Parameters measuring bank risk and their estimation

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Abstract

The paper develops estimation of three parameters of banking risk based on an explicit model of expected utility maximization by financial institutions subject to the classical technology restrictions of neoclassical production theory. The parameters are risk aversion, prudence or downside risk aversion and generalized risk resulting from a factor model of loan prices. The model can be estimated using standard econometric techniques, like GMM for dynamic panel data and latent factor analysis for the estimation of covariance matrices. An explicit functional form for the utility function is not needed and we show how measures of risk aversion and prudence (downside risk aversion) can be derived and estimated from the model. The model is estimated using data for Eurozone countries and we focus particularly on (i) the use of the modeling approach as a device close to an "early warning mechanism", (ii) the bank- and country-specific estimates of risk aversion and prudence (downside risk aversion), and (iii) the derivation of a generalized measure of risk that relies on loan-price uncertainty. Moreover, the model provides estimates of loan price distortions and thus, allocative efficiency.

Keywords: Financial Stability; Banking; Expected Utility Maximization; Sub-prime crisis; Financial Crisis; Eurozone; PIIGS.

JEL Classifications: G20, G21, C51, C54, D21, D22.

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1 Introduction

Recent problems with the banking sector have put issues of modeling risk at the forefront of research. Traditional risk measures like the z-score or the standard deviation of the returns on assets (ROA) are used widely but have no formal economic justification. In turn, questions related to financial stability which are intimately related to risk, remain unanswered. As one analyst remarks: "The problems of creating a solvency test for financials that operate in real-time or relative real-time is not easy. It's not hard to do after the fact, but at any one time, no one – not even the directors of the company really know what is embedded in the books at a financial [institution]. Société Générale, Barings, Northern Rock, Bear Stearns – the list of surprise blowup go on and on." (Hui, 2008).

Before proceeding it is important to clarify what we mean by risk in our setting. Each bank has a utility function (defined over profit) which is known to the bank but unknown to us. Outputs of the bank are various kinds of loans, and inputs include capital, labor and deposits -the so called financial intermediation approach to modeling banking technology. Output prices are stochastic and the bank maximizes expected utility of profits. Alternative approaches exist and we compare and contrast our results in Section 6.

In this paper we propose a structural model (although not a general equilibrium model as in Aspachs et al, 2006). The essential features of the model are, however, the same as we rely on the metrics of bank profitability and the probability of default explicitly through the financial institution's optimization problem. The model can be estimated using standard econometric techniques, like GMM for dynamic panel data and latent factor analysis for the estimation of covariance matrices. *The model relies on expected utility maximization for a financial institution under uncertain loan prices.* An important feature of the model is that it relies on the neoclassical approach to optimization with a well-defined technology set provided by its representation via a distance function. An explicit functional form for the utility function is not needed and we show how measures of risk aversion and prudence (downside risk aversion) can be derived and estimated from the model. The model is estimated using data for Eurozone countries and we focus particularly on:

(i) the use of the modeling approach as an "early warning mechanism" to the extent possible since only one crisis observation is available., (ii) the *bank- and country-specific estimates of risk aversion and prudence* (downside risk aversion); and

(iii) the derivation of a *generalized measure of risk* that relies on the loan-price uncertainty. The generalized measure of risk is generic to the bank system but it is time-varying.

(i) and (ii) rely on an expansion of the unknown utility function of the banks to estimate risk aversion (α_{it}) and downside risk aversion (δ_{it}) for bank i at time t. Risk aversion is $\alpha = -\frac{u''(\mu_\Pi)}{u'(\mu_\Pi)}$, the Arrow-Pratt measure, and $\delta = \frac{u'''(\mu_\Pi)}{u'(\mu_\Pi)}$ as the measure of downside risk aversion or "prudence", where $u()$ is the utility function and μ_Π denotes expected profits. It is important to mention that these measures can be estimated on a time-varying basis from the first order conditions of expected utility maximization of profits and that they are different for each bank.

The aim of the paper is to provide measures of risk close to what is known as "systemic risk", an issue that has naturally attracted considerable attention in the literature; see, for example Yang et al. (2010) and Yang and Zhou (2013). Yang et al. (2010) develop conditional co-skewness in the context of a bivariate regime-switching model and show that it is important for portfolio construction. In our context, conditional co-skewness matters as it relates to "prudence" through the third derivative of the utility function. Yang and Zhou (2013) focus on spillovers among financial institutions. Spillovers and interrelations among banks in this paper are taken into account via a dynamic factor model so an important aspect is taken into account.

The remainder of the paper is organized as follows. The model and main results are presented in section 2. The primal approach and its disadvantages are discussed in section 3. Data and estimation techniques are presented in section 4. The empirical results are discussed in section 5. We compare and contrast our results with alternative approaches in Section 6. The paper concludes with a summary of the approach and results.

2 The model

Suppose $\mathbf{x} \in \Re_+^K$ is a vector of inputs, $\mathbf{w} \in \Re_+^K$ is the vector of input prices, $\mathbf{y} \in \Re_+^M$ a vector of outputs and $\mathbf{p} \in \Re_+^M$ is the vector of their prices. We think of outputs as various types of loans while inputs include capital, labor etc.

