Trading Strategies with Implied Forward Credit Default Swap Spreads

Abstract

Credit default risk for an obligor can be hedged with either a credit default swap (CDS) or a constant maturity credit default swap (CMCDS). We find strong evidence of persistent differences in the hedging cost associated with the two comparable contracts. Between 2001 and 2006, it would have been more profitable to sell CDS and buy CMCDS while after the crisis between 2008 and 2013 the opposite strategy was profitable. Panel data tests indicate that for our sample period the implied forward CDS rates are unbiased estimates of future spot CDS rates. The changes in the company implied volatility is the main determinant of trading inefficiencies, followed by the changes in GDP and in the interest rates before the crisis, and the changes in sentiment index and in the VIX after the crisis.

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1. Introduction

Credit default risk for an obligor can be hedged with either a credit default swap (CDS) or a constant maturity credit default swap (CMCDS). An investor may be indifferent to the instrument used since both provide the same terminal payoff. Is it possible that over a period of several years one type of hedging could be cheaper than the other? Credit default swaps 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, British Bankers' Association (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. In a recent report by the International Organization of the Securities Commissions (IOSC 2012) it is revealed that at the end of 2011, the gross notional value of outstanding CDS contracts amounted to approximately $26 trillion, with a corresponding net notional value of approximately $2.7 trillion. Single name CDS accounts for almost 60% of the overall credit market in terms of gross notional.

Following the analogy with the constant maturity swap (CMS) contract, another traded credit derivative is the 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 contract the spread is floating and calculated according to an indexing mechanism. In particular, the spread is set equal to the observed reference CDS spread at each reset date, multiplied by a factor known as the participation rate (PR). 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 the same reference entity 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.

One might presume that during the expansion of the market new operators were joining, trades were increasing due to both the increase in the notional as well as in the number of traders. We might thus think that the market was growing and that traders could have different level of information and understanding of the market activity which in turn may lead to the occurrence of trading inefficiencies[1]. An important research issue then is the identification of the credit instrument to use for protection against default risk. If supply and demand conditions lead to an imbalanced market, it would be useful to know whether it is more cost effective to pay a floating premium spread rather than a fixed one. At any point in time, for a given company, buying protection with a fixed premium may lead to different costs than buying protection with a floating premium. Nevertheless, for the entire universe as a whole and for a long period of time, it should not make any difference what type of premium one is using. Otherwise, there would be a clear inefficiency in the credit market. This situation has already been investigated in interest rate markets. Brooks (2000) showed that for the interest rate swap market in the 1990s it was net profitable to pay floating and receive fixed. His study pointed out to a market anomaly regarding the interest rate swap market which emerged in the 80s and 90s.

The constant maturity credit default swaps work exactly like constant maturity interest rate swaps by resetting the premium every period in line with a reference rate. Upon default, the CDS and CMCDS contracts will offer buyers the same payoff protection. The main difference between the two default swaps is that one requires a fixed rate premium while the other requires a floating rate premium. The calculation of the floating rate premium is more elaborated than the derivation of a fixed rate

[1] We thank an anonymous referee for suggesting this interpretation.

premium for CDS. In addition, the floating rate premium is sensitive to the shape of the credit curve, whether upward trending or inverted or exhibiting humps due to liquidity pressure at some tenor maturities. Hence, in this paper we conjecture that market participants may favor overall one contract style over another when in fact they should be indifferent if the aim is to trade default protection on corporate single names. While this statement may be more credible for trading data before the subprime crisis, mainly due to the meteoric expansion of the CDS market, it is interesting to see if the same conclusion is still valid after the subprime crisis. In a nutshell, we explore the questions whether there are inefficiencies on single name credit markets, whether these inefficiencies existed only prior to the subprime crisis, whether the forward credit default swap rates calculations were biased and what are the possible determinants of the statistical arbitrage opportunities.

In order to investigate possible trading inefficiencies present on credit markets covering single name corporates, we calculate the forward CDS curves for a large database of obligors for which market CDS premia is available. To the best of our knowledge, this is the first study that takes into consideration the forward credit curves for the entire universe of corporate single names CDS traded in USD. We believe that the credit curves contain more useful information than just the individual rates along the term structure. In particular the shape of the credit curve determines the forward credit default rates and it contains useful information for investment strategies. Consider for example two companies that have identical five year CDS spreads. Suppose that one has a flat credit curve and the other has an upward trending credit curve. Even if an investor buys or sells simultaneously both names, the value of the two contracts will very likely evolve differently over the term of the contract. Therefore a pair trading strategy combining a CDS with a CMCDS (one long and one short) for the single-name companies may produce significant profit opportunities. This is because upon default, the pair of CDS and CMCDS contracts will give a net zero payment but before default the net payments may be more one sided across all companies throughout a long period. In this paper, we show that these opportunities existed before the crisis and also after the crisis, but the direction of the trade has changed after the crisis. For identifying the statistical arbitrage opportunities we perform an exhaustive analysis for a large database of corporate companies during two different periods, before the crisis between 2001 and 2006 and after the crisis between 2008 and 2013.

The analysis requires bootstrapping the survival probability curve from the market CDS spreads. To this end, we implement both nonparametric (e.g. piecewise constant hazard rates) and parametric (Nelson-Siegel interpolation and a method driven by an Ornstein-Uhlenbeck (OU) process for the hazard rates) methods and mostly used by investment banks in a real trading environment. By employing these models we hope to minimize any conclusion bias caused by model risk.

On a large universe of obligors, one expects *ex ante* that there is no difference which contract is used to hedge default risk. Nevertheless, we identify, *ex post*, the credit market inefficiencies that existed between 2001 and 2006, and between 2008 and 2013, in terms of the number of obligors, size of profits that could have been made and the timing of the opportunities. The inefficiencies detected are significantly different from zero, before and after the subprime crisis.

A possible explanation of the inefficiencies related to the forward CDS curves identified in this paper could be a bias related to forward curve calculations. To this purpose, we implement recent panel data testing procedures to test for the forward unbiasedness hypothesis and we show that the forward credit default swaps are unbiased estimators of future CDS rates. Subsequently, we identify several important determinants of the differential between CDS and CMCDS spreads. Our results show that statistical arbitrage opportunities that existed before the crisis were mainly driven by changes in firm-specific volatility, GDP, 10-year treasury rate and to a lesser extent investor sentiment index. After the crisis, the important determinants of trading inefficiencies were changes in firm-specific volatility, in the volatility index VIX, in the investor sentiment index and in the equity index.

The remainder of this paper is organized as follows. Section 2 briefly describes the linkages with previous works in credit risk and investments area. In Section 3 we review the pricing methodology of CDS and CMCDS contracts including the convexity adjustment for the latter contract as it was performed by investment banks. The dataset used for calibration and some examples illustrating some numerical issues are shown in Section 4. The results of the statistical arbitrage analysis based on a type of buy and hold trading (static) strategy and also on a dynamic day by day investment are reported in Section 5. In Section 6 we test the forward unbiasedness hypothesis while in Section 7 we analyse the determinants of the significant differences between CDS and CMCDS premia. Section 8 concludes.

2. Connection with Credit Risk Literature

One stream of the literature on CDS has focused on issues like the validity of the theoretical equivalence of CDS prices and credit bond spreads and the determinants of credit default swap changes[2]. Duffie (1999) and Hull & White (2000) 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 is tested in Blanco et al. (2005). Using a dataset of 33 U.S. and European investment-grade firms, the authors find that the parity relation holds on average over time for most companies, implying that the bond and CDS markets may price credit risk equally. Deviations from parity are

[2]The relevant literature on the determinants of credit default swap changes includes Ericsson et al. (2009), Zhang et al. (2009), Cao et al. (2010) and Tang & Yan (2010)

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 imperfections in the contract specification of CDS and measurement errors in computing the credit spread. For all the other companies they find only short-lived deviations from parity in the sample.

The CMCDS contract requires the reconstruction of the forward CDS curve. The evolution and calibration of these curves for the entire universe of corporate obligors can be decided from the models used by the major banks *in the period of investigation.* The CMCDS contract is the mirror image in credit markets of the CMS used in interest rate markets. Its main appeal is that it allows one to take views on the shape of the forward CDS curves. Evidence that there exists an over-the-counter CMCDS market is provided by the literature in this area, see Berd (2003), Calamaro & Nassar (2004), Brigo & Mercurio (2006), Krekel & Wenzel (2006), Li (2007), Jonsson & Schoutens (2009). There is comprehensive data available on corporate CDS spreads but there is no data available on CMCDS spreads. One possible explanation is that the CMCDS contracts embed the *forward CDS spread rates* and since there has never been a forward CDS or futures CDS contract available on the financial markets, the best banks could do is to us internal models calibrated on the available CDS spread market information in order to price CMCDS. Hence, at this point in time the best the researcher can do is to employ a suite of models used in practice by the investment banks for pricing credit products, and apply those models to derive the implied forward CDS curves for all obligors for which market CDS premia is available. The calculation requires bootstrapping the survival probability curve from the observed CDS quotes. To this end, the piecewise constant hazard rate method, the Nelson-Siegel interpolation and a method driven by an Ornstein-Uhlenbeck (OU) process for the hazard rates methods, utilised by the main investment banks, are implemented.

