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\* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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# Forecasting the fragility of the banking and insurance sector\*

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*Abstract* This paper considers the issue of forecasting financial fragility of banks and insurances using a panel data set of performance indicators, namely distance-to-default, taking unobserved common factors into account. We show that common factors are important in the performance of banks and insurances, analyze the influences of a number of observable factors on banking and insurance performance, and evaluate the forecasts from our model. We find that taking unobserved common factors into account reduces the the root mean square forecasts error of firm specific forecasts by up to 11% and of system forecasts by up to 29% relative to a model based only on observed variables. Estimates of the factor loadings suggest that the correlation of financial institutions has been relatively stable over the forecast period.

*JEL classification:* C53, G21, G22

*Keywords:* Financial stability; financial linkages; banking; insurances; unobserved common factors; forecasting

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# 1 Introduction

The credit crunch of 2007/08 demonstrates that financial linkages between banks and insurances are considerable within and across regions. This crisis has not only severely affected the solvency of major US banks but has also put insurers and several European banks under pressure. One reason for this is the sizable market for credit derivatives, which serves banks to reallocate their exposure to credit risks. The estimated volume of global credit default swaps outstanding in 2007 is \$62.17 trillion, which is a 100-fold increase compared to the market size in 2001 and is now about twice the size of the domestic credit volume in the G10 countries.<sup>1</sup> With a market share of around 20%, insurance companies are a major seller of credit protection. Additionally, insurance companies increasingly transfer insurance risks to capital markets by selling alternative risk transfer instruments such as catastrophe bonds.

The strong financial linkages within and between the banking and insurance sectors have important implications for financial stability. In particular, when forecasting systemic risk linkages within the financial sector need to be taken into account whether they are caused by financial linkages or by common shocks to the financial system.

In this paper, we consider the problem of forecasting the performance of banks and insurance companies individually and in aggregate in the presence of unobserved linkages and common shocks. We model the linkages between banks and insurances using unobserved common factors. Our econometric method is based on the CCE estimator of Pesaran (2006) and allows us to extract common factors while at the same time including observed variables in the regression. While the possibility of such a procedure has been hinted at by Pesaran (2006), we are not aware of any other application of this methodology to date. The first contribution of this paper is therefore of a methodological nature: the combined use of unobserved common factors and observed variables for forecasting in a panel data set.

In factor-based estimations in the literature the factors are usually obtained from panel data which are not modeled themselves by using observed variables, for example, Bernanke, Boivin and Elias (2005). This means that a large amount of other data are needed beyond the variables of interest in order to extract the factors. In our analysis, we can estimate the factors together with the parameters of the observed variables in the model and therefore only need a panel data set of the variables of interest.

The second major contribution of this paper is the investigation of the forecast performance of macroeconomic and factor augmented models of the fragility of banks and insurances. We use a number of macroeconomic variables to forecast the performance of banks and insurances in a panel data set

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<sup>1</sup>Source: International Swaps and Derivatives Association (ISDA)

spanning 211 banks and 120 insurance companies in 21 countries. We show that taking unobserved common factors into account leads to large improvements in the forecasts of the performance of individual financial institutions and in the forecast of systemic risk even after the macroeconomic variables have been accounted for. By estimating unobserved common factors for different groups we gain an insight into the importance of cross-sectoral and cross-regional factors and we find that information in firms in other regions and industries can improve the forecasts.

A large body of literature exists that considers the forecast of systemic risk in the financial sector, surveyed, for example, by De Bandt and Hartmann (2002). Much of the work concentrates either on one asset, such as currency crises, for example Frankel and Rose (1996) and Kumar, Moorthy and Perraudin (2002). There are, however, a number of papers that consider the issue of currency and banking crises such as Kaminsky and Reinhart (1999).

A number of studies have investigated the issue of risk transfer between the banking and the insurance sector. Allen and Carletti (2006) use a model with banking and insurance sectors and show that credit risk transfer can be beneficial when banks face uniform demand for liquidity. However, when they face idiosyncratic liquidity risk and hedge this risk in the interbank market, credit risk transfer can be detrimental to welfare by leading to contagion between the two sectors. Monks and Stringa (2005) consider individual events and find that there is no clear evidence of spill-overs from the UK life insurance sector to the UK banking sector as a whole. However, they find evidence of a reaction from bancassurers' equity prices to life insurance events, which suggest that there is potential channel for spill-overs to the banking sector via ownership. Slijkerman, Schoenmaker and de Vries (2005) show that the cross-sectoral tail-dependence between banks' and insurers' equity prices is lower than the within-sector equity tail-dependence.

However, most papers only investigate forecasts based on observable variables, examples are the early warning systems for currency crises discussed by Kaminsky, Lizondo and Reinhart (1998), Berg and Pattillo (1999), and Edison (2003). We will show that cross-sectoral information and unobserved common factors are important for forecasting systemic risk.

Another aspect of systemic risk is financial contagion as discussed, for example, by Pesaran and Pick (2007). Financial contagion is the direct effect of a crisis of one company or in one market on the performance of other companies or markets. In this paper we are not concerned with the source of the common factors but are interested in incorporating unobserved common factors in order to improve the forecast of systemic risk. In fact, Pesaran and Pick (2007) show that as the number of cross-section units increases contagion is observationally equivalent to a common factor and may therefore be captured by unobserved common factors.

We use distance-to-default (DD) as proposed by Crosbie and Bohn (2003)

as the measure of performance of the banks and insurances, which is in contrast to the papers on banking and insurance dependence mentioned above. DD is based on the theoretical option pricing model of Merton (1974). It is therefore an internally consistent measure but will suffer from any inappropriate assumptions made in the model. However, a large literature has found DD to be an empirically useful measure.

In a survey among financial stability reports issued by central banks, Cihák (2006) shows that DD is one of the most frequently used market-based risk indicators. An advantage of DD, as pointed out by Vassalou and Xing (2004), is that it combines information about stock returns with leverage and volatility information, and is therefore a more efficient indicator of default risk than simple equity price based indicators. Market-based risk measures have been found to be more reliable than other measures relying on financial statements (Hillegeist, Keating, Cram and Lundstedt 2004, Demirovic and Thomas 2007) and to predict supervisory ratings, bond spreads, and rating agencies' downgrades in both developed and developing economies better than "reduced form" statistical models of default intensities (Arora, Bohn and Zhu 2005). Bharath and Shumway (2008) compare DD to other measures of default and find that that DD "provide(s) useful guidance for building default forecasting models" (Bharath and Shumway 2008, p 1368). Furthermore, as pointed out by Demirovic and Thomas (2007) and Cihák (2006), market-based indicators such as DD incorporate market participants' forward-looking assessments, while accounting measures of risk, such as the  $z$ -score, are backward-looking. Gropp, Vesala and Vulpes (2006) and Chan-Lau, Jobert and Kong (2004) find that in mature and emerging market economies DD appears to be a good measure for predicting rating downgrades of banks. Finally, Gropp and Moerman (2004) show that the ability of this indicator to measure risk is not affected by the presence of explicit or implicit safety nets (e.g. 'too-big-to-fail').

