CMCDS Premia Implicit in the Term Structure of Corporate CDS Spreads*

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Abstract

Credit default risk for an obligor can be hedged away with either a credit default swap (CDS) contract or the alternative constant maturity credit default swap contract (CMCDS). An economic agent should be indifferent to which instrument is used since both cover the same risk with identical payoffs. On a large universe of obligors we find strong evidence that there is persistent difference in the default hedging premia carried by the two comparable contracts. It appears that, in general, it would have been more profitable to sell CDS and buy CMCDS. In addition, the implied forward CDS rates are unbiased estimates of the future spot CDS rates.

Keywords: Constant Maturity Credit Default Swaps, Forward Credit Spreads, Convexity Adjustment, Forward Rate Unbiasedness Hypothesis

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Abstract

Credit default risk for an obligor can be hedged away with either a credit default swap (CDS) contract or the alternative constant maturity credit default swap contract (CMCDS). An economic agent should be indifferent to which instrument is used since both cover the same risk with identical payoffs. On a large universe of obligors we find strong evidence that there is persistent difference in the default hedging premia carried by the two comparable contracts. It appears that, in general, it would have been more profitable to sell CDS and buy CMCDS. In addition, the implied forward CDS rates are unbiased estimates of the future spot CDS rates.

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Credit default swaps (CDS) have been instrumental in the increased trading in structured credit financial markets until the beginning of 2007 when the sub-prime crisis has started to develop. The British Bankers Association reported an exponential evolution of the total notional amount traded on global credit derivatives reaching $20 trillion by the end of 2006, (BBA(2006)). The single-name credit default swaps volume as a percentage of total credit derivatives volume was 33% in 2006, being by far the most important instrument in credit markets.

Following the analogy with the constant maturity swap (CMS) contract, another traded credit derivative is the constant maturity credit default swap (CMCDS). In such a contract the buyer pays a premium (spread) in exchange for protection; while in a CDS the spread is fixed, in a CMCDS the spread is floating and calculated according to an indexing mechanism. In particular, the spread is set equal to the prevailing reference CDS spread at each reset date times a factor known as the participation rate (PR). The reference constant maturity CDS spread does not have to have the same nominal maturity as the maturity of the contract itself and hence one could trade a 5-year CMCDS referenced by the 3-year or 7-year CDS spread.

The CMCDS instrument allows economic agents to take views on the future shape of the CDS curve. Moreover, combining a CDS and a CMCDS with reference to the same obligor leads to the complete elimination of credit default risk for that obligor, allowing investors to isolate spread risk (i.e. the risk of changes in the premium not related to an actual credit event) and to hedge default risk. In addition, CMCDS are useful for protection sellers to hedge against spread widening risk. Unwanted volatility may lead to accrual accounting and this is unacceptable in practice for obvious reasons. Thus, CMCDS with their floating credit spread, can be the solution. The liquidity of this contract is largely unknown but the above comparisons guarantee its survival and further development alongside the single-name CDS contract.

Duffie (1999) and Hull and White (2000) clearly point out that the credit default swap spread for a corporate should be very close to the spread of a par yield bond issued by the reference entity over the par yield risk-free rate to avoid arbitrage between the cash and the synthetic markets. The validity of the theoretical equivalence of CDS spreads and bond yield spreads has been tested in Blanco, Brennan, and Marsh (2005) where on a dataset of 33 U.S. and European investment-grade firms they find that this parity relation holds on average over time for most companies, suggesting that the bond and CDS markets may price credit risk equally. Deviation from parity are found only for three European firms, for which CDS prices are substantially higher than credit spreads for long periods of time. These cases are attributed to a combination of both imperfections in the contract specification of CDSs and measurement errors in computing the credit spread. For all the other companies they find only short-lived deviations from parity in the sample. A possible explanation is that the CDS market leads the bond market in determining the price of credit risk.

The relationship between credit default swaps and corporate spreads is investigated also in Longstaff, Mithal, and Neis (2005). They use the information in credit default swaps to obtain direct measures of the size of the default and nondefault components in corporate spreads. From CDS premia for 5-year contracts and the corresponding corporate bond prices for 68 firms traded during the period March 2001–October 2002, they find that the default component represents the majority of corporate spreads, accounting for more than 50% of the total corporate spread, even for the highest-rated investment-grade firms. Norden and Weber (2004) apply traditional event study methodology to show that CDS markets anticipate rating downgrades and that anticipation starts approximately 60-90 days before the announcement day. This result is consistent with Hull, Predescu, and White (2004) who confirm that reviews for downgrade contain also significant information. Pan and Singleton (2008) use a full term structure of sovereign CDS spreads to derive the market-implied default intensity and also the implicit loss rate. They argue that a lognormal process for the default intensity (as opposed to a square-root process used in Longstaff, Mithal, and Neis, 2005) is capable of capturing most of the variation in the term structure of spreads.

An economic agent should not have a preference *a priori* as to which credit instrument to use to protect against default risk, everything else being equal. What if, however, supply and demand conditions create consistently an imbalanced market where it is more profitable to pay a floating premium spread[1]? This paper provides compelling evidence that this may be the case in credit derivatives markets. In a nutshell we show that it is possible to have a CDS curve built from no-arbitrage prices and at the same time have fair CMCDS prices that will be in arbitrage vis-a-vis the corresponding CDS regarding credit risk.

The applied literature on CDS so far has focused either on issues like the validity of the theoretical equivalence of CDS prices and credit bond spreads or the determinants of credit default swap changes[2]. For any given name, the possible discrepancy between credit risk as traded with CDS or CMCDS becomes evident only with time. CMCDS prices are traded over the counter and the data necessary to extract the market's behavioral masterprint is almost impossible to obtain. Nonetheless, in order to facilitate the investigation, we determine the fair CMCDS prices for a large database of corporates for which market CDS premia is available. The main ingredient used for pricing credit derivatives is the survival probability curve and this is bootstrapped first from the observed CDS quotes. To this end both nonparametric (e.g. piecewise constant hazard rates) and parametric (Nelson-Siegel interpolation and a method driven by an OU process for the hazard rates)

[1]This situation appeared before in interest rate markets as documented by Brooks (2000) who showed *ex post* that on the interest rate swap market in the 1990s it was profitable net to pay floating and receive fixed.

[2]The literature on this particular aspect includes Tang and Yan (2008); Ericsson, Jacobs, and Oviedo (2008); Zhang, Zhou, and Zhu (2006) and Cao, Yu, and Zhong (2006).

methods common in practice are implemented. On a large universe of obligors one should expect *ex ante* that there is no difference which contract is used for hedging default risk. Nevertheless, we identify, *ex post*, the statistical credit arbitrage that had been available between 2001 and 2006, in terms of the number of obligors in relative arbitrage, size of profits that could have been made and the timing of the opportunities.

Our work differs from Pan and Singleton (2008) where the focus was on sovereign credit risk and from Blanco, Brennan, and Marsh (2005) and Longstaff, Mithal, and Neis (2005), where the comparison was made between the synthetic and cash credit markets, in that we investigate arbitrage between two synthetic credit markets. In addition, our sample of corporate reference entities is larger than used previously in the literature, with market panel data for approximately 200 obligors and it covers investment grade and non-investment grade companies. Last but not least, given that forward credit default swap curves are calibrated as an intermediary step to determine the CMCDS fair price, we test the forward unbiasedness hypothesis over the period covered in our study. Our results indicate that the forward CDS rates are unbiased estimators of spot CDS rates and that convexity adjustment plays an important role for calibration of CMCDS.

The remainder of this paper is organized as follows. The next section describes the pricing of CDS and CMCDS as it is done commonly in the industry, discussing also the convexity adjustment for the latter contract. The focus here is not on comparing the latest credit pricing models published in the literature but on employing robust and varied models employed by the main players in the credit markets to reconstruct the industry fair price for CMCDS that could have been quoted from the single-name market information on any given day during the period of our study. The dataset used for calibration and some individual examples regarding calibration issues are shown in section III. The results of the statistical arbitrage analysis based on a type of buy and hold trading strategy and also on a dynamic day by day investment are reported in section III. In section IV we test the forward unbiasedness hypothesis and the final section concludes.

I Market Models for CDS and CMCDS Pricing

In this section we describe briefly how premia for CDS and CMCDS contracts could be derived. The survival probabilities, that are the key for pricing in credit markets, are inferred from the market CDS spreads and subsequently used to determine the participation rate driving the CMCDS premium.

A The Pricing Framework for CDS and CMCDS

There is already an impressive and voluminous literature on the pricing of credit risk, spanned by the structural models class initiated by Merton (1974) and Black and Cox (1976) and reduced form framework described by Jarrow and Turnbull (1995); Jarrow, Turnbull, and Lando (1997) and Duffie and Singleton (1999). An advanced formalisation for valuation of single-name credit derivatives is presented in Jamshidian (2004), where the general subfiltration approach of Jeanblanc and Rutkowski (2000) to modelling default risk, containing the Cox-process setting of Lando (1998), is integrated with a numéraire invariant approach.

For valuation Hull and White (2000) is widely applied as a methodology. Consider a CDS contract with periodic premium $S(0,T)$ to be paid at times $s_1 < s_2 < \ldots < s_N = T$ or until default, in exchange for a single protection payment to be made at the default time τ, provided that $\tau \in (s_0, s_N]$. Let θ_t be the risk neutral default probability density at time t, so that the probability of default in $[0,T]$ is $\int_0^T \theta_t \mathrm{d}t$. The probability that no credit event occurs up to time t is $\pi_t = 1 - \int_0^t \theta_u \mathrm{d}u$. Denoting by R the recovery rate upon default, the periodic premium to be paid by the buyer of the CDS when the risk-free rate is constant and equal to r is

$$S(0,T)=\frac{(1-R)\int_0^T \mathrm{e}^{-ru}\theta_u \mathrm{d}u}{\sum_{i=1}^N \Delta(s_i,s_{i-1})\pi_{s_i}\mathrm{e}^{-rs_i}+\int_0^T a_u \mathrm{e}^{-ru}\theta_u \mathrm{d}u} \tag{1}$$

where a_u is the accrual payment at time u. Each term appearing in the summation at the denominator is the discounted present value of the expected payments made at time s_i, provided the reference entity survives until s_i. The second term represents the present value of the accrual payments. The numerator is the expected present value under the risk-neutral measure of the payoff received by the protection buyer.

In practice, one has to approximate somehow the integrals in (1). Moreover, the default intensity is assumed to be driven by a hazard rate λ and an entire discount curve $\{DF(t)\}_{t\geq 0}$ being already available from Libor-Swap rates[3]. Then, as described in Lando (2004) and Cherubini, Luciano, and Vecchiato (2004), assuming a monthly grid $\{u_j\}_j$ for default arriving and that default arrives on average in the middle of the time interval, the CDS premium spread is calculated as

$$S(0,T)=\frac{(1-R)\sum_j DF(u_j)[SP(u_{j-1})-SP(u_j)]}{\sum_{i=1}^N \Delta(s_i,s_{i-1})DF(s_i)\frac{1}{2}[SP(s_{i-1})+SP(s_i)]}. \tag{2}$$

where $SP(t)$ denotes the survival probability for time t.

