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An empirical comparison of credit spreads between the bond market and the credit default swap market

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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 empirical findings confirm the theoretical prediction that bond spreads and CDS spreads move together in the long run. Nevertheless, in the short run this relationship does not always hold. The deviation is largely due to different responses of the two markets to changes in credit conditions. By looking into the dynamic linkages between the two spreads, I find that the CDS market often moves ahead of the bond market in price adjustment, particularly for US entities. Liquidity also matters for their role in price discovery. Surprisingly, the terms of CDS contracts and the short-sale restriction in the cash market only have a very small impact.

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1. Introduction[1]

Credit risk pricing has received much attention among academics, practitioners and financial regulators. Since credit risk is involved in almost all financial activities, it is critical that such risk is correctly measured and efficiently priced in the market. For financial regulators, it is also very important to ensure that the credit risk exposure of banks and other financial institutions is not so high as to jeopardise the stability of the financial system. In the new capital adequacy framework released by the Basel Committee on Banking Supervision (BCBS) in June 2004, the main theme is to improve the measurement of banks' credit risk exposure.

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). Since the introduction of these credit protection instruments, the market has grown dramatically and become an important tool for financial institutions to shed or take on credit risk. 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 1.2 trillion at the end of 2001, and is expected to zoom up to USD 4.8 trillion by the end of 2004.[2]

Among various credit derivative instruments the credit default swap (CDS) is the most widely traded, capturing nearly half (45%) of the market share. A CDS provides 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 (bankruptcy, obligation acceleration, obligation default, failure to pay, repudiation / moratorium, or restructuring) occurs. In return, the protection buyer makes periodic payments to the seller until the maturity date of the CDS contract or when a 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 the credit risk of the reference entity in addition to its corporate bond yield from the cash market.[3]

This paper tries to address two important questions that have significant implications for risk managers and financial regulators. First, is the credit risk priced equally between the derivatives market and the traditional cash market (ie 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 (see Fitch (2003)), the answer to this question could have important implications for credit risk transfer within the banking industry and across financial sectors. Second, which market moves more quickly in reflecting changes in credit conditions (ie 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

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1 Contact: Research & Policy Analysis, Monetary and Economic Department, Bank for International Settlements, CH-4002 Basel, Switzerland. E-mail: haibin.zhu@bis.org. I would like to thank Robert Avery, Joseph Bisignano, Claudio Borio, Cristina Neto de Carvalho, Jenke ter Horst, Eli Remolona, Kostas Tsatsaronis and seminar participants at the Bank for International Settlements, the 2004 European Financial Management Association (EFMA) annual meeting and the Portuguese Finance Network 3rd Finance Conference for insightful comments. Data support by Angelika Donaubauer and Eustathios Triantafellou is also appreciated. The views represented in this paper are solely my own and do not necessarily reflect those of the BIS.

2 The two articles by Rule (2001a, b) provide excellent institutional backgrounds on the credit derivatives market.

3 The price of credit risk is also available from other financial instruments, such as financial guarantees and syndicated loans in the secondary market. However, these markets are either very small or very illiquid.

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 (2001, HV hereafter) and Hull et al (2003) compare the credit risk pricing between the bond market and the CDS market. Both suggest that, when swap rates are used as benchmark risk-free rates, the price discrepancies between bond spreads and CDS premia are quite small (about 10 basis points). Moreover, Hull et al 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 last issue is also examined in a recent paper by Longstaff et al (2003), who suggest that the derivatives market tends to lead the bond market in price discovery. However, the fact that the potential cointegration relationship across the markets is ignored in their study may introduce bias in their econometric results. Moreover, the weekly frequency of their dataset may not be appropriate to analyse the short-term dynamic interactions. To overcome these shortcomings I use a new dataset and adopt more rigid econometric techniques. The daily CDS data used in my study are constructed from a unique dataset provided by a major market broker, which provides a true reflection of market prices, volatility and liquidity. Based on the high-quality dataset I adopt the panel data technique to analyse the influence of various factors on price discrepancies between the two markets. In addition, since the two credit spreads are cointegrated in the long term, the vector error correction method (VECM) is more appropriate to examine the relative importance of the two markets in price discovery.[4]

The main findings are as follows. First, the credit risk tends to be priced equally in the two markets in the long run. In other words, no arbitrage opportunity exists in the long run. Second, market participants seem to use swap rates rather than treasury rates as the proxy for risk-free rates. I show that the failure of Treasury rates to proxy for risk-free rates could be largely attributed to tax considerations. Third, in the short run there is strong evidence of market inefficiency in that the two markets exhibit substantial price discrepancies. This is to a large extent due 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 adjustment. Fourth, the empirical findings also suggest that the relative importance of the two markets in price discovery can vary substantially across entities. Liquidity matters. But there is also evidence of market segmentation in that US entities behave very differently from those in other regions. Lastly and surprisingly, the existence of the delivery option in CDS contracts and the short-sale restriction in the cash market only have minor impacts on credit risk pricing.

The remainder of this paper is organised 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 spread 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.

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[4] The VECM technique is also adopted in a contemporaneous study by Blanco et al (2004). Their results on the leading role of the CDS market in price discovery are much stronger. The difference could be due to two reasons. First, while my study covers the period 1999-2002, their study covers only 2001 and 2002. Since the derivatives market grew very rapidly, its role in price discovery may have substantially improved in more recent years. Second, the dataset used in this paper consists of all transactions and "real" quotes in the market. By contrast, their dataset consists of "matrix" quotes filled by the data provider itself. The result may partly reflect the information advantage enjoyed by the data provider since it is a major broker in the market.

2. Theoretical framework

2.1. Valuation of bonds and CDSs

Since the 1970s there have been extensive studies on the pricing of credit risk. In general, measures of credit risk consist of three building blocks: probability of default (PD), loss given default (LGD) and correlation between PD and LGD.[5] The credit risk models can be divided into two major groups. The so-called structural-form models, which were pioneered by the Merton (1974) framework, model explicitly the firm value process and values corporate bonds using modern option theory. In Merton's world, a firm issues two types of assets: equities and bonds. A default happens if the total asset value falls below a default boundary.[6, 7] By contrast, reduced-form models (also known as intensity-based models), represented by Jarrow and Turnbull (1995), Duffie and Singleton (1999), Madan and Unal (1999) and Hull and White (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.

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 equivalence relationship between the two spreads. This equivalence relationship is the theoretical hypothesis to be tested in the empirical part of the paper.

I follow Duffie's (1999) work as a starting point. In a simplest version of the model, the risk-free rate 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 stated credit event (usually default) occurs. The payment upon default is the difference between the face value (100 units, for example) and the market value (M_t) 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 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. The logic is as follows.

Define q(t) as the risk neutral default probability for the underlying asset at time *t*, and accordingly, $Q(t)=1-\int_0^t q(s)ds$ as the risk neutral survival probability until time *t*. A CDS buyer pays a regular CDS premium (ρ) at time $t_1, t_2, \ldots t_N$ unless a default occurs, and similarly, a bondholder gets a regular coupon payment (*c*) at the same frequency. Based on these assumptions, the valuation of the CDS can be derived using the risk neutral valuation principle. In particular, the CDS premium satisfies the following condition:

$$\sum_{i=1}^{N} e^{-rt_i} Q(t_i)\rho = \int_0^{t_N} e^{-rt}(100 - M_t)q(t)dt \qquad (1)$$

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5 The relationship between PD and LGD has attracted more attention recently among practitioners and bank regulators, particularly when they consider the time dimension of credit risk exposures. See Altman et al (2002) for an extensive discussion on this issue. In addition, for portfolio credit risk measurement, the default correlation is also an important factor that should be taken into account (see Lowe (2002)).

6 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 the 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).

7 A major drawback of structural models is their poor empirical performance. For example, it is very difficult to generate reasonable levels of short-term bond yields from structural models, because almost all structural models assume that the firm's value changes smoothly. Eom et al (2002) acknowledge in their paper that the accuracy of the predictions by structural models is very questionable. A similar conclusion is drawn in a recent paper by Huang and Huang (2002), who suggest that structural models tend to systematically underpredict the credit risk in the corporate bond market.

where r is the constant risk-free rate. The left-hand side of equation (1) represents the present value of premium payment in the risk neutral world. The protection buyer pays the prespecified premium rate so long as the credit event does not arise. The right-hand side of equation (1) is the present value of protection payment the buyer can receive if the credit event occurs. In equilibrium, the two values should be equalised to ensure that no arbitrage opportunity exists.

Using the same risk neutral valuation method, the current price of the defaultable bond (a par fixed coupon bond) can be derived as follows.

$$P = 100 = \sum_{i=1}^{N} e^{-rt_i} Q(t_i) c + e^{-rt_N} \cdot 100 Q(t_N) + \int_0^{t_N} e^{-rt} M_t q(t) dt \tag{2}$$

The valuation of the defaultable bond consists of three parts: the value of coupon payments, the value of the principal repayment at maturity given that no default has occurred, and the market value of the bond if it defaults.

