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ORIGINAL ARTICLE

An Empirical Comparison of Credit Spreads between the Bond Market and the Credit Default Swap Market

Haibin Zhu

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Abstract This paper compares the pricing of credit risk in the bond market and the fast-growing credit default swap (CDS) market. The cointegration test confirms that the theoretical parity relationship between the two credit spreads holds as a long-run equilibrium condition. Nevertheless, substantial deviation from the parity can arise in the short run. The panel data study and the VECM analysis both suggest that the deviation is largely due to the higher responsiveness of CDS premia to changes in credit conditions. Moreover, it exhibits a certain degree of persistence in that only 10% of price discrepancies can be removed within a business day.

Keywords Credit default swap · Credit risk pricing · Price discovery

JEL Classification G1

Introduction

A remarkable innovation in the credit risk market in the past ten years has been the development of the credit derivatives market. Credit derivatives are over-the-counter financial contracts whose payoffs are linked to changes in the credit quality of an underlying asset (known as the reference entity). The market has grown dramatically and has become an important tool for financial institutions to shed or take on credit risk (Rule, 2001a,b). According to the biennial survey by the British Bankers' Association, the credit derivatives market grew from a USD 40 billion outstanding notional value in 1996 to an estimated USD 5 trillion in 2004, and is expected to reach USD 8.4 trillion by the end of 2006.

Among various credit derivative instruments the credit default swap (CDS) is the most widely traded, capturing nearly half (45%) of the market. A CDS provides

H. Zhu (✉)
Monetary and Economic Department,
Bank for International Settlements, CH-4002 Basel, Switzerland
e-mail: haibin.zhu@bis.org

insurance against the risk of default by a reference entity. The protection seller is obliged to buy the reference bond at its par value when a credit event (including bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation or moratorium, and restructuring) occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the CDS contract or when the credit event occurs, whichever comes first. This periodic payment, which is usually expressed as a percentage (in basis points) of its notional value, is called the CDS spread (or the CDS premium). Intuitively, this CDS spread provides an alternative market price of credit risk to the corporate bond yield from the cash market.

This paper tries to address two issues that have important implications for risk managers and financial regulators. First, is credit risk priced equally between the derivatives market and the cash market (i.e., the accuracy of credit risk pricing)? Although widespread trading of credit derivative instruments could potentially prompt active arbitrage of credit risk across markets, there are risks that these instruments are priced incorrectly (for example, because of low financial transparency and the existence of asymmetric information between protection buyers and sellers). Given the fact that the insurance sector and small regional banks have been net sellers of credit protection to large banks (Fitch, 2003), the answer to this question could have significant implications for credit risk transfer within the banking industry and across financial sectors. Second, which market responds more quickly to changes in credit conditions (i.e., the efficiency of price discovery)? If the two markets exhibit different responses, traders could potentially take the opportunity to gain from the price differentials.

Given the short history of the credit derivatives market and limited data availability, there has so far been little empirical work in this area. The relatively small empirical literature has focused on the determinants of CDS spreads and their role in forecasting rating events. Cossin and Hricko (2001), by using a small set of CDS transaction data, show that the determinants of CDS premia are quite similar to those of bond spreads, including ratings, yield curves, stock prices and leverage ratios. Houweling and Vorst (2005) and Hull et al. (2004) compare the pricing of credit risk between the bond market and the CDS market. Both papers suggest that, when swap rates are used as benchmark risk-free rates, the price differences between bond spreads and CDS premia are quite small (about 10 basis points). Moreover, Hull et al. (2004) and Norden and Weber (2004) find strong evidence that the CDS market anticipates credit rating announcements, particularly negative rating events.

This paper extends the existing studies by not only examining the long-term pricing accuracy in the CDS market relative to the bond market, but also looking into the underlying factors that explain the price differentials and exploring the short-term dynamic linkages between the two markets in the context of a time series framework. The most relevant studies along this direction are Longstaff et al. (2005) and Blanco et al. (2005). Longstaff et al. (2005) use weekly data and find that price differentials between bond spreads and CDS prices can be largely explained by measures of individual corporate bond illiquidity. Blanco et al. (2005) show that the parity relationship between the two credit spreads holds on average over time for most entities, but substantial deviation can arise in the short run either because of imperfections in contract specifications or due to a clear lead for CDS premia over bond spreads. This paper is similar in focusing on the price differentials between the two markets and their dynamics, but differs in important ways. First, in contrast to Longstaff et al. (2005), this study is based on daily observations and therefore provides further insights on the short-term dynamics in the price discovery process. Second, compared with Blanco et al. (2005), this study covers a substantially longer sample period (1999–2002 vs. January 2001–June 2002). The second half of year 2002 turns out to be particularly interesting as the market observed large fluctuations of credit conditions and substantial movements in credit spreads over that period. Third, this paper adopts both the panel data technique and the vector error correction model (VECM) to examine the role of the two markets in price discovery. The results are stronger in the sense that both regressions indicate a consistent picture. Finally, because statistical interpolation is unavoidable due to the paucity of CDS data, a major concern is whether the empirical results tend to be biased. While this issue has been largely ignored in previous studies, this paper chooses to use different interpolation methods based on different assumptions on the causes of missing observations, and finds that main results remain quite robust.

The main findings are as follows. First, consistent with previous studies, this paper confirms that the theoretical parity relationship between the two credit spreads holds as an equilibrium condition. In other words, although market developments can cause different changes in bond spreads and CDS premia, there exists a long-run relation tying the two prices together, i.e., that they should be equal to each other in equilibrium. Second, market participants seem to use swap rates rather than treasury rates as the proxy for risk-free rates. The failure of Treasury rates to proxy for risk-free rates could be attributed to tax considerations, the separation of Treasury yields from risk-free rates in recent years, or the liquidity component in swap spreads. Third, there is clear evidence that the two credit spreads can differ substantially in the short run, largely owing to their different responses to changes in the credit quality of reference entities. Overall, the derivatives market seems to lead the cash market in anticipating rating events and in price discovery. Finally, the short-term deviation exhibits a certain degree of persistence in that, on average, only 10% of the price discrepancy can be removed within a business day. Price discrepancies between the two markets, therefore, can exist for as long as $2-3$ weeks.

The remainder of this paper is organized as follows. Section 2 predicts the relationship between the credit spreads in the bond market and the derivatives market from a theoretical perspective, and introduces econometric techniques to be used in the empirical part. Section 3 describes the data. Section 4 compares the credit spreads between the two markets and studies the influence of various factors on price differentials. Section 5 examines the short-term dynamic interactions between the two markets. Section 6 concludes.

Theoretical Framework

Valuation of Bonds and CDSs

Since the 1970s there have been extensive studies on the pricing of credit risk. The credit risk models can be divided into two major groups. The so-called structural models, which were pioneered by Merton (1974), model explicitly the firm value process and value corporate bonds using modern option theory. In the Merton framework, a firm issues two types of assets: equities and bonds. A default occurs if the total asset value falls below a default boundary.[1] By contrast, reduced-form models (also known as intensity-based models), represented by Jarrow and Turnbull (1995), Duffie and Singleton (1999) and Madan and Unal (2000), typically treat default as a random stopping time with a stochastic arrival intensity. The credit spread is determined by risk neutral valuation under the absence of arbitrage opportunities. This method has been widely used in the pricing of credit default swaps, such as Acharya et al. (2002), Das (1995), Das and Sundaram (2000), Das et al. (2003), Duffie (1999), Hull and White (2000, 2001), Jarrow and Yildirim (2002), Schönbucher (2003) and many others.

Reduced-form representation provides a convenient framework to connect bond spreads with CDS premia. Using the risk neutral default probability and no-arbitrage conditions, it is straightforward to establish the parity relationship between the two spreads, which will be used as the testable hypothesis in the empirical part of the paper.

The logic behind the parity relationship is quite intuitive. In Duffie's (1999) simplified framework, the risk-free rate (r) is assumed to be constant over time. A CDS requires the protection buyer to pay a constant premium (ρ) until the contract matures or the pre-defined credit event (usually defined as default) occurs. The payment upon default is the difference between the face value and the market value of the underlying asset. For simplicity, I assume that there is no payment of the accrued CDS premium upon default.

No-arbitrage conditions suggest that this CDS can be replicated synthetically by shorting a par fixed coupon bond (a coupon rate of c) on the same reference entity with the same maturity date, and investing the proceeds in a par fixed coupon risk-free note. Hence, the CDS premium should be equal to the credit spread of the par fixed coupon bond. That is,

$$\rho = c - r \tag{1}$$

An investor can make arbitrage profits if this parity relationship is violated. For example, if ρ is greater than $c - r$, an investor can sell the CDS in the derivatives market, buy a risk-free bond and short the corporate bond in the cash market, and make arbitrage profits. If ρ is less than $c - r$, a reverse strategy can generate arbitrage returns.

