Equity and bond market signals as leading indicators of bank fragility

Reint Gropp, Jukka Vesala and Giuseppe Vulpes,[1]
European Central Bank

Abstract

We analyse the ability of equity market-based distances-to-default and subordinated bond spreads to signal a material weakening in banks' financial condition. Using option pricing, we show that both indicators are complete and unbiased indicators of bank fragility. We empirically test these properties using a sample of EU banks. Two different econometric models are estimated: a series of logit-models, which are estimated for a number of different time-leads, and a proportional hazard model. We find support in favour of using both the distance-to-default and spread as leading indicators of bank fragility, regardless of our econometric specification. However, while we find robust predictive performance of the distance-to-default between six and 18 months in advance, its predictive properties are quite poor closer to the default. In contrast, subordinated debt spreads seem to have signal value close to default only. We also find that the predictive power of spreads appears to be weakened by implicit safety nets. We find no such evidence for the distances-to-default. Further, we find support for the notion that the market-based predictors of default have predictive power even controlling for balance sheet information and that both indicators may complement each other. We interpret our finding as providing some measure of support for the use of market information in supervisors' early warning models.

1. Introduction

From a supervisory perspective the securities issued by banks are interesting for two reasons: first, market prices of debt and equity may increase banks' funding cost and, therefore, induce market discipline, which may complement traditional supervisory practices (such as capital requirements and on-site inspections) in ensuring the safety and soundness of banks. The market may play a particularly useful role in disciplining the risks of large, complex and internationalised banking organisations. Second, supervisors are considering the use of market data to complement traditional balance sheet data for assessing bank fragility. Market prices may efficiently summarise information beyond and above that contained in other sources. Moreover, market information is available at a very high frequency. Supervisors could use these signals as screening devices or inputs into supervisors' early warning models geared at identifying banks which should be more closely scrutinised.[2] Recently, it has also been suggested that subordinated debt spreads might be used as triggers for supervisors' disciplining action (Evanoff and Wall (2000a), Flannery (2000)).

A number of studies have analysed whether the market prices of the securities issued by banks signal the risks incurred by them. If the prices reflect banks' risks this is taken as evidence that markets can

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[1] Reint.Gropp@ecb.int, Jukka.Vesala@ecb.int, Giuseppe.Vulpes@ecb.int. Research assistance by Sandrine Corvoisier and Roberto Rossetti is gratefully acknowledged. The views expressed in this paper are solely those of the authors and not those of the ECB. We thank Allen Berger, Jürg Blum, Max Bruche, Vitor Gaspar, Myron Kwast, Mark Levonian, Simone Manganelli and seminar participants at the European Central Bank and the Basel Committee Research Task Force Conference on Applied Banking Research, which took place on 12-13 June 2001 in Oslo, for useful comments. All errors are the authors'.

[2] Supervisory early warning models combine a set of bank-level financial indicators (balance sheet, income statement and market indicators), as well as sometimes also other variables (eg macroeconomic conditions), to make a prediction about the future state of a bank. A growing number of supervisory agencies have been experimenting with this kind of model (see Gilbert et al (1999)).

indeed exert effective discipline on banks.[3] Studies using US data have found that banks' subordinated debenture spreads in the secondary market do reflect banks' (or bank holding companies') risks measured through balance sheet and other indicators (Flannery and Sorescu (1996), Jagtiani et al (2000), Flannery (1998 and 2000)). Morgan and Stiroh (2001) find the same to hold for the debenture spreads at issue. Sironi (2000) is the only study that we are aware of which provides evidence for European banks. He also concludes that banks' debenture spreads at issue tend to reflect cross-sectional differences in risk.

There is also some evidence that market signals could usefully complement supervisors' traditional information. Evanoff and Wall (2000b) find that subordinated debt spreads have some leading properties over supervisory CAMEL ratings. Conversely, DeYoung et al (2000) observe that on-site examinations produce information that affects the spreads. However, they find that spread changes reflect anticipated supervisory responses more often than new information. For example, bond investors in troubled banks react positively to increased supervisory oversight, hence substituting the market's own discipline. Finally, Berger et al (2000) conclude that supervisory assessments are generally less predictive of future changes in performance than equity and bond market indicators.

Finally, others have analysed the complementary role of the information contained in market prices vis-à-vis the information contained in rating agencies' assessments. Rating agencies are typically argued to be conservative and to respond mainly to risks which have already materialised (Altman and Saunders (2000)). Hand et al (1992) find that only unanticipated rating changes produce reaction in the US bond or equity markets (see also Goh and Ederington (1993)). Using European data, Gropp and Richards (2001) find that banks' bond spreads do not react to rating announcements, while equity prices do.

In general, research has focused on bond rather than equity market signals. This has been the case in part because mandatory subordinated debt issuance by banks has been prominently recommended as a new tool to discipline banks (eg Calomiris (1997)). The argument relies on the conjecture that subordinated debt holders have particularly strong incentives to monitor banks' risks, because they are uninsured and have junior status. In addition, signals based on equity prices are considered to be biased, because equity holders benefit from the upside gains that accrue from increased risk-taking (eg Hancock and Kwast (2001) and Berger et al (2000)). The relative importance of this moral hazard problem becomes the more pronounced the closer the bank is to insolvency, or the lower its charter value (eg Keeley (1990), Demsetz et al (1996), Gropp and Vesala (2001)).

However, as we will argue in this paper, there are several aspects which suggest that equity market signals may be attractive as monitoring devices. First, we show that unbiased equity-based fragility indicators can be derived. Second, there is broad consensus that the equity markets are efficient in processing available information. Empirical evidence strongly supports that equity holders respond rationally to news concerning: banks' asset quality (Docking et al (1997)), risks in LDC loans (eg Smirlock and Kaufold (1987), Musumeci and Sinkey (1990)), other banks' problems (eg Aharoney and Swary (1996)), or rating changes (ibid). Third, while bond spreads are conceptually simple, their implementation is difficult. For example, different bonds issued by the same bank may yield different estimates of the spread (Hancock and Kwast (2001)). Moreover, monitoring must concentrate on sufficiently liquid bonds in order to eliminate liquidity premia. In the European context, the construction of appropriate risk-free yield curves, which is a necessary ingredient to the calculation of spreads, may also be difficult especially for smaller countries, as further explained below.

In this paper, we first examine the properties of the market indicators in terms of their capability of capturing the major elements affecting default probability (*completeness*) and their alignment with supervisors' interests (*unbiasedness*). We show that a distance-to-default measure, derived using option pricing theory from the equity market data, is both complete and unbiased, as are uninsured bond yield spreads, provided that banks' asset value is still sufficiently high. Thus, these indicators are preferred over biased direct equity price-based measures and could represent useful leading indicators of bank fragility. The theory also suggests, however, that spreads may react only relatively late to a deterioration in the quality of a bank.

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[3] A much less researched question is whether a higher cost of funds actually discourages banks' risk-taking. Bliss and Flannery (2000) identify some beneficial market influences, but do not find strong evidence that equity and especially bond investors regularly influence managerial action.

We then empirically test banks' distances-to-default and subordinated bond spreads in relation to their capability of anticipating a material weakening in banks' financial condition. We use two different econometric models: a logit-model and a proportional hazard model. We find support in favour of using both indicators as leading indicators of bank fragility, regardless of our econometric specification. However, while we find robust predictive performance of the distance-to-default indicator between six and 18 months in advance, its predictive properties are quite poor closer to default. In contrast, subordinated debt spreads are found to have signal value, but only close to default. This is consistent with the predictions of theory. Our results also indicate that the subordinated debt-based signals are powerful predictors only for smaller banks, which are generally not implicitly insured against default. In contrast and as expected, the public safety net does not appear to affect the predictive power of the distance-to-default. We also find evidence that both indicators provide additional information relative to balance sheet data alone, but our results also suggest some complementarity between market and balance sheet data. Finally, we find support for our theoretical prediction that the two indicators together have more discriminatory power in predicting defaults than each alone.

A key issue for this as for any similar study is the definition of events of major financial problems at banks, as formal bank bankruptcies have been extremely rare in Europe. The study uses as such events downgradings of the Fitch/IBCA individual rating to category C or below indicating a severe concern. This is a sensible approach, because individual ratings exclude the effect of possible public support and focus on the true condition of the bank and, moreover, the majority of banks in our sample received public support or experienced a major restructuring after such a downgrading. Hence, the problems were severe enough to warrant major remedial action, even though there was no formal bankruptcy. The robustness of this definition and its possible implications are discussed at length later on. If anything, our approach should bias our findings against finding predictive power for the indicators.

The remainder of the paper is organised as follows: Section 2 examines the basic properties of the equity and bond market indicators and frames our empirical propositions. Section 3 defines our sample and the variables used in the empirical study. Section 4 contains descriptive analyses of the behaviour of the market indicators. Section 5 reports our econometric specifications and results. Section 6 presents some extensions and robustness checks. Finally, Section 7 concludes.

2. Properties of market indicators

In order to structure the analysis of the market indicators, we introduce two basic definitions:

Definition 1: Completeness

An indicator of bank fragility is called complete if it reflects three major determinants of default risk: (i) the market value of assets (V), reflecting all relevant information about earnings expectations; (ii) leverage (L), reflecting the contractual obligations the bank has to meet (defined as the book value of the total debt liabilities (D) per the given value of assets (D/V)); and (iii) the volatility of assets (σ), reflecting asset risk.

Definition 2: Unbiasedness

An indicator of bank fragility is called unbiased if it meets:

$$(i)\quad \frac{\partial Ind}{\partial V} < 0$$
$$(ii)\quad \frac{\partial Ind}{\partial L} > 0 \qquad (1)$$
$$(iii)\quad \frac{\partial Ind}{\partial \sigma} > 0$$

where *Ind* may represent any fragility indicator. The conditions require the indicator to be decreasing in the earnings expectations, and increasing in the leverage and asset risk. Definition 1 follows the usual approach in the commercial applications to define default risk measures (eg KMV Corporation (1999)). Definition 2 is more novel in this context and requires that any fragility indicator be aligned with

supervisors' conservative perspective. Hence, we would argue that only complete and unbiased indicators would be appropriate as early warning indicators of bank fragility, since only indicators with these two properties would fully and appropriately reflect the elements affecting default probabilities of banks.

We use option pricing theory and the valuation of equity and debt securities as a helpful tool to demonstrate some key properties of market-based fragility indicators. We consider a bank liability structure that consists of equity (E) and junior subordinated debt (J), and also some senior debt (I). This allows us to study the properties of the subordinated debt spreads directly. At the maturity date (T), payments can only be made to the junior claimants if the full promised payment has been made to the senior debt holders. To illustrate some of the basic concepts used below, suppose that both classes of debt securities are discount bonds and that the promised payments (book values) are I and J, respectively. ($D = I+J$) equals the total amount of debt liabilities. At the maturity date, the payoff profile of each security is as shown in Chart 1, depending on the asset value. To simplify notation, we assume that time to maturity equals T at the time of valuation of the equity and debt securities.

2.A Equity-based indicators

Equity holders have the residual claim on a firm's assets and have limited liability. As first realised by Merton (1977), equity can be modelled as a call option on the assets of the firm (here a bank), with a strike price equal to the total book value of the debt (see Chart 1). Thus, option pricing theory can be used to derive the market value and volatility of assets from the observable equity value (V_E) and volatility (σ_E), and D. Consider the basic Black and Scholes (1973) formula, valuing equity as:

$$
\begin{aligned}
V_E &= VN(d1) - De^{-rT}N(d2) \\
\sigma_E &= \left(\frac{V}{V_E}\right)N(d1)\sigma \\
d1 &\equiv \frac{\ln\left(\frac{V}{D}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \\
d2 &\equiv d1 - \sigma\sqrt{T}
\end{aligned}
\qquad (2)
$$

where N represents the cumulative normal distribution, r the risk-free interest rate, and T the time to the maturity of the debt liabilities.

We can see from (2) that V_E is complete, since market prices reflect the relevant information for capturing default risk (V, D and σ). However, V_E is increasing in σ, which violates condition (iii) in (1). Therefore, an increase in the share price may not be consistent with a reduction in default risk.

However, as an alternative consider the negative of the distance-to-default ($-DD$),[4] which we derive from the Black-Scholes model in Appendix I:

$$
(-DD) = -\frac{\ln\frac{V}{D} + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} = -\frac{\ln\left(\frac{1}{L}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \qquad (3)
$$

V and σ are solved from the non-linear two equation system (2). DD indicates the number of standard deviations (σ) from the default point at maturity ($V = D$). From (3) we can obtain a first result:

[4] A similar measure is the basic conceptual ingredient in KMV Corporation's model for estimating default risk (see KMV Corporation (1999)).

