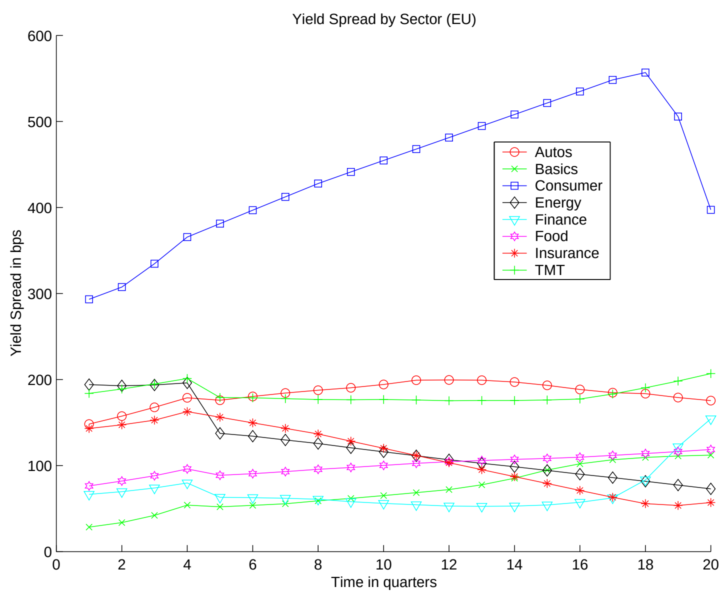


Figure 9: EU Yield Spread by Sector (treasury rates)

The yield spread by rating class corresponds to the ranking implied by ratings and the distance between ratings increases for lower ratings. As has been well documented, there is some overlap between rating classes. The volatility by rating is highest and increasing for A rating for long maturities and the lowest and most constant for AA rating which are mostly in the Finance sector (figure 10).

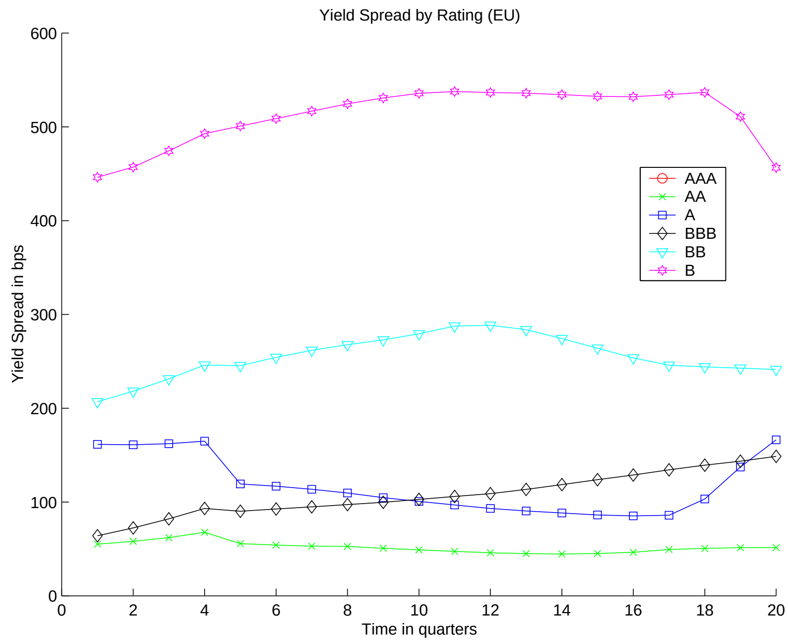


Figure 10: EU Yield Spread by Rating (treasury rates)

Default probability densities, q, are mostly below 1% for all maturities and all sectors. Only Finance and Energy deviate from this general trend with q's in the Finance sector increasing significantly for long maturities and with q's in the Energy sector overshooting the change in yield spreads underlying them. Never the less, it is also these two sectors that have the highest standard deviation of q's which makes reported means less reliable.

Default probabilities by rating range mostly between 0% and 2% with the lowest q's for AA rated firms and the highest for B. It is worth highlighting the fact that for very good ratings we tend to have some negative values. As pointed out at the beginning of this section, this can arise from overestimation of default probabilities due to the high proportion of spread resulting from liquidity risk and not credit risk. Finally, B rated firms, which in our sample are Alcatel and Ahold, two of the mayor credit blow ups of 2001, show rapidly falling and even negative q's for the last two quarters. This can be the result of poor data for these long maturities and recourse to extrapolated yield spreads. This is also reflected in the corresponding volatilities of q's (figure 11).

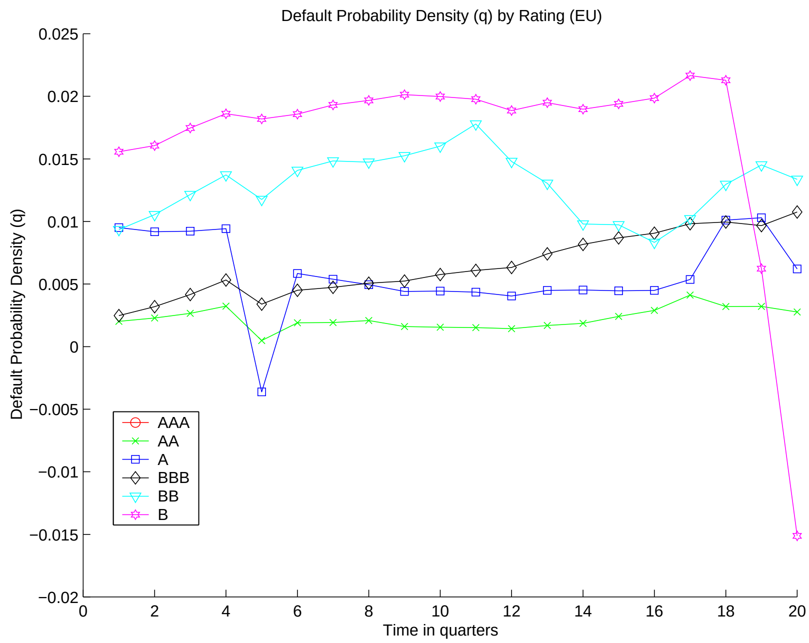
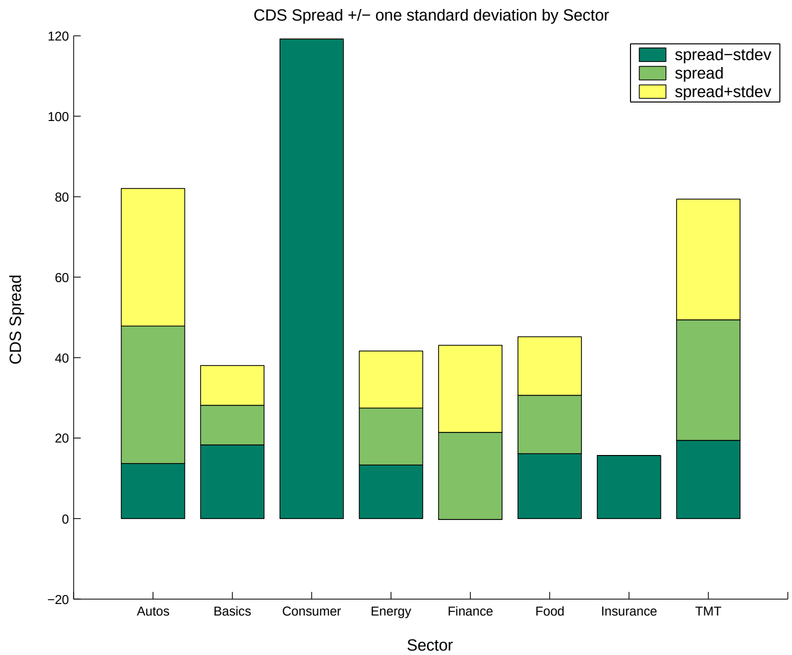


Figure 11: EU Default Probability Density (q) by Rating (treasury rates)

Finally, model CDS spreads per sector are the lowest for the Insurance and Finance Sectors which are the ones with better ratings. However, the standard deviation for the Finance sector is the largest relative to its mean. The sector with highest model CDS spreads is Consumer, that reflects the Ahold credit blow up. The spreads by rating respect the ranking we would expect, the lowest being for high rated companies and the highest for poorly rated companies. In our sample, the standard deviations of the AA and B ratings are the lowest and there is clearly an overlap between ratings when accounting for dispersion (figure 12).

The yield spreads with respect to the swap rates are much less dispersed than with respect to the treasury rates, but the main features in terms of ranking are not altered. The yield spreads by rating are in the expected order and again there is more overlap between good ratings than between



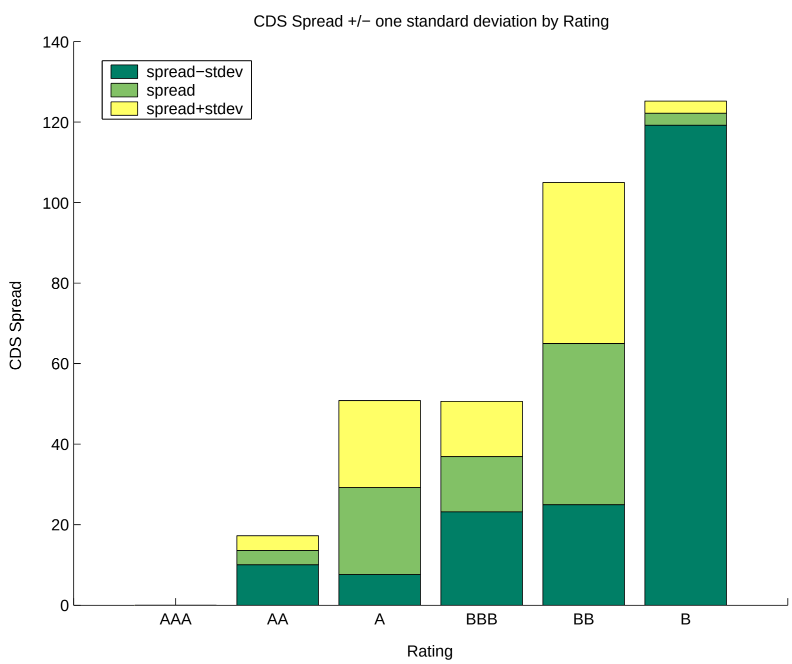


Figure 12: EU Model CDS Spreads by Sector and Rating (treasury rates)

non-investment grade sectors.

Default probability densities by rating follow the same trends as in the case of the treasury rates. However, once analyzed by sector there are mayor differences specially regarding the Consumer sector. We also see that most of the negative q's are in the Insurance sector, which has a high AA rating firm, Allianz. This is consistent with our explanation for negative q's. The other sector with negative q's is Energy. We can verify, however, that for this same maturity the volatility of q's is the highest so it is unlikely to be significant.