Now assume that an investor shorts the defaultable bond and purchases a par fixed rate (with a coupon rate of r) risk-free note. Since the risk-free rate is constant, the risk-free note can always be sold at par whenever the risky bond defaults. As the initial net investment is zero, the no-arbitrage condition requires that

$$0 = -\sum_{i=1}^{N} e^{-rt_i} Q(t_i) c - e^{-rt_N} 100 \cdot Q(t_N) - \int_0^{t_N} e^{-rt} M_t q(t) dt + \sum_{i=1}^{N} e^{-rt_i} r \cdot Q(t_i) + \int_0^{t_N} e^{-rt} \cdot 100 \cdot q(t) dt + e^{-rt_N} \cdot 100 \cdot Q(t_N)$$

$$\Rightarrow \quad \sum_{i=1}^{N} e^{-rt_i} Q(t_i)(c - r) = \int_0^{t_N} e^{-rt} (100 - M_t) q(t) dt \tag{3}$$

In the above equation, the first three items on the right-hand side represent the value of cash flows from shorting the risky bond and the last three items represent the value of cash flows from purchasing the par risk-free note. Comparing this equation with the pricing formula of credit default swaps, it is straightforward that the following condition holds:

$$\rho = c - r \tag{4}$$

That is, CDS spreads should be approximately equal to the credit spreads (yields minus risk-free rates) of the underlying bonds. 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.

Equation (4) provides a cornerstone for the empirical analyses. However, this equivalence relationship may not hold exactly in practice for several reasons. Economists usually make simplified assumptions, implying that the above relationship is at best an approximation. For example, we have assumed that the risk-free interest rate is constant. In reality, it moves randomly. Furthermore, Duffie and Liu (2001) suggest that the equivalence relationship holds for par floating notes rather than for par fixed notes.[8] In practice, due to data availability, most researchers use fixed coupon notes that are not priced at par. All these factors point to the deviation from the above equivalence relationship and therefore bond spreads may not equal CDS premia exactly.

Moreover, some institutional factors may also cause CDS premia to differ from bond spreads. 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, a CDS contract can usually be settled either by cash or by delivery of physical assets. When the latter method is chosen, the protection buyer can choose to deliver any valid assets from a large prespecified pool. The existence of delivery options implies that CDS premia would be higher. Third, the definition of credit events is a very controversial topic, yet it could play a significant role in determining the premium rate of a CDS contract. In the standard definition of credit derivatives issued by ISDA (International Swaps and Derivatives Association) in 1999, restructuring was included as one

[8] Duffie and Liu (2001) also suggest that the price differential is very small.

of the six major credit events. However, protection buyers and sellers often have an opposite understanding 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.[9] Fourth, CDSs are unfunded, contrary to the funding restriction in the cash market. This difference could cause the two spreads to react differently to changes in the underlying credit risk, generating price discrepancies between the two markets in the short run. Fifth, short-sale of bonds is practically not allowed. Therefore traders are not able to gain from the price differentials when the CDS premium is higher than the bond spread. The asymmetry in the ability to take on arbitrage opportunities may have important implications for the dynamic adjustment of credit spreads. Sixth, the existence of transaction costs will allow for the existence of small arbitrage opportunities between the two markets. Finally, the two spreads may include information other than credit risk, such as liquidity premia. The influence of these additional factors could be very different in the two markets.

2.2. Econometric methods

Since the main objective of this paper is to examine the long-term consistency and short-term dynamic linkages between bond spreads and the CDS premium, modern time series techniques, including cointegration test, Granger causality test, vector error correction model (VECM) and panel data regression, are most appropriate for the study.

The concept of cointegration test proposed by Engle and Granger (1987) is often used to test the long-term relationship among financial series, especially when the series tend to be non-stationary. 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. In the second step, we need to examine the order of cointegration for the two variables. Since the theory has predicted that the two prices should be equal in the long run, 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. That is, there is no arbitrage opportunity between the two markets in the long run.

To investigate the dynamic relationship between the two markets, the Granger causality test can be utilised as a starting point to provide insightful clues to the direction of the linkage. The Granger causality does not provide conclusive evidence on economic causality, but nevertheless is able to assess whether there is a consistent pattern of shifts in one series preceding the other. The results therefore provide grounds for further investigation of the causal mechanisms.

A typical Granger causality test between two variables X and Y can be estimated based on the following equation:

$$X_t = c + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_t \qquad (5)$$

If there is Granger causality from Y to X, then some of the β coefficients should be non-zero; if not, all of the β coefficients are zeros. Therefore the Granger causality test can be performed by testing the hypothesis: H_0: $\beta_1 = \cdots = \beta_p = 0$, which can be readily implemented using standard F-tests. A rejection of the hypothesis test implies that Y Granger causes X. If X also Granger causes Y, there is a feedback effect present.

However, the Granger causality test does not give a direct answer to the causality relationship. Therefore I have to utilise the VAR method for further investigation. 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, ie the VECM framework:

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

$$\begin{bmatrix} \Delta bond_t \\ \Delta cds_t \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} (cds_{t-1} - \alpha_i - \beta_i bond_{t-1}) + \begin{bmatrix} \sum_{j=1}^{p} \gamma_{1,j} \Delta cds_{t-j} \\ \sum_{j=1}^{p} \gamma_{2,j} \Delta cds_{t-j} \end{bmatrix} + \begin{bmatrix} \sum_{j=1}^{p} \varphi_{1,j} \Delta bond_{t-j} \\ \sum_{j=1}^{p} \varphi_{2,j} \Delta bond_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (6)$$

In equation (6) 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 vector autoregression (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. The estimated adjustment coefficients λ_1 and λ_2 measure the degree to which prices in a particular market adjust to correct pricing discrepancies from their long term trend. For example, if λ_1 is significantly positive, it implies that the cash market adjusts to remove pricing errors, ie, 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 CDS market moves after the cash market. 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.

3. 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 covers the period from 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. Each quote contains the following information: (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 denomination, volume, seniority and restructuring clause;[10] (iii) information on the quote itself, such as the date (exact time) on which the quote is placed, the price (premium) in basis points, the direction of the quote, and whether the quote is a real trade.[11] Hence these data are a true reflection of the market on each trading day and provide an accurate indication of price variation, volatility and market liquidity.

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 denomination, maturity, seniority and restructuring clauses. For example, 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 filtering criteria are then used: (i) the entity is either a bank or a corporate (sovereign entities are excluded); (ii) the contract is denominated in either US dollars (USD) or euros (EUR); (iii) there are at least 150 days with valid quotes for the contract during the sample period.[12]

The time series of CDS quotes are downloaded from the CreditTrade database. At each particular date, I calculate the average quotes using the following rules: (i) if both bids and asks are available, the average quote is defined as the middle point of average bid and average offer; (ii) if only one direction of quote is available, the quote is adjusted by the last available bid-ask spread; (iii) in case (ii), if the past bid-ask spread is not available, the quote is adjusted by the average bid-ask spread of the entity over the whole sample period.

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[10] 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.

[11] A trade counts as two quotes, with the bid quote equalling the offer.

[12] The CDS market is still not very liquid. Only 55 entities met these criteria in the database.

For each of the chosen reference entities, I retrieve the information for all bonds issued during the sample period. To avoid measurement errors caused by various options in corporate bonds, 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.[13] (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 requirements 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.[14]

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 1.1). All of them are investment grade bond issuers (with a range from AA- to BBB-), with some diversity by currencies (22 in US dollars and 2 in euros), by credit types (8 banks and 16 corporate companies), by regions (19 from the United States, 3 from Europe and 2 from Asia) and by types of restructuring clauses (19 with the modified restructuring (MR) clause and 5 with the old restructuring (OR) clause).[15] Table 1.2 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 alternatives as benchmark risk-free interest rates: the zero coupon Treasury rates and swap rates (in either US dollars or euros depending on the currency denomination of the contract). The five-year generic government rates can be constructed from daily quotes of a subset of Treasury bond data, and the five-year generic swap rates are readily available.

4. Empirical analysis I: price discrepancies between the two markets

4.1. Average price discrepancies

Figure (1) displays the time series of CDS premia and bond spreads for each of the 24 issuers using the midpoint of the quote. At a first glance, these series move closing with each other, especially bond spreads adjusted by swap rates and CDS premia. It also shows that credit conditions for most entities deteriorated in late 2001 and early 2002, reflecting the slowdown of the global economy and the sharp decline in the equity market. Entering the second half of 2002, overall credit conditions improved substantially.

A useful indicator of price discrepancies between the CDS market and the bond market is the basis spread, which is defined as the five-year CDS spreads minus the five-year bond spreads (bond yields minus risk-free rates). Tables 2.1 and 2.2 show statistics of the average pricing discrepancies (APD) and average absolute pricing discrepancies (AAPD) for each of the 24 entities over the sample period, and the averages of all entities over the four years and in each calendar year. Similarly, Figure (2)

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[13] It is a combination of the interpolation method and the matching method used by Houweling and Vorst (2001).

[14] This method may miss the term structure of the yield curve. However, for many entities the number of bond issues is limited. In addition, using the above maturity restrictions, the potential bias should be rather small.

[15] The two types of restructuring clauses differ mainly in the delivery option. For OR 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. As Table 1 shows, MR is mainly used for US entities and OR for European and Asian entities.

plots the time series of average basis spreads of all 24 entities on a daily basis. In all the calculations two alternative risk-free rates are used: Treasury rates and swap rates.

An important observation from the results is that, 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 risk-free rates, where the APD and AAPD are only 13 and 29 basis points. By contrast, the average price differential is 55 basis points (and 66 basis points in absolute terms) if Treasury rates are used as risk-free rates.

This finding suggests that swaps have become a better proxy for the risk-free rates than Treasuries, particularly as a benchmark for the pricing and hedging of private instruments.[16] Actually, the same conclusion has also been seen in previous studies (see Kocic et al (2000), HV and Hull et al (2003)). The difference could be attributable to different fundamental factors influencing Treasury rates and swap rates and their recent movements. As Reinhart and Sack (2002) point out, Treasury yields have become increasingly separated from the risk-free interest rate since 2000, possibly reflecting the benefits of holding Treasury securities (such as improved transparency and widespread use as collateral) or the movements in the supply schedule versus market demand.