However, this parity relationship may not hold exactly in practice for various reasons. Some of the key assumptions may not be satisfied in practice, causing

[1] There are five major ingredients in structural models: the risk-free interest rate process; firm value dynamics; the firm's leverage ratio; the default boundary; and the recovery ratio. At early stage, structural models have often been based on some simplified assumptions. For example, the risk-free rate is constant over time; the firm's leverage ratio is constant; a firm defaults if and only if its asset value falls below the face value of its debt; and the recovery ratio is constant. More recently, much effort has been devoted to relaxing some of these assumptions. Such extensions include the stochastic risk-free interest rate process proposed by Longstaff and Schwartz (1995); endogenously determined default boundaries by Anderson et al. (1996), Leland (1994) and Leland and Toft (1996); and the mean-reverting leverage ratio process in Collin-Dufresne and Goldstein (2001).

deviation from the above equivalence relationship. For example, we have assumed that the risk-free interest rate is constant. In reality, it moves randomly. Duffie and Liu (2001) also point out that the equivalence relationship holds for par floating notes, whereas empirical work typically has to rely on fixed coupon notes that are not priced at par. They suggest that this approximation coul have a small pricing effect. Moreover, institutional factors may also cause CDS premia to differ from bond spreads either temporarily or in a more persistent manner. First, the protection buyer usually needs to pay the accrued premium when a default occurs. Therefore the CDS premium tends to be lower after taking account of this accrued premium payment. Second, most CDS contracts are settled via physical delivery of underlying assets. In that case, the existence of the cheapest-to-deliver option, i.e., the protection buyer can choose the deliverable asset from a large pre-specified pool, implies that CDS premia would be higher. Third, the definition of credit events, which has been a very controversial topic in this area, can have an important impact on CDS pricing. In the standard definition of credit derivatives issued by the International Swaps and Derivatives Association (ISDA) in 1999, restructuring was included as one of the six major credit events. However, protection buyers and sellers often have conflicting views regarding whether a particular event should be included in this category. Such confusion makes it hard to predict the true value of a CDS contract.[2] Fourth, there is no initial exchange of cash flows in a CDS transaction, in sharp contrast to the cash constraint in the bond market. This difference could cause the CDS market to respond more quickly than the bond market to changes in the underlying credit risk, generating price discrepancies in the short run. Fifth, short-sale of corporate bonds is practically not allowed. Therefore traders are not able to gain from the price difference when the CDS premium is higher than the bond spread. The asymmetry in the ability to capitalize arbitrage opportunities may have important implications for the dynamic adjustment of credit spreads. Sixth, the existence of transaction costs will allow small arbitrage opportunities between the two markets. Finally, the two spreads may be influenced differently by factors besides credit risk, such as liquidity premia, which can drive a persistent wedge between the two spreads.

Econometric Methodology

To address the first issue on whether credit risk is priced equally between the two markets, I start by examining the levels and dynamics of price discrepancies between CDS premia and bond spreads. The panel data regression investigates the role of underlying factors that could contribute to the dynamics of pricing differentials. The variables of interest include credit risk factors, rating events, macro-financial conditions, terms of contracts and liquidity factors. In particular, this exercise provides insightful clues on the existence and persistence of price discrepancies, the causes of these pricing discrepancies and different responses of the two credit spreads to changes in underlying factors.

Nevertheless, the panel data study does not provide conclusive evidence on the long-run equilibrium relationship between the two credit spreads, or the role of

[2] ISDA recently decided to remove the restructuring clause from the terms of a standard contract and leave it as optional instead.

individual instruments in price discovery. To address these issues, time series techniques in dealing more than one financial time series, such as cointegration test and vector error correction model (VECM), are also employed.

The concept of cointegration test proposed by Engle and Granger (1987) is often used to test the long-term "equilibrium" relationship among non-stationary financial series. Since theory predicts that the two prices should be equal, a natural candidate for the cointegration relationship is $[1, -1]$. Therefore, I only need to test the stationarity of the basis spread, which is defined as the difference between the CDS spread and the bond spread. If each of the two prices follows an I(1) process, and the basis spread is stationary, the equivalence relationship predicted by the theory is not rejected. In other words, there is no arbitrage opportunity between the two markets in the long run.

The lead-lag relationship between the two credit spreads in price discovery can be investigated in the vector autoregression (VAR) framework, complemented by the evidence from the panel data study. Given that CDS spreads and bond spreads are cointegrated (at least as predicted by theory), an appropriate way is to use the error correction representation of the model, i.e., the VECM framework:

$$\begin{bmatrix} \triangle bond_t \\ \triangle cds_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} (cds_{t-1} - \alpha_i - \beta_i bond_{t-1}) + \begin{bmatrix} \sum_{j=1}^{p} \gamma_{1,j} \triangle cds_{t-j} \\ \sum_{j=1}^{p} \gamma_{2,j} \triangle cds_{t-j} \end{bmatrix} + \begin{bmatrix} \sum_{j=1}^{p} \varphi_{1,j} \triangle bond_{t-j} \\ \sum_{j=1}^{p} \varphi_{2,j} \triangle bond_{t-j} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix} \tag{2}$$

In Eq. 2 cds_t and $bond_t$ stand for CDS spreads and bond spreads at period t, and ϵ_{1t} and ϵ_{2t} are i.i.d. shocks. The two equations constitute a VAR model in first-order difference, with an additional term of lagged basis spreads (if $\alpha_i = 0$ and $\beta_i = 1$). The lagged basis spread is the error correction term that provides an added explanatory variable to explain changes in credit spreads. Without this term, the cointegration system estimated in differences is over-differenced. Following Davidson et al. (1978), the estimated adjustment coefficients λ_1 and λ_2 measure the degree to which prices in a particular market adjust to eliminate pricing "errors" from the long-run equilibrium relation. For example, if λ_1 is significantly positive, it implies that the cash market adjusts to remove pricing errors, i.e., the derivatives market moves ahead of the cash market in reflecting changes in credit conditions. Alternatively, if λ_2 is significantly negative, it implies that the bond market leads the CDS market in the absorption of information. If both coefficients are significant with correct signs, the relative magnitude of the two coefficients reveals which of the two markets leads in terms of price discovery.

Data

The CDS data are provided by CreditTrade, a leading broker in the trading of credit derivatives. Its Market Prices database contains about 1,400 reference entities and its coverage starts in July 1997. The data include CDS bids and offers that have been placed by traders or brokers, and all traded prices of deals that have been arranged through CreditTrade. Hence, the dataset provides a good reflection of market activity, liquidity and price variation. The information I used in this study includes: (i) the name of the reference entity, its rating information, industry classification and geographical location; (ii) information on the CDS contract, including the maturity date, currency of denomination, seniority and restructuring clause;[3] (iii) information on the quote itself, such as the date (exact time) on which the quote is placed, the price (premium) in basis points and the direction of the quote.

The sample period is chosen as from 1 January 1999 to 31 December 2002 due to very limited coverage in 1997–98. I first group the quotes by the characteristics of reference entities, including company names, currency of denomination, maturity, seniority and restructuring clauses. For instance, if two quotes are written on the same reference entity, but are denominated in different currencies, they are treated as two separate entities. The following two filtering criteria are then used: (i) the entity is either a bank or a corporate (sovereign entities are excluded); (ii) there are at least 150 days with valid quotes for the contract during the sample period. The filtering leaves me 55 entities to start with, all of which denominated in either US dollars (USD) or euros (EUR). I then construct the time series of daily CDS quotes for those entities, which are defined as the middle point of average bid and average offer on each day.

For each of the chosen reference entities, I retrieve the information for all bonds outstanding during the sample period. To avoid measurement errors caused by various options in corporate bonds (therefore bond spreads are comparable with CDS premia), I choose only bond issues that satisfy the following restrictions: (i) bonds must not be puttable, callable, convertible or reverse convertible; (ii) bonds must be denominated in the same currency as the CDS contract; (iii) bonds must not be subordinated, structured or company guaranteed; (iv) the coupon payments must be fixed-term.

The indicative yields for those bond issues that have passed the above filtering process are then downloaded from Bloomberg, and used to construct the time series of generic bonds that have the same time to maturity as credit default swaps (five-year for all of them). The five-year generic bond of an entity is constructed as follows.[4] (i) At each date, I select two quoted bonds, one whose maturity is shorter than, and another whose maturity is longer than the default swap's maturity, and linearly interpolate their spreads. In defining the bonds, I also impose the requirement that at least one of the two bonds has a remaining time to maturity between 3.5 years and 6.5 years. (ii) If no bond data are available for interpolation, but there is a quoted bond whose maturity is between 4.5 years and 5.5 years, its yield is used as an approximation for the yield of the generic bond.

The generic bond yields are then merged with the CDS quotes. Based on the number of meaningful observations in both markets, I am able to include a list of 24 entities (see Table 1). All of them are investment-grade bond issuers (with ratings ranging between AA- and BBB-), with some diversity by currency (22 in US dollars and 2 in euros), by sector (8 banks and 16 corporate companies), by region (19 from the United States, 3 from Europe and 2 from Asia) and by type of restructuring clause

[3] A typical CDS contract has a maturity of five years and a notional amount of EUR 5 million or USD 10 million, and is senior unsecured.

[4] It is a combination of the interpolation method and the matching method used by Houweling and Vorst (2005).