In the next section, we discuss the econometric approach. Section 3 describes the data used in the empirical study, which are analyzed in Section 4. Finally, Section 5 concludes.

## 2 The econometric model

We are interested in forecasting the fragility of banks and insurances as measured by their DD at  $T + h$  using the information up to time  $T$ , that is,  $\hat{y}_{i,T+h|T}$ , where  $i = 1, 2, \dots, N$  denotes the firms, that is, the banks and insurances. We will initially focus on forecasting the fragility of individual institutions and in second a step turn to forecasting the fragility of the banking and insurance sector in aggregate.

Suppose that  $y_{it}$  can be described by the following model

$$y_{it} = \boldsymbol{\alpha}'_i \mathbf{d}_t + \boldsymbol{\beta}'_i \mathbf{x}_{it} + u_{it}, \quad t = 1, 2, \dots, T + h \quad (1)$$

where  $\mathbf{d}_t$  is a  $l \times 1$  vector of observed common factors, including the intercept, and  $\mathbf{x}_{it}$  a  $k \times 1$  vector of individual specific regressors, including lags of  $y_{it}$ .

Further assume that a financial institution's performance is correlated with the performance of other institutions beyond what can be explained by the determinants contained in the vectors  $\mathbf{d}_t$  and  $\mathbf{x}_{it}$ . We introduce this via the error term,  $u_{it}$ , which is assumed to contain  $m$  unobserved common factors,

$$u_{it} = \boldsymbol{\gamma}'_i \mathbf{f}_t + \varepsilon_{it}, \quad (2)$$

where  $\boldsymbol{\gamma}_i$  is a  $m \times 1$  vector of parameters,  $\mathbf{f}_t$  is a  $m \times 1$  vector of unobserved common factors, and  $\varepsilon_i \sim (\mathbf{0}, \boldsymbol{\Sigma}_i)$ , where  $\boldsymbol{\Sigma}_i$  is a positive definite matrix.

Assume the individual specific regressors  $\mathbf{x}_{it}$ , the common observed and unobserved factors,  $\mathbf{d}_t$  and  $\mathbf{f}_t$ , have vector autoregressive forms,

$$\mathbf{x}_{it} = \mathbf{P}'_i \mathbf{x}_{i,t-1} + \boldsymbol{\eta}_{it}, \quad \boldsymbol{\eta}_t \sim \text{iid}(\mathbf{0}, \boldsymbol{\sigma}_\eta^2), \quad (3)$$

$$\mathbf{d}_t = \boldsymbol{\Lambda}' \mathbf{d}_{t-1} + \boldsymbol{\zeta}_t, \quad \boldsymbol{\zeta}_t \sim \text{iid}(\mathbf{0}, \boldsymbol{\sigma}_\zeta^2), \quad (4)$$

and

$$\mathbf{f}_t = \boldsymbol{\Theta}' \mathbf{f}_{t-1} + \boldsymbol{\xi}_t, \quad \boldsymbol{\xi}_t \sim \text{iid}(\mathbf{0}, \boldsymbol{\sigma}_\xi^2), \quad (5)$$

and  $\mathbf{x}_{it}$ ,  $\mathbf{d}_t$  and  $\mathbf{f}_t$  are assumed to be stationary. Clearly, we could assume higher order autoregressive processes for  $\mathbf{x}_{it}$ ,  $\mathbf{d}_t$  and  $\mathbf{f}_t$  but for expositional simplicity we restrict attention to first order auto-regressive cases. Also, the exogeneity of  $x_{it}$  and  $d_t$  with respect to  $f_t$  is assumed for ease of exposition and not strictly necessary.

## 2.1 Estimation of the parameters

The estimation of the parameters proceeds in three steps. First we estimate the error term  $u_{it}$  using the common correlated effects (CCE) estimator (Pesaran 2006), then recover the factors,  $\mathbf{f}_t$  using principle components analysis, and finally obtain the parameters in (1) via OLS estimation.

We estimate the residual,  $\hat{u}_i$ , described in (2) in a two step approach. In the first step we apply the CCE estimator of Pesaran (2006), who shows that augmenting the regression equation (1) by cross-section averages of  $y_{it}$  and  $\mathbf{x}_{it}$  eliminates the effects of unobserved factors and leads to a consistent estimation of  $\boldsymbol{\beta}'_i$ , which is

$$\hat{\boldsymbol{\beta}}_{it} = (\mathbf{X}'_i \mathbf{Q}_M \mathbf{X}_i)^{-1} \mathbf{X}'_i \mathbf{Q}_M \mathbf{y}_i, \quad (6)$$

where  $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots, y_{iT})'$ ,  $\mathbf{X}_i = (\mathbf{x}'_{i1}, \mathbf{x}'_{i2}, \dots, \mathbf{x}'_{iT})'$ ,  $\mathbf{Q}_M = \mathbf{I} - \mathbf{M}(\mathbf{M}'\mathbf{M})^{-1}\mathbf{M}'$ ,  $\mathbf{M} = (\bar{\mathbf{Z}}_w, \mathbf{D})$ ,  $\mathbf{D} = (\mathbf{d}'_1, \mathbf{d}'_2, \dots, \mathbf{d}'_T)'$ ,  $\bar{\mathbf{Z}}_w = (\bar{z}'_{w1}, \bar{z}'_{w2}, \dots, \bar{z}'_{wT})'$ ,  $\bar{z}_{wt} = (\sum_{i=1}^N w_i y_{it}, \sum_{i=1}^N w_i \mathbf{x}_{it})$ , and  $w_i$  is the weight of institution  $i$  in the financial system. The weights are such that

$$w_i = O(1/N), \quad \sum_{i=1}^N w_i = 1, \quad \sum_{i=1}^N |w_i| < c,$$

for some constant  $c$ .

Given the consistent estimation of  $\hat{\beta}_{it}$  we can calculate the residual

$$\nu_{it} = u_{it} + \alpha_i \mathbf{d}_t$$

as

$$\hat{\nu}_{it} = y_{it} - \hat{\beta}'_{it} \mathbf{x}_{it}$$

After obtaining the estimated residual  $\nu_{it}$  the common observed factors  $\mathbf{d}_t$  are integrated out to obtain an estimate of the residual  $u_{it}$ :

$$\hat{\mathbf{u}}_i = \mathbf{Q}_D \hat{\nu}_{it}, \quad (7)$$

with  $\mathbf{Q}_D = \mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ . An issue in the estimation of the parameters  $\alpha_i$  is the orthogonality of the unobserved common factors,  $\mathbf{f}_t$  to the observed common factors,  $\mathbf{d}_t$ . While not critical for forecasting, a violation of this assumption clearly would bias the parameter estimates from (1), and this limitation should be borne in mind when interpreting the results for the observed common factors.