The technology set is defined by:

$$\mathcal{T} = \left\{ (\mathbf{x}, \mathbf{y}) \in \Re^{K+M} : \mathbf{x}\,\text{can produce}\,\mathbf{y} \right\}$$

Suppose $(\mathbf{x}, \mathbf{y}) \in \mathcal{T}$ if and only if: $F(\mathbf{x}, \mathbf{y}) \geq 1$ for a general transformation function $F(\mathbf{x}, \mathbf{y})$. The banks face uncertain output prices as some loans might not perform or, alternatively, they perform to an extent that is unknown to the bank -which is the source of risk here. Suppose

$$\mathbf{p} = \mu + C'\varepsilon \tag{1}$$

where μ is a location parameter (the mean if exists), $\varepsilon \sim \mathcal{N}_M(0, I)$ and $C'C = \Sigma$, the covariance matrix assuming it exists. The lower diagonal matrix C is related to the Cholesky decomposition of Σ which is assumed positive definite. The profit of the bank is: $\Pi = p'y - w'x - \kappa$ where κ denotes fixed costs -see also Appelbaum and Ullah (1997).[1] The bank maximizes the expected utility of profits: $\mathscr{E}u(\Pi)$, where the expectation is taken with respect to ε. Profits can be written as:

$$\Pi = \left(\mu + C'\varepsilon\right)' \mathbf{y} - \mathbf{w}'\mathbf{x} - \kappa = \mu_\Pi + \varepsilon' C\mathbf{y}, \tag{2}$$

where expected profit is:

$$\mu_\Pi = \mu'\mathbf{y} - \mathbf{w}'\mathbf{x} - \kappa.$$

The problem of the bank can be restated as:

$$\max_{(x,y)\in\Re_+^{K+M}} : \mathscr{E}u\left(\mu_\Pi + \varepsilon' C\mathbf{y}\right), \text{ s.t}\, F(\mathbf{x}, \mathbf{y}) \geq 1. \tag{3}$$

From the first-order conditions of the expected utility maximization problem we have:

$$\frac{w_k}{w_1} = \frac{\partial F(\mathbf{x}, \mathbf{y}) / \partial x_k}{\partial F(x, y) / \partial x_1}, k = 2, .., K; \tag{4}$$

$$\frac{\mu_m + \sigma_m \Lambda_m}{\mu_1 + \sigma_1 \Lambda_1} = \frac{\partial F(\mathbf{x}, \mathbf{y}) / \partial y_m}{\partial F(\mathbf{x}, \mathbf{y}) / \partial y_1}, m = 2, ..., M, \tag{5}$$

where σ_m^2 is the mth diagonal element of Σ and $\mu = [\mu_m, m = 1, ..., M]$. Equation (4) shows that expected utility maximization requires cost minimization, as expected. In (5) we have defined the following expressions which will become quite important in our discussion:

$$\Lambda_m \equiv \frac{\mathscr{E}\left\{u'(\Pi)\,\varepsilon_m\right\}}{\mathscr{E}u'(\Pi)}, \ m = 1, ..., M \tag{6}$$

From (5) it is clear that expected utility maximization is consistent with ordinary profit maximization at relative output (or *shadow*) prices which are given by:

$$\tilde{p}_m \equiv \frac{\mu_m + \sigma_m \Lambda_m}{\mu_1 + \sigma_1 \Lambda_1}, \ m = 2, ..., M. \tag{7}$$

If, in fact, the transformation function is an *output distance function*, then exploiting its linear homogeneity with respect to outputs, we can establish (5) in a somewhat different form:

[1] See papers by Kumbhakar (2002a,b), Kumbhakar and Tsionas (2010) and Kumbhakar and Tveteras (2013). These papers do not deal with the (arguably more difficult) case of multiple outputs and thus many output prices which is the focus of the present paper.

$$\frac{\mu_m + \sigma_m \Lambda_m}{\sum_{m'=1}^{M} (\mu_{m'} + \sigma_{m'} \Lambda_{m'})} = \frac{\partial \log F(\mathbf{x}, \mathbf{y})}{\partial \log y_m}, \; m = 1, ..., M \tag{8}$$

We denote $\alpha = -\frac{u''(\mu_\Pi)}{u'(\mu_\Pi)}$ as the Arrow-Pratt measure of risk aversion and $\delta = \frac{u'''(\mu_\Pi)}{u'(\mu_\Pi)}$ as the measure of downside risk aversion or "prudence". We have $\alpha > 0$ and, normally, we would expect that $\delta \geq 0$. The left-hand-side of (8) would provide the *virtual* relative prices, $\tilde{p}_m$ that would be consistent with classical profit maximization - prices are normalized so that they lie on the boundary of the unit simplex in $\Re^M$. Besides the first two moments of prices, these virtual prices depend on Λ_ms which are related to the underlying utility function as in (7). Naturally, we wish to avoid expressing the utility function in a specific functional form since that would make the analysis specific to the particular functional form. In that way, we see that what we have assumed so far is enough to deliver measures of Arrow-Pratt measures of risk aversion as well as downside risk aversion.

As we show below, we have:

$$\Lambda \simeq -\frac{\alpha}{1 + \delta \cdot \mathrm{tr}\,(yy'\Sigma)} \cdot C\mathbf{y} \tag{9}$$

which is an $M \times 1$ vector whose elements are the Λ_ms.

