EQUITY AND BOND MARKET SIGNALS AS LEADING INDICATORS OF BANK FRAGILITY IN EUROPE

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Abstract

We analyse EU banks' equity market-based distances-to-default and subordinated bond spreads in the secondary market in relation to their capability of signalling a material weakening in banks' financial condition. Both indicators are demonstrated to be complete indicators of bank fragility, reflecting relevant information of default risk; and also to be aligned with the supervisors' conservative perspective. We use two different econometric models: a logit-model, estimated for a number of different time-leads, and a Cox 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 6 to 18 months in advance, its predictive properties are quite poor closer to the "default" events. In contrast, all banks' subordinated debt spreads seem to have signal value, but close to the "default" events only. Otherwise, they appear to be significantly diluted by the expectation of public bailout, which is not the case with the equity market-based distances-to-default.

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I. Introduction

The interest of the supervisory authorities in the markets for the securities issued by banks is currently two-fold: First, supervisors are promoting *market discipline* to complement their own functions in ensuring the safety and soundness of banks. This is deemed necessary because of the difficulty of monitoring the risks of large, complex and internationalised banking organisations, in particular.

Second, supervisors are considering the *use of market data* to complement their tools for assessing bank fragility (as other parties analysing banks, but without access to confidential information). The presumption is that the information efficiently summarised in market prices would enhance the power to identify fragile institutions in advance. These signals could be used as screening devices or inputs into supervisors' early warning models geared at identifying banks which should be more closely scrutinised.[2] Some observers have even suggested using subordinated debt spreads as triggers for supervisory discipline (Evanoff and Wall 2000a, Flannery 2000). These triggers would have the benefit of either convincing supervisors to act sooner, or possibly even permitting them to do so, as market information would represent objective third-party evidence of the bank's condition.

On the first issue, already a number of US studies have addressed whether the market prices of the securities issued by banks signal the risks incurred by them. The ability of these prices to reflect banks' risks, and so to affect banks' funding cost, would indicate that markets can indeed exert effective discipline on banks.[3] Since Flannery and Sorescu (1996), US studies have found that banks' subordinated debt spreads in the secondary market do reflect banks' (or bank holding companies') risks measured through balance-sheet and other risk measures (see surveys in 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 in our knowledge so far providing evidence for European banks. It also concludes that banks' debenture spreads at issue tend to reflect cross-sectional differences in risk.

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2 Supervisory early warning models combine a set of financial indicators (balance sheet, income statement and market indicators) as well as other variables (e.g. 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 models (see Gilbert et.al. 1999).

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.

On the second issue, US studies appear to support that market signals could usefully complement supervisors' traditional information. Evanoff and Wall (2000b) find that subordinated debt spreads have some leading properties against CAMEL ratings. Conversely, DeYoung et. al. (2000) observe that on-site examinations produce information that affects the spreads. However, they find that spread changes more often reflect anticipated regulatory responses 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.

The possible complementary role of the information contained in market prices vis-à-vis that already contained in rating agencies' assessments is of interest as well. In general, rating agencies are typically argued to be conservative and to respond mainly to already realised risks (e.g. Altman and Saunders 2000). Thus, market signals could provide leading information compared with the rating information. 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 the equity prices do.

Studies have so far concentrated more on the bond rather than equity market signals. The apparent reasons for this focus are, on one hand, that mandatory subordinated debt issuance by banks has been forcefully recommended and studied as a new tool to discipline banks (e.g. Calomiris 1997, and Kwast et. al. 1999). Subordinated debt-holders are uninsured and have junior status, which should create especially strong incentives to monitor banks' risks. On the other hand, the signals based on equity prices are deemed biased in contrast to bond market signals, because the limited liability equity-holders can benefit from the upside gains that accrue from increased risk-taking (e.g. Hancock and Kwast 2000, and Berger et. al. 2000). Equity gains in value as a call option on a bank's assets when the asset risk (asset value volatility) is increased. The relative importance of this bias (i.e. moral hazard) is found the greater, the closer the bank to insolvency, or equally, the lower its charter value (Keeley 1990, Demsetz et. al. 1996, and Gropp and Vesala 2001). Hence, the bias could distort the signals aimed at picking up banks facing a serious deterioration in their condition.

However, there are several aspects in favour of the equity market signals: First, as demonstrated in this paper, one can derive unbiased equity market-based fragility indicators, which are increasing in the asset value volatility. The probability of default estimates already derived from the equity market data in certain applications (e.g. KMV Corporation 1999) can represent such indicators.

Second, there is no apparent reason to doubt that the equity markets are efficient in processing available information on banks (as on other companies) and in reflecting this information into the equity prices. Empirical evidence broadly supports that equity-holders respond rationally to news concerning: banks' asset quality (Docking et. al 1997), risks in LDC loans (e.g. Smirlock and Kaufold 1987, and Musumeci and Sinkey 1990), other banks' problems (e.g. Aharoney and Swary 1996), or rating changes (op. cit).

Third, monitoring the market value of equity is important for prudential purposes. When it falls relative to debt, default risk is increased given the amount of asset risk and equity-holders value more asset value volatility, increasing the moral hazard. Indeed, some authors have acknowledged specific merit in following both equity and bond market indicators (e.g. Bliss and Flannery 2000, Hancock and Kwast 2000).

Fourth, while bond spreads are in principle easy indicators to interpret, implementing them in an appropriate manner is difficult. This may be foremost due to the large number of bonds outstanding by the same banks of various qualities, possibly yielding different signals (Hancock and Kwast 2000). Moreover, monitoring must concentrate on sufficiently liquid bonds in order to abstract from the premium on illiquid issues. 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 we will further explain below. While both equity and bond prices can be noisy, and hence difficult to interpret in practise, equity prices are unique and unambiguous. The equity markets are also often quite deep and liquid, increasing the efficiency of the market to factor relevant information into prices.

This paper aims to contribute by investigating the usefulness and leading properties of specific equity and bond market indicators of bank fragility, and by using data on European banks since the early 1990s.

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 demonstrate 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. Thus, these indicators are preferred over biased direct equity price-based measures and could represent useful leading indicators of bank fragility. However, the main handicap of the bond market signals as indicators of especially large and systemically relevant banks' fragility is that they might be substantially weakened by the presumption of public bailout in case of serious trouble.[4] Equity-based distance-to-default does not suffer from this handicap.

We then analyse banks' distances-to-default and subordinated bond spreads in the secondary market[5] in relation to their capability of anticipating a material weakening in financial condition, which is defined as a substantial downgrading in the "individual rating", excluding the chance of public support. These events appear to evidence major banking problems; after most such downgrading there is either a public support operation or a significant restructuring of the bank in question.

We use two different econometric models: a logit-model, estimated for a number of different time-leads, and the Cox proportional hazard model. We find support in favour of using both the distance-to-default and bond spreads 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 6 to 18 months in advance, its predictive properties are quite poor closer to the "default" events. In contrast, all banks' subordinated debt spreads are found to have signal value, but only close to the events. Otherwise, they appear to be significantly diluted by the expectation of implicit safety net and, hence, indicative only for (smaller) banks which do not enjoy from a presumed safety net. Also, we are unable to fully explain the much higher spreads in the UK during our sample period. Our results indicate that stronger expectations of a public safety net do not dilute the predictive power of the distance-to-default.

