

Forecasting the fragility of the banking and insurance sector*

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Abstract Linkages between banks and insurance companies are important when forecasting the fragility of the banking and insurance sectors. We propose a novel empirical framework that allows us to estimate unobserved linkages in panel data sets that contains observed regressors. 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 on observed variables only. 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

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1 Introduction

The credit crunch of 2007/08 demonstrated 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. This suggests that when forecasting systemic risk linkages within the financial sector need to be taken into account irrespective of whether they are caused by direct financial linkages or by common shocks to the financial system.

In this paper, we model the linkages between banks and insurances using unobserved common factors. Our econometric method is based on the CCE estimator of Pesaran (2006), which allows us to include observed variables and unobserved common factors in the same forecasting equation. This is in contrast to the current literature where the unobserved common factors are usually obtained from a range of variables that are not modeled themselves. An example of this approach is Bernanke, Boivin and Elias (2005). While the possibility of the combination of observed and unobserved factors 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.

The second 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 spanning 211 banks and 120 insurance companies in 21 countries. We show that incorporating unobserved common factors in addition to macroeconomic variables into forecasts leads to large improvements in forecast accuracy for individual financial institutions and for the systemic risk of the banking and insurance sectors. Given that we forecast the performance of firms in two industries and in geographically distinct regions, we analyze, which factors, that is, regional, industry-specific, or world wide factors, are important for forecasting financial fragility.

A large body of literature exists that considers the forecast of systemic risk in the

financial sector. See De Bandt and Hartmann (2002) for a survey. 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 insurances' 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 Allen and Gale (2000). Financial contagion is the direct effect of a crisis of one company or in one market on the performance of other companies or markets. Pesaran and Pick (2007) show that if the number of cross-section units is large contagion is observationally equivalent to an unobserved common factor. Hence, in our application where the number of firms is very large it is not possible to distinguish contagion from a common factor. However, we are not so much concerned with the source of the common factors but are interested in improving the forecast of firm specific and systemic risk. For the purposes of this paper this is therefore a minor drawback.

We use distance-to-default as proposed by Crosbie and Bohn (2003) as the measure of performance of the banks and insurances. Distance-to-default is based on the theoretical option pricing model of Merton (1974). While it is an internally consistent measure, it may rely on assumptions that are not met by the data and this may impact the results.

Despite these potential shortcomings a large literature has found that distance-to-default is empirically a useful measure.

An advantage of distance-to-default, 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 distance-to-default to other measures of default and find that that distance-to-default "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 distance-to-default 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 distance-to-default 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 a survey among financial stability reports issued by central banks, Cihák (2006) shows that distance-to-default is one of the most frequently used market-based risk indicators. This means that using distance-to-default makes our study directly relevant for financial stability analysis in practice.

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 distance-to-default 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. For this, we want to make use of observed regressors that have been found to have a significant influence on the fragility of banks and insurances in the literature and at the same time allow for unobserved common factors across banks and insurances.

Suppose that distance-to-default, denoted y_{it} , can be described by the following model

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

where \mathbf{d}_t is a $l \times 1$ vector of observed common factors, including the intercept, \mathbf{x}_{it} a $k \times 1$ vector of individual specific regressors, and ρ_i , $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ are the corresponding parameter vectors. Furthermore, assume that the performance of financial institutions is correlated beyond what can be explained by the observed determinants \mathbf{d}_t and \mathbf{x}_{it} , that is, the error term, u_{it} , contains 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 $\varepsilon_i \sim (\mathbf{0}, \sigma^2 \mathbf{I})$.

Under the assumption that future regressors are predictable from past observations, we can iterate (1) to obtain the following direct forecasting model

$$y_{i,T+h} = \tilde{\boldsymbol{\alpha}}'_i \mathbf{d}_T + \tilde{\rho}_i y_{i,T} + \tilde{\boldsymbol{\beta}}'_i \mathbf{x}_{iT} + \tilde{\boldsymbol{\gamma}}'_i \mathbf{f}_T + e_{i,T+h}. \quad (3)$$

where a tilde denotes the parameter from the direct forecast equation.