Using the estimated residuals,  $u_{it}$ , we can obtain estimates of  $\mathbf{f}_t$  using principal components analysis. Forecasting with factors obtained from principle components has been discussed in detail by Stock and Watson (2002a) and Stock and Watson (2002b). Given that we have a estimate of  $u_{it}$  in an unbalanced panel, we estimate the unobserved factors using the EM algorithm outlined by Stock and Watson (2002b). An issue in the estimation of the factors is the choice of  $m$ . For simplicity we fix the number of factors to  $m = 4$ . We have also performed the forecasts for smaller  $m$  and the results remain qualitatively unchanged.

## 2.2 Forecasting

In order to forecast  $y_{it}$  iterate (1) and (2)  $h$ -steps forward to obtain

$$y_{i,t+h} = \alpha'_i \mathbf{d}_{t+h} + \beta'_i \mathbf{x}_{i,t+h} + \gamma'_i \mathbf{f}_{t+h} + \varepsilon_{i,t+h}. \quad (8)$$

Recursive substitution yields

$$\begin{aligned} y_{i,t+h} &= \alpha'_i \Lambda_i^h \mathbf{d}_t + \beta'_i \mathbf{P}_i^h \mathbf{x}_{it} + \gamma'_i \Theta_i^h \mathbf{f}_t + \alpha'_i \sum_{j=1}^h \Lambda_i^{h-j} \zeta_{t+j} \\ &\quad + \gamma'_i \sum_{j=1}^h \Theta_i^{h-j} \xi_{t+j} + \beta'_i \sum_{j=1}^h \mathbf{P}_i^{h-j} \eta_{i,t+j} + \varepsilon_{i,t+h} \\ &= \mathbf{a}'_i \mathbf{d}_t + \mathbf{b}'_i \mathbf{x}_{it} + \mathbf{g}'_i \mathbf{f}_t + e_{i,t+h}. \end{aligned} \quad (9)$$

where  $\mathbf{a}_i$ ,  $\mathbf{b}_i$ ,  $\mathbf{g}_i$ , and  $e_{i,t+h}$  have the obvious definitions.



Hence, a forecast of  $y_{i,T+h}$  given the information up to time  $T$ ,  $\Omega_T$ , can be obtained from

$$E(y_{i,T+h}|\Omega_T) = \hat{\mathbf{a}}_i' \mathbf{d}_T + \hat{\mathbf{b}}_i' \mathbf{x}_{iT} + \hat{\mathbf{g}}_i' \hat{\mathbf{f}}_T, \quad (10)$$

where  $\hat{\mathbf{a}}_i$ ,  $\hat{\mathbf{b}}_i$  and  $\hat{\mathbf{g}}_i$  are estimates of  $\mathbf{a}_i$ ,  $\mathbf{b}_i$  and  $\mathbf{g}_i$  using the estimation methodology outlined above, and  $\hat{\mathbf{f}}_T$  is the estimate of  $\mathbf{f}_T$  obtained from extracting the first  $m$  principal components from the residuals,  $\mathbf{U} = (\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_N)$ , estimated in (7).

Alternatively we would be to estimate the models and construct forecasts based on Ridge or Lasso regressions as described by De Mol, Giannone and Reichlin (2008) or use methods along the lines of the GVAR modelling approach proposed by Pesaran, Schuermann and Weiner (2004) and Pesaran, Schuermann and Smith (forthcoming). However, while the relative efficiency of the different methods is an open question, our approach has the advantage that in addition to correcting for cross-section dependence it also delivers estimates of the factors and their loadings.

### 2.3 Forecasting systemic fragility

We now turn to forecasting the system-wide financial fragility, which is a main concern of financial supervisory authorities. A natural measure of systemic financial stability is the weighted average DD

$$\bar{y}_{T+h|T} = \sum_{i=1}^N w_i y_{i,T+h|T}. \quad (11)$$

This measure has been used by Tudela and Young (2003) with equal weights,  $w_i = N^{-1}$ . It is important to note that common factors that are not accounted for in the individual forecasts will not be averaged out of the systemic forecast. Hence, for an unbiased estimate of the systemic DD it is important to account for unobserved common factors, as pointed out by Chan-Lau and Gravelle (2005) and Cihák (2006).

However, the average DD may not be the best measure of systemic risk, since financial supervisors are mainly concerned about poorly performing institutions than about the averaged performance of the banking and insurance sector in which negative performance of individual institutions may be offset by the positive performance of other institutions. In order to address the downside risk of the financial system we also forecast the lower quartile weighted by market value

$$y_{T+h,T}^q = \sum_{i=1}^N w_i y_{i,T+h|T} \mathbf{I}(y_{i,T+h|T}) \quad (12)$$

where  $\mathbf{I}(y_{i,T+h|T})$  is an indicator function that is unity if  $y_{i,T+h|T}$  is in the lower quartile. This function can be thought of as the value at risk equivalent for the financial supervisor.

## 2.4 Evaluating the forecasts

We evaluate the forecasts using the RMSFE

$$\text{RMSFE}(h) = \sqrt{\frac{1}{M} \sum_{j=1}^M e_{i,T_j,h}^2}, \quad j = 1, 2, \dots, M \quad (13)$$

where  $e_{i,T_j,h} = (y_{j,T_j+h} - \hat{y}_{j,T_j+h|T_j})/h$ ,  $\hat{y}_{j,T_j+h|T_j}$  is the forecast based on the information up to  $T_j$ .

In order to assess whether forecasts from two models are significantly different we use the Diebold and Mariano (1995) test, which uses the loss differential

$$l(A, B) = e_{A,T,h}^2 - e_{B,T,h}^2$$

where  $A$  and  $B$  denote two forecast methods. The Diebold-Mariano statistic has a standard normal limiting distribution. For the individual forecasts we use a panel version of the Diebold-Mariano test, which is

$$\bar{s}(h) = \frac{1}{\sqrt{N}} \sum_{i=1}^N s_i(h) \quad (14)$$

where  $s_i(h)$  is the Diebold-Mariano statistic for cross-section unit  $i$ , which has a standard normal limiting distribution.

In our application the forecast sample is relatively short—between 9 and 12—which puts the approximation of the distribution of the  $s_i(h)$  by the standard normal into question. We therefore bootstrap the distribution of  $\bar{s}(h)$  to ensure that our results are not distorted by the short forecast sample. We are not aware of any discussion or application of such a bootstrap procedure in the literature and discuss the details of the bootstrap in Appendix B.

Finally, we calculate the Kuipers score

$$KS = H - F$$

where  $H$  is the proportion of DD observations in the lower quartile of the distribution that are correctly forecast to be in the lower quartile, and  $F$  are the proportion of DD observations that are forecast to be in the lower quartile but are not, see Granger and Pesaran (2000). Assuming financial authorities put particular supervisory effort on firms that are in the lower quartile of the DD distribution, the Kuipers score measures whether the authorities monitor the right firms.

## 3 Data and descriptive statistics

The measure of bank and insurance performance is distance-to-default (DD), which is the difference of the firm's value and the firm's liabilities, standard-

Table 1: Descriptive Statistics of Distance-to-Default

	Obs.	Mean	Std.Dev.	Min	Max
Banks	13518	5.164	3.307	-0.115	66.375
Insurances	7256	5.131	2.664	-2.145	50.805

ized by the volatility of the firm's value. The firm's value is derived from the Merton (1974) option value approach and details are given in Appendix A.