Proof of equation (9)

Our purpose is, first of all, to derive expressions for $\mathscr{E}u'(\Pi)$ as well as $\mathscr{E}\{u'(\Pi)\varepsilon\}$, where $\Pi = \mu_\Pi + \varepsilon' C\mathbf{y}$. Using a Taylor approximation around $\varepsilon = 0_{(M\times 1)}$ we have:

$$u'(\Pi) \simeq u'(\mu_\Pi) + u''(\mu_\Pi)\varepsilon' C\mathbf{y} + u'''(\mu_\Pi)\varepsilon' C\mathbf{y}\mathbf{y}' C'\varepsilon.$$

Taking expected values we obtain:

$$\mathscr{E}u'(\Pi) \simeq u'(\mu_\Pi) + u'''(\mu_\Pi)\mathscr{E}\mathrm{tr}\left(\mathbf{y}\mathbf{y}'C'\varepsilon\varepsilon'C\right) = u'(\mu_\Pi) + u'''(\mu_\Pi)\,\mathrm{tr}\left(\mathbf{y}\mathbf{y}'\Sigma\right).$$

Moreover,

$$\mathscr{E}\left\{u'(\Pi)\varepsilon\right\} \simeq u''(\mu_\Pi)\varepsilon' C\mathbf{y}\varepsilon + u'''(\mu_\Pi)\mathscr{E}\left\{\left[\varepsilon' C\mathbf{y}\mathbf{y}'C'\varepsilon\right]\varepsilon\right\}.$$

By the symmetry assumption the last term is zero and therefore:

$$\mathscr{E}\left\{u'(\Pi)\varepsilon\right\} \simeq u''(\mu_\Pi)\,C\mathbf{y}.$$

Using the definitions $\alpha = -\frac{u''(\mu_\Pi)}{u'(\mu_\Pi)}$ and $\delta = \frac{u'''(\mu_\Pi)}{u'(\mu_\Pi)}$, we obtain:

$$\Lambda \equiv \frac{\mathscr{E}\{u'(\Pi)\varepsilon\}}{\mathscr{E}u'(\Pi)} \simeq -\frac{\alpha}{1 + \delta\mathrm{tr}\,(\mathbf{y}\mathbf{y}'\Sigma)} \cdot Cy$$

□

Therefore, the Λ_ms can be related to *two fundamental characteristics of risk*, namely the Arrow-Pratt measures α and δ. It is important to emphasize that these measures depend on underlying bank profitability (since the banks maximize expected utility of profit) as well "probability of default" in the sense that loan price uncertainty is explicitly taken into account.

Next, we show how to estimate risk aversion and prudence parameters under output price uncertainty. The data requirementws are inputs $\mathbf{x}_{it}$ and outputs $\mathbf{y}_{it}$ of the bank and their prices $\mathbf{w}_{it}$ and $\mathbf{p}_{it}$ respectively. Suppose the output-distance-function $F(\mathbf{x}_{it}, \mathbf{y}_{it}; \theta)$ where $\theta \in \Re^d$ denotes a vector of unknown technology parameters.

Our approach to the problem relies on using equations (7) and (8). From (8) we have:

$$\frac{\tilde{p}_m y_m}{\tilde{p}_1 y_1} = \frac{\partial \log F(\mathbf{x}, \mathbf{y}) / \partial \log y_m}{\partial \log F(\mathbf{x}, \mathbf{y}) / \partial \log y_1}, m = 2, ..., M, \tag{10}$$

where $\tilde{p}_m \equiv \mu_m + \sigma_m \Lambda_m$. These equations can be written in the following form:

$$\log \frac{\tilde{p}_m}{\tilde{p}_1} + \log y_m - \log y_1 = \log \left\{ \frac{\partial \log F(\mathbf{x}, \mathbf{y}) / \partial \log y_m}{\partial \log F(\mathbf{x}, \mathbf{y}) / \partial \log y_1} \right\}. \tag{11}$$

The econometric model consists of the output-distance-function:

$$F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) = v_{it,1}, \tag{12}$$

where $v_{it,1}$ is an error term, along with the first order conditions:

$$\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}} + \log y_{m,it} - \log y_{1,it} = \log \left\{ \frac{\partial \log F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) / \partial \log y_{m,it}}{\partial \log F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) / \partial \log y_{1,it}} \right\} + v_{it,m}, m = 2, ..., M, \tag{13}$$

$$\log \frac{w_{k,it}}{w_{1,it}} + \log x_{k,it} - \log x_{1,it} = \log \left\{ \frac{\partial \log F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) / \partial \log x_{k,it}}{\partial \log F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) / \partial \log x_{1,it}} \right\} + e_{it,k}, k = 2, ..., K, \tag{14}$$

where $\tilde{p}_m$ is a complicated function of α, δ, μ, C and $\mathbf{y}$ as defined in (7). Recall that $C'C = \Sigma$. Finally, shadow prices and actual prices are related as follows:

$$\log \frac{p_{m,it}}{p_{1,it}} = \gamma_{m,it} + \log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}} + \xi_{it,m}, m = 2, ..., M, \tag{15}$$

where $\gamma_{it} = [\gamma_{2,it}, ..., \gamma_{M,it}]'$ is a vector of systematic deviations and $\boldsymbol{\xi}_{it} = [\xi_{it,2}, ..., \xi_{it,M}]'$ is a vector of random variables. In fact, these are related to allocative inefficiency distortions (Kumbhakar, 1997 and Kumbhakar and Tsionas, 2005).