Our work differs from Pan & Singleton (2008), where the focus is on sovereign credit risk, and from Blanco et al. (2005) and Longstaff et al. (2005), where the comparison is between the synthetic and cash credit markets, in that we investigate arbitrage between two synthetic credit markets for corporates. In addition, our sample of corporate reference entities covers market panel data for approximately 200 obligors for the period before the crisis and 650 obligors for the period after the crisis. The closest to our work is Jarrow et al. (2011) who considered statistical arbitrage in CDS markets in North America based on a reduced-form model of credit risk. The novelty in their paper resides in the affine model estimated for the term structure of CDS spreads of a given company leading to the identification of mis-valued CDS contracts along the credit curve. The model versus market statistical arbitrage is different from the ideas explored in our paper. We look mainly at the inefficiency resulted from trading the shape of forward CDS curves and what are the determinants of the inefficiencies.

3. Market Models for CDS and CMCDS Pricing

In this section, we describe how premia for CDS and CMCDS contracts are derived. The survival probabilities are inferred from the market CDS spreads and subsequently used to determine the participation rate driving the CMCDS premium.

3.1. The Pricing Framework for CDS and CMCDS

The methodology of CDS valuation described in Hull & White (2000) is applied here. 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

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

where a_u is the accrual payment at time u, $\Delta(s_i, s_{i-1})$ is the time accrual between the market paying coupon times s_{i-1} and s_i, which are quarterly, and $DF(u) = \exp\left(-\int_0^u r_t dt\right)$ is the discount factor calculated from deterministic interest rate curve $\{r_t, t \geq 0\}$ calibrated from market Libor and swap rates. The denominator is the risky PV01, the value of the premium leg assuming a premium of 1 basis point, with the first term indicating the value of a risky annuity and the second term representing 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.

Based on a complete database of UK main listed firms between 1979 and 2009, Bauer & Agarwal (2014) showed that hazard models are superior to alternative models such as accounting-based or contingent claims approach. They showed that there is a clear economic benefit of using a hazard rate model particularly when the performance is judged with return on risk weighted assets computed under Basel III. Hence, in this paper we employ four hazard rate models. For numerical calibration purposes standard practice in the industry was to approximate the integrals in (1). We assume that the default intensity is driven by a hazard rate λ, which can be either constant or stochastic. Let us assume a monthly grid $\{u_j : j \text{ non negative integer}\}$ for the time of default, and that the default arrives on average in the middle of the time interval. Thus, the CDS premium spread is calculated as

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

where $SP(\cdot)$ is the survival probability and n is time to maturity T in months.

In what follows, we discuss how to derive a CMCDS premium participation rate on single obligors based on the information from CDS markets. Closed-form solutions for constant maturity credit default swaps, as well as credit default swaps and credit default swaptions, are derived also in Krekel & Wenzel (2006), where a Libor market model with default risk is used. Further developments on CMCDS pricing can be found in Brigo & Mercurio (2006), Li (2007) and Jonsson & Schoutens (2009).

The participation rate impacts on the magnitude of the premia that will be paid under the terms of this contract and its size is strongly related to the slope of the CDS curve. 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 PR, we exploit the fact that the loss leg from a CMCDS is identical to the loss leg from a CDS on the same obligor and same maturity and thus the the fixed payment legs ought to coincide in their NPV. Hence, when the reference CDS has maturity m

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

where the right hand side term comes from (2). Therefore the formula for PR that is applied for all corporates in our sample is

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

The major problem with (3) 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 are 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 in addition to the forward CDS spread calculation, as described next.

The Forward CDS Spread and the Convexity Adjustment

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 $(t, t+m)$ can be 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 a discrepancy between the realised future rate and the implied forward rate. The difference is attributed mainly to a convexity adjustment. This issue 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 & Schoutens (2009). Our approach for taking into account a convexity adjustment is to use the default intensity described by the following OU process

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

The choice of an OU process for the hazard rate underpinning a credit derivative calculation is motivated by the fact that this model has been used in a real trading environment by investment banks and it has been also mentioned in the academic literature, see Brigo & Mercurio (2006), Duffie & Singleton (2003). Another advantage of employing this process is that calculations can be carried out analytically.

Then, as detailed in Calamaro & Nassar (2004), one can derive an approximate formula for the expected value of the future spread when the default intensity follows (5), which is different from the forward credit default swap rate FS over the same period. The OU hazard rate with convexity correction gives the formula for the expected future CDS

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

with $C_i = \frac{1-\mathrm{e}^{-\alpha s_i}}{k\alpha}$. The second term on the right in (6) is the adjustment term due to convexity correction. Then the PR 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:

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

Now we briefly describe the alternative methods we use to approximate the fair CM-CDS prices that come out of trading over the counter.

3.2. Extracting Survival Probability Curves

The schedule of fixed payments is quarterly as this is the dominating market standard for corporate entities. 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 and n corresponds to the number of months until maturity. It is evident that $k = \frac{n}{3}$ only if

$t_v = t_0 \equiv 0$, that is the settlement of the credit contract (t_v) coincides with a credit market quarterly coupon paying date (t_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. We take into account when the trading occurs within a month.

[Figure 1 about here.]

There are four methods (OU process with and without convexity adjustment, piecewise constant hazard rates, Nelson-Siegel interpolation) underpinning our results that are commonly used in practice to infer survival probabilities from CDS market quotes and which are presented next. We refer to Brigo & Mercurio (2006) and O'Kane & Turnbull (2003), for more technical details.

3.2.1. 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 $SP(t) = \mathbb{E}_0\left[\exp\left(-\int_0^t \lambda_s \mathrm{d}s\right)\right]$. When the hazard rate follows an OU process as in (5) the expectation can be derived in closed form (see for instance Vasicek 1977, Luciano & Vigna 2008)

$$
\begin{aligned}
SP(t) &= \exp[a(t) + b(t)\lambda_0], \qquad (8)\\
a(t) &= -\frac{(b(t)+t)(\alpha k - \frac{\sigma^2}{2})}{\alpha^2} - \frac{\sigma^2}{4\alpha} b(t)^2; \qquad b(t) = \frac{\mathrm{e}^{-\alpha t} - 1}{\alpha}. \qquad (9)
\end{aligned}
$$

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 equation:

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

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 et al. 2003). It can be shown that, under technical conditions (see Duffie & Singleton 2003), for any $w \in \mathbb{R}$

$$\mathbb{E}_t \left[\mathrm{e}^{\int_t^T -\Lambda(X_u)\mathrm{d}u + wX_T} \right] = \mathrm{e}^{a(T-t)+b(T-t)X_t} \tag{10}$$

where the coefficients $a(\cdot)$ and $b(\cdot)$ satisfy generalized Riccati ordinary differential equations. If we assume that the intensity itself is an affine process as in (5), then we can apply (10) with $w = 0$ and $\Lambda(x) = x$ and obtain analytically the result in (9).

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

3.2.2. Piecewise Constant Hazard Rates

The survival probabilities can be bootstrapped from (2) when there are sufficient maturities for traded contracts to cover the entire set of time points for which survival probabilities must be calculated. One common approach, feasible also in presence of a small number of maturities, advocated by O'Kane & Turnbull (2003), is to assume that the hazard rate curve is piecewise constant. Suppose that the CMCDS contract we are interested in is traded at time t_v and there are CDS market spreads for the same obligor for maturities $T_1, \ldots, T_M$. Denoting $\lambda_1 = \lambda_{0,T_1}$, $\lambda_i = \lambda_{T_{i-1},T_i}$, $i = 2, \ldots, M$, the survival function $SP(T - t_v)$ is then given by[3]

$$-\log SP(T-t_v) = \lambda_1(T-t_v)1_{[0,T_1)}(T-t_v) + \sum_{i=1}^{M-2} \left[\sum_{j=1}^{i} (\lambda_j - \lambda_{j+1})T_j + \lambda_{i+1}(T-t_v) \right] \times 1_{[T_i,T_{i+1})}(T-t_v) + \left[\sum_{j=1}^{M-1} (\lambda_j - \lambda_{j+1})T_j + \lambda_{i+1}(T-t_v) \right] 1_{[T_{M-1},\infty)}(T-t_v). \tag{11}$$

For each maturity expressed in months a numerical searching algorithm is applied

[3] $1_{\{A\}}(x)$ denotes the indicator function that is equal to one if $x \in A$ and zero otherwise.

to determine λ_i, $i = 1, \ldots, M$.

