CREDIT SPREADS: THEORY AND EVIDENCE ABOUT THE INFORMATION CONTENT OF STOCKS, BONDS AND CDSs*

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February, 2006

*Previously titled "The Market Price of Credit Risk in Stocks, Bonds and CDSs: Theory and Evidence". This paper was partially drafted during the visit of Santiago Forte (corresponding author) to the Department of Finance at Tilburg University. The authors acknowledge financial support from MEC Grants Ref: AP2000-1327 and Ref: BEC2002-0279, and thank Philippe Gagnepain, Hao Wang, Bas Werker and Max Bruche for helpful suggestions. They also acknowledge comments from seminar audiences at Universidad Carlos III de Madrid, Banco de España, ESADE, XIII Foro de Finanzas and C.R.E.D.I.T. 2005 Conference. They are also grateful to Banco Santander for allowing access to their data on CDS spreads. The usual disclaimers apply.

Abstract

This paper presents a procedure for computing homogeneous measures of credit risk from stocks, bonds and CDSs. The measures are based on bond spreads (BS), CDS spreads (CDS) and implied stock market credit spreads (ICS). We compute these measures for a sample of North American and European firms and find that in most cases, the stock market leads the credit risk discovery process with respect to bond and CDS markets.

There are many the economic agents who dedicate time and effort to estimating company credit risk. A few examples being: corporate bondholders, large investment banks ready to cover the risk that bondholders could experience through the sale of bond derivatives, such as Credit Default Swaps (CDSs), or shareholders worried about the interests that their company might have to face when the credit rating deteriorates[1]. Each of these assets (bonds, CDSs and shares) are traded in markets that differ in terms of organization (greater weight of organized markets in the case of shares, less weight in the bond market, and a clear domination of OTC markets for CDSs), liquidity (the stock market is generally the most liquid, followed by the bond market and the CDS market) and traders (the stock market probably has the highest proportion of least professional traders, followed by the bond market, and the CDS characterized by professional brokers and traders): three characteristics which are possibly not independent.

Because credit risk affects all these assets, information available about this risk eventually shows in their prices. However, given the structural differences between the markets we have described, it may be possible that such information appears in some prices with greater speed than in others. In this essay we develop a methodology that allows the evaluation of which of these prices, that is, which of these markets, incorporates this information first. We also apply the proposed methodology to a sample of North American and European companies.

When it comes to comparing the speed with which different markets incorporate new information in relation to credit risk, the following steps should be considered. Firstly, to formally define what is understood by the term ‘credit risk’. Secondly, to propose a quantitative variable that measures the perception that a certain market has of this risk in accordance with the given definition. Thirdly, to develop procedures and techniques to estimate the chosen variable given the available information for each market. And finally, to define a methodology to analyze the discovery process.

We may define credit risk as "risk created by loss associated with the default of the borrower, or the event of credit rating deterioration". Given that loss due to credit rating deterioration (downgrading) is a loss that stems from an increase in risk due to losses associated with the failure to pay, the key element is the possibility of failure (default). It seems therefore that a reasonable measure of the credit risk perceived by a certain market for the specific case of a particular company is *the premium that agents in that market would claim for the debt with possibility of failure, in relation to a debt of the same nature but without possibility of failure*. It seems natural on the other hand to name this premium the *credit spread.* Although it may not be reasonable to expect that different markets assign very different credit spreads to the same company on a permanent basis (as it would induce arbitrage opportunities), it is possible that such differences appear in the short run due to the structural differences between the markets described previously.

Of the three markets mentioned, the one in which the definition of the credit spread variable results more intuitive is perhaps the bond market. In principle, it would be enough to subtract from the bond yield of a particular company, the yield of an equivalent debt instrument without default risk, or the *equivalent rate.* This in fact fully corresponds to the variable that we wish to estimate. The problem is that such an equivalent rate simply does not exist. Traditionally Government bond yields have been used, however, corporate-Government yield spreads are explained only in part by the fact that Government bonds are seen as free from credit risk and corporate bonds are not. On one hand certain legal requirements induce the demand for Government bonds (Hull, Predescu and White (2004)), which tends to put their yield below the ideal equivalent rate. In recent years this factor has taken on greater relevance due to shocks in the bond supply (Reinhart and Sack (2001)). It can be gathered that Government bonds are generally more liquid than corporate bonds (Longstaff, Mithal and Neis (2005), and Chen, Lesmond and Wei (2005)) and have better tax treatment (Elton, Gruber, Agrawal and Mann (2001)), which also reduces their yields in comparison to our hypothetical *equivalent rate*. As a result, the use of Government bonds as an approximation would mean that the price assigned to credit risk in that market, that is, the credit spread, was probably overestimated.

An alternative which seems to provide better results is to use the swap rate, or fixed rate that is received as compensation for providing a floating rate, adjusted to the Libor (Reinhart and Sack (2001)). Hull, Predescu and White (2004), Longstaff, Mithal and Neis (2005), Houweling and Vorst (2005), and Blanco, Brennan and Marsh (2005) show that when swap rates are deducted from corporate bond yields instead of Government bond yields, the estimated premiums come closer to CDS spreads. As the spreads of the CDSs 'essentially' represent the price assigned to credit risk in this market, and it being unreasonable to expect systematic differences in the price given to such risk in different markets, we can conclude that the use of swap rates aids (at least to some extent) in extracting the credit risk component of bond yields. Two additional reasons can explain this result: Firstly, swap rates are not affected by legal requirements; and secondly, unlike Government bond yields swap rates are lacking in any special tax effect (Hull, Predescu and White (2004)). Despite these advantages, corporate bond yields still have on average a greater liquidity component than swap rates (Reinhart and Sack (2001)) and therefore, generally, these tend to be below the equivalent rate. One way to minimize this discrepancy is to select the most recently issued bonds. These being the most traded, their equivalent rate has a lower liquidity component and comes closer to swap rates. Given this information, we understand that by subtracting the corresponding swap rate from the yield of the most recently issued corporate bonds, a more reasonable estimation of the credit spread in the bond market is obtained, than by using Government bond yields.

On the other hand we have the relatively new CDS market. A standard CDS is basically an insurance contract through which an agent, the insured, makes periodical payments to another agent, the insurer, until the time that either the contract expires or the bond in reference in the contract fails, whichever happens first. In the event of the contract expiring without the bond failing, the insurer does not make any payment to the insured. In the event of the bond failing before the contract expires, the insurer compensates the insured for the difference between the face value and the bond market value after the failure and the contract is liquidated. The premium of the CDS, that is, the constant rate λ on the face value of the bond paid by the insured to the insurer as a quota for the protection, directly gives us a quite reasonable measurement of the credit risk price estimated by traders in this market. In effect, an equivalent definition for the variable that we have termed *credit spread* in relation to a certain company is the premium that agents in that market would be ready to pay when they have a debt with that company, to convert such a debt into a debt of the same nature, but without the possibility of default, which is precisely what λ represents.

There are however various reasons explaining why λ may differ from the price that we wish to estimate. For example, let us suppose that the bond in reference has a face value of 100. The insured then possesses a put option on the bond, with ‘strike’ equal to 100 and which is executable in the event of default. If a bond market value below 100 is justified only by its credit quality, then the CDS premium represents the credit spread in this market. However, within what we have generically termed ‘default’, possible restructurings are included in which not all debt instruments are necessarily liquidated. If there are reasons that have nothing to do with credit risk, but which justify the bond value being below 100 (liquidity concerns, long maturity, special clauses such as a conversion clause), then the CDS gives the insured, in the case of restructuring, the option to sell a bond that may be worth 80, for 100. This can happen even though a default has not been strictly produced, and although the price is not justified by the credit quality of the bond in question. Logically, the CDS premium will be higher than the premium that would be fixed solely for credit risk. Furthermore, the CDSs do not generally establish a bond, but a portfolio of reference bonds, generating by this means a ‘cheapest-to-deliver option’. However, the entirety of deliverable assets has been limited since May 2001 for North American CDSs (Blanco, Brennan and Marsh (2005)), tending to eliminate from the portfolio those bonds that, due to their special nature, could be traded with a substantial discount with regards to their face value, and to reconcile the CDS premium with the premium that strictly corresponds to the credit risk price in this market.

Other considerations, which can also deviate the CDS premium with regards to the premium that would be established solely for credit risk, have to do with the possibility that the contract fixes a final premium payment in the event of failure, prior to the exchange of bonds, and that said exchange is carried out at a price that may or may not include the accrued interests as well as the face value. These elements, however, seem to have a marginal effect on the CDS premiums[2].

So, finally, it may be that the CDS premium does not exactly represent the credit spread in this market, but we can assume that in the majority of cases it is a reasonable approximation.

Our last market is the stock market. In this case, the price that traders give to credit risk is not exactly explicit, and it becomes necessary to use a theoretical model which, based on stock market values and other financial data, enables us to derive the price that is implicitly assigned to company credit risk.

Merton (1974) was the first to establish a relationship between the market value of bonds and shares based on the theory of option pricing. His assumption of a zero coupon bond as the only debt instrument of the company opened the door to more elaborated models, the so-called *structural models.* A brief list of those that merit more attention include, of course, Merton (1974), but also Black and Cox (1976), Geske (1977), Leland (1994), Longstaff and Schwartz (1995), and Leland and Toft (1996).

The natural method of validating a structural model is to verify whether it is capable of generating theoretical premiums which are consistent, or not, with those traditionally observed in the bond market. This procedure is not exempt of difficulties, since in order to replicate the observed premiums there would be a need to introduce into the model all of those elements that help to explain such premiums, including for example liquidity risk (as we do not generally observe only the most liquid bonds), and, in the case of using Government bond yields as reference for the risk-free rate, a different taxation and even a demand for those bonds amplified by legal requirements[3].

Assuming that we only expect structural models to produce reliable estimates of the *pure credit spread*, the use of Government bond yields as reference for the risk-free rate does not only have the effect of overestimating the benchmark credit spread (the one that should be replicated), it also produces a bias in the spread predicted by the model. In fact, structural models usually establish a negative relationship between credit spreads and risk-free rate (Leland (1994) and Longstaff and Schwartz (1995)). This implies that if stock market participants perceive swap rates as the risk-free alternative to corporate bond yields, then the use of Government bond yields as an input in the model will also result in the predicted spread being overestimated. In short, if Government bond yields underestimate the reference risk-free rate for traders, then their use will overestimate both the credit spread in the bond market and that predicted by structural models in the stock market, making any comparison problematic.

Another common problem in most structural models is how to determine the default barrier. In this sense we are typically left with two alternatives: either we exogenously fix this level as in Longstaff and Schwartz (1995), or we follow Leland (1994) and Leland and Toft (1996) and derive it endogenously as an optimal decision for stockholders. This second alternative seems clearly more attractive, but still leaves aside the influence that other factors, such as liquidity constraints (Davydenko (2005)), or the particular insolvency code the firm is subject to (Franks, Nyborg and Torous (1996)), may have on the default boundary.

Alternative approaches have been proposed recently to test the predictions provided by different structural models. Under the view that corporate-Government yield spreads overestimate credit spreads, Huang and Huang (2003) test several structural models not according to their ability to replicate those spreads, but according to their ability to replicate observed rates of default. They conclude that structural models are capable of replicating these rates of failure for reasonable parameter values, but that those same parameters imply premiums that are typically below the said spreads[4]. It is tempting therefore to conclude that premiums generated in this way are those really attributable to credit risk. However, the idea that the replication of observed default rates through a structural model directly leads to the replication of the unobserved credit spreads in the stock market, and by extension in the bond market, should be taken with caution. The risk of default (a probability of failure strictly greater than zero) is a necessary element for credit risk to exist, but it is not the only element that affects the final price. The expected recovery rate, for example, assumes a fundamental part of the credit risk price estimation and, however, may at least partially depend on parameters that are relatively independent from those that lead to the replication of default rates.

In a more recent study, Eom, Helwege and Huang (2004) compare the bond spread prediction errors of different structural models, again using Government bond yields as reference for the risk-free rate. In this case model parameters are estimated for individual company data and not calibrated to match historical default rates by rating category as in Huang and Huang (2003). The main conclusion of their work is that structural models are not necessarily affected by premium *under-prediction*, but by *precision*.