Result 1

(-*DD*) is a complete and unbiased indicator of bank fragility for *V*>*V*' (given *D*). *V*' is defined as $De^{-(1/2\sigma^2+r)T}$.

Proof

(-*DD*) reflects *V*, *L* and σ; hence it is complete.

Clearly, $\frac{\partial(-DD)}{\partial V} < 0$ and $\frac{\partial(-DD)}{\partial L} > 0$. $\frac{\partial(-DD)}{\partial \sigma} = \frac{1}{2}\sqrt{T} + \sigma^{-2}T^{-1/2}\left(\ln\left(\frac{V}{D}\right) + rT\right) > 0$, when $V > De^{-(1/2\sigma^2+r)T}$.

(–*DD*) meets all the conditions in (1) when *V* is sufficiently large (given the amount of debt); hence, it is unbiased for *V*>*V*'.

(-*DD*) is unbiased for all positive values of *DD*, ie always when above the default point, since *DD*>0 when $V > De^{(1/2\sigma^2-r)T}$.[5] Hence, (-*DD*) is a complete and unbiased early warning indicator for all banks which are still solvent.

2.B Subordinated debt-based indicators

In determining the value of debt, it is important to explicitly account for subordination, since the payoff profile of the subordinated debt is different from the senior debt. Following Black and Cox (1976), the observable market value of subordinated debt (V_J) can be derived as a difference between two senior debt securities with the face values of (*I*+*J*) and *I*, and respective market values of (V_{I+J}) and (V_I) (see Chart 1):

$$V_J(V,D,\sigma,T) = V_{I+J}(V,I+J,\sigma,T) - V_I(V,I,\sigma,T). \tag{4}$$

The value of the individual senior debt securities can be expressed using the standard Merton (1990) option pricing formula. The value of the debt security (*I*+*J*) is affected by total leverage and equals:

$$V_{I+J} = (I+J)e^{-rT}\left(N(h_2(I+J)) + \frac{1}{Le^{-rT}}N(h_1(I+J))\right),$$
$$h_1(I+J) \equiv \frac{-1/2\sigma^2T + \ln\left(\frac{(I+J)e^{-rT}}{V}\right)}{\sigma\sqrt{T}}, \; h_2(I+J) \equiv \frac{-1/2\sigma^2T - \ln\left(\frac{(I+J)e^{-rT}}{V}\right)}{\sigma\sqrt{T}}. \tag{5A}$$

The other senior security (*I*) is valued as:

$$V_I = Ie^{-rT}\left(N(h_2(I)) + \frac{V}{Ie^{-rT}}N(h_1(I))\right) \tag{5B}$$

with $h_1(I)$ and $h_2(I)$ analogous to (5.A). Finally, the yield to maturity ($y(T)$) is defined from:

$$e^{-y(T)T}J = V_J, \text{ ie } y(T) = -\frac{1}{T}\ln\left(\frac{V_J}{J}\right) = -\frac{1}{T}\ln\left(\frac{V_{I+J}-V_I}{J}\right) \tag{6}$$

and the spread over and above the risk-free yield to maturity of the subordinated debt (*S*) equals $y(T)$-$r(T)$. *S* is equivalent to a credit risk premium, in the absence of any liquidity premia.

Based on (5) and (6) we can state a second result:

[5] Note that *V* can be somewhat less than *D* (*V*/*D* less than one) at the default point (*DD*=0) because of the drift and the interest rate effects at the time of valuation (<*T*).

Result 2

S is a complete and unbiased indicator of bank fragility for $V>V^*$ (given D=I+J). V^* is defined as $\left[I(I+J)\right]^{1/2} e^{-(1/2\sigma^2+r)T}$.

Proof

By (5) and (6), *S* reflects *V*, *L* and σ; hence, it is complete.

Unbiasedness:

$\frac{\partial S}{\partial V} = \frac{\partial y(T)}{\partial V} = -\frac{J}{TV_J}\left[\frac{\partial V_{I+J}}{\partial V} - \frac{\partial V_I}{\partial V}\right]$. Following Merton (1990), the value of a senior debt security is an increasing function in the value of assets, and it turns out that $\frac{\partial V_{I+J}}{\partial V} = N(h_1(I+J))$, and $\frac{\partial V_I}{\partial V} = N(h_1(I))$. Thus, $\frac{\partial S}{\partial V} = -\frac{J}{TV_J}\left[N(h_1(I+J)) - N(h_1(I))\right]$. The expression in the square brackets is always positive, because h_1 is increasing in the face value of debt. Since *J* and V_J are always positive, $\frac{\partial S}{\partial V} < 0$ always.

Second, $\frac{\partial S}{\partial L} = -\frac{J}{TV_J}\left(\frac{\partial V_{I+J}}{\partial L}\right)$. Since $\frac{\partial V_{I+J}}{\partial L} = -N(h_1(I+J))L^{-2} < 0$, $\frac{\partial S}{\partial L} > 0$ always.

Third, $\frac{\partial S}{\partial \sigma} = -\frac{J}{TV_J}\left(\frac{\partial V_J}{\partial \sigma}\right)$. Thus, the sign of $\frac{\partial S}{\partial \sigma}$ is the opposite of the sign of $\frac{\partial V_J}{\partial \sigma}$. According to Black and Cox (1976, p 360), V_J is a decreasing (increasing) function of σ for *V* greater than (less than) the point of inflection, V^*. Thus, for $V>V^*$, $\frac{\partial S}{\partial \sigma} > 0$.

Hence, *S* is unbiased for $V>V^*$ as it meets all the conditions in (1), and biased for $V<V^*$ by condition (iii).

V^* is a geometric average of (I+J) and I ("adjusted" for time to maturity, drift and interest rate effects), falling between the two face values (see Chart 1).[6] When the value of bank assets is high enough to cover both senior and junior debt, the interests of the senior and junior debt holders are aligned with each other and with the interests of the supervisor. Hence, when the bank is economically solvent (and equity has some value), the subordinated debt spread is an unbiased indicator of bank fragility. Since banks are likely to be monitored while being still sound enough to cover all debt, the spread can constitute a useful early indicator of deterioration in financial condition.

However, one should note that when the value of assets is lower than the threshold value V^* (which is to some extent below the total value of debt, depending on the amount of junior debt), the two groups of debt holders have conflicting interests. The junior claimants have interests similar to those of the equity holders to take on more asset risk, while the senior claimants' expected payoff is always decreasing in risk.[7]

The above investigation of the properties of the market signals is made in the context of a specific model: normal asset value diffusion and European option type (call for equity and put for debt). Namely, the market value of a debt instrument can also be expressed on the basis of the discounted value assuming no default risk and the value of a put option on the firm's assets (see Merton (1977) and Ron and Verma (1986)). The widespread use of the Merton model, also to generate quantitative probability of default estimates, speaks in favour of it. But unfortunately, the literature has not

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[6] Note that $V^*<V'$ as long as there is some junior debt outstanding.

[7] This effect has an impact on the role of subordinated debt holders in disciplining banks' risk-taking: the contribution can be actually negative once the bank has entered the zone of de facto insolvency. In this zone, the sole right to approve business policies should lie with the senior debt holders (or supervisors) in order to avoid moral hazard. Levonian (2001) also makes the point that the incentives of the subordinated debt holders do not always side with those of the supervisors.

established general conditions under which the unbiasedness property could be established and verified for specific asset-liability structures (eg for banks). Thus, the performance of the market signals is ultimately an empirical issue.

Notwithstanding this general point, the crucial feature that, say, the call option value is (monotonically) increasing in V and decreasing in L seems to be a much more general result than the monotonic and increasing relationship between the option value and σ in the Merton model, which produces the often cited equity price bias. This result may not obtain for certain ranges of V under different (and possibly more plausible) distributional assumptions, eg based on bounded returns (Bliss (2000)), more complex liability structures, or under different option types, eg barrier options (Bergman et al (1996)).[8] Hence, alternative modelling assumptions would tend to question the universal biasedness of the simple equity price-based indicators, rather than the unbiasedness of the *DD* or *S*-measures.[9]

The main concern of this paper is indeed an empirical one: whether complete and unbiased market indicators (as derived from a specific model) are capable of signalling an increase in the default risk in a timely fashion.[10] Traditional accounting measures such as leverage ratios or earnings indicators are generally incomplete and therefore less useful as indicators of bank fragility. Thus, the key proposition whose validity we test is as follows:

Proposition 1

The equity market-based (-DD) and the bond market-based S constitute early indicators of a weakening in a bank's condition.

Finally, it is of interest to study how the subordinated debt spread behaves as a function of the asset value (or the distance-to-default) to see how the spread would be predicted to react to a deterioration in financial condition. According to Black and Cox (1976), the subordinated debt value is an increasing and concave function of V for $V>V^*$, like senior debt. Hence, the spread is a convex and decreasing function of V for $V>V^*$. This means that the spread would remain stable and close to zero for large intervals of changes in V and only react significantly relatively close to the default point.[11] This can be illustrated by plotting the spread as a function of the distance-to-default (varying V, holding I,J constant), under specific assumptions for the other parameters (see Chart 2). While the subordinated debt spread reacts earlier and more than the senior debt spread, it moves up significantly only when *DD* is relatively low.

Hence, the equity-based distance-to-default measure can be expected to provide an indication of a weakening financial condition earlier than the subordinated debt spread. This is a direct consequence of the different payoff structures of the equity and subordinated debt holders (for $V>V^*$). Debt holders care only about the left tail of the distribution of returns, while equity holders are interested in the whole distribution of returns. In a nutshell, the theory predicts that the two indictors have qualitatively different predictive properties, because the response of the spreads to an increase in default probability is non-linear. Therefore, the distance-to-default measure would be predicted to deliver an earlier signal of fragility than the spread. In the empirical analysis, we examine the performance of (*-DD*) and *S* with respect to different time leads under the proposition that:

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[8] There does not seem to be consensus about how to model the distribution of bank asset returns. Ritchken et al (1993) find some consistency between the behaviour of bank equity and the outcomes from a barrier option framework.

[9] The analysis also relies on the idea that asset risk can be measured by asset variance, which seems to be relatively uncontested, while alternative approaches have also been proposed (foremost Harrison and Kreps (1979)).

[10] Empirical evidence has suggested that the actual spreads are higher than suggested by Merton's model. Franks and Torous (1989) and Longstaff and Schwartz (1995) argue that an additional element in the spread is the expectation that equity holders and other junior claimants receive in the bankruptcy settlement more than what is consistent with absolute priority. In addition, Anderson and Sundaresan (1996) suggest that debt holders are forced to accept concessions to pay less than originally agreed prior to formal bankruptcy proceedings. Mella-Barral and Perraudin (1997) incorporate this strategic debt service into an option pricing-based model and show that the spread widening impact can be significant.

[11] Bruche (2001) shows that the "hockey-stick" shape of the spread as a function of V can become more pronounced when one introduces into the basic pricing model asymmetric information and investors' coordination failure.

Proposition 2

The equity market-based (-DD) constitutes an earlier indicator of weakening in a bank's condition than S. S would react significantly only relatively close to the default point.

2.C Impact of the safety net

Following Merton (1977), the value of subordinated debt can be expressed in terms of two "no default risk" values for the senior debt securities (*I*+*J*) and *I* and two put option values (strike prices equalling the book values of debt as before).[12] A put option represents the value of the limited liability, ie equity holders' right of walking away from their debts in exchange for handing over the firm's assets to the creditors. In case of fully insured debt (like insured deposits), the put option component disappears, and the market value of the debt equals the "no-default-risk" value (and *S* is zero). There is no signal of fragility obtainable from the pricing of this debt. Hence, any market discipline requires that deposit insurance is explicitly restricted, leaving out some creditors with their money at stake (eg Gropp and Vesala (2001)).[13]

The literature (eg Dewatripont and Tirole (1993)) has also examined the problem related to the *credibility* of the restricted safety net. Losses from a failure of a significant bank might affect the banking system as a whole and, hence, imply systemic risk. In this case, it might be expected that the "systemic" banks would never be liquidated, or that the exposures of the systemically relevant debt holders (such as other banks) would always be covered, regardless of the features of the explicit safety net arrangements ("too big to fail"). If the implicit safety net is perceived to be unrestricted, the value of the put option is zero, since the debt holders would not face the risk of having to take over the assets of the bank. Thus, the market value of debt would again be equal to the "no default risk" value and all uninsured debt-based fragility indicators would be incomplete and fail to capture increased default risk.