Here we discuss how to derive a CMCDS on single obligors, given information from CDS markets. A more advanced theoretically pricing framework, similar to the formula for constant maturity swaps in the default free swap market under the Libor market model, is available in Brigo (2005). Closed-form solutions for constant maturity credit default swaps, as well as credit default swaps and credit default swaptions, are derived

[3]A continuum of discount factors is obtained with log-linear interpolation. The discount factor for $t\in[\mathcal{T}_j,\mathcal{T}_{j+1}]$, $DF(t)$ will be given by

$$\log(DF(t))=\frac{\mathcal{T}_{j+1}-t}{\mathcal{T}_{j+1}-\mathcal{T}_j}\log(DF(\mathcal{T}_j))+\frac{t-\mathcal{T}_j}{\mathcal{T}_{j+1}-\mathcal{T}_j}\log(DF(\mathcal{T}_{j+1})).$$

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also in Krekel and Wenzel (2006), where a Libor market model with default risk is used. Further developments on CMCDS pricing can be found in Brigo and Mercurio (2006) and more recently in Li (2007) and Jonsson and Schoutens (2008).

The participation rate (PR), as determined at the inception of the CMCDS contract, has the greatest impact on the magnitude of the premia that will be paid under the terms of this contract and its value is strictly related to the slope of the CDS curve but not to the level. A participation rate not exceeding 100%, reflects the fact that the CDS curve is upward sloping. On the other hand the participation rate can be bigger than 100%, indicating a downward slope for the term structure of CDS spreads. To derive the participation rate, we exploit the fact that since the loss leg from a CMCDS is identical to the loss leg from a CDS on the same obligor and same maturity, the fixed payment legs must be identical too. Hence, when the reference CDS has maturity m,

$$\begin{aligned}\text{PR}\sum_{i=1}^{N}\mathbb{E}_0[S(s_{i-1},s_{i-1}+m)]\Delta(s_i,s_{i-1})DF(s_i)\frac{1}{2}[SP(s_{i-1})+SP(s_i)]\\ = S(0,T)\sum_{i=1}^{N}\Delta(s_i,s_{i-1})DF(s_i)\frac{1}{2}[SP(s_{i-1})+SP(s_i)].\end{aligned}$$

Therefore the formula that will be applied here for all obligors is

$$\text{PR} = \frac{S(0,T)\sum_{i=1}^{N}\Delta(s_i,s_{i-1})DF(s_i)[SP(s_{i-1})+SP(s_i)]}{\sum_{i=1}^{N}\mathbb{E}_0[S(s_{i-1},s_{i-1}+m)]\Delta(s_i,s_{i-1})DF(s_i)[SP(s_{i-1})+SP(s_i)]}. \tag{3}$$

The major issue related to the previous formula is the evaluation of the expected value of future spreads in the denominator. It is clear that, when spreads evolve in a completely deterministic setting, future realised spreads will be completely determined from today's spread curve and thus the expected value equals the corresponding forward spread. However for high volatility names or long maturities a convexity adjustment is required.

A.1 The Forward CDS Spread

A long position in a forward default swap gives a credit protection that is active for a period of time in the future at a premium agreed upon today, but paid only during the active period of the contract. The price for a forward contract for default protection during the time period $(t, t+m)$ is calculated as in Berd (2003):

$$FS(t, t+m) = \frac{S(0, t+m) - \delta(t, t+m) S(0, t)}{1 - \delta(t, t+m)} \tag{4}$$

where

$$\delta(t, t+m) \equiv \frac{\text{RiskyPV01}(0, t)}{\text{RiskyPV01}(0, t+m)}.$$

In practice there is in general a discrepancy between the realised future rate and the implied forward rate. This difference is attributed mainly to a convexity factor.

A.2 The Convexity Adjustment

The convexity adjustment has been investigated in mathematical finance especially in interest rate derivatives pricing (see Pelsser, 2003; Benhamou, 2000, 2002; Henrard, 2005a,b). It plays an important role for CMCDS pricing as discussed also in Li (2007) and Jonsson and Schoutens (2008), and this is expected especially for long maturities and when the volatility is large. Our approach for taking into account a convexity adjustment is to use the default intensity described by the following Ornstein-Uhlenbeck (OU) process

$$\mathrm{d}\lambda_t = (k - \alpha\lambda_t)\mathrm{d}t + \sigma \mathrm{d}B_t. \tag{5}$$

Calamaro and Nassar (2004) derive an approximate formula for the expected value of the future spread, when the default intensity follows (5):

$$\mathbb{E}_0[S(s_i, s_i + m)] \approx FS(s_i, s_i + m) + \frac{1}{2}\sigma^2 C_i[FS(s_i, s_i + m) - S(0, m)] \tag{6}$$

with $C_i = \frac{1-\mathrm{e}^{-\alpha s_i}}{k\alpha}$. Then the participation rate formula can be rewritten as

$$\mathrm{PR} = \frac{S(0,T)}{\overline{FS}(0,T) + \frac{\sigma^2}{2}\frac{C(0,T)}{D(0,T)}} \tag{7}$$

where

$$D(0,T) = \sum_{i=1}^{n} \Delta(s_i, s_{i-1}) DF(s_i) \frac{1}{2}[SP(s_{i-1}) + SP(s_i)]$$

$$C(0,T) = \sum_{i=1}^{n} \Delta(s_i, s_{i-1}) DF(s_i) \frac{1}{2}[SP(s_{i-1}) + SP(s_i)] C_i [FS(s_{i-1}, s_{i-1} + m) - S(0, m)]$$

and $\overline{FS}(0,T)$ is a weighted average of the forward CDS spreads over the reset dates:

$$\overline{FS}(0,T) = \frac{\sum_{i=1}^{n} \Delta(s_i, s_{i-1}) DF(s_i)[SP(s_{i-1}) + SP(s_i)] FS(s_{i-1}, s_{i-1} + m)}{\sum_{i=1}^{n} \Delta(s_i, s_{i-1}) DF(s_i)[SP(s_{i-1}) + SP(s_i)]}.$$

B Extracting Survival Probability Curves

The schedule of fixed payments is quarterly as this is the dominating market standard. The number of quarters fitting into the pricing time grid until maturity T is equal to $k = \left[\frac{n}{3}\right]$, where $[x]$ denotes the integer part of x. It is evident that $k = \frac{n}{3}$ only if $t_v = t_0 \equiv 0$. The first premium is paid at time t_{n-3k+3} (which coincides with t_3 when n is a multiple of 3). A cash flow diagram is reported in Figure 1 for both the standard CDS contract and the CMCDS contract referencing the same entity.

[Figure 1 about here.]

The survival probability curves that are extracted from CDS market spreads are very important for the determination of the price of any other credit derivative. There are three methods underpinning our results that are commonly used in practice to infer survival probabilities from CDS market quotes and which are presented next, see also Brigo and Mercurio (2006) and O'Kane and Turnbull (2003), for more technical details.

B.1 Fitting the CDS Curve Using an OU Process for the Hazard Rate

With stochastic hazard rates the survival probability up to a time t under the risk-neutral measure is given by

$$SP(t) = \mathbb{E}_0 \left[\exp\left(-\int_0^t \lambda_s \mathrm{d}s \right) \right]. \tag{8}$$

When the hazard rate follows an OU process as in (5) the expectation can be derived in closed form (see also Vasicek, 1977; Luciano and Vigna, 2006)

$$\begin{aligned} SP(t) &= \exp[a(t) + b(t)\lambda_0], & (9) \\ a(t) &= -\frac{(b(t)+t)(\alpha k - \frac{\sigma^2}{2})}{\alpha^2} - \frac{\sigma^2}{4\alpha} b(t)^2; \qquad b(t) = \frac{\mathrm{e}^{-\alpha t} - 1}{\alpha}. & (10) \end{aligned}$$

One way to derive this formula is to express the stochastic intensity λ as a function Λ of an affine process X whose dynamics is given by the SDE:

$$\mathrm{d}X_t = f(X_t)\mathrm{d}t + g(X_t)\mathrm{d}\tilde{B}_t$$

where $\tilde{B}$ is a multidimensional Brownian motion and the drift $f(X_t)$ and the covariance matrix $g(X_t)g(X_t)'$ have affine dependence on X_t (see Duffie, Filipović, and Schachermayer, 2003). It is possible to show that that, under technical conditions (see Duffie and

Singleton, 2003), for any $w \in \mathbb{R}$

$$\mathbb{E}_t \left[\mathrm{e}^{\int_t^T -\Lambda(X_u)\mathrm{d}u + wX_T} \right] = \mathrm{e}^{a(T-t)+b(T-t)X_t} \tag{11}$$

where the coefficients $a(\cdot)$ and $b(\cdot)$ satisfy generalized Riccati ODEs. If we assume that the intensity itself is an affine process like in (5), then we can apply (11) with $w = 0$ and $\Lambda(x) = x$. In this case the ODEs can be solved analytically yielding (10).

Note that the condition $SP(0) = 1$ is automatically satisfied. There are four parameters to calibrate, k, α, σ and λ_0, and we follow the standard market practice and estimate the obligor individual parameters by minimising the residual error between the model implied CDS spread values and the values obtained from the CDS market.

B.2 Piecewise Constant Hazard Rates

The survival probabilities can be bootstrapped from eq. (2) when there are sufficient maturities for traded contracts to cover the entire set of time points for which survival probabilities must be calculated. However, this is rarely the case in practice although things may change in this market in the future. With a reduced set of maturities available one common approach advocated by O'Kane and Turnbull (2003) is to assume that the hazard rate curve is piecewise constant. Suppose the CMCDS contract we are interested in is traded at time t_v and there are CDS market spreads for the same reference obligor for maturities $T_1, \ldots, T_M$. Denoting $\lambda_1 = \lambda_{0,T_1}$, $\lambda_i = \lambda_{T_{i-1},T_i}$, $i = 2, \ldots, M$, and $\tau = T - t_v$ the survival function $SP(\tau)$ is then given as

$$\begin{aligned} -\log SP(\tau) = \lambda_1 \tau \mathbb{1}_{[0,T_1)}(\tau) + \sum_{i=1}^{M-2} \left[\sum_{j=1}^{i} (\lambda_j - \lambda_{j+1}) T_j + \lambda_{i+1} \tau \right] \mathbb{1}_{[T_i,T_{i+1})}(\tau) \\ + \left[\sum_{j=1}^{M-1} (\lambda_j - \lambda_{j+1}) T_j + \lambda_{i+1} \tau \right] \mathbb{1}_{[T_{M-1},\infty)}(\tau) \end{aligned} \tag{12}$$

For each maturity expressed in months a numerical searching algorithm is applied to determine λ_i, $i = 1, \ldots, M$.