In this paper we propose a modified version of the Leland and Toft (1996) model (referred to as LT from here on). One main difference is that while bankruptcy costs remain as an important input for the value of individual bonds in our case, we show that they may be assumed equal to zero in the valuation of the whole company. This is justified by the fact that bankruptcy costs affect the distribution of the firm's assets between different claimants in case of default (debtholders and 'lawyers'), but not the overall value of these assets; In this sense we follow Goldstein, Ju and Leland (2001). Another important difference is that we do not determine the default boundary as the optimal choice for stockholders. Instead, we directly calibrate this input to the model according to the information available in the CDS market. In addition, and contrary to what has usually been done in previous studies, we consider the swap rate as the reference risk-free rate to determine theoretical credit spreads. We show that all this makes it possible to generate theoretical credit risk premiums which are consistent with those observed in bond and CDS markets, while at the same time produces quite reasonable values for the default boundary. This first main result of the paper suggests that the traditional poor performance of structural models may be due to the use of an inappropriate risk-free rate, and to an incomplete understating of the determinants of the default boundary.

The relative speed with which different markets incorporate new information about companies' credit risk, has been the focus of recent studies. Blanco, Brennan and Marsh (2005) analyze the case of the bond and CDS markets. They consider a sample of 33 North American and European firms and conclude that the CDS market heads the bond market. Although the effect of specific variables from the stock market is studied, the essay does not formally include the stock market as a third market in the analysis of price discovery. With respect to the methodology, they assume that credit spreads in both markets (bonds and CDSs) are co-integrated, which allows them to carry out the analysis using a vector error correction model (VECM). Certainly, such an approach is interesting, but rests on the idea that credit spreads in each market follow a non-stationary process, an assumption difficult to verify if time series have relatively short spans, like in their sample (approximately a year and a half).

In a parallel work, Zhu (2004) considers an international sample of 24 issuers and finds that the CDS market and the bond market appear equally important in the incorporation of new information about companies' credit risk when the Granger causality test is implemented. When a VECM is used to analyze the price discovery process, results change indicating that the CDS market leads the bond market. Even though they consider a sample period of 4 years (from 1999 to 2002), more than 85% of the data come from the last two years, which may still result in a short period to test for non-stationarity.

The first paper to formally incorporate the stock market as a third market was by Longstaff, Mithal and Neis (2003), who propose a vector auto-regressive model (VAR) to analyze the lead-lag relations between weekly changes in CDS premiums, changes in bond spreads and stock returns. The leading process analysis is then performed by applying the Wald test over the coefficients of the lagged variables. With a sample of 68 North American companies for the period March 2001 – October 2002, they conclude that information flows first into the CDS and stock markets and then into the bond market.

Norden and Weber (2005) use the same VAR model proposed by Longstaff, Mithal and Neis (2003) to analyze the comovement of CDS, bond and stock markets using a sample of 58 companies for the period 2000 – 2002. Their work differs from that of Longstaff, Mithal and Neis (2003) in that they consider not only weekly but also daily data, the risk-free rate used is the swap rate and not the US Treasury bond yield, and their sample is international. In addition, they perform a price discovery analysis for the case of the CDS and bond markets similar to that of Zhu (2004). The results in Norden and Weber (2005) support the idea that information flows first into the stock market, then into the CDS market, and finally into the bond market. The evidence for the leading role of the CDS market with respect to the bond market is stronger in the case of North American companies than in the case of European companies.

This paper employs a VAR model to analyze the lead-lag relations between changes in bond spreads (BS), changes in CDS spreads (CDS) and changes in implied stock market credit spreads (ICS). Our analysis differs with respect to Blanco, Brennan and Marsh (2005) and Zhu (2004) in that we explicitly consider the stock market as a third market in the analysis. It also differs with regards to Longstaff, Mithal and Neis (2003) and Norden and Weber (2005) in that we deal with the price of credit risk also in the case of the stock market, and not only in the CDS and bond markets. In this sense, this is the first work in which a *strict price discovery analysis* is performed for the three markets simultaneously. This is important since credit spreads depend not only on the underlying value of the firm's assets but also on other variables, the case of the risk-free rate being perhaps the most evident. If bond spreads or credit default swap spreads are related only to stock returns, then at least one key variable is being omitted. Although it would be feasible to follow an approach similar to Kwan (1996) and correct the linear model by incorporating changes in the risk-free rate in addition to stock returns, the theory suggests, and the evidence supports, the idea that the relationship between changes in credit spreads on one hand, and changes in variables such as the underlying assets or the risk-free rate on the other, is highly non-linear, with this non-linearity better represented by means of a structural model. Specifically, Di Cesare and Guazzarotti (2005) show that changes in CDSs are better explained by changes in the theoretical credit spreads predicted by Merton's (1974) model, than by a linear model that accounts for changes in the underlying variables (leverage, risk-free rate and volatility). Consistent with this result, we find that the number of lead-lag relations between the stock market and the other two markets is higher when changes in the implied stock market credit spreads are considered instead of stock returns.

Also original to this paper is the consideration of different time periods in addition to different companies. This makes sense as the variables underlying the price discovery process, such as the different assets' relative liquidity, may change not only from company to company for a given time period, but also over time within one company. Odders-White and Ready (2006) document for instance a negative relation between credit rating and stock liquidity, while a similar result arises in Longstaff, Mithal and Neis (2005) for the case of corporate bonds.

Results of the price discovery analysis are consistent with the view that the stock market heads both the bond market and the CDS market, in terms of the credit risk price discovery process. This finding, which represents the second main contribution of the paper, proves to be robust to default barrier specification (calibrated or exogenously fixed), and to whether changes in the ICSs or stock returns are considered in the case of the stock market.

The remainder of the paper is organized as follows: Section I establishes the methodology with which the estimations in each market will be carried out and with which the price discovery analysis will be made; special attention is devoted to the credit risk price estimation in the case of the stock market. Section II describes the company sample. Section III analyzes the specific case of Ford Motor Credit Co., whilst Section IV extends the methodology to the full sample. Section V presents the robustness check, and lastly Section VI offers some conclusions and proposes future lines of research.

I. Methodology

A. Construction of Variables

A.1. The CDS Market

Let us begin with the CDS market, given that available data regarding this market will condition the methodology to be applied in the other two markets.

A CDS establishes an annual premium λ, in the form of basis points on the nominal value of the insured debt as payment for the protection, as well as the contract maturity. Although this maturity may be between just a few months and more than 10 years, the development of the market has tended to adopt the 5 years contract. Let us therefore assume that we have a series of daily CDS-5y premiums for a given company nominated in local currency. In accordance with the arguments in the introduction, we will consider this annual premium the credit spread estimated by CDS market participants. Therefore:

$$CDS_t = \lambda_t(5); \quad t = 1, ..., T \tag{1}$$

where $\lambda_t(5)$ is the CDS-5y premium for day *t*.

A.2. The Bond Market

The credit spread is usually a function of debt maturity. In other terms, a particular market's agents will not claim the same premium for bearing a given company's credit risk for a month as they would for bearing the credit risk for 10 years. We have assumed that in the CDS market the price we have is what traders assign to bear credit risk for 5 years, and therefore in order for our comparison to make sense, we must obtain the corresponding price in the bond market. However, although daily swap rates for 5 years are readily available, we rarely observe yields on corporate bonds that have exactly the same maturity. It is therefore necessary to perform an estimation of this constant yield for 5 years based upon the available bond prices.

Following the ideas of Blanco, Brennan and Marsh (2005) we will look for two bonds, which have the following characteristics:

1. Designated in local currency.
2. Without special clauses, such as a buyback clause.
3. One of the bonds throughout the period of reference (the period for which we have information of CDSs) has a maturity of less than 5 years but more than 1 year, whilst the other has a maturity of more than 5 years for the whole period.
4. Given the above characteristics, they are the most recently issued bonds and those that have maturity closer to 5 years.

Carrying out a linear interpolation between the two bonds' yields, it is possible to obtain an estimated series of yields for 5 years.

It is appropriate to restrict the bond to a maturity of less than 5 years and at the same time greater than 1 year, since, as the maturity is closer to zero, bond yields may remain constant, tend toward zero, or increase substantially depending on their credit rating, which would make the linear interpolation particularly inappropriate if we were to work with bonds that expire very quickly. With the same objective of minimising the effects of the linear interpolation, we will select those bonds that have maturity closer to 5 years. We finally select the most recently issued bonds, as they are generally the most liquid. If $y_t(5)$ is the yield for 5 years obtained for day *t*, and $r_t^s(5)$ is the corresponding swap rate (5 years and in local currency), then the estimated series of credit spreads in the bond market is:

$$BS_t = y_t(5) - r_t^s(5); \quad t = 1, ..., T \tag{2}$$

A.3. The Stock Market

A.3.1. Modifying the LT Model

In the case of the stock market, as already mentioned, we will consider a modified version of Leland and Toft (1996). Following the LT model, we assume that the value of the company's assets evolves in accordance with the diffusion process expressed as:

$$dV = (\mu - \delta)Vdt + \sigma Vdz \tag{3}$$

where μ is the expected assets return, δ is the fraction of the assets value dedicated to payment to investors, σ is the volatility of the assets return, and *z* is a standard Brownian motion process. If failure occurs on *V* reaching a specific critical point V_B, then the results obtained by LT imply that at any *t* the value of a bond with maturity τ, principal $p(\tau)$, coupon $c(\tau)$, and which receives a fraction $\rho(\tau)$ of the value of the company's assets in the event of default, is expressed as:

$$d(V,\tau,t)=\frac{c(\tau)}{r}+e^{-r\tau}\left[p(\tau)-\frac{c(\tau)}{r}\right][1-F(\tau)]+\left[\rho(\tau)V_B-\frac{c(\tau)}{r}\right]G(\tau) \quad (4)$$

where r represents the risk-free rate, and

$$F(\tau)=N[h_1(\tau)]+\left(\frac{V}{V_B}\right)^{-2a}N[h_2(\tau)] \quad (5)$$

$$G(\tau)=\left(\frac{V}{V_B}\right)^{-a+z}N[q_1(\tau)]+\left(\frac{V}{V_B}\right)^{-a-z}N[q_2(\tau)] \quad (6)$$

with

$$q_1(\tau)=\frac{-b-z\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad q_2(\tau)=\frac{-b+z\sigma^2\tau}{\sigma\sqrt{\tau}}$$

$$h_1(\tau)=\frac{-b-a\sigma^2\tau}{\sigma\sqrt{\tau}}; \qquad h_2(\tau)=\frac{-b+a\sigma^2\tau}{\sigma\sqrt{\tau}}$$

$$a=\frac{r-\delta-\sigma^2/2}{\sigma^2}; \qquad b=\ln\left(\frac{V}{V_B}\right); \qquad z=\frac{\left[\left(a\sigma^2\right)^2+2r\sigma^2\right]^{1/2}}{\sigma^2}$$

In the original model, LT find a closed expression for V_B as an endogenous result. It is specifically the assets' value that stockholders consider to be the optimum value for declaring a company bankrupt, and leaving it in the hands of the creditors. It may be preferable not to use this expression for various reasons: Firstly, because it is based on the hypothesis that the company issues debt always with the same principal, coupon and maturity, which can be an overly restrictive hypothesis. Most importantly, because many other factors such as liquidity constraints (Davydenko (2005)), or the specific insolvency code that would be applied to the company in case of default (Franks, Nyborg and Torous (1996)), may determine the point of bankruptcy instead of stockholders' wishes. Our alternative is to express the default point as a fraction β of the nominal value of the total debt issued P,[5] and to calibrate this parameter according to the information available in the CDS (or bond) market. The exact procedure is discussed in the next section. At this point we simply state that under this assumption the term $\rho(\tau)V_B$ in equations (4) - (6) is expressed as $\rho(\tau)\beta P$.

Let us assume that all the bonds have the same priority and therefore, in the event of bankruptcy, each creditor receives (after taking into account the possible costs of liquidation) the part that reflects their participation in the company's total debt. If liquidation costs, or bankruptcy costs, represent a fraction $\alpha \in [0,1]$ of the assets' value, then

$$\rho(\tau) = (1-\alpha)\frac{p(\tau)}{P} \tag{7}$$

and therefore, what each creditor will finally receive in the event of bankruptcy is

$$\rho(\tau)\beta P = (1-\alpha)\beta p(\tau) \tag{8}$$

now leaving formula (4) as

$$d(V,\tau,t) = \frac{c(\tau)}{r} + e^{-r\tau}\left[p(\tau) - \frac{c(\tau)}{r}\right][1-F(\tau)] + \left[(1-\alpha)\beta p(\tau) - \frac{c(\tau)}{r}\right]G(\tau) \tag{9}$$

Please note that the recovery rate is $(1-\alpha)\beta$.