The *perceived probability of bailout* will generally be less than one, since there is typically no certainty of public support under an explicitly restricted deposit insurance system. Authorities frequently follow a policy of constructive ambiguity in this regard. Under these circumstances debt-based indicators would have predictive power, but much less compared to a hypothetical completely uninsured case. In this context we take the existence of positive spreads on banks' uninsured debt issues as evidence that the perceived probability might be indeed less than one. However, the history of bank bailouts by the government (significant banks have not failed in Europe in recent history) suggests that spreads might nevertheless be substantially weakened in their power to lead banking problems as compared with the case where the absence of bailouts is fully credible. Gropp and Vesala (2001) find empirical support for this point. Their results suggest that banks' risk-taking in Europe was reduced in response to the introduction of explicit and restricted deposit insurance schemes. They also find evidence in favour of the notion that a number of banks are "too big to fail". In addition, Gropp and Richards (2001) find that banks' bond spreads do not appear to react to ratings announcements. Their findings could be interpreted as evidence in favour of widespread safety nets. After an extensive sensitivity analysis, they cannot exclude the possibility that bondholders expect to be insured against default risk in Europe.

As a rule, equity holders are not covered even in broad-based explicit safety nets. In addition, the existence of an implicit safety net would induce banks to take on increased leverage and asset risk, and these risk-taking incentives (moral hazard) would be the greater the more extensive the perceived safety net (see Gropp and Vesala (2001, Section 2)). While bond market indicators would not reflect this additional effect under a broad safety net, correctly specified equity indicators, such as (-*DD*), would.

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[12] For instance, $V_I = V_I e^{-y(T)T} = V_I^{RF} - V_{I,PO} = V_I e^{-r(T)T} - V_I e^{-r(T)T} N(-h2(I)) + VN(-h1(I))$, where $V_I^{RF} = Ie^{-r(T)T}$ denotes the "no-default-risk" value and V_{PO} the value of the put option.

[13] The put option value also represents the value of the deposit insurance guarantee, since by guaranteeing the debt the guarantor has in fact issued the put option on the assets (see Merton (1977)). Hence, the deposit insurance value (V_{PO}) could also be used as an unbiased bank fragility indicator (see Bongini et al (2001)) with the same characteristics as the market value of debt-based indicators.

Hence, we can formulate an additional proposition:

Proposition 3

If a bank were covered by an implicit or explicit partial guarantee, the bond spread S would be a weaker leading indicator of bank fragility than the negative distance-to-default (-DD).

Whether equity and bond markets are able to effectively process the available information and send early signals which are informative of banks' default risk is investigated below in a sample of European banks. We evaluate the usefulness of the preferred (complete and unbiased) market indicators (*-DD* and *S*) for this purpose (Proposition 1). We also test whether the spread reacts later than (*-DD*) (Proposition 2), and whether a perception of the safety net dilutes the predictive power of the bond market signals, but leaves the equity market signals intact (Proposition 3).

3. Empirical implementation

Our data set consists of monthly observations from January 1991 to March 2001. The relatively high frequency of the data highlights one fundamental advantage of market-based indicators relative to balance sheet indicators. We decided to use monthly data, rather than an even higher frequency, in order to eliminate some of the noise in daily equity and bond prices. The data set consists of those EU banks for which the necessary rating, equity and bond market information is available. In the sample selection process we started from roughly 100 EU banks which had obtained a "financial strength" rating from Fitch/IBCA.[14] The sample size was then largely determined by the availability of market data. The two subsamples used in evaluating the equity and bond market signals consist of 84 and 59 banks, respectively (see Table 1). The samples contain banks from 14 (equity sample) and 12 (bond sample) EU countries.

3.A Measurement of bank "failures"

We were faced with the problem that no European banks formally declared bankruptcy during our sample period. In the absence of formal bank defaults, we considered a downgrade in the Fitch/IBCA "financial strength" to C or below as an event of materially weakened financial condition.[15] There are 25 such downgrades in the equity and 19 in the bond subsample, 32 in total (Table 2). We defend our definition of bank "failure" on two grounds: first, the "financial strength rating" is designed to exclude the safety net and, hence, should indicate the bank's true financial condition. A downgrade to the level of C or below signifies that there are significant concerns regarding profitability and asset quality, management and earnings prospects. In particular when the rating falls to the D/E category very serious problems are indicated, which either require or are likely to require external support. Second, in many cases after the downgrade to C or below, public support was eventually granted or a major restructuring was carried out to solve the problem. As detailed in Table 2, 11 banks received public support and eight banks underwent a major restructuring after the downgrading. The support or restructuring operations also generally took place relatively soon after these events (six to 12 months). In the remaining cases, no public support or substantial restructuring took place. In part this is a reflection of sample truncation in March 2001, as six of the remaining 13 downgrades took place in late 2000 or early 2001 and an eventual intervention cannot be excluded. Given that the downgrades precede the actions aimed at resolving the problem by quite some time, we would argue that our proxy for bank failures is quite sensible and generally should bias our results against finding predictive power of the indicators.

Our study is similar to the US studies investigating the relationship between market information and supervisory ratings (for example Evanoff and Wall (2000b), DeYoung et al (2000) and Berger et al (2000)), while we use the "individual" ratings as signals of banking problems. While we are concerned

[14] For an explanation of a "financial strength" rating see below.

[15] See Appendix 2 for the exact definitions of the Fitch/IBCA rating grades.

about our relatively small sample sizes (at least in terms of number of banks, not in terms of data points; see below) Evanoff and Wall (2000b), for example, consider 13 downgrades in supervisory CAMEL ratings in a sample of 557 US banks, constituting the default events. Hence, compared to the previous literature our sample appears reasonably large and fairly balanced. Further, rather than use the Fitch/IBCA ratings, it could be argued that we should use supervisory ratings (such as CAMEL ratings) instead. Unfortunately, we did not have access to historical supervisory information on individual banks and, in some European countries, comparable ratings by supervisors do not exist. Clearly, the supervisory ratings may be based on more detailed information relative to ratings by a ratings agency, including confidential information obtained at on-site inspections, but they may also be subject to forbearance.

3.B Market indicators

We calculated the negative of the distance-to-default (-*DD*) for each bank in the sample and for each time period (*t*) (ie month) using that period's equity market data. The system of equations in (2) was solved by using the generalised reduced gradient method to yield the values for V_A and σ_A, entering into the calculation of (-*DD*). Variable definitions are given in Table 3 and descriptive statistics in Table 4.

As to the inputs to the calculation of (-*DD*), we used monthly averages of the equity market capitalisation (V_E) from Datastream. The equity volatility (σ_E) was estimated as the standard deviation of the daily absolute equity returns and we took the six-month moving average (backwards) to reduce noise (as eg in Marcus and Shaked (1984)). The presumption is that the market participants do not use the very volatile short-term estimates, but more smoothed volatility measures. This is not an efficient procedure as it imposes the volatility to be constant (it is stochastic in Merton's original model). However, equity volatility is accurately estimated for a specific time interval, as long as leverage does not change substantially over that period (see for example Bongini et al (2001)). The total debt liabilities (V_L) are obtained from published accounts and are interpolated (using a cubic spline) to yield monthly observations. The time to the maturing of the debt (T) was set to one year, which is the common benchmark assumption without particular information about the maturity structure. Finally, we used the government bond rates as the risk-free rates (r).[16] The values solved for V and σ were not sensitive to changes in the starting values.

We largely followed convention when calculating the monthly averages of the secondary market subordinated debt spreads (S). We used secondary market spreads, rather than those from the primary market, as we would argue that secondary market spreads are more useful for the ongoing monitoring of bank fragility. In the absence of mandatory issuance requirements, such as those proposed by Calomiris (eg 1997), banks' new issuance could be too infrequent, or limited to periods when pricing is relatively advantageous. As we were concerned about too thin or illiquid bank bond markets in Europe, we only selected bonds with an issue size of more than €150 million. This figure seemed the best compromise between maintaining sample size and obtaining meaningful monthly price series from Bloomberg and Datastream, which were our main data sources. In addition, in order to minimise noise in the data series, we attempted to use straight fixed rate subordinated debt issues only. We were largely able to obtain such bonds, but in some cases we had to permit floating rate bonds into the sample. We used the standard Newton iterative method to calculate the bond yields to maturity.

For the larger countries, we were able to find bank bonds issued in the domestic currency which met our liquidity requirement. In the case of smaller countries, banks more frequently issued foreign than domestic currency denominated bonds prior to the introduction of the euro. Hence, we largely resorted to foreign currency issues (Deutsche Mark, euro, US dollar and, in two cases, yen) and matched them to government bonds issued in the same currency. We were able to construct risk-free yield curves for Germany, France and the United Kingdom and calculated spreads for banks in those countries relative

[16] Our (-*DD*) measure is subject to the Black-Scholes' assumption of a cumulative normal distribution (N) for the underlying asset values. As pointed out by Bliss (2000), this assumption may not hold in practice. He argues that the normal distribution does not take into account that closer to the default point adjustment in debt liabilities is likely to take place. Hence, empirically better formulas could be found, while delivering fragility indicators with similar qualitative characteristics as the standard (-*DD*).

to the corresponding point on those curves. For the other smaller countries, we were unable to obtain sufficient data to construct full risk-free yield curves. We therefore instead matched the remaining term to maturity and the coupon of the bank bond to a government bond issued by the government of the country of the bank's incorporation in the same currency.

3.C Expectation of public support

We use the "support rating" issued by Fitch/IBCA to indicate the likelihood of public support. We regard as cases of more likely public support the rating grades 1 or 2 (see Appendix 2). The former grade indicates existence of an assured legal guarantee, and the latter a bank for which in Fitch/IBCA's opinion state support would be forthcoming. This could be, for example, because of the bank's importance for the economy. Hence, the likelihood of support could depend on the size of the institution ("too big to fail"), but a bank could also be possibly "systemically" important for other reasons. The weaker "support ratings" (from 3 to 5) depend on the likelihood of private support from the parent organisation or owners, rather than from public sources. The share of banks with a "support rating" of 1 or 2 is quite high (around 65% in the equity sample and 80% in the bond sample). This is not surprising, since we are considering banks with a material securities market presence as an issuer. These banks tend to be significantly larger, again as expected, than those with a rating of 3 to 5. Their average amount of total debt liabilities is roughly 10 times higher.

3.D Sample selection

Before we present the results, it may be worthwhile to examine the sample in a little more detail, in particular with respect to sample selection issues. The first question that arises relates to the relevant universe of banks. For the bond sample, the universe is determined by those EU banks that were rated by Fitch/IBCA during the 10-year period under investigation.[17] Out of this total, those banks remained in the sample for which we were able to calculate bond spreads, ie for which sufficiently liquid and sizeable bonds were outstanding and the data were available in Bloomberg. Hence, relative to the universe of 103 rated banks, we were able to obtain meaningful bond price data for 59 banks. Sample selection issues may be a problem if the banks in the sample differ in their likelihood of failure relative to those in the universe of banks. In particular, we were concerned that we had tended to over-sample failures. It turns out that this is not the case. The probability of failure during the sample period is around 33% both in the universe and in the sample. Nevertheless, the banks in the sample may differ in other important criteria from those in the universe. For example, given our requirement that the bank must have substantial subordinated debt outstanding, the banks in the sample may be larger than those in the universe. This is the case, although the difference is not statistically significant. Finally, a bias may arise due to differences in data availability of the banks in the sample. If banks that eventually fail remain in the sample for only a relatively short period of time prior to failure, the proportional hazard model may overstate the predictive power of indicators. There could be a number of reasons for this problem. One, given that we chose a fixed starting point for our sample (1991) and given that naturally all failed banks drop out after failure, the time period that non-failed banks remain in the sample is longer. This by itself should not constitute a problem for the estimation. However, if failures occur disproportionately at the beginning of the sample period, ie in 1991-94, this could result in overstating the predictive power of our indicators in the proportional hazard model. However, the average time period in the sample for banks which eventually failed is 34 months. This should give us ample data to obtain unbiased estimates.[18]

In the case of the stock price sample, we would argue that the relevant universe is somewhat smaller. Again taking those banks which had obtained a rating from Fitch/IBCA as the starting point, the universe of banks is further reduced by banks which are not listed on a major European stock

[17] Clearly, this universe is substantially different from the notion of all EU banks. For small, non-traded banks, such as savings banks or cooperative banks, the idea of the importance of market indicators is clearly not relevant. In any event, we would argue that market indicators are precisely of most use in the case of large, complex financial institutions, because for these, balance sheet information may be more difficult to interpret.