3.2.3. 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 (1987) function[4]

$$\Psi(t) = \alpha_0 + (\alpha_1 + \alpha_2)\left(\frac{1 - \exp(-\frac{t}{\alpha_3})}{\frac{t}{\alpha_3}}\right) - \alpha_2 \exp\left(-\frac{t}{\alpha_3}\right) \tag{12}$$

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 et al. (2003) argue against using humps as this may lead to overfitting problems. We therefore assume that $\alpha_2 = 0$ and estimate $\alpha_0, \alpha_1, \alpha_3$ only from CDS spread data using a nonlinear optimization algorithm for a suitable minimization function such as sum of squared errors.

4. Data Description and Some Examples

4.1. Single Name CDS Data

Our dataset consists of daily single-name composite spreads covering the period January 2001–November 2006 and the period June 2008–March 2013, for all corporates traded in US dollar and for maturities 6m, 1y, 2y, 3y, 4y, 5y, 7y, 10y, 15y, 20y, 30y downloaded from Markit, the industry standard provider in credit markets. The composite spread is the average spread for a credit contract from price information

[4]Markit, the leading data provider, employs a similar approach based on Nelson-Siegel interpolation to produce theoretical credit curves when liquidity of data is very low.

provided to Markit by its contributors. Markit applies a series of data quality tests to remove unreliable information from the sample set[5]. 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. Only the CDS market spreads related to senior tier of debt have been retained for liquidity reasons.

While some banks may feel that their CDS quotes are truly the market prices, the data from Markit on CDS spreads is the *only* data that can be viewed as the "market" data. Markit's database has been used in almost all recent research involving credit spreads. Moreover, from an industry point of view, the process of marking to market also implies calibrating the internal models to the credit curves provided by Markit.

Since the CDS prices were followed through according to the quarterly schedule of payments, we have selected only those reference entities for which at least one coupon payment was scheduled in 20 September 2001, for the first sample, and, likewise, all reference entities with at least one coupon payment scheduled on 20 June 2008, for the second sample. We kept in our samples only the names for which there was data for recovery rates and spreads covering the entire calendar of payments until the end of the survey period. A further reduction was due to the elimination of obligors with either low liquidity (only one or two maturities traded) or for which we faced numerical convergence problems again due to sparsity of the data. The final sample consists of 198 companies for the static analysis and 207 names for the dynamic analysis in the first period and 626 and 647, respectively, for the second period.

4.2. Reference Rate Yield Data

For our empirical analysis, we also need the calculation of discount rates, at daily frequency and over the entire sample period. While traditionally the government bond

[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.

yields were the obvious choice, more recently the yield curve build from Libor and swap contracts has been employed as a proxy for the riskless curve. The next best proxy would be the general collateral or repo rates as recommended by Duffie (1999) and Houweling & Vorst (2005) but the maturities for these rates are mainly up to one year. This does not fit our analysis which needs discounting from much longer maturities. 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. A continuum of discount factors is obtained with log-linear interpolation. The discount factor for $t \in [\mathcal{T}_j, \mathcal{T}_{j+1}]$, $DF(t)$, is given by

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

Data on the USD interest rates and it has been downloaded from Bloomberg.

5. Arbitrage Evidence in Credit Markets

The main aim of this section is to explore arbitrage opportunities when CDS and CMCDS contracts are two alternative instruments. A market participant should be indifferent to which instrument to use to hedge default risk. We show that the above conjecture was not true for either the period 2001–2006 or 2008-2013. We base our analysis on a quarterly comparison between the two competing contracts for a large sample of corporates in our dataset. Statistical arbitrage is explored by pairing the two contracts in opposite directions (buy CDS and sell CMCDS) and by looking at what would have been the net cumulative profit and loss for an investor employing a static strategy, similar to buy and hold. Then, we analyse the outcome of a dynamic trading strategy that assumes the investor enters the same trade every day between the 20th September 2001 and the 19th December 2001 and carries until November 2006, and again enters the same trade every day between 20th June 2008 and the

19th September 2008 and carries the trade until March 2013. With a large universe of obligors we can explore, *ex post*, the credit arbitrage in terms of the number of obligors and the size of profits that could have been made and the timing of the opportunities.

The relative value arbitrage position is monitored across all 20 quarters in each of the two periods of study. For each obligor in our sample the quarterly time series for the static strategy $\{y_i : i = 0, \ldots, 19\}$ is calculated as

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

where t_0 is the settlement date, PR^{t_0} is the participation rate on the day t_0, and S is the periodic premium of the CDS contract.

For illustration purposes, let us first consider two obligors with liquid CDS curves, namely AT&T and Goldman Sachs Gp Inc. In our analysis, the settlement date is the 20th September 2001, while the maturity of both the CDS and CMCDS contracts is five years ($T = 5$) with the CMCDS contract indexed to a five year CDS ($m = 5$). Table 1 reports descriptive statistics for y. The two obligors show a contrasting situation. AT&T has a positive mean net spread payments and negative median. The graphs of the time series y and its empirical density depicted in the top of Figure 2 suggest both negative and positive payments with the empirical density centered around zero. This is the typical outcome expected if there is no statistical credit arbitrage. Goldman Sachs however is quite the opposite, with all values between the 5% quantile and 95% quantile negative, under all methods. The graph of the spread payment series and the empirical density (see bottom of Figure 2) confirm that this name provided a great arbitrage opportunity. The illustration using AT&T and Goldman Sachs as reported above is exemplary. In what follows, we investigate whether the synthetic credit universe of corporates in our sample is closer to AT&T or to Goldman Sachs.

[Table 1 about here.]

[Figure 2 about here.]

5.1. Static Investment Analysis

For all companies in our sample we compute the net cumulative profit/loss (NCPL) that an investor would have realized by selling protection with CMCDS and buying protection via CDS. Both contracts are issued with five years maturity and same settlement date, the 20th September 2001 in the first period and the 20th June 2008 in the second period. For each company $j = 1, 2, \ldots, 198$ in the first sample and $j = 1, 2, \ldots, 626$ in the second sample, we compute the NCPL as

$$z_j = \sum_{i=0}^{k-1} \Delta(t_{n-3i}, t_{n-3(i+1)}) \left[\mathrm{PR}_j^{t_0} \times S_j(t_{n-3(i+1)}, t_{n-3(i+1)} + m) - S_j(t_0, t_0 + T) \right] \quad (13)$$

where t_i denotes a payment date, $S_j(u, u+m)$ denotes the CDS spread at time u for maturity m and company j, and $\mathrm{PR}_j^{t_0}$ is the participation rate for company j at t_0[6].

Table 2 reports the summary statistics for the NCPL calculated using the four methods described in Section 3 for all single name corporates, before and after the subprime crisis. The results indicate that, before the subprime crisis, there were significant trading opportunities in the single name CDS market in US. For the period 2001-2006, on average the NCPL measure of performance is negative, but its distribution is skewed towards the range of negative values. This means that the actual profitable strategy during that time was to trade long CDS and short CMCDS.

[Table 2 about here.]

[6]Following market practice, a cap is applied on the floating payment and the NCPL is derived as

$$z_j^{t_v,\mathrm{cap}} = \sum_{i=0}^{k-1} \Delta(t_{n-3i}, t_{n-3(i+1)}) \Big[\min\left\{800bps, \mathrm{PR}_j^{t_0} \times S_j(t_{n-3(i+1)}, t_{n-3(i+1)} + m)\right\} - S_j(t_0, t_0 + T) \Big].$$

The results obtained in this case do not differ from those calculated using (13).

For the period 2008-2013 on average there is a clear increase in the uncertainty of the cash-flows generated by this strategy, with large positive as well as large negative values. The results presented in Table 2 for the period 2008-2013 reveal that *overall* for the entire universe of single name CDS contracts, the paired trading strategy will not produce significant NCPL results generated by a buy and hold strategy. However, this does not mean that there were no names for which the NCPL performance measure was large in absolute value. The average sample values for the NCPL in this second period are not statistically significant. This may be caused by the fact that in the second period the strategy is put in place on the 20 June 2008, just before the Lehman Brothers collapse, that led to great uncertainty short term which was cleared out subsequently by the 20th March 2013. It is still possible that a more dynamic trading strategy to be able to adjust to the flow of information and still identify trading inefficiencies in the credit market system. This is shown shortly below in Section 5.2.

Table 3 reports the number of obligors with a positive (negative) NCPL at various threshold for both periods. Before the crisis, for all methods, we observe that there were at least 166 companies with a negative NCPL ranging. The results are consistent across the four methods at different NCPL thresholds. The same conclusion can be drawn for the second period, after the crisis when we also had a bigger sample of obligors, with the only important difference that the direction of the trading inefficiency was the opposite way of the pair trade. The main conclusion so far is that the NCPL measure was mainly negative before the crisis but it has changed to mainly positive after the crisis.