The total value of the debt is the value of all the company's bonds. Let us suppose that the company has *N* issued bonds, being τ_i the maturity of the *i*–th bond for $i = 1,\ldots,N$. Then

$$D(V,t) = \sum_{i=1}^{N} d(V,\tau_i,t) \tag{10}$$

where $d(V,\tau_i,t)$ corresponds to equation (9).

On the other hand, LT make a distinction between the market value of the company's assets and the market value of the same assets with leverage. As Goldstein, Ju and Leland (2001) state, such a distinction presents various difficulties, some as obvious as assuming that the equity capital value is an increasing function of the tax rate. We therefore prefer to use the alternative approach of the latter authors. The idea is that the value of the company's assets, indebted or not, should reflect the present value of all future cash flows that the company might generate, and that these cash flows would not be affected by leverage. On the contrary, the only thing this leverage does is to modify how these flows, and therefore the company value, are distributed between those agents who have rights to the cash flows. In this way, a company without debt is shared between shareholders and Government, where the Government acquires rights to the cash flows in the form of taxes. If the company issues debt, then there are four agents that have rights to the cash flows: the shareholders, the creditors, the Government and the 'lawyers', who receive part of the company's income in the event of bankruptcy. In order to simplify things, let us assume there are no taxes. Then, and in accordance with the previous arguments, the following relation for any *t* has to be met:

$$V(t) = S(V,t) + D(V,t) + BC(V,t) \quad (11)$$

where $S(V,t)$ and $BC(V,t)$ represent the market value of the equity capital and of the lawyer's fees in case of default, or simply bankruptcy costs, respectively[6]. Continuing with our line of reasoning that the indebtedness does not alter the value of the company but only its distribution, the existence of bankruptcy costs has the sole effect of transferring value from the creditors to the lawyers, who, to the detriment of the creditors, receive part of the company's value in the event of bankruptcy[7]. Therefore:

$$BC(V,t) = D(V,t \mid \alpha = 0) - D(V,t) = \sum_{i=1}^{N} \alpha\beta p(\tau_i) G(\tau_i) \quad (12)$$

Finally, we can use the formulas (11) and (12) to express $S(V,t)$ as

$$S(V,t) = V(t) - D(V,t \mid \alpha = 0) \quad (13)$$

A.3.2. Model Calibration

Credit spreads from the stock market at time *t*, could be estimated from equation (9) as the resulting premium from issuing at par value a hypothetical bond with maturity equal to 5 years. This bond should pay a coupon so that the following equation holds:

$$d(V,5,t \mid p) = p \quad (14.a)$$

Noting this coupon as $c_t(5, p)$, the bond yield is

$$y_t^E(5) = \frac{c_t(5, p)}{p} \tag{14.b}$$

and the estimated credit spread from the stock market is then the difference between the yield of this hypothetical bond and the risk-free rate:

$$ICS_t = y_t^E(5) - r_t \tag{14.c}$$

However, such a procedure requires, at each instant *t*, availability of information regarding:

I.1. Company value V_t.

I.2. Nominal value of total debt P_t.

I.3. Risk-free rate r_t.

I.4. Pay-out rate δ_t.

I.5. Asset Volatility σ_t.

I.6. Bankruptcy costs α_t.

I.7. Default point indicator β_t.

Parameters and variables which in the majority of cases are not observable, and which should therefore be calibrated.

We will assume from now on that bankruptcy costs, volatility of assets and default point indicator, are constant parameters[8]. It is possible that the hypothesis of constant volatility may appear particularly controversial. We find it, however, appropriate to apply an estimator of the long-run volatility instead of the short-run volatility when it comes to pricing a bond over a five year horizon. On the other hand, we should bear in mind that σ represents the volatility of the company's total assets, not of the equity capital, and that the hypothesis of constant assets' volatility is compatible with stochastic volatility in equity capital given that the company maintains debt between its financial sources.

With the objective of compiling the information described in points I.1 – I.7, we obtain the following information:

D.1. Daily data on stock market capitalization.

D.2. Accounting data referring to:

D.2.1. Short-term liabilities (STL).

D.2.2. Long-term liabilities (LTL).

D.2.3. Interest Expenses (IE).

D.2.4. Cash Dividends (CD).

Given that accounting data cannot be obtained on a daily basis, it is necessary to carry out an interpolation between available observations (normally on a quarterly, bi-annual or annual basis), with the objective of collecting the evolution of these variables over time.

Total liabilities (TL) are the sum of short-term liabilities and long-term liabilities. We can therefore approximate P_t as:

$$P_t = TL_t; \quad t = 1, ..., T \tag{15}$$

At the same time, we may express δ_t as a function of total asset value at *t*, as well as payments of dividends and interests:

$$\delta_t = \frac{CD_t + IE_t}{V_t}; \quad t = 1, \ldots, T \tag{16}$$

To estimate the series of assets' value V_t, as well as the volatility σ, we will make use of formula (13). It is worth noting now that such a formula includes the total value of debt without bankruptcy costs, and that the formula that expresses this is constructed from the characteristics of the company's individual bonds. It is therefore necessary to interpret available information on debt (short and long-term liabilities, as well as interest payments) in terms of individual bonds.

One possibility is to assume that debt consists of two bonds, one with nominal value equal to short-term liabilities, and another with nominal value equal to long-term liabilities. However, considering all debt reduced to just two instruments may make results largely dependent on the choice of their maturity. Our alternative is to assume that in each instant *t* there are 10 company bonds in the market: one with maturity of 1 year and principal equal to short-term liabilities STL_t, and nine with maturity from 2 to 10 years, each with principal equal to 1/9 of long-term liabilities LTL_t. Stohs and Mauer (1996) consider a wide sample of companies and find that 95% of total debt has maturity under 10 years. The proposed procedure offers the advantage of assuming that debt repayment is made in a relatively homogenous way, and throughout a period that reasonably corresponds to the literature.

The next step will be to assign to each of those bonds an annual coupon that represents a fraction of IE_t, proportional to the weight of its nominal value to the nominal value of total debt. Thus, debt's total value without bankruptcy costs is given in each moment t by (10) under the restriction $\alpha = 0$, where $N = 10$. Furthermore, we will need to collect the following information:

D.3. Daily data on the swap rate for years 1 to 10, that is, $r_t^s(\tau);\ \tau = 1, ..., 10$.

This in turn provides us with the rate to apply in (14):

$$r_t = r_t^s(5); \quad t = 1, ..., T \tag{17}$$

Following this we should determine the parameters α, σ and β, as well as the series V_t. Let us assume we already have values for α and β. In this case we could calibrate the series V_t and the parameter σ using the following algorithm:

1) Propose an initial value for σ, σ_0.[9]
2) Evaluate the series V_t, so that (13) is fulfilled for all t.
3) Estimate the volatility of V_t, σ_1, from the series obtained in 2.
4) Conclude if $\sigma_1 = \sigma_0$. Otherwise, propose σ_1 at step 1 and repeat until convergence.

This procedure generates (for a given value of β), a value for σ and a series V_t, which are consistent with observed stock market capitalization. In brief,

$$\left(V_t, \sigma; t = 1, \ldots, T\right) \equiv \left(V_t, \sigma; t = 1, \ldots, T\right)\Big| \; \textit{Is the solution of the algorithm} \tag{18}$$

We could therefore obtain implied credit risk premiums in accordance with (14), although this still requires us to specify α and β. We proceed by setting a value for α, specifically:

$$\alpha = 0.3 \tag{19}$$

which is in accordance with the literature[10].

It seems reasonable, on the other hand, to believe that the higher the credit spread level, the greater the discrepancy between spreads provided by different markets[11]. The relationship between stock market's based credit spreads and observed CDS premiums could be therefore given by the expression:

$$ICS_t = CDS_t \times e^{\varepsilon_t} \tag{20}$$

where ε_t are *i.i.d.* error terms with $E[\varepsilon_t] = 0$ and $Var(\varepsilon_t) = \sigma_\varepsilon$. A reasonable measure of the discrepancy between these series is then The Mean Squared Error:

$$MSE = \frac{1}{T} \sum_{t=1}^{T} \log\left(\frac{ICS_t}{CDS_t}\right)^2 \tag{21}$$

Since it seems unreasonable to expect significant differences between credit spreads coming form different markets, we may define β as the value of the default point indicator, which minimizes this measure of discrepancy between credit spreads, that is[12]:

$$\beta \equiv \underset{\beta}{\operatorname{argmin}}\left(MSE\right) \tag{22}$$

It is important to note that the choice of β using (22) does not guarantee a perfect adjustment between the ICS series on one hand and the CDS series on the other, in the same way that carrying out a linear regression does not guarantee an R-squared adjustment of 100%. Therefore, to apply such an adjustment does not prevent us from extracting conclusions about the validity of the model with respect to its capacity to generate ICS series, which are consistent with the CDS series whenever the obtained value for β is reasonable. Secondly, β modifies the general level of the ICSs, but not the sign of changes in that variable. This is important since it implies that the results of the price discovery analysis will be generally robust to a moderate bias in the estimation of β.

In summary, stock market-based credit spread estimation uses formula (14). The arguments in (14) (described in points I.1 – I.7) can be evaluated from data mentioned in D.1 – D.3, and formulae (14) - (22).

B. Analysis of Price Discovery

Once the BS, CDS and ICS series are constructed, we may establish the following VAR model for changes in credit spreads:

$$\Delta BS_t = a_1 + \sum_{z_1=1}^{Z_1} b_{1z_1} \Delta BS_{t-z_1} + \sum_{z_1=1}^{Z_1} c_{1z_1} \Delta CDS_{t-z_1} + \sum_{z_1=1}^{Z_1} d_{1z_1} \Delta ICS_{t-z_1} + e_{1t} \tag{23.a}$$

$$\Delta CDS_t = a_2 + \sum_{z_2=1}^{Z_2} b_{2z_2} \Delta BS_{t-z_2} + \sum_{z_2=1}^{Z_2} c_{2z_2} \Delta CDS_{t-z_2} + \sum_{z_2=1}^{Z_2} d_{2z_2} \Delta ICS_{t-z_2} + e_{2t} \tag{23.b}$$

$$\Delta ICS_t = a_3 + \sum_{z_3=1}^{Z_3} b_{3z_3} \Delta BS_{t-z_3} + \sum_{z_3=1}^{Z_3} c_{3z_3} \Delta CDS_{t-z_3} + \sum_{z_3=1}^{Z_3} d_{3z_3} \Delta ICS_{t-z_3} + e_{3t} \tag{23.c}$$

where the errors e_{it} are *i.i.d.*, and where Z_i for $i = 1, 2, 3$ may be defined according to the Schwarz criterion. Price discovery analysis is then carried out testing the null hypothesis that present changes in one given market are independent of past changes in another market. For example, if using the Wald test the null hypothesis $c_{11} = c_{12} = ... = c_{1Z_1} = 0$ is rejected, but we cannot reject the null hypothesis that $b_{21} = b_{22} = ... = b_{2Z_2} = 0$, then we have evidence that the CDS market incorporates new information about company credit risk faster than the bond market. Repeating this analysis for all possible cases we will finally obtain general conclusions about the price discovery process in the three markets. Additionally, we will carry out the Granger causality test for each couple of series. To do this we will consider one of the three possible couples of series and will establish the VAR model excluding the remaining series. We will then obtain the number of optimum lags according to the Schwarz criterion for the VAR model, and will carry out the causality test. We will repeat this procedure for the three possible couples of series.

II. Data Description

A. The CDSs Market

Our initial sample of CDSs contains daily data about 5-year premiums for 52 North American and European non-financial companies. This information has been provided by Banco Santander and spans the period from September 12th 2001 to June 25th 2003. We exclude those firms located in European countries that do not belong to the single currency zone, as the available CDSs for these companies are those designated in euros.

B. The Bond Market

Corporate bond yields satisfying Section I.*A.2.* requirements, as well as 5-year swap rates both in dollars and euros, are collected from Datastream.

C. The Stock Market

Stock market capitalization and accounting data have been obtained from Standard & Poor's from January 2nd 2001 to June 30th 2003. For some companies accounting data has been completed using available information from Datastream. The swap rate, as for the bond market, has been taken from Datastream, with maturities ranging from 1 to 10 years.

D. Implementation and Additional Limitations

The general procedure to estimate the ICSs from the stock market series described in section I.*A.3.*, is implemented in our case following the next steps:

I. Accounting data in each moment t is determined through linear interpolation between data on January 2nd 2001 and June 30th 2003.