[18] The average period in the sample of non-failing banks is, of course, longer with 76 months. Note that the maximum number of observations per bank is limited by our sampling period to 131 months.

exchange. It turns out that this concerns 11 banks. Of the remaining 92 banks, our sample contains 83 banks. The difference of nine banks is due to the unavailability of a stock price series in Datastream. The probability of failure in the sample is identical to that in the universe at one third. Again, we were concerned whether we observe the failing banks long enough to make meaningful inferences from the proportional hazard model. The average time of banks which eventually fail in the stock price sample is one month longer than those in the bond price sample, namely 35 months (non-failing banks: 73 months). Again, we feel that this should give us sufficient data to estimate the model.

4. Descriptive statistics

We constructed the sample for the empirical analysis as follows. For each month (t) of a downgrading ("default") event, we took all non-downgraded banks as a control sub-sample, and calculated all variables for both sub-samples with specified leads of x months.

As a first cut at the data, we conducted simple mean comparison tests to assess whether (*-DD*) and *S* are able to distinguish weaker banks within our data set. We also examined whether the indicators could lead the downgrading events by performing the mean comparison tests for various time leads (lead times of three, six, 12, 18 and 24 months). The results reported in Table 5 indicate that the banks that were downgraded had a significantly higher mean value of (*-DD*) than the non-downgraded banks up to and including 24 months prior to the downgrading events. We also find in the second panel that the banks that were downgraded had higher prior spreads (*S*) and that the spreads of the "defaulted" banks clearly increase as the "default" event is approached. However, the difference between "defaulted" and "non-defaulted" banks is never statistically significant when the full sample is considered. This suggests that *S* is a weaker leading indicator of bank fragility than (*-DD*).

The "default" indicators reflect two factors: first, the bank's ability to repay out of its own resources, and, second, the government's perceived willingness to absorb default losses on behalf of private creditors (see eg Flannery and Sorescu (1996)). Hence, in the third panel of Table 5 we limit the sample to those banks with a support rating of 3 or higher. We only present the *t*-tests up to *x* equals 12 months in order to maintain some sample size. Nevertheless, the figures given here should be interpreted with care, as even so sample sizes are small. The results offer further evidence that a safety net expectation can dilute the power of the spreads to reflect bank fragility, while there is no apparent impact on the distances-to-default. In this limited sample, there is now a significant difference in the mean values of *S* between "defaulted" and "non-defaulted" banks. Also in absolute terms, the difference in the average spreads is now higher.

5. Empirical estimation

5.A Estimation methods

We used two different econometric models to investigate the signalling properties of the market-based indicators of bank fragility. The first is a standard *logit-model* of the form:

$$\Pr[STATUS_t = 1] = \psi(\alpha_0 + \alpha_1 DI_{t-x} + \alpha_2 DSUPP_{t-x} * DI_{t-x}) \quad (7)$$

where $\psi(\,)$ represents the cumulative logistic distribution, DI_{t-x} the fragility indicator at time t-x, and

$$STATUS_t = \begin{cases} 1 \text{ if bank was downgraded to C or below at time } t \\ 0 \text{ otherwise} \end{cases}.$$

We estimate the model for different horizons separately, ie we investigate the predictive power of our two indicators three, six, 12, 18 and 24 months before the downgrading event. Generally, we would expect the predictive power to diminish as we move further away from the event. Significant and positive coefficients of the lagged market indicators (indicating a higher unconditional likelihood of

problems when the fragility indicators have a high value) would support the use of (-*DD*) or *S* as early indicators of bank fragility (Proposition 1).

We created a dummy variable (DSUPP), equalling one when the Fitch/IBCA "support rating" is 1 or 2 in order to control for the government's perceived willingness to absorb default losses and to test for whether this dilutes the power of the market indicators. To this end, we interacted this variable with the market indicators. A significant and negative coefficient of (DSUPP***S*) and insignificant coefficient of (DSUPP***(-*DD*)) would support Proposition 3. Since we use several observations for the same bank in case the bank does not "default" during our sample period, our observations are not independent within banks, while they are independent across banks. Therefore, we adjusted the standard errors using the generalised method based on Huber (1967).

Our second model is a *Cox proportional hazard model* of the form:

$$h(t,DI,X) = h_0(t)e^{\beta_1 DI + B_2 X} \tag{8}$$

where *h(t,DI,X)* represents the proportional hazard function, $h_0(t)$ the baseline hazard, and *X* some control variables (see below). Again, we calculated robust standard errors, as we had multiple observations per bank and used Lin and Wei's (1989) adjustment to allow for correlation of the residuals within banks. The model parameters were estimated by maximising the partial log-likelihood function

$$\ln L = \sum_{j=1}^{D} \left\{ \sum_{r \in D_j} \left(\beta_1 DI_r + B_2 X_r \right) - d_j \ln \left[\sum_{i \in R_j} \exp(\beta_1 DI_i + B_2 X_i) \right] \right\} \tag{9}$$

where j indexes the ordered failure times $t(j)$ (j=1,2,…D), D_j is the set of d_j observations that "default" at $t(j)$ and R_j is the set of observations that are at risk at time $t(j)$. The model allows for censoring in the sense that, clearly, not all banks "default" during the sample period.[19]

The two models provide a robustness check whether equity and bond market indicators have signalling property as regards bank "defaults". In addition, they also provide insights into two distinct questions: the logit-model permits a test of the unconditional predictive power of the indicators with different lead times, whereas the proportional hazard model yields estimates of the impact of the market indicators on the *conditional probability of "defaulting".* The latter means that we obtain "default" probabilities, conditional on surviving to a certain point in time and facing a certain (-*DD*) or *S* in the previous period.

5.B Logit estimation results

Table 6A reports the results from estimating logit-models with different time leads. An increased (-*DD*) value tends to predict a greater likelihood of financial trouble. The respective coefficient is significant at the 10% level for the six-, 12- and 18-month leads. Hence, we find support for Proposition 1: (-*DD*) appears to have predictive properties of an increased (unconditional) likelihood of bank problems up to 18 months in advance. The coefficient ceases to be significant more than 18 months ahead of the event. However, we found the insignificance of the coefficient of the three-month lead somewhat puzzling. We suspect that the reason is increased noise in the -*DD* measure closer to the default, as evidenced by the higher standard error for the three- than the six-month leads. It may be the case that many eventually downgraded banks exhibit a lowering in the equity volatility just before the downgrading, which causes the derived asset volatility measure to decrease as well, reducing the (-*DD*) value.

Turning back to Table 6A, we find that the coefficient of DSUPP***(-DD_{t-x}), measuring the impact of the safety net, is never statistically significant. Moreover, the hypothesis that the coefficient of (-DD_{t-x}) is zero for the banks with a strong expectation of government support is rejected for all lead times, except for x=24. The safety net does not appear to be important for the predictive power of the distance-to-default as an indicator of bank fragility.

[19] For more details on estimating hazard models see Kalbfleisch and Prentice (1980).

The results for the bond spreads, *S*, strongly support Proposition 1 as well (see Table 6B). The coefficients for lead times of up to 18 months are significant at least at the 5% level. The results also highlight that it is important to control for the expectation of public support in the case of spreads. The coefficient of the interacted term (DSUPP*S_{t-x}) is significant and negative, and a joint hypothesis test reveals that the coefficient on the spread is zero for the banks with a high (a rating of 1 or 2) expectation of public support. This finding is in contrast to the results using -*DD* as an indicator of bank fragility.

A convenient way to summarise the results of the logit models just described is given in Chart 3. The chart presents the coefficients from Tables 6A and 6B, normalised, such that the maximum effect is equal to one. It reveals that the maximum predictive power of spreads occurs quite shortly before default, around six to 12 months before. In contrast, *DD* has relatively little predictive power close to the event, but instead reaches its maximum no less than 18 months ahead of the default. These patterns correspond closely to the theoretical predictions of the option pricing framework discussed in Section II.

The results of discrete choice models may be quite sensitive to the underlying distributional assumptions, in particular in cases where the distribution of the dependent variable is as skewed as in this sample. Only 4% of the bond sample and 3% of the stock sample were "defaulting" observations. As a simple robustness check, we estimated the corresponding Probit-models and found essentially unchanged results, both in terms of magnitude and significance.[20]

5.C Hazard estimation results

Tables 7 and 8 give the *hazard ratios* and corresponding P-values for a model without additional control variables for both (-*DD*) and *S*. Only (-*DD*) is significant (at the 5% level); both indicators have the expected positive signs. The hazard ratios, indicating a greater conditional likelihood of "default", are increasing in the values of the fragility indicators, which is consistent with the logit results.

The tables also show the results for a test of the proportional hazard assumption (ie the zero-slope test), which amounts to testing whether the null hypothesis of a constant log hazard function over time holds for the individual covariates as well as globally. For (-*DD*), this assumption is violated. Hence, we present in Table 9 results from an alternative model specification, in which we use a dummy variable of the following form

$$ddind = \begin{cases} 1 \; if \; (-DD) > -3.2 \\ 0 \; otherwise \end{cases} \tag{10}$$

where -3.2 represents the 25th percentile of the distribution of (-*DD*). Hence, in this specification, we investigate whether banks with "short" distances-to-default are more likely to fail compared to all other banks. We find that the indicator significantly (at the 1% level) increases the hazard of a bank "defaulting", as before, and the model is no longer rejected due to the violation of the proportional hazard assumption.

We also examined the weaker performance of *S* than -*DD* in the baseline specification (as given in Tables 7 and 8). In the logit-model, we found that two factors significantly affect the predictive power of the spread: the presence of a safety net and whether or not the bank resides in the United Kingdom. Table 10 shows that the coefficient of the spread significantly improves when controlling for the United Kingdom by means of a dummy variable. *S* now is significant at the 1% level. In addition, the dummy for the United Kingdom is significant at the 5% level: higher spreads in the United Kingdom are associated with a significantly lower hazard ratio, ie a significantly lower likelihood of failure. For -*DD* the inclusion of the safety net dummy or the UK dummy do not materially affect the results, as in the logit specification, and are not reported here. Further, the logit results suggested that for banks which are likely to benefit from public support in case of trouble, the predictive power of bond spreads is reduced to zero. This finding is confirmed in Table 11.

[20] The results are available from the authors upon request.

The most convenient way to interpret the results is to consider the Nelson-Aalen *survivor functions*, which are depicted in Chart 4. The cumulative hazard functions display the probability of survival, given that the bank survived to period *t* and had a fragility indicator of a certain level. For convenience of presentation, we split the sample into those banks that have a default indicator in the top 25th percentile and all other banks. We can then test whether the survivor functions are significantly different and read the difference in the "default" probability at each point in time, given that the bank survived to that point. Using a log-rank test for both the distance-to-default and the spread, we can reject the equality of the survivor functions for the two groups at the 5% level. Excluding UK banks (the second part of the lower panel in Chart 4), we can reject equality at any significance level. Note that comparing the survivor functions with and without UK banks, excluding the UK banks results in a downward shift of both curves. Hence, excluding UK banks, all banks with a high spread (greater than 98 basis points) fail during the sample period. Only UK banks survive the entire sample period with a high spread. In this paper we will not explore this issue further. We only conclude that a UK spread puzzle remains, which we cannot explain.[21]

Even more interesting, we can immediately read off the difference in the survivor probability, given that a bank has remained in one or the other group. For (-*DD*), we find no difference in the hazard even after two years (24 months). Differences only arise subsequently: after 36 months, a bank which had a (-*DD*) > -3.2 for that period of time has a failure probability that is 20 percentage points higher relative to a bank that was consistently in the control group. This is consistent with the findings in the logit-model: (-*DD*) is found to be an indicator which has better leading properties for events further in the future. In contrast, spreads react only relatively shortly before default. Given survival, spreads essentially lose all their discriminating power after one year. The results also highlight that the prevalence of indicators matters, which suggests that the use of hazard models adds new insights relative to standard logit-models. Logit-models are unable to yield predictions which are conditional on default indicators having prevailed for periods of time.

Hence, in line with Proposition 2, the spread reacts more closely to the "default" point than (-*DD*). Put differently, banks may "survive" substantially longer with a short distance-to-default, but the likelihood of quite immediate problems is very high if they exhibit a high spread (in our definition of 100 basis points or above). As we show in the earlier part of this paper, the strong reaction of the spreads only close to the default point is explained by the non-linear payoff profile of subordinated debt holders.

Finally we present log-rank tests of the equality of survivor functions for those banks with an implicit safety net ("support rating" of 1 or 2) in Table 12. We find that the distance-to-default has more predictive power for banks which are likely to benefit from governmental support, and little predictive power for those that do not.[22] More importantly, Table 12 shows the importance of UK banks, as well as the safety net, for the predictive qualities of bond spreads. With UK banks included, we find only weak discriminating power of spreads even for banks which are not likely to receive public support in case of problems. Without UK banks, however, we find that spreads perform significantly better in case of banks with little or no public support, confirming our earlier results and Proposition 3.