[Table 3 about here.]

It is rather surprising that much of the statistical arbitrage was in the negative NCPL extreme, when the credit spread curves were narrowing. This finding emphasize the important role played by the shape of the CDS term structure curve, something that has been neglected in the credit risk literature so far. 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.

[Table 4 about here.]

[Table 5 about here.]

In Table 4 we report the average NCPL by sector. For the period before the subprime crisis, the sectors with most statistical arbitrage opportunities were Technology followed by Consumer Goods, Industrials, and Consumer Services. When convexity is taken into account Energy sector also showed viable statistical arbitrage opportunities. For the period after the subprime crisis, the NCPL performance measure indicates that there is a shift in efficiency, the average NCPL value for most sectors seems to decay. The results cross-classified by rating category and model for hazard default rate, reported in Table 5, show that before the crisis most trading inefficiencies could be found for companies rated A or BBB, where a negative mean NCPL is reported for all models. After the crisis, there is a clear reversal, with the average NCPL being positive under each model for all rating categories superior to B. However, these results may be influenced by the fact that the NCPL calculations were all calculated on a fixed date in 2008 when the financial markets were still turbulent, there was a lot of discussion that the crisis may contaminate the real economy and therefore credit risk sellers were perhaps more cautious in their valuation of credit default swap contracts.

5.2. Dynamic Investment Analysis

In this section, we report the results of the dynamic trading strategy for the CDS and CMCDS contracts, following the paired trades on a daily basis. This is a generalization of the static trading strategy in that the same algorithm is applied for many consecutive days. Our sample contains only the obligors for which there is data available until the maturity of the five year contract. For each company $j = 1, \ldots, 207$ in the period 2001-2006, and $j = 1, \ldots, 647$ over the period 2008-2013, we calculate the NCPL

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

for all settlement days t_v between 20th September 2001 and 19th December 2001[7] for the first period and between 20th June 2008 and 19th September 2008, for the second period. Hence, there are exactly 20 coupon payments on the CDS and CMCDS contracts that are paired and followed up cumulatively. For a given company j, n_j denotes 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 (ANCPL) denoted by $\bar{z}_j$. 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.

Table 6 reports the results for the ANCPL for the paired trade. As in the case of the static investment strategy, there is a clear shift of the ANCPL performance measure from a negative average value for the entire universe of single name corporates in the period 2001-2006 before the subprime crisis to a positive average value in the second period 2008-2013 after the subprime crisis. Furthermore, the inefficiencies detected

[7] Following the credit market convention, we compute the first term of the summation as follow

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

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

in both samples are strongly statistically significant for all four models used, except the method using convexity adjustment in the period prior to the crisis. Furthermore, while the inefficiency seems to change direction in the aftermath of the crisis, our analysis also shows that the magnitude of the paired payoff strategy has also increased significantly as revealed in the table by the values under the min and max headings.

The results suggest that overall there was credit statistical arbitrage before but also after the crisis. The magnitude of the ANCPL varies according to the method applied and it seems that the convexity correction could play a an important role.

[Table 6 about here.]

[Table 7 about here.]

The analysis presented in Table 7 and based on the ANCPL measure confirms the results and behaviour observed for the NCPL measure. In the period before the crisis, the majority of trade opportunities were for negative ANCPL, that is trade long CDS and short CMCDS. However, after the crisis, there were still trading opportunities but in the opposite direction, that is trade the pair short CDS and long CMCDS on the same obligor.

Table 8 and Table 9 show the mean ANCPL classified by sector and rating, respectively. For this dynamic strategy approach, before the crisis the majority of the trading opportunities seem to fall in the Consumer Goods sector where the mean ANCPL value across the companies in that sector varied across the models between -656.73 for the OU method and -290.51 for the OU with convexity method. With the exception of Consumer services, in this period, all sectors had a negative ANCPL. After the crisis the sector with the most profitable opportunities was Financials, followed by Consumer Services and Consumer Goods. This was true for all four models and all mean ANCPL values in that subtable were positive, indicating an important change in the relationship between the CDS and CMCDS spreads. Looking at the mean ANCPL by rating in Table 9, after the crisis there were limited opportunities for higher rating grades but there were substantial opportunities for the lower credit rated companies. This is not surprising since the turbulence of the sovereign bond crisis in Europe during the period 2008-2013 affected the default premia of many companies and therefore increased the CMCDS spread over time during that period. Thus, a B rated company for which a pair CDS and CMCDS trade will be initiated in June 2008 will carry the fixed CDS premium for the next five years while the CMCDS spread is reset at each quarter. Then, the differential between the CDS and CMCDS spreads will increase.

[Table 8 about here.]

[Table 9 about here.]

From the full set of results reported in this section, there is evidence of the existence of inefficiencies between CDS and CMCDS markets that allows statistical arbitrage opportunities. One possible explanation is that investors do not play a lot of attention to the shape of the credit curve for a particular company. If the shape of the credit curve for a single name corporate changes from flat (almost constant) to upward trending, the participation rate determined by formula (7) will change substantially. The participation rate determines the premium to be paid in the CMCDS contracts and it is a function of the weighted average of the forward CDS spreads over the reset dates. Thus, considering the graph in Figure 1 it becomes clear that even if the five-year CDS spread (so $m = 5$) stays the same, changes in the shape of the credit curve will impact on the calculations of the participation rate PR. Hence, we suggest that investors should consider not only the current values of a five-year CDS spread, say, with the desired maturity but to look at the entire credit curve that may contain information about the future values of the five-year CDS spread. If, for a particular company, the outlook shows that CDS premia are likely to increase then buying protection with a standard CDS is better. However, if the outlook shows that the future values of five-year CDS spreads are likely to decrease then getting protection with a CMCDS is more efficient. The argument works in reverse for an investor looking to sell credit protection, that is she should sell CMCDS when CDS spreads look to rise and sell CDS when the CDS spreads seem to decline. The failure to get this information into consideration is leading to the statistical arbitrage revealed in our empirical analysis above. It shows the importance of looking at the entire CDS curve and not only at individual maturities such as five-year. This conclusion calls for a further investigation on whether the forward CDS rates are unbiased estimators of future spot CDS rates. If the forward rates are biased, this could explain the statistical arbitrage opportunities identified in this paper. On the other hand, if the forward CDS rates are unbiased then the cause of arbitrage may lie elsewhere. In addition, unbiased estimators will give more confidence to apply our analysis with different data. Hence, in the next section we test the forward rate unbiasedness hypothesis.

6. 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 exchange rates (see Liu & 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 ought be stationary under the FRUH (see Froot & Frankel 1989, for instance). An alternative approach could be testing s_{t+k} and f_t for cointegration like in Baillie & Bollerslev (1989) and Hai et al. (1997).

In this paper we adopt the latter approach to a panel data analysis. This is the most appropriate approach given that our study follows a large number of companies over many years at quarterly intervals. This choice is motivated by our aim to study the inefficiencies in the credit default swap market as a whole. Any testing of a clear relationship between actual forward rates and future spot rates should have an explanatory power for the entire single name corporates universe. Aggregating either over time or cross-sectionally may have the effect of biasing our conclusions. Therefore we test for cointegration as implied by the FRUH and test for stationarity in the resulting panel forecasting errors $F_j(t_i, t_i + m|\mathscr{F}_{t_{i-1}}) - S_j(t_i, t_i + m)$. The FRUH cannot be rejected if the panel of forecasting errors is found to be stationary. Consistent with the notation used in Section 5, t_0 refers to the 20th September 2001 for the first sample, and to the 20th June 2008 for the second sample, $i = 1, \ldots, 20$ and m is five years. Thus, at each coupon paying day, we calculate the forward spread for a contract entered into the next quarter and five years maturity.

We apply the panel unit root test of Pesaran (2007) suitable in presence of a number of obligors much larger than the number of time observations and to take into account the cross-sectional dependence in the data. Let y_{it} $(i = 1, \ldots, M,\ t = 1, \ldots, Q)$ denote a variable observed both cross-sectionally and over time. The Pesaran (2007) test statistic we use is defined as $\text{CIPS}(M, Q) = M^{-1} \sum_{i=1}^{M} t_i(M, Q)$, representing the mean of the t-ratios of b_i in the OLS cross-sectionally augmented Dickey-Fuller regression

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

where $\bar{y}_t = M^{-1} \sum_{i=1}^{M} y_{it}$, $\Delta \bar{y}_t = M^{-1} \sum_{i=1}^{M} \Delta y_{it} = \bar{y}_t - \bar{y}_{t-1}$. The vector $\mathbf{d}_t$ represents the deterministic component. The relevant case for us is $\mathbf{d}_t = 0$, equivalent to no intercept and no trend, but for completeness of our econometric analysis we also consider $\mathbf{d}_t = 1$ when there is intercept and no trend, and $\mathbf{d}_t = (1, t)'$ with intercept and individual specific time trends. Cross-section dependence is controlled by including the cross-sectional means $\bar{y}_{t-1}$ and $\Delta \bar{y}_t$, in (14). The critical values are obtained from

Pesaran (2007, Table II(a)–(c)). We apply the CIPS test statistics when y_{it} represents the realized spreads (S), the forward spreads (FS) and the forecasting error ($S - F$).