Table 1 Descriptive information on the 24 CDS entities

Name	Currency	Credit type	Region	Restructuring	Days with quotes	Quotes (1999)	Quotes (2000)	Quotes (2001)	Quotes (2002)	Quotes (Total)
1. AOL Time Warner (AOL)	USD	Corp	N Am	MR	232	34	75	68	1256	1433
2. AT& T (ATT)	USD	Corp	N Am	MR	345	52	96	420	1306	1874
3. Bank of America (BOA)	USD	Bank	N Am	MR	234	26	81	258	278	643
4. Bear Stearns (BS)	USD	Bank	N Am	MR	291	62	167	275	243	747
5. Carnival Corp (CARN)	USD	Corp	N Am	MR	186	0	4	288	581	873
6. Daimler Chrysler (DAIM)	USD	Corp	Europe	OR	549	85	401	825	319	1630
7. Deutsche Telekom (DTEU)	EUR	Corp	Europe	FR	234	0	2	73	955	1030
8. Ford Motors (FM)	USD	Corp	N Am	MR	627	210	260	1084	1485	3039
9. France Telecom (FTEU)	EUR	Corp	Europe	FR	237	0	2	149	937	1088
10. General Motors (GM)	USD	Corp	N Am	MR	550	200	195	1054	1086	2535
11. Goldman Sachs (GS)	USD	Bank	N Am	MR	332	127	150	197	406	880
12. Household Finance Corp (HF)	USD	Bank	N Am	MR	321	117	105	208	1218	1648
13. Harrahs Operating Co (HO)	USD	Corp	N Am	MR	175	0	0	170	377	547
14. IBM (IBM)	USD	Corp	N Am	MR	223	51	41	211	490	793
15. Korea Development Bank (KDB)	USD	Bank	Asia	FR	455	154	263	404	212	1033
16. Eastman Kodak Co (KODA)	USD	Corp	N Am	MR	168	4	8	281	672	965
17. Lehman Brothers (LB)	USD	Bank	N Am	MR	289	50	216	292	269	827
18. Morgan Stanley Dean Witter (MS)	USD	Bank	N Am	MR	213	14	62	175	404	655
19. SBC Communications (SBC)	USD	Corp	N Am	MR	195	0	0	160	813	973
20. Sears Roebuck (SEAR)	USD	Corp	N Am	MR	393	137	180	206	1102	1625
21. Sprint Corp (SP)	USD	Corp	N Am	MR	259	59	15	319	942	1335
22. Sumitomo Bank (SUMI)	USD	Bank	Asia	FR	428	240	60	490	236	1026
23. Worldcom Inc (WC)	USD	Corp	N Am	MR	228	53	60	474	593	1180
24. Walt Disney (WD)	USD	Corp	N Am	MR	277	41	1	237	1120	1399
Total						1716	2446	8318	17300	29778

(19 with the modified restructuring (MR) clause and 5 with the full restructuring (FR) clause).[5] Table 1 also clearly reflects the rapid growth of the CDS market and the improvement in data coverage. The number of quotes for the 24 entities increased tenfold from 1999 (1,716 quotes) to 2002 (17,300 quotes).

Finally, Bloomberg provides data on risk-free interest rates. Throughout this paper, I use two alternative benchmark rates: the zero coupon Treasury rate and the five-year swap rate (in either US dollars or euros depending on the currency denomination of the contract). The five-year generic government rate can be constructed from daily quotes of a subset of Treasury bond data, and the five-year generic swap rate is readily available.

There is, however, an additional issue to be resolved before the data can be used for the time-series analysis, particularly the VECM test. This issue is the paucity of the data, especially in the CDS market.[6] Among the 24 entities, the most liquid name has 627 valid observations (days with at least one quote), and the least liquid one has only 168 observations over a four year period. Even during the most liquid period, CDS quotes are not necessarily available on a daily basis. Therefore, to undertake meaningful time series analysis, I need to fill in the missing observations to generate a regularly spaced (daily) time series. Three different approaches are used to this end.

The first approach is the EM algorithm, which is also known as the regression-based imputation method. This approach is implemented as follows. First, a regression model is estimated to match the time series dynamics of the credit spreads. The regression model is chosen to be as general as possible to reflect all available information. In particular, I use a VAR framework that includes a number of lead ($q = 1$) and lagged ($p = 5$) variables. Endogenous variables include the credit spreads in the two markets, the stock prices of the underlying entities, the regional stock market indices and the CDS market indices.[7] The interpolation starts with initial guesses about the values of the missing observations (such as interpolated averages). Then the VAR model is estimated and the forecast values are fitted to the missing observations. The new data are used to produce better estimates in the next round. This procedure is then iterated until there is convergence. It is called the EM algorithm because the model is usually fitted by maximizing likelihood and using predictions based on expected values. This approach is often used when the missing data are considered to reflect the failure of the database to capture the movements in the market. Hence the appropriate imputation method would assume that the dynamics of variables should follow the same process independently of whether prices are observed or not.

[5] The two types of restructuring clauses differ mainly in terms of the delivery option. For FR-type contracts, there is almost no restriction on the maturity of the deliverable obligations so long as they are "not greater than 30 years maturity beyond the credit event date." In contrast, MR has a 30-month restriction on the maturity of the deliverables beyond the credit date. MR is mainly used for US entities and FR for European and Asian entities. See Packer and Zhu (2005) on this topic.

[6] On average, valid CDS observations are available in only 20% of the sample dates; the number is 92% in the bond market.

[7] CreditTrade provides two investment grade CDS indices, one in North America and the other in Europe. Both series start from 1 January 2001. Therefore, this imputation method actually applies in 2001–02 only. This is not a problem because there are not many observations in 1999–2000 and imputation based on a small number of observed data is questionable.

The second approach is based on the EM method with an extension of the resampling scheme. The model estimation is done in exactly the same way by maximizing the likelihood and choosing the model that best fits the observed data, but with an additional step that uses a resampling scheme. In order to preserve the higher moment properties of the data, the imputed observations are constructed by adding every model prediction with a random error term, which is randomly chosen from the true prediction errors of the observed data. Such resampling is repeated for a number of times in implementing the VECM test, with the average coefficients used as statistical results. Compared with the EM method, this method can remove potential bias caused by mis-specification of higher moments.

The third approach is called the last-observation-carried-forward (LOCF) method, whereby the missing data are imputed using the most recent observed value. This method is consistent with the so-called mixture of distributions hypothesis (MDH, see Kalimipalli and Warga, 2002), which considers new quotes as market responses to the arrival of new information. When there is no new information, there is no new quote. If this explanation is plausible, the missing data reflect the absence of new information, and therefore the last available value might be the best approximation for the missing quotation.

This paper does not intend to find out the reasons behind missing observations, nor to test which imputation approach is superior. Instead, all three approaches are used in the VECM analysis. I use the imputed data series generated by the EM method in the baseline study, and then use the other series generated by alternative approaches for the purpose of checking the robustness.[8]

Empirical Analysis I: Price Discrepancies between the Two Markets

Average Price Discrepancies

Figure 1 shows the movements of CDS premia and the two bond spreads (defined as bond yields minus risk-free rates) for General Motors. There is a general upward trend in the spreads during the sample period, with substantial increases in late 2001 and the third quarter of 2002. Moreover, the three credit spreads move closely with each other, especially the bond spreads over swap rates and the CDS premia. These general patterns are also observed for most other entities. As Campbell and Taksler (2003) suggest, the general upward trend may reflect the slowdown in the macroeconomy and increased idiosyncratic equity volatility during the period under review.

A useful indicator of price differentials between the two markets is the basis spread, which is defined as the five-year CDS spread minus the five-year bond spread. Table 2 shows statistics of average pricing discrepancies (APD) and average absolute pricing discrepancies (AAPD) for each of the 24 entities over the sample period. Similarly, Fig. 2 plots the time series of average basis spreads

[8] I also impose a restriction that at most four consecutive missing observations can be imputed in the new series. With this restriction an additional 10% of the sample dates (or about one third of the final data) are filled with imputed CDS spreads. This is mainly a compromise between the continuity and reliability of the new data series. As a robustness check, I also use CDS series that fill up to a maximum of one, two and three missing observations, and another series that imputes all missing data. The results do not change significantly.