6. Robustness and extensions

As an extension, it is interesting to examine whether the market indicators contain information which is not already summarised in ratings. To this end, we controlled for the "individual rating" at the time the market indicators were observed. The results given in Table 13A for the (-*DD*) measure are fairly similar to those reported in Table 7A, although the significance of the (-*DD*) indicator is somewhat reduced. Overall, they suggest that the (-*DD*) indicator adds to the information obtainable from (Fitch/IBCA) ratings and the more the longer the time leads. The results are even stronger for the

[21] Gropp and Olters (2001) attempt an explanation using a political economy model. They argue that as the United Kingdom has a market-based financial system as opposed to continental Europe, which is bank-based, a political majority to bail out banks is more difficult to obtain in the United Kingdom. Investors, therefore, want to be compensated for this additional default risk and require higher spreads.

[22] This somewhat puzzling finding, which we would not want to oversell, may in fact have to do with sample composition.

spreads (see Table 13B). We conclude that both of the indicators analysed in this paper appear to contain additional information from ratings, at least in terms of their ability to predict bank "failures".

This also addresses the specific issue raised by our definition of "failures". Namely, there is the possibility that we would be using market indicators to predict rating downgradings, which could be based on the same set of information of the probability of default. However, as we find that the market indicators contain additional information compared to prevailing ratings, this concern does not seem to be warranted. However, even if the ratings contained completely similar information to our market indicators, we would find support in our standard logit and hazard models for using market indicators: high-frequency market data have leading properties over discrete bank problem events reflected in their individual ratings.

We also checked whether the distance-to-default measure performs better in terms of its (unconditional) predictive property than simpler equity-based indicators. First, we estimated the logit-models using the equity volatility as the fragility indicator. However, it turned out to be a significantly weaker predictor of "default". The coefficients of $\sigma_{E,t-x}$ were never statistically significant. The composite nature of the (-*DD*) apparently improves predictive performance and reduces noise. We found similar results for a simple leverage measure (V_E / V_L).[23]

Next, we wanted to explore whether our market indicators add information to that already available from banks' balance sheets. Conceptually, this is obvious: market-based indicators should fully reflect past balance sheet information as well as forward-looking expectations about the prospects of the bank. First note that we were unable to estimate the hazard model with balance sheet variables, as they are not available at a monthly frequency. Hence, we estimated logit models only.[24] Clearly, the choice of which balance sheet variables to use is arbitrary. We followed the previous literature (see eg Sironi (2000), Flannery and Sorescu (1996)) and considered a set of balance sheet indicators emulating the categories of CAMEL ratings (Capital adequacy, Asset quality, Management, Earnings, Liquidity).[25] Then, we calculated a composite score based on the bank's position in each year's distribution for every indicator.[26] In this way, we were able to consider the correlation between the different indicators, ie whether a bank is "strong" or "weak" by more than one indicator. We re-estimated the model containing only the market indicators, in order to ensure comparability given the reduced sample size. Second, we estimated a model only with balance sheet indicators, and third, a model combining market and balance sheet indicators. Here, we only report results for the 12 months time lead.

Results for the distance-to-default indicator (Table 14A) show that it adds some information to that already available from balance sheet data. In the model combining the distance-to-default and the balance sheet indicators, the distance-to-default indicator is significant (at the 5% level), and the model fit, as measured by the pseudo-R^2, increases from 0.20 to 0.24 over the one containing only balance sheet variables.[27] In addition, the significance of the distance-to-default indicator improves in the combined model, when compared with the model with only the distance-to-default indicator. This suggests that the distance-to-default indicator provides additional information to that of balance sheet

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[23] The results are available from the authors upon request.

[24] Even for the logit-models we were faced with a significant reduction in sample size. Since balance sheet data are available only on an annual basis, we used only end-year market indicators, rather than utilising all available monthly observations with the same horizon as in the earlier specifications.

[25] In order to maintain a sufficient sample size in the set of failed banks, we had to consider only four out of five indicators. Hence, the liquidity indicator was taken out of the analysis.

[26] The composite score is calculated in the following way:

- we considered the percentile ranking of the bank in each year distribution for every indicator;
- we divided the ranking distributions into four quartiles, and assigned a score varying from 0 (best) to 3 (worst) to the position of the bank in the rankings;
- we obtained the composite score by simply summing up the scores for each indicator, yielding a variable ranging from zero (a bank in good condition with all indicators) to 15 (a bank in bad condition with all indicators).

The FDIC uses a broadly similar approach for its CAMEL model (see FDIC (1994)).

[27] The likelihood-ratio test rejects the hypothesis of no significance of the distance-to-default indicator.

variables, but it does not replace the balance sheet indicators. In other words, the distance-to-default and the balance sheet indicators are both useful for the monitoring of banks and play a complementary role.

Empirical estimates from the same exercise for the spreads indicator are presented in Table 14B. They suggest that spreads also add some information to that already available from balance sheet data, although the evidence is weaker. As before, the model combining the spreads and the balance sheet indicators has a slightly better fit (in terms of pseudo-R^2) over the one containing only balance sheet variables. However, by itself spreads are not significant, even for the banks that are not expected to be supported. Our interpretation is that spreads are highly correlated with the balance sheet information and, hence, to some extent simply appear to reflect backward-looking information, rather than information about the future performance of the bank.

Clearly, tests of the sort presented here have the drawback that they can always be criticised on the basis of omitted variable bias, ie that some other balance sheet indicator may be more relevant. In order to alleviate this criticism, we have taken care to use variables in line with the previous literature and have also tried to emulate a CAMEL approach, which is used by many regulators. The most important result based on this exercise may be that we find some complementarity between market and balance sheet indicators.

Finally, we wondered whether the two market indicators might not provide complementary information to each other. In particular, in the previous section, we demonstrated that the two indicators have very different predictive properties through time. Spreads react late, but lose predictive power further away from the event. The distance-to-default is not a very strong indicator close to default, but has strong leading properties around two years out.[28] Table 15 gives the results from a model with both indicators included simultaneously. We find that both variables are significant at least at the 5% level.

Based on this finding, we can ask two further questions. One, which combination of spread and distance-to-default gives us the most discriminatory power? And, second, is this an improvement over using one or the other indicator alone? In Chart 5 we attempt to shed some light on both questions. In the top panel we have given the survivor functions for banks which are above the median in at least one of the indicators and are in the top 75th percentile in the other versus all other banks. We find that the survivor functions are not significantly different from one another. In the bottom panel, we have plotted the survivor functions for banks that are above the median in both indicators versus all other banks. Now the survivor functions are statistically significantly different at the 5% level. It turns out that the "above median in both indicators" criterion gives us maximum discriminatory power.

Further, comparing the lower panel of Chart 5 to Chart 4, we find that the combination of both indicators provides us with better discriminatory power than either indicator alone. In comparison to the distance-to-default (top panel of Chart 4), we have significantly more discriminatory power closer to the default, which we would attribute to the addition of information contained in spreads. Looking at the lower panel of Chart 4, we find that the addition of information contained in the distance-to-default to spreads reduces type one error dramatically. We are missing significantly fewer defaults when using a combination of both indicators, which is evident from the much flatter curvature of the top line in Chart 5 compared to Chart 4 (lower panel). Overall, we conclude that the market indicators appear to provide useful information not only relative to balance sheet information and ratings, but also to each other.

7. Conclusion

In this paper, we present evidence in favour of using market price-based measures as early indicators of bank fragility. We first argue that sensible indicators of bank fragility should be both *complete*, in that they should reflect all potential sources of default risk, and *unbiased*, in that they should reflect these risks correctly. We then demonstrated that it is possible to derive indicators satisfying both

[28] The simple correlation coefficient between the spread and the distance-to-default is -0.034, in itself suggesting that the two indicators measure different things. Note also that the sample sizes in Table 15 are reduced somewhat relative to earlier models, as they contain only those observations with both bond and stock market data during the same period.

qualities from equity as well as from debt prices. We find that the negative distance-to-default is a preferred indicator over other equity price-based indicators, since it is unbiased in the sense that it will correctly flag an increase in asset volatility. The standard bond spread also satisfies our conditions. We show that both indicators perform quite well as leading indicators for bank fragility in a sample of EU banks. Due to the absence of banks declaring formal bankruptcy, we measured a bank "failure" as a downgrading in the Fitch/IBCA "financial strength rating" to C or below. We argue that this measure of bank fragility may be sensible as in virtually all cases there was government support or a major restructuring in the wake of the event.

Specifically, we estimate both a logit and a proportional hazard model. The logit-model estimates suggest that both bond spreads and distances-to-default have predictive power up to 18 months in advance of the event. This was corroborated by the estimates obtained using the hazard model. The results, however, also point towards significant differences between the two indicators. One, the negative distance-to-default exhibits poor predictive power close to the event. Similarly, our results show that banks might "survive" relatively long periods of time with short distances-to-default. In contrast, bond spreads have a tendency to only react close to the default, ie they only react when the situation of the bank has already become quite desperate. This implies that banks tend to survive only relatively short periods of time with high spreads. These findings are consistent with the theoretical properties of the respective indicators, which we analyse in an option pricing framework. Second, we present some evidence that bond spreads predict financial difficulties only in the case of (smaller) banks which do not benefit from a stronger expectation of a public bailout. We measured this expectation in terms of the "support rating", indicating the likelihood of public intervention. The equity-based distance-to-default measure was not found sensitive to the expectation of an implicit safety net, which is in line with our priors. Finally, we demonstrate that, given the different properties of the bond and equity-based indicators, they also provide complementary information to each other, in particular with respect to reducing type I errors.

We interpret our findings in a way to suggest that supervisors (and possibly the literature) may want to devote more attention to the equity market when considering the use of the information embedded in the market prices of the securities issued by banks. Equity market data could provide supervisors with useful complementary information. The information may be complementary with respect both to balance sheet data and to bond-based market indicators.

As an important caveat, it should be stressed that there might be considerable practical difficulties in using either of the indicators proposed in this paper. For example, the distance-to-default measure, apart from its relative computational complexity, may be sensitive to shifts in derived asset volatility. This, in turn, may be due to irregularities in the equity trading in the period closer to default. Further, the measure is quite sensitive to the measure of equity volatility used and distributional assumptions about equity returns. Similarly, the calculation of bond spreads may be difficult in practice, because of relatively illiquid bond markets, resulting in noisy price data for bank bonds and the lack of reliable risk-free benchmarks (especially in smaller countries).

Tables

Table 1

Composition of banks by country and availability of equity and bond data

	Equity	Bond		Equity	Bond
Belgium	4	1	Italy	20	7
Denmark	2		Netherlands	3	4
Germany	10	16	Austria	3	2
Greece	3		Portugal	4	1
Spain	7	2	Finland	1	2
France	8	9	Sweden	3	3
Ireland	4	2	United Kingdom	11	10
			Total	**84**	**59**

Table 2

Downgrading events (to "individual rating" C or below) in the sample

Bank	Downgrading	Support / restructuring / other	Timing
A. Cases of public support			
Banco Español de Credito**	Jun 93	Public financial support	Dec 93
Banco di Napoli**	Jan 95	Public capital injection	Early 96
Banca Nazionale del Lavoro	Jun 97	Public capital support in the form of a transfer of Artigiancassa	During 96
Bankgesellschaft Berlin	Jun 99	Recapitalisation (partly government-owned bank)	During 01
CPR	Nov 98	Support from the parent group (CA)	End-98
Credit Lyonnais*	Jun 94	Public financial support	Spring 95
Credit Foncier de France	First rating (D) Apr 00	Public financial support	Apr 96
Erste Bank der Oesterreichischen Sparkassen	Feb 00	Capital injection (from the savings banks' system)	Oct 00
Okobank	Oct 94	Public capital injection	Oct 93-end-95
Skandinaviska Enskilda Banken	Jul 92	Government guarantee	Dec 92
Svenska Handelsbanken	Dec 92	Government guarantee	Dec 92

B. Cases of substantial restructuring			
Banca Popolare di Novara**	Oct 95	Major restructuring, eg new management	During 96
Bank Austria	Jun 96	Absorbed by West-Deutsche LB	May 97
Banque Natexis	Nov 96	Merger (Credit National and Banque Federal de BP)	Jan 97
Banque Worms	Nov 99	Sold to Deutsche Bank	Oct 00
CIC Group	Aug 95	Fully privatised	During 96
Commercial Bank of Greece	Dec 98	Sale of significant parts of operations (Ionian and Popular Bank)	Early 99
Entenial	Mar 99	Merger with Banque La Hénin-Epargne Crédit (BLH).	
Creditanstalt	Jan 97	Takeover by Bank Austria	Jan 97
C. Other cases			
Banca Commerciale Italiana	Jun 00	Weak performance and asset quality	
Banca di Roma	Nov 96	Depressed profitability and asset quality eg due to several acquisitions	
Banca Popolare di Intra**	Feb 01	Weak performance and asset quality	
Banca Popolare di Lodi	Jun 00	Weak performance and asset quality	
Banca Popolare di Milano**	Nov 95	Weak performance and asset quality	
Banca Popolare di Sondrio**	Mar 00	Weak performance and asset quality	
Banco Zaragozano**	Mar 95	Weak performance and asset quality	
Bayerische Landesbank*	Dec 99	Weak capital adequacy and asset quality	
Credito Valtellinese	Feb 01	Weak performance and asset quality	
Deutsche Genossenschaftsbank*	Nov 00	Weak performance and asset quality	
HSBC Bank*	May 91	Weak performance and asset quality	
Standard Chartered*	Jun 90	Weak performance and asset quality	
Westdeutsche Landesbank*	Nov 98	Exposures to Russia, weak capitalisation	

Source: Fitch/IBCA. * Only in the bond sample. ** Only in the equity sample.