II. We divide the sample period into natural half-yearly periods, allowing the parameter β to be adjusted for each of those periods. We therefore have a maximum of 4 observations for each company, that is, 01/2 (year 2001 / 2nd half, with observations only starting from September 12th), 02/1, 02/2 and 03/1 (with observations only until June 25th). Those companies for which there is no information for at least 3 consecutive periods have been eliminated, and no half-yearly period is included if it does not have at least 50 observations. These additional limitations leave us with a final sample of 21 companies and 25,371 daily data points. The total number of price discovery tests to be performed is 65, corresponding to an equal number of firm-period observations.

III. Once the companies that form our sample and the periods that will be included for each one are defined, we make a first estimation of β, β_{01-03}, assuming that it is constant throughout all periods.

It is important to realize that a change in β has two contrary effects over the mean level of the ICS series that we intend, somehow, to adjust to the mean level of the CDS series. On one hand there is a default probability effect (DPE), because a higher β implies a higher default point and therefore, a higher default probability and a higher mean level for the ICS series. On the other hand there is a recovery rate effect (RRE), which follows from the fact that a higher β implies a higher recovery rate and a lower mean level for the series. To see which effect dominates the other, and when, let us start by considering the limit case $\beta = 0$. For this value of β the recovery rate in case of default is zero, but because there is a null probability for this event (as the barrier is also at zero), all points of the ICS series will be equal to zero. An increase in β generates positive credit risk premiums, that is, for small values of β, the DPE dominates the RRE. As β increases the RRE tends to be higher, and eventually dominates the DPE. In the other limit case $\beta = 1/(1-\alpha)$, the default probability is 'very high', but as the recovery rate is equal to 1 there is no credit risk, so all points of the ICS series are again equal to zero.

In brief, the mean level of the ICS series is a concave function of β that takes value zero for $\beta = 0$ and $\beta = 1/(1-\alpha)$. Therefore when searching values for β using (22), we may find two quite different solutions depending on the starting value for the search: Either a small β, which implies a small default probability, but with a recovery rate $(1-\alpha)\beta$ that is also small, or a large β, which implies a high default probability but, also a large recovery rate. This large β is typically above 1, which is not rational from the point of view of shareholders[13]. For this reason we apply the following procedure with the objective of ensuring a more reasonable first solution (in which the DPE dominates the RRE):

III.1. Choose an initial value that is sufficiently small for β_{01-03}, β_0 (specifically 0.3), and define $\beta_1 = \beta_0 + 0.05$.

III.2. Evaluate $MSE_0 = MSE(\beta_0)$ and $MSE_1 = MSE(\beta_1)$.

III.3. If $MSE_1 < MSE_0$, then define again β_0 as $\beta_0 = \beta_1$ and go back to step III.1.

III.4. If $MSE_1 \geq MSE_0$, then look for the value of β that minimizes the MSE in the interval $(\beta_0 - 0.05, \beta_0 + 0.05)$.

It must be pointed out that each proposal for β implies a new estimation of the volatility of V_t, $\sigma(\beta)$.[14] For this estimation we use all available information, that is, stock market capitalization series and accounting data from 2nd January 2001 to the last date for which we have simultaneously available BS and CDS data. This means making the assumption that this value of β is also applicable to the period for which we have data from the stock market but not from the other markets.

IV. Once β_{01-03} is estimated, we can use its value as an initial guess for the estimation of the vector $\beta_s = \{\beta_{01/2}, \beta_{02/1}, \beta_{02/2}, \beta_{03/1}\}$. Again, each proposal of a vector β_s implies a new estimation of the volatility[15]. For those periods in which we only have information about the stock market we apply the closest (in time) value for β.

III. The Ford Motor Credit Co. Case

In order to validate the model we need to check whether or not it is capable of generating credit spreads that are consistent with those obtained in the bond and CDS markets for reasonable parameter values. It is evident that such verification will be more reliable the more we trust the information obtained from those markets. Because of this, we begin the analysis by focusing on the specific case of Ford Motor Credit Company. Ford Motor Company bonds, which represent around 10% of the North American bond market (Chen, Lesmond and Wei (2005)), are among the most liquid in this market, and the CDSs that have these bonds as reference are also among the most liquid in the CDS market. Moreover, results in Blanco, Brennan and Marsh (2005) are indicative of the absence of non-default components in both bond and CDS spreads for this company.

Figure 1 graphs BS, CDS and ICS time series for Ford Motor Credit Co[16]. Panel A of Table I shows the value of the estimated parameters in this case, as well as the resulting MSE adjustment of ICS and CDS series. The constant β is 0.93 and asset volatility is around 5%. When β is assumed to be constant the recovery rate $(1-\alpha)\beta$ is also constant and equal to 0.65.

<Figure 1 about here>

<Table I about here>

Panel B shows descriptive statistics of the three series, whilst Panel C collects measures of discrepancy usually considered in the literature: average basis (*avb*), percent average basis (*avb(%)*), average absolute basis (*avab*) and percent average absolute basis (*avab(%)*). The data confirms what is evident at first glance in the graph, a good adjustment between the different series. Particularly notable is the consistency between estimated credit spreads from the stock market and estimated credit spreads from the other two markets, obtained through reasonable values of unobserved parameters (Panel A).

Panel D shows the results of a first analysis of price discovery for each half-yearly period. The number of optimum lags for each equation of the model varies between 1 and 2 according to the Schwarz criterion. Likewise, t-statistic or F-statistic is shown from the Wald test for the null hypothesis that coefficients of explanatory variables are all equal to zero. The Panel also shows F-statistic that summarizes overall significance of each equation. The main conclusion from this Panel is that, in the case of Ford Motor Credit Co., and for the considered period, the stock market clearly headed the other markets in the incorporation of new information on the company's credit risk, without a clear leader pattern between bond market and CDS market. Results are confirmed in Panel E where Granger causality tests for the distinct couples of time series are shown. The number of optimum lags for each VAR model also varies between 1 and 2. It is worth noting here that differences between half-yearly periods eventually appear. For instance, the CDS market seemed to lead the bond market in the second half of 2001, and not headed by the stock market during the first half of 2003. This is indicative of a time varying feature in the price discovery process.

IV. Results for the Full Sample

We now extend the analysis to the total sample of 21 companies. Table II contains descriptive statistics, whilst Table III shows the distinct measures of discrepancy between series. Of the 21 companies, one stands out for the apparent excessive size of the MSE (1.2619). This company is the Spanish Petroleum Company, Repsol YPF SA. Figure 2 shows BS, CDS and ICS time series for this company. It is evident that the general level of ICS series is systematically below BS and CDS series. A detailed study of the company's circumstances reveals an interesting situation: As Standard & Poor's report of 26 March 2002 indicates, part of Repsol YPF SA's debt (8,000 million euros) was (at least at that time) subject to a clause that allowed creditors to declare the debt in default if the Argentinean subsidiary company YPF SA failed to pay its debt by an amount superior to 20 million dollars. This clause has the incentive effect on Repsol YPF SA to financially support YPF

SA. Moreover, Standard and Poor's remarked on the individual nature of this clause between European debt issuers. The effect that this clause may have on bond spreads of Repsol YPF SA and on CDSs traded on these bonds is remarkable (whether they are affected by this clause or not). We have decided therefore to eliminate this company from our sample.

<Table II about here>

<Table III about here>

<Figure 2 about here>

The company with the next largest MSE (0.1464) is Telecom Italia SPA. Although this MSE is not substantially greater than the values found in other companies, it is relevant that this company, together with Repsol YPF SA, is the only company to have a percentual average basis of two digits (-20%). It must be highlighted that this firm merged with Olivetti just a few months after our sample period, with news about the merger going back to 2001. Figure 3 shows CDS series for Telecom Italia SPA as well as CDS series for Olivetti. It is clear that, as the merger came closer, convergence of CDSs for the two companies could be observed. It seems reasonable to assume that the risk of the company that would result from the merger was being represented more and more by the CDSs of Telecom Italia SPA throughout our sample period, and that the CDSs represented less of the associated risk particular to the company's own financial situation. As in the case of Repsol YPF SA, the CDS market reflects in its premiums information that, being relevant in order to evaluate the credit risk of the company is not completely included in the evolution of the stock market capitalization nor in its accounts, but depends to some extent on the financial information of another company. We have decided therefore to also eliminate Telecom Italia SPA from the sample.

<Figure 3 about here>

The last company that we will eliminate is Royal Ahold. Figure 4 shows the three series of credit spreads for this firm. The leap at the end of February 2003 may be related to published information about accounting irregularities in its American subsidiary Foodservice. It is noteworthy to verify how the three markets react jointly (although in different magnitude) to this information. In spite of the interest generated by this case, and in order to prevent any possible bias in the general results, we prefer to remove this company from the sample.

<Figure 4 about here>

Tables II and III show averages for the 21 original companies, as well as averages that come from eliminating the three firms mentioned. Looking at Table III, Panel C, we find that the *avb* between ICSs and CDSs for the remaining 18 companies is always in the range of +/- 10 b.p., with the sole exception of Alcatel (-11.26 b.p.), the firm with the highest mean levels (Table II). The mean value of the *avb* is actually negligible (-0.45 b.p.). Of course it could be the case that the structural model was able to replicate the mean level of the CDSs through the calibration of β, whilst at the same time it fails in the precision over time series. This however is not the picture described by *avab*, with a mean value of 29.96 b.p., quite similar to the *avab* between CDSs and BSs found by Houweling and Vorst (2005) which is around 32 b.p.. Our results suggest that the structural model and the calibration methodology proposed in the paper generate ICSs that are, according to the literature, at least as good as bond spreads for explaining observed CDS premiums.

Panel A in Table III shows that BSs tend to be below CDSs (positive CDS/BS *avb*), which is consistent with results in Houweling and Vorst (2005) and Blanco, Brennan and Marsh (2005). This may indicate that cheapest-to-deliver option premium in CDS spreads is on average higher than liquidity premium in bond yields (a liquidity premium we tried to minimize in our sample). The mean *avab* found between CDSs and BSs is, on the other hand, 42.81 b.p., slightly above estimates in Houweling and Vorst (2005). Results however converge when the atypical *avab* of Fiat, a firm with a well known cheapest-to-deliver option premium in its CDSs, is eliminated (our mean *avab* falls to 32.31 b.p.) [17].

Finally, when comparing ICSs and BSs (Panel B), results are very close to those that emerge from a comparison between CDSs and BSs. This is a natural consequence of fitting ICS series to CDS series.

Table IV contains the parameter values that emerge from the estimation of ICS series where the three suspect companies are excluded from our original sample of 21. Looking at Panel A, which reflects the results of the first stage of the estimate, in which a constant β is assumed, the mean default point indicator is 0.79 and the associated mean recovery rate 0.55, very much in line with the historical average. On the other hand, the close relationship shown in Figure 5 between default point indicator and volatility stands out. Carrying out a linear regression in which the independent variable is $\sigma(\beta_{01-03})$ and the dependent variable is β_{01-03}, a negative slope is obtained which is significant at 1%. This is in line with predictions by structural models with endogenous bankruptcy. Interestingly, $\sigma(\beta_{01-03})$ alone explains 85% of the variability of β_{01-03}.

<Table IV about here>

<Figure 5 about here>

The value of β is at times slightly greater than 1, which is not strictly consistent with the hypothesis of stockholders' rationality. This is probably a consequence of the cheapest-to deliver option in CDS premiums we employ in the calibration. In effect we have the case in which, *ceteris paribus*, the higher the premiums we want to replicate, the higher the value of β we obtain (as the DPE dominates the RRE). For this reason, if the actual credit spread is to some extent overestimated by CDS premiums, then so is the value we derive for β. The case of Fiat represents a good example. We find however that values obtained for β are in general reasonable and in accordance with the hypothesis of stockholders' rationality, both from the point of view of the levels and from the point of view of their relationship with the firm's asset volatility.

Table V contains the results of the price discovery analysis. Panel A shows rejections of different null hypotheses in terms of the total number of companies and half-yearly periods in our sample. For example, Column A1 indicates that for 40 cases over 65 (62%) the null hypothesis stating that past changes in BSs are not important for explaining current changes in BSs is rejected at the 95% level of significance. From Panel A it can be seen that, for our sample, the most predictable market is the bond market (50 rejections of the null hypothesis of no significance of the model), followed by the CDS market (35) and lastly the stock market, being the least predictable (7 rejections). On 25 occasions, past changes in CDSs are important for explaining current changes in BSs, and on 18 occasions past changes in BSs are important for explaining current changes in CDSs. This lack of clear leadership between bond and CDS markets is confirmed by carrying out the Granger causality test.