The error terms are $\mathbf{V}_{it} = [v_{it,2}, ..., v_{it,M}, e_{it,2}, ..., e_{it,K}, \xi_{it,2}, ..., \xi_{it,K}]'$. We do not impose particular assumptions about these error terms other than they are orthogonal to variables involved in our moment conditions. For example, we do not make distributional assumptions. The output distance function is defined by a flexible, translog functional form which is used extensively in the literature:

$$\begin{aligned} F(\mathbf{x}_{it}, \mathbf{y}_{it}; \boldsymbol{\theta}) = a_i + b_t + \textstyle\sum_{k=1}^K \alpha_k x_{it,k} + \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \alpha_{kj} x_{i,tk} x_{i,tj} + \sum_{m=1}^M \beta_m y_{i,tm} \\ + \textstyle\frac{1}{2} \sum_{m=1}^M \sum_{j=1}^M \beta_{mj} y_{i,tm} y_{i,tj} + \sum_{k=1}^K \sum_{m=1}^M \gamma_{km} x_{i,tk} y_{i,tm} + v_{it,1}, \end{aligned} \tag{16}$$

where a_i and b_t represent bank and time effects[2], K is the number of inputs ($x_{i,tk}$ in logs), M is the number of outputs ($y_{i,tm}$ in logs) and $i = 1, ..., n$ represents a particular observation for the vector of all inputs $\mathbf{x}_{it} \in \Re^K$ and outputs $\mathbf{y}_{it} \in \Re^M$. As a transformation function we have $F(\mathbf{x}_{it}, \mathbf{y}_{it}) = 1$. From linear homogeneity of output distance function with respect to outputs, in log terms, we have $F(\mathbf{x}_{it}, h + \mathbf{y}_{it}) = h + F(\mathbf{x}_{it}, \mathbf{y}_{it})$ for any constant h so we may choose the constant to be the first output which results in:

$$\begin{aligned} -y_{it,1} = a_c + b_t + \textstyle\sum_{k=1}^K \alpha_k x_{it,k} + \frac{1}{2} \sum_{k=1}^K \sum_{j=1}^K \alpha_{kj} x_{i,tk} x_{i,tj} + \sum_{m=2}^M \beta_m \tilde{y}_{i,tm} \\ + \textstyle\frac{1}{2} \sum_{m=2}^M \sum_{j=2}^M \beta_{mj} \tilde{y}_{i,tm} \tilde{y}_{i,tj} + \sum_{k=1}^K \sum_{m=2}^M \gamma_{km} x_{i,tk} \tilde{y}_{i,tm} + v_{it,1}, \end{aligned} \tag{17}$$

where $\tilde{y}_{it,m} \equiv y_{it,m} - y_{it,1}, m = 2, ..., M$.

We allow for the endogeneity of $\mathbf{y}_{it}$, $\mathbf{x}_{it}$ and output prices $\mathbf{p}_{it}$ using GMM with instruments being log-relative input prices and time dummies. The instruments are motivated by the first-order conditions of profit maximization. Our implementation of GMM is the so-called CUE (continuously-updated-estimator) which has been shown to have better finite sample properties. Joint estimation of the first-order conditions in (13)-(17) is quite difficult because of the dependence on Λ_ms which are highly nonlinear functions of α and δ.[3]

In terms of estimation we proceed as follows:

i) We estimate jointly (17) and (14) by GMM to estimate the technology parameters, $\boldsymbol{\theta}$.

[2] In addition we include effects for commercial, investment, cooperative and savings banks.

[3] Another difficulty is that the first order conditions must be estimated in log form and we need to take account of the Jacobian of transformation due to endogeneity of the variables involved. Using GMM this is automatically taken into account.

ii) Given estimates $\hat{\boldsymbol{\theta}}$we recover $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ from (13) as follows:

$$\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}} = -\log y_{m,it} + \log y_{1,it} + \log \left\{ \frac{\partial \log F\left(\mathbf{x}_{it}, \mathbf{y}_{it}; \hat{\boldsymbol{\theta}}\right) / \partial \log y_{m,it}}{\partial \log F\left(\mathbf{x}_{it}, \mathbf{y}_{it}; \hat{\boldsymbol{\theta}}\right) / \partial \log y_{1,it}} \right\}. \tag{18}$$

iii) In turn, given $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ we solve[4] for bank-specific and time-varying estimates of α_{it}, δ_{it} given the expressions in (7) and (9). Parameters μ and $\Sigma$are assumed the same for all banks and years in the same country but different across countries and are estimated using their sample counterparts from (1).

iv) Parameters γ_m and estimates $\hat{\xi}_{it,m}$ can be recovered, if desired, from GMM estimation of (15).

The fundamental merit of this estimation procedure is that we can obtain bank-specific and time-varying estimates of α_{it}, δ_{it} without a random effects assumption which necessitates distributional assumptions.