Table 3

Definition of variables

Variable	Definition
Market value of equity (V_E)	Monthly average equity market capitalisation (millions of euros)
Equity volatility (σ_E)	6-month moving average (backwards) of daily absolute equity returns (%)
Book value of debt liabilities (D)	Total debt liabilities (interpolated monthly observations) (millions of euros)
Market value of assets (V)	Derived (equations (2)) monthly average of the total asset value (millions of euros)
Volatility of assets (σ)	Derived (equations (2)) monthly estimate of the asset value volatility (%)
Negative of the distance-to-default (-DD)	Monthly average (-DD) calculated from V_A, σ_A, and V_L(equation (3))
Spread (S)	Calculated monthly average subordinated debt spread of the yield to maturity over the risk-free yield to maturity
Dummy indicating expected public support (DSUPP)	Dummy variable equalling one if Fitch/IBCA support rating 1 or 2 (zero otherwise)
Status variable (STATUS)	Binary variable equalling one if a bank experiences a downgrading in Fitch/IBCA “individual rating” to C or below (zero otherwise)

Table 4

Descriptive statistics

Variable	*t-x*	Nobs	Mean	Std dev	Min	Max[1]
Market value of equity (V_E) (millions of euros)	x = 3 months	1043	10,212	17,452	13.64	191,638
	x = 6 months	1043	10,047	17,305	11.80	229,167
	x = 12 months	1040	9,043	15,597	13.79	183,195
	x = 18 months	1039	8,363	14,509	13.64	129,555
	x = 24 months	1036	7,377	13,226	11.84	104,839
Equity volatility (σ_E)	x = 3 months	1043	0.27	0.14	0.01	2.01
	x = 6 months	1043	0.27	0.14	0.01	2.01
	x = 12 months	1040	0.28	0.14	0.01	0.71
	x = 18 months	1039	0.27	0.15	0.01	2.06
	x = 24 months	1036	0.25	0.14	0.01	2.06
Book value of debt liabilities (*D*) (millions of euros)	x = 3 months	1043	94,862	117,375	464.95	715,825
	x = 6 months	1043	91,921	113,277	441.31	688,596
	x = 12 months	1040	86,908	106,286	397.59	636,515
	x = 18 months	1039	82,799	100,645	358.20	556,785
	x = 24 months	1036	79,308	95,969	305.34	490,866
Market value of assets (*V*) (millions of euros)	x = 3 months	1043	99,500	120,350	568.99	735,885
	x = 6 months	1043	96,617	116,403	519.16	710,957
	x = 12 months	1040	90,818	108,557	484.66	652,365
	x = 18 months	1039	85,963	102,492	365.65	569,511
	x = 24 months	1036	81,478	96,825	312.37	499,827
Volatility of assets (σ)	x = 3 months	1043	0.04	0.05	0.00	0.65
	x = 6 months	1043	0.04	0.05	0.00	0.65
	x = 12 months	1040	0.04	0.04	0.00	0.28
	x = 18 months	1039	0.04	0.05	0.00	0.73
	x = 24 months	1036	0.03	0.04	0.00	0.73
Negative of the distance-to-default (-*DD*)	x = 3 months	1043	– 5.64	6.00	– 87.71	0.99
	x = 6 months	1043	– 5.60	5.71	– 91.12	0.99
	x = 12 months	1040	– 5.28	5.01	– 71.71	– 1.20
	x = 18 months	1039	– 5.62	6.57	– 133.89	1.05
	x = 24 months	1036	– 5.90	6.46	– 130.44	1.05
Spread (*S*) (%)	x = 3 months	478	0.89	1.14	– 0.49	6.02
	x = 6 months	474	0.87	1.15	– 0.40	6.08
	x = 12 months	457	0.79	1.04	– 0.27	6.07
	x = 18 months	432	0.75	1.04	– 0.82	6.32
	x = 24 months	407	0.70	1.06	– 0.62	6.23

[1] The large max values for equity and asset volatility are due to Banca Popolare dell'Emilia Romagna, which had very high volatility levels from December 1996 to May 1997. This observation was not found to affect the econometric results.

Table 5

Ability of (-*DD*) and *S* to distinguish weaker banks: mean value tests, all banks

	Status	Nobs	Mean	Std error	Difference[1]	Difference < 0[2]
Equity			($-DD_{t-x}$)			
x = 3 months	0	1018	– 5.68	0.19	– 1.58	– 3.490 ***
	1	25	– 4.10	0.41		
x = 6 months	0	1018	– 5.64	0.18	– 1.79	– 5.335 ***
	1	25	– 3.85	0.28		
x = 12 months	0	1018	– 5.31	0.16	– 1.62	– 4.887 ***
	1	22	– 3.69	0.29		
x = 18 months	0	1018	– 5.66	0.21	– 1.93	– 5.181 ***
	1	21	– 3.72	0.31		
x = 24 months	0	1018	– 5.93	0.20	– 1.55	– 2.823 ***
	1	18	– 4.38	0.51		
Bond			S_{t-x}			
x = 3 months	0	457	0.88	0.05	– 0.19	– 0.68
	1	21	1.07	0.27		
x = 6 months	0	454	0.86	0.05	– 0.18	– 0.55
	1	20	1.04	0.32		
x = 12 months	0	438	0.79	0.05	– 0.10	– 0.37
	1	19	0.89	0.26		
x = 18 months	0	417	0.74	0.05	– 0.12	– 0.43
	1	15	0.86	0.27		
x = 24 months	0	393	0.70	0.05	– 0.03	– 0.13
	1	14	0.73	0.26		
Bond[3]			S_{t-x}			
x = 3 months	0	78	0.24	0.02	– 0.55	– 1.997 **
	1	5	0.79	0.25		
x = 6 months	0	72	0.22	0.02	– 0.36	– 2.90 **
	1	5	0.58	0.12		
x = 12 months	0	67	0.22	0.02	– 0.38	– 1.556 *
	1	4	0.60	0.25		

Note: Two sub-sample *t*-tests (unequal variances) are reported for the difference in mean values of ($-DD_{t-x}$) and S_{t-x} in the sub-samples of downgraded (SATUS=1) and non-downgraded banks (STATUS=0). *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

[1] Mean (STATUS=0) – Mean (SATUS=1). [2] *t*-statistics for testing the hypothesis that difference is negative. [3] Banks with low public support expectation and excluding UK banks.

Table 6A

Predictive performance of the distance-to-default indicator: logit-estimations, all banks

x = 3 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 2.803 ***	0.454	– 6.170	0.000
($-DD_{t-3}$)	0.113	0.091	1.240	0.216
DSUPP*($-DD_{t-3}$)	0.158	0.105	1.510	0.130
Number of observations	1043		Log likelihood	– 114.35
F-test[1]	5.22 **		Pseudo R^2	0.0307
x = 6 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 2.620 ***	0.440	– 5.950	0.000
($-DD_{t-6}$)	0.182 *	0.096	1.890	0.058
DSUPP*($-DD_{t-6}$)	0.112	0.109	1.030	0.302
Number of observations	1043		Log likelihood	– 114.04
F-test[1]	6.44 **		Pseudo R^2	0.0333
x =12 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 2.889 ***	0.451	– 6.400	0.000
($-DD_{t-12}$)	0.212 **	0.105	2.030	0.043
DSUPP*($-DD_{t-12}$)	0.018	0.117	0.150	0.880
Number of observations	1040		Log likelihood	– 103.96
F-test[1]	3.78 **		Pseudo R^2	0.0247
x = 18 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 2.686 ***	0.541	– 4.960	0.000
($-DD_{t-18}$)	0.287 *	0.149	1.920	0.054
DSUPP*($-DD_{t-18}$)	– 0.014	0.126	– 0.110	0.913
Number of observations	1039		Log likelihood	–102.742
F-test[1]	4.29 **		Pseudo R^2	0.0322
x = 24 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 3.301 ***	0.594	– 5.560	0.000
($-DD_{t-24}$)	0.171	0.130	1.320	0.188
DSUPP*($-DD_{t-24}$)	– 0.034	0.113	– 0.300	0.761
Number of observations	1036		Log likelihood	– 89.315
F-test[1]	1.11		Pseudo R^2	0.0163

Note: All models are estimated using the binary variable STATUS as the dependent variable. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

[1] F-test for the hypothesis that the sum of the coefficients of ($-DD_{t-x}$) and DSUPP*($-DD_{t-x}$) is zero (ie that the coefficient of ($-DD_{t-x}$) is zero for banks with a greater expectation of public support). $\chi 2$ values reported. [2] Standard errors adjusted.

Table 6B

Predictive performance of the spread indicator: logit-estimations, all banks

x = 3 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 3.361***	0.387	– 8.680	0.000
(S_{t-3})	2.838***	1.120	2.530	0.010
DSUPP*(S_{t-3})	– 2.546**	1.100	– 2.310	0.021
Number of observations	364		Log likelihood	– 69.854
F-test[1]	1.41		Pseudo R^2	0.064
x = 6 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 3.497***	0.421	– 8.300	0.000
(S_{t-6})	4.073***	1.555	2.620	0.009
DSUPP*(S_{t-6})	– 3.745***	1.513	– 2.480	0.010
Number of observations	361		Log likelihood	– 66.464
F-test[1]	1.86		Pseudo R^2	0.071
x = 12 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 3.416***	0.402	– 8.500	0.000
(S_{t-12})	3.186**	1.311	2.430	0.015
DSUPP*(S_{t-12})	– 2.781**	1.286	– 2.160	0.031
Number of observations	348		Log likelihood	– 64.379
F-test[1]	2.09		Pseudo R^2	0.052
x = 18 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***z***	***P>| z |***
Constant	– 3.528***	0.437	– 8.070	0.000
(S_{t-18})	2.706**	1.112	2.430	0.015
DSUPP*(S_{t-18})	– 2.402**	1.088	– 2.210	0.027
Number of observations	328		Log likelihood	– 52.302
F-test[1]	0.67		Pseudo R^2	0.044
x = 24 months				
Explanatory variable	**Coefficient**	**Robust std error[2]**	***Z***	***P>| z |***
Constant	– 3.433	0.470	– 7.300	0.000
(S_{t-24})	2.305	2.280	1.010	0.312
DSUPP*(S_{t-24})	– 2.062	2.194	– 0.940	0.347
Number of observations	310		Log likelihood	– 50.013
F-test[1]	0.29		Pseudo R^2	0.015

Note: All models are estimated using the binary variable STATUS as the dependent variable and excluding UK banks. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

[1] F-test for the hypothesis that the sum of the coefficients of (S_{t-x}) and DSUPP*(S_{t-x}) is zero (ie the coefficient of (S_{t-x}) is zero for banks with a greater expectation of public support). $\chi 2$ values reported. [2] Standard errors adjusted.