Hence, a forecast of $y_{i,T+h}$ given the information up to time T , Ω_T , is obtained from

$$E(y_{i,T+h} | \Omega_T) = \hat{\boldsymbol{\alpha}}'_i \mathbf{d}_T + \hat{\rho}_i y_{i,T} + \hat{\boldsymbol{\beta}}'_i \mathbf{x}_{iT} + \hat{\boldsymbol{\gamma}}'_i \hat{\mathbf{f}}_T, \quad (4)$$

where $\hat{\boldsymbol{\alpha}}_i$, $\hat{\rho}_i$, $\hat{\boldsymbol{\beta}}_i$ and $\hat{\boldsymbol{\gamma}}_i$ are estimates of the parameters in (3), and $\hat{\mathbf{f}}_T$ are the estimates

of \mathbf{f}_T . The forecast requires estimates of the parameters and the factors, and we turn to them now. The estimation proceeds in two steps: first, we estimate the unobserved common factors, \mathbf{f}_t from (1) and (2). Then we estimate the parameters, $\tilde{\boldsymbol{\alpha}}_i$, $\tilde{\rho}_i y_{i,T}$, $\tilde{\boldsymbol{\beta}}_i$, and $\tilde{\gamma}_i$ in (4).

In order to estimate the unobserved common factors, we need estimates of the parameters, ρ_i and $\boldsymbol{\beta}_i$, which are obtained using the CCE estimator of Pesaran (2006) applied to (1) for each firm separately. Hence, we make no assumption about parameter homogeneity between firms. It should be noted that the theoretical arguments put forward by Pesaran do not consider the inclusion of lagged dependent variables on the right hand side of (1). However, the results from Monte Carlo experiments reported in Appendix A.3 suggest that the estimator delivers consistent estimates also for regressions including lagged dependent variables.

Given the consistent estimation of ρ_i and $\boldsymbol{\beta}_i$ we can calculate the residual

$$v_{it} = u_{it} + \boldsymbol{\alpha}_i \mathbf{d}_t$$

as

$$\hat{v}_{it} = y_{it} - \hat{\rho}_i y_{i,t-1} - \hat{\boldsymbol{\beta}}_i' \mathbf{x}_{it}.$$

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

$$\hat{u}_i = \mathbf{Q}_D \hat{v}_{it}, \tag{5}$$

with $\mathbf{Q}_D = \mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{D})^{-1}\mathbf{D}'$ and $\mathbf{D} = (\mathbf{d}'_1, \mathbf{d}'_2, \dots, \mathbf{d}'_T)'$. An issue when integrating out \mathbf{d}_t is the orthogonality of the unobserved common factors, \mathbf{f}_t to the observed common factors, \mathbf{d}_t . A violation of this assumption clearly would bias the parameter estimates of the common factors, and this limitation should be borne in mind when interpreting their results. For the forecasts obtained from this procedure this is, however, of no consequence.

The unobserved common factors, \mathbf{f}_t , are then extracted from the estimated residuals, \hat{u}_{it} , 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 an 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 total number of factors to $m = 4$. We have also performed the forecasts for different m and the results remain qualitatively unchanged.

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 modeling approach proposed by Pesaran, Schuermann and Weiner (2004) and Pesaran, Schuermann and Smith (2009). 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, which we will exploit below to analyze the extent of the dependence across regions and industries.

2.1 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 distance-to-default

$$\bar{y}_{T+h|T} = \sum_{i=1}^N w_i y_{i,T+h|T}. \quad (6)$$

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 distance-to-default it is important to account for unobserved common factors, as pointed out by Chan-Lau and Gravelle (2005) and Cihák (2006).

However, the average distance-to-default 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 per-

formance of other institutions. In order to address the downside risk of the financial system we also forecast the lower quartile weighted by market value

$$y_{T+h,T}^q = \sum_{i=1}^N w_i y_{i,T+h|T} \mathbf{I}(y_{i,T+h|T}) \quad (7)$$

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.

2.2 Evaluating the forecasts

We evaluate the forecasts using the RMSFE

$$\text{RMSFE}(h) = \sqrt{\frac{1}{M} \sum_{j=1}^M e_{i,T_j,h}^2}, \quad j = 1, 2, \dots, M \quad (8)$$

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

$$\bar{s}(h) = \frac{1}{\sqrt{N}} \sum_{i=1}^N s_i(h) \quad (9)$$

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

Finally, we calculate the Kuipers score

$$KS = H - F$$

where H is the proportion of distance-to-default observations in the lower quartile of the distribution that are correctly forecast to be in the lower quartile, and F are the proportion of distance-to-default 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 distance-to-default distribution, the Kuipers score measures whether the authorities monitor the right firms.

