Forecasting the fragility of the banking and insurance sectors*

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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 contain observed regressors. We find that taking unobserved common factors into account reduces the root mean square forecasts error of firm specific forecasts by up to 9%, of system forecasts by up to 14%, and by up to 39% for systemic forecasts of more distressed firms 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.
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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. The crisis not only severely affected the solvency of major US banks but also put insurers and several European banks under pressure. This suggests that forecasts of systemic risk need to take linkages within the financial sector 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) and allows us to extract unobserved common factors from the residuals of our econometric model rather than from extraneous variables. 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 Eliasz (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 forecasts from a panel data set.

The second contribution of this paper is the investigation of the forecasting 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 210 banks and 117 insurance companies in 20 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. We forecast the performance of firms in two industries and in geographically distinct regions, and we analyze, which factors, 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, the current literature investigates forecasts based on observable variables only. 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. In this paper, however, we are not concerned with the source of the common factors but are interested in improving the forecast of firm specific and systemic risk.

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), which is an internally consistent measure of financial distress. While it relies on assumptions that may not be met by the data, 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 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, Čihák (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 the practice of financial stability analysis.

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, $\hat{y}_{i,T+h|T}$, where $i = 1, 2, \ldots, N$ denotes the individual banks and insurances. We base our forecasts on observed regressors that the literature found to significantly influence the fragility of banks and insurances. At the same time we allow for unobserved common factors across banks and insurances that capture linkages between the institutions not accounted for by the observed regressors.

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

$$y_{it+h} = \boldsymbol{\alpha}_i'\boldsymbol{d}_t + \rho_i y_{it} + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + u_{it+h}, \quad t = 1, 2, \ldots T \tag{1}$$

where $\boldsymbol{d}_t$ is a $l \times 1$ vector of observed common factors, including the intercept, $\boldsymbol{x}_{it}$ a $k \times 1$ vector of individual specific regressors, and ρ_i, $\boldsymbol{\alpha}_i$, and $\boldsymbol{\beta}_i$ are parameter vectors. Note that a regressor, x_{jit}, $j = 1, 2, \ldots, k$, can be identical across a subset of firms but cannot be identical across all i. Furthermore, assume that the performance of financial institutions is correlated beyond what can be explained by the observed determinants because the error term, u_{it}, contains m unobserved common factors,

$$u_{it} = \boldsymbol{\gamma}_i'\boldsymbol{f}_t + \varepsilon_{it}, \tag{2}$$

where $\boldsymbol{\gamma}_i$ is a $m \times 1$ vector of parameters, $\boldsymbol{f}_t$ is a $m \times 1$ vector of unobserved common factors, and $\boldsymbol{\varepsilon}_i \sim (\boldsymbol{0}, \sigma_i^2\boldsymbol{I})$. The firm specific error term, u_{it} is therefore composed of common factors, $\boldsymbol{f}_t$, and a firm specific component, ε_{it}, which are not captured by the observed regressors.

The forecast of $y_{i,T+h}$ conditional the information up to time T is therefore

$$\hat{y}_{i,T+h|T} = \hat{\boldsymbol{\alpha}}_i' \boldsymbol{d}_T + \hat{\rho}_i y_{i,T} + \hat{\boldsymbol{\beta}}_i' \boldsymbol{x}_{iT} + \hat{\boldsymbol{\gamma}}_i' \hat{\boldsymbol{f}}_{T+h}, \tag{3}$$

where $\hat{\boldsymbol{\alpha}}_i$, $\hat{\rho}_i$, $\hat{\boldsymbol{\beta}}_i$ and $\hat{\boldsymbol{\gamma}}_i$ are estimates of the parameters in (1) and (2), and $\hat{\boldsymbol{f}}_{T+h}$ is a forecast of $\boldsymbol{f}_{T+h}$.

The forecast requires estimates of the parameters and the unobserved common factors. The problem is that consistent estimation of the unobserved common factors requires consistent estimates of the parameters. Consistent OLS estimation of the parameters, in turn, requires estimates of the unobserved common factors. We solve this problem by using a two step procedure: first, we estimate the unobserved common factors, $\boldsymbol{f}_t$, from (1) and (2), employing principal components and the CCE estimator. In the second step, using the estimates of the unobserved common factors, we estimate the parameters, $\boldsymbol{\alpha}_i$, ρ_i $\boldsymbol{\beta}_i$, and $\boldsymbol{\gamma}_i$ in (3) by OLS and forecast $\hat{\boldsymbol{f}}_{T+h}$ using a VAR in $\hat{\boldsymbol{f}}_t$, $t = 1, 2, \ldots, T$.