Table 7

Performance of the distance-to-default indicator: proportional hazard estimation, all banks

Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
(-*DD*)	0.728**	0.115	2.02	0.04
Number of subjects	84	Time at risk		5365
Number of failures	25	Starting log likelihood		– 100.49
Number of observations	5365	Final log likelihood		– 96.71
Wald χ^2	4.08**	Zero-slope test		7.66***

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8

Performance of the bond spread: proportional hazard estimation, all banks

Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
S	1.00	0.002	0.75	0.455
Number of subjects	59	Time at risk		3604
Number of failures	19	Starting log likelihood		– 69.76
Number of observations	3604	Final log likelihood		– 69.54
Wald χ^2	0.56	Zero-slope test		0.40

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9

Performance of the distance-to-default indicator: proportional hazard estimation using a dummy variable, all banks

Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
Dummy for (-*DD*) >-3.2	2.69***	1.034	2.57	0.01
Number of subjects	84	Time at risk		5365
Number of failures	25	Starting log likelihood		– 100.49
Number of observations	5365	Final log likelihood		– 97.86
Wald χ^2	6.62***	Zero-slope test		1.52

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10

Performance of the bond spread: proportional hazard estimation controlling for the UK, all banks

Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
S	1.01***	0.002	2.74	0.006
Dummy for UK	– 0.065**	0.080	– 2.25	0.025
Number of subjects	59	Time at risk		3604
Number of failures	19	Starting log likelihood		– 69.76
Number of observations	3604	Final log likelihood		– 65.18
Wald χ^2	8.76***	Zero-slope test (global test)		1.86

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 11

Performance of the bond spread: proportional hazard estimation controlling the level of support, UK banks excluded

Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
S	1.02***	0.005	3.79	0.000
Dummy "high support"**S*	– 0.99***	0.005	– 2.71	0.007
Number of subjects	49	Time at risk		2720
Number of failures	18	Starting log likelihood		– 61.51
Number of observations	2720	Final log likelihood		– 57.07
Wald χ^2	16.38***	Zero-slope test (global test)		2.58

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 12

The role of the safety net and the UK location: log-rank tests for equality of survivor functions, all banks

	χ^2	$P > \chi^2$
(-*DD*)		
Dummy "high support" equal to 1	4.94**	0.03
Dummy "high support" equal to 0	0.90	0.34
S		
Dummy "high support" equal to 1	1.95	0.16
Dummy "high support" equal to 0	3.30*	0.07
***S*; excluding UK banks**		
Dummy "high support" equal to 1	7.81***	0.005
Dummy "high support" equal to 0	30.19***	0.000

Note: Estimated using the Cox regression in Tables 9 and 11. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 13A

Predictive performance of the distance-to-default indicator: logit-estimations, controlling for the Fitch/IBCA individual rating before the event

x = 6 months

Explanatory variable	Coefficient	Robust std Error	*z*	*P*>| *z* |
Constant	– 3.888***	0.709	– 5.490	0.000
($-DD_{t-6}$)	0.186	0.117	1.590	0.112
DSUPP*($-DD_{t-6}$)	0.092	0.127	0.730	0.468
$INDRAT_{t-6}$	0.357**	0.168	2.120	0.034
Number of observations	959		Log likelihood	– 105.237
F-test	4.52**		Pseudo R^2	0.0916

x = 12 months

Explanatory variable	Coefficient	Robust std Error	*z*	*P*>| *z* |
Constant	– 3.954***	0.663	– 5.960	0.000
($-DD_{t-12}$)	0.208*	0.120	1.730	0.084
DSUPP*($-DD_{t-12}$)	0.022	0.136	0.160	0.873
$INDRAT_{t-12}$	0.321**	0.151	2.120	0.034
Number of observations	931		Log likelihood	– 96.997
F-test	3.22*		Pseudo R^2	0.0685

x = 18 months

Explanatory variable	Coefficient	Robust std Error	*z*	*P*>| *z* |
Constant	– 3.431***	0.754	– 4.550	0.000
($-DD_{t-18}$)	0.290*	0.163	1.780	0.075
DSUPP*($-DD_{t-18}$)	0.017	0.151	0.110	0.913
$INDRAT_{t-18}$	0.277*	0.150	1.850	0.064
Number of observations	909		Log likelihood	– 93.172
F-test	4.25**		Pseudo R^2	0.0669

Note: Logit-estimations are reported for the sample of downgraded and non-downgraded banks, controlling for the individual rating before the event. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

See notes to Table 7A.

Table 13B

Predictive performance of the spread indicator: logit-estimations, controlling for the Fitch/IBCA individual rating before the event

x = 3 months

Explanatory variable	Coefficient	Robust std error	*z*	*P*>| *z* |
Constant	– 9.659**	3.954	– 2.440	0.015
(S_{t-3})	2.277***	0.797	2.860	0.004
DSUPP*(S_{t-3})	– 1.994***	0.747	– 2.670	0.008
$INDRAT_{t-6}$	1.610	1.015	1.590	0.113
Number of observations	305		Log likelihood	– 36.639
F-test[1]	1.48		Pseudo R^2	0.355

x = 6 months

Explanatory variable	Coefficient	Robust std error	*z*	*P*>| *z* |
Constant	– 8.366***	2.990	– 2.800	0.005
(S_{t-6})	3.364**	1.555	2.160	0.030
DSUPP*(S_{t-6})	– 3.068**	1.458	– 2.100	0.035
$INDRAT_{t-6}$	1.253	0.809	1.550	0.122
Number of observations	295		Log likelihood	– 36.458
F-test[1]	1.38		Pseudo R^2	0.316

x = 12 months

Explanatory variable	Coefficient	Robust std error	*z*	*P*>| *z* |
Constant	– 7.837***	2.874	– 2.730	0.006
(S_{t-12})	3.078***	1.169	2.630	0.008
DSUPP*(S_{t-12})	– 2.790***	1.092	– 2.560	0.010
$INDRAT_{t-12}$	1.158	0.810	1.430	0.153
Number of observations	283		Log likelihood	– 35.293
F-test[1]	0.62		Pseudo R^2	0.283

Note: Logit-estimations are reported for the sample of downgraded and non-downgraded banks, controlling for the individual rating before the event and excluding UK banks. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

See notes to Table 7B.

Table 14A

Information content of the distance-to-default indicator: logit-estimations, all banks

Model with only the distance-to-default indicator
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*Z*	*P>| z |*
Constant	– 1.790***	0.492	– 3.640	0.000
(DD_{t-x})	0.249**	0.121	2.070	0.039
DSUPP*(DD_{t-x})	0.005	0.119	0.040	0.970
Number of observations	408		Log likelihood	– 82.626
F-test[1]	3.97**		Pseudo R^2	0.035

Model with only balance sheet indicators
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*Z*	*P>| z |*
Constant	– 7.105***	1.082	– 6.570	0.000
SCORE	0.574***	0.121	4.740	0.000
Number of observations	408		Log likelihood	– 68.588
			Pseudo R^2	0.199

Model with the distance-to-default indicator and balance sheet indicators
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*Z*	*P>| z |*
Constant	– 6.232***	1.155	– 5.390	0.000
(DD_{t-x})	0.242**	0.110	2.200	0.028
DSUPP*(DD_{t-x})	– 0.044	0.127	– 0.340	0.732
SCORE	0.585***	0.125	4.670	0.000
Number of observations	408		Log likelihood	– 65.360
F-test[1]	3.03*		Pseudo R^2	0.238

Note: All models are estimated using the binary variable STATUS as the dependent variable. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. SCORE is a synthetic variable summarising the ranking of the bank with regard to four indicators representing respectively capital adequacy, asset quality, efficiency and profitability.

See notes to Table 7B.

Table 14B

Information content of the spreads indicator: logit-estimations, all banks

Model with only the spreads indicator
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*z*	*P*>| *z* |
Constant	– 2.451***	0.405	– 6.060	0.000
(S_{t-x})	2.999**	1.353	2.220	0.027
DSUPP*(S_{t-x})	– 2.575*	1.328	– 1.940	0.053
Number of observations	144		Log likelihood	– 49.388
F-test[1]	2.00		Pseudo-R^2	0.055

Model with only balance sheet indicators
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*z*	*P*>| *z* |
Constant	– 6.272***	1.269	– 4.940	0.000
SCORE	0.548***	0.142	3.850	0.000
Number of observations	144		Log likelihood	– 40.260
			Pseudo-R^2	0.230

Model with the spreads indicator and balance sheet indicators
x = 12 months

Explanatory variable	Coefficient	Robust std error[2]	*z*	*P*>| *z* |
Constant	– 6.305***	1.233	– 5.110	0.000
(S_{t-x})	2.079	1.627	1.280	0.201
DSUPP*(S_{t-x})	– 1.662	1.600	– 1.040	0.299
SCORE	0.514***	0.138	3.730	0.000
Number of observations	144		Log likelihood	– 39.136
			Pseudo-R^2	0.251

Note: All models are estimated using the binary variable STATUS as the dependent variable. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. SCORE is a synthetic variable summarising the ranking of the bank with regard to four indicators representing respectively capital adequacy, asset quality, efficiency and profitability. The models exclude UK banks.

See notes to Table 7B.

Table 15

Performance of the distance-to-default and the bond spread: proportional hazard estimation, UK banks excluded

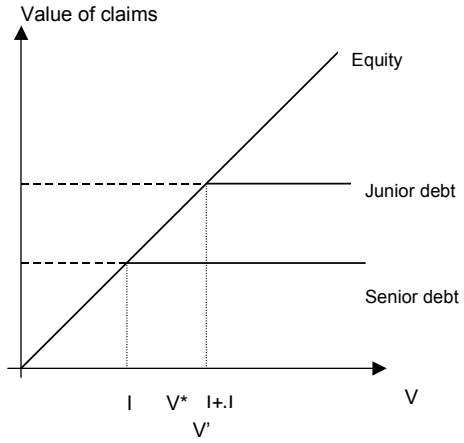
Explanatory variable	Hazard ratio	Robust std error	*z*	*P*>|*z*|
Dummy for (-*DD*) >-3.2	4.01**	2.55	2.19	0.029
S	1.01***	0.004	2.77	0.006
Dummy "high support"**S*	– 0.99**	0.005	– 2.41	0.016
Number of subjects	34	Time at risk		1494
Number of failures	10	Starting log likelihood		– 31.17
Number of observations	1494	Final log likelihood		– 27.94
Wald χ^2	12.90***	Zero-slope test (global test)		2.65

Note: Estimated using Cox regression. Log-likelihood given in the text. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Charts

Chart 1

Payoff profiles at maturity of equity, senior and junior debt



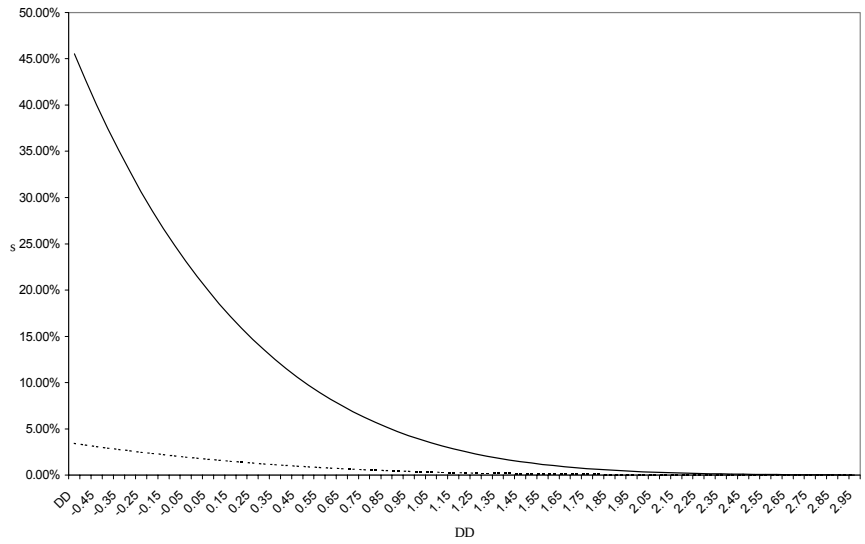
Payoffs at maturity

	V **< I**	**I <** ***V*** **< I+J**	***V*** **> I+J**
Equity	0	0	*V*-I-J
Junior debt	0	*V*-I	J
Senior debt	*V*	I	I

Chart 2

Predicted spread (Black-Cox) (% of face value) as a function of distance-to-default

Subordinated debt (solid line), senior debt (dashed line)



Parameter assumptions: σ=0.05, r=0.05, T=1, I+J=1, I/(I+J)=0.9.

Chart 3

Summary of logit-estimation results

The chart displays the pattern of coefficients on the two indicators from Tables 6A and 6B with different horizons. The coefficients were normalised, such that the largest effect is equal to unity.