Next, we use the normalizing restriction $\sum_{m'=1}^{M} (\mu_{m'} + \sigma_{m'} \Lambda_{m'}) = 1$ that output prices lie on the boundary of the unit simplex in $\Re^M$. The restriction implies a relationship between α and δ. In turn, from Λ_m in (9) we can recover one of α or δ while the other can be recovered from the restriction. As Λ is both time-varying and bank- specific we can exploit this fact to deliver time-varying and bank-specific estimates of both α and δ.

The output distance function and first order conditions (14) as well as (15) are estimated separately for all banks in each country. Estimation of the output distance function includes bank- and time-specific fixed effects and is performed using the CUE version of GMM starting from a random selection of initial conditions for the parameters, centered around the OLS estimator.

Random initial conditions are generated using 100 different random seeds. Different initial conditions did not lead to different parameter estimates suggesting that, in this instance, the objective function is not multimodal.

Given an $R \times 1$ set of moment conditions $\mathscr{E} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i) = O_{(R\times 1)}$ where $\boldsymbol{\theta} \in \Theta \subseteq \Re^k$, $\mathscr{Y}_i$ denotes all available data, the empirical analogue is[5]:

$$\min_{\boldsymbol{\theta}\in\Theta} : f(\boldsymbol{\theta}) = \left[N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\right]' \mathbf{W} \left[N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\right],$$

for some weighting matrix $\mathbf{W}$, where N denotes the number of available observations. In the first stage we set $\mathbf{W} = \mathbf{I}$, the identity matrix. Since the optimal weighting matrix is $\mathbf{W}^{-1} \propto \mathscr{E}\left[\boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y})\, \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y})'\right]$ the problem is re-solved using $\mathbf{W}^{-1} = N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\, \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)$. Therefore, the optimization problem for CUE-GMM is the following:

$$\begin{gathered} \min_{\boldsymbol{\theta}\in\Theta} f(\boldsymbol{\theta}) = \\ \left[N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\right]' \left[N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\, \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\right]^{-1} \left[N^{-1} \sum_{i=1}^{N} \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)\right]. \end{gathered} \tag{19}$$

Given $\mathbf{G} = N^{-1} \sum_{i=1}^{N} \frac{\partial \boldsymbol{g}(\boldsymbol{\theta}, \mathscr{Y}_i)}{\partial \boldsymbol{\theta}}$, the well-known asymptotic result can be used to obtain the asymptotic covariance matrix of the estimator:

$$N^{1/2}\left(\hat{\boldsymbol{\theta}}_{GMM} - \boldsymbol{\theta}\right) \to \mathscr{N}\left(0,\ \left[\mathbf{G}'\mathbf{W}\mathbf{G}\right]^{-1}\right).$$

Moreover, Hansen's J-statistic $J = Nf(\boldsymbol{\theta}) \to \chi^2_{R-k}$. The same strategy is used to estimate, first, (17) and (14), and, second, (15).

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[4]This involves a solution in terms of α, δ of a nonlinear system of equations given the data, (7) and (9).

[5]We rely on moment conditions using as instruments the inputs and time as well as their squares and interactions plus country-specific effects. Hansen's J test has a p-value of 0.31 failing to reject the null hypothesis of orthogonality between output distance function errors and the specific instruments. Exclusion of country-specific effects produces a Hansen test whose p-value is 0.001. The minimization problem is solved using a standard conjugate-gradients algorithm. More computational details are available on request.

3 Generalized Measure of Risk

For the $M \times 1$ vector of output prices $\mathbf{p}$ we have observations for a given country $(c = 1, ..., C)$ and a given bank within a country $(b = 1, ..., B_c)$. So, in practice, the vector $\boldsymbol{p}_{ct} = [p_{cb,t}]$ is possibly very high-dimensional for a given time period $(t = 1, ..., T)$. This is especially the case because we want to combine countries (for example, peripheral countries or PIIGS versus non-periphery.) Moreover, in order to estimate the time-varying conditional covariance matrix of prices, $\mathbf{\Sigma}_t$, we must account for the fact that they do not have a constant conditional mean. Since we do *not* typically have large T (but we do have large N where N is the number of banks and T is the number of time periods) we assume the following process:

$$p_{cb,t} = \mathbf{a}_b + \mathbf{A}_c p_{cb,t-1} + u_{cb,t}. \tag{20}$$

The vector $p_{cb,t}$ is $M \times 1$ which is low-dimensional since in the leading case we have two or three outputs. Notation $\boldsymbol{A}_c$ means that estimation is performed using data for all banks *in a given* country c. Here, $\mathbf{a}_b$ is $M \times 1$ and $\mathbf{A}$ is matrix $M \times M$. The process is a vector autoregression with a time-varying covariance matrix. The notation $\mathbf{a}_b$ means that we include bank-specific effects. The model in 20 is estimated using data for a given country and all banks and time periods available for that country (or group of countries.) The model can be estimated using standard GMM techniques for dynamic panel data. We use moments of the type proposed in Arellano and Bover (1995) and Blundell and Bond (1999) [also Handbook of Econometrics, chapter 53].