The remainder of the paper is organised as follows: Section II examines the basic properties of the equity and bond market indicators and frames our empirical propositions. Section III defines our sample and the variables used in the empirical study. Section IV contains descriptive analyses of the behaviour of the market indicators. Section V reports our econometric specifications and results. Finally, Section VI concludes.

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4 Flannery (2000) calls for more evidence on the issue whether the "too-big-to-fail"-problem affects the debenture spreads.

5 The secondary market spreads may be more interesting for the ongoing monitoring of bank fragility than the spreads at issue. In the absence of mandatory issuance requirements, such as those proposed by Calomiris (e.g. 1997), banks' new issuance could be too infrequent, or limited to periods when pricing is advantageous.

II. Properties of market indicators and empirical propositions

Any indicator of bank fragility should reflect the three major determinants of default risk: (i) the *market value of assets* (V_A), reflecting all relevant information about earnings expectations; (ii) the *book value of debt liabilities* (V_L), reflecting the contractual obligations the bank has to meet; and (iii) the *volatility of the asset value* (σ_A), reflecting asset risk. An indicator incorporating all these elements could be called *complete*. While V_L is observable, V_A and σ_A are not. This is particularly the case for banking due to the lack of secondary markets for bank assets. Therefore, market value and volatility of assets have to be proxied or derived from observable variables.

The fragility (or default probability) indicators (DI) should also be aligned with the *supervisors' conservative perspective*. Therefore, any such indicator should meet the following conditions:

$$\text{(i)}\ \frac{\partial \mathrm{DI}}{\partial \mathrm{V_A}}\Big|\mathrm{V_L} < 0, \text{(ii)}\ \frac{\partial \mathrm{DI}}{\partial \mathrm{V_L}}\Big|\mathrm{V_A} > 0, \text{and (iii)}\ \frac{\partial \mathrm{DI}}{\partial \sigma_\mathrm{A}} > 0. \tag{1}$$

These conditions require the indicator to be decreasing in the earnings expectations (given the amount of debt liabilities), increasing in leverage, and increasing in the asset risk. If one or more of the three conditions are not met, we will call the indicator *biased*.

A complete and unbiased indicator would be more appropriate as an early indicator of bank fragility than an incomplete or biased indicator, since the latter would not fully or appropriately capture the elements affecting the default probability.

II.A Equity market indicators

We find the basic option-pricing theory adequate and helpful to demonstrate the key properties of the market indicators. Equity-holders have the residual claim on a firm's assets and have limited liability. According to Merton's (1977) well-known idea, equity can be modelled as a *call option* on the assets, with a strike price equal to the book value of debt, capturing the above properties. 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 the book value of debt liabilities (V_L). We resort to the basic Black and Scholes' (1972) (BS) formula:

$$
\begin{aligned}
&V_E = V_A N(d1) - V_L e^{-rT} N(d2), \text{and} \\
&\sigma_E = \left(\frac{V_A}{V_E}\right) N(d1)\sigma_A, \text{ where} \\
&d1 \equiv \frac{\ln\left(\frac{V_A}{V_L}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}, d2 \equiv d1 - \sigma_A\sqrt{T},
\end{aligned} \tag{2}
$$

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 equity market indicators based on V_E are complete, since market prices reflect the relevant information for capturing default risk (V_A, V_L and σ_A), but also the bias in directly using them can be readily appreciated. The well-recognised bias of equity prices or market capitalisation (also in relation to sectoral or market indices) as signals of fragility arises, because V_E is increasing in σ_A. More specifically, the call option value[6] embedded in the equity value increases with the asset risk (violating condition (iii) in (1)). Therefore, an increase in the share prices and market capitalisation may not be consistent with decreased default risk.

However, it is possible to derive clearly unbiased equity market-based fragility indicators. The negative of the distance-to-default (-DD),[7] derived from the BS model, represents such an indicator (see Appendix 1 for its derivation):

$$
(-DD) = -\frac{\ln\frac{V_A}{V_L} + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} \equiv -d2, \tag{3}
$$

where V_A and σ_A are solved from the non-linear two equation system in (2). DD indicates the number of standard deviations (σ_A) from the default point ($V_A = V_L$).

Result 1. *(-DD) is a complete and unbiased indicator of bank fragility.*

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6 The call option value (V_{CO}) can be expressed as $V_{CO} = V_E N(d1) - V_L e^{-rT} N(d2)$. It is increasing in σ_A, since d1 is increasing and d2 decreasing in σ_A. According to Bliss (2000), however, this property of a straightforward (monotonic and increasing) relation between the asset value volatility and the call option value may depend on the specific distribution assumption for the underlying asset value.

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

(-DD) reflects V_A,V_L, and σ_A, hence it is complete. Clearly, $\frac{\partial(-DD)}{\partial V_A}|V_L < 0$ and $\frac{\partial(-DD)}{\partial V_L}|V_A > 0$. $\frac{\partial(-DD)}{\partial \sigma_A} = \frac{1}{2}\sqrt{T} + \sigma_A^{-2} T^{-1/2}\left(\ln\left(\frac{V_A}{V_L}\right) + rT\right) > 0$, since $\ln\left(\frac{V_A}{V_L}\right) > 0$, when above the default point. (–DD) meets (1) (i), (ii), and (iii); hence, it is unbiased.■

Thus, the composite measure (-DD) is preferred indicators, and we will apply it in the empirical investigation.[8]

II.B Bond market indicators

Following Merton (1977), also risky debt can be valued using the option-pricing framework. Namely, the observable market value of the debt (MV_L) can be expressed as the value assuming no default risk (MV^*_L)[9] minus the value of the *put option* on the firm's assets (V_{PO}). The put option represents the value of the limited liability, i.e. equity-holders' right of walking away from their debts in exchange for handing over the firm's assets to the creditors. The strike price is again the book value of debt. Hence:

$$\begin{aligned} & MV_L = V_L e^{-y(T)T} = MV_L^* - V_{PO} = V_L e^{-r(T)T} - V_L e^{-r(T)T} N(-d2) + V_A N(-d1) \Leftrightarrow \\ & MV_L = (1 - N(-DD))MV_L^* + V_A N(-d1), \end{aligned} \tag{4}$$

where y(T) is the yield to maturity on the debt issued by the firm. The second equation shows that the reduction in the market value from the "no-default-risk" value is increasing in (-DD) and decreasing in V_A. That is, it is increasing in the default risk.

Because it is common to discuss bond pricing in terms of yields rather than values, (4) can be rewritten as below, following Merton (1974) and assuming that the firm has only one type of debt:

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8 Equity volatility would also constitute a complete (ref. equations (2)) and unbiased fragility indicator as it meets all the conditions in (1). It is simpler to observe than (-DD), but less straightforward to interpret, since (-DD) directly indicates how close the firm is to the default point in terms of the standard deviations of asset value. We also found in our estimations that (-DD) performs better than σ_E. Equity volatility is usually regarded as a proxy for asset risk, which is appropriate as it is increasing in σ_A.