B.3 Calibration with Nelson-Siegel Interpolation

Another possibility is to consider a deterministic time-varying hazard rate such that $\int_0^t \lambda(s)\mathrm{d}s = \Psi(t)t$. The role of function $\Psi(t)$ is to capture any term structure variation. One of the common choices for function $\Psi(t)$ is the Nelson-Siegel (see Nelson and Siegel, 1987) function[4]

$$\Psi(t) = \alpha_0 + (\alpha_1 + \alpha_2)\left(\frac{1 - \exp(-\frac{t}{\alpha_3})}{\frac{t}{\alpha_3}}\right) - \alpha_2 \exp\left(-\frac{t}{\alpha_3}\right) \tag{13}$$

This function can generate many different curve shapes. The parameter α_0 is the long term mean of the default intensity. Parameter α_1 is the deviation from the mean, with $\alpha_1 > 0$ implying a downward sloping intensity and $\alpha_1 < 0$ implying an upward sloping term structure. In addition the reversion rate toward the long-term mean is negatively related to $\alpha_3 > 0$. The parameter α_2 is responsible for generating humps when it is different from zero. Bluhm, Overbeck, and Wagner (2003) argue against using humps as this may lead to overfitting problems. Here we shall assume that $\alpha_2 = 0$ and estimate $\alpha_0, \alpha_1, \alpha_3$ from CDS spread data using a nonlinear optimization algorithm for a suitable minimization function such as sum of squared errors or sum of absolute errors, see Appendix A for details.

[4]Markit, the leading data provider from which we obtained our data, are using a similar approach based on Nelson-Siegel interpolation to produce theoretical credit curves in the situations where liquidity of data is very low.

II Data Description and Some Examples

A Single Name CDS Data

Our dataset consists of daily single-name composite spreads covering the period January 2001–November 2006 for maturities 6m, 1y, 2y, 3y, 4y, 5y, 7y, 10y, 15y, 20y, 30y downloaded from Markit, the industry standard provider in credit markets. Our period of study includes the Ford and GM rating agency downgrade event in May 2005 but it stops before the current credit and liquidity crisis started. This deliberate cutoff choice is motivated by the fact that the current credit crisis is still ongoing at the time of the analysis and also because the twists and turns in terms of national bank policy making and the interplay between the investment banks as liquidity providers but also as main buyers of securitised credit risk requires a separate case study analysis.

The composite spread is the average spread for an instrument provided to Markit by its contributors after prices and spreads failing the data quality tests have been removed from the sample set. For each day and for each obligor there is also a recovery rate reported that we use later in our analysis. Additional information like sector, rating and country are reported as well[5]. Only the CDS market spreads related to senior tier of debt have been retained for reasons of liquidity.

Our sample of analysis is larger than the one investigated by Blanco, Brennan, and Marsh (2005) and covers more maturities. Sovereign reference entities were not included in our analysis[6] because the mechanics behind price determination, recovery rates and liquidity determinants are different to the credit corporate synthetic market.

Since the CDS prices were followed through according to the quarterly schedule of

[5] Markit only builds composites when there are at least three contributors to each composite. The cleaning process includes testing for stale, flat curves and outlying data. On average Markit rejects approximately 45% of the CDS data received due to failure under any combination of the three criteria above.

[6] An exquisite analysis for sovereign credit default swaps is provided by Pan and Singleton (2008).

payments, we have selected first only those reference entities for which at least one coupon payment was scheduled in 2001. There were 446 obligors remaining after this first filtering. Out of these companies we kept in only those names for which there is data for recovery rates and spreads covering the entire calendar of payments until the end of survey period. This process resulted in 295 companies. The last step was to eliminate the obligors with low liquidity that have only one or two maturities traded or for which there were numerical instability issues when fitting the data with our methods as discussed in section C. This way we selected a sample of 198 companies available on 20th September 2001 and 207 names for our dynamic analysis that started trading at some time during 2001, on which our results are based[7]. Table I describes the cross-classification of the reference entities by the average rating and sectors[8].

[Table I about here.]

B Reference Rate Yield Data

The numerical results presented in section III depend on the calculation of discount factors and implicitly on the proxy used for the risk-free interest rate. While traditionally the government bond yields are the obvious choice, more recently the yield curve build from Libor and swap contracts has been employed as a proxy for the riskless curve. Perhaps the next best proxy would be the general collateral or repo rates as recommended by Duffie (1999) and Houweling and Vorst (2005) but the maturities for these rates are mainly up to one year. This does not fit our style of analysis which needs discounting from much longer maturities.

[7]The total number of companies vary a little bit across the methods applied. This was due to not counting companies that had numerical calibration problems for the method considered. The largest number of companies in our sample, on 20th September 2001, was 198.

[8]Our sample excludes the obligors classified as Government.

Sundaresan (1991) pointed out that swap rates have credit premia embedded and moreover there is counterparty risk, although Duffie and Huang (1996) indicate that this is only about one or two basis points. More elaborated discussion on this matter is presented in McCauley (2002) and Collin-Dufresne and Solnik (2001).

The discount factor curves are constructed daily from Libor rates with maturities 1 month to 11 months and swap rates with maturities 1y, 2y, 3y, 4y, 5y, 7y, 10y, 20y, 30y. Where necessary the discount factors are determined by log-linear interpolation. Data has been downloaded from Bloomberg and it is widely available for the USD interest rates.

C Some Numerical Examples

In order to calculate the CMCDS premium for a particular corporate we need to a) determine the Libor-swap discount curve and the survival probabilities using one of the methods of subsection B; b) calculate the entire family of CDS forward curves using (4); these are in turn used to c) get from (3) the participation rate that will indicate the magnitude of premium to be paid.

As an illustration of the methods mentioned above to bootstrap the survival probabilities we consider the term structure of CDS spreads on a particular day for three obligors that are representative for the type of numerical problems encountered with this sample: i) a firm with large CDS premia and spreads available for all maturities; ii) a firm with small CDS premia and few maturities available; iii) a firm with small CDS premia and all maturities available. Thus, the following obligors are analysed with respect to data on October 3rd 2005: Abitibi Consol Inc, Microsoft Corp and Tesco PLC (see Table II).

[Table II about here.]

Example 1: Nelson Siegel and Piecewise constant hazard rates methods. The parameter estimates $\widehat{\boldsymbol{\alpha}}$ and $\widehat{\boldsymbol{\alpha}}_w$ for the Nelson Siegel approach and the hazard rate underpinning the piecewise constant model are reported in Table III along with the participation rates for a CMCDS contract with maturity $T = 5$ years where the reference floating spread maturity was $m = 5$ year as well. Microsoft presents more difficulties for fitting due to lack of data for the entire spectrum of maturities. By contrast, the other two companies in this example have more data observations. In Figure 2 the corresponding survival probabilities together with the observed CDS spreads are also plotted. The results shown here indicate that each method may perform better than the alternatives for some reference entity.

[Table III about here.]

[Figure 2 about here.]

Example 2: OU process and Convexity adjustment. Here we assume an OU process for the default intensity and we also evaluate the impact of the convexity adjustment on the participation rate for the same three obligors mentioned above. The calibrated CDS curves and observed CDS market values are plotted in Figure 3. Given the limited number of observations for Microsoft it is not surprising that the fit is quite poor and this results in $\hat{\sigma} = 0$. The estimated parameters and participation rates are reported in Table IV. Moreover the convexity adjustment seems to have a significant impact on the calculation of participation rate for Tesco, with a substantial reduction from 64.82% down to 49.89%.

[Table IV about here.]

[Figure 3 about here.]

The two examples depicted above indicate that the method with piecewise constant hazard rate of O'Kane and Turnbull (2003) is a viable alternative for obligors with reduced liquidity. The downside, however, is that this procedure seems to consistently underestimate the observed CDS curves for more liquid names. Furthermore, this method is much slower computationally than Nelson-Siegel and OU approaches that offer a very good fit when there is sufficient liquidity.

III Arbitrage Evidence in Credit Markets

The CDS and CMCDS contracts are mainly used in the market to hedge the same risk, default risk. A market participant should be indifferent to which instrument to use in relation to a given reference entity. However, the analysis below clearly indicates that the above conjecture was not true for the period 2001–2006. Our investigation is based on a quarterly comparison between the two competing contracts for the most liquid companies in the dataset. First we exemplify the statistical arbitrage by pairing the two contracts in opposite directions. Then we look at what would have been the net cumulative profit and loss for an investor employing this strategy in a static manner, similar to buy and hold. Next we take one step further and analyse the dynamic trading strategy assuming the swap is entered into between 20th September 2001 and the successive reset date, in order to understand whether it would have been more profitable to sell CDS and to buy CMCDS on the same obligor or viceversa. With a large universe of obligors we can explore, *ex post*, the credit arbitrage in terms of the number of obligors in relative arbitrage, size of profits that could have been made and the timing of the opportunities.

A Net Coupon Payment on the Paired Trading Strategy CMCDS–CDS

The relative value arbitrage position can be monitored at each quarterly reset date. For each obligor in our sample the quarterly time series $\{y_i\}_{i=0,\ldots,19}$ is calculated, where

$$y_i = \mathrm{PR}^{t_0} \times S(t_{3i}, t_{3i} + m) - S(t_0, t_0 + T),$$

t_0 is the settlement date and PR^{t_0} is the participation rate on the day t_0. The summary statistics of this time series will indicate whether, overall, the floating leg in CMCDS is above or below the fixed CDS.

For exemplification we consider two obligors with liquid CDS curves, AT&T and Goldman Sachs Gp Inc. The analysis is performed for 20th September 2001 for five year maturity contracts with reference floating CDS rate indexed to five year CDS as well. Table V shows the descriptive statistics for the series y. The two examples show a contrasting situation. AT&T has a positive mean net spread payments and negative median. The plots of the time series y and the empirical densities depicted in Figure 4 suggests that sometimes the payments would have been negative and sometimes positive. Overall the empirical density distribution for this name is roughly balanced around zero. This is the typical situation that is expected to realise under no arbitrage. Goldman Sachs however is quite the opposite. The entire range defined by the 5% quantile and 95% quantile is negative, under all methods. The graph of the spread payment series and the empirical distributions confirm that this name provided a great arbitrage opportunity. The main scope of this paper was to investigate whether the synthetic credit universe of corporate companies looks more like AT&T or there are a sufficient number of names like Goldman Sachs.

[Table V about here.]

[Figure 4 about here.]

B Static Investment Analysis

In this first analysis we compute for all companies in our sample the net cumulative profit/loss (NCPL) that an economic agent would have realized being long a CMCDS and short a CDS, both with same maturity of five years, corresponding to the trading date of 20 September 2001. In other words, for $j = 1, 2, \ldots, 198$ we compute the quantity[9]

$$z_j = \sum_{i=0}^{k-1} \Delta(t_{n-3i}, t_{n-3(i+1)}) \left[\mathrm{PR}_j^{t_v} \times S_j(t_{n-3(i+1)}, t_{n-3(i+1)} + m) - S_j(t_v, t_v + T) \right].$$

where, as usual t_i denotes a payment date, t_v is the trading date and $S_j(u, u+m)$ denotes the CDS spread at time u with maturity term m for company j and $\mathrm{PR}_j^{t_v}$ is the participation rate[10] for company j at time t_v. An illustration of the analysis is given in Figure 1.