In order to estimate the unobserved common factors, we obtain initial estimates of the parameters ρ_i and $\boldsymbol{\beta}_i$ using the CCE estimator of Pesaran (2006), which is applied to (1) for each firm separately. The CCE estimator integrates out the unobserved common factors by introducing cross-section averages into the regression equation (1) and it delivers consistent estimates of ρ_i and $\boldsymbol{\beta}_i$. Given that we employ the estimator for each firm separately, 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 estimate

$$\nu_{it} = u_{it} + \boldsymbol{\alpha}_i \boldsymbol{d}_{t-h}$$

as

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

After obtaining the residuals, $\hat{\nu}_{it}$, the common observed factors, $\boldsymbol{d}_{t-h}$, are integrated out, which yields an estimate of u_{it},

$$\hat{\boldsymbol{u}}_i = \boldsymbol{Q}_D \hat{\boldsymbol{\nu}}_i, \tag{4}$$

where $\boldsymbol{u}_i = (u_{i,h+1}, u_{i,h+2}, \ldots, u_{iT})$, $\boldsymbol{Q}_D = \boldsymbol{I} - \boldsymbol{D}(\boldsymbol{D}'\boldsymbol{D})^{-1}\boldsymbol{D}'$ and $\boldsymbol{D} = (\boldsymbol{d}_1', \boldsymbol{d}_2', \ldots, \boldsymbol{d}_{T-h})'$. An issue when integrating out $\boldsymbol{d}_t$ is the orthogonality of the unobserved common factors, $\boldsymbol{f}_{t+h}$, to the observed common factors, $\boldsymbol{d}_t$. A violation of this assumption would bias the parameter estimates of the common factors, and this limitation should be borne in mind when interpreting their results. The forecasts obtained from this procedure, however, remain unbiased.

The unobserved common factors, $\boldsymbol{f}_t$, are then extracted from the 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, 2002b). Given that the $\hat{u}_{it}$ form 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 $m = 2$. We have also performed the forecasts for different m and the results remain qualitatively unchanged. The principle components analysis of the residuals delivers factors up to T. However, for forecasting we require $\hat{\boldsymbol{f}}_{T+h}$. As suggested by Pesaran, Pick and Timmerman (2010), we use a VAR model of $\hat{\boldsymbol{f}}_t$ to obtain forecasts of $\hat{\boldsymbol{f}}_{T+h}$, where the lag length is selected by BIC.

An alternative 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.

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

$$\bar{y}_{T+h|T} = \sum_{i=1}^{N} w_i y_{i,T+h|T}. \tag{5}$$

This measure has been used by Tudela and Young (2003) with equal weights, $w_i = N^{-1}$. It is important to note that if common factors are not accounted for in the individual forecasts, they 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).

Financial supervisors are largely concerned with poorly performing institutions. The average distance-to-default may not fully reflect this because in the average distance-to-default the negative performance of an individual institution may be offset by the positive performance of another institution. In order to address this, we also forecast the lower quintile of the distribution of distance-to-defaults

$$y^q_{T+h,T} = \sum_{i=1}^{N} w_i y_{i,T+h|T} \mathrm{I}_q(y_{i,T+h|T}) \tag{6}$$

where $\mathrm{I}_q(y_{i,T+h|T})$ is an indicator function that is unity if $y_{i,T+h|T}$ is in the lower quintile. This function can be thought of as a value-at-risk equivalent for the financial supervisor. Throughout our analysis we weigh firms according to their market value.

2.2 Evaluating the forecasts

We evaluate the forecasts using the RMSFE

$$\mathrm{RMSFE}(h) = \sqrt{\frac{1}{M}\sum_{j=1}^{M} e^2_{iT_jh}}, \quad j = 1, 2, \ldots, M \tag{7}$$

where $e_{iT_jh} = (y_{j,T_j+h} - \hat{y}_{j,T_j+h|T_j})/h$, $\hat{y}_{j,T_j+h|T_j}$ is the forecast based on the information up to T_j, where T_j represents the last observation in each of the M expanding windows that we use to construct the forecasts.