[Table 10 about here.]

The results are reported in Table 10 and they indicate overall that both the realized spreads and the calculated forward rates are non-stationary before and after the crisis. When we look at the panel of forecasting errors, the test leads to a rejection of the null of non-stationarity, with only one exception, the Nelson-Siegel method when both the intercept and a deterministic trend are included in the panel regression (14) before the crisis and for the Nelson-Siegel model with and without intercept and trend after the crisis. This means that, in general, the forward CDS spread calculated using the four methods considered is an unbiased estimator for the future CDS rates before and after the crisis. Hence, the trading inefficiencies cannot be attributed to a bias resulting from forward rates calculations. Notice that we did not report any results for the OU method with convexity adjustment. This is because the same forward default rates are calculated under the OU method and under the OU method with convexity adjustment so the results of the CIPS tests are identical.

7. The Determinants of the difference between CDS and CMCDS premia

The literature on the determinants of credit spreads has grown over the last decade. An important early reference is Collin-Dufresne et al. (2001) who tried to see if the variables explaining the corporate bond credit spreads also explain the changes in credit spreads. Their conclusion was that those theoretical variables carry little explanatory power but there might be a common systematic factor not captured. Nonetheless, Campbell & Taksler (2003) and Cremers et al. (2008) advocate the idea that the firm's volatility, in particular the option implied volatility, contains substantial information on the credit spread. More recently Zhang et al. (2009) and Ericsson et al.

(2009) run linear regression analysis to identify the linkage between credit spreads and key economic variables such as firm-specific volatility or risk-free rates.

In this section, we explore some possible explanations of the significant quarterly differences between CDS and CMCDS, denoted subsequently by $\text{Spread}_{i,t}$. In addition to the main variables listed above investigated in the literature, we also consider as explanatory variables the change in GDP, the change in University of Michigan Consumer Sentiment index, the change in Russell 200 index, change in VIX index. Since premia are paid in arrears, $\text{Spread}_{i,t}$ represents the difference for company i and period t. Our dataset spans the period September 2001 to September 2006 and June 2008 to June 2013, respectively, and it consists of quarterly series where the dependent variable $\text{Spread}_{i,t}$ is explained by a set of potential explanatory variables. Hence, we have 20 coupon payment dates for each single-name company in the sample.

We use panel data regression analysis in the same spirit and framework as highlighted in Section 6. First, the following dynamic equation is estimated:

$$\begin{aligned} \text{Spread}_{i,t} &= \alpha_i + \beta_1 * \text{Spread}_{i,t-1} + \beta_2 * \Delta\text{IV}_{i,t} + \beta_3 * \Delta\text{IV}_{i,t-1} \\ &\quad + \beta_4 * \overline{\text{Spread}}_t + \beta_5 * \overline{\text{Spread}}_{t-1} + \beta_6 * \overline{\Delta\text{IV}}_t + \beta_7 * \overline{\Delta\text{IV}}_{t-1} + \epsilon_{i,t} \end{aligned} \tag{15}$$

where $\Delta\text{IV}_{i,t}$ is the change of firm specific implied volatility (ATM) from a call option maturing in 30 days. Moreover, we also insert cross-sectional means (all terms with bar) of regressors and dependent variable to control for cross-sectional dependence in the data.

Secondly, in a second dynamic regression the cross-sectional mean terms are replaced by a series of macro-variables which in the previous equation were indistinguishably incorporated into the common factors.

$$\begin{aligned}\text{Spread}_{i,t} = \alpha_i + \beta_1 * \text{Spread}_{i,t-1} + \beta_2 * \Delta\text{IV}_{i,t} + \beta_3 * \Delta\text{IV}_{i,t-1} \\ + \gamma_1 * \Delta\text{GDP}_t + \gamma_2 * \Delta\text{TRES}_t + \gamma_3 * \Delta\text{SENT}_t \\ + \gamma_4 * \Delta\text{RUSS}_t + \gamma_5 * \Delta\text{VIX}_t + \epsilon_{i,t} \quad (16)\end{aligned}$$

The macro-variables considered are ΔGDP_t = change in the U.S. GDP (data is obtained from the Federal Reserve Economic Database[8]); ΔTRES_t = change in the 10-year Treasury Constant Maturity Rate; ΔSENT_t= change in the Investor sentiment (we consider the University of Michigan Consumer Sentiment); ΔRUSS_t= change in the Russell 2000 index, and ΔVIX_t=change in the VIX index.

[Table 11 about here.]

[Table 12 about here.]

The results for equation (15) are presented in Table 11 for the 2001-2006 period and in Table 12 for the 2008-2013 period. Likewise, the results for equation (16) are shown in Table 13 for the period before the crisis and in Table 14 for the period after the crisis. First of all, all models show correct specification and remarkable goodness-of-fit, in both periods. We notice a high degree of persistence in the data generating process for $\text{Spread}_{i,t}$ which shows a high autocorrelation coefficient, above 0.8 for all regressions before the crisis and above 0.5 for all regressions after the crisis. Highly significant and positive is also the impact of the implied volatility variable. Table 13 reports the results where cross-sectional means are replaced by macro-variables in order to capture the cross sectional dependence between companies.

There is evidence of a statistical significant negative impact of the changes in GDP on Spreads for the "Piecewise Constant" and "OU" methods, before and after

[8]http://research.stlouisfed.org/fred2/

crisis, but this variable is not significant when hazard rates are calculated with the OU convexity. One possible explanation is that GDP provides some kind of overall market driver that could be an information proxy for the convexity correction term. The negative sign is correct since a decrease in GDP will lead to more turbulent credit markets and an increase in the difference between the CDS spread rate and the CMCDS spread rate. The changes in the 10y Treasury yield have a weak positive statistical significance, for the "Piecewise Constant" and "OU" methods before the crisis, see Table 13, but they are not significant at all after the crisis as revealed in Table 14. It is well known that after the crisis interest rates went into a downward spiral movement reaching very low levels that remained like that for long periods.

On contrast, except for the OU method with convexity adjustment, the investor sentiment variable has a statistical significant positive impact before the crisis (Table 13) and a statistical significant negative impact after the crisis (Table 14). This is an important behavioural characteristic captured by the data we have analysed in this paper. The change in credit markets from over-optimism before the crisis to pessimism after the crisis is well documented in the literature.

Table 13 shows that there is no evidence of an influence from the Russell 2000 index or the VIX index before the crisis. This is not surprising given that the volatility is variation is already captured through firm-specific option implied volatility. However, in the period 2008-2013 there is significant negative influence of both stock and volatility index, as illustrated by the results in Table 14. The Lehman Brothers collapse and the long series of problems in the banking sector, realised losses coming from rogue trading as in the case of UBS and Societe Generale, failure of stress testing exercises conducted in USA and Europe, and so many other potential problems related to capital adequacy ratios and new banking regulation being introduced, all these are strongly reflected in sharp changes in volatility indices, equity indices and sentiment indices that drive the increase in the difference between the current CDS rates and the future average credit default premia quantified by CMCDS rates. This conclusion is true also when calculating hazard rates with the OU method with convexity adjustment, which was not true for the other determinant variables like GDP and Treasury rates. Therefore, we can conjecture that the impact of macroeconomic variables like GDP and interest rates is equivalent to the convexity adjustment of hazard rates, whereas equity index, implied volatility index and sentiment index are significant drivers of inefficiencies in credit markets particularly in the 2008-2013 period. Our results confirm other recent results in the literature, most notably, Gemmill & Keswani (2011) who investigated why spreads on corporate bonds are so much larger than expected losses from default. They found that systematic factors make very little contribution to spreads, even if higher moments or downside effects are taken into account. Moreover, they reveal that spreads are strongly related to idiosyncratic equity volatility. Our study confirms their conclusion that credit spreads may be large because they include a large risk premium related to investors fears of extreme losses.

[Table 13 about here.]

[Table 14 about here.]