9 I.e. the discounted value of the interest and principal payments, using the risk-free interest rate, r(T).

$$S \equiv y(T)-r(T) = -\frac{1}{T}\ln\left\{N(h2)+\frac{1}{k}N(h1)\right\}, \text{where}$$

$$h1 \equiv -\frac{1/2\sigma_A^2 T - \ln(k)}{\sigma_A\sqrt{T}}, h2 \equiv -\frac{1/2\sigma_A^2 T + \ln(k)}{\sigma_A\sqrt{T}}, \text{and } k \equiv \frac{V_L e^{-r(T)T}}{V_A}, \tag{5}$$

$$\text{where } e^{-y(T)T} = \left(\frac{MV_L}{V_L}\right),$$

where S, the spread over and above the risk free yield to maturity, indicates the credit *risk premium* (in the absence of any liquidity premium).[10]

Result 2. *S is a complete and unbiased indicator of bank fragility.*

By (5), S reflects V_A,V_L, and σ_A, hence it is complete. By (4) $\frac{\partial(MV_L)}{\partial(-DD)} < 0$ and $\frac{\partial(MV_L)}{\partial(V_A)} > 0$. Hence, S is unbiased, since it is decreasing in MV_L.■

The completeness of the bond spread, as the equity market indicators, is not surprising, since market prices should reflect all available information. Traditional accounting measures, such as leverage ratios or earnings indicators can be incomplete and therefore less appropriate than (-DD) and S.

As noted, complete and unbiased market indicators should be capable of signalling an increase in the default risk in a timely fashion. [11] Thus, the key proposition whose validity we will test in the empirical analysis 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.*

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[10] 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 (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.

[11] 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.

II.C Impact of the safety net

In case of fully *insured debt* (like insured deposits), the market value of that debt equals the "no-default-risk" value ($MV_L = MV^*_L$) (Merton 1977, Ron and Verma 1986). Hence, there is no signal of bank fragility obtainable from the pricing of this debt. Any market discipline also requires that deposit insurance is explicitly restricted, leaving out some creditors with their money at stake (e.g. Gropp and Vesala 2001).

The literature (e.g. 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 (i.e. the "*too-big-to-fail issue*"). 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 be equal to the "no-default-risk" value also in this case and all uninsured debt-based fragility indicators would be incomplete and fail to capture increased default risk.

The *perceived probability of bailout* can actually be less than one for many banks, since there is typically no certainty of public support under an explicitly restricted deposit insurance system, as authorities follow the policy of constructive ambiguity. Under these circumstances the put option would play some role, but the debt-based fragility indicators would be weaker. The existence of positive spreads on banks' uninsured debt issues suggests that the perceived probability might be indeed less than one. However, the history of bank bailouts by the government (significant banks have not actually failed in Europe) 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 a reducing effect on banks' risk taking in Europe when explicit and restricted deposit insurance schemes were introduced, but they also produce evidence in favour of the "too-big-to-fail" contention.[12]

The equity-holders are affected by the safety net in a different way. First, the market value of equity can fall down to the call option value (i.e. close to zero) when the earnings prospects and asset quality are reduced, even when liquidation is always

[12] In addition, the findings of Gropp and Richards (2001) that banks' bond spreads do not appear to react to ratings announcements could be taken as evidence in favour of widespread safety nets.

prevented. Hence, it behaves differently from the market value of debt, which remains unaffected when the safety net is in place. Second, the existence of the safety net would, according to the literature, 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). However, (-DD) would still capture these elements increasing the de facto default risk.

Hence, we can formulate an additional proposition for the empirical study:

Proposition 2. *If the expectation of the public safety net were relevant for a particular bank, the uninsured bond spread (S) would be a weaker leading indicator of bank fragility than (-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 naturally an empirical question. Our goal is to evaluate the usefulness of the preferred (complete and unbiased) market indicators (-DD and S) for this purpose (Proposition 1). We will also test whether the perception of the safety net dilutes the predictive power of the bond market signals, but leaves the equity market signals intact (Proposition 2).

III. Empirical implementation

Our data set is assembled on a *monthly basis*, starting from January 1991. A yearly frequency would likely be too sparse to examine the leading properties of the market indicators. On the other hand, using monthly data allows us to abstract from the noise in the daily equity and bond market data. The data set consists of the EU banks, for which the necessary rating, equity and bond market information is available.

We started from roughly 200 rated EU banks. The sample was then limited by the availability of market data. The two sub-samples used in evaluating the equity and bond market signals, respectively, differ due to data availability: the equity market sample has 83 and the bond market sample 60 banks (see Table 1). There are banks from 14 (equity sample) and 12 (bond sample) EU countries.

III.A Events of banking problems

We were faced with the common problem that no European banks formally declared bankruptcy during our sample period. In the absence of actual bank defaults, we considered a substantial downgrading in the Fitch/IBCA "individual bank rating" to the C category or below as an event of materially weakened financial condition. These downgradings were allocated to each month, depending on the dates of the events. There are 25 such downgradings in the equity and 21 in the bond sub-sample, 32 such banks in total (see Table 2).

We found this choice reasonable for two main reasons: First, the "individual ratings" exclude any safety net expectations and, hence, they should indicate banks' actual financial condition. A downgrading by Fitch/IBCA 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 downgrading 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 (9 of them only after the downgrading event), and 8 banks underwent a major restructuring after the downgrading. The support or restructuring operations also often took place relatively soon after these events. In the remaining cases, major financial problems were indicated, but no public support or substantial restructuring were required.

Hence, the specific downgradings we look at should indeed evidence material banking problems.[13] Also because the downgradings tend to precede rather than lag the actions aimed at resolving the problem, it is sensible to study the behaviour of the market signals prior to the downgrading events.

Our study is similar to the US studies investigating the relationship between market information and supervisory ratings (Evanoff and Wall 2000b, DeYoung et. al. 2000, and Berger et. al. 2000, op. cit), while we use the "individual ratings" as signals of banking problems.[14] We do not have similar access to historical supervisory information on individual banks. The supervisory ratings may of course be based on more information, including confidential information, but they may also be subject to forbearance.

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[13] The control sub-sample of the non-downgraded banks should not contain cases of problems of a similar magnitude, also since these banks have not so far received a similar downgrading in their "individual ratings". We might nevertheless miss some problem cases due to lack of market data (e.g. some Scandinavian banks in the early-1990s).

[14] Evanoff and Wall (2000b) consider 13 downgradings in supervisory CAMEL ratings in a sample of 557 US banks, constituting the default events. Hence, our sample appears reasonably large.

III.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) (i.e. month) using that period's equity market data. The system of two equations in (2) was solved by using the generalised reduced gradient method to yield the V_A and σ_A values, entering into the calculation of the (-DD) values. Variable definitions are given in Table 3 and descriptive statistics in Table 4.