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

$$l(A, B) = e^2_{iT_jh|A} - e^2_{iT_jh|B}$$

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

$$\bar{s}(h) = \frac{1}{\sqrt{N}}\sum_{i=1}^{N} s_i(h) \tag{8}$$

where $s_i(h)$ is the Diebold-Mariano statistic for cross-section unit i. The panel Diebold-Mariano statistic also 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 quintile of the distribution that are correctly forecast to be in the lower quintile, and F are the proportion of distance-to-default observations that are forecast to be in the lower quintile but are not (see Granger and Pesaran 2000). Assuming financial authorities put particular supervisory effort on firms that are in the lower quintile of the distance-to-default distribution, the Kuipers score measures whether the authorities monitor the right firms.

3 Data and descriptive statistics

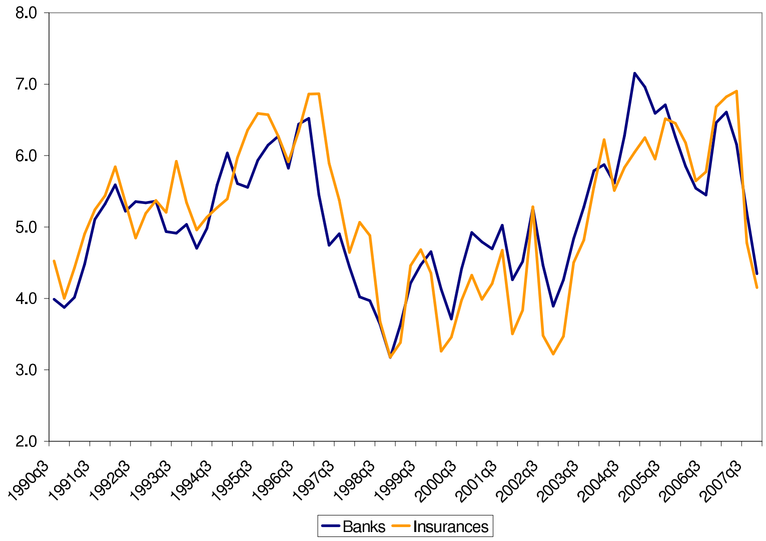
The measure of bank and insurance performance is distance-to-default, which is a widely used indicator to assess the credit risk of publicly-listed firms. It measures the difference of the firm's value and the firm's liabilities, standardized by the volatility of the firm's value. The firm's value is 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. That were in total 280 banks and 158 insurance companies. 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 1991Q3 to 2007Q4.

In the estimation we will estimate up to 18 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 210 banks and 117 insurance companies, including also a number of firms that disappeared later during the crisis in 2008 due to default. 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. Moreover, 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. Additional evidence on the performance of distance-to-default in tracking distress of financial institutions is presented in Appendix A.1, where we plot time series of the distance-to-default of two banks that were in crisis in the past. It can be seen that distance-to-default clearly reflects the financial difficulty of the banks.

Figure 1: Average DD by Sector over Time



Explanatory variables We use macroeconomic as well firm-specific variables as predictors for distance-to-default. This is motivated by recent research by Carling, Lindé and Roszbach (2007) who show that macroeconomic and firm-specific variables have significant explanatory power for firm default risk. Taking macroeconomic conditions into account helps explain the absolute level of default risk, whereas firm-specific information will be informative about a firm's relative default risk.

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 et al. 2007). Some of these variables, e.g. market value or the leverage ratio, are directly or indirectly 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. Thus, we focus in our analysis only on firm-specific variables, which are not directly related to any of the variables used for the calculation of distance-to-default. The variables used are the growth rate of dividends per share for each firm and the growth rate of earnings per share for each firm.