The failure of Treasury rates to proxy for risk-free rates can also be explained by the special tax status of Treasuries. In the United States, yields from Treasury notes are exempt from state income taxes, while yields from corporate bonds are not. If this tax exemption effect is taken into account, the corresponding price errors become much smaller. The formula to adjust for risk-free rates, as proposed by Elton et al (2001), is:

$$r_f = \frac{r_{treasury}}{1-(1-\tau_g)\tau_s} \qquad (7)$$

where τ_g and τ_s are federal and state income tax rates respectively. Elton et al proposed two alternative values for $\tau \equiv (1-\tau_g)\tau_s$: $\tau=4\%$ and $\tau=6.7\%$. Using the adjusted Treasury rates, the APD and AAPD are reduced by 15-30 basis points on average (column 3 and column 4 in Tables 2.1 and 2.2 and Figure (2)), about 20-50% of the initial price errors. Although these numbers are still higher than those corresponding with swap rates, the discrepancies are much less remarkable.

Moreover, the results also suggest that the price differentials could be very different across entities and across time. For example, for euro-denominated contracts (Deutsche Telecom and France Telecom), the average price differentials are smaller when Treasuries are used as risk-free rates. This observation might imply that the market practice on risk-free rates may be different in the European market from that in the US market. The difference could be attributable to institutional reasons (legal, tax and policy framework), or unequal movements in underlying factors that affect Treasury rates, or it could be simply a result of market segmentation.

Finally, the levels of price discrepancies also change over time. For example, price differentials associated with swap rates are very close to zero in 1999-2001. However, entering 2002, the CDS spreads turn out to be much higher than bond spreads. By contrast, if Treasury rates are used to proxy for risk-free rates, the price differentials are much lower in 2002 than in previous years. This phenomenon might be attributable to the fact that the credit quality for most entities deteriorated in year 2002 and the two markets exhibit different responses to the changes. I will leave this issue to be examined in more detail in the latter part of this paper.

4.2 Determinants of basis spreads

The previous analysis shows that, although the two credit risk prices tend to be equal over time (as the theory has predicted), in the short run they could be different from each other. In Section 2 I have discussed a number of reasons that could explain the deviation from the equivalence relationship. It is helpful, therefore, to examine the determinants of basis spreads.

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[16] 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 equation (4), or a result of bad choice of risk-free rates. The cointegration test results (see section 5) support the latter explanation.

Here I use the panel data technique to find out the common pattern of basis spread movements. The explanatory variables include:

1. Lagged basis spreads

The theory predicts that the average basis spread is always zero, ie, the basis spread movement is a mean-reverting process. The coefficient of lagged basis spread, therefore, should be less than 1. When the coefficient is very close to zero, it implies that the speed of returning to long-term averages is faster.

2. Changes in credit spread (DCDS)

Credit spreads in the two markets could change with credit conditions. If both markets price the credit risk accurately and efficiently, the change in credit conditions should be reflected equally in the two markets. In other words, if the coefficient is not significantly different from zero, it suggests that the two markets have exhibited similar responses to credit events and that arbitrage opportunities do not even exist in the short run. Conversely, a coefficient that is significantly different from zero implies different responses and market inefficiency in the short run.

3. Ratings and rating events

Houweling and Vorst (2001) suggest that the price discrepancy could be different for high-grade and low-grade bond issues. Intuitively, a same magnitude of price differential is 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, … CCC+ are transformed into the numbers 1, 2, 3, …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 (2003) 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 that can capture the impact of such 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].[17] In each of the dummy variables a value of 1 refers to a downgrade of the rating, -1 refers to an upgrading and 0 to no change in the rating.

4. Contractual arrangements

The terms of CDS contracts could have an impact on CDS spreads. Here I include three dummy variables to capture the currency denomination (*DUMEUR*, 1 if denominated in euros and 0 otherwise), the credit type (*DUMCORP*, 1 if corporate and 0 otherwise) and the type of restructuring clause (*DUMOR*, 1 for OR and 0 for MR). The restructuring clause dummy variable is most 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.

5. Liquidity factors

Both CDS premia and bond spreads may include price information unrelated to the underlying credit risk, among which a very important piece of information is the liquidity premium. While it is difficult to find the best proxy for liquidity factors, here three good

[17] The intervals follow Hull et al (2003).

candidates are available: the bid-ask spreads in the CDS market and the bond market, and the number of CDS quotes. To avoid noisy information I use the average bid-ask spreads (*BAS_CDS* and *BAS_Bo*nd) and the aggregate number of CDS quotes (*NCDS*) on the 10 business days before and after ([t-10, t+10]) rather than on that particular date. As the existing literature has suggested, high liquidity often tends to be associated with a lower bid-ask spread and high volume. Therefore, a lower bid-ask spread in the CDS market and more CDS quotes would imply that the liquidity premium embedded in the CDS spread is smaller. Therefore the basis spread tends to be lower. In other words, *BAS_CDS* has a positive effect and *NCDS* has a negative effect. Similarly, *BAS_Bond* has a negative effect on the basis spread.

6. Macroeconomic conditions

To test the pricing accuracy I also include two macro financial variables: Treasury rates and regional stock market indices (S&P500 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 economy and financial market conditions and thus have an impact on the pricing of credit risk. However, if both markets are efficient in pricing the macro effect, their impact on basis spreads should be zero.

Table 3 reports the results of panel data regressions. The empirical results, independently of whether swap rates or Treasury rates are used as risk-free rates, are very similar. In both regressions the explanatory power of the model is very high. Overall credit factors play a dominant role in affecting basis spreads.

First, the coefficient of lagged basis spreads is significantly less than one, confirming the mean-reverting process of basis spreads. At the same time, the size of the coefficient suggests that the speed of this reverting process is rather slow: only 7-9% of price errors can be corrected on the next business day. Therefore, price differentials persistent for a number of days.

Second, the coefficient of CDS spread changes is significantly different from zero. This result suggests that the CDS market and the bond market respond differently to changes in credit conditions. Exactly, the result says that, for a 10 basis point increase in the CDS spread, there is only a 1 basis point 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, as in HV, I find evidence that ratings are statistically associated with price discrepancies between the two markets. However, the impact is economically insignificant in that a one-notch rating change only causes a 1 basis point difference in the basis spread. Since all entities are investment grade, this study is not able to confirm whether a shift from investment grade to speculative grade would have a larger impact (as indicated by HV).

Fourth, the regressions find strong evidence that, although there seems to be no pricing difference at least 30 days before or 10 days after a rating event, the two markets do behave differently during the short intervals around the rating change. CDS spreads increase (decrease) faster than bond spreads by more than 2 basis points per day within the 30 business days before a rating downgrade (upgrade). The price discrepancies accumulated during this period can be almost fully removed shortly after the rating event (about 6 bp per day in the next 10 days). In other words, the derivatives market seems to have done a better job in incorporating future rating events into the price.

Fifth, market conditions do not affect basis spreads. That is, the overall macroeconomic conditions have an equal impact on both markets and are not sources of pricing inefficiency.

Sixth, the terms of CDS contracts have an impact on basis spreads but their economic relevance is rather weak. The significance of the currency dummy coefficient restates the difference between the US market and the European market. The credit type of entities does not matter. Surprisingly, the dummy of restructuring clauses has the opposite sign to that expected. Nevertheless, given that it is merely a 5 basis point difference, it is reasonable to think that the difference in the two deliverable options is minor and is not priced in the markets at all.

Seventh, liquidity factors in the CDS market are statistically significant but have opposite signs to what the theory has predicted. This is a little surprising but could be justified by two reasons. On the one hand, all 24 entities in this study are very liquid in both markets. Hence the component of liquidity premium in credit spreads could be very small and there is not necessarily any difference across the entities. On the other hand, their impacts are rather minor. A standard deviation difference in the CDS bid-ask spread (about 20 basis points) will change the basis spread by only 4-5 basis points. Similarly, a standard deviation difference in the number of CDS quotes (about 40) will only cause a difference of about 1 basis point.

There is another interesting issue regarding the possibility of asymmetry in the dynamic adjustment in the basis spread. Such an asymmetry could exist because of the limited ability of market players to short corporate bonds (see Section 2). To examine this issue I rerun the panel data regression by including a dummy variable that indicates a positive lagged basis spread (excluding the two macro financial variables because they are not statistically significant). If the above argument is valid, the coefficient of the dummy variable should have a positive sign because it takes longer to remove price errors when the CDS spread is higher. The results, as shown in Table (3), are not very supportive. When swap rates are used, the effect is not significant at all. But when Treasury rates are used, the result seems to support the hypothesis as the pricing errors are more persistent when the basis spread is positive.[18]

To summarise, the results suggest that there exists market inefficiency in that the two markets respond very differently in the short run to changes in credit conditions. Credit factors are very important in generating the deviation from the equivalence relationship. Rating events, changes in credit conditions and dynamic adjustments of the two spreads explain most of the short-term price discrepancies. The other factors, such as terms of contracts, liquidity and the short-sale restriction, only have a very small impact.