Investigating how many companies have negative NCPL with the method based on the Nelson-Siegel interpolation, the result is about 85%, with the method employing the piecewise constant hazard rates approximately 88% while when the participation rate is calculated assuming a OU process for the evolution of the hazard rate, there is more than 90%. For the latter method we can also make the evaluation taking into consideration the convexity adjustment. Although there is a slight reduction the number of companies

[9]Actually we compute the first term of the summation as follows:

$$\begin{aligned} &\Delta(t_3, t_v)\mathbb{1}_{\{t_3 - t_v > 1mth\}} \left[\mathrm{PR}_j^{t_v} \times S_j(t_3, t_3 + m) - S_j(t_v, t_v + T) \right] \\ &+\Delta(t_3, t_v)\mathbb{1}_{\{t_3 - t_v \leq 1mth\}} \left[\mathrm{PR}_j^{t_v} \times S_j(t_6, t_6 + m) - S_j(t_v, t_v + T) \right] \\ &= \Delta(t_3, t_v) \left[\mathrm{PR}_j^{t_v} \left(S_j(t_3, t_3 + m)\mathbb{1}_{\{t_3 - t_v > 1mth\}} + S_j(t_6, t_6 + m)\mathbb{1}_{\{t_3 - t_v \leq 1mth\}} \right) - S_j(t_v, t_v + T) \right] \end{aligned}$$

to take into account the different behavior of the first coupon.

[10]To be precise this should read $\mathrm{PR}_j^{t_v}(m, T)$.

with negative NCPL is still high at 85.5%[11].

[Table VI about here.]

The summary statistics reported in Table VI indicate that, not only on average the NCPL was negative, but its distribution is skewed towards the range of negative values. The plots representing the outcome distribution of z_j and described in Figure 5 for all methods confirm this conclusion. The analysis shows that there has been statistical arbitrage between the CDS market and the CMCDS market overall. The direction of the arbitrage is clearly in favor of selling CDS and buying CMCDS. Nonetheless, as can be seen from figure 5, there were also obligors for which it would have been profitable to buy single-name CDS and sell CMCDS with same maturity.

[Figure 5 about here.]

The number of companies for which arbitrage was possible and the relative size of it are described in Table VII. The numbers are consistent across the methods applied for calculating the CMCDS premium.

[Table VII about here.]

From a portfolio analysis point of view, obligors can be ranked according to their NCPL z_j. Table VIII shows a list of the companies with $z_j < -250$ bps and those with $z_j > 250$ bps for all methods applied here; similarly for the -500 and 500 bps and -1000 and 1000 bps bounds. Appendix B contains the five companies with the largest NCPL z_j, negative and positive.

[11] Note that, following market practice, we also applied a cap on the floating payment and computed

$$z_j^{t_v,\text{cap}} = \sum_{i=0}^{k-1} \Delta(t_{n-3i}, t_{n-3(i+1)}) \Big[\min \left\{ 800bps, \text{PR}_j^{t_v} \times S_j(t_{n-3(i+1)}, t_{n-3(i+1)} + m) \right\} - S_j(t_v, t_v + T) \Big]$$

but the results are exactly the same.

[Table VIII about here.]

The large possible difference in cumulative realised profit and loss is somehow surprising given that both trades cover the same risk of default. The CMCDS financial product is not so much sensitive to the levels of the premia but to the shape of the CDS curve or alternatively the survival curve. According to three methods out of four, the exception being the Nelson-Siegel method, Hasbro Inc is the company with the largest negative NCPL over this static investment with both the contracts initiated on 20/09/2001. On the other hand, with the exception of the piecewise constant hazard rate approach, all methods indicate that Global Marine Inc is the company with maximum positive NCPL. It is perhaps not very surprising to see that every method indicated General Motors and Ford[12] among the five companies with the largest NCPL z_j.

C Dynamic Investment Analysis

The next step of our analysis is to compare the evolution of the two credit protection contracts, CDS and CMCDS, by following the paired trades on a daily basis. Our sample represents only those obligors for which there is data available until the maturity of the five year contract. Hence, for each company j we consider the quantity

$$z_j^{t_v} = \sum_{i=0}^{k-1} \Delta(t_{n-3i}, t_{n-3(i+1)}) \left[\mathrm{PR}_j^{t_v} \times S_j(t_{n-3(i+1)}, t_{n-3(i+1)} + m) - S_j(t_v, t_v + T) \right]$$

for all settlement days t_v between 20th September 2001 and 19 December 2001. For a given company j, we denote by n_j the number of days t_v for which we can determine $z_j^{t_v}$. The yardstick measure for comparison is the average net cumulative profit and loss

[12] It is well known that both names have been the source of the credit spreads widening in 2005. Ford Motor Credit Corp has also been discussed in Blanco, Brennan, and Marsh (2005). In our database there are two reference entities related to Ford, one called Ford Motor Co and another one called Ford Motor Credit Co. Although the latter is a subsidiary of the former the two entities are legally separated vis-a-vis a credit event and as such we have treated them separately.

(ANCPL) payments

$$\bar{z}_j = \frac{1}{n_j} \sum_{t_v=1}^{n_j} z_j^{t_v}.$$

Each paired trade that starts on any given day within the above period is followed through maturity and the profit and loss is calculated and reported comparatively on an average basis.

The descriptive statistics in Table IX suggest again that, overall, there was credit arbitrage during the five year period. The magnitude of the ANCPL varies according to the method applied and it seems that the convexity correction could play a major role. The graphical representation of the ANCPL $\bar{z}_j$ corresponding to the all obligors in the sample illustrated in (Figure 6) confirms the finding of arbitrage and also point out to large opportunities both sides of the trade[13].

[Table IX about here.]

[Figure 6 about here.]

As in the previous section in Table X we report the number of companies at various levels of ANCPL. Our analysis clearly indicates the skewness towards the negative levels in the results pointing out to the existent arbitrage during that period.

[Table X about here.]

In Appendix B we list for each computational method the five companies with the most extreme ANCPL, negative or positive. Once again the two Ford entities and General Motors are listed because of their spreads widening associated with rating downgrade in 2005. Perhaps more surprising is the longer side of the list with companies that would have provided negative ANCPL, three of them Hasbro Inc, J C Penney Co Inc

[13]For the Nelson-Siegel method roughly 85% of sample has negative ANCPL; with the OU hazard rate approach the result is almost the same 87% but when taking convexity adjustment into account only 70% of our sample produces negative ANCPL.

and Pennzoil Quaker St Co with arbitrage of magnitude over 10%. There seems to be little explanation for this empirical finding other than the fact that the implied forward CDS curves at the time when the participation rate is considered were far away from the realised CDS rates later on.

[Table XI about here.]

The existence of arbitrage between CDS and CMCDS markets spanning the same universe of obligors points out to a fundamental question that has not been yet investigated in credit markets: are the forward CDS rates unbiased estimators of future spot CDS rates? If the forward rates are biased then the statistical arbitrage identified here would have an easy explanation. On the other hand if the forward CDS rates are unbiased then the existence of arbitrage is even more valuable and the methods described here can be used to replicate the results with future data.

IV Testing the Forward Unbiasedness Hypothesis for CDS Rates

The forward rate unbiasedness hypothesis (FRUH) postulates that the forward rate is an unbiased predictor of the corresponding future spot rate. This hypothesis has been extensively tested for other asset classes, particularly for exchange rates (see Liu and Maddala, 1992; Maynard, 2003; Westerlund, 2007, among the others), either by regressing the future spot rate, s_{t+k} on a constant and the forward rate, f_t, or by checking for a unit slope in a regression of the spot return $s_{t+k} - s_t$ on the forecasting error, $f_t - s_t$, which are both stationary under the FRUH, (see Froot and Frankel, 1989, for instance). An alternative approach could be testing s_{t+k} and f_t for cointegration like in Baillie and Bollerslev (1989) and Hai, Mark, and Wu (1997).

The approach we follow here is to impose the cointegrating vector implied by the FRUH and then to test for stationarity in the resulting panel of forecasting errors $F_j(t_i, t_i + m|\mathcal{F}_{t_{i-1}}) - S_j(t_i, t_i + m)$ where, consistent with application of section III, t_0 is September 20, 2001, $n = 20$ and m is five years. This means that at each coupon paying day we calculate the forward for a contract entered into the next quarter and maturity five years.

The FRUH cannot be rejected if the panel of forecasting errors is found to be stationary. Since we find strong evidence of cross-section dependence, as suggested by principal component analysis, we use the panel unit root test of Pesaran (2007). Given a panel of data y_{it} ($i = 1, \ldots, N$, $t = 1, \ldots, T$), the test statistic, $\text{CIPS}(N, T) = N^{-1} \sum_{i=1}^{N} t_i(N, T)$, is the mean of the t-ratios of b_i in the OLS estimates in the cross-sectionally augmented Dickey-Fuller regression

$$\Delta y_{it} = a_i' \boldsymbol{d}_t + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it}, \tag{14}$$

where $\bar{y}_t = N^{-1} \sum_{i=1}^{N} y_{it}$, $\Delta \bar{y}_t = N^{-1} \sum_{i=1}^{N} \Delta y_{it} = \bar{y}_t - \bar{y}_{t-1}$. Here $\boldsymbol{d}_t$ represents the deterministic component and we let $\boldsymbol{d}_t = 0$ in the case of no intercept and no trend, $\boldsymbol{d}_t = 1$ in the case of intercept and no trend, and $\boldsymbol{d}_t = (1, t)'$ in the case of individual specific time trends. Cross-section dependence is captured by including the cross-sectional mean $\bar{y}_{t-1}$ and its first difference, $\Delta \bar{y}_t$, in (14). The critical values are obtained from Pesaran (2007, Table II(a)–(c)). We calculate the test statistic for the realized spreads, the forward spreads as well as for the forecasting error. In other words, in our application we set $y = S$, $y = F$ and $y = S - F$, where we have omitted the indices for convenience.

[Table XII about here.]

The results are reported in Table XII and they indicate that both the realized spreads and the calculated forward rates appear to be non-stationary. When we look at the panel of forecasting errors, the test lead to a rejection of the null of non-stationarity, with only two exceptions, i.e. the two Nelson Siegel methods when both the intercept and a deterministic trend are included in the panel regression (14). This means that, in general the forward CDS spread calculated using the four methods considered is an unbiased estimator for the future CDS rates. This result is not in contradiction with the fact that the forward CDS rate is not an unbiased estimate of the future CDS rate under the risky forward measure, with the difference given by the convexity adjustment. Our testing is done under the real or physical measure and the results can differ.

V Conclusions and Discussion

This paper addresses the paucity of literature on CMCDS and points out two major findings. First, empirical evidence suggests that there have been substantial arbitrage opportunities between the two synthetic credit markets, CDS and CMCDS respectively, in recent times. Secondly, the forward unbiasedness hypothesis is not rejected over a panel sample of corporate reference entities with liquid trading between 2001 and 2006.

In this study a large database of market single-name credit default swap premia has been used to produce the corresponding fair constant maturity credit default prices. The arbitrage identified here is statistical in nature and it relates to the elimination of default risk while consistently making profits. Our analysis is *ex post* and it covers the period 2001-2006, stopping short of the current credit and liquidity crisis that is still in full development. The constant maturity credit default swaps fair premia were calculated with several common market models and all our conclusions were consistent across all four methods employed.

While trading gains from CDS spreads widening on companies such as Ford and General Motors in 2005 is not really a surprise, the majority of credit arbitrage revealed was in the opposite direction, with many more names benefitting from spreads tightening beyond the expected levels implied by the forward curves. A possible explanation for our empirical results is that the static strategy of buying CMCDS and selling CDS proves very profitable ex-post for almost all names because it is implemented in a period of significant decrease in the CDS spreads in the market. The decrease is beyond what the forward rates imply. This conclusion may form the basis of a conjecture that there was too much liquidity pumped up in the financial system through various channels, well beyond the actual needs of the real economy, and this may have triggered problems in credit markets. Since the situation now seems to go in reverse, if the same strategy would be studied in a period of significant upward trend in CDS spreads, then the reverse strategy (buying CDS and selling CMCDS) may prove profitable ex-post.