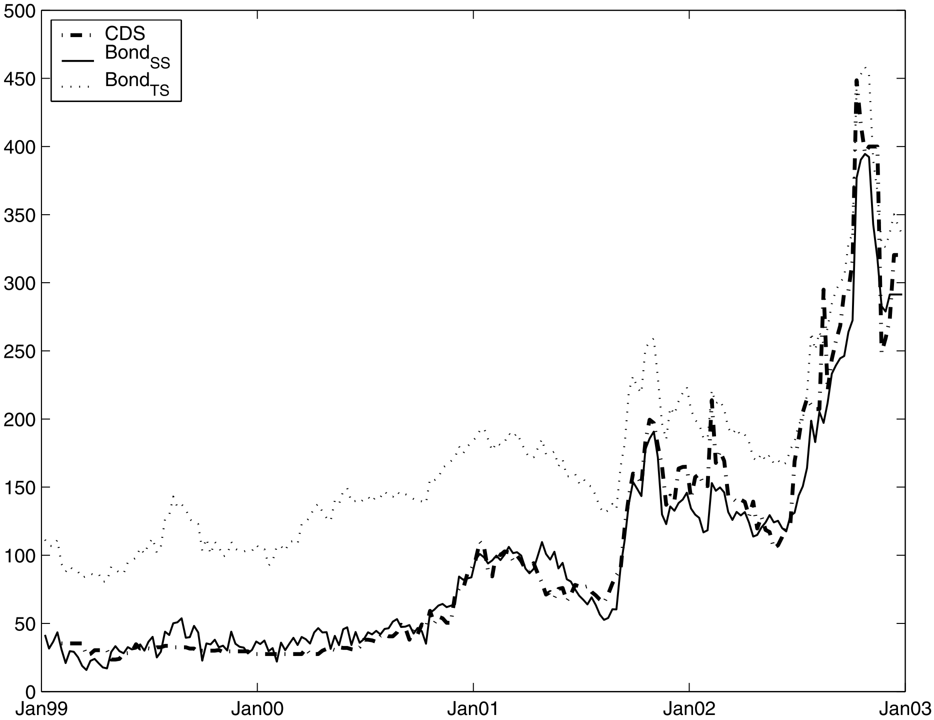

Fig. 1 An example of the three credit spreads: the General Motors. Note: The three credit spreads refer to the credit default swap premia (CDS) and the bond spreads adjusted by swap rates ($Bond_{SS}$) and Treasury rates ($Bond_{TS}$) respectively

of all 24 entities on a daily basis. As mentioned above, in all the calculations two alternative benchmark rates are used: swap rates and Treasury rates.

Overall, the prices of credit risk in the two markets are very close to each other. This is particularly true when swap rates are used as the risk-free benchmark for bond yields. In this case, the APD and AAPD are only 15 and 29 basis points respectively. By contrast, the average price differential is −52 basis points (and 64 basis points in absolute terms) if Treasury rates are used as the risk-free benchmark.

The finding that the swap rate is a better proxy for the risk-free rate than Treasuries, particularly as a benchmark for the pricing and hedging of private instruments, is in line with previous studies (see Kocić et al., 2000; Houweling and Vorst, 2005; Hull et al., 2004).[9] The failure of Treasury rates to proxy for risk-free rates can be attributable to several factors. First, Elton et al. (2001) discuss the impact of the special tax status of Treasuries in the United States, namely that yields from Treasury notes are exempt from state income taxes. Taking account this tax exemption effect reduces the basis spreads substantially. Using the adjustment

[9] This conclusion may be debatable because it is inevitably a joint test of the equivalence relationship and the hypothesis for the benchmark risk-free rate. Significant price errors might be due to the failure of the no-arbitrage condition as specified in Eq. 1, or a result of bad choice of risk-free rates. The cointegration test results (see Section 5) support the latter explanation.

Table 2 Price discrepancies between the CDS market and the bond market. The basis spread is defined as the CDS premium minus the bond spread, the latter defined as the five-year generic bond yield minus the five-year risk-free rate. $Basis_1$ and $Basis_2$ are the basis spreads that use swap rates and Treasury rates as risk-free rates respectively. $Basis_{2,\tau_1}$ and $Basis_{2,\tau_2}$ are similar to $Basis_2$ but take into account the tax effect. The adjustment factor, $\tau = (1 - \tau_g)\tau_s$, is 0.04 and 0.067, respectively. The table reports the average price discrepancies and average absolute price discrepancies between the CDS market and the bond market for each entity during the sample period. In the last four rows, average price discrepancies for all entities in each calendar year are also included

	Average price discrepancies (APD)				Average absolute price discrepancies (AAPD)			
	$Basis_1$	$Basis_2$	$Basis_{2,\tau_1}$	$Basis_{2,\tau_2}$	$\lvert Basis_1\rvert$	$\lvert Basis_2\rvert$	$\lvert Basis_{2,\tau_1}\rvert$	$\lvert Basis_{2,\tau_2}\rvert$
AOL	31.20	−25.36	−8.11	4.36	37.44	54.75	44.04	38.85
ATT	29.73	−40.76	−22.20	−8.77	40.65	63.27	52.90	47.35
BOA	3.64	−67.48	−48.55	−34.86	8.08	67.48	48.55	35.24
BS	−14.02	−91.41	−70.81	−55.91	15.38	91.41	70.81	55.91
CARN	−17.65	−92.62	−75.17	−62.54	40.13	94.33	77.91	67.15
DAIM	4.27	−72.90	−53.08	−38.74	7.96	72.90	53.08	38.76
DTEU	53.96	29.46	–	–	53.96	32.72	–	–
FM	9.47	−65.01	−45.25	−30.96	14.61	65.59	47.11	35.87
FTEU	2.41	28.19	–	–	69.13	60.27	–	–
GM	5.96	−68.15	−48.51	−34.30	14.75	68.84	50.15	37.11
GS	5.75	−67.27	−47.05	−32.43	9.16	67.27	47.05	32.42
HF	22.83	−45.08	−26.08	−12.33	31.25	51.98	37.48	31.23
HO	−25.05	−90.61	−74.28	−62.48	31.65	90.61	74.48	62.96
IBM	32.15	−37.53	−19.66	−6.74	33.12	41.65	29.61	25.13
KDB	19.13	−62.62	−41.21	−25.72	20.18	62.62	41.41	27.10
KODA	−4.44	−76.88	−59.50	−46.92	34.33	78.23	65.27	57.54
LB	−3.22	−79.59	−58.89	−43.91	9.85	79.59	58.89	43.91
MS	23.71	−43.34	−25.09	−11.89	25.39	43.34	25.37	15.37
SBC	22.46	−39.62	−23.98	−12.68	32.05	52.47	41.32	35.06
SEAR	0.53	−72.38	−52.59	−38.27	19.12	74.49	56.04	43.09
SP	30.63	−33.53	−15.69	−2.79	43.33	57.57	52.48	50.19
SUMI	−15.03	−91.20	−72.76	−59.42	20.82	91.20	72.76	59.42
WC	74.30	−0.86	18.23	32.05	74.68	37.42	38.82	44.03
WD	15.04	−47.76	−30.82	−18.56	17.29	47.76	31.49	21.81
Average	14.91	−52.26	−40.96	−27.44	29.35	64.49	50.77	41.16
Avg 1999	2.18	−71.16	−47.13	−29.75	12.11	71.33	47.93	31.55
Avg 2000	4.33	−91.59	−66.20	−47.84	12.61	91.60	66.52	48.97
Avg 2001	1.44	−74.55	−55.58	−42.67	19.18	75.74	58.09	46.37
Avg 2002	32.20	−20.48	−12.72	−2.57	39.70	45.42	28.53	24.53

formula proposed by Elton et al., the APD and AAPD are reduced by $20 - 50\%$ on average (see Table 2 and Fig. 2).[10] Although the price differentials are still higher than those corresponding with swap rates, the difference is much less pronounced. Second, as Reinhart and Sack (2002) point out, Treasury yields have become increasingly separated from the risk-free interest rate since 2000, possibly reflecting

[10] The adjustment formula is $r_f = \frac{r_{treasury}}{1-(1-\tau_g)\tau_s}$, where τ_g and τ_s are federal and state income tax rates respectively. Elton et al. (2001) proposed two alternative values for $\tau \equiv (1 - \tau_g)\tau_s$: $\tau = 4\%$ and $\tau = 6.7\%$.

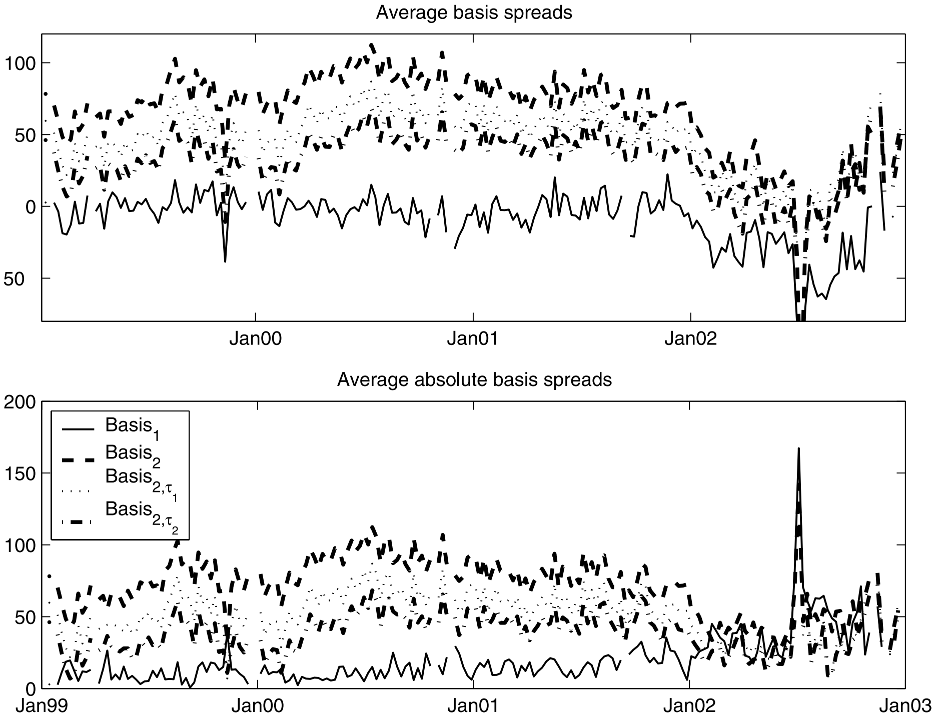

Fig. 2 Pricing discrepancies between CDS spreads and bond spreads. Note: $Basis_1$, $Basis_2$, $Basis_{2,\tau_1}$ and $Basis_{2,\tau_2}$ are defined in Table 2. In each panel, the four curves from the top to the bottom refer to $Basis_2$, $Basis_{2,\tau_1}$, $Basis_{2,\tau_2}$ and $Basis_1$ respectively

the benefits of holding Treasury securities (such as improved transparency and the widespread use of Treasuries as collateral) or the movements in the supply schedule versus market demand. As a result, Treasury rates drop below the "true" risk-free curve and the corresponding basis spreads can become negative. Moreover, Liu et al. (2006) show that much of the variation in Treasury rates is attributable to liquidity factors. By contrast, movements in swap rates and CDS spreads are mainly driven by changes in default risk. This liquidity component tends to cause the deviation from the parity relationship when Treasuries are used as the benchmark.