5. Empirical analysis II: dynamic relationship between the two markets

5.1. 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. As the theory has predicted, 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 summarises the results of unit root tests (ADF tests without a trend) for the two credit spreads and basis spreads. All credit spread series need to be first-order differenced for stationarity. In addition, in 15 (11 if Treasury rates are used as risk-free rates)[19] out of the 24 entities, CDS spreads and bond spreads are cointegrated in a way the theory has predicted. 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 rest of the entities.

This result suggests that the two markets price the credit risk equally in the long run. This is not very surprising. After all, they are two prices of the same risk, and market forces would eventually remove the arbitrage opportunity between the two markets.

5.2. Short-term dynamic interactions

The next step is to examine the short-term dynamic linkages between the two spreads, in particular which market is more efficient in reflecting changes in the credit risk of underlying entities. However, an obstacle is the paucity of the data, especially in the CDS market.[20] Among the 24 entities, the most

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[18] The difference could be due to the fact that basis spreads are mostly negative if using Treasuries. A positive basis spread corresponding with Treasury rates implies a large positive basis spread associated with swap rates. The insignificance of the coefficient in the first regression may reflect the fact that the short-sale restriction does not matter for small pricing errors because transaction costs alone will eat away arbitrage profits.

[19] To save space, I focus on the results that use swap rates as risk-free rates and attach those corresponding with Treasury rates in the parenthesis thereafter.

[20] On average, only 35% of the sample dates have valid CDS quotes and 92% in the bond market.

liquid name has 627 valid observations (days with at least one quote), and the least liquid one has only 168 observations in four years (Table 1). A serious problem is that, even in 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. Here two different approaches are used.

The first approach is the EM algorithm, which is also known as the regression-based imputation method. This approach consists of two steps. First, a regression model is estimated to match the time series dynamics of the variable of interest. Second, the estimated model is used to predict (impute) the missing values. It is called the EM algorithm because the model is usually fitted by maximising likelihood and the predictions by taking the 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. The main advantage of this method is that the model fitting process can preserve the statistical properties of the observed data, and therefore the imputed data will not cause important changes in the results of statistical analysis.

The second 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 the 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 aim to test the validity of the above two hypotheses. Instead, both approaches are used in the time series analysis. I use the imputed data series generated by the EM method in the baseline study,[21] and then use the other series generated by alternative approaches as a robustness check.

The EM imputation 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 the following VAR type of model, which 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 index.[22] Defining $Y_t = [cds_t \; bond_t \; stock_t \; Equityindex_t \; CDSindex_t]'$, I consider the model

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{q} \delta_i Y_{t+i} + \varepsilon_t \tag{8}$$

The model is estimated in an iterative way. The interpolation starts with initial guesses about the values of the missing observations (such as interpolated averages). Then the model (equation (8)) 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.

Using the imputed data series, I examine the dynamic relationship between bond spreads and CDS spreads. I first run Granger causality tests on the relationship between the two series for each entity. The tests are performed using equation (5), where *X* and *Y* are substituted by the first-order difference of the two credit spreads. The lag length is chosen using the Akaike information criterion (AIC), the Bayesian information criterion (BIC) 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. Table 5 reports the

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21 I also impose a restriction that at most four consecutive missing observations can be imputed in the new series. 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.

22 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 the small number of observed data is questionable.

results of Granger causality tests with five lagged periods, but the results are very similar when the range of lags varies from one to five days.

According to Table 5, the Granger causality operates from the CDS market to the bond market in 14 (15) out of 24 entities, and in the reverse direction in 16 (17) names. Among them there exists a two-way causality relationship for 10 (12) entities. In other word, Granger causality tests indicate a close dynamic connection between the two markets, but there is no clear evidence that this connection goes in a certain direction.

A further investigation can be implemented by utilising the VECM method. Based on equation (6), I run the regression for each entity, with the length of the lags determined by AIC, BIC and SIC. 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 equation (6) is estimated by allowing α_i and β_i to be freely determined within the model.

As introduced in Section 2, the significance and magnitude of the λ coefficients tell us which of the two markets moves to adjust for price discrepancies, and the speed of this adjustment. The relative magnitude of the two λ coefficients is a reflection of the role of each market in price discovery.

The results are summarised in Table 6. Out of the 24 entities, there are 18 (16) names for which λ_1 is significantly positive, or equivalently, the bond market moves to correct the price discrepancies. Similarly, there are 10 (8) entities for which the derivatives market adjusts its price in response to price discrepancies (λ_2 is significantly negative).[23] To be more specific, there is a strong one-way linkage from the CDS market to the bond market in 13 (12) entities, from the bond market to the CDS market in 5 (4) entities, and a strong two-way linkage in 5 (4) entities. Following Gonzalo and Granger (1995), I also compute a measure that reflects the contribution of each market to price discovery.[24] The measure is defined as the ratio of the speed of adjustment in the two markets ($\lambda_1/(\lambda_1-\lambda_2)$), 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 is in the reverse direction and the bond market leads the derivatives market. When the measure is close to 1/2, both markets contribute to price discovery and there is no clear evidence on which market is more important.

This measure (Table 6) gives us similar results on the dynamic relationship between the two markets. The average ratio of 0.653 (0.658) favours the hypothesis that the CDS market moves ahead of the bond market. This is consistent with the argument that the derivatives instrument tends to be more efficient in price discovery because 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 (Figure (1)), their credit spreads increased substantially. If the CDS market moves ahead of the bond market, in the short term the CDS spreads could become higher than bond spreads and the pricing errors persist for a while. This effect results in positive basis spreads (using swap rates) during this particular period. By contrast, in previous years the credit conditions were less volatile, and therefore pricing errors were almost 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.

However, it is premature to conclude that the CDS market has taken over the cash market in price discovery. Bond spreads move first for several entities. Interestingly, it seems that their role is quite different depending on the geographical location of the entities. In the last two rows of Table 6, I

[23] The sum of the two λ coefficients is about 0.11 (0.08) on average, which is close to the mean-reverting coefficient in the panel data study.

[24] The variance decomposition analysis does not work here, mainly because the innovations in the two markets are correlated and there is no clear way to solve the identification problem in the VAR system.

calculate the average λ and the average contributional ratios in the US and non-US markets. The difference in the results is quite striking. The derivatives market in the United States turns out to have been more active in reflecting changes in the credit market, with more significant λ_1 and higher contributional ratios. By contrast, in Europe and Asia the bond market seems to still lead the derivatives market in price discovery. This, again, could reflect difference or segmentation of the market across regions.

Figure (3) also plots the contributional ratios with liquidity factors and ratings. As expected, higher liquidity in the CDS market is associated with a more active role of the derivatives market in price discovery. At the same time, the rating class of the entities is not relevant to the pattern of dynamic connection between the two markets.

5.3. Robustness check

The above results may be biased because of the particular method used for data interpolation. There are two possible sources of the bias. First, the EM algorithm tries to match the statistical properties of the observed data. However, as model predictions use expected values, the imputed data can only match the first-order moment but the higher order moments might be misspecified. The misspecification of the high moments (eg lower variance) can be a source of bias in the dynamic analysis. Second, if the missing observation is simply a reflection of no arrival of new information, ie no changes in the entity's credit risk, the EM algorithm turns out to be inappropriate. In the remaining part of this paper, as a robustness check, I also construct the CDS spreads using two other methods that can mitigate the above two potential problems.

The first method is based on the EM method with an extension of the resampling scheme. The model estimation is done in exactly the same way by maximising likelihood and choosing the model that best fits the observed data. The difference is the use of a resampling scheme in the second step. In order to preserve the high moment property, the imputed data are constructed by adding every model prediction with a random error term. The error term is randomly chosen from the true prediction errors of the observed data. This resampling is implemented a number of times. For each imputed series, I carry out the same econometric analysis as in the previous section. Table 7 reports the averages of these statistics based on 100 resampling imputations.

The second method is the LOCF method mentioned above, which substitutes the last available quotation for the missing data. The results of dynamic analysis using this method are shown in Table 8.

Overall, the main results are largely consistent with those in the baseline analysis. First, the two markets move together in the long run, supporting the theoretical prediction that there is no arbitrage opportunity between the two markets. More than half of the entities pass the hypothesis test that the two spreads cointegrate with each other with the equivalence relationship. And all of the remaining entities pass the Johansen cointegration test. Second, a preliminary Granger causality test suggests that there are strong linkages between the two markets. Third, the VECM analysis favours the hypothesis that the derivatives market is more responsive to changes in credit conditions. Similarly, market liquidity has an impact on the role of the two instruments in price discovery. Finally, the results also suggest distinctive dynamics between US and non-US entities, where the derivatives market moves ahead of the bond market for the former group and the cash market leads the derivatives market for the latter group.

The robustness of the results is very striking considering that these imputation methods are based on completely different assumptions on the causes of missing observations. While the LOCF method explains missing data as no changes in credit conditions, 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. For example, if 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. By nature the EM method will treat part of the jump as having occurred at date t, while the LOCF assumes that nothing has changed before date *t+1*. Therefore, by using the LOCF method, the jumps in CDS prices tend to occur at a later time. In other words, the derivatives market appears to be less responsive to credit market changes. This hypothesis is to some extent supported by the above exercise: on average the contribution measure is lower when the LOCF method is adopted. Nevertheless, the main findings remain very robust, no matter which imputation method has been used. This suggests that bias due to statistical imputation has only a marginal effect and the derivatives market does play a leading role in price discovery, particularly for the group of US entities.