Finally, the model CDS spreads when using swap rates are ranked as expected. This time we have an AAA firm, Nestle, which was not available in the treasury sample. This results from our extrapolation procedure and the negative spreads resulting in the treasury sample, which led us to drop this firm. Otherwise, the mean model CDS are well behaved and the standard deviations are increasing. The case of B rated firms stands out because of it's low standard deviation. This reflects the fact that both firms in this rating class where blow up cases and their mean spreads are fairly close. The model CDS by sector is lowest for Insurance, Finance and Basics with low dispersion and highest for Consumer, Autos and TMT. This reflects both homogeneity of sectors and reflects distribution of ratings among sectors.

7 Model Error Analysis

7.1 Statistical Analysis of Pricing Errors

Although the results this far have been in line with our expectations and reflect basic trends and stylized facts, we still haven't assessed the goodness of fit of the pricing model implemented. [15] Let us recall that the Hull and White model is a proposal for pricing credit default swaps and, from the point

[15] IBM, Bell South and AIG (US sample) and Carrefour, Accor, LVMH and Metro (EU sample) were dropped for the error analysis and the regressions since they presented outlier features or too few observations.

of view of a financial practitioner, its relevance depends importantly on its ability to replicate market data. [16] It is important to recall that the data available was for last price CDS quotes. They are an average of bid and ask prices and a priori, do not necessarily reflect the actual transaction prices. However, after inspection of some available transaction data, we could verify that the transaction prices corresponded to bid prices (the lower end) and hence, that "last price" quotes would tend to overestimate the true transaction price. This will be reflected in positive pricing errors. Another source of under estimation can be the choice of recovery rates. Those proposed by Altman et. al (1996) are lower than the 50% recovery frequently used. As shown by Hull and White (2000), when yield curves are upward sloping, model CDS spreads are positively related to recovery rates. A final source of miss-pricing of CDS spreads comes from not considering counterparty default risk, that is, the risk that the protection seller may himself default. This issue is incorporated into the model by Hull and White (2000b).

We will initially present mean errors and standard deviations by ratings and sectors both in absolute and relative terms, that is, as a percentage of market price. Then we will explore the errors with the help of a set of Z-statistics following Houweling and Vorst (2002), which follow standard normal distributions. This will allow us to carry out simple statistical tests and compare errors between ratings and choice of benchmark risk free rate.

7.1.1 US Errors

In the US sample, we have no B rated firms. For both specifications, swap rates and treasury rates, the size of the errors increases as ratings worsen. In the treasury specification errors range from 1.78bps to 164bps, and in the swap case they go from 7.8bps to 161bps. The sectors with the lowest errors

[16] From an academic point of view we will be interested in other aspects such as the information set available in bond prices regarding credit risk and the interpretation of errors. In any case the model helps both academics and practitioners to organize their ideas and think about credit issues

are Defense and TMT for both specifications.

Figures 13and 14graph the mean errors and corresponding standard deviations by ratings and sectors. As in the EU sample, both statistics are lower for good ratings confirming the difficulties in pricing CDS on badly rated firms. Table 4 shows the same errors but as a percentage of the market CDS. In the case of treasuries, the errors range from 5% to 42%, with the lowest errors on investment grade issuers. This implies that the model manages to account for between 60% and 95% of CDS prices. Similarly, errors by sector are around 30% meaning that, on average, the model explains 70% of CDS prices. In the case of swap rates, the general trends hold but the errors are slightly higher ranging from 25% to 54% by rating and around 40% by sector. This result contrasts with those found by Houweling and Vorst (2002).

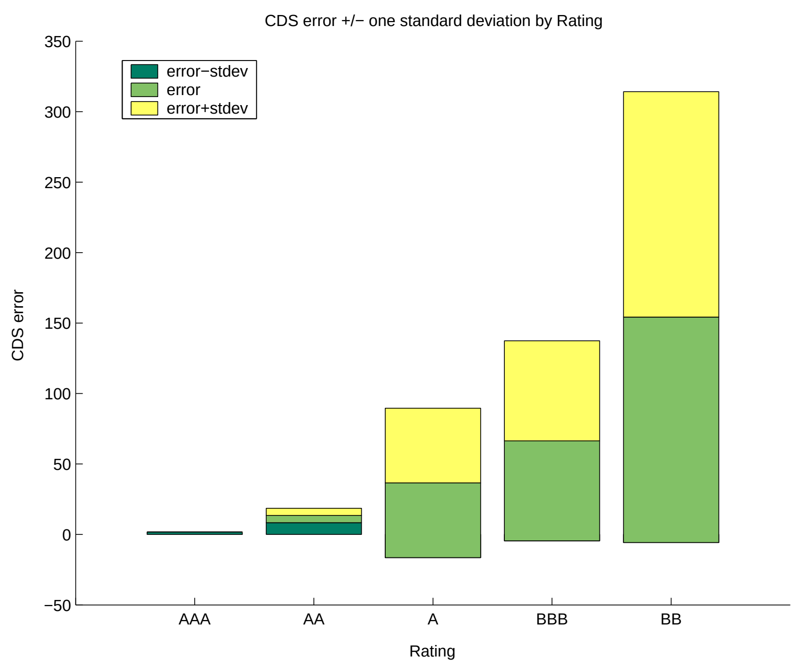


Figure 13: US Error by Rating in bps(Nominal) (Treasury rates)

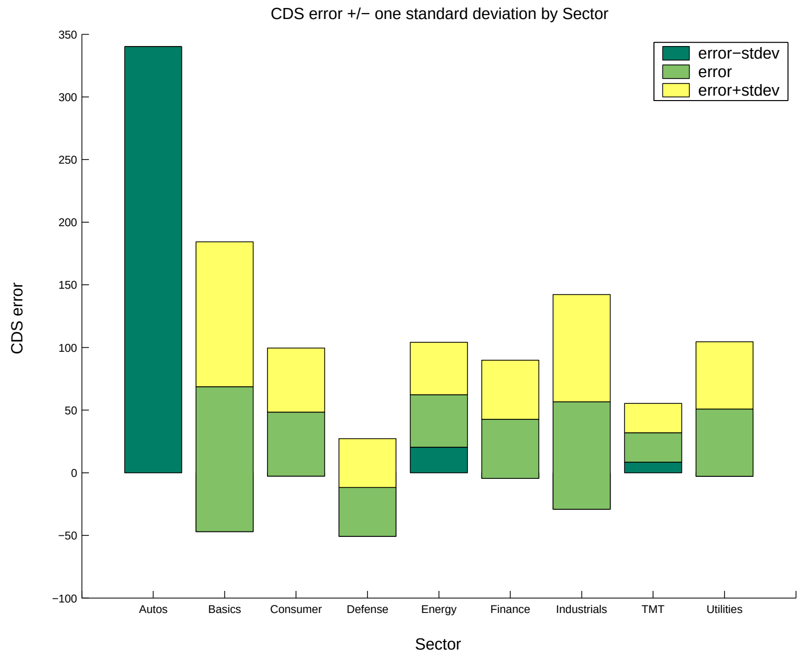


Figure 14: US Error by Sector in bp(Nominal) (Treasury rates)

7.1.2 EU errors

From figures 15and 16 it can be seen that in the EU sample the lowest pricing errors are for CDS's from well rated issuers. A and AA have the lowest pricing errors, 39bps and 35bps, as well as the lowest dispersion of errors, whereas BB has both the highest mean, around 300bps, and the highest dispersion, 212bps. Interestingly, we arrive to price fairly well the B rated firms, Ahold and Alcatel, even though these two firms had quite extreme values during the study period. As far as sectors are concerned, the best pricing is achieved for the Energy and Finance sectors with errors below 30bps and 41bps respectively, and very small standard deviations. The lowest dispersion is in the Basics sector with only 7bps of standard deviation. The worst, both in terms of average error and of dispersion around these errors, was the Autos sector. This results from the heterogeneity of the firms in this sector as seen in their rating. It also comes from the fact that we have two important credit blow-ups, Ford and Fiat, together with other low risk firms.

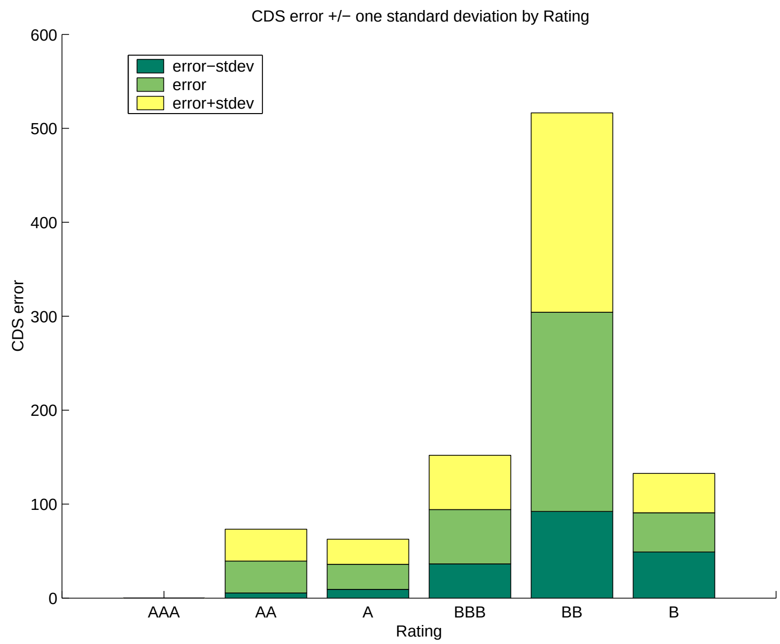


Figure 15: EU Error by Rating in bps (Nominal) (Treasury rates)

Although the mean errors do tell us a lot about the performance of the model for the different subsamples, we could also be interested in having an idea of the magnitude of these errors with respect to the market CDS quotes. After calculating the errors and standard deviations of errors as a percentage of market prices, we see that the error percentage is lower for good ratings than for poor ratings. We tend to underestimate the spread for good ratings and to over estimate the spread for very bad ratings. Results are particularly bad for rating B as a percentage of market CDS. This due to the extreme high volatility of CDS spreads for this rating class. By sectors the lowest percentage error is in the Energy sector. The most disperse mean errors are in the TMT sector.