Several empirical studies find a negative relationship between the default probability and the earning ratio of a firm. Shumway (2001), for instance, shows evidence that firms with higher earnings relative to assets are less likely to fail. Similarly, Carling et al. (2007) find that the median earnings of healthy firms are consistently more than twice as high as for defaulting ones. Asquith and Mullins (1983) show that dividends can be used as a simple, comprehensive signal of a firm's recent performance and its future prospects. Michaely, Thaler and Womack (1995) find that typically equity investors react positively to dividend initiations and negatively to dividend omissions. Thus, we expect a positive relationship between the growth rate of the dividends per share and the performance measure distance-to-default.

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

1. Long rate: Growth rate of the 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 the stock market index for each country
6. REER: Growth rate of the real effective exchange rate for each country
7. Unemployment rate: Growth rate of the 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
11. KA-open: Chinn-Ito index measuring a country's degree of capital account openness for each country
12. Financial openess: Sum of relative insurance and financial service import and export for each country

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. 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.

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. The overall impact of domestic credit growth and financial institutions' performance is ambiguous.

Industrial production, GDP growth, and the unemployment rate are included to capture adverse macroeconomic shocks. Theory predicts that adverse shocks affecting the 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), and Bikker and Hu (2002). Dovern, Meier and Vilsmeier (2010) also point to the importance of macroeconomic shocks for the banking sector. 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, given 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.

Pasricha (2009) shows that financial market integration can influence the performance of financial firms. A measure of financial openness is the Chinn-Ito index (KA-open), which measures a country's degree of capital account openness (Chinn and Ito 2008)—a large value indicates low restrictions of cross-border financial transactions. We also add a financial openness indicator, which measures the sum of exports and imports of insurance and financial services relative to the overall level of service exports and imports.

Tang and Yan (2010) observe that market sentiment is an important factor for default risk. We include the price/earnings (P/E) ratio of the US stock market and the VIX as observed common regressors 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 is usually high, which is why the VIX is sometimes called the 'fear index'. The VIX provides important information about investor risk sentiment and market volatility. We expect a negative impact of the VIX on distance-to-default.

4 Empirical analysis

In the first instance, we test for the existence of cross-section correlation between the performance of banks and insurances before and after accounting for 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 the correct size in panels with N large relative to T. 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, Europe, and, fourth, Asia and Australia.

The third columns of Table 1 reports the average pairwise correlation coefficients of the distance-to-default, which are quite sizeable: around 0.29 across all institutions and as large as 0.68 for banks in North America. The economic variables included in our forecast exercise capture some of the cross-section correlation, which results in lower average pairwise correlation coefficients of the residuals of equation (1), u_{it}, which are in the fourth column of the table. However, the average pairwise correlation coefficient of the residuals remain quite sizeable. Furthermore, the CD test statistics in the fifth column of Table 1 show that the correlations are statistically significant as all CD test statistics exceed any conventional significance level—under the null of no cross-section dependence the CD test has a standard normal distribution. This suggest that even after accounting for the regressors in our data set considerable cross-section dependence remains within but also

Table 1: Cross-section dependence test

Region	Industry	$\bar{\hat{\rho}}_y$	$\bar{\hat{\rho}}_u$	CD
all	Banks & Insur.	0.29	0.13	216.04
	Banks	0.28	0.13	141.93
	Insurances	0.35	0.18	107.05
	Banks vs Insur.	0.29	0.11	86.77
USA/ Canada	Banks & Insur.	0.60	0.30	161.38
	Banks	0.68	0.37	95.97
	Insurances	0.50	0.31	80.68
	Banks vs Insur.	0.54	0.28	73.73
Europe	Banks & Insur.	0.29	0.16	112.10
	Banks	0.30	0.15	67.84
	Insurances	0.33	0.21	57.02
	Banks vs Insur.	0.28	0.14	48.58
Japan/ Korea/ Australia	Banks & Insur.	0.27	0.23	106.40
	Banks	0.25	0.25	100.31
	Insurances	0.49	0.29	15.42
	Banks & Insur.	0.33	0.17	17.50

$\bar{\hat{\rho}}_y$ denotes the average pair-wise correlation coefficient of the dependent variable, distance to default, $\bar{\hat{\rho}}_u$ denotes the average pair-wise correlation coefficient of the residual of the individual specific OLS estimation of (1), where the correlation coefficient is calculated for all pairs of institutions in the given region and industry, and CD denotes the CD test statistic of cross-section independence applied to the residuals of the individual specific OLS estimations.