Another important observation is that price differentials appear to change over time. For example, basis spreads associated with swap rates were very close to zero in 1999–2001. However, entering 2002, CDS spreads turned out to be much higher than bond spreads. In contrast, by using Treasuries as risk-free rates, the price differentials were much lower in 2002 than in previous years. This phenomenon might be a result of the general deterioration in credit conditions in year 2002 and the different responses between the two markets. This issue will be examined in more detail in the latter part of this paper.

Determinants of Basis Spreads

Whereas price differentials between the two markets are very small on average over time (as the theory has predicted), there is substantial variation over time (Fig. 2) and cross entities (Table 2). Section 2 lists a number of reasons that could explain the deviation from the equivalence relationship. Here the panel data technique is adopted to examine the determinants of basis spread movements. The explanatory variables include:

- Lagged basis spreads. The theory predicts that the average basis spread should be zero, implying that the basis spread movement is a mean-reverting process. The speed of adjustment to the long-term equilibrium can be measured by the coefficient of lagged basis spread. A coefficient between 0 and 1 confirms the mean-reverting process. Moreover, when the coefficient is smaller, it implies that the speed of returning to long-term averages is faster.
- Changes in credit spread (△CDS). Credit spreads in the two markets could move in response to changing credit conditions. If both markets price credit risk accurately and efficiently, the change in credit conditions should be reflected equally in the two markets. In other words, a coefficient of △CDS not significantly different from zero suggests that the two markets exhibit similar responses to credit events and that arbitrage opportunities do not exist even in the short run. Conversely, a coefficient that is significantly different from zero implies different responses and the deviation from equilibrium in the short run. In this case, the sign of the coefficient indicates the relative responsiveness of the two instruments. For example, a significantly positive coefficient implies that, for the same change in fundamentals, the CDS spread changes more significantly than the bond spread.
- Ratings and rating events. Houweling and Vorst (2005) suggest that the price discrepancy could be different for high-grade and low-grade bond issues. Intuitively, a same level of absolute price differential is proportionally less important for low-grade bond issuers because the credit spread is higher. In this study I include the time series of the *S&P* rating for each entity. The rating categories AAA, AA+, AA, $\cdots$, CCC+ are transformed into the numbers 1, 2, 3, $\cdots$, 17.

  Another issue of interest is whether the bond market and the CDS market have different predicting power over future rating events. As Hull et al. (2004) and Norden and Weber (2004) have pointed out, the derivatives market tends to anticipate future rating events. However, so far no research has been conducted on whether the derivatives market and the bond market behave differently before and after a credit event. To examine this issue I include five dummy variables (following Hull et al., 2004) that can capture the impact of rating actions: $DUMB6190$, $DUMB3160$ and $DUMB0130$ represent a rating event occurring on future days $[t+61, t+90]$, $[t+31, t+60]$, $[t+1, t+30]$, respectively; $DUMA0110$ and $DUMA1130$ represent a past rating event during $[t-1, t-10]$ and $[t-11, t-30]$. In each of the dummy variables a value of 1 refers to a downgrade of the rating, -1 to an upgrading and 0 to no action.
- Contractual arrangements. The terms of CDS contracts could have an impact on CDS spreads. Here I include two dummy variables to capture the credit type ($DUMCORP$, 1 if corporate and 0 otherwise) and the type of restructuring clause ($DUMFR$, 1 for full-restructuring and 0 for modified-restructuring). The restructuring clause dummy variable is especially interesting. The restriction on the maturity of the deliverables in MR contracts implies that the value of the delivery option is lower and therefore their CDS spreads should be lower. The

coefficient of the dummy variable is expected to be positive and its magnitude represents the economic value of the difference in delivery options.

- Liquidity. Both CDS premia and bond spreads may be influenced by factors unrelated to the underlying credit risk, chief among which is the liquidity of the respective securities. There is no universally accepted proxy for liquidity factors. I use the bid-ask spread differential to represent the relative liquidity between the two instruments. To be more specific, this measure is defined as the average bid-ask spread in the CDS market in the past 20 business days minus the average bid-ask spread in the bond market over the same period.[11] A lower bid-ask spread differential implies that, for the particular entity, the CDS market is relatively more liquid than the cash market. Therefore the basis spread tends to be lower, implying a positive coefficient.
- Macroeconomic conditions. To test the pricing accuracy I also include two macro financial variables: Treasury rates and regional stock market index (*S&P* 500 in the United States, *EURO STOXX* 50 in Europe and *Nikkei* 225 in Asia). It is well known that these two variables reflect the performance of the macroeconomy and the financial market and thus have an impact on the pricing of credit risk. However, if both markets are equally efficient in pricing the changes in macro-financial conditions, their impact on basis spreads should be zero.

Table 3 reports the results of panel data regressions with random effects (favored by the Hausman test). The empirical results are very similar, independently of whether swap rates or Treasury rates are used as the benchmark. Overall, credit factors appear to play an important role in affecting basis spreads.

First, the coefficient of lagged basis spreads is significantly less than one, confirming that the credit spread movement is a mean-reverting process. At the same time, the size of the coefficient suggests that the speed of this mean reversion is rather slow: only 7 –8% of price errors can be corrected on the next business day. That is, it takes about 8 business days to correct half of the price discrepancy.

Second, the coefficient of $\triangle$CDS is significantly different from zero. This result suggests that the CDS market and the bond market respond differently to changes in credit conditions. The size of the coefficient implies that, for a 10 basis points increase in the CDS spread, there is only a 3 basis points increase in the bond spread. This could be a major source of price differentials in the two markets, particularly in 2002 when credit conditions were very volatile.

Third, ratings are statistically insignificant, in contrast to the findings in Houweling and Vorst (2005). However, there is some evidence that the two markets behave differently before and after a rating event. The results suggest that CDS spreads increase (decrease) faster than bond spreads by about 2 basis points per day during the interval of 60 −90 days before a rating downgrade (upgrade). And during the 10 days after the credit event, bond spreads increase

[11] It is very likely that the bid-ask spread is a highly endogenous variable and has a strong interaction with credit spreads, therefore I use the lagged bid-ask spread differential to avoid the potential endogeneity problem.

Table 3 Determinants of basis spreads: a panel data study (random effects). (i) $Basis_1$ and $Basis_2$ represent the basis spreads using swap rates and Treasury rates as risk-free rates respectively. Dummy($Basis_{i,t-1}$) is an indicator of positive basis spreads on the previous business day. $\triangle$CDS is the change in CDS spreads, and SP rating is the rating of the entity at day t. The five dummies of rating changes refer to whether there is a downgrade (1), an upgrade (-1) or no rating change (0) between days $[t+61, t+90]$ (DUMB6190), $[t+31, t+60]$ (DUMB3160), $[t+1, t+30]$ (DUMB0130), $[t-1, t-10]$ (DUMA0110) and $[t-11, t-30]$ (DUMA1130), respectively. The Treasury rate refers to the rate in the same national currency, and the general equity market index refers to S& P 500 for US entities, STOXX 50 for European and Nikkei 225 for Asian ones. The two dummy variables indicate that the CDS contract includes a full-restructuring clause (DUMFR) and the credit type is "corporate" (DUMCORP). The liquidity factor refers to the difference between the average bid-ask spread in the CDS market in the past 20 business days and that in the bond market. (ii) The Hausman test favors the random effect specification. (iii) t-statistics in the parenthesis. The only exception is the lagged basis spread, where the t-statistics is calculated for the hypothesis that the coefficient equals to one