As to the inputs to the calculation of the (-DD) values, we took 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 6-month moving average (backwards) to abstract from noise (as e.g. in Marcus and Shaked 1984). The presumption is that the market participants do not use the very volatile short-tern 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 (e.g. Bongini et. al. 2001). The total debt liabilities (V_L) are obtained from published accounts and are interpolated (using 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).[15]

The BS formula assumes a cumulative normal distribution (N) for the underlying asset values. As pointed out by Bliss (2000), this assumption may not hold in practice. A major reason could be that the normal distribution does not take into account that closer to the default point adjustment in debt liabilities will likely take place. However, the exact modelling of the distribution is more relevant when one aims at realistic probability of default estimates (which is especially difficult for banks due to the shortage of actual defaults to draw upon). The basic BS formula is sufficient for our purposes to examine the performance of the (-DD) measure.[16]

We largely followed convention when calculating the monthly averages of the secondary market *subordinated debt spreads* (S). 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 euro 150 million. This figure seemed the best compromise between maintaining

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[15] The values solved for V_A and σ_A were not sensitive to changes in the starting values.

[16] For the BS formula, the implied probability of default is just N(-DD) (see Appendix 1).

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 fixed rate, straight, 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. For the smaller countries, we were largely unable to find them. In these countries, banks more frequently issued foreign than domestic currency-denominated bonds prior to the introduction of the euro. Hence, we largely used foreign currency issues (DM, euro, USD and in one or 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 UK and calculated spreads for banks in those countries relative to the corresponding point on those curves. For the other smaller countries, we were so far unable to obtain sufficient data to construct full risk-free yield-curves. We therefore resorted to matching 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.

III.C Expectation of public support

In order to test for the validity of Proposition 2, 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. 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 be possibly "systemically" important also for other reasons. The weaker "support ratings" (from 3 to 5) depend on the likelihood of private support from the parent organisation or owners, not anymore assuming public support.

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) as expected, 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.

IV. Descriptive analyses

We constructed our sample for the empirical analyses 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. Hence, we use several observations for the same bank in case the bank does not "default" during our sample period.

We conducted *t-tests* to assess whether (-DD) and S are able to distinguish weaker banks within our data set so that the mean values of these indicators differ in a statistically significant manner in the two sub-samples of "defaulted" and "non-defaulted" banks. We also examined in a preliminary fashion whether the indicators could lead the downgrading events by performing the tests for various time leads up to two years (x = 3, 6, 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 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). Table 5 omits UK banks, since their spreads are, on average, significantly higher (by around 100 basis points) than those of the other banks in our sample.[17] The inclusion of the UK banks, however, does not change the basic results. We control for this level-difference in the empirical estimations by adding dummy variables.

The "default" indicators will actually 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 (e.g. Flannery and Sorescu 1996). The two market indicators will reflect the first point very well, only if we control for the second.

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[17] Also Sironi (2000) finds that the UK banks' spreads are significantly higher. He considers that this is, inter alia, due to a weaker presumption of government support.

Table 6 offers 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. Namely, for the banks with a "support rating" of 3 or higher, 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. The (-DD) of downgraded banks continues to be significantly higher, when only the banks without a strong presumption of government support are considered. We only present the t-tests up to x equal 12 months, since beyond that the number of downgraded banks that can be included becomes low. A caveat is in order, since that number is in any case low in this comparison as far as the spreads are considered (see Table 6).

V. Empirical estimations

V.A Empirical models

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:

$$\mathrm{STATUS}_t = \psi(\alpha_0 + \alpha_1 \mathrm{DI}_{t-x} + \alpha_2 \mathrm{DSUPP}_{t-x} * \mathrm{DI}_{t-x}) \tag{6}$$

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

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

We ran the model for different horizons separately, i.e. we investigate the predictive power of our two indicators 3, 6, 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 2. Then, the safety net expectation would be the reason of weak bond market signals in case of "systemically important" (or guaranteed banks), rather than just the inefficiency or noisiness of the market signals.

We considered the possibility of further including balance sheet measures in the regression, but refrained from doing so for two reasons: First, in theory they should already be incorporated in our complete indicators, as they reflect all relevant available information at time (t-x). Second, we are using monthly data to estimate the model and balance sheet information is available less frequently (annually or semi-annually). Naturally, should one strive to develop a full-fledged early warning model, additional explanatory variables might improve the model performance.

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 a generalised method based on Huber (1967).

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

$$\mathrm{TDF} = h_0(t)e^{\beta_1 \mathrm{DI} + B_2 X}, \tag{7}$$

where TDF represents the time to "default", measured in months, $h_0(t)$ the baseline hazard, 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

$$\ln L = \sum_{j=1}^{D} \left\{ \sum_{r \in D_j} (\beta_1 \mathrm{DI}_r + B_2 X_r) - d_j \ln\left[\sum_{i \in R_j} \exp(\beta_1 \mathrm{DI}_i + B_2 X_i) \right] \right\}, \tag{8}$$

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.

The two models, aside from providing a robustness check whether equity and bond market indicators have signalling property as regards bank "defaults", also provide insights into two decidedly different 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.

V.B Logit-estimation results

Table 7.A reports the results from estimating the *logit-models* with the different time-leads. According to the estimated coefficients, an increased (-DD) value tends to predict a greater likelihood of financial trouble. The respective coefficient is significant at the 10%-level for the 6, 12 and 18-month leads. Hence, (-DD)s have certain predictive properties (in line with Proposition 1) of an increased (unconditional) likelihood of future problems up to 18 months in advance, which represents a quite substantial lead-time. The coefficient ceases to be significant for the lead of two years. This is an interesting finding, because it suggests that the (-DD) has a desirable time-series property; namely that it could signal an increase in the likelihood of financial problems over time.

The insignificance of the coefficient capturing the 3-month lead is somewhat puzzling. The reason seems to be increased noise in the (-DD) measure closer to the surfacing of the financial problems, as e.g. the standard error of the (-DD)s is higher for the 3 than the 6-month leads among the downgraded banks (see Table 5). More specifically, 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. This could be a result of lowered trading activity in this period.[18]

The results support the predictive performance of the spreads as well up to 18 months in advance (see Table 7.B).[19] The coefficients in case of a 3-month lead are also significant, in contrast to (-DD). However, the predictive capability only holds for banks with a weaker "support rating" than 2, i.e. the banks with a lower expectation of public support. The coefficient of the interacted term (DSUPP*S_{t-x}) is significant and negative,

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[18] In order to assess the impact of the point-in-time (-DD)s and their greater noisiness, we also estimated the logit-models using less bouncy averages of the (-DD)s over a time-frame of 6 months before (t-x). The results were similar to those presented in Table 7.A, but now the coefficients of (-DD_{t-x})s were more strongly significant and also the coefficient for (-DD_{t-3}) was significantly positive.