As a cross validating procedure we also tested whether the forward CDS spreads calculated as part of the CMCDS pricing process are unbiased estimates of the future spot CDS spreads. Using panel data tests we fail to reject the unbiasedness hypothesis. Unfortunately, there is no market for a forward credit default swap contract that will allow us to test directly the *market* forward CDS with the spot CDS. Our results are based on fair premium calculations for the former while using the market price for the latter. Accepting that the forward CDS rates are unbiased estimates of future spot rates means that the statistical arbitrage identified is of a different nature. One may argue that the dynamics of the credit curve was more accelerated than the forward credit curves simply implied.

Our research opens up several avenues to further analysis. An obvious one is a similar investigation for the sovereign names. This market has its own characteristics due to the fact that bankruptcy is not a possible event for a sovereign underlying. Additionally, we have not considered reference CDS spreads other than the 5-year maturity and an exploration of the next most liquid maturities such as 3-year and 10-year may reveal additional empirical linkages between the family of forward CDS curves and the market CDS curves. Finally, the forward unbiasedness hypothesis can be tested on other panel data based on different reference rates and horizons.

References

Baillie, Richard T., and Tim Bollerslev, 1989, Common stochastic trends in a system of exchange rates, *Journal of Finance* 44, 167–181.

Benhamou, Eric, 2000, Pricing Convexity Adjustment with Wiener Chaos, FMG discussion paper 351 London School of Economics.

——— , 2002, A Martingale Result for Convexity Adjustment in the Black Pricing Model, Working paper London School of Economics.

Berd, Arthur M., 2003, Forward CDS spreads, *Lehman Brothers Quantitative Credit Research Quarterly* pp. 40–44.

Black, Fisher, and John C. Cox, 1976, Valuing corporate securities: Some effects of bond indenture provisions, *Journal of Financial and Quantitative Analysis* 31, 351–367.

Blanco, Roberto, Simon Brennan, and Ian W. Marsh, 2005, An empirical analysis of the dynamic relation between investment-grade bonds and credit default swaps, *Journal of Finance* 60, 2255–2282.

Bluhm, Christian, Ludger Overbeck, and Christoph Wagner, 2003, *An Introduction to Credit Risk Modelling* (Chapman & Hall/CRC: Boca Raton).

Brigo, Damiano, 2005, Constant maturity credit default swap pricing with market models, Discussion paper, Available at www.damianobrigo.it.

——— , and Fabio Mercurio, 2006, *Interest Rate Models - Theory and Practice: With Smile, Inflation and Credit* (Springer: Berlin Heidelberg New York) 2 edn.

British Bankers' Association, 2006, *BBA Credit Derivatives Report 2006.*

Brooks, Robert, 2000, *Interest Rate Modeling and the Risk Premiums in Interest Rate Swaps* (Blackwell: Oxford).

Calamaro, Jean Paul, and Tarek Nassar, 2004, CMCDS: The path to floating credit spread products, *Deutsche Bank Global Markets Research* pp. 1–27.

Cao, Charles, Fan Yu, and Zhaodong Zhong, 2006, The information content of option-implied volatility for credit default swap valuation, Working paper University of California, Irvine.

Cherubini, Umberto, Elisa Luciano, and Walter Vecchiato, 2004, *Copula Methods in Finance* (John Wiley & Sons).

Collin-Dufresne, Pierre, and Bruno Solnik, 2001, On the term structure of default premia in the swap and LIBOR markets, *Journal of Finance* 56, 1095–1115.

Duffie, Darrell, 1999, Credit swap valuation, *Financial Analysts Journal* 55, 73–87.

———, Damir Filipović, and Walter Schachermayer, 2003, Affine processes and applications in finance, *Annals of Applied Probability* 13, 984–1053.

Duffie, Darrell, and Ming Huang, 1996, Swap rates and credit quality, *Journal of Finance* 51, 921–949.

Duffie, Darrell, and Kenneth J. Singleton, 1999, Modeling term structures of defaultable bonds, *The Review of Financial Studies* 12, 687–720.

———, 2003, *Credit Risk* (Princeton University Press: Princeton).

Ericsson, Jan, Kris Jacobs, and Rodolfo Oviedo, 2008, The determinants of credit default swap premia, *Journal of Financial and Quantitative Analysis* Forthcoming.

Froot, Ken A., and Jeffrey A. Frankel, 1989, Forward discount bias: Is it an exchange risk premium?, *The Quarterly Journal of Economics* 104, 139–161.

Hai, Weike, Nelson Mark, and Yangru Wu, 1997, Understanding spot and forward exchange rate regressions, *Journal of Applied Econometrics* 12, 715–734.

Henrard, Marc, 2005a, Convexity adjustment and delivery option in Australian dollar 90 Day Bills Futures, Manuscript EconWPA.

——— , 2005b, Eurodollar Futures and Options: Convexity Adjustment in HJM One-Factor Model, Discussion paper, Available at SSRN http://ssrn.com/abstract=682343.

Houweling, Patrick, and Ton Vorst, 2005, Pricing default swaps: Empirical evidence, *Journal of International Money and Finance* 24, 1200–1225.

Hull, John, Mirela Predescu, and Alan White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking and Finance* 28, 2789–2811.

Hull, John, and Alan White, 2000, Valuing credit default swaps I: No counterparty default risk, *Journal of Derivatives* 8, 29–40.

Jamshidian, Farshid, 2004, Valuation of credit default swaps and swaptions, *Finance and Stochastics* 8, 343–371.

Jarrow, Robert, and Stuart Turnbull, 1995, Pricing derivatives on financial securities subject to credit risk, *Journal of Finance* 50, 53–86.

——— , and David Lando, 1997, A Markov model for the term structure of credit risk spreads, *The Review of Financial Studies* 10, 481–523.

Jeanblanc, Monique, and Marek Rutkowski, 2000, Modelling of default risk: Mathematical tools, Manuscript Department of Mathematics, Universite d'Evry.

Jonsson, Henrik, and Wim Schoutens, 2008, Pricing constant maturity credit default swaps under jump dynamics, Discussion paper, K.U. Leuven.

Krekel, Martin, and Jörg Wenzel, 2006, A unified approach to credit default swaption and constant maturity credit default swap valuation, Technical report Fraunhofer-Institut für Techno- und Wirtschaftsmathematik.

Lando, David, 1998, On Cox processes and credit risky securities, *Review of Derivatives Research* 2, 99–120.

——— , 2004, *Credit Risk Modeling: Theory and Applications* (Princeton University Press).

Li, Anlong, 2007, Valuation of swaps and options on constant maturity cds spreads, Discussion paper, SSRN paper.

Liu, Peter C., and G. S. Maddala, 1992, Rationality of survey data and tests for market efficiency in the foreign exchange markets, *Journal of International Money and Finance* 11, 366–381.

Longstaff, Francis A., Sanjay Mithal, and Eric Neis, 2005, Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market, *Journal of Finance* 60, 2213–2253.

Luciano, Elisa, and Elena Vigna, 2006, Non mean reverting affine processes for stochastic mortality, Working paper Collegio Carlo Alberto.

Maynard, Alex, 2003, Testing for forward-rate unbiasedness: On regression in levels and in returns, *The Review of Economics and Statistics* 85, 313–327.

McCauley, Robert, 2002, International market implications of declining treasury debt, *Journal of Money, Credit, and Banking* 34, 952–966.

Merton, Robert, 1974, On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Nelson, Charles R., and Andrew F. Siegel, 1987, Parsimonious modelling of yield curves, *Journal of Business* 60, 473–489.

Norden, Lars, and Martin Weber, 2004, Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements, *Journal of Banking and Finance* 28, 2813–2843.

O'Kane, Dominic, and Stuart Turnbull, 2003, Valuation of credit default swaps, *Lehman Brothers Quantitative Credit Research Quarterly* pp. 1–17.

Pan, Jun, and Kenneth J. Singleton, 2008, Default and recovery implicit in the term structure of sovereign CDS spreads, *Journal of Finance* 63, 2345–2384.

Pelsser, Antoon, 2003, Mathematical foundation of convexity correction, *Quantitative Finance* 3, 59–65.

Pesaran, M. Hashem, 2007, A simple panel unit root test in the presence of cross section dependence, *Journal of Applied Econometrics* 22, 265–312.

Sundaresan, Suresh, 1991, Valuation of swaps, in S. Khoury, ed.: *Recent Developments in International Banking and Finance* (North Holland: Amsterdam).

Tang, Dragon Yongjun, and Hong Yan, 2008, Market conditions, default risk and credit spreads, Working paper University of Hong Kong and University of South Carolina.

Vasicek, Oldrich, 1977, An equilibrium characterization of the term structure, *Journal of Financial Economics* 5, 177–188.

Westerlund, Joakim, 2007, Estimating cointegrated panels with common factors and the forward rate unbiasedness hypothesis, *Journal of Financial Econometrics* 5, 491–522.

Zhang, Benjamin Yibin, Hao Zhou, and Haibin Zhu, 2006, Explaining credit default swap spreads with the equity volatility and jump risks of individual firms, Working paper BIS and Federal Reserve Board.

Appendix A Details on Parameter Estimation

A OU Process

Given a set of CDS spreads with maturities $\{t_n\}_{n\in\mathcal{M}}$, in order to estimate the vector of parameters $\boldsymbol{\theta} = (\lambda_0, \sigma, k, \alpha)'$, we first compute the theoretical CDS premium spread, $S(0, t_n; \boldsymbol{\theta})$ following formula (2) and then solve the optimization problems[14]

$$\arg\min_{\boldsymbol{\theta}} \sum_{n\in\mathcal{M}} \left[S(0,t_n) - S(0,t_n;\boldsymbol{\theta})\right]^2 \quad \text{or} \quad \arg\min_{\boldsymbol{\theta}} \sum_{n\in\mathcal{M}} \left|S(0,t_n) - S(0,t_n;\boldsymbol{\theta})\right|.$$

subject to the constraints

$$\theta > 0$$
$$SP'(T_M) < 0$$

where T_M is the last maturity (20yr) of the available CDS data and

$$SP'(t) = \frac{k}{\alpha}(1 - \mathrm{e}^{-\alpha t}) + \lambda_0 \mathrm{e}^{-\alpha t} - \frac{\sigma^2}{2\alpha^2}(1 - \mathrm{e}^{-\alpha t})^2$$

[14] Also the weighted objective functions of the form (18)–(19) have been considered.