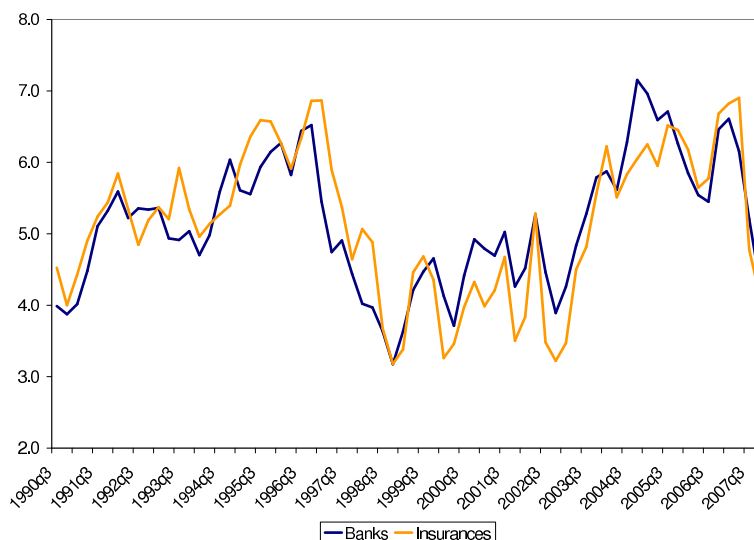
The underlying data to calculate the quarterly DD measure are provided by Datastream. We collected the data for all banks and (life- and non-life) insurance companies located in the EU-15 (except Luxembourg), Norway, Switzerland, USA, Canada, Australia, Japan, and Korea for which data were available, see Table 6. A difficulty is to correctly classify a financial firm as a bank or an insurer that exploits a portfolio of activities in both areas, banking and insurance. We follow the Datastream classification scheme in which all companies are coded to both a US styled SIC primary and secondary industry code designation as well as to their corresponding Dow Jones Global Industry Grouping. The sample covers the period from 1990Q3 to 2007Q4.

In the estimation we will estimate up to 16 parameters. We therefore deleted all banks and insurances for which we had in total less than 30 observations and those where we had serious concerns about the data quality, either due to very small market shares or because of a subsidiary status. This leaves us with data for 211 banks and 120 insurance companies. A more detailed sample composition is listed in Table 6 in Appendix C.

Table 1 shows summary statistics of the DD variable. The average performances of banking and insurance companies are comparable. Figure 1 plots the average DD value for the banking and insurance sector over time. The high correlation of the two series is immediately obvious. Moreover, the DD values for the banking and insurance sector show a cyclical pattern and peak in 1996 and a subsequent decline in the following years. From end of 2002 onwards, both sectors seem to recover on average and have reached a new peak end of 2004. With the start of the financial turmoil in 2007, the performance measure of banks and insurances declined again sharply.

Figure 2 gives an example of the time series of the DD of two banks that were in financial distress in the past, and where the government or the central bank had to intervene. Banco Español de Crédito received public financial support in December 1993 and Svenska Handelsbanken was rescued by obtaining a government guarantee in December 1992. Prior and during the crisis events, DD dropped sharply, reaching a negative figure a quarter after the intervention in the case of Banco Español de Crédito and a value close to zero at the crisis event in the case of Svenska Handelsbanken.

Figure 1: Average DD by Sector over Time

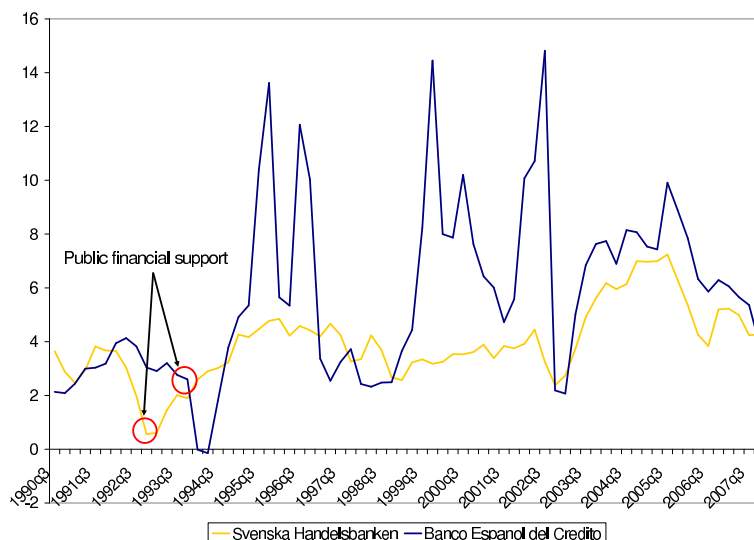


**Explanatory variables** The aim is to predict DD from a macroeconomic perspective. Firm specific variables frequently used in the literature on firm default are mostly based on balance-sheet variables and market-driven variables (Zmijewski 1984, Altman 1993, Shumway 2001, Carling, Lindé and Roszbach 2007). These variables are accounted for in the construction of DD in a model based approach, and it is therefore not necessary to include them as regressors in our model. Furthermore, recent research, such as Carling et al. (2007), indicates that macroeconomic variables have significant explanatory power for firm default risk and that taking macroeconomic conditions into account allows to pin down the absolute level of default risk, while firm-specific information can only make reasonable accurate ranking of firms' according to default risk.

We use the following macroeconomic variables as candidate variables in the forecasting model:

1. Long rate: Level of 10yr bond yield for each country
2. Industrial production: Growth rate of industrial production for each country
3. Inflation: Growth rate of consumer price index for each country
4. Domestic credit: Growth rate of domestic credit for each country
5. Equity returns: Growth rate of stock market index for each country
6. REER: Growth rate of real effective exchange rate for each country

Figure 2: DD for Banco Español de Crédito and Svenska Handelsbanken



7. Unemployment rate: Level of unemployment rate for each country
8.  $\Delta$  GDP: Growth rate of GDP for each country
9. P/E ratio: Price-Earning ratio in the US stock market
10. VIX: Chicago Board of Exchange Volatility Index

These variables are commonly used in the literature. For the banking sector, Demirgüç-Kunt and Detragiache (1998) show that the probability of a banking crisis increases with the level of interest rates. The explanation is that high real interest rates are likely to hurt bank balance sheets as high lending rates result in a larger fraction of non-performing loans. Von Hagen and Ho (2004) find the opposite, namely that banking performance increases with the (lagged) level of real interest rates, indicating that banking crises tend to follow real interest rates in the previous period. Shiu (2004) focusses on the determinants of insurance performance and shows that general insurers are more likely to perform well when the interest rate level is high. The explanation is that insurance companies invest a large proportion of their investment portfolios in bonds. However, long-term interest rates also reflect inflation expectations. As pointed out by Demirgüç-Kunt and Detragiache (1998), von Hagen and Ho (2004), and Shiu (2004) inflation is negatively associated with bank and insurance performance, because it might be a proxy for macroeconomic mismanagement that affects the whole economy including the banking sector.