The OU method with convexity adjustment provides different results than the other three methods but this is as expected since it is more elaborate. The convexity adjustment in essence includes a second order term in the calculation of the hazard rates. Methods that do not have this term are simpler to use but are more exposed to sudden changes in market conditions such as falls in GDP or interest rate reductions by the Fed, so the regression models will allow more macroeconomic variables to provide significant information. Furthermore, for the OU with convexity adjustment method as well, after the crisis, the implied volatility variables are all significant, both the individual ones for single-names under investigation and the index volatility capturing the overall view on the economy. This confirms the recent findings in Wang et al. (2013) that the firm-level volatility has an important explanatory power for credit spreads.

The analysis for the second period confirms to a high degree the results found in the first period analysis but it also reveals some changes in behaviour on this market, with more attention being paid to the implied volatility of the companies under study and of the entire market and also to the changes in sentiment index and less to GDP and interest rates.

8. Concluding Remarks

This paper presented some innovative trading strategies in corporate credit markets based on forward CDS curves and hence on the shape of the credit spread curve. Our research unearthed a clear market anomaly across the entire universe of US corporate companies for which CDS contracts were traded over the periods January 2001–November 2006 and June 2008–March 2013, respectively.

First, a large database covering the entire universe of market single-name credit default swap premia was employed to produce the corresponding constant maturity credit default prices. Then we paired trades with fixed premia against trades with floating premia, by analogy with interest rate swap markets, and we determined the overall performance of the paired and opposite trading, which should produce net results close to zero in efficient markets.

Our results are presented across four methods known to be used by investment banks for pricing CMCDS, thus avoiding model risk. We measured the size of the statistical arbitrage through a buy and hold type of static strategy and also its dynamic version consisting of investing daily between two market reset dates. The main conclusion is that investors could have taken advantage to sell CDS and buy CMCDS, or in other words received fixed and pay floating before the crisis and do the opposite, after the crisis.

Trading gains were observed during periods when CDS spreads were widening. However, before the crisis the majority of credit statistical arbitrage identified was in the opposite direction, when credit spreads were shrinking, with most names benefiting from spreads tightening beyond the expected levels implied by the forward curves. The decrease is beyond what the forward default curves imply, pointing to the 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. The situation was reversed in the second period, after the crisis, when credit spreads were increasing, possibly as a reaction to an increase in implied volatility in equity markets.

We also tested whether the forward CDS spreads, calculated as part of the pricing process for CMCDS, were unbiased estimates of the future spot CDS spreads. Using panel data tests, we failed to reject the unbiasedness hypothesis. Accepting that the forward CDS rates are unbiased estimates of future spot rates means that the statistical arbitrage identified cannot be attributed to an estimation bias.

In addition, we investigated possible determinants of the difference between CDS and CMCDS premia. From a panel regression analysis there is evidence of a change in behaviour on the credit markets after the subprime crisis. The dynamic panel regression also shows a high-degree of persistence in spreads. It is perhaps not surprising that changes in implied volatility of the single-name company are strongly significant in explaining the trading inefficiencies. This variable was the most important determinant of the statistical arbitrage opportunities. The next most important determinants were the changes in sentiment index and changes in volatility. Other variables like GDP and 10y treasury rate may have impacted the CDS-CMCDS differential only as a substitute of the convexity adjustment in calculating hazard rates.

APPENDIX

Details on Parameter Estimation

OU Process

Given a set of CDS spreads with maturities $\{t_n\}_{n\in\mathscr{T}}$, 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

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

subject to the constraints $\theta > 0$, $SP'(T_M) < 0$ where T_M is the last maturity (20yr) of the available CDS data and $SP'(t) = \frac{k}{\alpha}(1 - \mathrm{e}^{-\alpha t}) + \lambda_0 \mathrm{e}^{-\alpha t} - \frac{\sigma^2}{2\alpha^2}(1 - \mathrm{e}^{-\alpha t})^2$.

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

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

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

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 $U_{\boldsymbol{\alpha}}$:

$$\alpha_0 > 0, \quad \alpha_3 \;>\; 0 \tag{17}$$

$$SP(t) - SP(t+1) \;\geq\; 0 \quad \text{for any } t > 0. \tag{18}$$

The condition (18) is equivalent to $\alpha_0 + \alpha_1 \exp\left(-\frac{t}{\alpha_3}\right) \geq 0$ 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 $\tilde{f}(\breve{\boldsymbol{\alpha}}) < \tilde{f}(\tilde{\boldsymbol{\alpha}})$ or $\breve{f}(\breve{\boldsymbol{\alpha}}) < \breve{f}(\tilde{\boldsymbol{\alpha}})$. In particular, provided that the number, $\mathscr{N}$, 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	$\frac{2}{\mathscr{N}-6}$%

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Figure 1: Comparison of premia calculations for CDS and CMCDS contracts referenced by the same obligor. At each quarterly market payment time $t_0, t_3, t_6, ...$ the fixed CDS rate $S(t_v, t_v + T)$ is paired with the floating premium given by the product of participation rate PR^{t_v} and the realised reference market spot rate $S(t_{3i}, t_{3i} + m)$. The actual coupon is calculated by multiplying those rates to the quarter period using the market money count conventions. The time t_v shows the day when the trading is realised, which may not coincide with a market scheduled coupon paying day t_0; if t_v is within one month of t_3 then the first coupon is paid at t_6, otherwise it is paid at t_3.

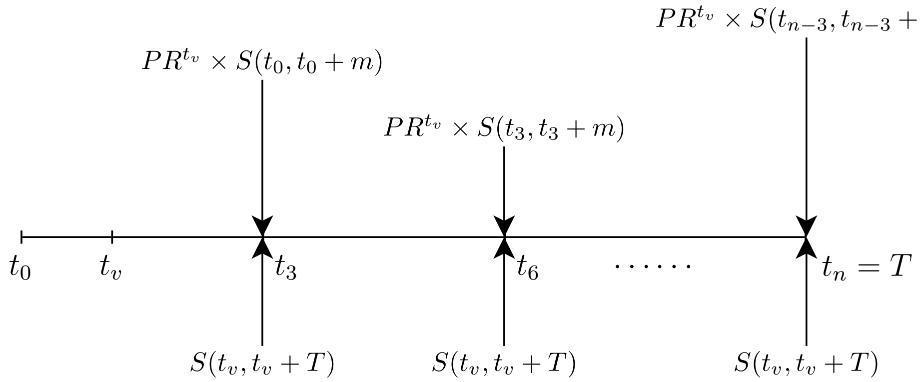
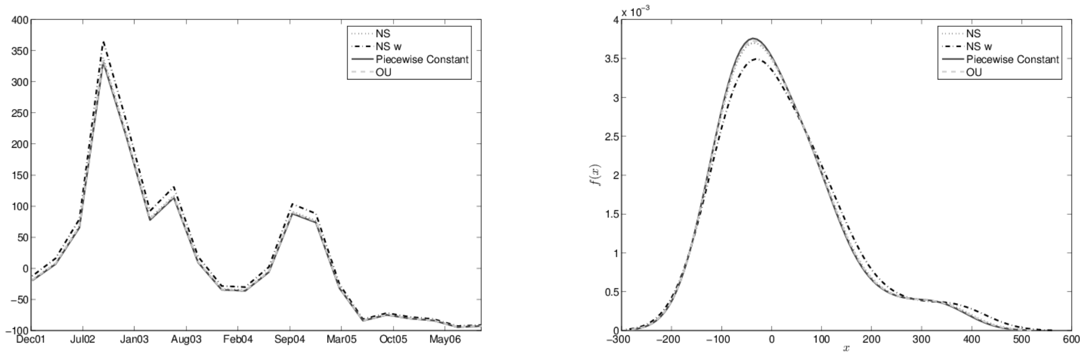
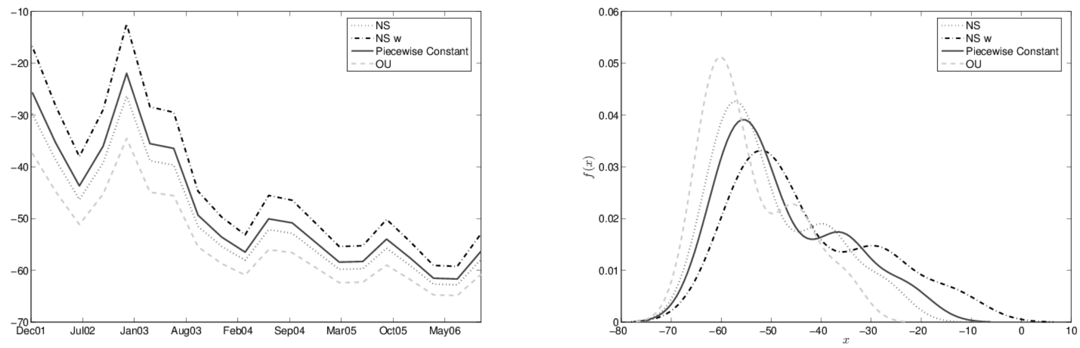


Figure 2: Comparative series of net coupon spreads (basis points) for the paired strategy short CDS long CMCDS settled on 20 September 2001, for two obligors AT&T and Goldman Sachs Gp Inc.; “Piecewise Constant” is for the bootstrapping procedure with piecewise constant hazard rates, “NS” the Nelson-Siegel interpolation, “NS w” the Nelson-Siegel interpolation with weights in the objective function and “OU” the method with the OU process. Coupons are paid quarterly between December 2001 and September 2006.