The results with the swap rate as benchmark risk free rate are qualitatively not very different from those with treasuries. Errors are smallest for good ratings and larger for poor ratings and the sectors where firm ratings are most homogenous have the lowest standard deviations, as is the case of Basics and Energy. The same holds for errors in relative terms. In nominal terms errors for rating classes AAA to A range from 7.52bps to 40.99bps. For BBB to B, they go from 90.39bps to 305.41bps. The errors for Energy and Finance are the lowest at 32bps and 43bps respectively. As percentage of CDS market price, the lowest error was in the Consumer sector with only 2% error, which indicates that the pricing for Ahold was very successful and that the large error in the B rating class comes entirely from Alcatel.

In order to evaluate the significance of these results, we compute Z statistics as described below.

We calculate two types of pricing error: the Mean Pricing Errors (MPE) and the Mean Absolute Pricing Errors (MAPE) each of these by entity, by rating and by sector. The MPE will give us an idea of whether we under, or overestimate CDS prices, the MAPE will be useful in evaluating the performance of different model specifications.

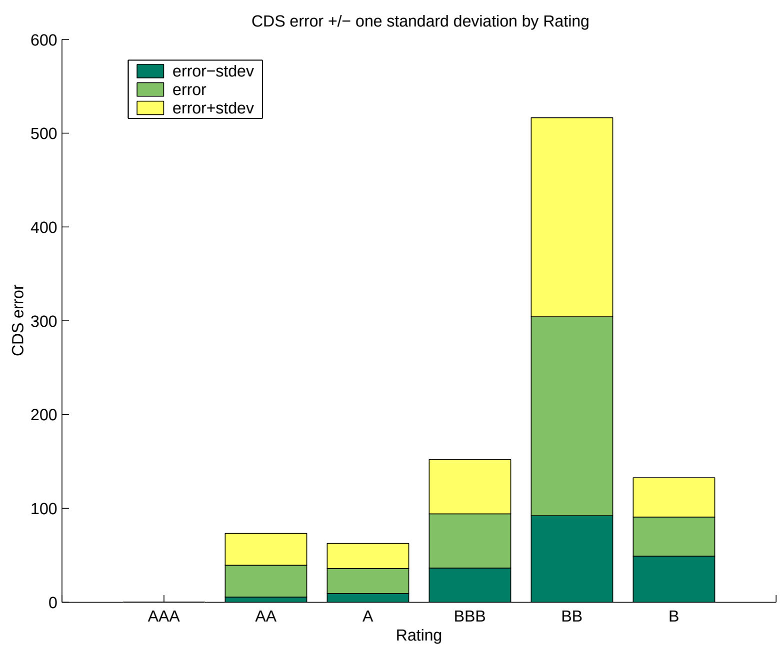


Figure 16: EU Error by Sector in bps (Nominal) (Treasury rates)

The first type of statistic we compute are one-sample Z-tests by entity. We then calculate these by rating and by sector both for the US and the EU sample and for the model using the treasury rates and the model using the swap rates. These statistics are defined as $Z_i = \sqrt{N}\frac{MPE_i}{stdev_i}$, where N is the number of observations and stdev is the standard deviation. This statistic follows asymptotically a standard normal distribution.

The second type of statistic is a paired Z-test between consecutive rating classes. This test will show whether the model manages to better price CDS's for some rating classes over others. In particular, we want to compare investment with non-investment grade, given that earlier research has found under performance in the high yield environment. The test statistic is defined as $Z_{ij} = \sqrt{N}\frac{d_{ij}}{stdev_{ij}}$ where d_{ij} and $stdev_{ij}$ are the mean and standard deviation respectively of $d_{ij} = MAPE_{it} - MAPE_{jt}$ for $t = 1, ..., N$. The same type of test will allow us to compare the errors between the model using the swap rate and the model using the treasury rates, and to evaluate the effect of using more or fewer bonds in the bootstrapping procedure.

Finally, we calculate root mean squared errors by rating for all model specifications. This statistic is defined as: $RMSE = \frac{1}{N}\sqrt{\frac{1}{n_t}\sum_{i=1}^{n_t} e_i^2}$ where $e_i = CDSmarket_i - CDSmodel_i$, N is the total number of observations in the sample and n_t is the number of observations per day for a particular rating class.

Tables 1 and 2 present all the summary statistics by rating and by sector for the EU treasury sample. We see that in all cases the errors are statistically different from 0 and the model performance by rating changes a lot. Although mayor trends carry over for the swap case, there are some differences worth mentioning.

The same statistics were calculated when implementing with the swap rates. The one-sample z statistics confirm that the errors are statistically significant, both if considered by rating and by sector. This indicates that there is room for model development and that either the information in bond spreads is not enough to price CDS, or the information is not used efficiently

Statistics	AAA	AA	A	BBB	BB	B		
error mean	NA	39.3566	35.9873	94.2542	304.2935	90.8664		
error stdev	NA	33.95	26.72	57.83	212.08	41.79		
z	NA	4.4896	6.4594	6.5195	2.4852	3.0749		
rmse	NA	54.1105	70.7699	122.9879	418.5327	198.3002		
mape mean	NA	43.0276	59.5376	108.9013	404.7392	198.3002		
Statistics	Autos	Basics	Consumer	Energy	Finance	Food	Insurance	TMT
error mean	201.7138	43.1663	132.6584	30.6759	41.899	73.5653	44.5104	92.6201
error stdev	188.7807	7.1172	0	11.9513	44.592	50.4983	0	45.4603
z	2.6173	12.1301	NA	8.513	4.4072	3.2575	NA	6.1121
Statistics	AAA/AA	AA/A	A/BBB	BBB/BB	BB/B			
d mean	NA	9.381	41.8354	299.8357	-211.7242			
d stdev	NA	24.33	49.98	114.43	225.3			
zp	NA	7.2334	16.9089	39.0416	-9.111			

Table 1: EU Treasury Error statistics in bps(Nominal)

Statistics	AAA	AA	A	BBB	BB	B		
error mean	NA	0.665	0.5346	0.6632	0.7591	-6.1699		
error stdev	NA	0.1325	0.3188	0.1039	0.1018	5.1461		
z	NA	19.431	8.0416	25.5426	12.9106	-1.6956		
rmse	NA	0.6776	1.2277	0.6916	0.8314	1.6676		
mape mean	NA	0.6646	1.128	0.6824	0.8301	1.6676		
Statistics	Autos	Basics	Consumer	Energy	Finance	Food	Insurance	TMT
error mean	0.7416	0.5984	-1.0239	0.4711	0.6156	0.6659	0.7276	-0.6423
error stdev	0.1062	0.0874	0	0.2645	0.2868	0.0314	0	3.7739
z	17.1025	13.7015	NA	5.9076	10.0683	47.4545	NA	-0.5106
Statistics	AAA/AA	AA/A	A/BBB	BBB/BB	BB/B			
d mean	NA	0.1216	-0.3885	0.1552	0.8507			
d stdev	NA	0.6819	1.4484	0.0548	1.4166			
zp	NA	3.3449	-5.4187	42.1985	5.8222			

Table 2: EU Treasury Error statistics as percentage of market price (Relative)

by the model.[17] The last set of statistics in the statistics tables, test whether the difference in the errors between rating classes are statistically significant. We see that the model does perform differently by rating class.

In percentage terms, the errors in the Consumer and TMT sector are not significantly different from 0 as well as the errors for the B rating. A third interesting result is that the percentage errors for rating AAA and AA are not significantly different. All these results support the idea that the model, on average performs best for investment grade firms.

Tables 3 and 4 report all set of statistics for the US treasury sample. It is worth highlighting that the mean errors for BB rating, Basics and Industrials are not statistically different from 0 for the treasury sample. This indicates that,on average, best pricing was achieved for these three subsamples. In percentage terms, the same result holds for BB but now it is Defense and Industrials that are best priced. In the swap specification, only the errors of the Defense sector are statistically different from 0 in nominal terms. As percentages, this is the case for BB, Defense and Industrials. Notice that there is overlap between the definitions by sector and by rating. In all cases, the errors vary substantially with rating class. This will be further exploited in the following section.

The last set of tests, reported in Table 5, compares the errors resulting from the swap and treasury specifications and between a model implementation with few or many bonds for the bootstrapping procedure. In the first half of the table we see that on average better pricing is achieved using the treasury rates rather than the swap rates both for US and EU denominated CDS. This is at odds with results found by Houweling and Vorst (2002) and with general belief that swap rates have replaced treasuries as the risk free benchmark. It supports the critique in Longstaff, Mihal and Neis (2003) regarding the use of swap rates a risk free benchmarks.

Finally, the second half of the table tests whether implementing the model

[17] A model-free proxy for the cost of protection could be used as a robustness test (Longstaff, Mihal and Neis (2003).

Statistics	AAA	AA	A	BBB	BB	B			
error mean	1.7838	13.4598	36.6182	66.4168	154.2541	NA			
error stdev	0	5.11	53.02	70.95	159.95	NA			
z	NA	5.8893	3.0104	5.0414	1.6703	NA			
rmse	58.0362	17.0236	129.9007	87.3253	275.6035	NA			
mape mean	57.2182	16.0053	90.6934	64.9044	241.4888	NA			
Statistics	Autos	Basics	Consumer	Defense	Energy	Finance	Industrials	TMT	Utilities
error mean	340.1214	68.6748	48.4391	-11.7426	62.2349	42.6861	56.6129	31.8815	50.8672
error stdev	0	115.6841	51.1305	38.9622	41.8369	47.2118	85.681	23.4305	53.7104
z	NA	1.6791	2.9958	-0.4262	4.2075	3.132	1.1444	1.9243	3.1411
Statistics	AAA/AA	AA/A	A/BBB	BBB/BB	BB/B				
d mean	-47.0424	79.0982	-24.6599	177.2153	NA				
d stdev	21.1561	46.0765	79.7298	91.3291	NA				
zp	-34.8047	27.2513	-6.2013	40.4238	NA				

Table 3: US Treasury Errors statistics in bps (Nominal)

Statistics	AAA	AA	A	BBB	BB	B			
error mean	0.053	0.3733	0.3108	0.4286	0.287	NA			
error stdev	0	0.0883	0.2652	0.3697	0.5404	NA			
z	NA	9.4512	5.1077	6.2441	0.9197	NA			
rmse	1.1488	0.4652	2.0034	0.5878	0.7131	NA			
mape mean	1.1258	0.4457	1.2761	0.5428	0.6973	NA			
Statistics	Autos	Basics	Consumer	Defense	Energy	Finance	Industrials	TMT	Utilities
error mean	0.7767	0.3381	0.454	-0.405	0.4969	0.4405	0.1206	0.3794	0.3201
error stdev	0	0.3132	0.1852	0.7872	0.1879	0.1813	0.5016	0.2062	0.2646
z	NA	3.0541	7.7516	-0.7275	7.4808	8.4156	0.4166	2.6015	4.012
Statistics	AAA/AA	AA/A	A/BBB	BBB/BB	BB/B				
d mean	-0.7447	0.6837	-0.7291	0.1655	NA				
d stdev	0.3003	0.3365	1.2652	0.1704	NA				
zp	-38.8124	32.2539	-11.5542	20.2261	NA				

Table 4: US Treasury Error statistics as percentage of market price (Relative)

Statistics	AAA	AA	A	BBB	BB	B				
US										
z	1.0642	-11.2839	-12.3792	-20.4286	-21.8651	NA				
EU										
z	NA	-12.5455	-3.4127	-16.4312	-3.0522	4.513				
US										
z	59.9033	30.6968	33.0864	8.1712	54.993	32.2297	31.6091	28.9978	12.9192	8.7903
EU										
z	1.5237	-6.1807	10.8145	-5.197						

Table 5: Paired z tests between Treasury and Swap rates by Rating and between Long and Wide Method by Entity

with more bonds results in lower pricing errors. To do so, the model was implemented for a selection of entities with only 4 bonds per entity and then with as many as available. In the case of the US, it is clear that the inclusion of more bonds for the calculation of the model parameters does contribute to the performance of the model. The case is not that clear cut for EU denominated CDS. We suspect this could be because of differences in liquidity of bonds used. It is sensible to think that the more liquid bonds are included in the model, the better the pricing will be, but that adding not so liquid bonds worsens the results.