6. 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 on average equal to each other. However, in the short run there are quite significant pricing discrepancies between the two markets. I show that the pricing discrepancies could be largely due to their different responses to changes in credit conditions. The panel data study and the VECM analysis both suggest that the derivatives market tends to move ahead of the bond market, and the liquidity factor matters for the adjustment dynamics. Moreover, the study also points to a certain degree of market segmentation in that market practice differs considerably between the United States and other regions, including the choice of risk-free rates and the dynamic interaction. In particular, while the derivatives market leads the cash market in price discovery in the US market, this has not happened in the other regions. Looking forward, the dynamic linkages between the two markets could potentially evolve over time with the rapid development of the derivatives market, and the availability of better data sources will encourage further investigation in this research area.

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Tables and Figures

Table 1.1

Descriptive information on the 24 CDS entities

Name	Currency	Credit type	Region	Restruc-turing clause	Days with valid quotes
1. AOL Time Warner (AOL)	USD	Corporate	N America	MR	232
2. AT& T (ATT)	USD	Corporate	N America	MR	345
3. Bank of America (BOA)	USD	Bank	N America	MR	234
4. Bear Stearns (BS)	USD	Bank	N America	MR	291
5. Carnival Corp (CARN)	USD	Corporate	N America	MR	186
6. DaimlerChrysler (DAIM)	USD	Corporate	Europe	OR	549
7. Deutsche Telekom (DTEU)	EUR	Corporate	Europe	OR	234
8. Ford Motors (FM)	USD	Corporate	N America	MR	627
9. France Telecom (FTEU)	EUR	Corporate	Europe	OR	237
10. General Motors (GM)	USD	Corporate	N America	MR	550
11. Goldman Sachs (GS)	USD	Bank	N America	MR	332
12. Household Finance Corp (HF)	USD	Bank	N America	MR	321
13. Harrahs Operating Co (HO)	USD	Corporate	N America	MR	175
14. IBM (IBM)	USD	Corporate	N America	MR	223
15. Korea Development Bank (KDB)	USD	Bank	Asia	OR	455
16. Eastman Kodak Co (KODA)	USD	Corporate	N America	MR	168
17. Lehman Brothers (LB)	USD	Bank	N America	MR	289
18. Morgan Stanley Dean Witter (MS)	USD	Bank	N America	MR	213
19. SBC Communications (SBC)	USD	Corporate	N America	MR	195
20. Sears Roebuck (SEAR)	USD	Corporate	N America	MR	393
21. Sprint Corp (SP)	USD	Corporate	N America	MR	259
22. Sumitomo Bank (SUMI)	USD	Bank	Asia	OR	428
23. Worldcom Inc (WC)	USD	Corporate	N America	MR	228
24. Walt Disney (WD)	USD	Corporate	N America	MR	277

Table 1.2

Descriptive information on the 24 CDS entities (continued)

Name	Number of quotes					End-of-year S&P rating			
	1999	2000	2001	2002	Total	1999	2000	2001	2002
AOL	34	75	68	1256	1433	-	-	BBB+	BBB+
ATT	52	96	420	1306	1874	AA-	A	BBB+	BBB+
BOA	26	81	258	278	643	A+	A+	A+	A+
BS	62	167	275	243	747	A	A	A	A
CARN	0	4	288	581	873	-	A	A	A
DAIM	85	401	825	319	1630	A+	A	BBB+	BBB+
DTEU	0	2	73	955	1030	-	AA-	A-	BBB+
FM	210	260	1084	1485	3039	A+	A	BBB+	BBB
FTEU	0	2	149	937	1088	-	AA-	BBB+	BBB-
GM	200	195	1054	1086	2535	A	A	BBB+	BBB
GS	127	150	197	406	880	A+	A+	A+	A+
HF	117	105	208	1218	1648	A	A	A	A
HO	0	0	170	377	547	-	-	BBB-	BBB-
IBM	51	41	211	490	793	A+	A+	A+	A+
KDB	154	263	404	212	1033	BBB	BBB	BBB+	A-
KODA	4	8	281	672	965	A+	A+	A-	BBB+
LB	50	216	292	269	827	A	A	A	A
MS	14	62	175	404	655	A+	AA-	AA-	A+
SBC	0	0	160	813	973	-	-	AA-	AA-
SEAR	137	180	206	1102	1625	A-	A-	A-	A-
SP	59	15	319	942	1335	BBB+	BBB+	BBB+	BBB-
SUMI	240	60	490	236	1026	BBB+	BBB+	BBB+	BBB+
WC	53	60	474	593	1180	A-	A-	BBB+	BBB
WD	41	1	237	1120	1399	A	A	A-	BBB+
Total	***1716***	***2446***	***8318***	***17300***	***29778***				

Table 2.1

Average price discrepancies between the CDS market and the bond market

	$E(BASIS_1)$	$E(BASIS_2)$	$E(BASIS_{2,\tau 1})$	$E(BASIS_{2,\tau 2})$
AOL	26.66	-38.49	-19.65	-6.02
ATT	26.91	-47.32	-28.46	-14.81
BOA	2.80	-70.78	-51.34	-37.28
BS	-13.29	-91.70	-70.38	-54.96
CARN	-23.96	-99.28	-81.47	-68.57
DAIM	3.80	-72.17	-52.29	-37.91
DTEU	51.83	26.22		
FM	8.70	-66.57	-46.35	-37.71
FTEU	53.57	27.84		
GM	4.81	-70.73	-50.57	-35.99
GS	4.70	-70.54	-49.83	-34.85
HF	16.82	-56.48	-36.24	-21.60
HO	-22.60	-87.13	-70.91	-59.18
IBM	30.46	-39.74	-21.42	-8.17
KDB	19.04	-60.98	-39.48	-23.92
KODA	-1.27	-71.50	-54.27	-41.80
LB	-4.43	-81.28	-60.36	-45.22
MS	18.84	-52.23	-33.82	-20.51
SBC	17.02	-44.94	-28.98	-17.43
SEAR	-0.80	-72.76	-52.41	-37.69
SP	32.56	-30.24	-12.77	-0.13
SUMI	-17.03	-92.75	-74.30	-60.95
WC	67.15	-8.15	11.33	25.43
WD	15.74	-47.37	-30.29	-17.94
Average	*13.25*	*-54.96*	*-43.38*	*-29.34*
Average in 1999	*2.94*	*-68.45*	*-45.19*	*-28.35*
Average in 2000	*4.19*	*-90.28*	*-64.76*	*-46.30*
Average in 2001	*1.36*	*-75.31*	*-56.28*	*-43.26*
Average in 2002	*29.55*	*-24.42*	*-15.73*	*-5.57*

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 effects. The adjustment factor, $\tau=(1-\tau_g)\ \tau_s$, is 0.04 and 0.067, respectively. The table reports the average 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.

Table 2.2

Average absolute price discrepancies between the CDS market and the bond market

	$E(\|BASIS_1\|)$	$E(\|BASIS_2\|)$	$E(\|BASIS_{2,\tau 1}\|)$	$E(\|BASIS_{2,\tau 2}\|)$
AOL	32.41	59.08	44.20	35.48
ATT	36.87	64.60	52.54	45.37
BOA	7.71	70.78	51.34	37.48
BS	14.78	91.70	70.38	54.96
CARN	40.84	100.58	83.73	72.24
DAIM	8.04	72.17	52.29	37.95
DTEU	51.97	30.60		
FM	13.89	67.17	48.13	36.13
FTEU	70.31	60.11		
GM	13.42	71.29	51.83	38.15
GS	8.85	70.54	49.83	34.85
HF	24.51	62.05	44.81	35.05
HO	30.26	87.13	71.04	59.49
IBM	31.28	42.33	29.18	24.03
KDB	21.26	62.31	41.53	27.69
KODA	38.49	76.37	63.81	56.88
LB	10.17	81.28	60.36	45.22
MS	22.31	52.23	34.03	22.90
SBC	28.66	54.06	41.38	34.53
SEAR	17.54	74.12	54.67	41.13
SP	48.90	58.91	53.79	52.11
SUMI	22.35	92.75	74.30	60.95
WC	78.35	42.37	43.05	48.59
WD	18.18	47.42	30.96	21.10
Average	*28.81*	*66.33*	*52.14*	*41.74*
Average in 1999	*13.17*	*69.36*	*47.07*	*31.56*
Average in 2000	*12.37*	*90.28*	*65.01*	*47.29*
Average in 2001	*19.37*	*76.47*	*58.59*	*46.65*
Average in 2002	*38.81*	*47.79*	*30.45*	*26.09*

The definitions are the same as in Table 2.1 except that the basis spread is calculated in absolute terms on each day.