[19] We estimated (6) using S_{t-x} with intercept and interactive dummies for UK banks. Table 7.B reports the results from this model, including the UK dummies. The dummies were significant, as the UK banks' spreads are significantly different. In the interest of space, we do not report these coefficients here.

and, according to the F-tests, the spread coefficient is zero for the banks with a greater expectation of public support. In contrast, our results indicate that stronger expectations of a public safety net do not dilute the predictive power of the (-DD) measure. There is no statistically significant difference among banks according to presumed government backing.[20]

A caveat is in order here, since particularly the spreads may be subject to measurement and data quality uncertainty, which is a major handicap in implementing them as a monitoring variable. The measurement of the (-DD)s is also subject to some uncertainty as regards the establishment of the volatility estimates and the specific assumptions behind the BS formula.[21]

As an extension, is interesting to examine whether the market indicators actually contain information, which is not already summarised in publicly available information such as ratings. To this end, we compared banks with the same “individual rating” at the time the market indicators were observed. Within this group there were both eventually downgraded and non-downgraded banks. We then ran the logit-models using the smaller sample of identically rated banks. The results given in Table 8.A for the (-DD) measure are quite similar to those reported in Table 7.A.[22] They suggest that the (-DD) indicator adds to the information obtainable from (Fitch/IBCA) ratings. The results are similar also for the spreads (see Table 8.B) compared with those from the full sample-estimations.

Finally, 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 ran the logit-models using the equity volatility as the fragility indicator. It, however, 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. Second, the same findings held for a simple leverage measure (V_E/ V_L).

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20 The coefficient of the interacted variable DSUPP*(-DD_{t-x}) is never statistically significant. Moreover, F-tests reject the hypothesis that the coefficient of (-DD_{t-x}) is zero for the banks with a strong expectation of government support (except for x=24).

21 We also tested for the robustness of our logit-model estimation results by running corresponding Probit-models. While different results could follow, especially when the samples are unbalanced by STATUS, we did not find a significant impact on the estimated coefficients.

22 We only report the time-leads until 12 months in advance, since otherwise the number of “defaulted” banks becomes too small. We also omitted the results for the (-DD) measure when x equal 3 months, since the results are practically the same.

V.C Hazard-estimation results

Tables 9 and 10 give the *hazard ratios* and corresponding P-values for a model without any control variables for both (-DD) and S. Both indicators are significant: (-DD) at the 1% and S at the 10%-level; and 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 (i.e. the zero-slope test), which amounts to testing, whether the null hypothesis of a constant log hazard-function over time holds for the individual co-variates as well as globally. For (-DD), this assumption is violated. Hence, we present in Table 11 results from an alternative model specification, in which we use a dummy variable of the following form

$$\text{ddind} = \begin{cases} 1 \text{ if } (-\text{DD}) > -3.2 \\ 0 \text{ otherwise} \end{cases}, \tag{9}$$

where –3.2 represents 25[th] percentile of the distribution of (-DD). Hence, in this specification, we investigate whether (-DD)s predictive qualities are largely driven by (weaker) banks with relatively high (-DD)s. 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 9 and 10). 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 UK. While we do not find here a significant effect of the safety net dummy, Table 12 shows that the coefficient of the spread significantly improves when controlling for the UK by means of a dummy variable. S now is significant at the 1%-level. In addition, the dummy for the UK is significant at the 5%-level: higher spreads in the UK are associated with a significantly lower hazard ratio, i.e. 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.

The most convenient way to interpret the results is to consider the Nelson-Aalen *cumulative hazard functions*, which are depicted in Chart 1. The cumulative hazard functions display the probability of "default", 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 in those banks that have a default indicator in the top 25th percentile and all other banks. We can then test whether the cumulative hazard 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 cumulative hazard functions for the two groups at the 5%-level.

Even more interesting, we can read the difference in the "default" probability, given that a bank has remained in one or the other group. For (-DD), we find no difference in the hazard even after 2 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% 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, banks with a spread of 95 basis points or more for 24 months are 30% more likely to fail, which increases after 36 months to 60%. The results also highlight that the prevalence of indicators matters, which suggests that the use of hazard-models add 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, it turns out that, empirically, S might react more close to the "default" 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). This corresponds to our earlier results, which we attributed to a reduction in measured volatility of stock prices. S does not apparently suffer from this kind of a measurement problem closer to the "default" event. The strong reaction of the spreads close to the "default" may also be explained by the presumption that debt-holders only react when they judge a significantly increased probability of default, as they only face the downside risks.[23]

We present, finally, log-rank tests of the equality of cumulative hazard functions for those banks with an implicit safety net ("support rating" of 1 or 2) and UK banks in

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[23] In terms of equation (4), this property is reflected in the relatively smaller difference between the market and "no-default-risk" value of the debt farther away from the default point, compared with the more than proportionally greater difference closer to that point. The implied probability of default N(-DD) is quite small for high DD values and more than proportionally higher for low DD values. This property is obviously dependent on the distributional assumption for the asset value.

Table 14. We cannot reject the equality for the "supported" versus "non-supported" banks for both indicators. However, we do find significant differences between the hazard functions in continental Europe and the UK for both indicators.[24]

Hence, we have apparently contrasting findings concerning the dilution of the signal obtainable from the bond spreads depending on whether we use the logit or the hazard-specification. However, the two approaches are different. The logit-estimations test for the (unconditional) predictive signals from the market indicators with specific lead-times, while the hazard-specification measures the impact of the signal on the conditional likelihood of "defaulting" in the following month. Since we found robust evidence that the spreads mostly react only close to the "default" events, the results from the logit and hazard-models are not necessarily in disagreement as to the weak longer-term predictive power of the spreads as bank fragility indicators when there is stronger presumption of public support.

VI. Conclusion

In this paper, we found evidence in favour of using option-pricing-based distance-to-default, derived from equity market data, as early indicators of bank fragility. We first demonstrated that it is a preferred indicator over biased equity price-based indicators, since it captures the major elements affecting default risk (completeness). It is also aligned with the supervisors' conservative perspective (unbiasedness). It performed as a leading indicator for our cases of apparent bank difficulty in the EU since early 1990s, measured as a downgrading in the Fitch/IBCA "individual rating" to or below the C-level. We found support to the use of these events, since in many cases there was a government support or major restructuring after such an event.

More specifically, our results from logit-model estimations supported that distance-to-default has certain predictive properties up to 18 months in advance. Also in our additional hazard-specification, distance-to-default was found to be an indicator, which has significant leading properties for events further in the future. Based on our findings, however, its predictive property is poor close to the "default" events, which we attributed to typically erratic equity trading behaviour. Banks might also "survive" relatively long with short distances-to-default.

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[24] While we might attribute the difference for spreads to the more credible absence of a safety net even for bigger banks in the UK, the reason for the difference in the case of the distance-to-default remains somewhat unclear.

In the logit-estimations, the subordinated bond spreads were found to predict financial difficulty longer in advance only in the case of (smaller) banks, which do not enjoy 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, in line with our prior reasoning.