(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)

Table 1: Summary statistics for the net coupon spreads (basis points) of the paired strategy short CDS long CMCDS across all four methods, for two obligors AT&T and Goldman Sachs Gp Inc.. Coupons are paid quarterly between December 2001 and September 2006. For AT&T there is inconclusive evidence of an inefficiency whereas the negative values for Goldman Sachs in the entire domain suggests a clear inefficiency available for this reference entity.

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 2: Summary statistics across all obligors in the sample for the calculated net cumulative profit/loss (NCPL) on the paired trade short CDS long CMCDS for the period 2001-2006 and the period 2008-2013. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson-Siegel, piecewise constant, OU process, OU with convexity. The t-test values and associated p-values are used to test whether NCPL values are significantly different from zero.

Method	mean	median	std	min	max	t-stat	p-value
	2001-2006						
Nelson-Siegel	-176.56	-153.79	416.17	-1450.21	1221.59	-5.97	2.37E-09
Piecewise Constant	-185.48	-157.05	387.73	-1485.07	1121.22	-6.73	1.68E-11
OU Process	-188.80	-160.52	413.96	-1476.73	1366.11	-6.41	1.38E-10
OU with convexity	-169.55	-157.21	428.35	-1474.86	1366.11	-5.57	2.55E-08
	2008-2013						
Nelson-Siegel	5.29	40.90	737.17	-8620.59	2141.00	0.18	0.85
Piecewise Constant	5.77	40.11	733.79	-8689.00	1869.14	0.19	0.84
OU Process	-25.12	12.14	731.24	-8620.59	1835.47	-0.85	0.38
OU with convexity	25.48	37.41	759.23	-8620.59	3830.95	0.84	0.40

Table 3: 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 for 2001-2006 and 2008-2013. "NS" denotes the Nelson-Siegel interpolation, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
		2001-2006		
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
		2008-2013		
pos	397	393	339	375
neg	229	233	287	251
> 250 bps	129	130	105	130
> 500 bps	51	46	46	60
> 1000 bps	15	13	13	19
< -250 bps	66	61	66	58
< -500 bps	41	41	41	34
< -1000 bps	21	19	22	18

Table 4: Mean NCPL values for each sector for the period 2001-2006 and the period 2008-2013. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson-Siegel, piecewise constant, OU process, OU with convexity.

	Nelson-Siegel	Piecewise Constant	OU Process	Ou with convexity	Number of
		2001-2006			Companies
Basic Materials	-47.59	4.56	-80.78	-51.87	18
Consumer Goods	-258.09	-310.28	-262.48	-327.36	48
Consumer Services	-231.19	-235.29	-235.37	-205.07	29
Energy	59.25	60.20	29.71	291.92	12
Financials	-110.04	-111.38	-126.62	-120.50	22
Healthcare	-91.22	-99.51	-85.47	-85.42	7
Industrials	-237.65	-241.16	-249.20	-235.25	31
Technology	-486.90	-468.28	-485.24	-485.24	11
Telecommunications	35.84	42.35	18.35	18.57	9
Utilities	-23.69	-38.15	-52.62	112.02	11

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2008-2013			Companies
Basic Materials	199.21	204.11	164.68	262.56	55
Consumer Goods	-65.19	-62.18	-98.33	-31.44	88
Consumer Services	-30.40	-23.15	-61.42	-12.89	79
Energy	124.90	119.63	95.82	105.21	68
Financials	-28.44	-22.66	-49.76	-17.33	107
Healthcare	9.73	-22.06	-30.47	55.69	36
Industrials	-69.03	-66.75	-98.71	-93.46	78
Technology	76.45	81.69	33.28	293.44	21
Telecommunications	-145.42	-143.31	-167.01	-132.96	39
Utilities	75.42	70.00	38.83	78.30	55

Table 5: Mean NCPL values for each rating category for the period 2001-2006 and the period 2008-2013. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson Siegel, piecewise constant, OU process, OU with convexity.

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2001-2006			Companies
AA	-186.38	-194.52	-194.82	-181.28	38
A	-277.80	-311.15	-291.93	-340.47	54
BBB	-240.41	-236.59	-255.58	-220.58	50
BB	-118.87	-124.86	-128.77	-59.71	31
B	-7.47	6.13	-21.94	30.70	14
CCC	266.78	280.29	260.26	377.58	11

	Nelson-Siegel	Piecewise Constant	OU Process	Ou with convexity	Number of
		2008-2013			Companies
AA	25.89	23.40	5.15	28.98	117
A	27.73	30.66	1.78	26.03	141
BBB	44.03	38.69	9.30	54.10	199
BB	114.56	119.51	79.60	180.38	103
B	-303.46	-293.67	-343.10	-215.34	44
CCC	-492.42	-478.93	-524.43	-498.96	22

Table 6: Summary statistics for average net cumulative profit/loss (ANCPL) on the paired trade long CDS short CMCDS. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson Siegel, piecewise constant, OU process, OU with convexity. The t-test values and associated p-values are used to test whether NCPL values are significantly different from zero.

Method	mean	median	std	min	max	t-stat	p-value
				2001-2006			
Nelson-Siegel	-105.43	-109.61	296.00	-1494.80	1129.92	-5.12	2.98E-07
Piecewise Constant	-156.20	-152.14	277.61	-1090.60	1100.49	-8.10	0.00
OU Process	-173.20	-160.07	280.55	-1475.95	1048.46	-8.88	0.00
OU with convexity	-42.73	-82.53	451.02	-1294.75	2.18	-1.36	0.17
				2008-2013			
Nelson-Siegel	360.52	116.34	720.13	-288.41	3498.77	12.73	0.00
Piecewise Constant	307.92	74.88	689.11	-297.28	3498.77	11.37	0.00
OU Process	281.07	54.18	672.76	-301.73	3498.77	10.63	0.00
OU with convexity	281.52	54.52	673.03	-301.66	3498.77	10.64	0.00

Table 7: 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, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
		2001-2006		
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
		2008-2013		
pos	392	380	371	372
neg	255	267	276	275
>250 bps	253	222	211	211
>500 bps	154	136	129	129
>1000 bps	88	78	76	76
<-250 bps	13	17	20	20
<-500 bps	0	0	0	0
<-1000 bps	0	0	0	0

Table 8: Mean ANCPL for each sector for the period 2001-2006 and the period 2008-2013. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson-Siegel, piecewise constant, OU process, OU with convexity.

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2001-2006			Companies
Basic Materials	-20.50	-36.59	-40.38	7.38	18
Consumer Goods	-441.44	-597.04	-656.73	-290.51	48
Consumer Services	23.34	0.48	-5.08	69.87	30
Energy	-26.93	-43.23	-45.69	-3.19	14
Financials	-17.98	-35.72	-40.03	19.87	25
Healthcare	5.00	-13.83	-15.12	30.16	7
Industrials	-16.59	-35.98	-40.37	26.08	33
Technology	11.93	-6.58	-9.53	40.03	8
Telecommunications	-9.81	-27.06	-32.40	22.07	9
Utilities	24.40	3.15	-0.24	55.18	15

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2008-2013			Companies
Basic Materials	317.00	262.33	234.47	234.94	55
Consumer Goods	413.89	358.03	329.67	330.14	89
Consumer Services	471.66	412.23	382.07	382.57	83
Energy	135.05	92.24	70.76	71.12	68
Financials	653.75	586.66	552.30	552.87	116
Healthcare	121.57	80.60	60.08	60.42	36
Industrials	334.08	286.26	261.85	262.26	80
Technology	152.63	111.46	90.62	90.96	21
Telecommunications	292.64	243.25	217.19	217.62	41
Utilities	146.82	108.15	88.02	88.36	58

Table 9: Mean ANCPL values for each rating category for the period 2001-2006 and the period 2008-2013. Results are presented for four models under study described by the way it calibrates the hazard rate of default: Nelson-Siegel, piecewise constant, OU process, OU with convexity.