Domestic credit growth is used in many studies on banking crises as a measure of successful financial liberalization. In our sample of industrialized

countries, we interpret domestic credit as a proxy for the state of business in the banking sector, and therefore the profitability of banking in the economy, which would suggest a positive relationship between domestic credit growth and DD. However, as shown in several previous studies, such as Goldstein (1998) and von Hagen and Ho (2004), banking problems are often preceded by credit booms, implying a negative relationship between domestic credit growth and DD. Thus, the overall impact of domestic credit growth and financial institutions' performance depends on which of the two factors is more dominant.

Industrial production, GDP growth, and the unemployment rate are included to capture adverse macroeconomic shocks. Theory predicts that adverse shocks affecting the whole economy will increase the non-performing loans of banks, which decreases bank performance. This is also consistent with the observation that systemic banking crisis are associated with fluctuations in the business cycle, see Gorton (1988), Kaminsky and Reinhart (1999), Demirgüç-Kunt and Huizinger (1998) and Demirgüç-Kunt and Detragiache (1998), Bikker and Hu (2002). Insurance performance is less likely to be affected by fluctuations in the business cycle. We therefore expect a smaller effect of these three variables on the DD values of insurance companies.

The real effective exchange rate (REER) is added to account for exchange rate risks. An unexpected depreciation of the domestic currency might cause banking problems if domestic banks borrow in foreign currency and lend in domestic currency, or because bank borrowers might hold foreign loans. In both cases, a depreciation threatens the profitability of banks either through a currency mismatch or through an increase in non-performing loans.

Shiu (2004) argues that the fact that the insurance industry holds a large share of its investment portfolio in equities high returns on equities enhance their investment performance. Thus, we expect a positive relationship between the DD value of insurance companies and equity returns.

We include the price/earnings (P/E) ratio of the US stock market and the VIX into our regression to control for the effect of general market sentiments on the DD value of banks and insurance companies. A higher P/E ratio means that investors are paying more for each unit of income. It is likely that the stock prices of banks and insurance companies are affected by these market sentiments. In periods of high P/E ratios, the stock price of banks and insurance companies increases independent of the firm's performance, which causes an increase in their DD value. Thus, we expect a positive relationship between the P/E ratio and our performance measure.

The VIX, which measures the expected level of (implied) volatility in a range of options on the S&P 500 index over the next 30 days. The VIX is often used to measure investors' view of market riskiness and has a more forward looking character than the P/E ratio. When stock markets are trending upwards, there is generally a low level of volatility in the markets. Conversely, when markets are falling, the volatility level usually is high, this

is why the VIX is often also called the ‘fear index’. The VIX provides important information about investor risk sentiment and market volatility. that can be helpful in evaluating potential market turning points and measuring market liquidity. We expect a negative impact of the VIX on DD. Finally, we add the lagged dependent variable as an explanatory variables in the regression.

## 4 Empirical analysis

In the first instance, we test for the existence of cross-section correlation between the performance of banks and insurances after correcting for the correlation due to the explanatory variables listed in Section 3. In our data set  $N$  is considerably larger than  $T$  and we therefore use the CD test of Pesaran (2004). Unlike the test of Breusch and Pagan (1980), the CD test has correct size in panels with large  $N$  and small  $T$  dimensions.

We perform the cross-section correlation test within and between the sectors and regions in our sample. The regions that we consider are the following: first, all countries in our data set, second, North America, third, the Europe, and, fourth, Asia and Australia. The results in Table 2 show that all the CD test statistics, reported in the third column, are significant at any conventional significance level. The fourth column gives the estimated average pairwise correlation coefficient of the residuals,  $u_{it}$ , between the institutions, and it can be seen that these are quite sizeable. This suggest that even after accounting for the macroeconomic variables in our data set considerable cross-section dependence remains within but also across regions and industries, which suggests that the accuracy of forecasts may be improved by incorporating cross-section dependence.

### 4.1 Firm specific forecasts

We now turn to recursive out-of-sample forecasting of DD for the firms in our data set. The first one- and four-quarter ahead forecasts use the data from 1990Q3 up to 2003Q4 for the estimation of the model. Subsequently the observation of the next quarter are added to the data for the estimation and another set of forecasts is constructed. This leads to 12 one-quarter ahead forecasts for each firm or 2673 one-quarter ahead forecasts overall, and 8 four-quarter ahead forecasts for each firm, which resulted in 2085 four-quarter ahead forecasts

Given the short time series of observations per firm we select the optimal set of individual specific regressors for each firm and each forecast period according to BIC. Given that we are interested in the effect of unobserved common factors, we always include the observed common factors as their omission might be seen as unduly favoring the unobserved common factor forecasts.

Table 2: Cross-section dependence test

Region	Industry	CD	$\bar{\rho}_{ij}$
all	Banks & Insur.	474.91	0.32
	Banks	284.99	0.30
	Insurances	197.19	0.37
	Banks vs Insur.	222.09	0.32
USA/ Canada	Banks & Insur.	172.58	0.64
	Banks	125.82	0.51
	Insurances	288.87	0.56
Europe	Banks & Insur.	139.94	0.54
	Banks	200.92	0.37
	Insurances	112.68	0.35
Japan/ Korea/ Australia	Banks & Insur.	89.95	0.40
	Banks	98.05	0.36
	Insurances	104.09	0.24
Australia	Banks & Insur.	86.77	0.23
	Insurances	20.86	0.41
	Banks & Insur.	26.24	0.27

CD denotes the CD test statistic,  $\bar{\rho}_{ij}$  the average pair-wise correlation coefficient, where the correlation coefficient is calculated for all pairs of institutions in the given region and industry.

The base line model without unobserved common factors is compared to models that make different assumption about the pervasiveness of the unobserved common factors. This also allows some insights into the nature of the common factors: whether they are specific to the particular industry and the particular region under consideration, or whether factors affect an industry in all countries or a region in both industries, or whether the same factors influence banks and insurances across all OECD countries.

We therefore use four different schemes to estimate the factors:

- Fac-1: Industry and region specific unobserved common factors. The factors are estimated separately for Asia/Australia, Europe and North America and within the regions separately for banks and insurances.
- Fac-2: Industry specific factors. The factors are separately estimated for banks and insurances but pooled across regions.
- Fac-3: Region specific factors. The factors are pooled across banks and insurances but estimated separately for Asia/Australia, Europe and North America.



- Fac-4: Factors are common across regions and industries and are pooled across all firms in the data set.

In each scheme we estimate the unobserved common factors by extracting the first  $m$  principal components from the residuals of the institutions in the particular region and industry considered in the particular scheme. These factors are then used to form forecasts of the distance-to-default of the individual firms.

The results assessing the forecasts for individual firms are reported in Table 3. The first panel shows the one-quarter ahead forecasts. It can be seen that forecasts that use factors that are pooled across all firms (Fac-4) have the smallest RMSFE. Furthermore, all factor-based forecasts have a lower RMSFE than the forecasts that do not take factors into account. The best forecast, Fac-4, reduces the RMSFE by 11% below that of the forecast without unobserved common factors.