7.2 The Determinants of Pricing Errors

The Hull and White model implemented relies only on information contained in the debt market. Spreads are not modelled but rather taken directly from bootstrapped zero curves both for risky and risk free rates. As seen in the last section, there is significant miss-pricing. This could be either due to inefficient or inappropriate use of the information revealed by the bonds market, or to the need of appealing to information in other markets such as the equities market in order to correctly price credit derivatives. We will explore the second hypothesis by trying to explain the pricing errors with variables from the equities market. This implicitly assumes that markets are fragmented and that bond markets and credit spreads therein do not allow for correctly assessing the probability of default (Collin, Dufresne (2001)).

The motivation for this section comes from the literature on structural models briefly outlined in the Literature Review. The Hull and White model belongs to the family of reduced, or intensity based models, which consider default as an exogenous, surprise event. Structural models incorporate variables related to fundamentals at firm level. By considering data from equities market, we aim to investigate if this reduced form model does leave out relevant information that a structural model would not omit.

Since we obtain pricing errors per entity and for a certain time period, it seems reasonable to account for these two dimensions when analyzing the determinants of the errors. We specify our regression model as a panel of firms and consider initially a linear specification. The dependent variable is the errors and the explanatory variables are price of equity, market value or market capitalization, turn over, implied volatility, earnings per share and price to earnings ratio. The general form of the regression equation is as follows:

$$\begin{aligned} E_{it} &= \nu + \alpha_i + \beta_1 P_{it} + \beta_2 MV_{it} + \beta_3 EPS_{it} + \beta_4 PE_{it} + \beta_5 TO_{it} + \beta_6 VOL_{it} \\ &\quad + \beta_7 EU3MRF_t + \beta_8 EUSLOPERF \\ &\quad + \beta_9 US3MRF + \beta_1 0USSLOPERF + \epsilon_{it} \end{aligned} \tag{10}$$

Subindex i stands for the cross section dimension and t for the time dimension. We will investigate whether α_i should be modelled as a fixed or a as a random effect.

We will also test whether the effect of each of these variables varies according to rating class. Our specification includes the short term, three month risk free rate and the slope of the yield curve defined as the difference between the 10 year rate and the 3 month rate for both domestic and foreign markets. By including these variables, we want to assess if the pricing model incorporates all information in risk free rates or not and account for business cycle effects as documented in Alessandrini (1998). We would expect the short term domestic rates to have no explanatory power of the errors. However, the 10 year rate was not an input to the model, so we could expect the slope of the yield curve to explain part of the miss-pricing. The slope has been found to be a good indicator of future economic activity. A positive slope predicts economic expansion and a downward sloping curve, recessions. We expect the coefficient on this variable to be negative. It has been shown that the model is better suited for pricing CDS on well rated issuers. With a downward sloping yield curve, predicting recession, transition probabilities towards lower ratings become more correlated with economic variables and expectations of down gradings increase. As ratings tend to evolve with a lag, or at least slower than financial markets incorporate news, we can expect these future perspectives to be reflected in bond spreads but not in ratings.

Including foreign interest rates can reflect the interactions between dollar and euro markets. It has been well documented that business cycles of the euro zone and the dollar zone move in parallel with a lag. A positive slope of the dollar risk free rate can be a predictor of positive slopes of the euro yield curve and of future booms. In the same way, downward sloping dollar curves can precede euro zone recessions. We expect the sign of the dollar yield curve slope to be negative for the euro zone sample.

The turn over variable is the number of shares traded per day expressed in thousands. We take this as a proxy for the liquidity of bonds from each particular issuer and expect the corresponding coefficient to be negative. This reflecting the fact that default probabilities calculated from illiquid bonds are less accurate than those calculated from liquid ones.

The market capitalization variable is a measure of the size of the firm. The inclusion of this characteristic in our error equation will account for differences between large and small firms in areas such as transparency, public scrutiny, availability of information, etc. Market capitalization can also be a proxy for liquidity. Under either interpretation we expect the coefficient on this variable to be negative.

Earnings per share is a measures of current firm performance. It makes reference to fundamental variables linked to the utilization of assets and the value of these assets to claim holders. Unlike share prices, they are not subject to speculative bubbles and can better reflect the economic conditions of the firm. However, this measure should be approached with prudence as it depends on accounting methods.

Price per earnings ratio is an indication of how expensive a share is with respect to the performance of the firm. A high PE ratio shows that investors think that the firm has good growth opportunities, that its earnings are relatively safe or both. PE has to be interpreted cautiously as it can be due to either very low earnings or high price. We expect a negative sign on PE.

Implied volatility from call options can be seen as an indication of variability in the value of the assets of the firm. The higher this volatility is, the more likely we are to hit a default threshold, as defined in structural models. We therefore expect the effect of this variable to be positive.

The price of equities is the most direct and obvious choice of variable to try to identify information in the equities market not available in the bonds market. Stock prices are an indication of future prospects of firms. As stock prices rise, future default probabilities can be expected to fall as the leverage ratio tends to improve. On the other hand, demand for protection for these issuers will fall and this demand effect will have a negative effect on CDS prices. The expected sign is therefore negative.

The regression equation was estimated assuming fixed and random effects. Hausman specification tests were performed so as to choose the best estimators possible. Recall that the null hypothesis in the Hausman specification test is that the true model is a random effects model and the alternative is a fixed effects model. The test is based on evaluating whether the difference between the random and the fixed, or within estimators is significant. If the difference is significant, we reject the null hypothesis. The fixed effects estimator is consistent under both hypothesis but inefficient under the hypothesis of random effects, whereas the random effects estimator is consistent, unbiased and of minimum variance under the null hypothesis, but biased under the alternative, fixed effects model (Baltagi 1995).

Unlike many panel data sets where the time dimension is smaller than the cross section dimension, our data set is characterized by a relatively long time dimension as compared to the cross section dimension. For the US sample we have 57 firms and for the EU 60. Because of this structure, it is likely that problems of heteroscedasticity and autocorrelation within the panels may be more important than the effects across panels. The heterogeneity across panels is accounted for by the fixed effects estimator but adjustments must be made for violation of regression hypotheses within panels.

We initially estimate the set of equations with the within estimator, or fixed effects method. Most coefficients have the expected signs for both the EU and US sample. However, the Durbin Watson statistic is below 2 indicating serial correlation. Through inspection of the regression residuals, we see that the residuals follow cycling paths for some cross section units confirming positive serial correlation. Standard errors and t-statistics are therefore biased. The residual graphs also indicate heteroscedasticity within panels.

We estimate our linear specification including an AR(1) term to account for serial correlation and we use robust standard errors and a GLS estimator to account for heteroscedasticity. The results are reported in the appendix.

In the case of the EU sample, we can verify that the AR(1) term is statistically significant and has corrected for serial correlation. It is positive and lower than 1 revealing a stationary residual process. The sign of performance measures such as P, EPS and PE are negative as expected. The sign of MV and volatility term is positive. Although the sign of the turnover variable is statistically significant, it is not economically significant. All interest rate variables are significant. The domestic interest rates have positive sign, whereas the foreign interest rates have negative signs. This is understandable since the pricing model isolates credit risk by taking yield spreads, the level and market risk in short term interest rates are not included. On the other hand, we frequently had poor information on short term risky rates.

Most results are similar for the US sample, however, in this case the coefficients of MV and TO are not economically nor statistically significant. In the case of interest rate variables, all are significant and of the expected sign except for the short term euro rate. In both cases most of the variance of pricing errors can be explained with the included variables. However, this high R^2 can be an indication of specification problems and a result of the non-stationarity of the series. This will be dealt with below.

We next investigate whether the effect of these variables changes per rating class. We include interaction terms between P and the rating dummies and VOL and the rating dummies. In the case of the US sample, we find that the effect is not statistically different between rating classes for neither variables. In the EU sample, the effect of P(equity prices) on pricing errors is lower for AA rated firms but higher for A and BBB rated firms. This with respect to AAA rated firms. The effect of volatility is smaller on lower rating classes than on better rated firms.

The high coefficient of serial correlation can be an indication of model miss-specification as well as of pure serial correlation. When performing Augmented Dickey-Fuller tests we could not reject the presence of unit roots. To correct for non-stationarity, we estimated the same specifications above in first differences excluding the intercept. The results are qualitatively the same for both samples. The sign and significance of the coefficients do not change. The same holds when including coefficients per rating class. The results for the EU sample are presented in table 6. Results including rating effects are shown in table 7

The results above suggest that indeed equity market data does provide additional information about the credit quality of issuers. This information helps explaining the pricing errors. Variables such as EPS as well as data from the derivatives market, such as implied volatilities, have the potential to be included in a CDS pricing model. The results ratify the findings of Collin, Dufresne (2001). regarding market segmentation. Presence of serial correlation is frequent in financial market studies reflecting lag effects of

Dependent Variable: D(E?)				
Method: GLS (Cross Section Weights)				
Included observations: 433				
Total panel (unbalanced) observations 4074				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(P?)	-0.3030	0.0340	-8.9106	0.0000
D(MV?)	-0.0006	0.0001	-9.9228	0.0000
D(EPS?)	-1.3188	0.1511	-8.7300	0.0000
D(PE?)	-0.1749	0.0555	-3.1521	0.0016
D(TO?)	0.0000	0.0000	3.3031	0.0010
D(VOL?)	0.0613	0.0096	6.3930	0.0000
D(EU 3M RF)	1933.9296	80.1787	24.1202	0.0000
D(EU SLOPE RF)	1251.2186	35.8441	34.9073	0.0000
D(US 3M RF)	-787.0268	252.9377	-3.1115	0.0019
D(US SLOPE RF)	-233.5676	24.1167	-9.6849	0.0000
R-squared	0.0447		F-statistic	21.1224
Adjusted R-squared	0.0426		Prob(F-statistic)	0.0000
Durbin-Watson stat	2.0858			

Table 6: EU Regression in First Differences

unexpected shocks.