3 Data and descriptive statistics

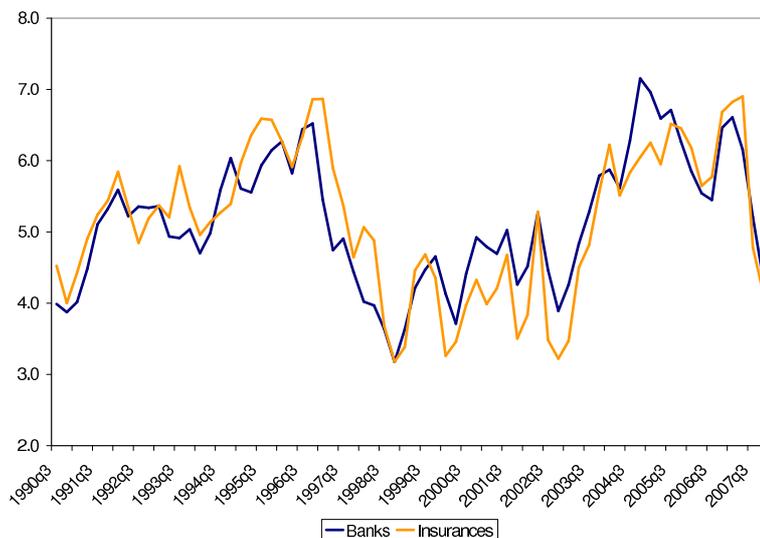
The measure of bank and insurance performance is distance-to-default, which is the difference of the firm's value and the firm's liabilities, standardized by the volatility of the firm's value. The firm's value is derived from the Merton (1974) option value approach and details are given in Appendix A.1.

The underlying data to calculate the quarterly distance-to-default measure are provided by Datastream. We collected the data for all listed 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 B.

Figure 1 plots the average distance-to-default value for the banking and insurance sector over time. The high correlation of the two series is immediately obvious. More-

Figure 1: Average DD by Sector over Time



over, the distance-to-default 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.¹

Explanatory variables The aim is to predict distance-to-default 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 distance-to-default 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.

¹In order to obtain some evidence on the performance of distance-to-default in tracking distress of financial institutions, we plot time series of the distance-to-default of two banks that were in crisis in the past in Figure 3 in Appendix A.1. In the two cases under consideration distance-to-default does reflect the financial difficulty of the banks.

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
7. Unemployment rate: Level of unemployment rate for each country
8. Δ 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 distance-to-default. 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 distance-to-default. 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 distance-to-default 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 distance-to-default 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 distance-

to-default 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 distance-to-default 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 distance-to-default. 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 1 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

Table 1: Cross-section dependence test

Region	Industry	CD	$\hat{\rho}_{ij}$
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
	Banks vs Insur.	139.94	0.54
Europe	Banks & Insur.	200.92	0.37
	Banks	112.68	0.35
	Insurances	89.95	0.40
	Banks vs Insur.	98.05	0.36
Japan/ Korea/ Australia	Banks & Insur.	104.09	0.24
	Banks	86.77	0.23
	Insurances	20.86	0.41
	Banks & Insur.	26.24	0.27

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

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 distance-to-default 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.

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 2. 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.

Table 2: 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. An asterisk indicates significance at the 95% level.

The panel Diebold-Mariano statistics suggest that the factor-based forecasts are significant improvements in all cases—an asterisk indicates significance at the 95% level. 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 2 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 2 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 3. 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 case as they are based on 12 aggregate forecasts only. When forecasting the lower quartile of the distribution 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 distance-to-default 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 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 2. While, the Diebold Mariano test shows that the differences in the ability of the different forecast models to forecast the average and the lower quartile distribution of distance-to-default are not significant, these test should be interpreted with caution given the small number of aggregate forecasts.

Table 3: 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 2. The average RMSFEs are scaled up by 100 for ease of exposition. An asterisk indicates significance at the 95% level.

Table 4: 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.

4.3 The determinants of distance-to-default

An interesting byproduct 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, thus, covering the sample from 1990Q3 to 2007Q3. The parameters of the regressors \mathbf{x}_{it} , $\hat{\beta}_{it}$ are obtained from the CCE estimator using the cross-section averages across all firms. The parameters for the common regressors, $\hat{\alpha}_{it}$ 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 4. 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 vari-

ables the long term interest rate and the unemployment rate 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 distance-to-default, 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.