This test is in Panel B. Looking at Column B1, where the stock market is exclueded, we observe that in 25 cases the null hypothesis that changes in BSs do not cause, in Granger's sense, changes in CDSs, is rejected. The contrary hypothesis is rejected for exactly the same number of cases. This general pattern appears however as the result, not of an equal importance of both markets over time, but of a rotating leading role of these. As an example, the bond market seemed to lead the CDS market during the first half of 2002, whilst the contrary happened during the second half of the same year.

For ICSs, we may see (Panel A) that only in 8 (5) cases the hypothesis that past changes in BSs (CDSs) are important for explaining current changes in ICSs is rejected. Similarly we observe that in 19 (24) cases, the hypothesis that past changes in ICSs help to explain current changes in BSs (CDSs) is rejected. The overall impression is that the stock market is leading the other two markets in most cases, a result that appears independent of the time period considered.

<Table V about here>

V. Robustness Check

It may be the case that previous results are biased because of the particular form in which we measure changes in the perception of credit risk in the stock market. In particular, it is possible that the use of CDS series to calibrate the default barrier is affecting the conclusions. To check this possibility we repeat the analysis imposing an exogenously fixed value for β of 0.73 (Leland (2004)). Table VI contains the results of the new price discovery analysis. These indicate that main conclusions on the leading role of the stock market are robust to the specification of the default boundary. Table VII on the other hand reflects the new values for the different measures of the basis. Imposing a constant 0.73 for the default point indicator (close to the mean of 0.79 we get from the calibration) implies a relatively low mean *avb* (-33.35 b.p. when new ICSs are compared with CDSs, 5.28 when compared with BSs), but with a large dispersion around this mean. The result reveals the importance of the default barrier for precision in determining the credit spread within the structural model.

<Table VI about here>

<Table VII about here>

As a final robustness check, we follow Longstaff, Mithal and Neis (2003) and Norden and Weber (2005), and use stock returns instead of changes in ICSs for the case of the stock market. The objective is to verify whether our findings still hold under this more standard approach. Two main conclusions emerge from results in Table VIII: Firstly, the stock market still appears as the leading market under this alternative specification. Secondly, the number of statistically significant lead-lag relations between the stock market on one hand, and the bond and CDS markets on the other, falls with respect to the case in which changes in ICSs are considered. As an example, the Granger causality test indicates that in just 1 (6) case(s) past changes in CDSs (BSs) are important for explaining current stock returns. This happened in 5 (8) occasions when changes in ICSs where considered (see Table III). In the same way, past stock returns appear important for explaining current changes in CDSs (BSs) in 27 (19) cases, whilst in the previous analysis this type of dependence appeared in 29 (22) out of 65 possible cases.

<Table VIII about here>

To summarize, we find that the stock market leads bond and CDS markets in the credit risk discovery process. This result is robust to default barrier specification (calibrated from CDS data or exogenously set). The result is also robust to the use of stock returns or changes in ICSs for the analysis. Of all these possible formulations, the one proposed in this paper is that which enables a better representation of the dynamic relationship between the stock market and the other two markets.

VI. Conclusions

Credit risk is a fundamental element in bond, CDS and stock prices. These assets are traded in markets that differ greatly in terms of organization, liquidity and traders, which can give rise to new information on credit risk being incorporated into the price of some assets more quickly than into others. This paper establishes a methodology that allows the analysis of which markets incorporate this information first, and applies the methodology to a sample of North American and European companies.

We begin with a formal definition of credit risk: risk due to losses associated with the event of failure to pay by the borrower, or the event of deterioration of its credit rating. We then propose a measure of this risk in accordance with the definition given: the credit spread, or premium that agents of a certain market would claim for the debt with a possibility of default by a certain company, in relation to a debt of the same nature, but with no possibility of default. As a next step we define the form in which such a variable can be estimated for each market based on the available information. More specifically, we establish that credit spreads in the bond market can be measured by the differential between the yield on corporate bonds and the corresponding swap rate. In the CDS market, by observed CDS premiums, and in the stock market, by the theoretical premium generated by a modified version of the Leland and Toft (1996) model. Here the distinction between the value of the levered assets and the non-levered assets of a company is avoided, and the default boundary is determined based on the available information in other markets.

From the application of our methodology to the sample, it is deduced that the proposed modification of the Leland and Toft (1996) model generates implied credit spreads in the stock market which are consistent with estimated credit spreads in other markets. This allows us, for the first time in the literature as far as we know, to present comparable estimates of the credit spread from the three markets. On carrying out a linear regression in which default point indicator acts as a dependent variable and asset volatility acts as an independent variable, we find a negative and significant relationship in line with what was established by structural models with endogenous default. Volatility alone explains 85% of the variability of the (constant) indicator point of bankruptcy in our sample.

The price discovery analysis is carried out by means of a VAR model for daily credit spread changes in each of the three markets. Results indicate that in most cases the stock market headed the other two markets, with no clear pattern of leadership between the bond and CDS markets. Even though the leading role of the stock market is shown as robust to the time period considered, the equal importance of the bond and CDS markets may be affected when looking at specific time periods. As an example, the bond market seemed to lead the CDS market in our sample during the first half of 2002, whilst the inverse situation took place during the second half of the same year.

Future work should verify the results obtained here using a larger sample of companies and time periods. This would also allow the validation of the proposed structural model as well as the calibration procedure employed. It must be remembered that although the calibration is based on stock market capitalization and accounting information, we estimate the default point to make credit spreads from the stock market consistent with credit spreads estimated in the CDS market, or alternatively, in the bond market. In many cases however, information on credit spreads in these last two markets is either unavailable, difficult to find, or simply unreliable; and it will be precisely in these circumstances when the information on implied credit spreads from stock market is most valuable. In this sense the procedure we employ offers a clear advantage over reduced form models, even though both share the idea of calibrating model parameters to reflect credit risk premiums estimated in other markets. In effect, the default point indicator we obtain may be related to 'fundamentals'. It would be suitable therefore to study, based on companies for which sufficient information exists on these other markets, whether a functional relationship can be established between the default point indicator on one hand, and those fundamentals on the other, in a way that stock market credit spreads could be derived even in the absence of information about the spreads in other markets. The strong relationship found between default point indicator and firm's asset volatility is a clear example and a first step in this direction. At the same time, recent studies have demonstrated the potential of the maximum likelihood estimation for the non-observed parameters in the structural models. Some examples would be the works of Duan, Gauthier, Simonato and Zaanoun (2003), Duan, Gauthier and Simonato (2004), Ericsson and Reneby (2004a, 2004b), and Bruche (2005). It would also be interesting to study the possible application of this method of estimation to the model proposed in this paper. All these possibilities are left for future research.

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Footnotes

[1] We could of course include central banks, whose objective is to ensure the health of the financial system.

[2] See Hull, Predescu and White (2004).

[3] In a recent paper Ericsson and Renault (2006) propose a structural model that incorporates both credit and liquidity risk.

[4] They likewise show that the proportion of the total premium represented by the estimated credit risk premium is greater when swap rates are used instead of Government bond yields as a measure of the risk-free rate.

[5] Leland (2004) demonstrates that when it comes to predicting default probabilities, it is equivalent to using the expression obtained in LT or the term βP for an adequate value of β.

[6] Of course identifying all the bankruptcy costs with lawyers' fees is quite restrictive, but seems to be a useful way of considering such costs. It is interesting on the other hand to verify that when there are no taxes there is no 'formal' contradiction between the approach of LT and that of Goldstein, Ju and Leland (2001). If we identify the sum of the equity capital and debt as the *market value* of the company, this will be expressed as $v(V,t) = S(V,t) + D(V,t) = V(t) - BC(V,t)$, which is in line with the results of LT in the absence of taxes. However, now $V(t)$ will not be interpreted as the market value of the company's assets that are not indebted, but instead, as the *economic value* of the company or the present value of all the cash flows that the company might generate.

[7] At the time of issuing debt, the existence of bankruptcy costs will result in creditors claiming a greater interest rate, implying an indirect loss for the shareholders.

[8] Although we consider β as a constant in the sense that it does not vary in daily terms, it may be useful as we will see, to allow its value to be readjusted in monthly, quarterly, bi-annual or annual terms.

[9] Vassalou and Xing (2004) establish a similar procedure for calibrating the volatility in the Merton (1974) model, using the volatility of the equity capital as an initial proposal to derive the volatility of the company's assets. This is a reasonable way to proceed although not necessarily the most efficient: The volatility of equity capital will be greater than the company's assets volatility anyway. Therefore, this procedure starts the search with a biased estimation of the volatility to be estimated. In our case we start from the value of 0.2, which is used in many calibration exercises. We have checked that, in any case, the result obtained is robust with regards to the initial proposed value.

[10] See Leland (2004).

[11] See, for example, Bruche (2005).

[12] Obviously the CS series could also be taken as reference in the calculation of β.

[13] A value of β greater than 1 implies that the total assets value is greater than the total nominal value of the debt in the event of failure. In this case the stockholders could simply sell the assets, liquidate the debt, and be left with the surplus instead of leaving all assets in the hands of creditors and lawyers.

[14] See algorithm described in Section I.*A.3.*

[15] In this case we omit the leaps between each six month period to prevent a bias in the estimation of σ.

[16] The stock market data has been taken from the parent company Ford Motor Company.

[17] For a discussion on the reasons behind the CDS/BS basis, and a detailed analysis of the case of Fiat, see Blanco, Brennan and Marsh (2005).

Table I

Ford Motor Credit Co. This table has five panels. Panel A contains the calibration parameters used in computing the ICS for Ford Motor Credit Co. Panel B shows descriptive statistics for the three measures (BS, CDS and ICS) of credit spreads. Panel C shows the basis for the three series. Panel D contains the results of the price discovery exercice using the Wald test. Panel E contains the results of the Granger causality test. *** Indicates significance at the 1% level, ** indicates significance at the 5% level and * indicates significance at the 10% level.

A: CALIBRATION PARAMETRES

		$\beta_{01/2}$	0.9419
β_{01-03}	0.9375	$\beta_{02/1}$	0.9407
$(1-\alpha)\beta_{01-03}$	0.6563	$\beta_{02/2}$	0.9424
$\sigma(\beta_{01-03})$	0.0520	$\beta_{03/1}$	0.9279
		$\sigma(\beta_{01/2}-\beta_{03/1})$	0.0518
		MSE	0.0104

B: DESCRIPTIVE STATISTICS

BS				CDS				ICS			
Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.
129.5	713.6	309.4	129.8	125.0	650.0	310.6	127.9	126.3	662.7	309.7	126.2

C: BASIS

CDS vs BS				ICS vs BS				ICS vs CDS			
avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)
1.15	0.60	15.36	5.36	0.31	0.82	25.43	8.56	-0.84	0.42	24.47	8.07

Table I Continued

D: PRICE DISCOVERY - WALD TEST												
	ΔBS				ΔCDS				ΔICS			
	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL
01/2	-1.48	2.34**	2.41**	5.99***	0.04	-0.24	2.22**	1.81	0.96	-0.59	-0.86	0.66
02/1	-1.11	3.31***	2.17**	5.48***	18.21***	7.70***	2.92*	8.57***	1.16	-0.14	-1.49	1.11
02/2	3.52***	-0.59	5.62***	21.57***	6.30***	-3.52***	1.69*	17.44***	0.09	-0.24	-2.04**	1.57
03/1	-1.86*	1.77*	7.53***	20.65***	23.54***	2.90*	14.27***	17.89***	-0.33	2.10**	-0.30	1.49

E: PRICE DISCOVERY - GRANGER CAUSALITY TEST						
	VAR (ΔBS,ΔCDS) MODEL		VAR (ΔBS,ΔICS) MODEL		VAR (ΔCDS,ΔICS) MODEL	
01/2	BS dngc CDS	0.00	BS dngc ICS	0.59	CDS dngc ICS	0.01
	CDS dngc BS	11.14***	ICS dngc BS	11.52***	ICS dngc CDS	5.01**
02/1	BS dngc CDS	20.99***	BS dngc ICS	1.40	CDS dngc ICS	0.05
	CDS dngc BS	4.52**	ICS dngc BS	5.04**	ICS dngc CDS	4.33**
02/2	BS dngc CDS	30.49***	BS dngc ICS	0.00	CDS dngc ICS	0.05
	CDS dngc BS	2.88*	ICS dngc BS	31.72***	ICS dngc CDS	9.57***
03/1	BS dngc CDS	27.51***	BS dngc ICS	0.06	CDS dngc ICS	4.38**
	CDS dngc BS	2.80*	ICS dngc BS	57.10***	ICS dngc CDS	28.65***

Table II

Descriptive Statistics. Descriptive statistics for the three measures of credit spreads .