Table 3

Determinants of basis spreads: a panel data study (fixed effects)

Dependent variable	$BASIS_1$				$BASIS_2$			
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	-1.298	0.19	-3.154	1.25	-6.123	0.36	-11.0***	4.11
Lagged BASIS	0.919***	93.54	0.915***	87.00	0.930***	101.17	0.907***	86.73
Dummy($Basis_{i,t-1}$>0)			0.971	1.22			6.586***	4.44
DCDS	0.903***	75.60	0.903***	75.54	0.907***	77.18	0.903***	77.25
SP rating	1.000*	1.81	1.092***	2.83	1.283**	2.33	1.599**	4.16
Dummy (changes in rating)								
DUMB6190	1.153	0.90	1.127	0.89	0.947	0.74	0.838	0.67
DUMB3160	-0.152	0.12	-0.189	0.16	-0.452	0.37	-0.178	0.15
DUMB0130	2.419*	1.81	2.330*	1.83	2.125	1.60	2.020	1.60
DUMA0110	-6.158***	3.22	-6.488***	3.44	-6.235***	3.27	-5.951***	3.18
DUMA1130	-0.935	0.57	-1.056	0.65	-1.691	1.04	-1.258	0.78
Market condition								
Treasury rate	0.523	0.95			-0.312	0.57		
Equity index	-0.0006	0.56			-0.0002	0.83		
Dummies								
DUMEUR	3.670**	2.19	3.696**	2.23	6.794***	3.84	5.362***	3.04
DUMOR	-5.502**	1.85	-3.443*	2.26	-5.314*	1.78	-6.008***	3.91
DUMCORP	-0.748	0.35	-1.611	1.19	-0.981	0.46	-1.570	1.18
Liquidity factors								
BAS_CDS	-0.217***	7.68	-0.215***	7.62	-0.218***	7.73	-0.251***	8.68
BAS_Bond	0.084	0.89	0.085	0.91	0.075	0.80	0.062	0.67
NCDS	0.025***	3.45	0.023***	3.33	0.028***	3.81	0.032***	4.59
Number of observations	*3176*		*3187*		*3175*		*3185*	
R^2	*0.85*		*0.85*		*0.90*		*0.90*	

$Basis_1$ 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. DCDS is the change of CDS spread, 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. Equity index refers to S&P 500 (for US entities), STOXX 50 (European entities) or Nikkei 225 (Asian entities). The three dummy variables indicate that the CDS contract is denominated in euros (DUMEUR), has an OR type of restructuring clause (DUMOR), and the credit type is “corporate” (DUMCORP). The three liquidity factors are the average bid-ask spread in the CDS market and the bond market, and the number of CDS quotes between days [t-10, t+10].

The panel regression also includes dummies for each entity and the results are omitted here. * means that the coefficient is significantly different from zero at a confidence level of 90%, and ** and *** at 95% and 99% respectively.

Table 4

Unit root and cointegration test results

	Swap rates as risk-free rates				**Treasury rates as risk-free rates**			
	Bond spread$_1$	**CDS spread**	**BASIS$_1$**	**Cointe-gration**	**Bond spread$_2$**	**CDS spread**	**BASIS$_2$**	**Cointe-gration**
AOL	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
ATT	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
BOA	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(1)	$\beta\neq1$
BS	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(1)	$\beta\neq1$
CARN	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
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)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
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)	$\beta\neq1$
HF	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
HO	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
IBM	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
KDB	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(0)	Yes
KODA	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
LB	I(1)	I(1)	I(0)	Yes	I(1)	I(1)	I(1)	$\beta\neq1$
MS	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
SBC	I(1)	I(1)	I(1)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
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)	$\beta\neq1$	I(1)	I(1)	I(1)	$\beta\neq1$
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	*24*	*24*		*15*	*24*	*24*		*11*

Table 5

Granger causality test results

	Bond spread$_1$		**Bond spread$_2$**	
	CDS spreads do not Granger cause bond spreads	**Bond spreads do not Granger cause CDS spreads**	**CDS spreads do not Granger cause bond spreads**	**Bond spreads do not Granger cause CDS spreads**
AOL	1.644	2.631*	1.322	2.237
ATT	5.441*	2.510*	5.582**	2.698*
BOA	0.975	2.700*	0.813	3.015*
BS	3.203**	12.065**	2.185	13.950**
CARN	0.314	1.611	0.276	2.970*
DAIM	9.243**	3.147**	9.147**	3..949**
DTEU	3.246**	0.977	4.415**	1.446
FM	10.125**	69.460***	9.966**	72.488**
FTEU	3.719**	8.268**	3.564**	6.687**
GM	11.381**	6.336**	11.730**	8.388**
GS	0.840	2.244*	0.508	2.214
HF	2.274*	1.843	2.387*	2.966*
HO	2.566*	0.476	2.389*	1.360
IBM	1.913	2.420*	3.024*	3.104*
KDB	0.398	5.690**	0.325	5.072**
KODA	4.699**	8.925**	3.600**	9.718**
LB	2.007	4.342**	4.489**	5.139**
MS	1.062	1.959	0.870	4.931**
SBC	0.966	0.345	1.013	1.136
SEAR	35.465**	17.683**	31.909**	21.270**
SP	5.046**	0.703	5.596**	1.248
SUMI	1.561	1.106	1.578	0.893
WC	9.127**	78.569**	8.530**	90.678**
WD	4.046**	2.648*	5.890**	2.896*
Total	*14*	*16*	*15*	*17*

The two bond spreads are calculated using swap rates and Treasury rates as the risk-free rate, respectively. * rejected at 5%, ** rejected at 1%

Table 6

VECM test results: baseline study

	Bond spread$_1$			**Bond spread$_2$**		
	λ_1	λ_2	**Ratio**	λ_1	λ_2	**Ratio**
AOL	0.087*	0.014	1	0.073*	0.021	1
ATT	0.074*	-0.013	0.856	0.060*	-0.003	0.949
BOA	0.079	-0.093*	0.460	-0.063	-0.067*	0
BS	0.169*	0.001	1	0.032	-0.018	0.645
CARN	0.085*	0.016	1	0.068*	0.007	1
DAIM	0.090*	-0.079*	0.530	0.024	-0.033	0.417
DTEU	0.023	-0.082*	0.216	0.029	-0.077*	0.277
FM	0.098*	-0.025	0.794	0.043*	-0.008	0.850
FTEU	0.018	-0.081*	0.183	0.025	-0.074*	0.254
GM	0.068*	-0.005	0.932	0.034*	0.0004	1
GS	0.085*	-0.050*	0.627	0.042*	-0.002	0.952
HF	0.169*	-0.022	0.884	0.109*	-0.022	0.832
HO	0.011	-0.089*	0.108	-0.003	-0.082*	0
IBM	0.015*	0.016*	0	0.005*	0.005*	1
KDB	0.112*	-0.059*	0.654	0.057*	-0.039*	0.591
KODA	-0.009*	0.003	0.745	-0.010*	0.003	0.754
LB	0.056*	0.017	1	0.056*	-0.043	0.564
MS	0.053*	-0.040*	0.568	0.048*	-0.053*	0.475
SBC	0.018*	-0.017	0.516	0.018*	-0.013	0.577
SEAR	0.197*	0.063*	1	0.128*	0.035	1
SP	0.176*	0.023	1	0.158*	-0.005	0.972
SUMI	0.004	-0.039*	0.082	0.017	-0.038*	0.307
WC	0.240*	-0.144*	0.625	0.214*	-0.160*	0.572
WD	0.123*	-0.016	0.884	0.071*	-0.016	0.818
Significant λ_1 (+) or λ_2 (-)	*18*	*10*		*16*	*8*	
Average	*0.085*	*-0.029*	*0.653*	*0.051*	*-0.028*	*0.658*
Avg(US))	*0.095*	*-0.019*	*0.737*	*0.057*	*-0.022*	*0.735*
Avg(nonUS)	*0.049*	*-0.068*	*0.333*	*0.030*	*-0.052*	*0.369*

The ratio is defined as $\lambda_1/(\lambda_1-\lambda_2)$ 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 entitles. * means that the coefficient is significantly different from zero at a confidence level of 95%.

Table 7

Robustness check 1: using EM algorithm with resampling scheme

(N=100)

	Bond spread$_1$			**Bond spread$_2$**		
	λ_1	λ_2	**Ratio**	λ_1	λ_2	**Ratio**
AOL	0.084*	0.009	1	0.074*	0.016	1
ATT	0.079*	-0.017	0.827	0.064*	-0.005	0.925
BOA	0.071	-0.119*	0.375	-0.062	-0.078*	0
BS	0.170*	0.001	1	0.032	-0.019	0.624
CARN	0.088*	0.016	1	0.072*	0.003	1
DAIM	0.090*	-0.098*	0.480	0.024	-0.042*	0.369
DTEU	0.022	-0.092*	0.196	0.029	-0.087*	0.253
FM	0.097*	-0.048	0.669	0.043*	-0.017	0.716
FTEU	0.013	-0.090*	0.088	0.019	-0.082*	0.141
GM	0.068*	-0.019	0.786	0.034*	-0.008	0.821
GS	0.085*	-0.060*	0.586	0.042*	-0.005	0.902
HF	0.168*	-0.029	0.855	0.109*	-0.028	0.800
HO	0.028*	-0.061*	0.316	-0.001	-0.093*	0
IBM	0.016*	0.019	0	0.006*	0.007	1
KDB	0.124*	-0.070*	0.646	0.064*	-0.046*	0.585
KODA	0.004	-0.0003	0.737	-0.001	0.002	0.749
LB	0.059*	0.018	1	0.055*	-0.055	0.504
MS	0.076*	-0.101*	0.435	0.047*	-0.067*	0.413
SBC	0.018*	-0.021	0.465	0.018*	-0.017	0.522
SEAR	0.201*	0.050	1	0.131*	0.026	1
SP	0.176*	-0.023	0.898	0.157*	-0.039	0.814
SUMI	0.008	-0.039*	0.159	0.017	-0.043*	0.276
WC	0.230*	-0.189*	0.551	0.214*	-0.199*	0.508
WD	0.123*	-0.024	0.839	0.071*	-0.021	0.771
Significant λ_1 (+) or λ_2 (-)	*19*	*10*		*16*	*9*	
Average	*0.087*	*-0.041*	*0.621*	*0.052*	*-0.037*	*0.612*
Avg(US))	*0.097*	*-0.032*	*0.702*	*0.058*	*-0.031*	*0.688*
Avg(nonUS)	*0.051*	*-0.077*	*0.314*	*0.031*	*-0.060*	*0.325*

* means that the coefficient is significantly different from zero at a confidence level of 95% in at least 90 out of the 100 simulations.