Further research is needed to investigate the exact form of the relation between credit markets and equity markets to account for non linearities. We would also like to asses problems of endogeneity. It has been suggested that the credit derivatives market incorporates news faster than bond and equity markets (Longstaff, Mihal and Neis (2003)). This would call for a more dynamic setup such as a VAR model or a dynamic panel data model following Arellano and Bond (1991). Finally, the issue of attrition in unbalanced panel data should be assessed.

Dependent Variable: D(E?)				
Method: GLS (Cross Section Weights)				
Included observations: 433				
Total panel (unbalanced) observations 4074				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(P?)	-0.1542	0.0428	-3.6028	0.0003
D(MV?)	-0.0010	0.0001	-13.1531	0.0000
D(EPS?)	-1.0883	0.1736	-6.2679	0.0000
D(PE?)	-0.0860	0.0720	-1.1933	0.2328
D(TO?)	0.0000	0.0000	3.9536	0.0001
D(VOL?)	0.6548	0.0316	20.7112	0.0000
D(EU 3M RF)	1954.8348	74.0949	26.3829	0.0000
D(EU SLOPE RF)	1286.6762	34.9918	36.7707	0.0000
D(US 3M RF)	-757.8916	244.9635	-3.0939	0.0020
D(US SLOPE RF)	-230.2570	23.5987	-9.7572	0.0000
D(P?)*RR2?	0.3409	0.0520	6.5516	0.0000
D(P?)*RR3?	-0.0526	0.0482	-1.0911	0.2753
D(P?)*RR4?	-0.3994	0.0649	-6.1561	0.0000
D(P?)*RR5?	-4.2718	10.2467	-0.4169	0.6768
D(P?)*RR6?	-119.4811	615.9346	-0.1940	0.8462
D(VOL?)*RR2?	-0.5676	0.0323	-17.5557	0.0000
D(VOL?)*RR3?	-0.6772	0.0330	-20.4925	0.0000
D(VOL?)*RR4?	-0.5371	0.0396	-13.5633	0.0000
D(VOL?)*RR5?	-0.9220	0.3240	-2.8457	0.0045
D(VOL?)*RR6?	0.6921	8.0223	0.0863	0.9313
R-squared	0.0569		F-statistic	12.8645
Adjusted R-squared	0.0524		Prob(F-statistic)	0.0000
Durbin-Watson stat	2.0863			

Table 7: EU Regression in First Differences with Rating Effects

Dependent Variable: D(E?)				
Method: GLS (Cross Section Weights)				
Included observations: 411				
Total panel (unbalanced) observations 6602				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(P?)	-0.4231	0.0845	-5.0102	0.0000
D(MV?)	0.0000	0.0000	0.1234	0.9018
D(EPS?)	-3.4484	0.6320	-5.4564	0.0000
D(PE?)	-0.0275	0.0081	-3.3721	0.0008
D(TO?)	0.0000	0.0000	0.0954	0.9240
D(VOL?)	0.1177	0.0450	2.6174	0.0089
D(EU 3M RF)	-491.4339	154.8932	-3.1727	0.0015
D(EU SLOPE RF)	-495.5093	94.8919	-5.2218	0.0000
D(US 3M RF)	-776.0917	114.4960	-6.7783	0.0000
D(US SLOPE RF)	-580.0520	67.8786	-8.5454	0.0000
R-squared	0.0159		F-statistic	11.8554
Adjusted R-squared	0.0146		Prob(F-statistic)	0.0000
Durbin-Watson stat	2.1699			

Table 8: US Regression Estimated in First Differences

8 Conclusion

This paper has implemented and tested the performance of one reduced type credit derivatives pricing model. Although the theoretical literature on CDS pricing has grown rapidly in the last few years, empirical work and testing of these models is scarce. As far as we know, only four papers have explored the performance of these models (Hoeweling and Vorst (2002), Aunun-Nerin, Cossin, Hricko and Huang (2002), Longstaff, Mihal and Neis (2003) and Zhang (2003)). Other papers have implemented pricing models without analyzing their fit to market data (Skinner and Diaz (2003)).

Despite the simplifying assumptions of the model, which render it tractable and provide clear and intuitive effects for each factor affecting CDS prices, we found that the model does replicate the main market trends. Term structures of yield spreads were calculated on a daily basis for each entity in the sample through a bootstrapping procedure. Special care was taken in the choice of bonds to be included as inputs, making sure they were liquid and had no embedded options. Calculated yield spreads are ranked by rating class as expected and their term structure increases with maturity. The density of default probabilities accurately reflect the implied credit risk from bond spreads. Finally, theoretical CDS spreads reflect the main stylized facts seen in market CDS's and reflect credit risk as implied by credit ratings. In terms of performance, the model systematically underestimates CDS prices. The goodness of fit changes among subsamples with the best fit observed in the US dollar denominated sample with treasury rates as the risk free rate. The worst fitting was for the EU sample with swap rates as the benchmark risk free rate. This last result is opposite to that found by (HV2002), and suggests that treasuries are still the reference risk free in the CDS market.

Evidence suggesting that bond and equity markets are fragmented and provide different sets of information on security issuers motivated the search for the determinants of pricing errors. In particular, we tried to explain these errors with variables related to the equity and financial ratios of firms. We found that earnings per share, stock prices, PE ratios and volatility of stock prices help explain part of the miss-pricing and could therefore be useful in pricing CDS. The slope of the yield curve also helped accounting for miss-pricing. This reflects the relevance of business cycle effects on credit risk dynamics. All this emphasizes the need of going beyond debt markets when evaluating and pricing credit risk.

Although the model is a good starting point when pricing and thinking about credit risk, pricing errors make evident the need for further research both theoretical and empirical. The precise effect of non-debt variables and their incorporation into an implementable model of CDS pricing remains a promising field of research.

9 References

ALESSANDRINI, Fabio, Credit Risk, Interest risk and the Business Cycle, Mmoire de diplme, DEEP, Universit de Lausanne, 1998.

ALTMAN, Edward, Kishore Vellore, "Almost Everything You Wanted to Know About Recoveries on Defaulted Bonds", Financial Analysts Journal, Nov/Dec 1996.

AUNON-NERIN, Daniel, Didier Cossin, Tomas Hricko, Zhijiang Huang, Exploring for the determinants of Credit Risk in Credit Default Swap Transaction Data: Is fixed income markets' information sufficient to evaluate credit risk?, Fame Research paper, Dec. 2002.

BALTAGI Badi H., Econometric Analysis of Panel Data, Wiley Finance, 1996.

BLACK Fischer, Myron Scholes, "The Pricing of Options and Corporate Liabilities", Journal of Political Economy, 81 May-June 1973.

BRENNAN Michael J., Eduardo S. Schwartz, Conditional Predictions of Bond Prices and Returns, The Journal of Finance, Vol. 35, No. 2, December 28-30, 1979.

COLLIN-DUFRESNE Pierre, Robert S. Goldstein and J. Spencer Martin, The Determinants of Credit Spread Changes, The Journal of Finance, Vol. 56, No. 6, December 2001.

COSSIN Didier, Hugues Pirotte, Advanced Credit Risk analysis, John Wiley and Sons Ltd, London, New York, 2000.

COUDERC, F., O. Renault, O. Scaillet, "Credit Risk Dynamics: Forecasting Rating Transition Matrices", EIR Third Annual Conference, Geneva, September 2003.

DAS Sanjiv, Sundaram Rangarajan, Sundaresan Suresh, A Simple Unified Model for Pricing Derivative Securities with equity, interest-rate, default and liquidity risk, Working paper 2002.

DAS, Sanjiv Ranjan; Sundaram, Rangarajan K, A Discrete-Time Approach to Arbitrage-Free Pricing of Credit, New York University, Salomon Center Working Paper: S/99/21. p 23. April 1999.

DUFFIE Darrel, Ken Singleton, Econometric Modeling of Term Structures of Defaultable Bonds, 1994.

DUFFIE Darrel, Ken Singleton, Modeling Term Structures of Defaultable Bonds, Review of Financial Studies, vol. 12 (1999), pp. 687-720.

DUFFEE, Gregory, Estimating the Price of Default Risk, The Review of Financial Studies, Vol. 12, issue 1, 1999.

DUFFEE, Gregory, The Relation between Treasury Yields and Corprate Bond Yield Spreads, Journal of Finance, v53, 1998, pp.2225-2242.

FRANCIS, Jack Clark, Joyce A. Frost, J. Gregg Whittaker ed., The Handbook of Credit Derivatives, McGrawhill, 1999.

HOUWELING, Patrick, Jaap Hoek, Frank Kleibergen, The Joint Estimation of Term Structures and Credit Spreads, Journal of Empirical finance, 8, July 2001.

HOUWELING, Patrick, Ton Vorst, An empirical comparison of default swap pricing models, Working paper, Erasmus University, Rotterdam, June 2002.

HULL, John, “Options, Futures and other Derivatives”, Prentice Hall, 2000.

HULL, John, Alan White, Valuing credit default Swaps I: No counterparty Default Risk, Journal of Derivatives, 2000.

HULL, John, Alan White. Valuing credit default Swaps II: Modeling Default Correlations, Journal of Derivatives, 2001.

JARROW, Robert, Stuart Turnbull, Pricing Derivatives on financial securities subject to credit risk., Journal of Finance, 50:53-85, 1995.

JARROW, Robert, David Lando, Stuart Turnbull, A Markov Model for the Term Structure of Credit Risk Spreads, The Review of Financial Studies, Vol. 10, issue 2, 1997.

LELAND, H.E, “Risky Debt, Bond Covenants and Optimal Capital Structure”, Journal of Finance, 49, 1994.

LELAND, H.E, K.B. Toft, “Optimal Capital Structure, endogenous Bankruptcy and the Term Structure of Credit Spreads”, Journal of Finance, 50, 1996.