The panel Diebold-Mariano statistics suggest that the factor-based forecasts are significant improvements in all cases—an asterisk indicates that the 95% bootstrap confidence interval did not contain zero. Furthermore, the forecasts that pool information across industries but not regions (Fac-2) are dominated by the forecasts that pool information across regions and industries or only across regions.

The lower panel of Table 3 reports the results for the four-quarters ahead forecasts. Here we also find that all forecasts based on factors are better than the forecasts that do not use unobserved factors. This improvement is significant for forecasts taking region and industry specific factors (Fac-1) and industry specific (Fac-2) into account. The forecasts with region and industry specific factors have the lowest RMSFE and reduce the RMSFE by about 8% compared to those without unobserved common factors.

Table 3 also reports the Kuipers score for the different forecasts models. For  $h = 1$  the forecasts based on factors that are estimated for firms within regions and industries (Fac-1) and factors that are pooled across regions (Fac-3) have a higher Kuipers score than forecasts that are constructed without unobserved common factors. However, for  $h = 4$  the picture reverses and no factor based forecast has a higher Kuipers score.

## 4.2 System wide forecasts

The results for the forecasts of the system wide financial stability are reported in Table 4. For  $h = 1$  the forecasts with the lowest RMSFE are the ones based on factors that pool information across industries and regions, which reduces the RMSFE by 29% against that of the forecast without unobserved factors. Again all factor based forecasts are improvements over those without factors. The differences are significant at the 10% level but the tests should be interpreted with caution as they are based on 12 aggregate forecasts only. When forecasting the lower quartile of the distribution

Table 3: RMSFE and panel Diebold-Mariano test for individual forecasts

	No fac.	Fac-1	Fac-2	Fac-3	Fac-4
<i>One-quarter ahead forecasts</i>					
RMSFE	2.131	1.907	1.924	1.926	1.902
panel Diebold-Mariano statistics					
No fac.		13.654*	8.198*	14.541*	13.320*
Fac-1			-5.230*	0.102	-1.610
Fac-2				3.148*	6.096*
Fac-3					0.720
Kuipers scores					
	0.362	0.397	0.330	0.402	0.338
<i>Four-quarter ahead forecasts</i>					
RMSFE	2.653	2.448	2.561	2.528	2.595
panel Diebold-Mariano statistics					
No fac.		2.214*	6.106*	1.01	0.151
Fac-1			-0.047	-3.633*	-2.743*
Fac-2				-2.911*	-3.142*
Fac-3					0.190
Kuipers scores					
	0.269	0.168	0.109	0.234	0.156

No fac: No factors beyond the observed regressors; Fac-1: region and industry specific factors; Fac-2: industry specific factors; Fac-3: region specific factors; Fac-4: factors across regions and industries. The panel Diebold-Mariano statistics are for the loss function  $l(A, B) = e_{A,T,h}^2 - e_{B,T,h}^2$ , where  $A$  is the forecast errors obtained from the method given in the column on the left and  $B$  are the forecast errors from the method given in the top row. We used 1000 bootstrap repetitions. An asterisk indicates that the 95% confidence interval did not contain zero.

of distance-to-default all forecasts using unobserved common factors have a lower RMSFE, the only exception is the forecast using region specific factors (Fac-3). Using region and industry specific factors leads to an improvement of 28% of the RMSFE over the forecast without unobserved common factors. However, again the differences are not statistically significant.

The aggregate forecasts for  $h = 4$  also vastly improve when taking unobserved factors into account. The RMSFE average forecast of DD is improved by up to 23% when pooling the information across industries for the principle components estimation. However, when forecasting the lower quartile of the distribution of the distance-to-default for  $h = 4$ , we do not find that taking unobserved common factors into account leads to an improvement of

Table 4: RMSFE and Diebold-Mariano test for systemic forecasts

	No fac.	Fac-1	Fac-2	Fac-3	Fac-4
<i>One-quarter ahead forecasts</i>					
Average					
RMSFE	0.324	0.236	0.258	0.288	0.231
Diebold-Mariano statistics					
No fac.		1.740	1.641	1.401	1.552
Fac-1			-1.181	-1.654	0.273
Fac-2				-1.433	0.901
Fac-3					1.460
Lower quartile					
RMSFE	0.228	0.164	0.183	0.243	0.217
Diebold-Mariano statistics					
No fac.		1.191	0.881	-0.821	0.422
Fac-1			-0.919	-1.202	-1.671
Fac-2				-0.915	-1.279
Fac-3					0.670
<i>Four-quarters ahead forecast</i>					
Average					
RMSFE	0.536	0.491	0.416	0.512	0.490
Diebold-Mariano statistics					
OLS		0.644	0.717	0.383	0.436
Fac-1			0.777	-0.725	0.038
Fac-2				-0.878	-1.347
Fac-3					0.410
Lower quartile					
RMSFE	0.276	0.307	0.286	0.299	0.401
Diebold-Mariano statistics					
OLS		-0.952	-0.663	-1.218	-1.654
Fac-1			1.241	0.347	-2.133
Fac-2				-0.886	-1.829
Fac-3					-2.054

See footnote of Table 3. The significance of the Diebold-Mariano test statistics is assessed against the standard normal distribution. The average RMSFEs are scaled up by 100 for ease of exposition.

the RMSFE. Forecasts ignoring unobserved factors have the lowest RMSFE. This result coincides with the result that the Kuiper score for  $h = 4$  is the highest for the forecast model ignoring unobserved factors, as shown in Table 3. While, the Diebold Mariano test shows that the differences in the ability of the different forecast models to forecast the average and the lower quantile distribution of DD are not significant, these test should be interpreted with caution given the small number of aggregate forecasts.

### 4.3 The determinants of distance-to-default

An interesting by-product of the forecasts are the parameter estimates and the optimal choice of variables according to BIC. Here we report the average parameter estimate of the variables that are included in the model and the probability of a variable being included in the optimal model based on BIC for the last forecast, that is based on the sample from 1990Q3 to 2007Q3. The parameters of the regressors  $\mathbf{x}_{it}$ ,  $\hat{\boldsymbol{\beta}}_{it}$  are obtained from the CCE estimator in (6) using the cross-section averages across all firms. The parameters for the common regressors,  $\hat{\boldsymbol{\alpha}}_{it}$  are estimated by OLS using the estimated unobserved common factors and therefore rely on the orthogonality of the unobserved common factors.

The estimation results are given in Table 5. The second and third columns show the average of the estimated coefficients across banks conditional on being in the optimal set of regressors base on BIC and the probability of inclusion in the model. The fourth and fifth column show the same results for insurances.

The figures in column 1 and 2 indicate that the average of the individual determinants of banking performance show the expected sign in most cases. The variable that is included most often is the lagged dependent variable. From the macroeconomic variables the long term interest rate and the unemployment date are included most often. However, all variables are included in a substantial subset of the models.

The long term interest rate is positively related to DD, which confirms the findings in the empirical literature. Inflation influences the performance measure negatively for both banks and insurances. The positive sign of domestic credit suggests that this variable acts as a measure of the health of banking business. Out of the cyclical variables unemployment and GDP for insurances have the expected sign, while industrial production and GDP for banks have the opposite sign to theoretical predictions. Out of these variables, however, unemployment seems to be the most important.