				A: BS				B: CDS				C: ICS			
	Sector	Obs.	Rating	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.
ALCATEL	Equip.	398	Baa1/Baa2/Ba1/B1	130.8	1655.7	567.1	378.9	202.0	1750.0	648.1	418.9	176.7	1932.0	636.9	394.2
BMW AG	Autos	367	A1	10.7	39.0	24.9	4.9	20.0	52.0	32.6	7.4	14.5	84.7	34.4	12.8
CARREFOUR SA	Retail	443	A1	15.1	54.2	31.7	9.0	19.0	75.0	34.7	11.6	16.5	78.3	35.1	12.5
DAIMLERCHRYSLER AG	Autos	444	A3	62.7	185.9	97.5	24.5	87.0	215.0	137.9	23.8	66.6	322.0	139.7	45.6
DEUTSCHE TELEKOM AG	Telec.	341	A3/Baa1/Baa3	44.1	214.3	150.5	35.2	87.0	405.0	218.8	65.5	113.7	384.3	218.1	63.9
ENDESA	Utilit.	439	Aa3/A2/Baa1	38.3	152.6	69.1	28.5	25.0	205.0	73.1	45.3	24.4	226.1	74.0	47.2
FIAT SPA	Autos	370	Baa2/Baa3/Ba1	118.5	710.6	352.4	156.5	167.0	1100.0	573.6	242.7	115.6	1001.8	565.6	261.3
FORD MOTOR CREDIT CO	Autos	432	A2/A3	129.5	713.6	309.4	129.8	125.0	650.0	310.6	127.9	126.3	662.7	309.7	126.2
FRANCE TELECOM	Telec.	448	A3/Baa1/Baa3	65.6	429.5	172.8	54.5	90.0	660.0	270.9	119.1	99.9	905.7	274.2	134.4
GENERAL MOTORS ACCEPTANCE CORP	Autos	432	A2/A3	92.9	436.4	211.4	80.5	100.0	430.0	217.3	76.6	93.2	396.4	218.1	77.9
KONINKLIJKE KPN NV	Telec.	452	Baa3/Baa2/Baa1	44.9	826.1	210.6	182.0	60.0	875.0	243.6	187.4	81.9	868.1	237.5	169.4
KONINKLIJKE PHILIPS ELECTRONICS NV	Equip.	418	A3/Baa1	43.7	130.1	78.9	21.7	54.0	170.0	101.1	30.2	56.6	211.3	102.5	34.3
PORTUGAL TELECOM SGPS SA	Telec.	311	A3	39.7	172.6	79.5	32.0	38.0	175.0	76.6	31.0	39.0	191.0	76.3	28.9
REPSOL YPF SA	Energ.	365	Baa1/Baa2	65.2	529.9	245.6	107.3	55.0	620.0	267.5	159.2	51.3	147.6	88.5	21.6
ROYAL AHOLD	Retail	391	Baa1/Baa3/B1	49.1	1370.5	187.8	262.7	43.0	1750.0	189.1	279.3	37.4	909.7	172.8	197.6
RWE AG	Utilit.	445	Aa3/A1	7.9	74.5	37.8	13.6	17.0	103.0	58.8	23.4	12.3	165.8	56.0	31.2
SIEMENS AG	Equip.	443	Aa3	0.8	54.6	22.0	9.6	31.0	90.0	50.4	13.1	21.1	126.3	52.4	19.4
TELECOM ITALIA SPA	Telec.	436	Baa1	81.0	168.1	109.1	18.2	82.0	175.0	119.0	21.0	40.6	210.4	95.1	29.5
TELEFONICA SA	Telec.	366	A2/A3	48.5	203.4	90.6	32.6	38.0	275.0	105.3	56.4	46.0	231.9	103.5	48.5
VEOLIA ENVIRONNEMENT	Utilit.	370	A3/Baa1	54.7	260.0	98.6	27.7	50.0	195.0	100.2	34.5	38.1	251.7	102.4	39.2
VOLKSWAGEN AG	Autos	346	A1	24.7	63.2	44.1	8.8	25.0	90.0	56.0	16.2	17.6	123.9	58.7	23.7
Mean/21				55.63	402.12	151.96	77.07	67.38	479.05	185.01	94.79	61.39	449.12	173.88	86.63
S.D./21				37.59	440.49	133.38	97.49	49.48	509.90	165.68	108.48	44.75	454.81	163.43	97.91
Mean/18				54.06	354.23	147.15	68.35	68.61	417.50	183.86	85.06	64.44	453.54	183.06	87.25
S.D./18				40.18	408.05	142.15	93.89	53.13	447.49	177.86	105.72	47.76	471.33	174.75	100.57

Table III

Basis: Statistics for the basis between the three measures of credit spreads.

	A: CDS vs BS				B: ICS vs BS				C: ICS vs CDS				
	avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)	MSE
ALCATEL	81.02	22.02	119.33	26.98	69.75	21.60	94.48	24.74	-11.26	2.08	108.21	16.41	0.0402
BMW AG	7.78	32.24	8.03	33.08	9.58	38.67	10.74	42.78	1.80	6.74	8.81	26.90	0.1001
CARREFOUR SA	3.01	15.73	10.69	37.51	3.44	17.71	11.69	40.59	0.43	2.41	5.69	15.99	0.0378
DAIMLERCHRYSLER AG	40.38	44.32	40.41	44.34	42.25	44.99	44.33	46.77	1.87	2.57	32.67	23.97	0.0873
DEUTSCHE TELEKOM AG	68.35	46.71	68.55	46.88	67.57	48.12	68.81	48.90	-0.78	1.98	30.01	14.74	0.0356
ENDESA	4.07	1.62	16.65	24.61	4.92	-0.29	18.60	26.70	0.85	2.38	12.60	15.03	0.0356
FIAT SPA	221.24	64.62	221.24	64.62	213.19	59.57	215.52	60.23	-8.05	-2.54	91.39	16.22	0.0521
FORD MOTOR CREDIT CO	1.15	0.60	15.36	5.36	0.31	0.82	25.43	8.56	-0.84	0.42	24.47	8.07	0.0104
FRANCE TELECOM	98.04	52.37	98.12	52.44	101.39	54.05	101.73	54.31	3.35	1.79	44.42	15.72	0.0344
GENERAL MOTORS ACCEPTANCE CORP	5.90	4.27	14.16	7.42	6.67	5.01	23.08	11.73	0.77	1.19	25.38	12.16	0.0211
KONINKLIJKE KPN NV	33.01	21.14	37.77	22.15	26.94	22.27	44.99	25.68	-6.07	2.04	36.60	16.05	0.0389
KONINKLIJKE PHILIPS ELECTRONICS NV	22.16	30.57	23.15	31.82	23.61	32.35	25.08	33.87	1.44	3.63	18.94	18.25	0.0594
PORTUGAL TELECOM SGPS SA	-2.94	-2.91	7.25	9.59	-3.23	-0.21	16.37	19.57	-0.29	3.99	17.37	23.19	0.0670
REPSOL YPF SA	34.97	10.58	44.62	15.52	-157.09	-56.84	157.14	56.91	-192.06	-58.70	192.11	58.77	1.2619
ROYAL AHOLD	1.36	-2.86	21.06	12.32	-14.98	-1.53	38.96	17.94	-16.34	2.13	38.91	14.58	0.0358
RWE AG	15.08	41.60	17.50	48.08	18.22	49.56	21.80	59.20	3.14	5.80	12.09	23.48	0.0854
SIEMENS AG	28.40	193.08	28.42	193.13	30.44	192.53	30.64	193.14	2.04	5.19	12.13	23.83	0.0797
TELECOM ITALIA SPA	9.92	9.26	12.19	11.40	-13.97	-11.91	25.76	24.22	-23.90	-20.00	29.39	24.93	0.1464
TELEFONICA SA	19.15	18.07	19.57	18.77	17.39	19.67	21.76	24.69	-1.76	2.64	18.87	18.09	0.0452
VEOLIA ENVIRONNEMENT	1.57	0.23	10.65	10.85	4.13	6.09	27.29	27.97	2.56	6.46	26.37	26.40	0.1102
VOLKSWAGEN AG	11.86	25.76	13.69	30.53	14.54	32.50	19.85	44.41	2.69	4.79	13.29	23.68	0.0828
Mean/21	33.59	29.95	40.40	35.59	22.15	27.37	49.72	42.52	-11.45	-1.10	38.08	20.78	0.1175
S.D./21	51.14	42.20	51.07	39.71	65.19	46.53	52.50	37.89	41.99	14.27	43.51	10.10	0.2643
Mean/18	36.62	34.00	42.81	39.34	36.17	35.83	45.68	44.10	-0.45	2.98	29.96	18.79	0.0568
S.D./18	54.52	44.35	54.70	41.84	52.38	43.75	50.05	40.23	4.05	2.29	27.52	5.25	0.0284

Table IV

Calibration Parameters. Calibration parameters obtained using equations (18) and (22). *** Indicates significance at the 1% level.

	A			B				
	β_{01-03}	$(1-\alpha)\beta_{01-03}$	$\sigma(\beta_{01-03})$	$\beta_{01/2}$	$\beta_{02/1}$	$\beta_{02/2}$	$\beta_{03/1}$	$\sigma(\beta_{01/2}-\beta_{03/1})$
ALCATEL	0.5852	0.4096	0.3594	0.5314	0.6122	0.6263	0.5208	0.3593
BMW AG	0.8083	0.5658	0.1474	-	0.9007	0.8064	0.6932	0.1469
CARREFOUR SA	0.8336	0.5835	0.1884	0.8962	0.8519	0.8555	0.7398	0.1883
DAIMLERCHRYSLER AG	0.9670	0.6769	0.0920	1.0010	1.0661	0.9951	0.9063	0.0864
DEUTSCHE TELEKOM AG	0.5333	0.3733	0.2893	-	0.5601	0.5462	0.4719	0.2905
ENDESA	1.0155	0.7109	0.0799	1.0279	1.0329	0.9972	0.9530	0.0811
FIAT SPA	1.0574	0.7402	0.0210	-	1.0542	1.1011	1.0398	0.0219
FORD MOTOR CREDIT CO	0.9375	0.6563	0.0520	0.9419	0.9407	0.9424	0.9279	0.0518
FRANCE TELECOM	0.6734	0.4714	0.2067	0.7524	0.7390	0.6370	0.6181	0.2049
GENERAL MOTORS ACCEPTANCE CORP	0.9133	0.6393	0.0529	0.9171	0.9226	0.9148	0.8980	0.0528
KONINKLIJKE KPN NV	0.6226	0.4358	0.2455	0.6038	0.6168	0.6821	0.6098	0.2433
KONINKLIJKE PHILIPS ELECTRONICS NV	0.3681	0.2577	0.4198	0.4379	0.4271	0.3529	0.2561	0.4192
PORTUGAL TELECOM SGPS SA	0.8135	0.5694	0.2028	-	0.9107	0.8558	0.7332	0.2023
RWE AG	0.8716	0.6101	0.0751	0.9067	0.9033	0.8604	0.8018	0.0747
SIEMENS AG	0.5631	0.3942	0.2490	0.5745	0.6498	0.5571	0.4632	0.2489
TELEFONICA SA	0.8800	0.6160	0.2132	-	0.9425	1.0335	0.7724	0.2113
VEOLIA ENVIRONNEMENT	0.9169	0.6418	0.0868	-	1.0548	1.0068	0.8929	0.0827
VOLKSWAGEN AG	0.9079	0.6355	0.0714	-	0.9546	0.9115	0.8671	0.0696
Mean	0.7927	0.5549	0.1696	0.7810	0.8411	0.8157	0.7314	0.1687
S.D.	0.1905	0.1334	0.1136	0.2092	0.1926	0.2044	0.2074	0.1138
REGRESSION: $\beta_{01-03} = a + b\sigma(\beta_{01-03})$	a	1.0559***						
	b	-1.5521***						
	Adj. R-Sq.	0.8471						

Table V

Price Discovery. This table has two panels. Panel A contains the results of the price discovery exercice using the Wald test for each period. Panel B contains the results of the Granger causality test (dngc = does not Granger causes). In both cases the numbers shown are the rejections at the 95% level of significance of the null hypothesis of no relationship. Adj. Rs represent mean values.