The modeling of a dynamic covariance matrix in large dimensions is well known to be an exceedingly difficult matter and standard extensions of the GARCH model do not work well, see for example Engle and Kroner (1995) and Silvennoinen and Teräsvirta (2009).[6]

Given the residuals[7] $\hat{u}_{cb,t}$ we follow Connor and Korajczyk (1986, 1988), Stock and Watson (2002), Bai and Ng (2002, 2011) and Bai (2003) to model the time-varying covariance matrix using a latent factor model with the principal components simplification, which has been shown to work well in practice (see in addition Bai and Li (2010), Forni et al (2000) and Lehmann and Modest (1988)). Suppose $X_t = [\hat{u}_{c1,t}, ..., \hat{u}_{cB_c,t}]'$ for simplicity in notation. The latent factor model in vector form is:

$$X_{it} = \mu_i + \lambda_i' f_t + \varepsilon_{it}, \tag{21}$$

where the factors f_t $(r \times 1)$ and factor loadings λ_i $(r \times 1)$ are unobserved. Here, the index i corresponds to (c, b). In matrix notation we have[8]:

$$X_t = \mu + \mathbf{\Lambda} f_t + \varepsilon_t, \tag{22}$$

where $\mathbf{\Lambda} = [\lambda_1, ..., \lambda_N]'$ and μ, ε_t are defined in conformable manner. Moreover,

$$\mu_t \equiv \mu + \mathbf{\Lambda} f_t, \tag{23}$$

the time-varying conditional mean. The principal components estimator makes use of the decomposition:

$$\mathbf{S} = \sum_{i=1}^{N} b_i^2 h_i h_i', \tag{24}$$

where $\mathbf{S}$ is the sample covariance matrix, b_i^2 is the i th largest eigenvalue and h_i denotes the corresponding eigenvector (Bai and Shi, 2011). The principal components estimator for Λ is then given by:

[6] See also Bai and Shi (2011) for the wider issues in high-dimensional settings, along with Bai and Ng (2008), Bai and Li (2010), Bai (2010), Chamberlain and Rothschild (1983), and Jones (2001).

[7] Suppose $\hat{u}_t = [\hat{u}_{c1,t}, ..., \hat{u}_{cB,t}]'$. It is to be noted that since $\hat{u}_t = u_t + (\hat{u}_t - u_t) = u_t + e_t$ and $e_t = o_p(1)$ the analysis carries through in the sense that the principal component analysis is asymptotically valid.

[8] $\mathbf{\Lambda}$ is not to be confused with Λ_m s.

$$\hat{\mathbf{\Lambda}} = [b_1 h_1, ..., b_r h_r], \tag{25}$$

which gives:

$$\hat{\mathbf{\Sigma}} = \hat{\mathbf{\Lambda}}\hat{\mathbf{\Lambda}}' + \hat{\Omega}_\varepsilon, \tag{26}$$

where $\hat{\Omega}_\varepsilon = \text{diag}\left(\mathbf{S} - \hat{\mathbf{\Lambda}}\hat{\mathbf{\Lambda}}'\right)$ is the estimator for the diagonal covariance of the error terms ε_t. The advantage of the estimator despite, of course, its simplicity is that it can be applied for a given time period, treating different banks as variables within a given country and a given time period, yielding consistent estimators for $\hat{\mathbf{\Sigma}}_t$ (Bai, 2003, 2004). There are a number of procedures to select the number of factors, r, see Bai and Ng (2012) who proposed information criteria.

Estimates $\hat{\mu}_t$ and $\hat{\mathbf{\Sigma}}_t$, can be obtained as follows. First, $\hat{\mu}_t$ can be obtained from (23) after μ and Λ have been estimated by standard maximum likelihood techniques. Since estimation is done period-by-period an unrestricted covariance matrix Σ_t can be estimated based on Bai (2003, 2004) to avoid restrictive assumptions about its elements.

The data set[9] includes commercial, cooperative, savings, investment and real-estate banks in Eurozone countries that are listed in the IBCA-Bankscope database over the period 2001–2011 . After reviewing the data for reporting errors and other inconsistencies we obtain an unbalanced panel dataset of 29,023 observations, which includes a total of 4,065 different banks . For the definition of bank inputs and outputs, we follow the vast majority of the literature and employ the financial intermediation approach[10]proposed by Sealey and Lindley (1977), which assumes that the bank collects funds, using labor and physical capital, and transforms them into loans and other earning assets. In particular, we specify three inputs, labor, physical capital and financial capital, and two outputs, loans and other earning assets (which include government securities, bonds, equity investments, CDs, T-bills, and equity investment). With respect to input prices, the price of financial capital is computed by dividing total interest expenses by total interest bearing borrowed funds, while the price of labor is defined as the ratio of personnel expenses to total assets. Moreover, the price of physical capital is defined as the ratio of other administrative expenses to fixed assets. Regarding the calculation of output prices, the price of loans is defined as the ratio of interest income to total loans, while the price of other earning assets is defined as total non-interest income to total other earning assets[11].

The number of banks by year included in our sample is: 2001: 2,214; 2002: 2,028; 2003: 1,909; 2004: 1,994; 2005: 3,053; 2006: 3,075; 2007: 3,042; 2008: 2,990; 2009: 2,951; 2010: 2,949 and 2011: 2,818. The additions to the sample are not necessarily new market entrants, but rather successful banks that are added to the database over time. Exits from the sample are due either to bank failures or to mergers with other banks or are a consequence of changes in the coverage of the Bankscope database. Our sample covers the largest credit institutions in each country, as defined by their balance sheet aggregates. Due to the specific features of the German banking system (large number of relatively small banks), our sample is dominated by German banks. Descriptive statistics of the data are provided in the Appendix.