LONGSTAFF, Francis A, Sanjay Mihal, Eric Neis, "The Credit Default Swap Market: Is Credit Protection Priced Correctly?", Working Paper, UCLA, 2003.

LONGSTAFF, Francis A, Schwartz, Eduardo S., A Simple Approach to Valuing Risky Fixed and Floating Rate Debt, Journal of Finance Vol. 50 (3). p 789-819. July 1995.

MADAL, Dilip, Haluk Unal, "Pricing the Risk of Default", Working Paper, The Wharton School, 1996.

MARTEAU Didier, David Dehache, Les Produits Derivs de crdit, Eska, Paris, 2001.

MERTON, Robert, "On the Pricing of Corporate Debt: the risk structure of interest rates", Journal of Finance, 29, 1974.

PERRAUDIN, William, Alex Taylor, "Liquidity and Bond Market Spreads", Working Paper, University of Cambridge, 2003.

SCHONBUCHER, Philipp, Credit Derivatives Pricing Models: Models, Pricing and Implementation, Wiley Finance, 2003.

SCHONBUCHER, Philipp J., A Tree Implementation of a credit spread model for credit derivatives, June 1999.

SKINNER Frank, Antonio Diaz, An Empirical Study of Credit Default Swaps, ISMA Center, The University of Reading, January 2003.

ZHANG, Franc, "What did the Credit Market Expect of Argentina Default? Evidence from Default Swap Data", Working Paper, Federal Reserve, 2003.

Table 9: US Sample

Sector	Company	Rating	Nb of Bonds	Nb of CDS Quotes
Autos	Fiat	BB3	5	310
	Ford	BB1	4	304
	General Motors	BBB1	4	294
	Renault	BBB	4	162
	Volkswagen	A2	4	175
	Volvo	A3	4	174
Basics	Bayer	A2	6	403
	Saint Gobain	A2	4	178
	Lafarge	BBB2	5	369
	Linde	BBB1	4	428
Consumer	Accor	BB2	4	442
	Ahold	B	3	460
	Carrefour	A1	4	453
	LVMH	BBB1	5	242
	Metro	BBB2	4	453
Energy	EDF	AA3	4	91
	Endesa	A3	4	367
	Enel	A1	4	365
	Iberdrola	A2	5	367
	RWE	A1	4	368
	National Grid	BBB1	4	167
	Repsol	BB2	4	367
	Suez	A3	4	177
	Vattenfal	A3	4	175
	Vivendi E	BBB2	5	176
	Total Final ELF	AA2	4	345
Food	Nestle	AAA	5	324
	Parmalat	BBB3	6	5
	Unilever	A1	4	150
	BAT	BBB1	4	271
	Gallaher	BBB3	4	265
	Imperial Tobacco	BBB3	5	269

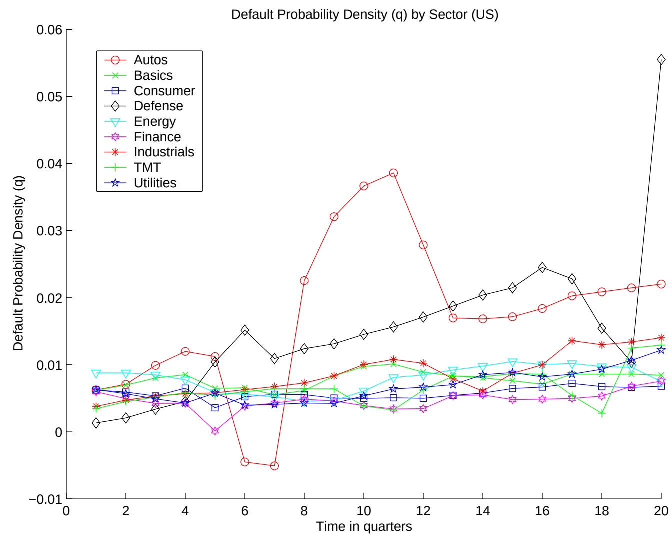
Sector	Company	Rating	Nb of Bonds	Nb of CDS Quotes
Finance	Abbey	AA3	4	159
	ABN	AA3	4	237
	BCP	AA2	4	161
	BES	A1	4	158
	BSCH	A2	5	271
	Barclay	AA2	4	163
	BBVA	AA3	5	263
	BNP	AA3	8	255
	Commerzbank	BBB1	7	262
	Crdit Agricole	AA3	8	156
	Crdit Lyonnais	AA3	4	250
	Crdit Suisse	A1	5	100
	Deutsche Bank	A2	6	260
	Dresdner	A2	7	259
	Bank of Scotland	AA2	4	99
	Hypos-Vereinsbank	AA3	8	260
	HSBC	AA1	4	30
	ING	A2	6	158
	Intesa	A1	4	256
	RBOS	AA2	4	458
	IMI	A1	6	237
	Socit Gnrale	AA3	8	167
Insurance	Allianz	AA3	4	270
TMT	Deutsche Telecom	BBB2	5	486
	France Telecom	BBB3	6	486
	KPN	BBB1	4	485
	Olivetti	BBB2	4	483
	Telia	A2	4	188
	Tele Danemark	BBB1	4	187
	Telefonica	A3	4	479
	Vodafone	A2	4	189
	Alcatel	B1	4	481
TOTAL			300	

Table 10: EU Sample

Sector	Company	Rating	Nb of Bonds	Nb of CDS Quotes
Autos	Ford	BBB1	6	65
Basics	Georgia Pacific	BB2	4	335
	International Paper	BBB2	12	429
	Mead Westvaco	BBB2	5	429
	Sonoco Product	A3	4	67
	Weyerhaeuser	BBB2	8	65
	Air Products	A2	6	428
	Eastman Chemicals	BBB2	4	65
	Praxair	A3	4	65
Consumer	Eastman Kodak	BBB2	4	405
	General Mills	BBB2	8	320
	Kraft Foods	A3	4	328
	Altria Group	BBB2	7	424
	Procter & Gamble	AA3	6	409
	Sears Roebuck	BBB2	4	420
	Wal - Mart	AA2	4	410
	Lowe's	A3	8	48
	Albertson's	BBB1	10	416
	Safeway	BBB2	4	56
Defense	Boeing	A3	5	418
	Northrop Grumm	BBB3	5	133
Energy	Anadarko Perto	BBB1	4	406
	Devon Energy	BBB2	5	319
	Conoco Phillip	A3	5	416
	Marathon Oil	BBB1	5	128
	Occidental Petroleum	BBB2	4	416
	Unocal	BBB2	9	423
	Valero Energy	BB3	8	328
	Ashland	BBB2	7	54

Sector	Company	Rating	Nb of Bonds	Nb of CDS Quotes
Finance	American Express	A1	5	434
	CIT	A2	8	434
	Houshold Fina	A2	4	434
	AIG	AAA	4	345
	Bank of America	AA3	6	434
	Bank One	A2	4	434
	CitiGroup	AA2	10	434
	JP Morgan	A1	4	434
	Washington Mutual	BBB1	5	351
	Wells Fargo	AA3	4	434
	Bear Stearns	A2	5	434
	Lehman Brothers	A2	4	434
	Merrill Lynch	A1	5	434
Industrials	Deere	A3	4	410
	Tyco	BB1	4	413
	Cat	A2	5	9
TMT	Bell South	A1	4	430
	Century Tel	BBB2	11	254
	IBM	A1	4	443
	Wal Disney	BBB1	4	443
Utilities	American Electric	BBB1	5	413
	Constelation	A2	7	65
	Cinergy	A3	4	65
	Con Edison NY	AAA	4	427
	Dominion Resourses	BBB1	7	428
	Duke Capital	BBB1	4	65
	Energy East	BBB1	4	29
	Exelon	BBB1	4	65
	First Energy	BBB2	4	339
	Nisource	BBB3	6	339
	Progress Energy	BBB1	4	30
Total			326	

A Yield Spread, q and model CDS Graphs



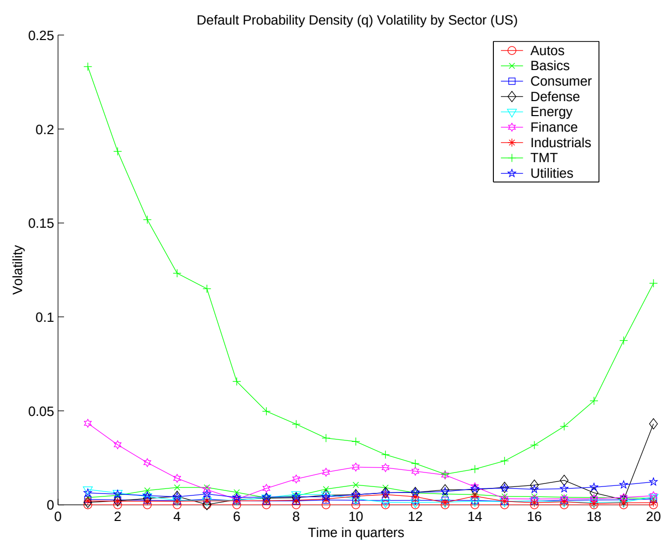


Figure 17: US Default Probability Density (q), and Volatility of q by Sector (treasury rates)