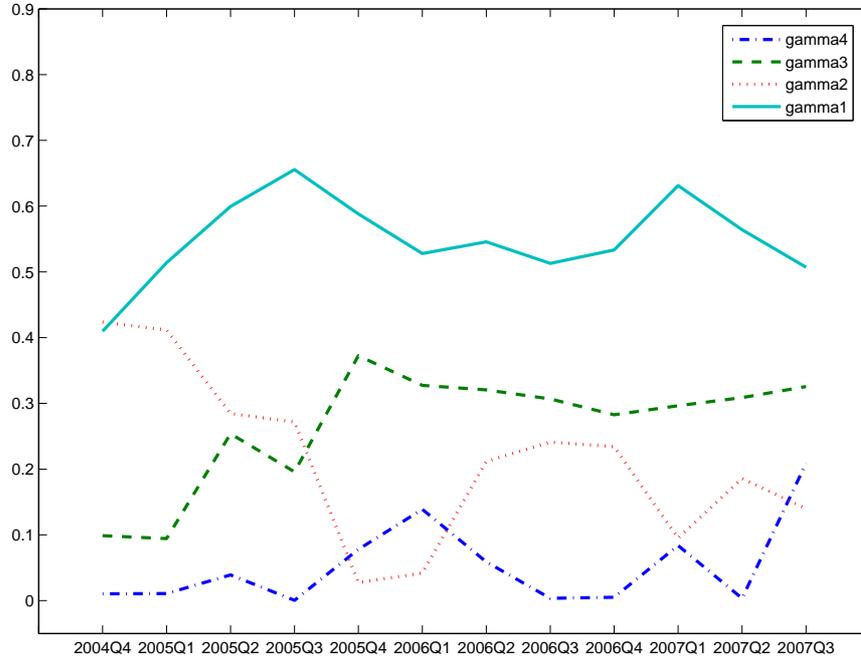
The parameters for the common observed factors show that the P/E ratio for banks and the VIX enter with the correct sign compared to our a priori expectations. However, these two parameters should be interpreted with caution, given that they rely on orthogonality to the unobserved factors. The parameters for insurances are very similar. The only exception is the 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 2. 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. 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

Figure 2: Time series of $\bar{\gamma}$ over the forecast period



'gamma₁' denotes the estimated parameters for the first principal component, 'gamma₂' that of the second, 'gamma₃' that of the third, and 'gamma₄' 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.

factors into account leads up to 11% reduction in the RMSFE of the forecasts of individual firms distance-to-default. Furthermore, the forecasts are more accurate in tracking the position of a firm within the distribution of distance-to-default. 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 Mathematical appendix

A.1 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 μ_V and a constant diffusion rate equal to σ_V ,

$$dV_t = \mu_V V_t dt + \sigma_V V_t dW_t, \quad (10)$$

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

$$V_T = V_t \exp \left((\mu_V - \frac{1}{2}\sigma_V^2)(T-t) + \sigma_V \sqrt{(T-t)}\epsilon_T \right), \quad (11)$$

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

$$\begin{aligned} \mathbb{P}(V_T \leq B) &= \mathbb{P}(\ln V_T \leq \ln B) \\ &= \mathbb{P} \left(-\frac{\ln(\frac{V_t}{B}) + (\mu_V - \frac{1}{2}\sigma_V^2)(T-t)}{\sigma_V \sqrt{(T-t)}} \geq \epsilon_T \right) \end{aligned} \quad (12)$$

On basis of equation (12), Crosbie and Bohn (2003) define distance-to-default as

$$DD = \frac{\ln(\frac{V_t}{B}) + (r - \frac{1}{2}\sigma_V^2)(T-t)}{\sigma_V \sqrt{(T-t)}}, \quad (13)$$

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 (13), we first have to determine the two unknown parameters V_t and σ_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 ,

$$S_T = \max(V_T - B, 0) = (V_T - B)^+. \quad (14)$$

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 :