B Nelson-Siegel

Given $\boldsymbol{\alpha} = (\alpha_0, \alpha_1, \alpha_3)'$ in the parameter space $U_{\boldsymbol{\alpha}} \subset \mathbb{R}^3$, we solve the minimization problems

$$\tilde{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \sum_{n\in\mathcal{M}} \left[S(0,t_n) - S(0,t_n;\boldsymbol{\alpha})\right]^2 = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \tilde{f}(\boldsymbol{\alpha})$$

or

$$\breve{\boldsymbol{\alpha}} = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \sum_{n\in\mathcal{M}} \left|S(0,t_n) - S(0,t_n;\boldsymbol{\alpha})\right| = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \breve{f}(\boldsymbol{\alpha})$$

where $S(0,t_n;\boldsymbol{\alpha})$ denotes the theoretical CDS spread maturing at time t_n with a Nelson-Siegel function with parameter $\boldsymbol{\alpha}$. The optimization should be done under the following constraints which identify $U_{\boldsymbol{\alpha}}$:

$$\alpha_0 > 0, \quad \alpha_3 \; > \; 0 \tag{15}$$

$$SP(t) - SP(t+1) \; \geq \; 0 \quad \text{for any } t > 0. \tag{16}$$

The condition (16) is equivalent to

$$\alpha_0 + \alpha_1 \exp\left(-\frac{t}{\alpha_3}\right) \geq 0 \tag{17}$$

which is obtained by imposing that the function $\Psi(t) \times t$ is not increasing. As far as the choice of the function to be minimized, in practice we set $\hat{\boldsymbol{\alpha}} = \tilde{\boldsymbol{\alpha}}$ unless $\tilde{f}\left(\breve{\boldsymbol{\alpha}}\right) < \tilde{f}\left(\tilde{\boldsymbol{\alpha}}\right)$ or $\breve{f}\left(\breve{\boldsymbol{\alpha}}\right) < \breve{f}\left(\tilde{\boldsymbol{\alpha}}\right)$. To reflect the fact that CDS contracts with different maturities may have different levels of liquidity we also consider *weighted* minimization :

$$\tilde{\boldsymbol{\alpha}}_w = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \sum_{n\in\mathcal{M}} w_n \left[S(0,t_n) - S(0,t_n;\boldsymbol{\alpha})\right]^2 = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \tilde{f}_w(\boldsymbol{\alpha}) \tag{18}$$

or

$$\breve{\boldsymbol{\alpha}}_w = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \sum_{n\in\mathcal{M}} w_n \left| S(0,t_n) - S(0,t_n;\boldsymbol{\alpha}) \right| = \arg\min_{\boldsymbol{\alpha}\in U_{\boldsymbol{\alpha}}} \breve{f}_w(\boldsymbol{\alpha}). \tag{19}$$

In particular, provided that the number, N, of contracts at some point in time is more than six we attach to each CDS market spread the following weights:

Maturity t_n (Months)	w_n
60	40%
36	30%
12	15%
84	6%
120	4%
24	3%
All the Other	$\frac{2}{N-6}\%$

Appendix B Reference entities with arbitrage

Panel A reports the top five companies with negative NCPL for each method of calculation. Panel B reports the top five companies with the largest NCPL. "NS" denotes the Nelson-Siegel interpolation, "lambda" the bootstrapping procedure with piecewise constant hazard rates, "OU" and "OU conv" are the methods with the OU process without and with convexity adjustment, respectively.

Panel A

NS	lambda	OU	OU conv
Lucent Tech Inc	Hasbro Inc	Hasbro Inc	Hasbro Inc
LA Pac Corp	Pennzoil Quaker St Co	LA Pac Corp	LA Pac Corp
Pennzoil Quaker St Co	LA Pac Corp	Pennzoil Quaker St Co	Pennzoil Quaker St Co
Hasbro Inc	CNA Finl Corp	Cap One Bk	Lucent Tech Inc
CNA Finl Corp	Cap One Bk	Cap One Finl Corp	Cap One Bk

Panel B

NS	lambda	OU	OU conv
Finl Sec Assurn Inc	Wyeth	Wyeth	Wyeth
Ford Mtr Co	Gen Mtrs Corp	Ford Mtr Co	Ford Mtr Co
Gen Mtrs Corp	Gillette Co	Gen Mtrs Corp	Gen Mtrs Corp
Gillette Co	Global Marine Inc	Gillette Co	Gillette Co
Global Marine Inc	Ford Mtr Co	Global Marine Inc	Global Marine Inc

Panel A reports the top five companies with negative ANCPL for each method of calculation. Panel B reports the top five companies with the largest ANCPL. "NS" denotes the Nelson-Siegel interpolation, "lambda" the bootstrapping procedure with piecewise constant hazard rates, "OU" and "OU conv" are the methods with the OU process without and with convexity adjustment, respectively.

Panel A

NS	lambda	OU	OU conv
J C Penney Co Inc	Hasbro Inc	J C Penney Co Inc	J C Penney Co Inc
Hasbro Inc	Pennzoil Quaker St Co	Hasbro Inc	Pennzoil Quaker St Co
Pennzoil Quaker St Co	J C Penney Co Inc	Pennzoil Quaker St Co	Hasbro Inc
Aetna Inc.	ServiceMaster Co	ServiceMaster Co	ServiceMaster Co
ServiceMaster Co	Aetna Inc.	Aetna Inc.	Aetna Inc.

Panel B

NS	lambda	OU	OU conv
Ford Mtr Cr Co	Ford Mtr Cr Co	Ford Mtr Cr Co	Textron Inc
Toys R Us Inc	Toys R Us Inc	Toys R Us Inc	Wyeth
Ford Mtr Co	Ford Mtr Co	Ford Mtr Co	Gen Mtrs Corp
Williams Cos Inc	Williams Cos Inc	Williams Cos Inc	Williams Cos Inc
Gen Mtrs Corp	Gen Mtrs Corp	Gen Mtrs Corp	Wells Fargo & Co

Figure 1: Comparison of premia calculations for CDS and CMCDS referenced by the same obligor; the time t_v shows the day when the trading is realised, which may not coincide with a market scheduled coupon paying day.

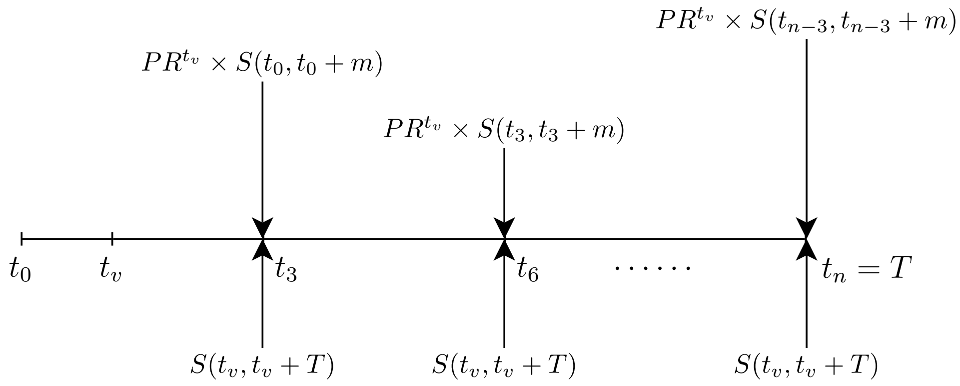
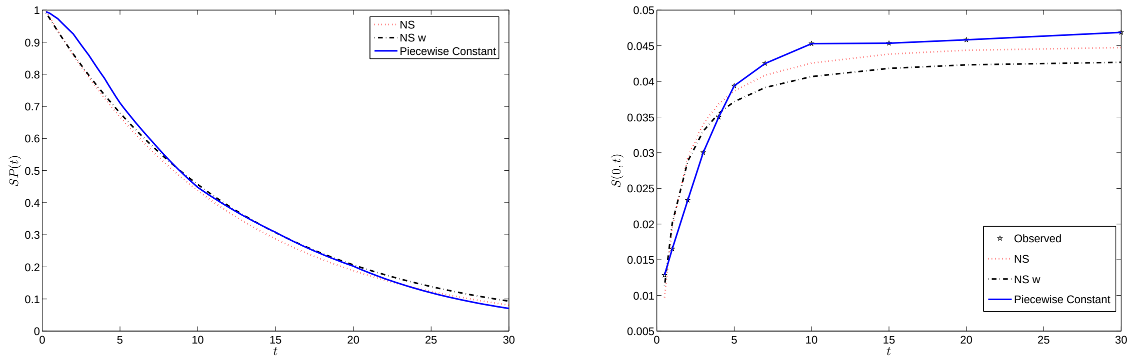
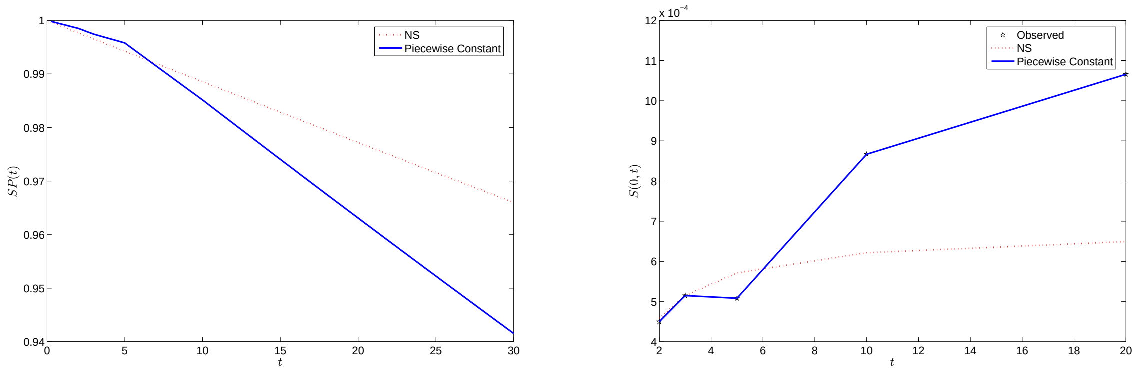


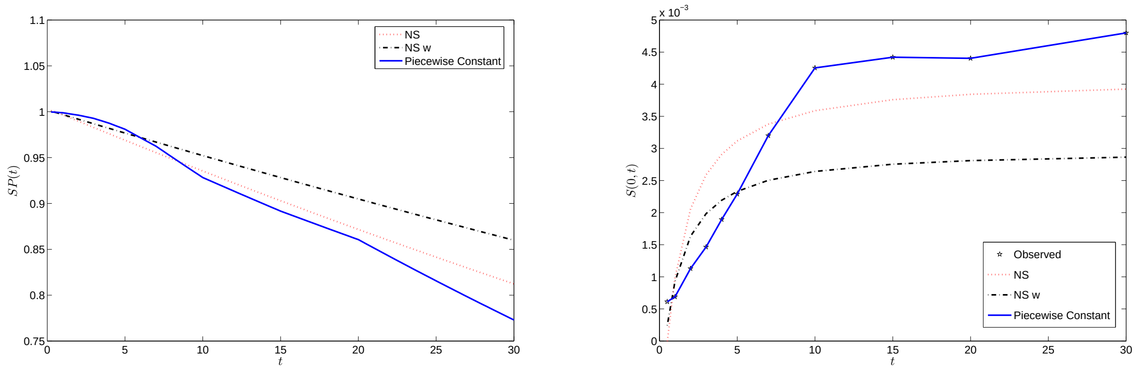
Figure 2: Bootstrapped survival probabilities and CDS curves for October 3rd 2005 for Abitibi Consol Inc, Microsoft Corp and Tesco PLC. "Piecewise Constant" denotes the bootstrapping procedure with piecewise constant hazard rates, "NS" the Nelson-Siegel interpolation and "NS w" the Nelson-Siegel interpolation with weights in the objective function.