The parameters for the common observed factors show that the P/E ratio for banks and the VIX enter with the correct sign compared to our a priori expectations. However, these two parameters should be interpreted with caution, given that they rely on orthogonality to the unobserved factors. The parameter for insurances are very similar. The only exception is the

Table 5: Determinants of distance-to-default

	$\bar{\theta}$	$p$	$\bar{\theta}$	$p$
	Banks		Insurances	
lagged dep.var.	0.450	0.820	0.385	0.600
long rate	2.177	0.171	0.439	0.233
ind.prod.	-0.025	0.123	-0.374	0.192
inflation	-0.138	0.166	-0.300	0.200
equity ret.	-0.017	0.137	0.017	0.167
REER	0.020	0.166	0.117	0.200
unemploy.	-0.201	0.194	-0.230	0.258
GDP	-0.130	0.123	0.184	0.192
intercept	2.889	–	5.431	–
P/E ratio	0.017	–	-0.022	–
VIX	-0.050	–	-0.057	–

The estimates are from the last one-step ahead forecast with data up to 2007Q3.  $\bar{\theta}$  are the average coefficients conditional on the variable being included in the best model according to BIC.  $p$  denotes the proportion of forecasts that included the respective variable.

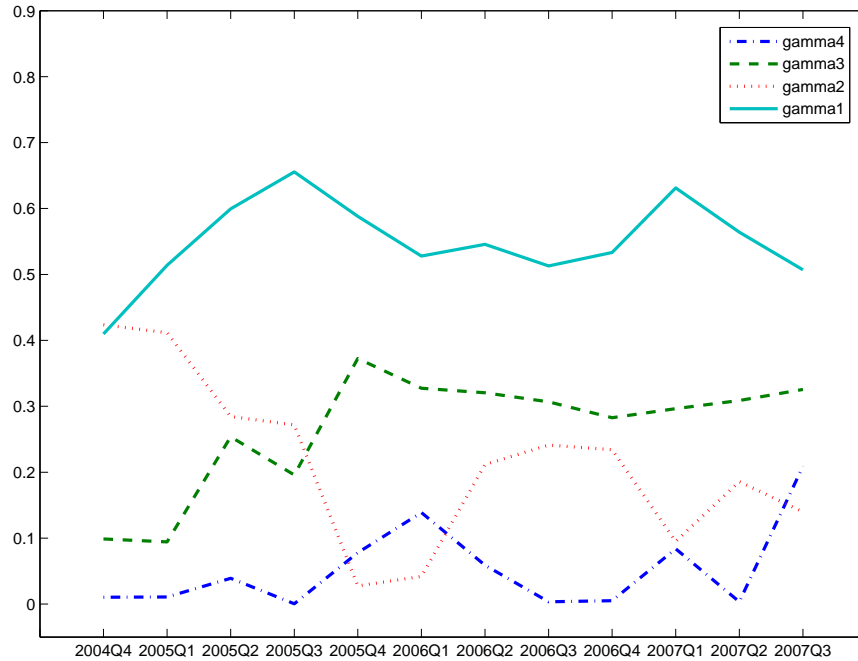
negative sign of REER.

Finally, the increasing use of credit derivatives and other financial products that are traded on a global scale would suggest that the correlation between the institutions may have increase. In order to shed light on this we plot the parameter estimates of the first four principal components over the forecast period in Figure 3. It can be seen that the factor loadings have increased very mildly at best over our relatively short forecast period, which does not seem to lend itself to the interpretation of a drastically increased correlation between institutions. However, we leave it to future research to investigate this issue in greater detail.

## 5 Conclusion

In this paper we argue that not only the financial linkages between banks but also the linkages between banks and insurance companies are important when analyzing and forecasting their fragility. Our empirical analysis is based on the performance measure distance-to-default (DD). We investigate the importance of a number of macroeconomic variables and unobserved factors on the performance of banks and insurances. We find that unobserved common factors play an important role. In particular, taking the unobserved factors into account leads up to 11% reduction in the RMSFE of the fore-

Figure 3: Time series of  $\bar{\gamma}$  over the forecast period



‘gamma<sub>1</sub>’ denotes the estimated parameters for the first principal component, ‘gamma<sub>2</sub>’ that of the second, ‘gamma<sub>3</sub>’ that of the third, and ‘gamma<sub>4</sub>’ that of the fourth principal component. The dates on the  $x$ -axis gives the last observation in the estimation sample for the respective parameter estimates; all samples start in 1999Q3.

casts of individual firms DD. Furthermore, the forecasts are more accurate in tracking the position of a firm within the distribution of DD. Systemic risk can also be forecast better as the aggregate RMSFE is reduced by 29% in one-quarters ahead forecasts and by 23% in four-quarters ahead forecasts. Furthermore, estimates of the factor loadings suggest that the correlation between banks has not increased throughout the forecast period.

## A A structural model of credit risk: Distance-to-default

The indicator ‘distance-to-default’ has been introduced by Crosbie and Bohn (2003) and is based on the derivative pricing model proposed by Merton (1974), which is the prototype of many firm-value models.

In Merton’s model a firm finances itself by equity and debt. Debt is of zero-coupon form with face value  $B$  and maturity  $T$ . Let  $S_t$  and  $B_t$  denote the equity and debt value at time  $t$ , then a firm’s asset value is simply the sum of these two, i.e.  $V_t = S_t + B_t$ ,  $0 \leq t \leq T$ . Default occurs if the firm cannot meet its payments to the debt holders, that means if  $V_T \leq B$ .

Following Black and Scholes (1973), the value of a firm’s assets  $V_t$  follows a geometric Brownian motion with a constant drift equal to the risk free interest rate  $\mu_V$  and a constant diffusion rate equal to  $\sigma_V$ ,

$$dV_t = \mu_V V_t dt + \sigma_V V_t dW_t, \quad (15)$$

where  $W_t$  is a standard Brownian motion. It follows that the value of the firm’s asset at any time  $T$  is given by

$$V_T = V_t \exp \left( \left( \mu_V - \frac{1}{2} \sigma_V^2 \right) (T - t) + \sigma_V \sqrt{(T - t)} \epsilon_T \right), \quad (16)$$

where  $\epsilon_T = \frac{W_T - W_t}{\sqrt{(T - t)}} \sim N(0, 1)$ . The default probability of the firm is then

$$\begin{aligned} P(V_T \leq B) &= P(\ln V_T \leq \ln B) \\ &= P \left( - \frac{\ln(\frac{V_t}{B}) + (\mu_V - \frac{1}{2} \sigma_V^2)(T - t)}{\sigma_V \sqrt{(T - t)}} \geq \epsilon_T \right) \end{aligned} \quad (17)$$

On basis of equation (17), Crosbie and Bohn (2003) define distance-to-default as

$$DD = \frac{\ln(\frac{V_t}{B}) + (r - \frac{1}{2} \sigma_V^2)(T - t)}{\sigma_V \sqrt{(T - t)}}, \quad (18)$$

where  $r$  denotes the deterministic and risk-free interest rate. Thus, distance-to-default measures the number of standard deviations that the firm’s asset value is away from the default point  $B$ .