$$S_t = V_t \Phi(d_{t,1}) - B \exp(-r(T-t)) \Phi(d_{t,2}), \quad (15)$$

where

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

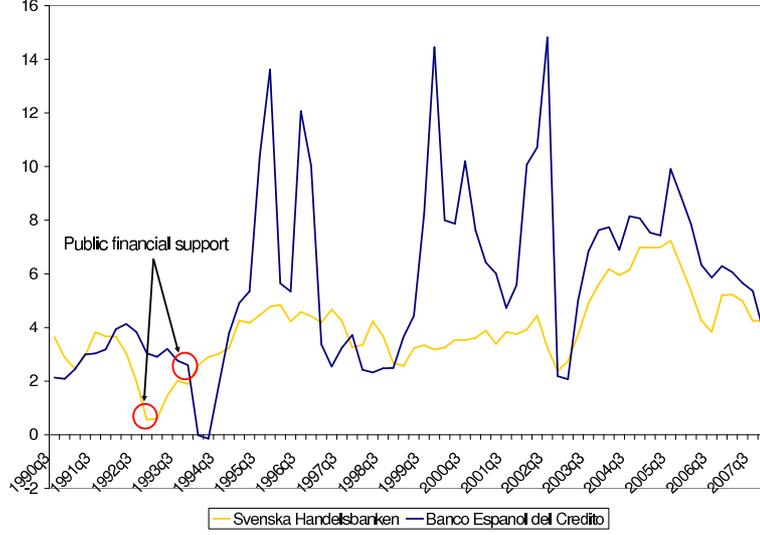
Further, from Ito's lemma the following relationship between equity and asset volatilities can be derived:

$$\sigma_S = \sigma_V \frac{V_t}{S_t} \Phi(d_1). \quad (16)$$

Equations (15) and (16) describe now a set of two non-linear equations with two unknowns, i.e. V_t and σ_V , that can be solved numerically by using a generalized gradient method.² Based on these estimates, distance-to-default in equation (13) can be calculated.

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

Figure 3: DD for Banco Español de Crédito and Svenska Handelsbanken



A.2 Distance-to-default in times of crises

Figure 3 gives an example of the time series of the distance-to-default 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, distance-to-default 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.

A.3 Monte Carlo experiment

A.3.1 Experimental design

We use an experimental set-up identical to that of Pesaran (2006) with the exception that we introduce a lagged dependent variable in the regression in place of autocorrelated errors. The data are generated as

$$y_{it} = \alpha_i(1 - \rho_i)^{-1} + \rho_i y_{i,t-1} + \beta_i' \mathbf{x}_{it} + \gamma_i' \mathbf{f}_t + \sigma_{\varepsilon,i} \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, 1), \quad (17)$$

where $i = 1, 2, \dots, N$ denote the cross-section units, $t = -49, -48, \dots, 1, \dots, T$ denotes time, and the first 50 observations are discarded before the estimation. The 2×1 vector of regressors, \mathbf{x}_{it} , is generated as

$$\mathbf{x}_{it} = \mathbf{A}_i \mathbf{d}_t + \mathbf{\Gamma}_i \mathbf{f}_t + \boldsymbol{\nu}_t, \quad (18)$$

and the error terms, $\boldsymbol{\nu}_t = (\nu_{1t}, \nu'_{2t})$, are autocorrelated,

$$\nu_{jt} = \rho_\nu \nu_{j,t-1} + (1 - \rho_\nu^2)^{1/2} \zeta_{jt}, \quad \zeta_{jt} \sim \text{N}(0, 1), \quad j = 1, 2.$$

The parameters in equations (17) and (18) are

$$\alpha_i \sim \text{N}(1, 1), \quad \text{vec}(\mathbf{A}) \sim \text{N}(0.5\boldsymbol{\nu}_4, 0.5\mathbf{I}_4),$$

where $\boldsymbol{\nu}_4 = (1, 1, 1, 1)'$, \mathbf{I}_4 is an identity matrix with four rows, and α_i and \mathbf{A} are not changed across replications. Furthermore, $\boldsymbol{\beta}_i \sim \text{N}(\boldsymbol{\nu}_2, 0.04\mathbf{I}_2)$,

$$\mathbf{\Gamma} = \begin{pmatrix} \gamma_{i11} & 0 & \gamma_{i13} \\ \gamma_{i21} & 0 & \gamma_{i23} \end{pmatrix} \sim \begin{bmatrix} \text{N}(0.5, 0.5) & 0 & \text{N}(0, 0.5) \\ \text{N}(0, 0.5) & 0 & \text{N}(0.5, 0.5) \end{bmatrix},$$

and $\gamma_i \sim \text{N}(\mathbf{g}, \mathbf{G})$, where $\mathbf{g} = (1, 1, 0)'$ and \mathbf{G} is a diagonal matrix with elements $(0.2, 0.2, 0)'$ on the diagonal. Hence, for brevity, we restrict attention to the case where the rank condition discussed by Pesaran (2006) is satisfied.