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 up to 2003Q4 for the estimation of the model. Subsequently, the observations of the next quarter are added to the data available for the estimation and another set of forecasts is constructed. Iterating this forward until the end of the sample leads to 12 one-quarter ahead forecasts for each firm or 3886 one-quarter ahead forecasts overall, and 8 four-quarter ahead forecasts for each firm, which resulted in 2915 four-quarter ahead forecasts.

Given the limited number of observations per firm, we select the optimal set of individual specific regressors for each firm and each forecast period according to BIC. However, 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 countries in our sample.

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 $m = 2$ 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 all factor-based forecasts have a lower RMSFE than the forecasts that do not take factors into account. Furthermore, forecasts that use factors that are pooled across all firms (Fac-4) have the smallest RMSFE. The panel Diebold-Mariano statistics suggest that the factor-based forecasts are significant improvements when factors are pooled across firms in a region or across all firms—an asterisk indicates significance at the 5% level.

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 have a lower RMSFE than the forecasts that do not use unobserved factors. The improvements are significant in all cases. The forecasts with region specific factors have the lowest RMSFE and reduce the RMSFE by about 9% compared to those 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
One-quarter ahead forecasts					
RMSFE	1.805	1.772	1.792	1.773	1.757
panel Diebold-Mariano statistics					
No fac.		1.905	0.811	2.096*	3.318*
Fac-1			−1.000	−0.088	0.822
Fac-2				1.028	−2.825*
Fac-3					1.001
Kuipers scores					
	0.161	0.116	0.177	0.128	0.168
Four-quarter ahead forecasts					
RMSFE	3.228	2.941	3.117	2.937	3.073
panel Diebold-Mariano statistics					
No fac.		6.004*	2.229*	5.248*	3.064*
Fac-1			−3.243*	0.088	−2.574*
Fac-2				3.146*	1.044
Fac-3					−2.387*
Kuipers scores					
	0.042	0.234	0.176	0.345	0.154

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 $l(A, B) = e^2_{iT_j h|A} - e^2_{iT_j h|B}$, 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 5% level.

Table 2 also reports the Kuipers scores for the different forecasts models. For $h = 1$ the forecasts based on factors that are pooled within industries (Fac-2) and factors that are pooled across all firms (Fac-4) have a higher Kuipers score than forecasts that are constructed without unobserved common factors. For $h = 4$ all models that incorporate unobserved common factors have a higher Kuipers score. This suggests that taking unobserved factors into account helps financial supervisors to better forecast which firms that are likely to be in acute stress.

Table 3: RMSFE and Diebold-Mariano test for systemic forecasts

	No fac.	Fac-1	Fac-2	Fac-3	Fac-4
One-quarter ahead forecasts					
Average					
RMSFE	0.147	0.137	0.140	0.138	0.141
Diebold-Mariano statistics					
No fac.		1.233	1.703	1.555	0.883
Fac-1			−0.416	−0.187	−0.701
Fac-2				0.374	−0.666
Fac-3					−0.628
Lower quintile					
RMSFE	0.492	0.427	0.516	0.384	0.492
Diebold-Mariano statistics					
No fac.		1.315	−0.779	1.556	0.003
Fac-1			−1.292	1.736	−1.185
Fac-2				1.596	1.096
Fac-3					−1.486
Four-quarters ahead forecast					
Average					
RMSFE	0.358	0.344	0.326	0.309	0.333
Diebold-Mariano statistics					
OLS		1.039	2.129*	3.433*	0.789
Fac-1			0.522	1.073	0.522
Fac-2				1.356	−0.478
Fac-3					−1.767
Lower quintile					
RMSFE	0.925	0.647	0.783	0.655	0.563
Diebold-Mariano statistics					
OLS		1.300	1.299	1.395	1.609
Fac-1			−1.229	−0.259	0.817
Fac-2				1.452	1.890
Fac-3					0.854

See footnote of Table 2. The average RMSFEs are scaled up by 100 for ease of exposition.