In order to be able to calculate a firm’s distance-to-default on basis of equation (18), we first have to determine the two unknown parameters  $V_t$  and  $\sigma_V$ . To do so, we make use of the fundamental idea of the Merton model, which says that the shareholders payoff at time  $T$  can be considered as a European call option on the firm’s assets  $V_T$  with the strike price equal to the face value of the debt outstanding  $B$ ,

$$S_T = \max(V_T - B, 0) = (V_T - B)^+. \quad (19)$$

If the value of the firm’s assets exceeds the liabilities,  $V_T > B$ , debt holders will receive the full face value of debt  $B$  and equity holders receive the

balance  $S_t = V_t - B$ . If the value of the firm's assets is less than its liabilities, the firm cannot meet its financial obligations. In this case debt holders receive the actual firm value  $V_T$  and shareholders receive nothing,  $S_T = 0$ .

Applying the Black-Scholes call-option formula, we can derive the following relationship between the current equity value  $S_t$  and the firm's asset value  $V_t$ :

$$S_t = V_t \Phi(d_{t,1}) - B \exp(-r(T-t)) \Phi(d_{t,2}), \quad (20)$$

where

$$d_{t,1} = \frac{\ln(\frac{V_t}{B}) + (r + \frac{1}{2}\sigma_V^2)(T-t)}{\sigma_V \sqrt{T-t}}, \quad \text{and} \quad d_{t,2} = d_{t,1} - \sigma_V \sqrt{T-t}.$$

Further, from Ito's lemma the following relationship between equity and asset volatilities can be derived:

$$\sigma_S = \sigma_V \frac{V_t}{S_t} \Phi(d_1). \quad (21)$$

Equations (20) and (21) describe now a set of two non-linear equations with two unknowns, i.e.  $V_t$  and  $\sigma_V$ , that can be solved numerically by using a generalised gradient method.<sup>2</sup> Based on these estimates, distance-to-default in equation (18) can be calculated.

## B Bootstrap procedure for the panel Diebold-Mariano test

In order to test whether a difference in forecasts is significant we calculate a panel Diebold-Mariano test statistic as explained in Section 2.4. As the small sample properties are unknown we calculate confidence intervals using a block bootstrap procedure, where each block is the Diebold-Mariano statistic for a cross-section unit,  $i$ . The reason to use a block bootstrap is that the time series of forecasts from each cross-section unit are relatively short and, in particular for larger  $h$ , likely to be autocorrelated.

The bootstrap confidence intervals are calculated as follows. We first obtain the panel Diebold-Mariano statistic

$$\bar{s}(h) = \frac{1}{\sqrt{N}} \sum_{i=1}^N s_i(h)$$

where  $s_i(h)$  is the Diebold-Mariano statistic for cross-section unit  $i$ . Next we obtain  $B = 1000$  samples of  $\bar{s}_b(h)$ ,

$$\bar{s}_b(h) = \frac{1}{\sqrt{N}} \sum_{i=1}^N s_i^b(h), \quad b = 1, 2, \dots, B,$$

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<sup>2</sup>We thank Reint Gropp and Jukka Vesala for providing their visual basic codes to calculate the distance-to-default measures.



where the  $s_i^b(h)$  are sampled from the set of  $\{s_i(h)\}_{i=1}^N$  with replacement. Confidence intervals are then calculated as

$$\bar{s}(h) - \sqrt{v_s^2} z_{B,(1-q)} \text{ and } \bar{s}(h) - \sqrt{v_s^2} z_{B,q} \quad (22)$$

where  $z_{B,\alpha}$  is the value of the  $\alpha$  quantile in the sample of  $z_b = [\bar{s}_b(h) - E(\bar{s}_b(h))]/\sqrt{\text{VAR}(\bar{s}_b(h))}$ , and the variance of  $\bar{s}(h)$ ,  $v_s^2$ , is calculated via the jackknife.

## C Data sources

The data used for the calculation of the D2D have the following sources:

- Total Liabilities = (Total Assets) - (Total Share Capital and Reserves)  
Total Assets: Datastream, annual frequency interpolated to quarterly data  
Total Share Capital and Reserves: Datastream, annual frequency interpolated to quarterly data
- Market Value: Datastream, quarterly frequency
- Interest rates: short-term interest rates (3-months): Datastream, quarterly frequency
- Equity prices: Datastream, daily frequency to calculate 6-month moving averages.

The macroeconomic data have the following sources:

- Long-term interest rate: OECD Economic Outlook.
- Industrial production: IMF International Financial Statistics, line 66, transformed into growth rates:  $\Delta \text{indp}_t = 100 \ln(\text{indp}_t / \text{indp}_{t-4})$
- Inflation: IMF International Financial Statistics, line 64, transformed into growth rates:  $\text{infl}_t = 100 \ln(\text{CPI}_t / \text{CPI}_{t-4})$
- Domestic credit: IMF International Financial Statistics, line 32, transformed into growth rates:  $\Delta \text{domcr}_t = 100 \ln(\text{domcr}_t / \text{domcr}_{t-4})$
- Equity returns: IMF International Financial Statistics, line 62, transformed into growth rates:  $\Delta \text{eqret}_t = 100 \ln(\text{eqret}_t / \text{eqret}_{t-4})$
- Real effective exchange rate: IMF International Financial Statistics, line REU, transformed into growth rates:  $\Delta \text{reer}_t = 100 \ln(\text{reer}_t / \text{reer}_{t-4})$
- Unemployment ratios: OECD Economic Outlook.

- Growth rates of GDP: IMF International Financial Statistics, line 62, transformed into growth rates:  $\Delta GDP_t = \ln(GDP_t/GDP_{t-4})/100$
- CBOE Volatility Index VIX: Chicago Board Options Exchange website (www.cboe.com).
- The price-earnings ratio is based on the S&P500 composite provided by Datastream.

We have tested the variables for stationarity using the panel unit root test of Im, Pesaran and Shin (2003). In order to conserve space, the results are not reported here but can be obtained from the authors. They do, however, suggest that the assumption of stationarity is a reasonable one.

Table 6: Sample composition

	<b>Banks</b>	Life Insurances	Non-Life Insurances	<b>Total Insurances</b>
Australia	8	1	1	2
Austria	2	-	2	2
Belgium	4	-	-	0
Canada	8	3	2	5
Denmark	7	-	2	2
Finland	1	-	1	1
France	6	1	3	4
Germany	4	1	9	10
Greece	-	-	-	0
Ireland	3	1	1	2
Italy	17	3	8	11
Japan	61	-	6	6
Korea	3	-	3	3
Netherlands	2	2	-	2
Norway	1	1	-	1
Portugal	5	-	-	0
Spain	13	-	2	2
Sweden	4	-	-	0
UK	6	6	7	13
USA	40	8	40	48
Switzerland	16	2	4	6
Total	211	29	91	120

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