The observed and the unobserved common factors are generated as independent AR(1) processes,

$$d_{1t} = 1, \quad d_{2t} = \rho_d d_{2,t-1} + (1 - \rho_d^2)^{1/2} \xi_{dt}, \quad \xi_{dt} \sim \text{N}(0, 1),$$

$$\mathbf{f}_t = \mathbf{\Lambda} \mathbf{f}_{t-1} + \mathbf{\Sigma}_f \boldsymbol{\xi}_t, \quad \boldsymbol{\xi}_t \sim \text{N}(\mathbf{0}, \mathbf{I}_3),$$

$\mathbf{\Lambda}$ and $\mathbf{\Sigma}_f$ are diagonal matrices with elements $\lambda_{ii} = 0.5$ and $\sigma_{f,ii} = (1 - 0.5^2)^{1/2}$ on the diagonal.

We set ρ_i equal to 0.5. We then estimate the parameters ρ_i and $\boldsymbol{\beta}_i$ using the CCE estimator, an infeasible OLS estimator that includes the unobserved common factors, \mathbf{f}_t ,

Table 5: Small sample properties of the CCE, infeasible OLS, and naive OLS estimators of the AR coefficient with $\rho_i = 0.5$

$T \setminus N$	Bias					RMSFE				
	20	30	50	100	200	20	30	50	100	200
<i>CCE</i>										
20	-0.061	-0.063	-0.063	-0.064	-0.063	0.071	0.069	0.067	0.066	0.065
30	-0.035	-0.037	-0.037	-0.037	-0.038	0.042	0.042	0.041	0.039	0.039
50	-0.016	-0.017	-0.018	-0.018	-0.019	0.023	0.022	0.021	0.020	0.020
100	-0.004	-0.004	-0.005	-0.005	-0.006	0.011	0.009	0.009	0.007	0.008
200	0.002	0.002	0.001	0.001	-0.000	0.008	0.007	0.005	0.004	0.003
<i>infeasible OLS</i>										
20	-0.027	-0.027	-0.027	-0.029	-0.029	0.035	0.033	0.031	0.031	0.030
30	-0.017	-0.017	-0.018	-0.018	-0.018	0.023	0.021	0.020	0.019	0.019
50	-0.010	-0.010	-0.010	-0.010	-0.010	0.014	0.013	0.012	0.011	0.011
100	-0.005	-0.005	-0.005	-0.005	-0.005	0.008	0.007	0.006	0.006	0.005
200	-0.003	-0.002	-0.002	-0.003	-0.003	0.005	0.004	0.004	0.003	0.003
<i>naive OLS</i>										
20	0.018	0.015	0.016	0.018	0.015	0.060	0.058	0.055	0.056	0.053
30	0.035	0.035	0.036	0.037	0.036	0.058	0.057	0.058	0.056	0.056
50	0.051	0.050	0.050	0.052	0.052	0.063	0.061	0.061	0.062	0.063
100	0.061	0.061	0.062	0.063	0.064	0.066	0.066	0.066	0.067	0.068
200	0.067	0.067	0.068	0.068	0.069	0.070	0.070	0.070	0.070	0.071

The table reports the bias and the RMSFE for the mean group estimate of the autoregressive parameter in (17), $\sum_{i=1}^N \hat{\rho}_i$, where the individual parameters are estimated using the CCE estimator (Pesaran 2006), infeasible OLS, which includes the unobserved common factors in the regression, and naive OLS, which ignores the unobserved common regressors.

in the regression, and a naive OLS estimator that ignores the unobserved common factors in the estimation. We consider only the (more challenging) heterogeneous parameter case and all estimations are therefore mean group estimations. We report the bias and the root mean square error.

A.3.2 Results

The results are in Table 5, which shows the bias and RMSFE of the mean group estimates of ρ_i . For the CCE and the infeasible OLS estimates the bias reduces as T increases and the RMSFE is reduced as both T and N increase, although increases in T are more important. For $T = 20$ the infeasible OLS estimates have bias and RMSFE about half the size of those of the CCE estimates. For large T , however, the difference in bias and RMSFE becomes very small and for practical purposes there is not difference between the two estimates. The naive OLS estimates are clearly inconsistent. For small T they benefit from the smaller number of parameters that are estimated but as T increases they estimates do not converge to the true value of the parameter.

B 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: $\Delta indp_t = \ln(indp_t/indp_{t-4}) * 100$
- Inflation: IMF International Financial Statistics, line 64, transformed into growth rates: $infl_t = \ln(CPI_t/CPI_{t-4}) * 100$
- Domestic credit: IMF International Financial Statistics, line 32, transformed into growth rates: $\Delta domcr_t = \ln(domcr_t/domcr_{t-4}) * 100$
- Equity returns: IMF International Financial Statistics, line 62, transformed into growth rates: $\Delta eqret_t = \ln(eqret_t/eqret_{t-4}) * 100$
- Real effective exchange rate: IMF International Financial Statistics, line REU, transformed into growth rates: $\Delta reer_t = \ln(reer_t/reer_{t-4}) * 100$
- 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).