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2001-2006			Companies
AA	-590.72	-766.20	-835.60	-430.12	40
A	-24.25	-41.08	-44.41	4.35	57
BBB	-0.56	-19.41	-23.58	34.36	53
BB	24.93	-0.75	-6.05	80.05	32
B	81.42	56.77	53.78	117.24	14
CCC	116.29	83.06	72.10	189.84	11

	Nelson-Siegel	Piecewise Constant	OU Process	OU with convexity	Number of
		2008-2013			Companies
AA	-39.94	-68.39	-82.74	-82.51	145
A	46.98	11.97	-5.88	-5.57	120
BBB	175.94	130.93	108.28	108.66	47
BB	574.89	501.87	465.03	465.64	107
B	1570.36	1447.17	1383.15	1384.22	203
CCC	2408.17	2295.83	2235.35	2236.38	25

Table 10: CIPS Pesaran's test statistics for panel data. 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

	2001-2006			2008-2013		
	S	FS	$S-FS$	S	FS	$S-FS$
Nelson-Siegel	-1.27	-1.13	-2.19**	-1.28	-0.76	-1.33
OU process	-1.25	-1.20	-2.51**	-1.50	-1.50	-3.44**
Piecewise Constant	-1.31	-1.21	-2.80**	-1.25	-1.24	-3.60**

Intercept only

	2001-2006			2008-2013		
	S	FS	$S-FS$	S	FS	$S-FS$
Nelson-Siegel	-1.68	-1.60	-2.43**	-1.78	-1.14	-1.52
OU process	-1.58	-1.49	-2.54**	-1.99	-1.90	-3.90**
Piecewise Constant	-1.67	-1.51	-2.88**	-1.78	-1.72	-3.59**

Intercept and trend

	2001-2006			2008-2013		
	S	FS	$S-FS$	S	FS	$S-FS$
Nelson-Siegel	-2.03	-2.00	-2.49	-2.198	-1.40	-1.85
OU process	-1.93	-1.93	-2.74**	-2.48	-2.39	-4.12**
Piecewise Constant	-2.04	-1.85	-2.90**	-2.18	-2.15	-3.55**

Table 11: Estimated coefficients for regression (15) by different methods of calculation of the CMCDS spread for the period 2001-2006. P-values computed using robust standard errors are reported in parenthesis. "NS" denotes the Nelson-Siegel interpolation, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
Spread(-1)	0.8233	0.8242	0.8263	0.8592
	(0.000)	(0.000)	(0.000)	(0.000)
ΔIV	3.8297	3.9542	3.9179	1.8780
	(0.000)	(0.000)	(0.000)	(0.380)
ΔIV(-1)	2.9548	3.1269	3.0841	-0.0391
	(0.000)	(0.000)	(0.000)	(0.989)
$\overline{\text{Spread}}$	0.8096	0.7945	0.7952	-0.5044
	(0.000)	(0.000)	(0.000)	(0.630)
$\overline{\text{Spread}}(-1)$	-0.6465	-0.6329	-0.6362	0.4099
	(0.000)	(0.000)	(0.000)	(0.654)
$\overline{\Delta\text{IV}}$	-3.2678	-3.3411	-3.3175	-0.1598
	(0.000)	(0.000)	(0.000)	(0.922)
$\overline{\Delta\text{IV}}(-1)$	-2.8722	-3.0397	-2.9986	1.3354
	(0.000)	(0.000)	(0.000)	(0.745)
Adjusted R^2	0.7520	0.7447	0.7499	0.7269
σ	50.00	53.25	52.26	130.06
Wald (joint)	6450	7290	7180	157000
	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) test	-0.4270	-0.5776	-0.3993	1.0520
	(0.669)	(0.564)	(0.690)	(0.293)
AR(2) test	-0.6791	-0.6474	-0.6655	-0.6276
	(0.497)	(0.517)	(0.506)	(0.530)

Table 12: Estimated coefficients for regression (15) by different methods of calculation of the CMCDS spread for the period 2008-2013. P-values computed using robust standard errors are reported in parenthesis. "NS" denotes the Nelson-Siegel interpolation, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
Spread(-1)	0.6077	0.6083	0.6152	0.4938
	(0.000)	(0.000)	(0.000)	(0.000)
ΔIV	9.6091	10.1827	9.9603	15.9263
	(0.000)	(0.000)	(0.000)	(0.001)
ΔIV(-1)	6.1992	6.9207	6.9569	9.3771
	(0.000)	(0.000)	(0.000)	(0.079)
$\overline{\text{Spread}}$	0.9355	0.9293	0.9227	0.3746
	(0.000)	(0.000)	(0.000)	(0.293)
$\overline{\text{Spread}}(-1)$	-0.5566	-0.5533	-0.5562	-0.0422
	(0.000)	(0.000)	(0.000)	(0.848)
$\overline{\Delta\text{IV}}$	-9.3174	-9.8595	-9.6285	-12.6830
	(0.000)	(0.000)	(0.000)	(0.000)
$\overline{\Delta\text{IV}}(-1)$	-6.0113	-6.7002	-6.7165	-7.0648
	(0.000)	(0.000)	(0.000)	(0.184)
Adjusted R^2	0.7200	0.6167	0.6591	0.8889
σ	132.1329	144.0567	144.2024	490.665
Wald (joint)	961.7	1267	1757	1861
	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) test	-0.5149	-0.5714	-0.722	-0.9362
	(0.607)	(0.568)	(0.470)	(0.349)
AR(2) test	-0.3639	-0.3029	0.1545	0.6718
	(0.716)	(0.762)	(0.877)	(0.502)

Table 13: Estimated coefficients for regression (16) by different methods of calculation of the CMCDS spread for the period 2001-2006. P-values computed using robust standard errors are reported in parenthesis. "NS" denotes the Nelson-Siegel interpolation, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
Spread(-1)	0.8221	0.8226	0.8247	0.8587
	(0.000)	(0.000)	(0.000)	(0.000)
ΔIV	3.3804	3.4795	3.4423	1.7705
	(0.000)	(0.000)	(0.000)	(0.333)
ΔIV(-1)	2.1229	2.2524	2.2154	-0.0820
	(0.004)	(0.005)	(0.004)	(0.97)
ΔGDP	-0.1189	-0.1229	-0.1181	-0.0399
	(0.000)	(0.001)	(0.001)	(0.552)
ΔTRES	5.3754	5.9644	6.0299	5.9645
	(0.105)	(0.069)	(0.07)	(0.212)
ΔSENT	0.6949	0.8093	0.7912	-0.7709
	(0.077)	(0.042)	(0.047)	(0.607)
ΔRUSS	-0.0070	-0.0192	-0.0159	0.0680
	(0.865)	(0.636)	(0.695)	(0.39)
ΔVIX	-25.5932	-38.9971	-35.7055	240.7870
	(0.685)	(0.558)	(0.585)	(0.287)
Adjusted R^2	0.7341	0.7271	0.7324	0.7270
σ	52.30	55.61	54.60	130.41
Wald (joint)	11160	11760	11820	111800
	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) test	-0.4081	-0.5624	-0.3501	1.043
	(0.683)	(0.574)	(0.726)	(0.297)
AR(2) test	-0.4036	-0.3700	-0.3680	-0.6682
	(0.687)	(0.711)	(0.713)	(0.504)

Table 14: Estimated coefficients for regression (16) by different methods of calculation of the CMCDS spread for the period 2008-2013. P-values computed using robust standard errors are reported in parenthesis. "NS" denotes the Nelson-Siegel interpolation, "Piecewise Constant" 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	Piecewise Constant	OU	OU conv
Spread(-1)	0.6126	0.6133	0.6198	0.4958
	(0.000)	(0.000)	(0.000)	(0.000)
ΔIV	8.7586	9.2779	9.0631	14.6401
	(0.000)	(0.000)	(0.000)	(0.001)
ΔIV(-1)	3.8099	4.2579	4.3046	5.8863
	(0.000)	(0.000)	(0.000)	(0.042)
ΔGDP	-0.1314	-0.1184	-0.1055	-0.0330
	(0.000)	(0.000)	(0.000)	(0.783)
ΔTRES	0.9659	-2.6025	-6.2660	9.5315
	(0.929)	(0.810)	(0.520)	(0.771)
ΔSENT	-2.5059	-2.6850	-2.6740	-3.0440
	(0.002)	(0.002)	(0.001)	(0.253)
ΔRUSS	-0.0734	-0.0717	-0.0573	-0.1353
	(0.029)	(0.018)	(0.029)	(0.149)
ΔVIX	-9.8513	-10.7572	-10.6097	-18.0371
	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted R^2	0.7053	0.5962	0.6418	0.8883
σ	135.58	147.87	147.85	491.88
Wald (joint)	782.4	1036	1590	7483
	(0.000)	(0.000)	(0.000)	(0.000)
AR(1) test	-0.4875	-0.5309	-0.6584	-0.9436
	(0.626)	(0.595)	(0.510)	(0.345)
AR(2) test	-0.7642	-0.7041	-0.1259	0.5828
	(0.445)	(0.481)	(0.900)	(0.560)