Breaking the sample into periphery versus non-periphery as well as France and Germany separately, we can apply the factor model in (22) for separate samples whose dimensionality is less than the dimensionality of the full sample in terms of the number of banks. In turn we can apply the principal-components estimator in (25) and (26). The principal-components estimator has also been applied to each country separately following preliminary estimation of (20). For the factor models, the use of Schwarz information criterion (Bai and Ng, 2012) which turned out to give one factor for the vast majority of cases, including the groups of periphery, non-periphery as well as France and Germany taken separately as a two-country group.

[9]The author is grateful to Natasha Koutsomanoli-Filippaki who generously provided the data set and its description.

[10]For a review of the various approaches that have been proposed in the literature for the definition of bank inputs and outputs see Berger and Humphrey (1992).

[11]The Bankscope database reports published financial statements from banks worldwide, homogenized into a global format, which are comparable across countries and therefore suitable for a cross-country study. Nevertheless, it should be noted that all countries suffer from the same survival bias.

4 Empirical results

The expected utility framework provides a wealth of information regarding risk in financial intermediation. First of all, we report results[12] related to Arrow-Pratt measures of risk aversion (α) and downside risk aversion (δ). These measures are bank-specific as well as time-varying due to the solution of equation in (15). Second, the use of a latent factor model as in (22) provides a *generalized measure of risk* which is given by the determinant $\det(\mathbf{\Sigma}_t)$ or its log. This measure of risk relies on all output prices collectively. Although it reflects the "risk" of the banking system as a whole it should be accompanied by considerations of risk aversion, formalized by estimates of α and δ. This is important as there cannot be a single measure of "risk" without a reference framework provided by a behavioral assumption which, in this paper, is expected utility maximization. In that way, financial stability depends not only on underlying, statistical or econometric measures of risk like the z-score or even the generalized variance $\det(\mathbf{\Sigma}_t)$ but rather on the propensity of the system to increase risk aversion and prudence (downside risk aversion) during periods of crises. Conversely, an increase of risk accompanied by an increase in risk aversion and prudence can show that a crisis is developing and can, at least in principle, provide us with an *early warning mechanism*.

There remains the question of whether measures of risk aversion and prudence are rather retrospective in nature since, for example, risk aversion can rise in response to a crisis. From the perspective of expected utility maximization and almost every other behavioral assumption based on optimization (excluding cost minimization) this cannot be the case. Since the bank has more information about its assets, capital and loan performance, it will react to a deterioration of its financial position by taking the appropriate measures, before a generalized crisis has taken place. The bank will not react to the generalized crisis but rather *to its own* deterioration of financial indices based *on its own* optimizations using *its own* information. Distress signals from the entire banking sector will contribute to an increase of risk aversion and prudence, but this is the retrospective, not the prospective element lying at the heart of an increase in measures of prudence and risk aversion.

In Figures 1 and 2 we provide histograms of these key parameters across all financial institutions and years. Relevant estimates are provided in Tables 1, 2 and 3 in the next section (where we provide a comparison with other risk measures).

These distributions, which combine evidence from all countries and all time periods are clearly multimodal indicating at least that there is considerable heterogeneity either over time or across banking systems in different countries. We use the term "periphery" for Portugal, Ireland, Italy, Greece and Spain.

In Figure 3, estimates of risk aversion are reported for the European banking system excluding the periphery (thick line), France, Germany and the periphery's banking system. It is impressive that risk aversion in the system as a whole (excluding peripheral countries) started increasing *before* the sub-prime crisis. Yet, for peripheral countries this happened *after* the crisis had been developed. It remains important, however, that an early warning signal is indeed at work here as overall risk aversion for the system started increasing at least one year before the sub-prime crisis. However, as only one crisis observation is available, we prefer to take this as evidence rather than as definitive conclusion.

In Figure 4, measures of prudence (downside risk aversion) are reported. For the system as a whole (excluding the periphery) as well as for France and Germany prudence increases steadily throughout 2001-2011. For the periphery the 2000s start with negative downside risk aversion which increases to values around zero and ends up with values close to 1.5.

In Figure 5, the generalized risk (variance) measures are reported. These measures are increasing throughout the 2001-2011 period indicating the accumulation of risk resulting from the expansion of credit. Possibly as the result of adopting policies of fiscal restraint[13], the generalized risk especially for

[12] To avoid cluttering the paper, we present results in graphical form. All estimation results are available on request.

[13] Fiscal restraint refers to consolidation in national budgets, and the restructuring of policies related to taxes and public expenditures in the periphery. Countries like Ireland, Portugal and Greece were subjected to so called "austerity" or adjustment programs in order to make their debt sustainable and recapitalize the banking sector. These policies are well known in the EU and the international press, have been active in criticizing or supporting them over the years after 2009. Recapitalization of banks for example and bail out packages were huge. We prefer not to model these variables explicitly for three reasons. First, we do not know from the data base we use (or any other publicly available) how each bank was bailed out. Second, the rescue plans are reflected in the background to our model and, therefore, they should

the periphery seems to decrease during 2010-2011 for the system as a whole (except the periphery) as well as France and Germany but notably not for the peripheral countries themselves.