Finally, the price-earnings ratio is based on the S&P500 composite provided by Datastream.

Table 6: Sample composition

	Banks	Life Insurances	Non-Life Insurances	Total Insurances
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

References

- Allen, Franklin, and Douglas Gale (2000) 'Financial contagion.' *Journal of Political Economy* 108(1), 1–33.
- Allen, Franklin, and Elena Carletti (2006) 'Credit risk transfer and contagion.' *Journal of Monetary Economics* 53(1), 89–111.
- Altman, Edward I. (1993) *Corporate Financial Distress and Bankruptcy: A Complete Guide to Predicting and Avoiding Distress and Profiting from Bankruptcy* (New York: John Wiley and Sons).

- Arora, N., J. Bohn, and F. Zhu (2005) ‘Reduced form versus structural models of credit risk: A case study of three models.’ Moody’s KMV *White Paper*.
- Berg, Andrew, and Catherine Pattillo (1999) ‘Predicting currency crises: The indicator approach and an alternative.’ *Journal of International Money and Finance* 18(4), 561–586.
- Bernanke, Ben S., Jean Boivin, and Piotr Eliasch (2005) ‘Measuring the effect of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach.’ *Quarterly Journal of Economics* 120, 387–422.
- Bharath, Sreedhar T., and Tyler Shumway (2008) ‘Forecasting default with the Merton distance to default model.’ *Review of Financial Studies* 21(3), 1339–1369.
- Bikker, J. A., and H. Hu (2002) ‘Cyclical patterns in profits, provisioning and lending of banks and procyclicality of the new Basel capital requirements.’ BNL *Quarterly Review* 221, 143–175.
- Black, Fischer, and Myron Scholes (1973) ‘The valuation of options and corporate liabilities.’ *Journal of Political Economy* 81, 637–654.
- Breusch, T. S., and Adrian R. Pagan (1980) ‘The Lagrange multiplier test and its application to model specification in Econometrics.’ *Review of Economic Studies* 47, 239–253.
- Carling, Kenneth, Tor J. J. Lindé, and Kasper Roszbach (2007) ‘Corporate credit risk modelling and the macroeconomy.’ *Journal of Banking and Finance* 31(3), 845–868.
- Chan-Lau, Jorge A., and Toni Gravelle (2005) ‘The END: A new indicator of financial and nonfinancial corporate sector vulnerability.’ IMF *Working paper* 05/231.
- Chan-Lau, Jorge A., Arnaud Jobert, and Janet Kong (2004) ‘An option-based approach to bank vulnerabilities in emerging markets.’ IMF *Working paper* 04/33.
- Cihák, Martin (2006) ‘How do central banks write on financial stability?’ IMF *Working paper* 06/133.
- Crosbie, Peter, and Jeff Bohn (2003) ‘Modeling default risk.’ *mimeo*, Moody’s KMV.
- De Bandt, Olivier, and Philipp Hartmann (2002) ‘Systemic risk: A survey.’ In *Financial Crises, Contagion and the Lender of the Last Resort*, ed. C. Goodhart and G. Illing (Oxford: Oxford University Press) pp. 249–97.
- De Mol, Christine, Domenico Giannone, and Lucrezia Reichlin (2008) ‘Forecasting using