4.2 System wide forecasts

The results for the forecasts of the system wide financial stability are reported in Table 3. For $h = 1$ all forecasts that incorporate unobserved common factors have a lower RMSFE than the baseline forecast. The forecasts with the lowest RMSFE are those based on factors that pool information across industries and regions, which reduces the RMSFE by 7% compared to that of the forecast without unobserved factors. The differences are not significant, which is not surprising given that they are based on only 12 aggregate forecasts. When forecasting the lower quintile of the distribution of distance-to-default, all forecasts using unobserved common factors have a lower RMSFE, the only exception is the forecast pooling factors within an industry (Fac-2). Using region specific factors leads to an improvement of 9% of the RMSFE over the forecast without unobserved common factors.

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 14% when pooling the information across industries within regions for the principle components estimation. In the case of region specific factors and in that of industry specific factors the improvements are statistically significant. When forecasting the lower quintile of the distribution of the distance-to-default for $h = 4$, we also find that taking unobserved common factors into account also leads to large improvements in the RMSFE. Pooling factors across all firms reduces the RMSFE by 39%.

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. We report the average parameter estimate of the variables that are included in the optimal model based on BIC in the last forecast with $h = 1$ and the probability of a variable being included. These are the estimates from the largest estimation window from 1991Q3 to 2007Q3. The parameters of the lagged dependent variable and the regressors $\boldsymbol{x}_{it}$ are obtained from the CCE estimator 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 4. The second and fourth column 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 third and fifth column show the same results for insurances.

The variable that is included most often is the lagged dependent variable. From the economic variables the indicators for financial openness and

Table 4: Determinants of distance-to-default

	Banks		Insurances	
	$\bar{\boldsymbol{\theta}}$	p	$\bar{\boldsymbol{\theta}}$	p
lagged dep.var.	0.310	0.848	0.274	0.603
Δlong rate	0.001	0.124	0.094	0.172
Δind.prod.	−0.092	0.176	−0.918	0.129
inflation	0.087	0.238	−0.694	0.216
Δdom.credit	0.025	0.176	0.306	0.259
Δequity ret.	−0.006	0.171	−0.012	0.138
REER	−0.119	0.224	−0.102	0.155
Δunemploy.	0.011	0.243	0.008	0.121
ΔGDP	0.027	0.114	2.512	0.138
ΔDividends	0.041	0.119	−0.096	0.129
ΔEarn.	0.001	0.167	0.011	0.103
Fin.Openness	0.293	0.314	−0.799	0.388
KA-open	0.781	0.233	−0.022	0.086
intercept	0.418	–	0.327	–
P/E ratio	0.565	–	1.017	–
VIX	0.755	–	1.824	–

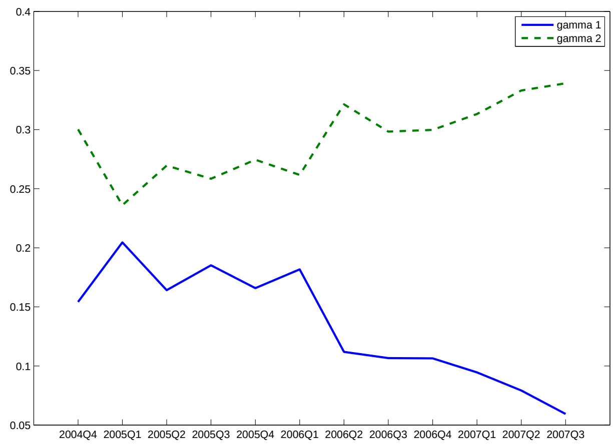
The estimates are from the last one-step ahead forecast with data up to 2007Q3. $\bar{\boldsymbol{\theta}}$ are the average coefficients conditional on the variable being included in the best model according to BIC. p denotes the proportion of forecasts that included the respective variable.

capital account openness, the inflation rate, and the unemployment rate are included most often. However, all variables are only included in a subset of the models.

The growth rate of 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 positively for both banks but negatively for insurances. The positive sign of domestic credit suggests that this variable acts as a measure of the health of banking business. GDP growth increases distance-to-default as expected. However, the results of the other cyclical variables do not have the expected sign.

For banks dividend and earnings growth increases the distance-to-default. The same is true for earnings growth for insurances but the result for dividend growth is reversed. Financial openness improves distance-to-default for banks but has a negative sign for insurance companies and it is the economic variable most often included. Capital account openness positive

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



'gamma$_1$' denotes the estimated parameters for the first principal component, and 'gamma$_2$' that of the second principal component. The dates on the x-axis gives the last observation in the estimation sample for the respective parameter estimates.

affects distance-to-default for banks.