Dependent variables	$Basis_1$				$Basis_2$			
	coef	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*	*coef*	*t-stat*
Lagged Basis	0.92	(8.6)	0.92	(8.0)	0.94	(7.4)	0.92	(7.4)
Dummy($Basis_{i,t-1} > 0$)			0.32	(0.4)			3.25	(2.5)
$\triangle$ CDS	0.72	(35.7)	0.72	(35.6)	0.71	(35.4)	0.71	(35.5)
SP rating	0.38	(1.2)	0.35	(1.1)	0.43	(1.2)	0.50	(1.7)
Changes in ratings								
DUMB6190	2.21	(1.9)	2.18	(1.9)	1.99	(1.7)	2.04	(1.8)
DUMB3160	0.56	(0.5)	0.50	(0.4)	0.21	(0.2)	0.16	(0.1)
DUMB0130	−0.31	(0.3)	−0.33	(0.3)	−0.68	(0.6)	−0.91	(0.9)
DUMA0110	−3.55	(2.2)	−3.58	(2.2)	−3.56	(2.2)	−3.37	(2.1)
DUMA1130	−1.57	(1.2)	−1.58	(1.2)	−1.88	(1.4)	−1.80	(1.4)
Market condition								
Treasury rate	0.66	(1.1)	0.66	(1.1)	−0.28	(0.5)	−0.45	(0.8)
Equity index (%)	−0.001	(1.4)	−0.001	(1.4)	−0.001	(1.5)	−0.001	(1.6)
Dummies								
DUMFR	−1.61	(0.6)	−1.60	(0.6)	−0.84	(0.3)	−1.50	(0.6)
DUMCORP	−0.75	(0.5)	−0.70	(0.4)	−0.93	(0.6)	−1.21	(0.8)
Liquidity factors								
Spread differential	0.10	(3.3)	0.11	(3.3)	0.09	(2.3)	0.07	(2.3)
Number of observations	1684		1684		1683		1683	
Hausman test	6.52		7.51		7.98		9.76	

(decrease) more substantially by about 3.5 basis points per day, largely offsetting the price discrepancies accumulated before. This implies that the derivatives market does a better job in incorporating future rating events into the price.

Fourth, market conditions and contractual terms ($DUMCORP$ and $DUMFR$) do not affect basis spreads. The insignificance of the first three variables (the Treasury rate, the equity market index and $DUMCORP$) is consistent with theoretical prediction, reflecting that changes in overall macroeconomic conditions and the industry factor have an equal impact on the two markets and hence are not sources of pricing inefficiency. It is a little surprising that the type of restructuring clause does not have any pricing impact. This might be due to the insignificance of the economy value of the delivery option, or the market's failure in pricing the delivery option during the period under review,[12] or the absence of an arbitrage market because the two types of contracts are usually traded in different markets: the MR-type contract is mainly adopted in the United States, while the FR-type contract is popular in Europe and Asia.

Fifth, the liquidity factor is statistically significant and has the expected sign. A higher bid-ask spread in the CDS market relative to the bond market indicates that the derivative contract is less liquid. As a result, the basis spread is higher. However, the impact of liquidity is not economically significant: a one-standard-deviation variation in the bid-ask spread differential only changes the basis spread by 2 basis points. Arguably, this might be due to the fact that the sample list only includes the most liquid names in both markets and the size of liquidity premium is rather small.

Finally, there is another interesting issue regarding the possibility of asymmetric dynamic adjustments in the basis spread, as the existence of impediments to short sales of corporate bonds imposes limits to arbitrage when the CDS premium is higher (see Section 2.1). Such an asymmetry can cause positive basis spreads to exhibit higher persistency than negative ones. To examine this issue I estimate the panel regression by including a dummy variable that indicates a positive lagged basis spread. If the short-sale restriction argument is valid, the coefficient of the dummy variable would be positive. This prediction is supported by the regression using Treasuries as risk-free rates. In contrast, when swap rates are used, the asymmetry in the adjustment process disappears. This is perhaps related to the large liquidity component of swap spreads as found in Liu et al. (2006). They show that liquidity considerations explain a significant portion of Treasuries, but have little impact on swap rates. In other words, the swap rate has been appropriately adjusted for the cost of short selling in the cash market. Hence, the short-sale restriction effect cancels out in the regression associated with swap rates.[13]

To summarize, although the parity relationship between the two credit spreads appears to hold on average over a long time horizon, substantial deviation from the parity can arise in the short run. A casual examination of the data suggests that the price difference is higher than the transaction cost in about 10% of observations, the latter of which defined as the average of bid-ask spreads in the two markets. During an extremely volatile period, the price discrepancy can be as large as 50–100

[12] Packer and Zhu (2005) compare the CDS spreads of the same entity but of different restructuring clauses, and find that the FR contract is on average priced higher than the MR contract by 3–4 basis points. They also detect a trend towards a more uniform valuation of contractual terms from year 2003 to 2004.

[13] I thank an anonymous referee for proposing this explanation.

basis points, much higher than the average transaction cost (15–20 basis points).[14] The panel regression suggests that the deviation from the parity is largely attributable to credit factors rather than contractual arrangements and macro-financial conditions. The derivatives market appears to respond more strongly to changes in credit conditions, and the speed of spread convergence is slow. Nevertheless, it remains to be unanswered whether the stronger response of the CDS spread is a manifestation of a more efficient role of the derivative instrument in price discovery, or it is due to the overreaction of CDS spreads to changes in credit conditions.

Empirical Analysis II: Dynamic Relationship between the Two Markets

Long-Term Consistency between the Two Credit Spreads

This section examines the long-term co-movements and short-term dynamic linkages between CDS premia and bond spreads using the methods described in Section 2.2. I first test the cointegration relationship between the two spreads. The test is divided into two steps. First, the standard Dickey-Fuller unit root test is applied to the two credit spread series to confirm their non-stationarity. The second step examines the existence of a cointegration relationship between the two variables. As the theory predicts, a natural candidate for the cointegration relationship is: $cds_{it} = \alpha_i + \beta_i \cdot bond_{it}$, with $\alpha_i = 0$ and $\beta_i = 1$.

Table 4 summarizes the results of unit root tests (ADF tests without a trend) for the two credit spreads and basis spreads. All credit spread series (except the bond spread for Bank of America) need to be differenced for stationarity. In addition, in 14 (12 if Treasury rates are used)[15] out of the 24 entities, CDS spreads and bond spreads are cointegrated in a way consistent with theory. Moreover, when I remove the restriction on cointegration coefficients, the Johansen cointegration test (Johansen, 1988, 1991) finds supporting evidence of a cointegration relationship between the two spreads for the other 9 (11) entities. Overall, the cointegration test supports the view that the two credit spreads share a common stochastic trend, meaning that no arbitrage opportunity exists in the long run.

Short-Term Dynamic Interactions

The next objective is to examine the short-term dynamic linkages between the two spreads, in particular which market is more efficient in reflecting changes in the default risk of underlying entities. For this purpose I run the VECM regression (see Eq. 2) for each reference entity. As introduced in Section 2, the significance and magnitude of the two coefficients on the error correction term, λ_1 and λ_2, measure

[14] The arbitrage profit could be smaller or even disappear if taking into account the price impact of arbitrage transactions, or if considering that the arbitrage cost might be even higher since the synthetic 5-year bond is not traded in the market.

[15] To save space, I focus on the results that use swap rates as risk-free rates and report those corresponding with Treasuries in the parentheses hereafter.

Table 4 Unit root and cointegration test results

	Swap rates as risk-free rates				Treasury rates as risk-free rates			
	Bond spread	CDS spread	$Basis_1$	Cointegration	Bond spread	CDS spread	$Basis_2$	Cointegration
AOL	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
ATT	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
BOA	I(0)	I(1)	I(0)		I(0)	I(1)	I(1)	
BS	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	yes
CARN	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
DAIM	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
DTEU	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
FM	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
FTEU	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
GM	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
GS	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(1)	$\beta \neq 1$
HF	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
HO	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
IBM	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
KDB	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
KODA	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
LB	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
MS	I(1)	I(1)	I(0)	yes	I(1)	I(1)	I(1)	$\beta \neq 1$
SBC	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
SEAR	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
SP	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
SUMI	I(1)	I(1)	I(1)	$\beta \neq 1$	I(1)	I(1)	I(1)	$\beta \neq 1$
WC	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
WD	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
Total	23	24		14	23	24		12

which of the two markets adjusts to eliminate price discrepancies, and the speed of this adjustment. The relative magnitude of the two λ coefficients is an indicator of the relative importance of each market in price discovery. Moreover, the VECM study on individual entities allows the dynamic linkages between the two spreads to be different across entities, therefore providing further insights on the issue of interest.

In the baseline study I use the imputed data series generated by the EM method (see Section 3). The lag length in the VECM study is chosen using the Akaike information criterion (AIC) and the Schwarz information criterion (SIC). The lag selection turns out to be one or two periods for most entities, with a maximum of five days. In addition, the VECM is estimated with the restriction that $\alpha_i = 0$ and $\beta_i = 1$ if the entity has passed the cointegration test with this parameter specification. Otherwise Eq. 2 is estimated by allowing α_i and β_i to be freely determined within the model.