- a large number of predictors: Is Bayesian shrinkage a valid alternative to principal components.’ *Journal of Econometrics* 146(2), 318–328.
- Demirgüç-Kunt, Asli, and Enrica Detragiache (1998) ‘The determinants of banking crises in developing and developed countries.’ *IMF Staff Papers*.
- Demirgüç-Kunt, Asli, and H. Huizinger (1998) ‘Determinants of commercial bank interest margins and profitability: Some international evidence.’ *World Bank Economic Review* 13, 379–408.
- Demirovic, Amer, and Dylan C. Thomas (2007) ‘The relevance of accounting data in the measurement of credit risk.’ *European Journal of Finance* 13(3), 253–268.
- Diebold, Francis X., and Roberto S. Mariano (1995) ‘Comparing predictive accuracy.’ *Journal of Business and Economic Statistics* 12, 253–263.
- Edison, Hali J. (2003) ‘Do indicators of financial crises work? an evaluation of an early warning system.’ *International Journal of Finance and Economics* 8(1), 11–53.
- Goldstein, Morris (1998) ‘The Asian financial crisis: Causes, cures, and systematic implication.’ Peterson Institute for International Economics *Policy Analyses in International Economics* 55.
- Gorton, G. (1988) ‘Banking panics and business cycles.’ *Oxford Economic Papers* 40(4), 751–781.
- Granger, Clive W. J., and M. Hashem Pesaran (2000) ‘Economic and statistical measures of forecast accuracy.’ *Journal of Forecasting* 19(7), 537–560.
- Gropp, Reint J., and Gerard Moerman (2004) ‘Measurement of contagion in bank equity prices.’ *Journal of International Money and Finance* 23(3), 405–459.
- Gropp, Reint J., Jukka Vesala, and Giuseppe Vulpes (2006) ‘Equity and bond market signals as leading indicators of bank fragility.’ *Journal of Money, Credit, and Banking* 38(2), 399–428.
- Hagen, Jürgen von, and Tai-Kuang Ho (2004) ‘Money market pressure and the determinants of banking crises.’ *Journal of Money, Credit, and Banking* 39(5), 1037–1066.
- Hillegeist, Stephen A., Elisabeth K. Keating, Donald P. Cram, and Kyle G. Lundstedt (2004) ‘Assessing the probability of bankruptcy.’ *Review of Accounting Studies* 9, 5–24.
- Kaminsky, Graciela L., and Carmen M. Reinhart (1999) ‘The twin crises; the causes of banking and balance-of-payments problems.’ *American Economic Review* 89(3), 473–

500.

- Kaminsky, Graciela L., Saul Lizondo, and Carmen M. Reinhart (1998) ‘Leading indicators of currency crises.’ *IMF Staff Papers* 45(1), 1–48.
- Merton, Robert C. (1974) ‘On the pricing of corporate debt: The risk structure of interest rates.’ *Journal of Finance* 29, 449–470.
- Monks, Allan, and Marco Stringa (2005) ‘Inter-industry linkages between UK life insurers and UK banks: An event study.’ Bank of England *Financial Stability Review* 18, 127–134.
- Pesaran, M. Hashem (2004) ‘General diagnostic tests for cross section dependence in panels.’ *Cambridge Working Paper in Economics* 0435.
- (2006) ‘Estimation and inference in large heterogeneous panels with a multifactor error structure.’ *Econometrica* 74(4), 967–1012.
- Pesaran, M. Hashem, and Andreas Pick (2007) ‘Econometric issues in the analysis of contagion.’ *Journal of Economic Dynamics and Control* 31(4), 1245–1277.
- Pesaran, M. Hashem, Til Schuermann, and L. Vanessa Smith (2009) ‘Forecasting economic and financial variables with global VARs.’ *International Journal of Forecasting* 25(4), 642–675.
- Pesaran, M. Hashem, Til Schuermann, and Scott M. Weiner (2004) ‘Modeling regional interdependencies using a global error-correcting macroeconomic model.’ *Journal of Business and Economic Statistics* 22(2), 129–162.
- Shiu, Y. (2004) ‘Determinants of United Kingdom general insurance company performance.’ *British Actuarial Journal* 10(5), 1079–1110.
- Shumway, Tyler (2001) ‘Forecasting bankruptcy more accurately: A simple hazard model.’ *Journal of Business* 74(1), 101–124.
- Slijkerman, Jan F., Dirk Schoenmaker, and Caspar G. de Vries (2005) ‘Risk diversification by European financial conglomerates.’ Tinbergen Institute *Discussion Paper* 110/2.
- Stock, James H., and Mark W. Watson (2002a) ‘Forecasting using principle components from a large number of predictors.’ *Journal of the American Statistical Association* 97(460), 1167–1179.
- (2002b) ‘Macroeconomic forecasting using diffusion indexes.’ *Journal of Business and*

Economic Statistics 20(2), 147–162.

Tudela, Merxe, and Garry Young (2003) ‘Predicting default among UK companies: A Merton approach.’ Bank of England *Financial Stability Review*.

Vassalou, Maria, and Yuhang Xing (2004) ‘Default risk in equity returns.’ *Journal of Finance* 59(2), 831–868.

Zmijewski, M. E. (1984) ‘Methodological issues related to the estimation of financial distress prediction models.’ *Journal of Accounting Research* 22, 59–82.