Table 8

Robustness check 2: using last-observation-carried-forward interpolation

	Bond spread$_1$				**Bond spread$_2$**			
	CI test	λ_1	λ_2	**ratio**	**CI test**	λ_1	λ_2	**Ratio**
AOL	$\beta \neq 1$	0.082*	-0.006	0.927	$\beta \neq 1$	0.070*	-0.002	0.970
ATT	Yes	0.069*	-0.016	0.813	Yes	0.055*	-0.008	0.875
BOA	$\beta \neq 1$	0.068*	-0.032	0.680	$\beta \neq 1$	-0.019	-0.059*	0
BS	$\beta \neq 1$	0.126*	-0.002	0.986	Yes	0.022	-0.019	0.542
CARN	$\beta \neq 1$	0.098*	0.007	1	$\beta \neq 1$	0.088*	0.001	1
DAIM	Yes	0.051	-0.156*	0.245	Yes	0.006	-0.053*	0.094
DTEU	Yes	0.019	-0.093*	0.172	Yes	0.026	-0.091*	0.225
FM	Yes	0.064*	-0.051*	0.558	Yes	0.027*	-0.017	0.618
FTEU	$\beta \neq 1$	0.014	-0.098*	0.123	$\beta \neq 1$	0.018	-0.092*	0.164
GM	Yes	0.067*	-0.016	0.804	Yes	0.028*	-0.004	0.868
GS	Yes	0.073*	-0.054*	0.575	Yes	0.025*	-0.009	0.744
HF	Yes	0.159*	-0.018	0.899	Yes	0.088*	-0.009	0.912
HO	Yes	0.022	-0.067*	0.244	$\beta \neq 1$	-0.005	-0.108*	0
IBM	$\beta \neq 1$	0.005	0.006	0	$\beta \neq 1$	-0.004	-0.007	0
KDB	$\beta \neq 1$	0.009	-0.145*	0.058	$\beta \neq 1$	-0.027*	-0.097*	0
KODA	$\beta \neq 1$	0.015*	-0.011	0.572	$\beta \neq 1$	0.015*	-0.010	0.591
LB	$\beta \neq 1$	0.080*	-0.050*	0.614	$\beta \neq 1$	0.033*	-0.048*	0.403
MS	Yes	0.030	-0.048*	0.387	$\beta \neq 1$	-0.006	-0.046*	0
SBC	$\beta \neq 1$	0.019*	-0.023	0.447	$\beta \neq 1$	0.018*	-0.021	0.461
SEAR	Yes	0.165*	0.023	1	Yes	0.099*	0.008	1
SP	Yes	0.131*	-0.022	0.859	Yes	0.144*	-0.015	0.881
SUMI	Yes	0.010	-0.035*	0.224	Yes	0.011	-0.047*	0.194
WC	Yes	0.197*	-0.132*	0.599	Yes	0.191*	-0.103*	0.650
WD	Yes	0.111*	-0.040	0.738	Yes	0.062*	-0.030	0.675
Significant λ_1 (+) or λ_2 (-)	*14*	*16*	*11*		*13*	*14*	*10*	
Average		*0.070*	*-0.045*	*0.564*		*0.039*	*-0.037*	*0.495*
Avg(US))		*0.083*	*-0.029*	*0.669*		*0.047*	*-0.027*	*0.589*
Avg(non US)		*0.021*	*-0.105*	*0.164*		*0.007*	*-0.076*	*0.136*

* means that the coefficient is significantly different from zero at a confidence level of 95%.

Figure 1

Credit spreads

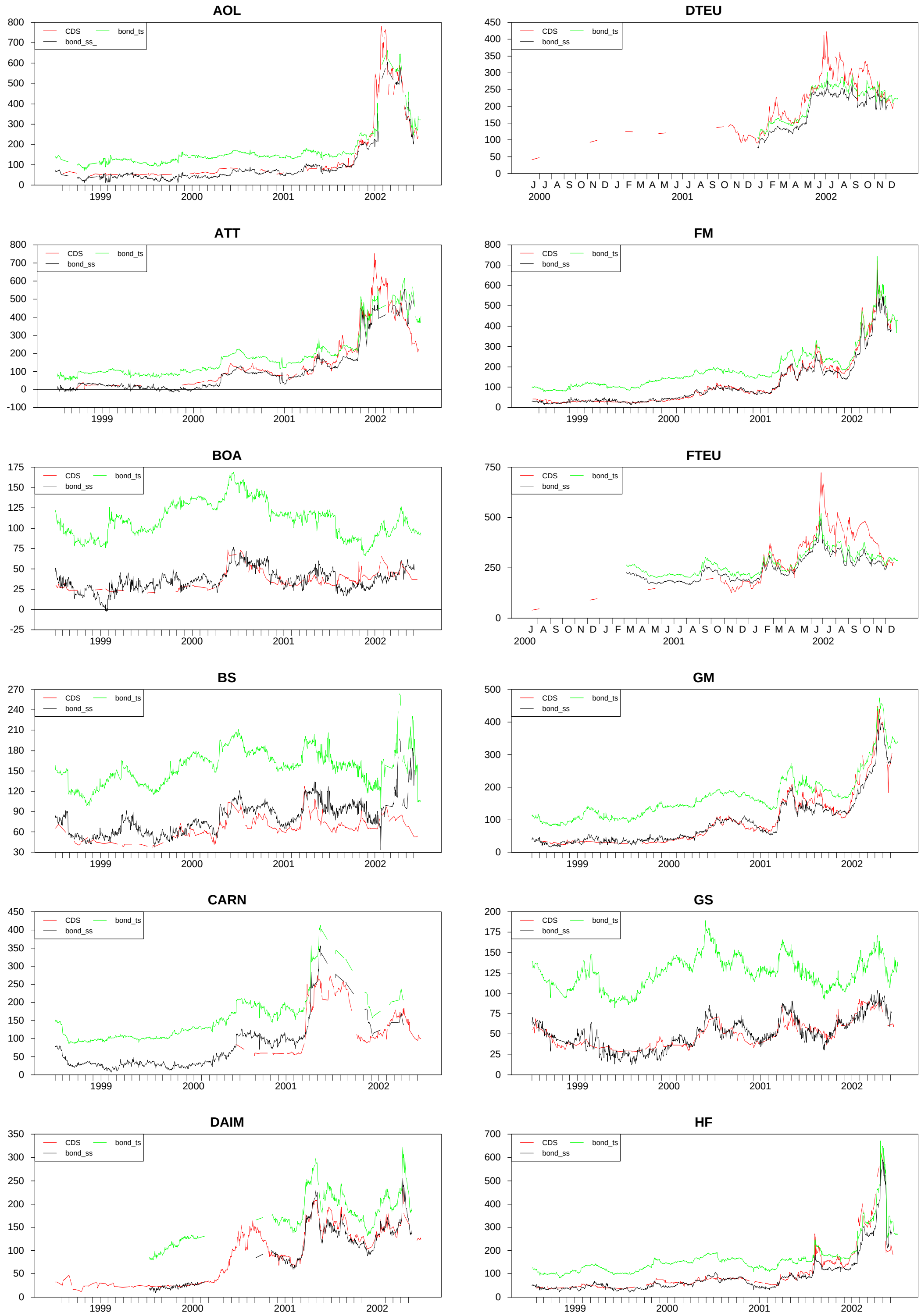


Figure 1

Credit spreads (continued)