A: WALD TEST

		A1: ΔBS					A2: ΔCDS					A3: ΔICS				
Period	N	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs
01/2	11	6	4	3	6	0.1357	1	1	3	3	0.0410	0	1	0	1	0.0170
02/1	18	10	7	4	14	0.1348	7	8	7	14	0.1592	3	2	1	3	0.0127
02/2	18	11	9	6	13	0.1263	6	3	6	7	0.0595	3	0	4	2	0.0180
03/1	18	13	5	6	17	0.1882	4	6	8	11	0.0781	2	2	2	1	0.0081
All	65	40	25	19	50	0.1474	18	18	24	35	0.0891	8	5	7	7	0.0136

B: GRANGER CAUSALITY TEST

		B1: VAR (ΔBS,ΔCDS) MODEL		B2: VAR (ΔBS,ΔICS) MODEL		B3: VAR (ΔCDS,ΔICS) MODEL	
Period	N	CS dngc CDS	CDS dngc CS	CS dngc ICS	ICS dngc CS	CDS dngc ICS	ICS dngc CDS
01/2	11	2	4	0	3	1	4
02/1	18	10	7	2	4	2	8
02/2	18	7	9	4	9	0	9
03/1	18	6	5	2	6	2	8
All	65	25	25	8	22	5	29

Table VI

Price Discovery. Robustness Check 1: β fixed in 0.73. This table has two panels. Panel A contains the results of the price discovery exercice using the Wald test for each semester. Panel B contains the results of the Granger causality test (dngc = does not Granger causes). In both cases the numbers shown are the rejections at the 95% level of significance of the null hypothesis of no relationship. Adj. Rs represent mean values.

A: WALD TEST

		A1: ΔBS					A2: ΔCDS					A3: ΔICS				
Period	N	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	ΔICS-L	MODEL	Adj. Rs
01/2	11	6	4	1	6	0.1285	1	1	2	3	0.0357	0	1	1	1	0.0308
02/1	18	11	8	4	14	0.1346	7	8	6	14	0.1612	3	2	2	4	0.0167
02/2	18	11	9	5	13	0.1208	6	3	5	6	0.0594	1	0	4	2	0.0113
03/1	18	14	6	6	17	0.1868	4	6	9	12	0.0815	1	1	1	2	0.0038
All	65	42	27	16	50	0.1442	18	18	22	35	0.0897	5	4	8	9	0.0140

B: GRANGER CAUSALITY TEST

		B1: VAR (ΔBS,ΔCDS) MODEL		B2: VAR (ΔBS,ΔICS) MODEL		B3: VAR (ΔCDS,ΔICS) MODEL	
Period	N	BS dngc CDS	CDS dngc BS	BS dngc ICS	ICS dngc BS	CDS dngc ICS	ICS dngc CDS
01/2	11	2	4	0	1	1	3
02/1	18	10	7	1	5	3	9
02/2	18	7	9	2	8	1	8
03/1	18	6	5	1	7	1	8
All	65	25	25	4	21	6	28

Table VII

Basis: β is fixed in 0.73. Statistics for the basis between the three measures of credit spreads.

	A: CDS vs BS				B: ICS vs BS				C: ICS vs CDS				
	avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)	avb	avb(%)	avab	avab (%)	MSE
ALCATEL	81.02	22.02	119.33	26.98	269.15	60.61	270.17	60.71	188.13	36.55	214.36	39.02	0.1353
BMW AG	7.78	32.24	8.03	33.08	1.92	-0.23	16.68	66.77	-5.87	-25.07	17.35	55.38	1.0784
CARREFOUR SA	3.01	15.73	10.69	37.51	-10.41	-23.38	18.96	60.33	-13.42	-41.10	14.72	44.60	0.5580
DAIMLERCHRYSLER AG	40.38	44.32	40.41	44.34	-84.70	-86.40	84.70	86.40	-125.08	-90.34	125.08	90.34	7.6385
DEUTSCHE TELEKOM AG	68.35	46.71	68.55	46.88	277.47	191.96	277.47	191.96	209.12	105.06	209.12	105.06	0.5294
ENDESA	4.07	1.62	16.65	24.61	-66.99	-97.58	66.99	97.58	-71.06	-97.82	71.06	97.82	18.3352
FIAT SPA	221.24	64.62	221.24	64.62	-352.34	-99.99	352.34	99.99	-573.58	-100.00	573.58	100.00	125.8666
FORD MOTOR CREDIT CO	1.15	0.60	15.36	5.36	-308.04	-99.61	308.04	99.61	-309.18	-99.61	309.18	99.61	32.5449
FRANCE TELECOM	98.04	52.37	98.12	52.44	245.83	134.02	246.00	134.15	147.79	54.78	155.40	58.21	0.2643
GENERAL MOTORS ACCEPTANCE CORP	5.90	4.27	14.16	7.42	-210.22	-99.52	210.22	99.52	-216.12	-99.53	216.12	99.53	31.8895
KONINKLIJKE KPN NV	33.01	21.14	37.77	22.15	176.68	94.90	176.68	94.90	143.67	63.42	143.74	63.44	0.2725
KONINKLIJKE PHILIPS ELECTRONICS NV	22.16	30.57	23.15	31.82	229.54	288.90	229.54	288.90	207.37	210.58	207.37	210.58	1.2664
PORTUGAL TELECOM SGPS SA	-2.94	-2.91	7.25	9.59	-28.24	-28.27	32.67	37.80	-25.30	-26.69	29.44	36.13	0.3436
REPSOL YPF SA	34.97	10.58	44.62	15.52	-242.23	-98.53	242.23	98.53	-277.21	-98.61	277.21	98.61	19.1725
ROYAL AHOLD	1.36	-2.86	21.06	12.32	122.93	77.19	122.93	77.19	121.57	82.67	129.64	83.13	0.3776
RWE AG	15.08	41.60	17.50	48.08	-31.02	-85.97	31.02	85.97	-46.10	-90.47	46.10	90.47	10.2033
SIEMENS AG	28.40	193.08	28.42	193.13	115.59	605.26	115.59	605.26	87.19	176.31	87.38	176.64	1.0409
TELECOM ITALIA SPA	9.92	9.26	12.19	11.40	-67.80	-62.14	67.82	62.15	-77.73	-65.79	77.73	65.79	1.7440
TELEFONICA SA	19.15	18.07	19.57	18.77	-30.70	-30.71	32.35	34.25	-49.84	-39.83	50.84	42.11	0.4938
VEOLIA ENVIRONNEMENT	1.57	0.23	10.65	10.85	-92.51	-93.69	92.51	93.69	-94.08	-93.79	94.08	93.79	12.9556
VOLKSWAGEN AG	11.86	25.76	13.69	30.53	-42.00	-95.48	42.00	95.48	-53.85	-96.70	53.85	96.70	16.6131
Mean/21	33.59	29.95	40.40	35.59	-6.10	21.49	144.61	122.44	-39.69	-16.00	147.78	87.95	13.4916
S.D./21	51.14	42.20	51.07	39.71	183.41	173.42	108.60	123.46	193.13	97.17	129.63	42.47	27.7617
Mean/18	36.62	34.00	42.81	39.34	5.28	33.27	151.27	135.24	-33.35	-14.13	145.49	88.86	14.5572
S.D./18	54.52	44.35	54.70	41.84	192.64	189.06	113.64	134.17	197.25	99.92	135.90	45.65	29.7554

Table VIII

Price Discovery. Robustness Check 2: Stock returns instead of changes in ICSs. This table has two panels. Panel A contains the results of the price discovery exercice using the Wald test for each period. Panel B contains the results of the Granger causality test (dngc = does not Granger causes). In both cases the numbers shown are the rejections at the 95% level of significance of the null hypothesis of no relationship. Adj. Rs represent mean values.

A: WALD TEST

		A1: ΔBS					A2: ΔCDS					A3: R				
Period	N	ΔBS-L	ΔCDS-L	R-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	R-L	MODEL	Adj. Rs	ΔBS-L	ΔCDS-L	R-L	MODEL	Adj. Rs
01/2	11	6	4	3	6	0.1380	1	1	3	3	0.0539	1	0	1	0	-0.0021
02/1	18	11	7	4	14	0.1340	8	8	7	13	0.1428	1	0	1	1	-0.0011
02/2	18	11	9	5	13	0.1211	6	3	5	7	0.0601	2	0	2	1	0.0076
03/1	18	15	5	4	16	0.1843	4	6	8	11	0.0760	1	1	0	1	0.0013
All	65	43	25	16	49	0.1450	19	18	23	34	0.0864	5	1	4	3	0.0018

B: GRANGER CAUSALITY TEST

		B1: VAR (ΔBS,ΔCDS) MODEL		B2: VAR (ΔBS,R) MODEL		B3: VAR (ΔCDS,R) MODEL	
Period	N	BS dngc CDS	CDS dngc BS	BS dngc R	R dngc BS	CDS dngc R	R dngc CDS
01/2	11	2	4	1	3	0	3
02/1	18	10	7	1	4	0	8
02/2	18	7	9	3	6	0	8
03/1	18	6	5	1	6	1	8
All	65	25	25	6	19	1	27

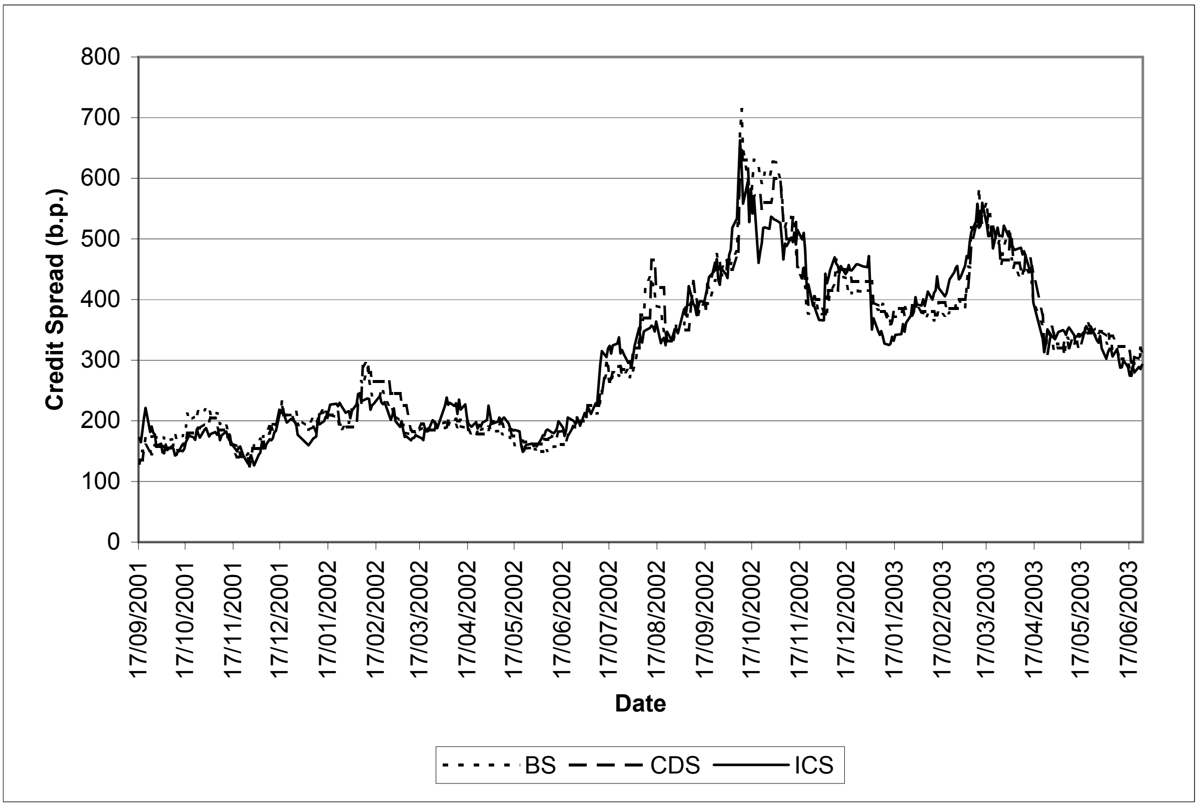

Figure 1. BS, CDS and ICS series for Ford Motor Credit Co.