The parameters for the common observed factors show that the P/E ratio enters with the correct sign compared to our a priori expectations. The VIX has a positive sign, too. However, these two parameters should be interpreted with caution, given that they rely on orthogonality to the unobserved factors.

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 increased. In order to shed light on this we plot the parameter estimates of the unobserved common factors 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 micro- and macroeconomic variables and unobserved common factors on the performance of banks and insurances. The unobserved common factors capture a range of influences that are either difficult or impossible to measure, such as the sentiment of the financial sector, trade between banks and insurances, network centrality and counter party risk, or the competitiveness of the financial sector.

We find that unobserved common factors play an important role. In particular, taking the unobserved factors into account leads up to 9% 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 7% in one-quarters ahead forecasts, by 14% in four-quarters ahead forecasts, and by up to 39% for banks that are in the lowest quintile of the distance-to-default distribution. Importantly, taking unobserved common factors into account improves the forecast also at the four quarter horizon, which is the more relevant horizon for financial supervision.

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). 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,

$$dV_t = \mu_V V_t dt + \sigma_V V_t dW_t, \tag{9}$$

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

$$V_T = V_t \exp\left((\mu_V - \frac{1}{2}\sigma_V^2)(T-t) + \sigma_V\sqrt{(T-t)}\epsilon_T\right), \tag{10}$$

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

$$\begin{aligned} \mathrm{P}(V_T \leq B) &= \mathrm{P}(\ln V_T \leq \ln B) \\ &= \mathrm{P}\left(-\frac{\ln(\frac{V_t}{B}) + (\mu_V - \frac{1}{2}\sigma_V^2)(T-t)}{\sigma_V\sqrt{(T-t)}} \geq \epsilon_T\right) \end{aligned} \tag{11}$$

On basis of equation (11), Crosbie and Bohn (2003) define distance-to-default as

$$DD = \frac{\ln(\frac{V_t}{B}) + (r - \frac{1}{2}\sigma_V^2)(T-t)}{\sigma_V\sqrt{(T-t)}}, \tag{12}$$

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 (12), 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,

$$S_T = \max(V_T - B, 0) = (V_T - B)^+. \tag{13}$$

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:

$$S_t = V_t \Phi(d_{t,1}) - B \exp\left(-r(T-t)\right) \Phi(d_{t,2}), \tag{14}$$

where

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

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

$$\sigma_S = \sigma_V \frac{V_t}{S_t} \Phi(d_1). \tag{15}$$

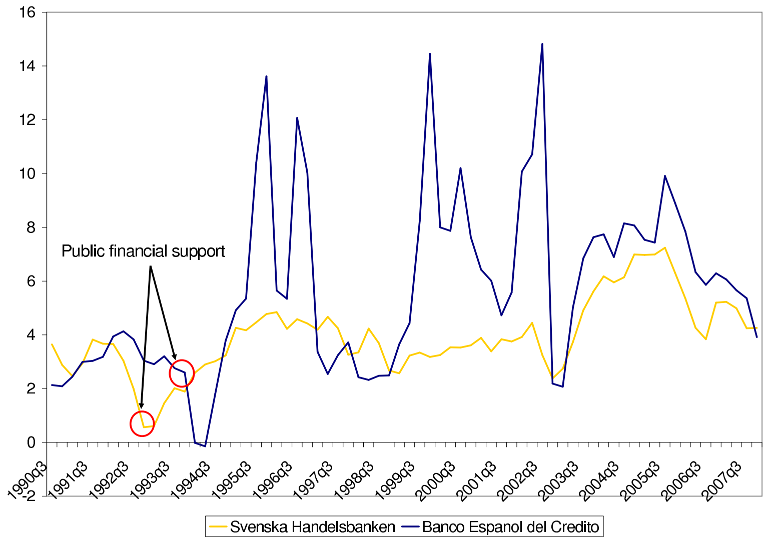
Equations (14) and (15) describe now a set of two non-linear equations with two unknowns, i.e. V_t and σ_V, that can be solved numerically by using a generalized gradient method.[1] Based on these estimates, distance-to-default in (12) can be calculated.