(a) Abitibi Consol Inc: Bootstrapped Survival Probabilities (left) and CDS spreads (right)

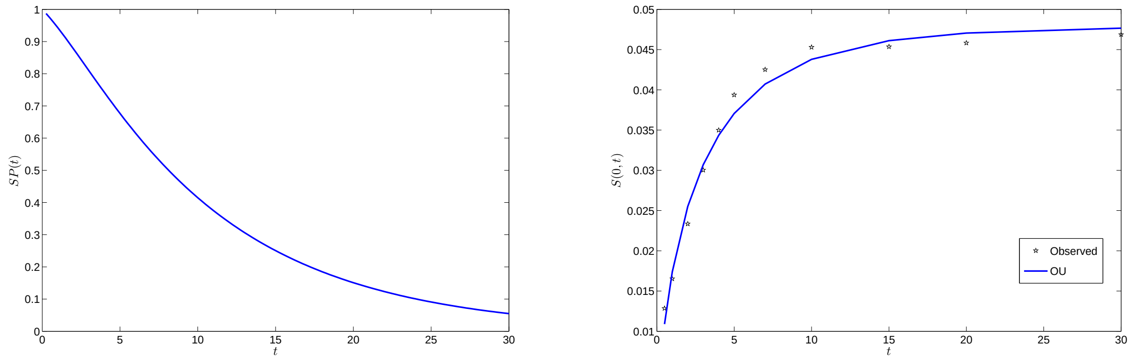


(b) Microsoft Corp: Bootstrapped Survival Probabilities (left) and CDS spreads (right)

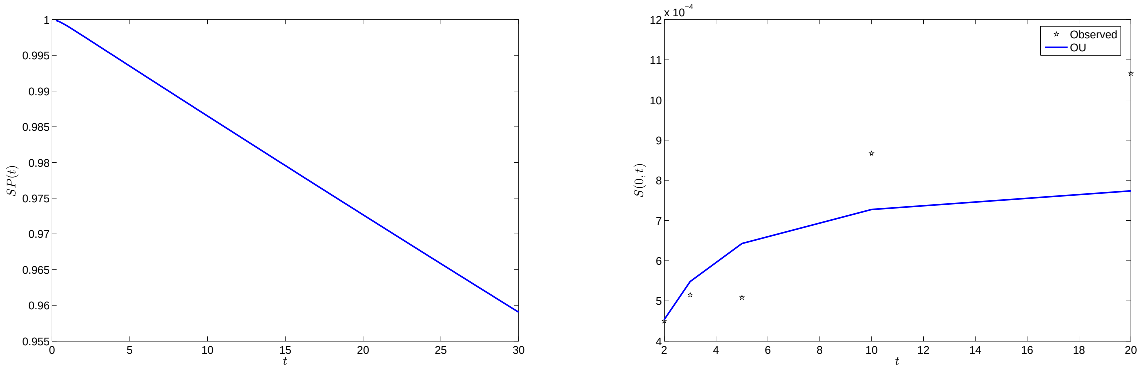


(c) Tesco PLC Bootstrapped Survival Probabilities (left) and CDS spreads (right)

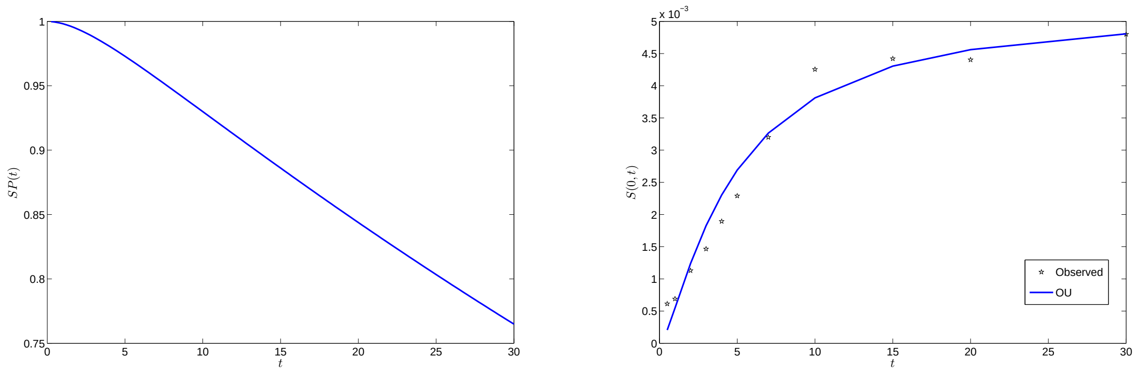
Figure 3: Bootstrapped survival probabilities and CDS spreads for October 3rd 2005 for Abitibi Consol Inc, Microsoft Corp and Tesco PLC using the OU process.



(a) Abitibi Consol Inc: Bootstrapped Survival Probabilities (left) and CDS spreads (right)

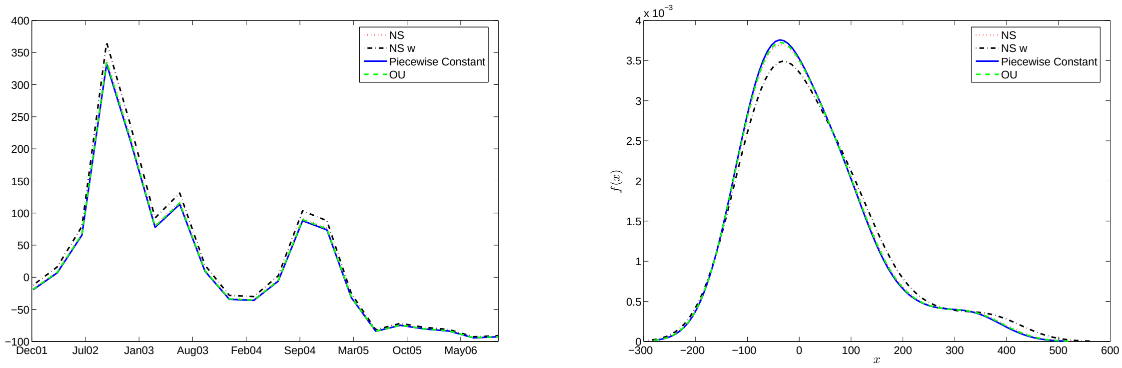


(b) Microsoft Corp: Bootstrapped Survival Probabilities (left) and CDS spreads (right)

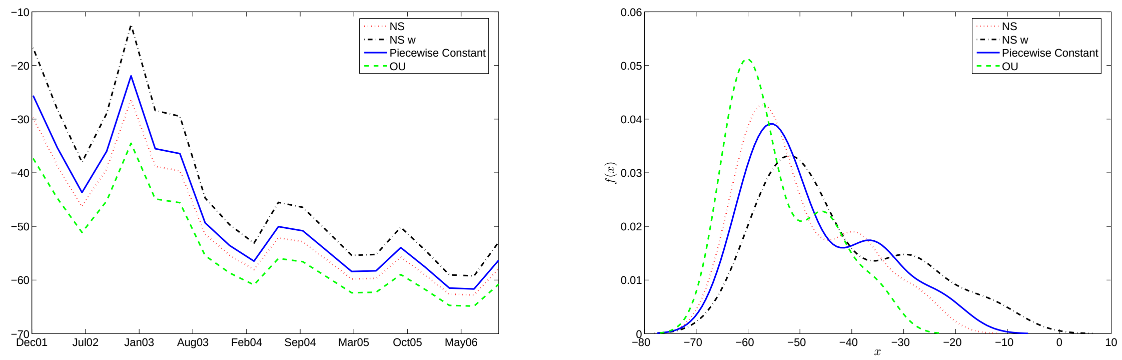


(c) Tesco PLC Bootstrapped Survival Probabilities (left) and CDS spreads (right)

Figure 4: Comparative series of net coupon spreads (basis points) for the paired strategy short CDS long CMCDS settled on 20 September 2001; "Piecewise Constant" is for the bootstrapping procedure with piecewise constant hazard rates, "NS" the Nelson-Siegel interpolation, "NS w" the Nelson-Siegel interpolation with weights in the objective function and "OU" the method with the OU process.

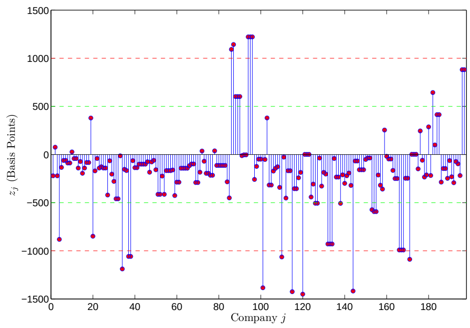


(a) AT&T: Series of net coupon spreads payments (left) and smoothed empirical density (right)

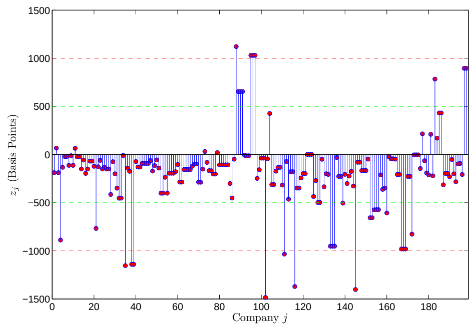


(b) Goldman Sachs Gp Inc: Series of net coupon spreads payments (left) and smoothed empirical density (right)

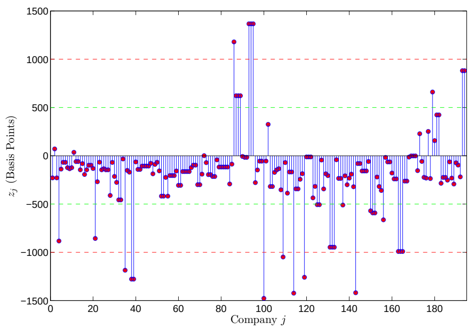
Figure 5: The calculated net cumulative profit/loss (NCPL), z_j, on the paired trade short CDS long CMCDS for all obligors.



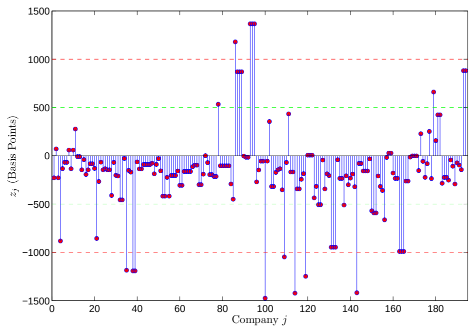
(a) Nelson Siegel



(b) Piecewise Constant

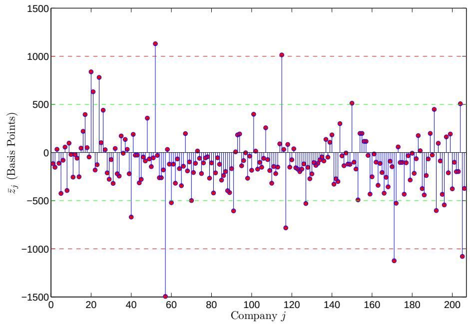


(c) OU process

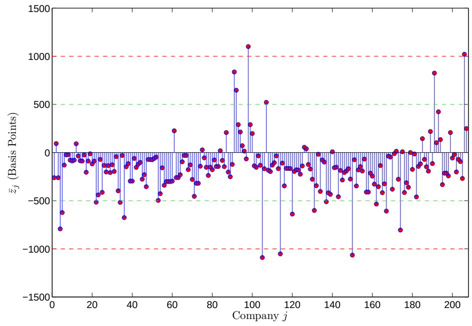


(d) OU process with convexity adjustment

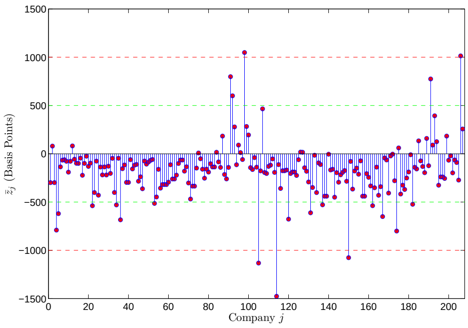
Figure 6: The calculated average net cumulative profit/loss (ANCPL), $\bar{z}_j$, on the paired trade short CDS long CMCDS for all obligors.