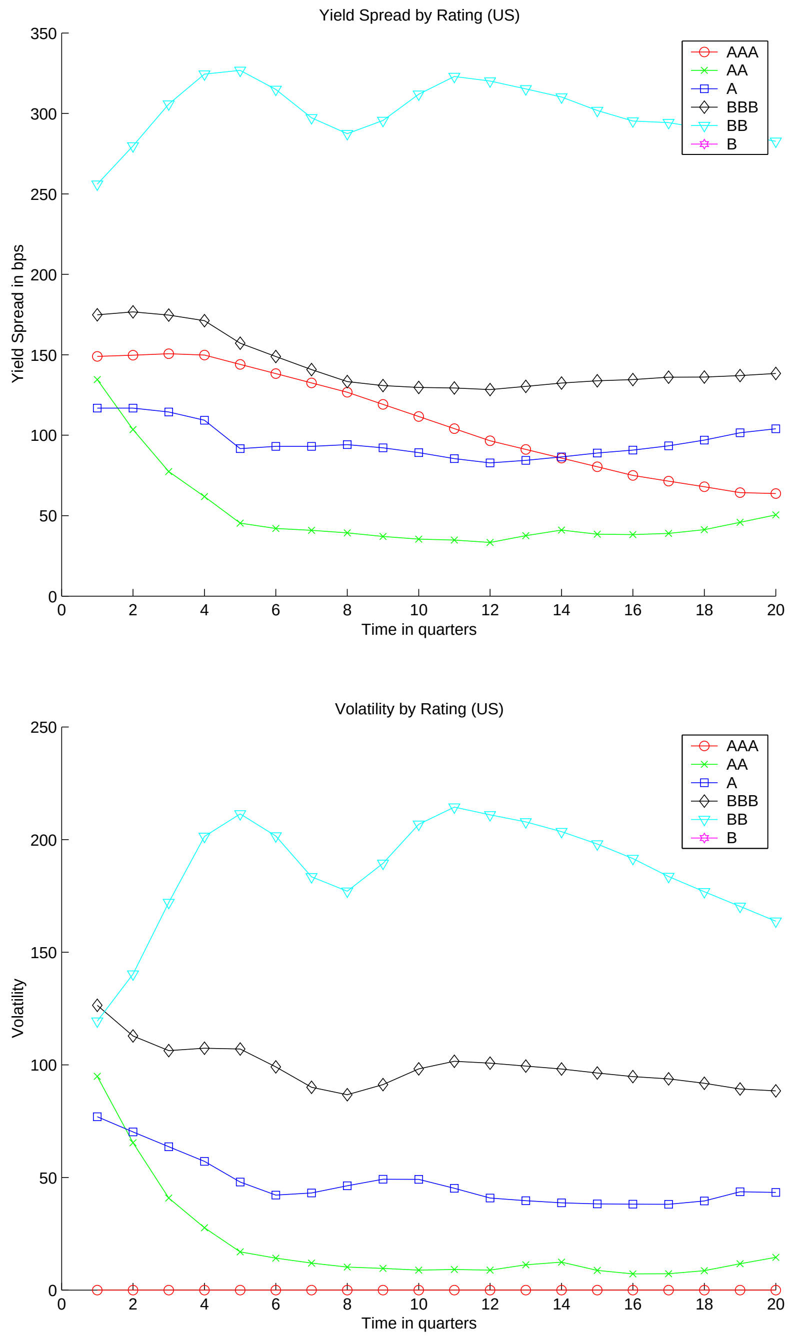


Figure 18: US Yield Spread and Volatility of Yield Spread by Rating (swap rates)

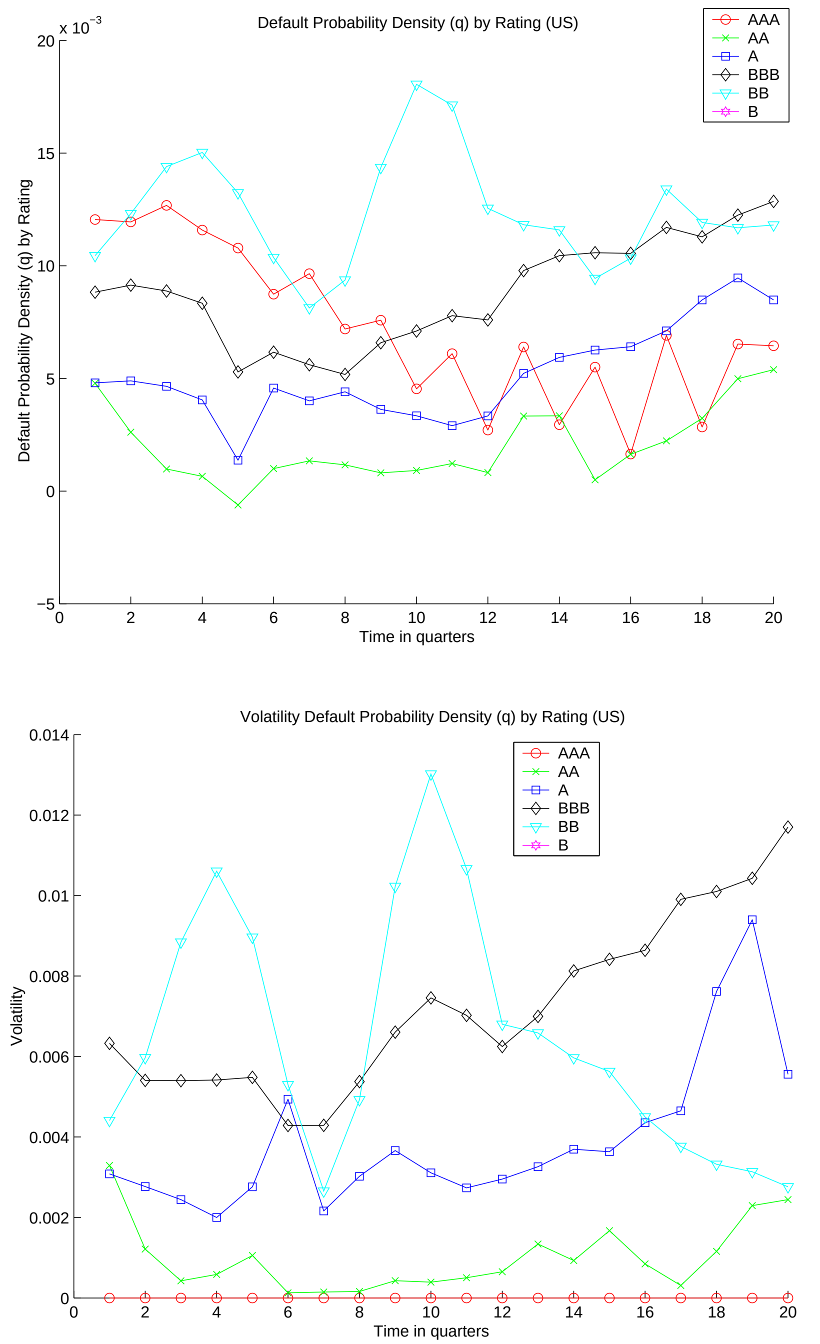
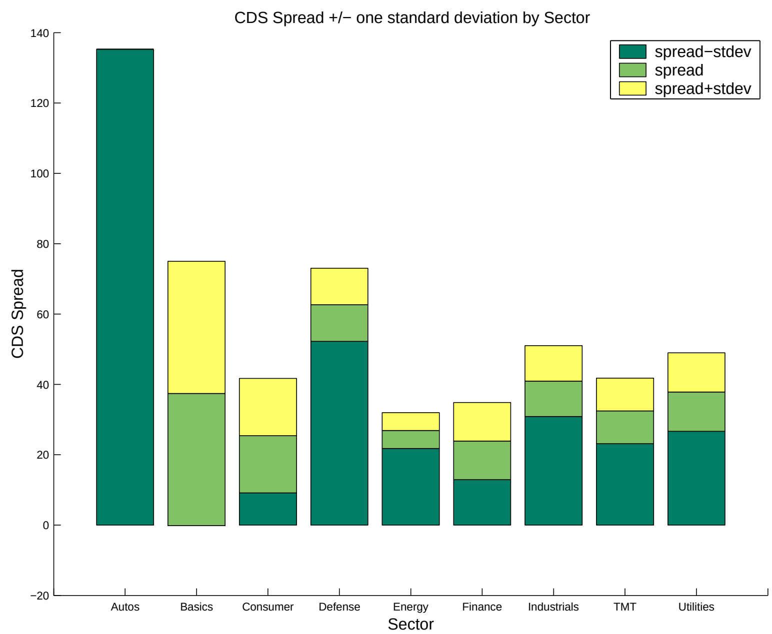


Figure 19: US Default Probability Density (q), and Volatility of q by Rating (swap rates)



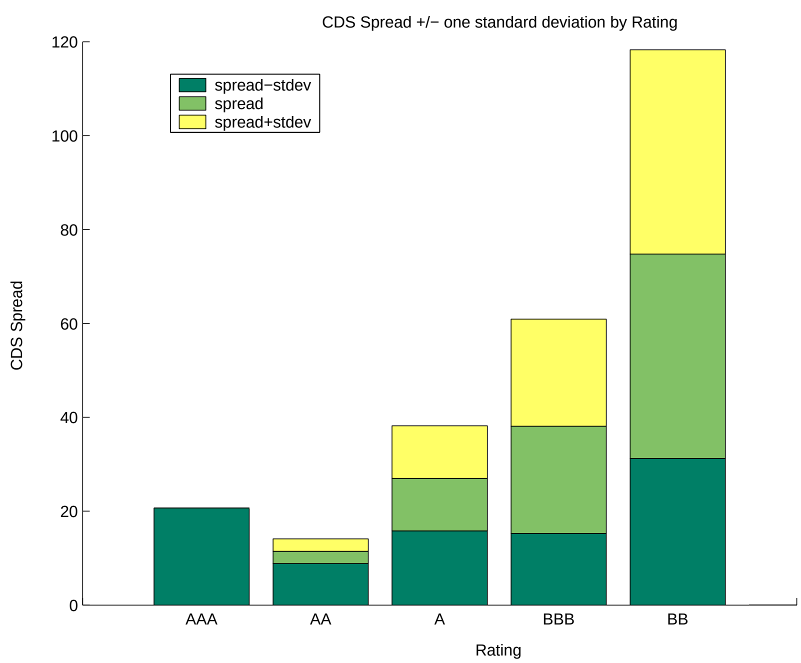


Figure 20: US Model CDS Spreads by Sector and Rating (swap rates)

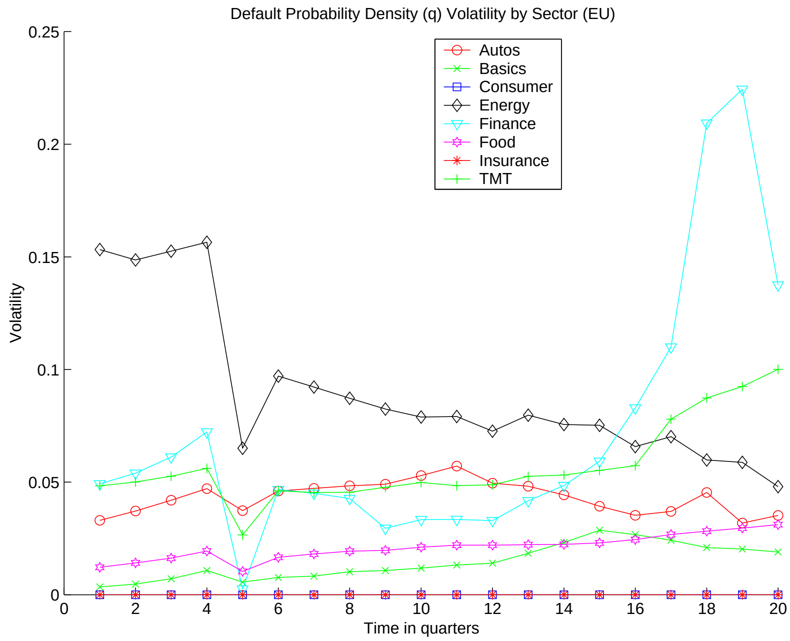


Figure 21: EU Volatility of q by Sector (treasury rates)