The hazard-results indicate, however, that all banks' spreads do react very close to the "default" events in a manner, which indicates a substantially greater (conditional) probability of "defaulting". Hence, it turned out that, empirically, the spreads might react more close to the "default" than the distances-to-default. We attributed this finding (at this stage) to the presumption that uninsured debt-holders tend to react only when they judge a considerably increased probability of default based on the information available to them, as they are merely faced with the downside risks.

All in all, our findings suggest that more attention should be devoted 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 focus has up until now been quite much on the subordinated debt spreads.

According to our results, the main practical difficulty in using the distance-to-default measure, apart from its relative complexity, as a part of a supervisory early warning system is that it can be sensitive to shifts in derived asset volatility. This, in turn, may be due to irregularities in the equity trading in the period closer towards a "default" event. The measurement of equity volatility and the distributional assumptions for the option-pricing theory are also subject to uncertainty. The major practical difficulties in assembling the bond spreads are related to difficulty and some uncertainty in calculating the spreads, both because of potentially weak price data on bank bonds and difficulty of establishing the risk-free benchmarks (especially for small countries). Also, we are unable to fully explain the much higher spreads in the UK during our sample period.

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Table 1.

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

	Equity	Bond		Equity	Bond
Belgium	3	1	Italy	20	7
Denmark	2		Netherlands	3	4
Germany	11	16	Austria	3	2
Greece	5		Portugal	4	1
Spain	8	2	Finland	1	2
France	8	9	Sweden	3	3
Ireland	4	2	United Kingdom	11	10
			Total	**83**	**60**

Table 2.

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

Bank	Downgrading	Support / restructuring / other	Timing
A. Cases of public support			
Banco Espanol de Credito**	June 93	Public financial support	Dec. 93
Banco di Napoli**	Jan. 95	Public capital injection	Early-96
Banco Nazionale del Lavoro	June 97	Public capital support in the form of a transfer of Artigiancassa	During 96
Bankgesellschaft Berlin	June 99	Re-capitalisation (partly government owned bank)	During 01
CPR	Nov. 98	Support from the parent group (CA)	End-98
Credit Lyonnais*	June 94	Public financial support	Spring 95
Credit Foncier de France	First rating (D) April 00	Public financial support	April 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	July 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, e.g. new management	During 96
Bank Austria	June 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	March 99	Merger with Banque La Hénin-Epargne Crédit (BLH).	
Creditanstalt	Jan. 97	Take-over by Bank Austria	Jan. 97
C. Other cases			
Banca Commerciale Italiana	June 00	Weak performance and asset quality	
Banca di Roma	Nov. 96	Depressed profitability and asset quality e.g. due to several acquisitions	
Banca Popolare di Intra**	Feb. 01	Weak performance and asset quality	
Banca Popolare di Lodi	June 00	Weak performance and asset quality	
Banca Popolare di Milano**	Nov. 95	Weak performance and asset quality	
Banca Popolare di Sondrio**	March 00	Weak performance and asset quality	
Banco Zaragozano**	March 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*	June 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 euro)
Equity volatility (σ_E)	6-month moving average (backwards) of daily absolute equity returns (%)
Book value of debt liabilities (V_L)	Total debt liabilities (interpolated monthly observations) (millions of euro)
Market value of assets (V_A)	Derived (equations (2)) monthly average of the total asset value (millions of euro)
Volatility of assets (σ_A)	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
Market value of equity (V_E)	x = 3 months	1190	10,414.63	17,358.73	13.64	191,638.50
	x = 6 months	1190	10,325.29	17,315.68	11.80	229,166.60
	x = 12 months	1187	9,329.10	15,637.97	13.79	183,194.90
	x = 18 months	1186	8,639.02	14,615.08	13.64	129,555.00
	x = 24 months	1183	7,756.20	13,498.53	11.84	104,839.40
Equity volatility (σ_E)	x = 3 months	1190	0.27	0.14	0.01	2.01
	x = 6 months	1190	0.27	0.14	0.01	2.01
	x = 12 months	1187	0.28	0.13	0.01	0.71
	x = 18 months	1186	0.27	0.15	0.01	2.06
	x = 24 months	1183	0.26	0.15	0.01	2.06
Book value of debt liabilities (V_L)	x = 3 months	1190	96,781.24	120,687.30	464.95	715,825.40
	x = 6 months	1190	93,748.14	116,515.20	441.31	688,596.30
	x = 12 months	1187	88,406.56	109,021.80	397.59	636,515.10
	x = 18 months	1186	83,918.67	102,677.10	358.20	556,785.40
	x = 24 months	1183	80,247.43	97,692.48	305.34	490,865.50
Market value of assets (V_A)	x = 3 months	1190	101,530.40	123,921.40	568.99	735,884.60
	x = 6 months	1190	98,640.95	119,941.70	519.16	710,956.70
	x = 12 months	1187	92,578.36	111,588.70	484.66	652,365.20
	x = 18 months	1186	87,450.19	104,826.30	365.65	569,511.20
	x = 24 months	1183	82,909.19	99,073.89	312.37	499,827.60
Volatility of assets (σ_A)	x = 3 months	1190	0.04	0.05	0.00	0.65
	x = 6 months	1190	0.04	0.05	0.00	0.65
	x = 12 months	1187	0.04	0.04	0.00	0.28
	x = 18 months	1186	0.04	0.05	0.00	0.73
	x = 24 months	1183	0.03	0.04	0.00	0.73
Negative of the distance-to-default (-DD)	x = 3 months	1190	-5.60	5.87	-87.71	0.99
	x = 6 months	1190	-5.57	6.02	-91.12	0.99
	x = 12 months	1187	-5.15	4.78	-71.71	-1.20
	x = 18 months	1186	-5.49	6.45	-133.89	1.05
	x = 24 months	1183	-5.67	6.17	-130.44	1.05
Spread (S)[1)]	x = 3 months	415	0.58	0.84	-0.49	5.86
	x = 6 months	414	0.56	0.84	-0.40	5.84
	x = 12 months	398	0.47	0.60	-0.27	5.41
	x = 18 months	379	0.43	0.58	-0.82	5.12
	x = 24 months	358	0.37	0.56	-0.62	5.12

1) Excluding UK banks.

Table 5.

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

*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.*

	Status	Nobs	Mean	Std. error	Difference[1]	Difference < 0[2]
Equity			**($-DD_{t-x}$)**			
x = 3 months	0	1165	-5.63	0.17	-1.53	-3.432***
	1	25	-4.10	0.41		
x = 6 months	0	1165	-5.61	0.18	-1.76	-5.252***
	1	25	-3.85	0.28		
x = 12 months	0	1165	-5.18	0.14	-1.49	-4.591***
	1	22	-3.69	0.29		
x = 18 months	0	1165	-5.52	0.19	-1.80	-4.941***
	1	21	-3.72	0.31		
x = 24 months	0	1165	-5.69	0.18	-1.32	-2.425**
	1	18	-4.38	0.51		
Bond[3]			**S_{t-x}**			
x = 3 months	0	396	0.57	0.04	-0.28	-1.12
	1	19	0.85	0.25		
x = 6 months	0	381	0.46	0.03	-0.27	-0.85
	1	17	0.73	0.27		
x = 12 months	0	381	0.46	0.03	-0.27	-0.99
	1	18	0.70	0.25		
x = 18 months	0	366	0.43	0.03	-0.19	-0.75
	1	13	0.61	0.25		
x = 24 months	0	346	0.37	0.03	-0.09	-0.405
	1	12	0.46	0.21		

1) Mean (STATUS=0) – Mean (SATUS=1). 2) t-statistics for testing the hypothesis that Difference is negative. 3) Excluding UK banks.