The results are summarized in Table 5. Overall, there is evidence that the derivatives market tends to lead the cash market in price discovery. Out of the 24 entities, there are 17 (14) names for which λ_1 is significantly positive, or equivalently, the bond market moves to correct the price discrepancies. Similarly, there are 7 (6) entities for which the derivatives market adjusts its price in response to price discrepancies (λ_2 is

Table 5 VECM test results: the baseline study. The ratio is defined as $\frac{\lambda_1}{\lambda_1 - \lambda_2}$ with a range between 0 and 1. Avg(US) is the average coefficient for US entities and Avg(nonUS) is the average for non-US entities. Significantly positive λ_1 and negative λ_2 (at a confidence level of 95%) are boldfaced

	Bond spread$_1$			Bond spread$_2$		
	λ_1	λ_2	Ratio	λ_1	λ_2	Ratio
AOL	**0.080**	0.007	1	**0.074**	0.010	1
ATT	**0.084**	−0.016	0.838	**0.072**	−0.009	0.886
BOA	–	–	–	–	–	–
BS	**0.166**	−0.022	0.884	0.070	−0.026	0.729
CARN	**0.083**	−0.019	0.810	0.080	−0.029	0.730
DAIM	**0.146**	−0.006	0.963	**0.057**	−0.002	0.960
DTEU	0.011	**−0.098**	0.099	0.015	**−0.101**	0.127
FM	**0.097**	**−0.099**	0.494	**0.056**	**−0.056**	0.502
FTEU	0.010	**−0.083**	0.108	0.016	**−0.077**	0.170
GM	**0.065**	0.015	1	**0.039**	0.015	1
GS	**0.137**	−0.036	0.792	−0.010	**−0.049**	0
HF	**0.228**	−0.024	0.905	**0.185**	−0.031	0.857
HO	0.022	**−0.079**	0.218	0.008	**−0.077**	0.098
IBM	**0.008**	0.007	1	**0.033**	−0.013	0.721
KDB	**0.133**	−0.028	0.824	0.076	−0.024	0.759
KODA	0.019	0.032	0	0.007	0.038	0
LB	−0.002	**−0.002**	0	**0.086**	0.018	1
MS	**0.103**	−0.030	0.773	**0.063**	−0.010	0.857
SBC	**0.024**	**−0.037**	0.387	**0.018**	−0.025	0.424
SEAR	**0.269**	0.067	1	**0.204**	0.046	1
SP	**0.114**	0.001	1	**0.090**	0.008	1
SUMI	−0.007	**−0.032**	0	0.000	**−0.035**	0
WC	**0.240**	0.116	1	**0.216**	0.113	1
WD	**0.125**	−0.008	0.939	**0.066**	−0.009	0.877
Significant λ_1 (+) or λ_2 (−)	17	7		14	6	
Average	0.094	−0.016	0.653	0.066	−0.014	0.639
Avg(US)	0.103	−0.007	0.724	0.076	−0.005	0.705
Avg(nonUS)	0.059	−0.049	0.399	0.033	−0.048	0.403

significantly negative). To be more specific, there is a strong one-way linkage from the CDS market to the bond market in 15 (13) entities, from the bond market to the CDS market in 5 (5) entities, and a two-way linkage in 2 (1) entities. Interestingly, the sum of the two adjustment coefficients (λ) is about 0.11 (0.08) on average, which is close to the mean-reverting coefficient in the panel data study.

Following Gonzalo and Granger (1995), I also compute a measure that reflects the contribution of each market to price discovery. The measure is defined as the ratio of the speed of adjustments in the two markets ($\frac{\lambda_1}{\lambda_1 - \lambda_2}$), with a lower bound of 0 and an upper bound of 1. When the measure is close to 1, it implies that the CDS market plays a leading role in price discovery and the bond market moves afterwards to correct for pricing discrepancies. When the measure is close to 0, the dynamics point to reverse direction with the bond market leading the derivatives market. When the measure is close to $\frac{1}{2}$, both markets contribute approximately equally to price discovery.

This measure (Table 5) gives us similar results on the dynamic relationship between the two markets. The average ratio of 0.653 (0.639) favors the hypothesis that the bond market, rather than the derivatives market, adjusts to eliminate the deviation from their long-run equilibrium relation. This suggests that the previous finding that the CDS spread responds more strongly to changing credit conditions is not a result of price overreaction in the derivatives market. Instead, the derivatives instrument appears to be more efficient in price discovery, which might be attributable to the fact that there is neither a funding restriction nor a short-sale restriction in the CDS market.

Looking backward, this finding is able to explain the substantial increase in basis spreads related to swap rates in year 2002 and the heterogeneity of average price discrepancies (Section 4.1). As most entities experienced a deterioration in credit conditions in 2002, their credit spreads increased substantially. If the CDS market moves ahead of the bond market, in the short term CDS spreads could increase faster than bond spreads and the pricing errors persist for a while due to slow convergence. This effect results in positive basis spreads (using swap rates) during this adjustment period. By contrast, in previous years, when the credit conditions were less volatile, pricing errors were around their long-term average value of zero. This explanation is further supported by looking into the cross-entity difference of price discrepancies. For some entities that experienced the most severe credit shocks during the sample period, such as AOL Time Warner, AT& T, Sprint and Worldcom, their average price discrepancies (using swap rates) turn out to be much higher. This, again, could be due to the leading role of the derivatives market in reflecting credit changes for those entities.[16]

Robustness Check

The above results may be biased because of the particular method used for data interpolation. To check the robustness of these results I conduct the same econometric exercises as in Section 5.2 but using two alternative imputation methods to fill in the missing observations. One is the EM method with an extension of a resampling scheme. Table 6 reports the averages of adjustment coefficients based on 100 resampling imputations. The other method is the LOCF approach, which substitutes the last available quotation for the missing data. The results are reported in Table 7.

Overall, the main results are largely consistent with those in the baseline analysis. The two credit spreads are tied together with a common trend in the long run, supporting the theoretical prediction that there is no arbitrage opportunity between the two markets in equilibrium relation. More than half of the entities pass the hypothesis test that the two spreads cointegrate with each other with the equivalence relationship. And most of the other entities pass the Johansen

[16] However, it might be premature to conclude that the CDS market has taken over the cash market in price discovery. Bond spreads move first for a few entities in this study. Interestingly, it seems that their role is quite different depending on the geographical location of the entities. As shown in the last two rows of Table 5, the leading role of the derivatives market is more prominent for American entities. In contrast, for the five non-US entities the cash market appears to have a more important role in price discovery. This might be due to different market practices. Packer and Zhu (2005) also find evidence of geographic differences in the pricing of restructuring terms across the US, Europe and Asia.

Table 6 Robustness check 1: using EM algorithm with resampling schemes (N = 100). The boldface coefficients are λ_1 (λ_2) that are significantly positive (negative) at a significance level of 95% in at least 90 out of the 100 simulations

	Bond spread$_1$			Bond spread$_2$		
	λ_1	λ_2	Ratio	λ_1	λ_2	Ratio
AOL	**0.080**	0.002	1	**0.074**	0.005	1
ATT	**0.090**	−0.017	0.844	**0.078**	−0.010	0.890
BOA	–	–	–	–	–	–
BS	**0.164**	−0.024	0.876	**0.070**	−0.027	0.724
CARN	**0.082**	−0.025	0.769	**0.079**	−0.035	0.698
DAIM	**0.156**	−0.015	0.917	**0.062**	−0.007	0.896
DTEU	0.011	**−0.111**	0.086	0.014	**−0.115**	0.112
FM	**0.095**	**−0.122**	0.440	**0.056**	**−0.067**	0.454
FTEU	0.009	**−0.099**	0.075	0.014	**−0.090**	0.128
GM	**0.065**	0.005	1	**0.039**	0.008	1
GS	**0.135**	−0.045	0.753	−0.007	**−0.057**	0
HF	**0.226**	−0.033	0.874	**0.184**	−0.040	0.821
HO	0.024	**−0.089**	0.213	0.011	**−0.088**	0.106
IBM	**0.008**	0.008	0	**0.030**	−0.013	0.865
KDB	**0.148**	**−0.041**	0.784	0.087	**−0.037**	0.702
KODA	0.024	0.026	1	0.020	0.038	0
LB	0.006	−0.0001	0	**0.091**	0.009	1
MS	**0.102**	−0.036	0.742	**0.062**	−0.011	0.854
SBC	**0.024**	−0.037	0.394	**0.018**	−0.025	0.422
SEAR	**0.267**	0.052	1	**0.201**	0.035	1
SP	**0.113**	−0.016	0.880	**0.089**	−0.008	0.930
SUMI	−0.006	**−0.039**	0	0.007	**−0.038**	0.133
WC	**0.248**	0.130	1	**0.225**	0.125	1
WD	**0.126**	−0.006	0.958	**0.067**	−0.008	0.893
Significant λ_1 (+) or λ_2 (−)	17	6		16	7	
Average	0.095	−0.023	0.636	0.068	−0.020	0.637

cointegration test. In addition, the VECM analysis favors the hypothesis that the derivatives market is more responsive to changes in credit conditions. Using the resampling scheme yields as strongly supportive evidence as in the baseline study. When the LOCF approach is adopted, the leading role of the derivatives market is less obvious, but there is still weakly supportive evidence when swap rates are used.