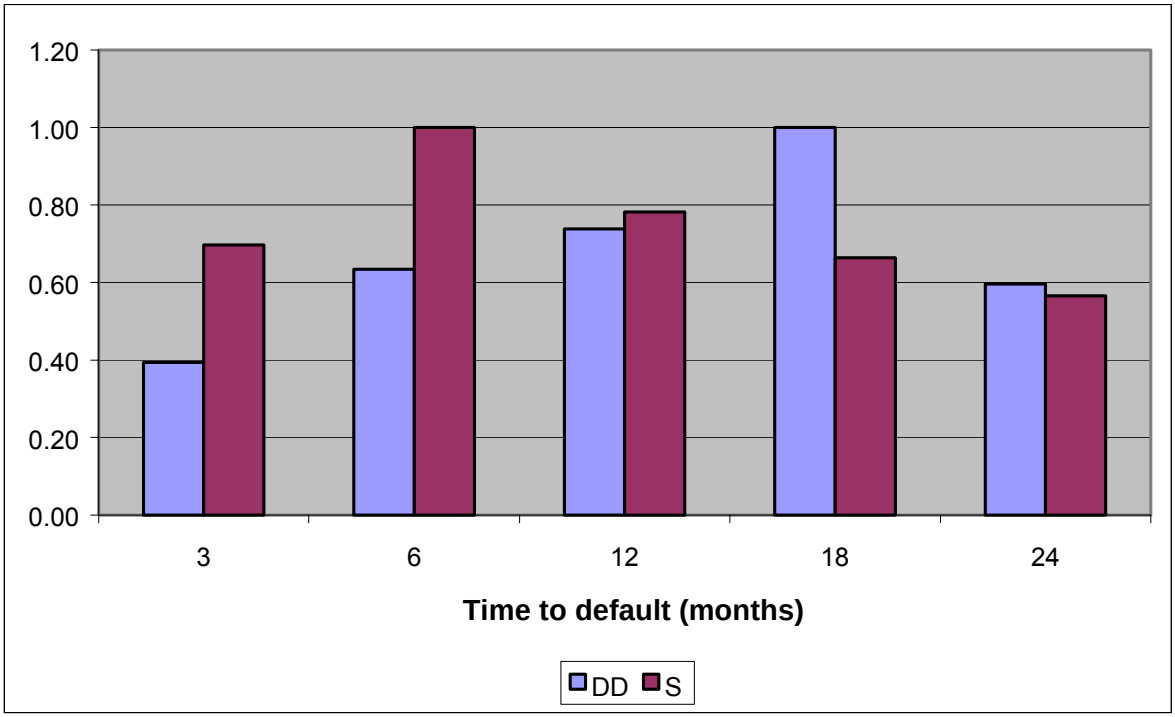
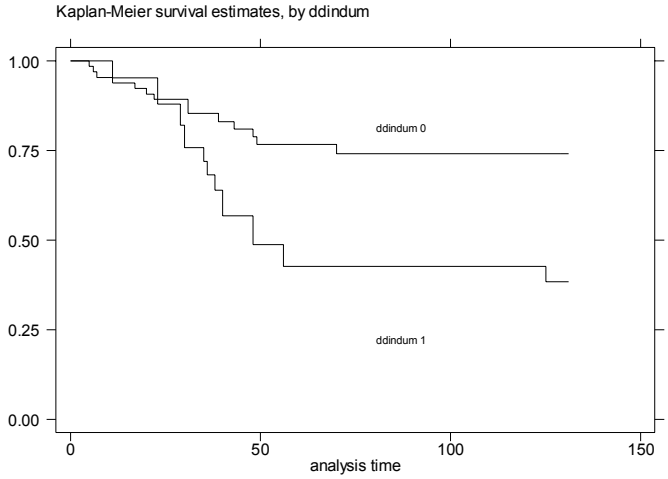


Chart 4

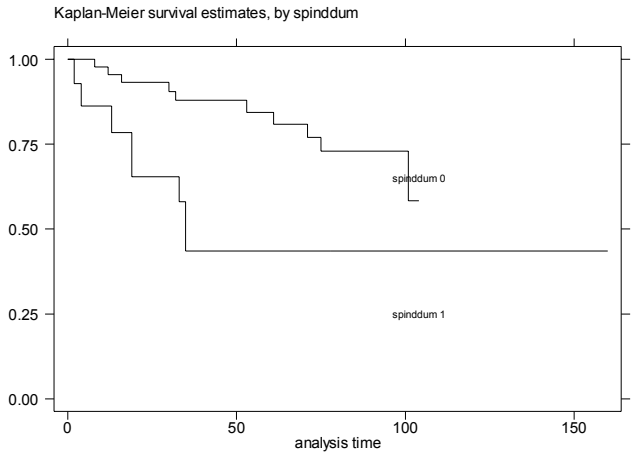
Survivor functions for the distance-to-default and spread

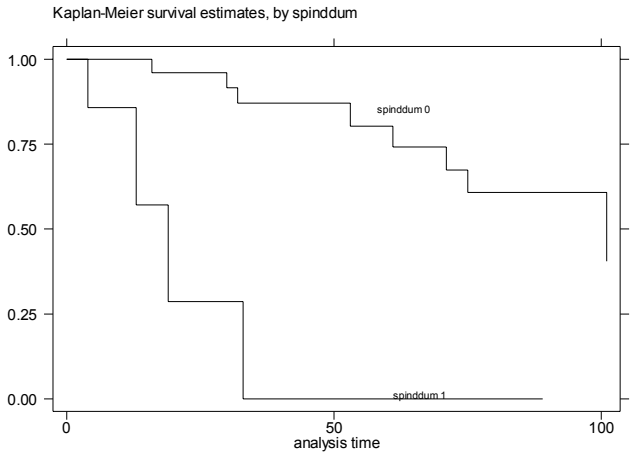
A. Distance-to-default



ddindum=1 if (–*DD*) > -3.2 and 0 otherwise. Analysis time is measured in months. Log-rank test for equality (χ^2 distributed) is equal to 6.08, which rejects equality at the 5%-level.

B. Spreads

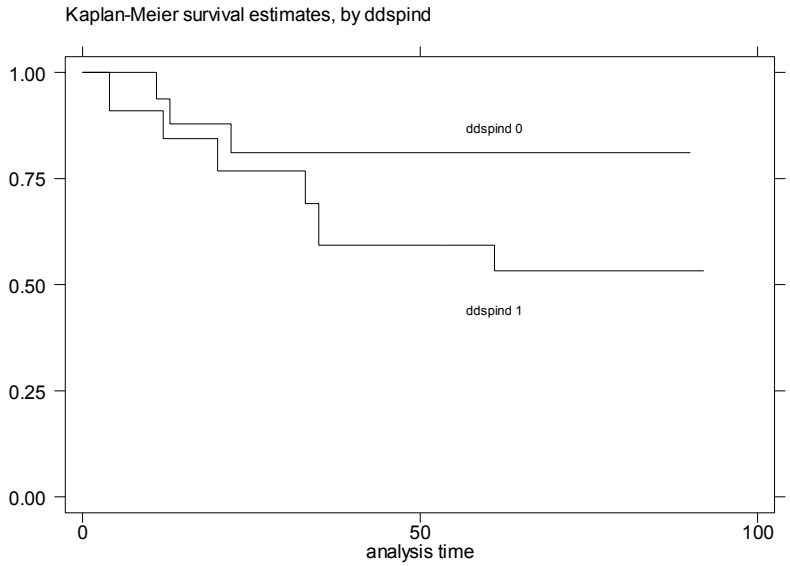




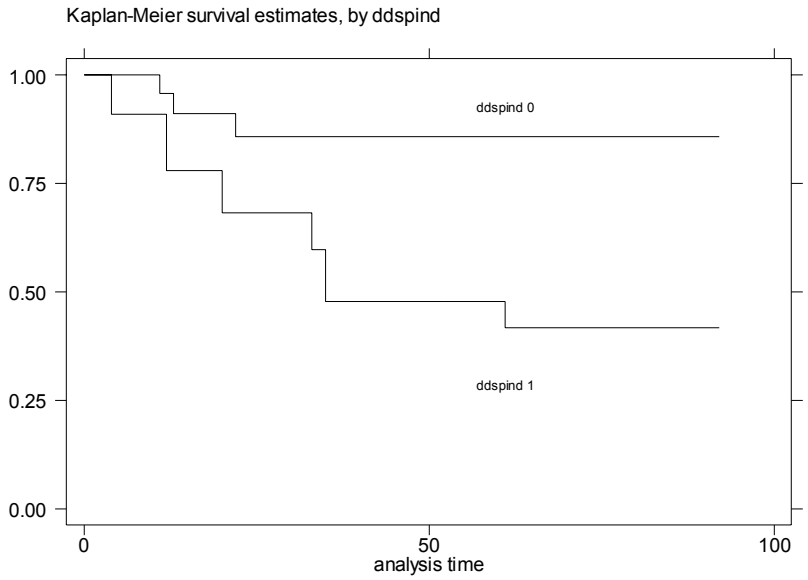
spinddum=1 if *S*>98 basis points and 0 otherwise. Panel B excludes UK banks. Analysis time is measured in months. Log-rank test for equality (χ^2 distributed) is equal to 4.73 and 25.9, respectively. Equality is rejected at the 5% (with UK banks) and at any significance level (without UK banks).

Chart 5

Survivor functions for the distance-to-default and spread, both indicators in the same model



At least one of the two indicators in top half and the other in top 75th percentile. Survival functions are not statistically significantly different (Chi squared of 1.04).



Both indicators in top half of the respective distributions. Survival functions are statistically significantly different at the 5% level (Chi squared of 4.1).

Appendix 1:
Distance-to-default according to the Black and Scholes formula[29]

In the BS model the time path of the market value of assets follows a stochastic process:

$$\ln V_A^T = \ln V_A + \left(r - \frac{\sigma_A^2}{2}\right)T + \sigma_A\sqrt{T}\varepsilon,$$

which gives the asset value at time T (ie maturity of debt), given its current value (V_A). ε is the random component of the firm's return on assets, which the BS model assumes normally distributed, with zero mean and unit variance, $N(0,1)$.

Hence, the current distance d from the default point (where $\ln V = \ln D$) can be expressed as:

$$d = \ln V^d - \ln D = \ln V + (r - \frac{\sigma^2}{2})T + \sigma\sqrt{T}\varepsilon - \ln D <=>$$

$$\frac{d}{\sigma\sqrt{T}} = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} + \varepsilon.$$

That is, the distance-to-default (*DD*)

$$DD \equiv \frac{d}{\sigma\sqrt{T}} - \varepsilon = \frac{\ln\left(\frac{V}{D}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

represents the number of standard deviations (σ_A) that the firm is from the default point.

The implied probability of default (*IPD*) can be defined as the probability that the asset value is less or equal to the book value of debt liabilities when the debt matures:

$$IPD \equiv \Pr\left[\ln V^T \le \ln D\right] <=> \Pr\left[\ln V + \left(r - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}\varepsilon \le \ln D\right], \text{ie}$$

$$IPD = \Pr\left[-\frac{\ln\frac{V}{D} + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \le \varepsilon\right] = \Pr\left[(-DD) \le \varepsilon\right].$$

Given that ε is normally distributed, $IPD = N(-DD)$.

[29] See KMV Corporation (1999) for a similar derivation and more ample discussion.

Appendix 2:
Ratings definitions used by Fitch/IBCA

Fitch/IBCA's individual ratings attempt to assess how a bank would be viewed if it were entirely independent, and could not rely on external support. These ratings are designed to assess a bank's exposure to, appetite for and management of risk, and thus represent the view on the likelihood that it would run into significant difficulties. The principal factors analysed to evaluate the bank and determine these ratings include profitability and balance sheet integrity, franchise, management, operating environment and prospects.

Fitch/IBCA distinguishes among the following categories:

A. **A very strong bank.** Characteristics may include outstanding profitability and balance sheet integrity, franchise, management, operating environment or prospects.

B. **A strong bank.** There are no major concerns regarding the bank. Characteristics may include strong profitability and balance sheet integrity, franchise, management, operating environment or prospects.

C. **An adequate bank which, however, possesses one or more troublesome aspects.** There may be some concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects.

D. **A bank which has weaknesses of internal and/or external origin.** There are concerns regarding its profitability and balance sheet integrity, franchise, management, operating environment or prospects.

E. **A bank with very serious problems which either requires or is likely to require external support.**

Note that, in addition, there are gradations between these five rating categories, ie A/B, B/C, C/D, and D/E.

The **support ratings** do not assess the quality of a bank. Rather, they are Fitch/IBCA's assessment of whether the bank would receive support should this be necessary:

1. A bank for which there is a clear legal guarantee on the part of the state, or a bank of such importance both internationally and domestically that, in Fitch/IBCA's opinion, support from the state would be forthcoming, if necessary. The state in question must clearly be prepared and able to support its principal banks.

2. A bank for which, in Fitch/IBCA's opinion, state support would be forthcoming, even in the absence of a legal guarantee. This could be, for example, because of the bank's importance to the economy or its historical relationship with the authorities.

3. A bank or bank holding company which has institutional owners of sufficient reputation and possessing such resources that, in Fitch/IBCA's opinion, support would be forthcoming, if necessary.

4. A bank for which support is likely but not certain.

5. A bank, or bank holding company, for which support, although possible, cannot be relied upon.

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