Table 6.

Ability of (-DD) and S to distinguish weaker banks: mean value tests, banks with lower public support expectation

Two sub-sample t-tests (unequal variances) are reported for the difference in mean values of (-$DD_{t\text{-}x}$) and $S_{t\text{-}x}$ *in the sub-samples of downgraded (SATUS=1) and non-downgraded banks (STATUS=0), both when the "support rating" weaker than 2. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels.*

	Status	Nobs	Mean	Std. error	Difference[1]	Difference < 0[2]
Equity			**(-$DD_{t\text{-}x}$)**			
x = 3 months	0	436	-6.37	0.38	-1.68	-2.161**
	1	12	-4.69	0.68		
x = 6 months	0	436	-6.43	0.41	-2.25	-4.128***
	1	12	-4.18	0.36		
x = 12 months	0	436	-5.96	0.32	-2.58	-5.748***
	1	10	-3.38	0.31		
Bond[3]			**$S_{t\text{-}x}$**			
x = 3 months	0	89	0.25	0.02	-0.55	-1.972**
	1	5	0.79	0.28		
x = 6 months	0	83	0.23	0.02	-0.35	-2.850**
	1	5	0.58	0.12		
x = 12 months	0	78	0.22	0.02	-0.38	-1.549*
	1	4	0.60	0.25		

1) Mean (STATUS=0) – Mean (SATUS=1). 2) t-statistics for testing the hypothesis that Difference is negative. 3) Excluding UK banks.

Table 7.A

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

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

x =3 months

Explanatory variable	Coefficient	Robust std. error[2]	z	P>│z│
Constant	-2.952***	0.458	-6.450	0.000
$(-DD_{t-3})$	0.112	0.093	1.210	0.227
DSUPP*$(-DD_{t-3})$	0.156	0.105	1.490	0.136
Number of observations	1190		Log likelihood	-117.803
F-test[1]	5.01**			

x =6 months

Explanatory variable	Coefficient	Robust std. error[2]	z	P>│z│
Constant	-2.795***	0.441	-6.340	0.000
$(-DD_{t-6})$	0.176*	0.097	1.820	0.069
DSUPP*$(-DD_{t-6})$	0.109	0.109	1.000	0.315
Number of observations	1190		Log likelihood	-117.630
F-test[1]	6.06**			

x =12 months

Explanatory variable	Coefficient	Robust std. error[2]	z	P>│z│
Constant	-3.057***	0.465	-6.570	0.000
$(-DD_{t-12})$	0.208*	0.108	1.920	0.054
DSUPP*$(-DD_{t-12})$	0.015	0.118	0.120	0.901
Number of observations	1187		Log likelihood	-107.153
F-test[1]	3.280*			

x =18 months

Explanatory variable	Coefficient	Robust std. error[2]	z	P>│z│
Constant	-2.961***	0.519	-5.710	0.000
$(-DD_{t-18})$	0.259*	0.142	1.820	0.069
DSUPP*$(-DD_{t-18})$	-0.018	0.125	-0.140	0.886
Number of observations	1186		Log likelihood	-102.742
F-test[1]	3.66*			

x =24 months

Explanatory variable	Coefficient	Robust std. error[2]	z	P>│z│
Constant	-3.613***	0.535	-6.760	0.000
$(-DD_{t-24})$	0.140	0.116	1.200	0.228
DSUPP*$(-DD_{t-24})$	-0.041	0.109	-0.370	0.710
Number of observations	1183		Log likelihood	-92.135
F-test[1]	0.75			

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

Table 7.B

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

*All models are estimated using the binary variable STATUS as the dependent variable and including (intercept and interactive) dummy variables for the UK banks. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.*

x = 3 months

Explanatory variable	Coefficient	Robust std. error(2	z	P>│z│
Constant	-3.495***	0.385	-9.070	0.000
(S_{t-3})	2.841***	1.109	2.560	0.010
DSUPP*(S_{t-3})	-2.564**	1.090	-2.350	0.019
Number of observations	545		Log likelihood	-72.398
F-test(1	1.37			

x = 6 months

Explanatory variable	Coefficient	Robust std. error(2	z	P>│z│
Constant	-3.627***	0.420	-8.640	0.000
(S_{t-6})	3.968**	1.571	2.530	0.012
DSUPP*(S_{t-6})	-3.661**	1.529	-2.390	0.017
Number of observations	542		Log likelihood	-69.158
F-test(1	1.68			

x =12 months

Explanatory variable	Coefficient	Robust std. error(2	z	P>│z│
Constant	-3.576***	0.402	-8.890	0.000
(S_{t-12})	3.229**	1.314	2.460	0.014
DSUPP*(S_{t-12})	-2.791**	1.288	-2.170	0.030
Number of observations	522		Log likelihood	-71.314
F-test(1	2.45			

x =18 months

Explanatory variable	Coefficient	Robust std. error(2	z	P>│z│
Constant	-3.690***	0.440	-8.390	0.000
(S_{t-18})	2.775**	1.119	2.480	0.013
DSUPP*(S_{t-18})	-2.457**	1.091	-2.250	0.024
Number of observations	498		Log likelihood	-56.286
F-test(1	0.71			

x =24 months

Explanatory variable	Coefficient	Robust std. error(2	Z	P>│z│
Constant	-3.571***	0.467	-7.640	0.000
(S_{t-24})	2.322	2.362	0.980	0.326
DSUPP*(S_{t-24})	-2.117	2.278	-0.930	0.353
Number of observations	469		Log likelihood	-56.522
F-test(1	0.23			

1) F-test for the hypothesis that the sum of the coefficients of (S_{t-x}) and DSUPP(S_{t-x}) is zero (i.e. the coefficient of (S_{t-x}) is zero for banks with a greater expectation of public support). χ^2 values reported. 2) Standard errors adjusted.*

Table 8.A

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

*Logit-estimations are reported for a sub-sample of downgraded and non-downgraded banks, consisting only of banks with the same "individual rating" before the event. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels.*

x =6 months

Explanatory variable	Coefficient	Robust std. error	z	P>∣z∣
Constant	-2.311***	0.487	-4.750	0.000
($-DD_{t-6}$)	0.205*	0.124	1.650	0.098
DSUPP*($-DD_{t-6}$)	-0.083	0.122	-0.680	0.495
Number of observations	463		Log likelihood	-83.273
F-test	1.53			

x =12 months

Explanatory variable	Coefficient	Robust std. error	z	P>∣z∣
Constant	-2.353***	0.585	-4.020	0.000
($-DD_{t-12}$)	0.360*	0.189	1.910	0.057
DSUPP*($-DD_{t-12}$)	-0.217	0.163	-1.320	0.185
Number of observations	471		Log likelihood	-66.630
F-test	1.39			

See notes in Table7.A.