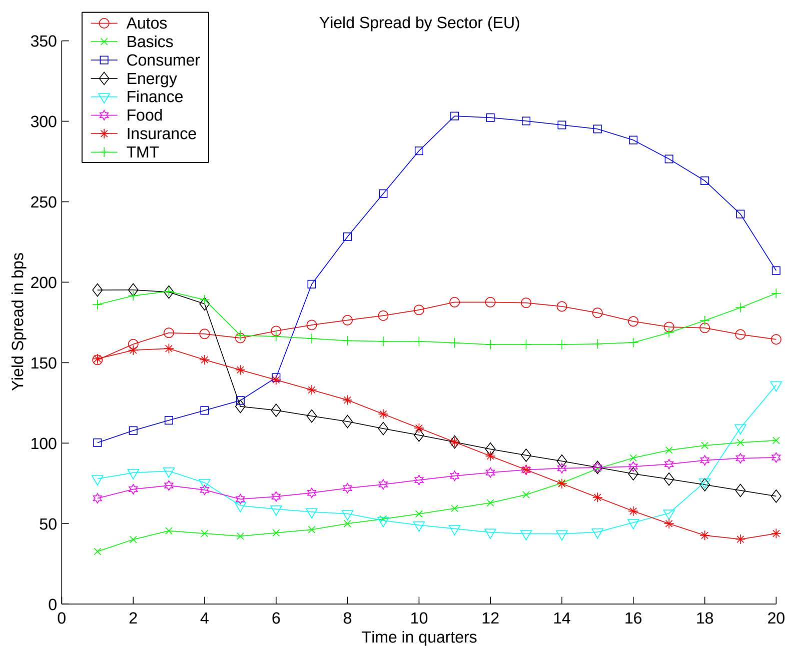


Figure 22: EU Yield Spread by Sector (swap rates)

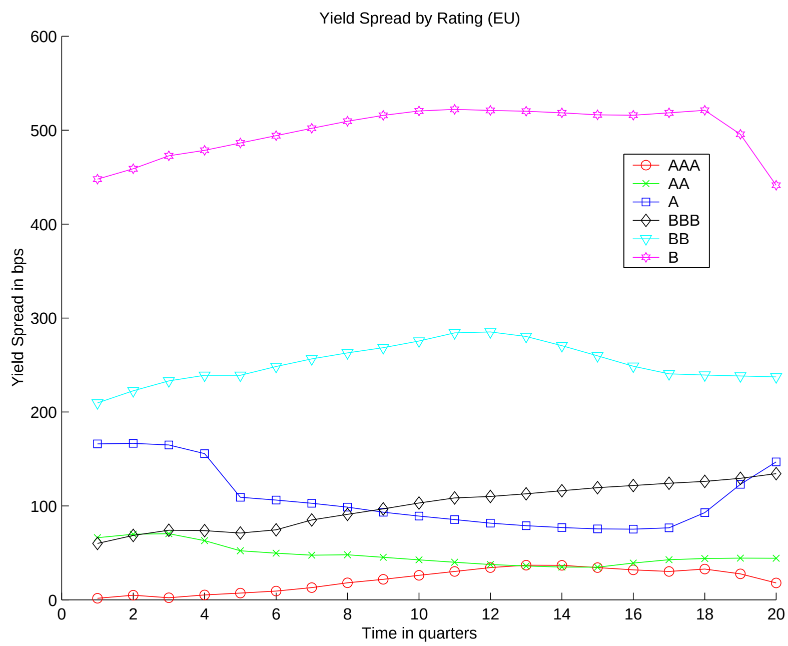


Figure 23: EU Yield Spread by Rating (swap rates)

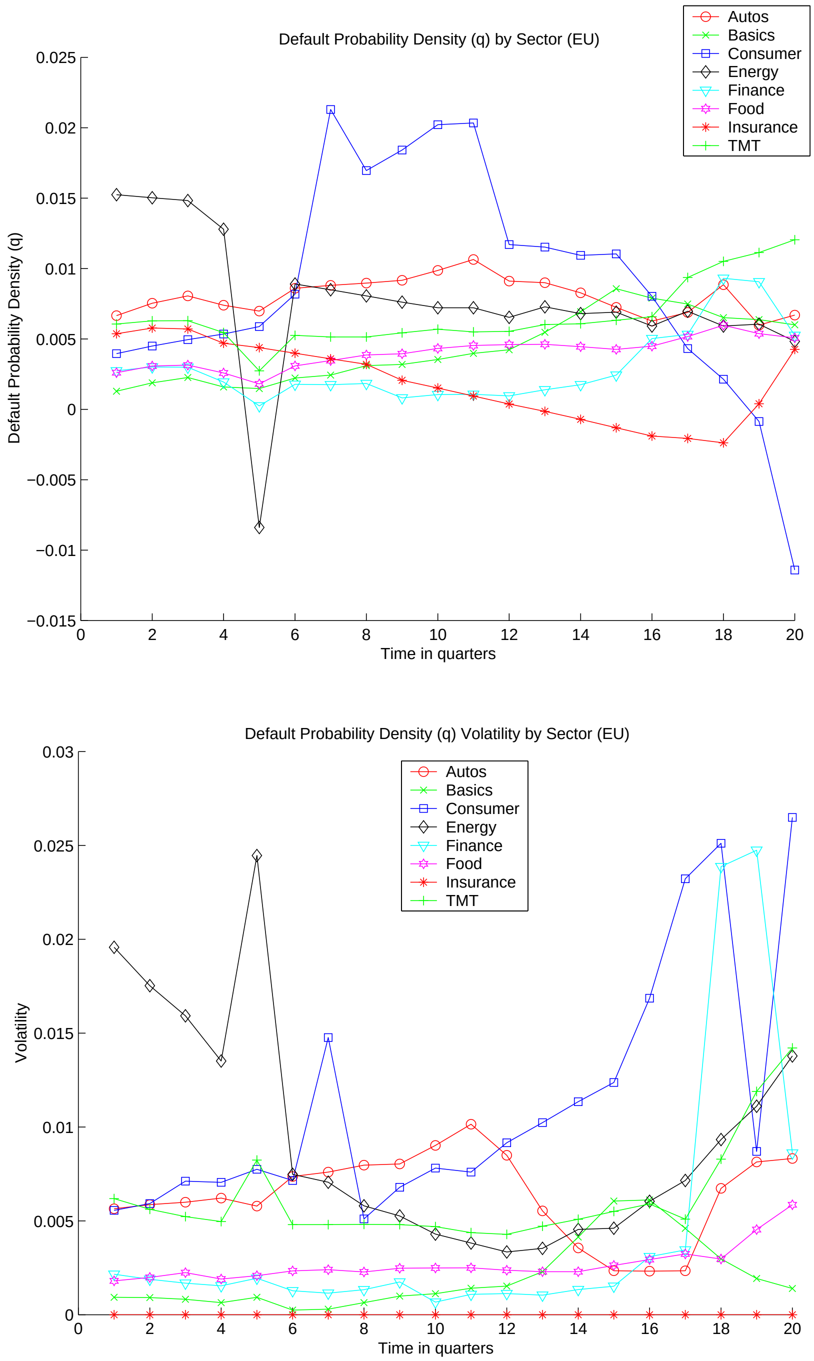


Figure 24: EU Default Probability Density (q), and Volatility of q by Sector (swap rates)

B Regressions

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Dependent Variable: E?				
Method: GLS (Cross Section Weights)				
Included observations: 447				
Total panel (unbalanced) observations 6602				
Convergence achieved after 10 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Cross sections without valid observations dropped				
P?	-0.4368	0.0862	-5.0654	0.0000
MV?	0.0000	0.0000	0.3345	0.7380
EPS?	-2.8275	0.6041	-4.6804	0.0000
PE?	-0.0299	0.0082	-3.6321	0.0003
TO?	0.0000	0.0000	0.5788	0.5627
VOL?	0.1242	0.0448	2.7695	0.0056
EU 3M RF	-204.0358	177.5683	-1.1491	0.2506
EU SLOPE RF	-402.5259	97.7004	-4.1200	0.0000
US 3M RF	-681.6952	123.4579	-5.5217	0.0000
US SLOPE RF	-540.6191	65.9223	-8.2009	0.0000
AR(1)	0.9711	0.0050	195.2540	0.0000
Fixed Effects				
R-squared	0.9728		F-statistic	23444.3959
Adjusted R-squared	0.9726		Prob(F-statistic)	0.0000
Durbin-Watson stat	2.1505			

Table 11: US Regression with AR(1) term

Dependent Variable: E?				
Method: GLS (Cross Section Weights)				
Included observations: 490				
Total panel (unbalanced) observations 4074				
Convergence not achieved after 100 iteration(s)				
White Heteroskedasticity-Consistent Standard Errors & Covariance				
Cross sections without valid observations dropped				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
P?	-0.1609	0.0371	-4.3306	0.0000
MV?	-0.0008	0.0001	-16.2392	0.0000
EPS?	-1.2333	0.1497	-8.2408	0.0000
PE?	-0.0949	0.0264	-3.5957	0.0003
TO?	0.0000	0.0000	4.4893	0.0000
VOL?	0.6388	0.0289	22.1091	0.0000
EU 3M RF	2250.4253	71.0093	31.6920	0.0000
EU SLOPE RF	1339.2073	30.3777	44.0852	0.0000
US 3M RF	-594.7559	163.6447	-3.6344	0.0003
US SLOPE RF	-301.0903	20.5333	-14.6635	0.0000
P?*RR2?	0.3039	0.0464	6.5458	0.0000
P?*RR3?	-0.0887	0.0382	-2.3214	0.0203
P?*RR4?	-0.3212	0.0543	-5.9109	0.0000
P?*RR5?	3.4093	9.8525	0.3460	0.7293
P?*RR6?	-72.0741	464.4360	-0.1552	0.8767
VOL?*RR2?	-0.5446	0.0295	-18.4531	0.0000
VOL?*RR3?	-0.6625	0.0293	-22.6309	0.0000
VOL?*RR4?	-0.5096	0.0364	-13.9916	0.0000
VOL?*RR5?	-0.1941	0.2503	-0.7756	0.4380
VOL?*RR6?	0.8344	8.2055	0.1017	0.9190
AR(1)	0.9621	0.0046	208.5184	0.0000
Fixed Effects				
R-squared	0.9787		F-statistic	9250.2996
Adjusted R-squared	0.9785		Prob(F-statistic)	0.0000
Durbin-Watson stat	2.0666			

Table 12: EU Regression with AR(1) term and Rating Effects