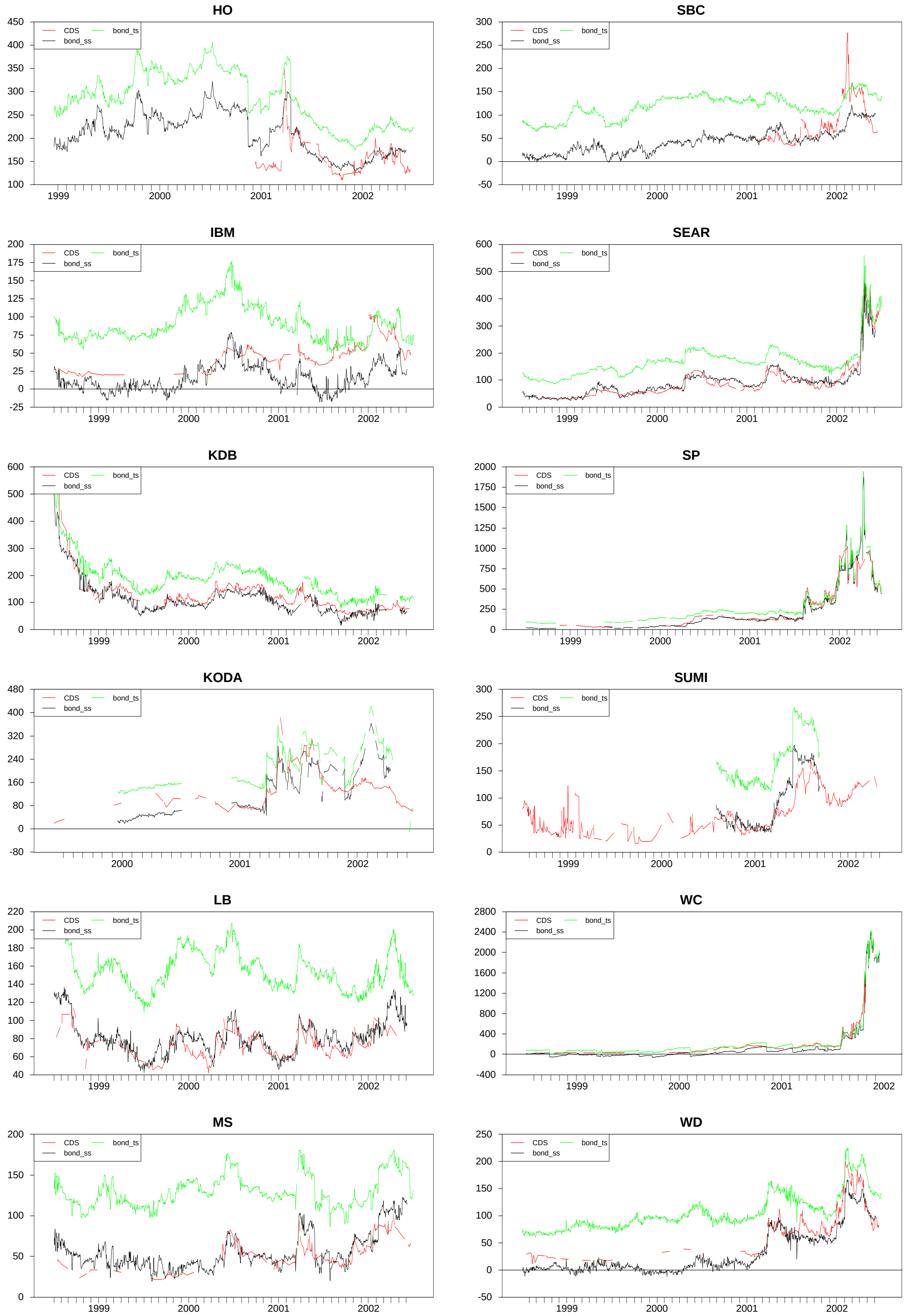
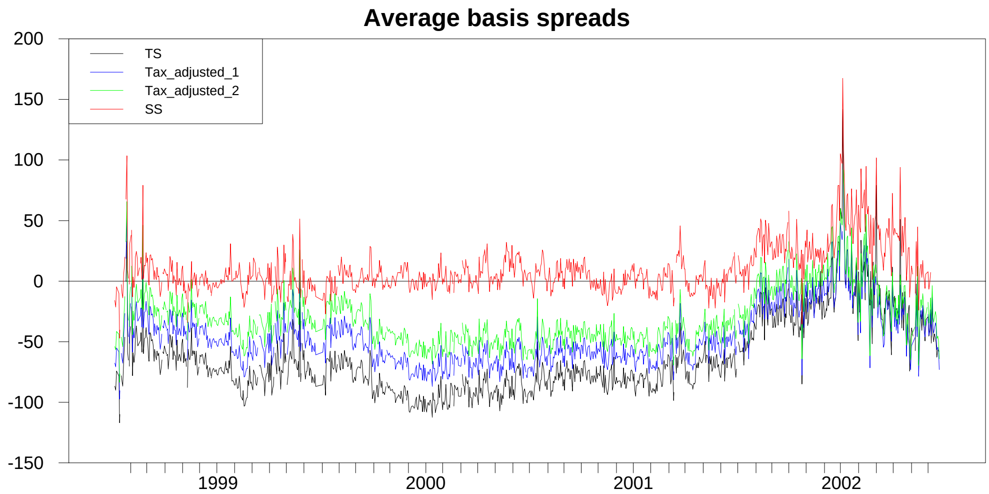


Figure 2

Pricing discrepancies between CDS spreads and bond spreads



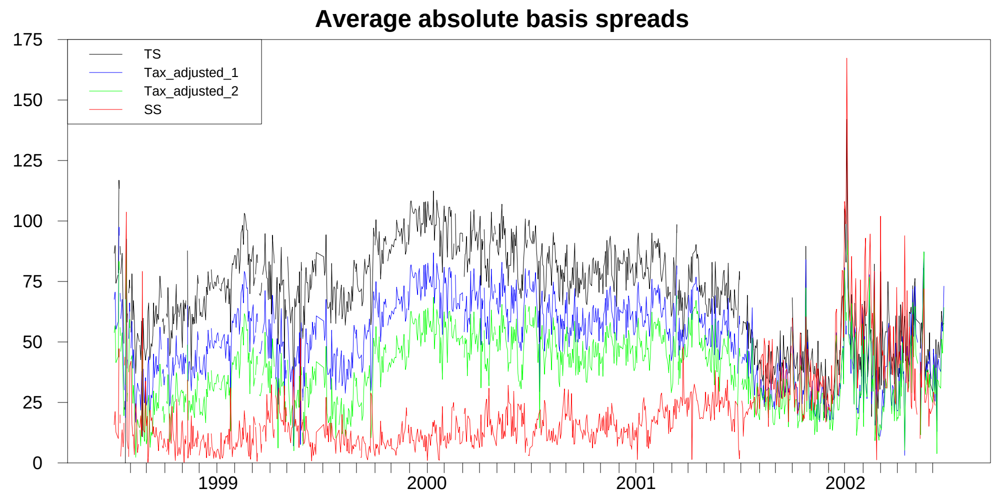
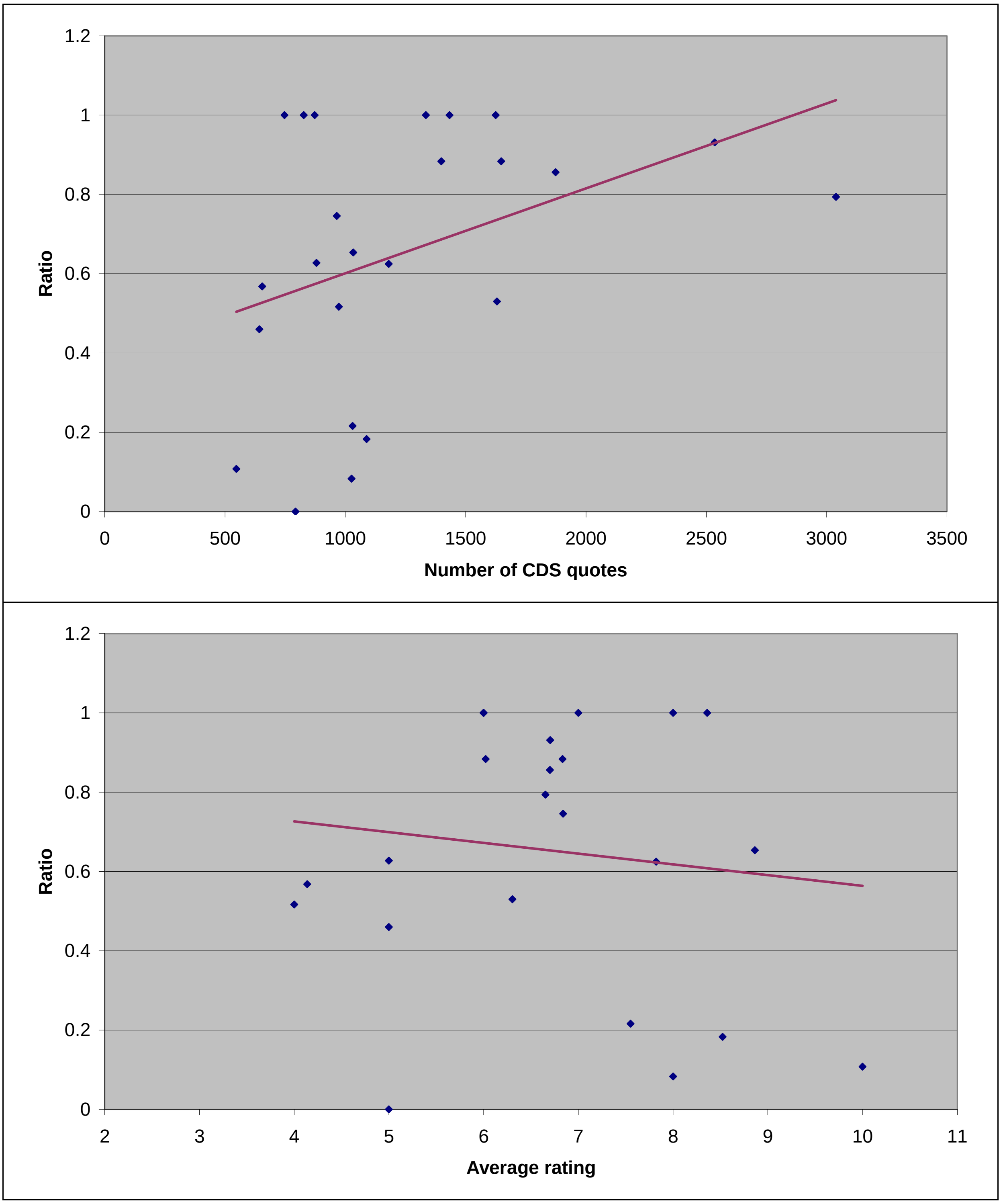


Figure 3

What determines the contribution of the derivatives market in price discovery?



The ratio is defined as $\lambda_1/(\lambda_1-\lambda_2)$ with a range between 0 and 1 (Table 6). The upper panel shows the relationship between the ratio and the number of CDS quotes for each entity. The lower panel shows the relationship between the ratio and average rating, with 2, 3, … 11 representing the rating categories AA+, AA, … BB+, respectively.

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