Table 8.B

Predictive performance of the bond spread indicator: logit-estimations, identically-rated banks

*Logit-estimations are reported for a sub-sample of downgraded and non-downgraded banks, consisting only of banks with the same "individual rating" before the event. *, **, *** indicate statistical significance at the 10%, 5% and 1% levels.*

x =3 months

Explanatory variable	Coefficient	Robust std. error	z	P>∣z∣
Constant	-2.655***	0.434	-6.120	0.000
(S_{t-3})	3.055**	1.512	2.020	0.043
DSUPP*(S_{t-3})	-2.662*	1.510	-1.760	0.078
Number of observations	182		Log likelihood	-56.065
F-test(1	2.830*			

x =6 months

Explanatory variable	Coefficient	Robust std. error	z	P>∣z∣
Constant	-2.802***	0.468	-5.990	0.000
(S_{t-6})	4.374**	1.757	2.490	0.013
DSUPP*(S_{t-6})	-3.967**	1.738	-2.280	0.022
Number of observations	182		Log likelihood	-53.486
F-test(1	2.430			

x =12 months

Explanatory variable	Coefficient	Robust std. error	z	P>∣z∣
Constant	-2.722***	0.452	-6.020	0.000
(S_{t-12})	3.544**	1.781	1.990	0.047
DSUPP*(S_{t-12})	-3.018*	1.776	-1.700	0.089
Number of observations	175		Log likelihood	-51.885
F-test(1	3.040*			

See notes in Table7.B.

Table 9.

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

*Estimated using Cox regression. The dependent variable is the number of months in the sample. 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.*

Explanatory variable	**Hazard ratio**	**Robust std. error**	**z**	**P>│z│**
(-DD)	0.232***	0.116	2.92	0.004
Number of subjects	83	Time at risk		5365
Number of failures	25	Starting log likelihood		-100.49
Number of observations	5365	Final log likelihood		-95.44
Wald χ^2	8.52***	Zero-slope test		4.72**

Table 10.

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

*Estimated using Cox regression. The dependent variable is the number of months in the sample. 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.*

Explanatory variable	**Hazard ratio**	**Robust std. error**	**z**	**P>│z│**
S	1.40*	0.273	1.73	0.083
Number of subjects	58	Time at risk		3257
Number of failures	17	Starting log likelihood		-60.82
Number of observations	3257	Final log likelihood		-59.64
Wald χ^2	3.00*	Zero-slope test		0.56

Table 11.

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

*Estimated using Cox regression. The dependent variable is the number of months in the sample. 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.*

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	82	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

Table 12.

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

*Estimated using Cox regression. Log-likelihood given in the text. The dependent variable is the number of months in the sample. Standard errors are corrected for clustering using Wei and Lin's (1989) method. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels.*

Explanatory variable	**Hazard ratio**	**Robust std. error**	**z**	**P>│z│**
S	1.01***	0.002	2.78	0.005
Dummy for UK	0.067**	0.081	-2.22	0.026
Number of subjects	58	Time at risk		3552
Number of failures	18	Starting log likelihood		-65.96
Number of observations	3552	Final log likelihood		-61.45
Wald χ^2	8.86***	Zero-slope test (global test)		1.62

Table 13.

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

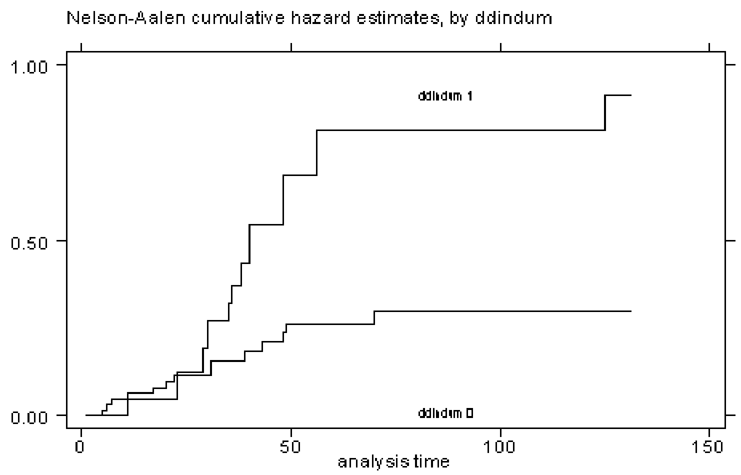
*Estimated using the Cox regression in tables 9 and 12. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels.*

	χ^2	P > χ^2
(-DD)		
"Support rating" equal to 1 or 2	2.27	0.13
Dummy for the UK	2.77*	0.096
S		
"Support rating" equal to 1 or 2	0.82	0.36
Dummy for the UK	3.00*	0.08

Chart 1.

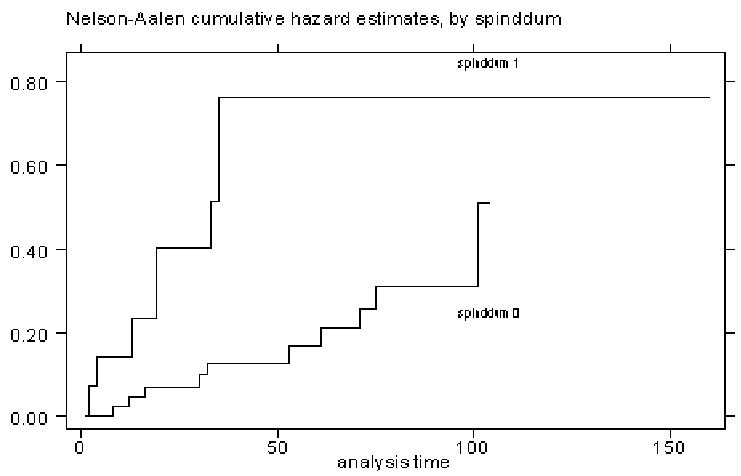
Cumulative hazard functions for the distance-to-default and spread

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. Analysis time is measured in months. Log-rank test for equality (χ^2 distributed) is equal to 4.73, which rejects equality at the 5%-level.

Appendix 1.

Distance-to-default according to the Black and Scholes formula[25]

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 (i.e. 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 $\ln V_A = \ln V_L$) can be expressed as:

$$D = \ln V_A - \ln V_L = \ln V_A + (r - \frac{\sigma_A^2}{2})T + \sigma_A \sqrt{T} \varepsilon - \ln V_L \iff$$

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

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

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

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:

$$IPD \equiv \Pr\left[\ln V_A^T \le \ln V_L\right] \iff \Pr\left[\ln V_A + \left(r - \frac{\sigma_A^2}{2} \right) T + \sigma_A \sqrt{T} \varepsilon \le \ln V_L \right], \text{i.e.}$$

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

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

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25 See KMV Corporation (1999) for a similar derivation and more ample discussions.