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 intervened. 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.

[1] We thank Reint Gropp and Jukka Vesala for providing their Visual Basic code to calculate the distance-to-default measure.

Figure 3: DD for Banco Español de Crédito and 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

$$y_{it} = \alpha_i(1-\rho_i)^{-1} + \rho_i y_{i,t-1} + \boldsymbol{\beta}_i'\boldsymbol{x}_{it} + \boldsymbol{\gamma}_i'\boldsymbol{f}_t + \sigma_{\varepsilon,i}\varepsilon_{it}, \quad \varepsilon_{it} \sim \mathrm{N}(0,1)\,, \quad (16)$$

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

$$\boldsymbol{x}_{it} = \boldsymbol{A}_i\boldsymbol{d}_t + \boldsymbol{\Gamma}_i\boldsymbol{f}_t + \boldsymbol{\nu}_t, \quad (17)$$

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

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

The parameters in equations (16) and (17) are

$$\alpha_i \sim \mathrm{N}(1,1)\,, \quad \mathrm{vec}(\boldsymbol{A}) \sim \mathrm{N}(0.5\boldsymbol{\iota}_4, 0.5\boldsymbol{I}_4)\,,$$

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

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

and $\gamma_i \sim \mathrm{N}(\boldsymbol{g}, \boldsymbol{G})$, where $\boldsymbol{g} = (1,1,0)'$ and $\boldsymbol{G}$ 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,

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

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

$\boldsymbol{\Lambda}$ and $\boldsymbol{\Sigma}_f$ 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, $\boldsymbol{f}_t$, 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 from 2000 repetitions.

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

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

	Bias					RMSFE				
$T \backslash N$	20	30	50	100	200	20	30	50	100	200
CCE										
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
infeasible OLS										
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
naive OLS										
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 (16), $\sum_{i=1}^{N} \hat{\rho}_i$, 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. The results are from 2000 repetitions.

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.

Firm-specific indicators have the following sources:

- Dividends per share: Datastream, transformed into growth rates: $\Delta \text{div}_{it} = 100 \cdot \ln(div_{it}/div_{i,t-4})$.
- Earnings per share: Datastream, transformed into growth rates: $\Delta \text{earn}_{it} = (earn_{it} - earn_{i,t-4})/marketvalue_{i,t-4}$.

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: $\Delta indp_t = 100 \cdot \ln(indp_t/indp_{t-4})$
- Inflation: IMF International Financial Statistics, line 64, transformed into growth rates: $infl_t = 100 \cdot \ln(CPI_t/CPI_{t-4})$
- Domestic credit: IMF International Financial Statistics, line 32, transformed into growth rates: $\Delta domcr_t = 100 \cdot \ln(domcr_t/domcr_{t-4})$
- Equity returns: IMF International Financial Statistics, line 62, transformed into growth rates: $\Delta eqret_t = 100 \cdot \ln(eqret_t/eqret_{t-4})1$
- Real effective exchange rate: IMF International Financial Statistics, line REU, transformed into growth rates: $\Delta reer_t = 100 \cdot \ln(reer_t/reer_{t-4})$
- Unemployment rates: OECD Economic Outlook.
- Growth rates of GDP: IMF International Financial Statistics, line 62, transformed into growth rates: $\Delta GDP_t = 100 \cdot \ln(GDP_t/GDP_{t-4})$
- KA-open: Chinn-Ito index, `http://www.uoregon.edu/~jpiger/us_recession_probs.htm`.
- Financial openess: World Development Indicator (WDI), (Import of insurance and financial services (in % of service imports)) + (exports of insurance and financial services (in % of service exports)).
- 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.

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Table 6: Sample composition

	Banks	Total Insurances
Australia	8	2
Austria	2	1
Belgium	4	0
Canada	8	4
Denmark	7	2
Finland	1	1
France	6	4
Germany	4	10
Ireland	3	2
Italy	17	11
Japan	61	6
Korea	3	3
Netherlands	2	2
Norway	1	1
Portugal	5	0
Spain	13	2
Sweden	4	0
Switzerland	15	6
UK	6	13
USA	40	47
Total	210	117

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