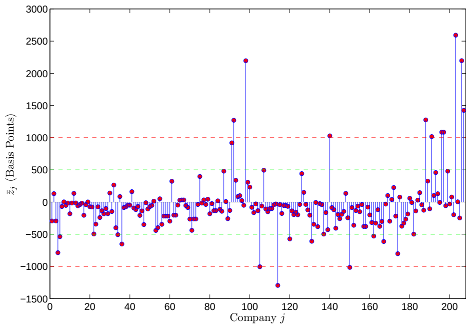
(a) Nelson Siegel



(b) Piecewise Constant



(c) OU process



(d) OU process with convexity adjustment

Table I: Number of reference entities in our sample for 20th September 2001 by sector and average rating

	AAA	AA	A	BBB	BB	B	CCC	NA	Total
Basic Materials	0	0	7	6	1	1	0	0	15
Consumer Goods	0	3	9	17	4	7	0	1	41
Consumer Services	0	1	5	15	5	1	1	0	28
Financials	4	8	15	10	1	1	0	0	39
Government	2	3	1	0	0	0	0	0	6
Health Care	0	1	3	1	1	0	0	1	7
Industrials	1	0	10	17	0	1	0	0	29
Oil & Gas	1	1	5	4	0	1	0	0	12
Technology	0	0	3	3	1	1	0	1	9
Telecommunications	0	0	1	2	1	1	0	0	5
Utilities	0	0	3	8	2	0	0	0	13
Total	8	17	62	83	16	14	1	3	204

Table II: Market quotes (basis points) on October 3rd 2005 (Source: Markit).

Maturity (Months)	Abitibi Consol Inc	Microsoft Corp	Tesco PLC
6	128.41	–	6.13
12	165.26	–	6.89
24	233.47	4.50	11.29
36	300.28	5.15	14.65
48	349.90	–	18.93
60	393.73	5.08	22.90
84	425.10	–	31.99
120	452.91	8.67	42.54
180	453.55	–	44.20
240	458.28	10.66	44.03
360	468.68	–	48.00
R	0.3929	0.4	0.394

Table III: Parameter estimation and calculation of participation rates. Panel A reports $\hat{\boldsymbol{\alpha}}$ and Panel B $\hat{\boldsymbol{\alpha}}_w$, the estimated parameters for the Nelson-Siegel method and the Nelson-Siegel with weights in the objective function, respectively. Panel C shows the participation rates for a CMCDS with $T = m = 5$ using the bootstrapping procedure with piecewise constant hazard rates (lambda), the Nelson-Siegel interpolation (NS) and the Nelson-Siegel interpolation with weights in the objective function (NS w)

Panel A

	Abitibi Consol Inc	Microsoft Corp	Tesco PLC
$\hat{\alpha}_0$	0.0844	0.0012	0.0071
$\hat{\alpha}_1$	-0.1790	0.0000	-0.0230
$\hat{\alpha}_3$	0.1001	0.1550	0.1631

Panel B

	Abitibi Consol Inc	Microsoft Corp	Tesco PLC
$\hat{\alpha}_{w0}$	0.0795	—	0.0051
$\hat{\alpha}_{w1}$	-0.1443	—	-0.0141
$\hat{\alpha}_{w3}$	0.0793	—	0.1420

Panel C

PR	Abitibi Consol Inc	Microsoft Corp	Tesco PLC
NS	0.7788	0.7393	0.5429
NS w	0.8254	—	0.7497
lambda	0.7727	0.5900	0.5191

Table IV: Parameter estimation (Panel A) and calculation of participation rates (Panel B) for the method with the OU process with and without convexity adjustment.

Panel A

	Abitibi	Microsoft	Tesco
k	0.0379	0.0037	0.0040
α	0.3727	2.6324	0.2902
λ_0	0.0498	0.0000	0.0001
σ	0.0088	0.0000	0.0258

Panel B

PR	Abitibi	Microsoft	Tesco
With convexity adjustment	0.7408	0.6090	0.6482
Without convexity adjustment	0.7390	0.6090	0.4989

Table V: Summary statistics for the net coupon spreads (basis points) of the paired strategy short CDS long CMCDS across all four methods.

AT&T

Method	mean	median	std	min	max	5% Percentile	95% Percentile
Nelson Siegel	18.95	-11.24	112.38	-94.02	338.99	-93.19	276.84
Nelson Siegel weighted	26.95	-5.05	119.09	-92.76	366.10	-91.89	300.25
OU process	18.04	-11.95	111.61	-94.16	335.90	-93.34	274.18
Piecewise Constant	16.92	-12.81	110.68	-94.33	332.12	-93.52	270.92

Goldman Sachs Gp Inc

Method	mean	median	std	min	max	5% Percentile	95% Percentile
Nelson Siegel	-50.13	-54.11	11.00	-62.79	-26.36	-62.71	-28.05
Nelson Siegel weighted	-42.95	-48.07	14.14	-59.24	-12.38	-59.14	-14.56
OU process	-54.32	-57.63	9.16	-64.87	-34.51	-64.80	-35.92
Piecewise Constant	-47.86	-52.19	11.99	-61.67	-21.94	-61.58	-23.78

Table VI: Summary statistics for the calculated net cumulative profit/loss (NCPL) on the paired trade short CDS long CMCDS.

Method	mean	median	std	min	max	5% Percentile	95% Percentile
Nelson Siegel	-176.56	-153.79	416.17	-1450.21	1221.59	-991.74	602.12
Piecewise Constant	-185.48	-157.05	387.73	-1485.07	1121.22	-969.47	565.17
OU Process	-188.80	-160.52	413.96	-1476.73	1366.11	-991.23	582.15
OU Process with convexity adjustment	-169.55	-157.21	428.35	-1474.86	1366.11	-991.23	634.84

Table VII: Number of obligors with a positive (negative), larger than 250 bps (smaller than −250 bps), larger than 500 bps (smaller than −500 bps) and larger than 1000 bps (smaller than −1000 bps) NCPL by different methods of calculation. "NS" denotes the Nelson-Siegel interpolation, "lambda" the bootstrapping procedure with piecewise constant hazard rates, "OU" and "OU conv" are the methods with the OU process without and with convexity adjustment, respectively.

	NS	lambda	OU	OU conv
pos	29	23	19	28
neg	168	175	175	166
> 250 bps	17	13	14	17
> 500 bps	11	10	10	11
> 1000 bps	5	4	4	4
< -250 bps	53	53	55	54
< -500 bps	23	23	23	23
< -1000 bps	9	7	8	8

Table VIII: List of obligors with NCPL in absolute value larger than 500 bps for all methods of calculation. Those marked with * have NCPL larger than 1000 bps in absolute value.

$z_j < -500$ bps	$z_j > 500$ bps
Aetna Inc.	Ford Mtr Co *
Arrow Electrs Inc	Ford Mtr Cr Co
CNA Finl Corp *	GA Pac Corp
Cap One Bk *	GATX Finl Corp
Cap One Finl Corp *	Gen Mtrs Corp *
Hasbro Inc *	Gillette Co *
J C Penney Co Inc *	Global Marine Inc *
LA Pac Corp *	Toys R Us Inc
Motorola Inc	Williams Cos Inc
NOVA Chems Corp	Wyeth
Nabors Inds Inc	
Nordstrom Inc	
Pennzoil Quaker St Co *	
Raytheon Co	
Reebok Intl Ltd	
Roche Hldgs Inc	
ServiceMaster Co	
Shaw Comms Inc	
Sherwin Williams Co	

Table IX: Summary statistics for average net cumulative profit/loss (ANCPL) on the paired trade short CDS long CMCDS.

Method	mean	median	std	min	max	5% Percentile	95% Percentile
Nelson Siegel	-105.43	-109.61	296.00	-1494.80	1129.92	-522.32	395.29
Piecewise Constant	-156.20	-152.14	277.61	-1090.60	1100.49	-544.99	229.40
OU Process	-173.20	-160.07	280.55	-1475.95	1048.46	-549.41	204.11
OU Process with convexity adjustment	-42.73	-82.53	451.02	-1294.75	2592.18	-530.53	934.47

Table X: Number of obligors with a positive (negative), larger than 250 bps (smaller than -250 bps), larger than 500 bps (smaller than -500 bps) and larger than 1000 bps (smaller than -1000 bps) ANCPL by different methods of calculation. "NS" denotes the Nelson-Siegel interpolation, "lambda" the bootstrapping procedure with piecewise constant hazard rates, "OU" and "OU conv" are the methods with the OU process without and with convexity adjustment, respectively.

	NS	lambda	OU	OU conv
pos	52	30	26	55
neg	154	177	181	152
> 250 bps	14	9	10	22
> 500 bps	7	6	5	11
> 1000 bps	2	2	2	10
< -250 bps	49	61	64	45
< -500 bps	11	14	16	12
< -1000 bps	3	3	3	3

Table XI: List of obligors with ANCPL in absolute value larger than 500 bps for all methods of calculation. Those marked with * have ANCPL larger than 1000 bps in absolute value.

$\bar{z}_j < -500$ bps	$\bar{z}_j > 500$ bps
Aetna Inc.	Ford Mtr Co
Agrium Inc	Ford Mtr Cr Co
CNA Finl Corp	Gen Mtrs Corp *
Hasbro Inc *	Toys R Us Inc
J C Penney Co Inc *	Williams Cos Inc *
LA Pac Corp	
Mattel Inc	
Pennzoil Quaker St Co *	
SUPERVALU INC	
ServiceMaster Co	

Table XII: CIPS test statistics. Here S is for the spot five year CDS spread and F is the forward CDS spread corresponding to the spot spread. No asterisk denotes lack of significance at 5% level and two asterisks denote significance at 1% level.

No intercept and no trend

	S	FS	$S-FS$
Nelson Siegel	-1.27	-1.13	-2.19**
Nelson Siegel weighted	-1.25	-1.54	-2.08**
OU process	-1.25	-1.20	-2.51**
Piecewise Constant	-1.31	-1.21	-2.80**

Intercept only

	S	FS	$S-FS$
Nelson Siegel	-1.68	-1.60	-2.43**
Nelson Siegel weighted	-1.58	-1.66	-2.17**
OU process	-1.58	-1.49	-2.54**
Piecewise Constant	-1.67	-1.51	-2.88**

Intercept and trend

	S	FS	$S-FS$
Nelson Siegel	-2.03	-2.00	-2.49
Nelson Siegel weighted	-1.93	-1.78	-2.27
OU process	-1.93	-1.93	-2.74**
Piecewise Constant	-2.04	-1.85	-2.90**