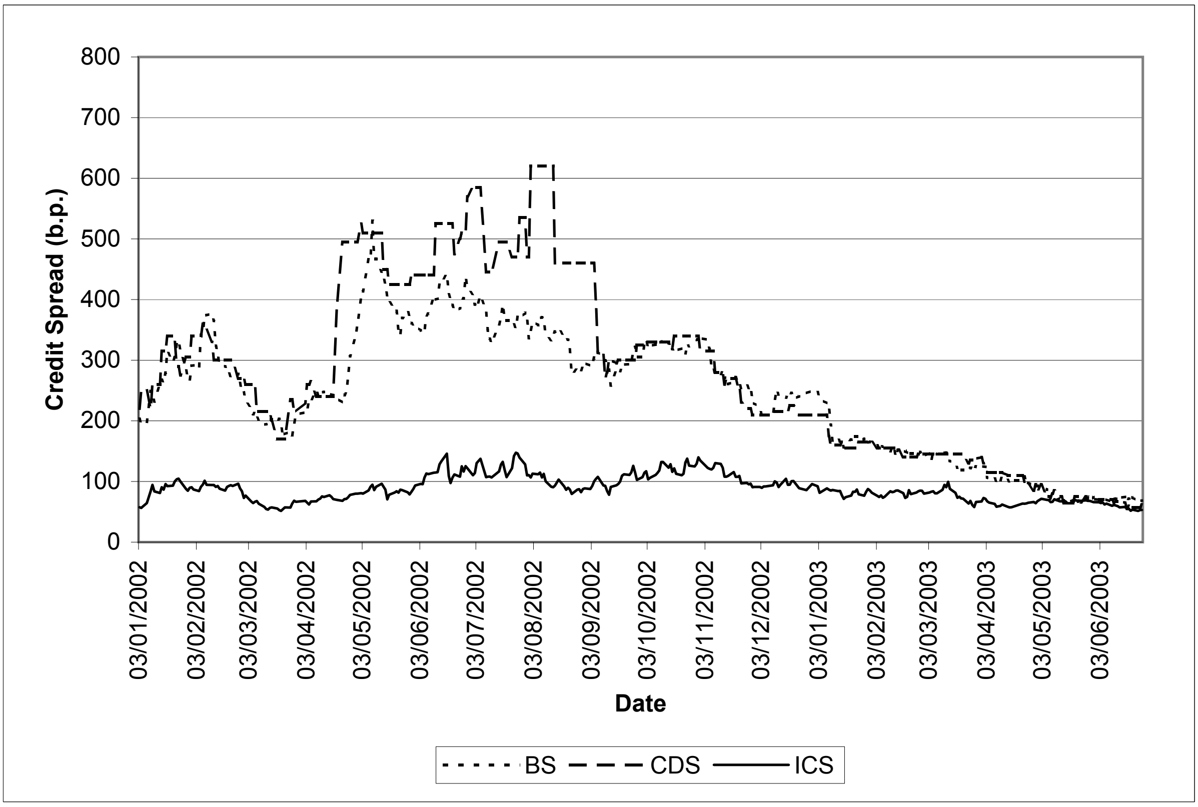

Figure 2. BS, CDS and ICS series for Repsol YPF SA.

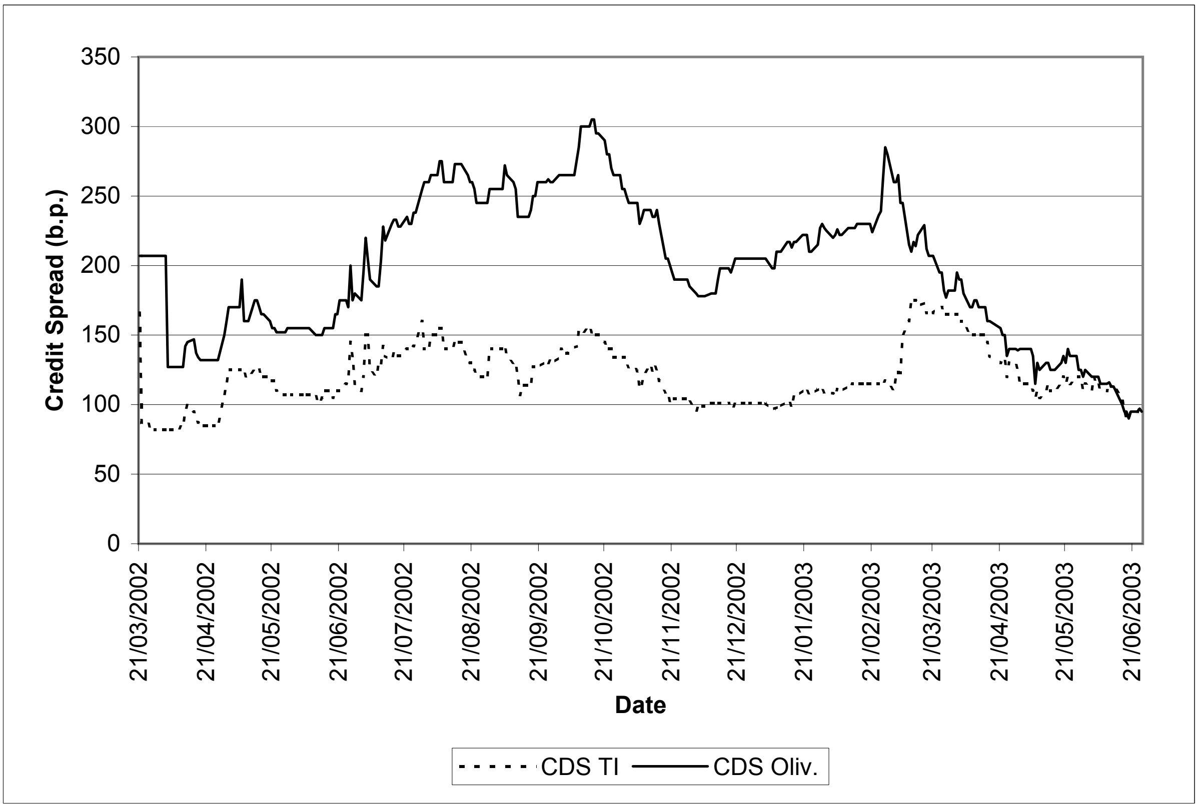

Figure 3. CDS series for Telecom Italia SPA and Olivetti.

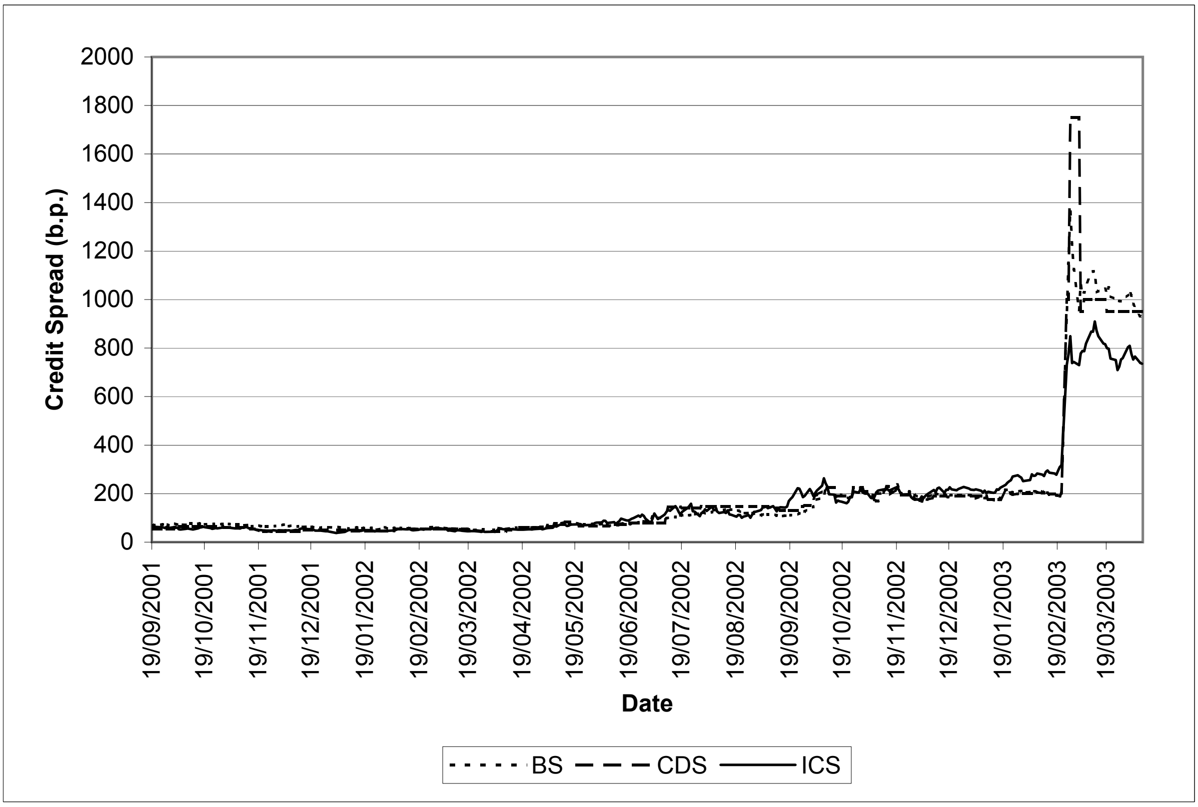

Figure 4. BS, CDS and ICS series for Royal Ahold.

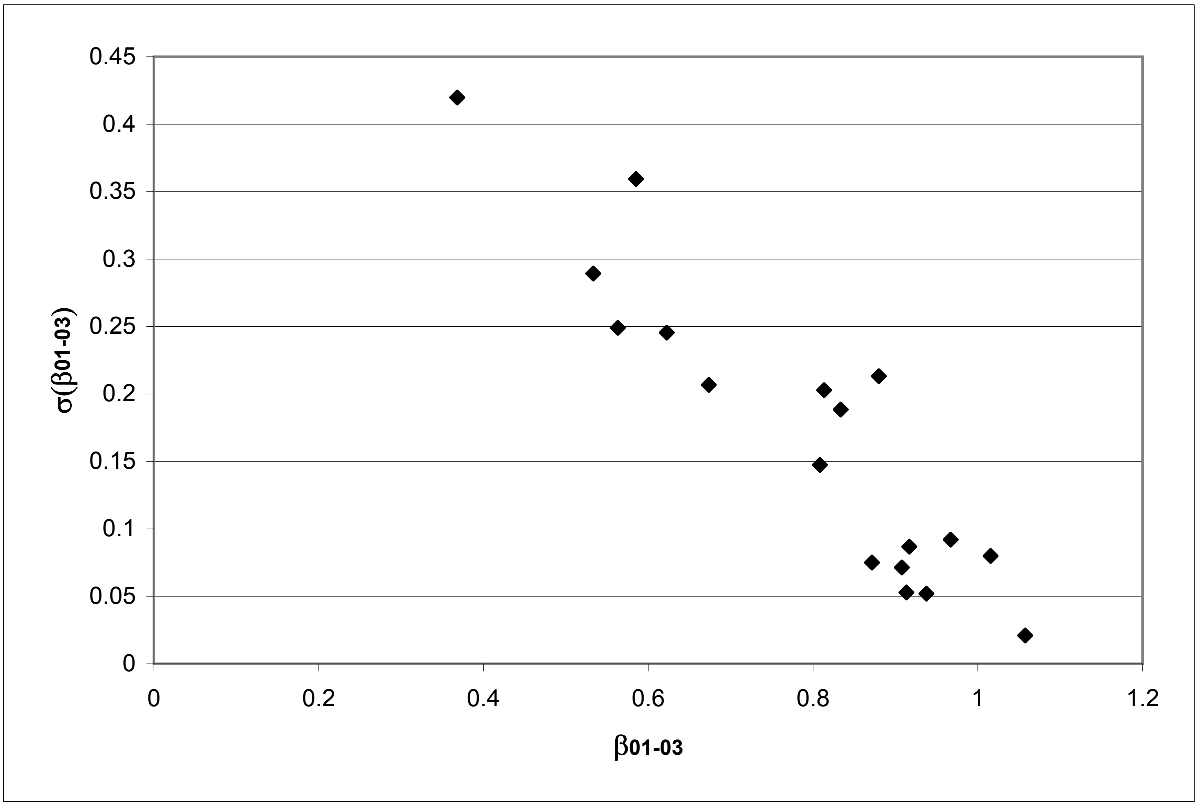

Figure 5. $\beta_{01\text{-}03}$ vs $\sigma(\beta_{01\text{-}03})$. This figure represents the constant default point indicator for each firm vs. the associated total assets volatility.