The robustness of the results is quite striking considering that these imputation methods are based on completely different assumptions on the causes of missing observations. For example, the LOCF method interprets missing data as indicating that there have been no changes in credit conditions, while the EM method assumes that the dynamics during the missing data period follows exactly the same process as reflected in extant observations. Since the missing data problem is mainly confined to the CDS market, we expect that using the LOCF method will produce a much weaker result on the role of the derivatives market in price discovery. Consider for instance that the CDS quote is unobserved at a particular date t, and there is a jump of CDS premia between date $t-1$ and $t+1$, the two methods will produce very different estimates. The EM method treats part of the jump as having occurred at

Table 7 Robustness check 2: using the last-observation-carried-forward (LOCF) interpolation. Significantly positive λ_1 and negative λ_2 (at a confidence level of 95%) are boldfaced

	Bond spread$_1$				Bond spread$_2$			
	CI test	λ_1	λ_2	Ratio	CI test	λ_1	λ_2	Ratio
AOL	$\beta \neq 1$	**0.088**	−0.025	0.781	$\beta \neq 1$	**0.082**	−0.023	0.778
ATT	yes	**0.074**	−0.012	0.858	yes	**0.061**	−0.007	0.902
BOA	yes	0.057	**−0.061**	0.480	$\beta \neq 1$	−0.005	**−0.098**	0
BS	$\beta \neq 1$	**0.215**	0.029	1	yes	0.044	−0.025	0.637
CARN	$\beta \neq 1$	**0.089**	−0.041	0.687	$\beta \neq 1$	**0.085**	−0.047	0.647
DAIM	yes	0.064	**−0.117**	0.355	yes	0.009	−0.035	0.213
DTEU	yes	0.001	**−0.111**	0.010	yes	0.004	**−0.117**	0.033
FM	yes	**0.068**	**−0.195**	0.258	yes	**0.034**	**−0.092**	0.271
FTEU	$\beta \neq 1$	0.007	**−0.112**	0.056	$\beta \neq 1$	0.007	**−0.114**	0.060
GM	yes	**0.059**	−0.006	0.911	yes	**0.032**	0.005	1
GS	yes	**0.102**	−0.041	0.715	$\beta \neq 1$	−0.028	−0.025	1
HF	$\beta \neq 1$	**0.061**	**−0.131**	0.319	$\beta \neq 1$	0.019	**−0.076**	0.200
HO	$\beta \neq 1$	0.017	**−0.116**	0.126	$\beta \neq 1$	0.003	**−0.112**	0.026
IBM	$\beta \neq 1$	−0.009	−0.006	1	no	–	–	–
KDB	yes	**0.087**	**−0.123**	0.412	yes	0.007	**−0.090**	0.071
KODA	no	–	–	–	no	–	–	–
LB	yes	**0.070**	−0.013	0.846	$\beta \neq 1$	0.032	**−0.100**	0.242
MS	yes	**0.088**	−0.032	0.734	$\beta \neq 1$	**0.044**	**−0.042**	0.513
SBC	$\beta \neq 1$	**0.023**	−0.023	0.497	$\beta \neq 1$	**0.017**	−0.020	0.455
SEAR	yes	**0.229**	0.043	1	yes	**0.143**	0.025	1
SP	yes	0.076	−0.085	0.473	yes	0.061	−0.062	0.496
SUMI	$\beta \neq 1$	−0.017	**−0.046**	0	yes	0.007	**−0.045**	0.129
WC	yes	**0.243**	−0.066	0.786	yes	**0.212**	−0.044	0.829
WD	yes	**0.117**	−0.017	0.874	yes	**0.059**	−0.018	0.767
Significant λ_1 (+) or λ_2 (−)	14	12	9		12	10	10	
Average		0.079	−0.057	0.573		0.042	−0.053	0.466

date t, while the LOCF method assumes that nothing has changed before date $t+1$. Therefore, jumps in CDS prices tend to occur at a later time when the imputation follows the LOCF method. In other words, by construction the LOCF provides a lower bound of the role of the derivatives market in price discovery. Indeed, this intuition is supported by the above results: on average the contribution measure is lower when the LOCF method is adopted. Nevertheless, the robustness of main findings, irrespective of which imputation method is used, suggests that bias due to statistical imputation does not overshadow the higher responsiveness of the derivatives market to changes in credit conditions than the cash market.

Conclusions

This paper has examined the impact of the development of the credit derivatives market on the pricing of credit risk, and how CDS spreads interact with prices in the bond market. The analysis confirms the theoretical prediction that the two prices should be equal to each other in equilibrium. However, in the short run substantial pricing discrepancies can exist between the two markets. I show that the deviation could be largely due to different responses of the two spreads to changes in credit conditions. The panel study and the VECM analysis suggest that, in general, the derivatives market moves ahead of the bond market in price discovery. Moreover, such price discrepancies can exist for several weeks as the speed of convergence is rather slow. These results imply that the derivatives market plays a key role in improving the efficiency of the price discovery mechanism for corporate credit risk. From the perspective of monitoring developments in this market, the results indicate that CDS spreads are more likely to provide an accurate gauge of the price of default risk than bond spreads.

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References

Acharya VV, Das SR, Sundaram RK (2002) Pricing credit derivatives with rating transitions. Financ Anal J 58:28 – 44
Anderson R, Sundaresan S, Tychon P (1996) Strategic analysis of contingent claims. Eur Econ Rev 40:871–881
Blanco R, Brennan S, March IW (2005) An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps. J Finance 60:2255–2281
Campbell J, Taksler G (2003) Equity volatility and corporate bond yields. J Finance 58:2321–2349
Collin-Dufresne P, Goldstein R (2001) Do credit spreads reflect stationary leverage ratios? J Finance 56:1929–1957
Cossin D, Hricko T (2001) Exploring for the determinants of credit risk in credit default swap transaction data. Working Paper
Das SR (1995) Credit risk derivatives. J Deriv 2:7–21
Das SR, Sundaram RK (2000) A discrete-time approach to arbitrage-free pricing of credit derivatives. Manage Sci 46:46 – 62
Das SR, Sundaram RK, Sundaresan SM (2003) A simple unified model for pricing derivative securities with equity, interest-rate, and default risk. Working Paper, Santa Clara University
Davidson J, Hendry D, Srba F, Yeo S (1978) Econometric modelling of the aggregate time-series relationship between consumers’ expenditure and income in the United Kingdom. Econ J 88: 661–692
Duffie D (1999) Credit swap valuation. Financ Anal J 55:73 – 87
Duffie D, Liu J (2001) Floating-fixed credit spreads. Financ Anal J 57:76 – 87
Duffie D, Singleton K (1999) Modeling term structures of defaultable bonds. Rev Financ Stud 12:687–720
Elton E, Gruber M, Agrawal D, Mann C (2001) Explaining the rate spread on corporate bonds. J Finance 56:247–277
Engle R, Granger C (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica 55:251–276
Fitch IBCA (March 2003) Global credit derivatives: risk management or risk? Special report
Gonzalo J, Granger C (1995) Estimation of common long-memory components in cointegrated systems. J Bus Econ Stat 13:27–36

Houweling P, Vorst T (2005) Pricing default swaps: empirical evidence. J Int Money Financ 24:1200–1225
Hull J, White A (2000) Valuing credit default swaps I: no counterparty default risk. J Deriv 8(1):29 – 40
Hull J, White A (2001) Valuing credit default swaps II: modeling default correlations. J Deriv 8(3):12–22
Hull J, Predescu M, White A (2004) The relationship between credit default swap spreads, bond yields, and credit rating announcements. J Bank Financ 28:2789–2811
Jarrow RA, Turnbull SM (1995) Pricing derivatives on financial securities subject to credit risk. J Finance 50:53–85
Jarrow RA, Yildirim Y (2002) Valuing default swaps under market and credit risk correlation. J Fixed Income 11:7–19
Johansen S (1988) Statistical analysis of cointegrating vectors. J Econ Dyn Control 12:231–254
Johansen S (1991) Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. Econometrica 59:1551–1580
Kalimipalli M, Warga A (2002) Bid/ask spread and volatility in the corporate bond market. J Fixed Income 82–91
Kocić A, Quintos C, Yared F (2000) Identifying the benchmark security in a multifactor spread environment. Lehman Brothers Fixed Income Derivatives Research Report
Leland HE (1994) Corporate debt value, bond covenants, and optimal capital structure. J Finance 49:1213–1252
Leland HE, Toft KB (1996) Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. J Finance 51:987–1019
Liu J, Longstaff F, Mandell R (2006) The market price of credit risk: an empirical analysis of interest rate swap spreads. J Bus, forthcoming
Longstaff F, Schwartz E (1995) A simple approach to valuing risky fixed and floating rate debt. J Finance 50:789–820
Longstaff F, Mithal S, Neis E (2005) Corporate yield spreads: default risk or liquidity? New evidence from the credit default swap market. J Finance 60:2213–2253
Madan D, Unal H (2000) A two-factor hazard-rate model for pricing risky debt and the term structure of credit spreads. J Financ Quant Anal 35:43–65
Merton R (1974) On the pricing of corporate debt: the risk structure of interest rates. J Finance 29:449–470
Norden L, Weber M (2004) Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements. J Bank Financ 28:2813–2843
Packer F, Zhu H (March 2005) Contractual terms and CDS pricing. BIS Q Rev, 89–100
Reinhart V, Sack B (2002) The changing information content of market interest rates. BIS Pap (12):340–357
Rule D (June 2001a) The credit derivatives market: its development and possible implications for financial stability. In: Financial Stability Review. Bank of England, pp 117–140
Rule D (December 2001b) Risk transfer between banks, insurance companies and capital markets: an Overview. In: Financial Stability Review. Bank of England, pp 137–159
Schönbucher PJ (2003) Credit derivatives pricing models: models, pricing, implementation. Wiley Finance