In Figure 6, risk aversion coefficient (α) sample distributions are reported for the peripheral countries over time. These distributions result from bank- and country-specific measures. These distributions are evidently non-normal and show the evolution of risk aversion over time from, basically, lower to higher values. It is not until 2008 that the financial system in the peripheral countries starts to develop increasing aversion towards risk, that is in the middle or even after the sub-prime crisis. The distributions clearly shift to the right after 2007-2008 showing that the banking system adjusted with a considerable lag, contrary to the non-periphery whose (aspects of) sample distributions are summarily reported in Figure 3. For non-peripheral countries the distributions of risk aversion started shifting to the right as early as 2006 providing most likely an "*early warning mechanism*" with regard to the following sub-prime crisis: We consider this an important aspect of the model in terms of modeling and forecasting financial stability -although, as we mentioned before, only one crisis observation is available.

In terms of interpreting our results, we feel that the following point is important: In the core countries it was the toxic assets that were the issue. The crisis stemed from the banks. This is true for some peripheral countries as well, e.g. Spain. In peripheral countries such as Greece, for example, the crisis moves from the sovereign to the banks. This distinct aspect of the crisis, with its dichotomy between periphery versus non-periphery, provides an explanation for the findings in Figure 3 and onwards. It is, for example, well known that the financial turmoil in late 2007 resulting from the collapse of the mortgage market was due to the unprecedented issuance volume of credit default swaps (CDS) from 1998 to 2007 (Stanton and Wallace, 2011). Buch, Eckmeier, and Prieto (2014) analyzed a macroeconomic vector autoregression for the United States with a set of factors summarizing conditions in about 1,500 commercial banks. Their main findings are as follows: "Backward-looking risk of a representative bank declines, and bank lending increases following expansionary shocks. Forward-looking risk increases following an expansionary monetary policy shock. There is, however, substantial heterogeneity in the transmission of macroeconomic shocks, which is due to bank size, capitalization, liquidity, risk, and the exposure to real estate and consumer loans". Another channel through which substantial heterogeneity in the transmission of macroeconomic shocks can arise, is precisely because of, possibly substantial, heterogeneity in the degree of risk aversion which, in this paper, is the main focus of our modeling and estimation. We find that risk aversion as well as downside risk aversion vary over time. This leaves open the possibility that it is the risk attitudes of banks that are responsible for the heterogeneity in their responses instead of "forward-looking" or "backward-looking" risk. At any rate, through the application of simple estimation techniques, we are able to deliver bank-specific and time-varying estimates of important aspects of risk along with a generalized risk measure of the banking sector with a solid foundation in economic theory.

5 Comparison with alternative approaches

5.1 General discussion

A well known risk measure is the z-score defined as $z = \frac{R+cap}{\sigma_R}$, where R is a measure of return like the return on assets (ROA) or the return on equity (ROE), cap stands for the capitalization ratio, and σ_R is a measure of volatility of return. The Z-score is widely used in the banking literature to measure a bank's probability of insolvency. It is attributed to Boyd and Graham (1986), Hannan and Hanweck (1988) and Boyd et al. (1993), and plays an important role in the assessment of both individual bank risk as well as overall financial stability.

The problems with such a catch-all measure, apart from its apparent simplicity are many: (i) It does not account for the degree of risk aversion implicit in the construction of portfolios of financial institutions. (ii) It does not provide by itself an estimate, when used in practice, of the proper measure of variance; which is why in many studies panel data is used (see the excellent study by Lepetit

how up as deep restructuring in the deposits – loans relation, the loan totals and their composition. Third, as a result of that they are expected to show up in different estimates of risk aversion, prudence and generalized risk if the model is anywhere close to reality.

and Strobel, 2013). (iii) Although insolvency is, apparently, of interest, there is a transition stage to insolvency characterized by increasing "risk". This "risk" is difficult to measure when using the z-score. (iv) Consequently, it becomes increasingly apparent that it is difficult to find a proper measure of "risk", such as $var(\mathbb{X})$, making the calculation of z-scores problematic and the construction of "early warning signals" quite difficult. For example, in time series studies, the measurement of variance does not allow, so far at least, for time-varying measures while in panel studies, repeated cross sections have to be used: Since it is implicitly assumed that the variance remains constant over time for the same financial institution, this introduces significant biases in the measurement of insolvency or the assessment of financial stability. (vi) The development of the literature on financial stability tends to move away from the simple z-score and adopts a wider perspective on "risk". There is the related literature on identification of banking crises and construction of early warning mechanisms, see, for example, Berg (1999), Disyatat (2001), Demirguc-Kunt and Detragiache (2011), Kaminsky and Reinhart (1996, 1999), Logan (2000), and Vila (2000).

As stated in a seminal paper by Aspachs, Goodhart, Segoviano, Tsomocos and Zicchino (2006):

> "In the ECB Financial Stability Review (December, 2005, p. 131), it is stated bluntly that "there is no obvious framework for summarising developments in financial stability in a single quantitative manner." This is, to say the least, a considerable disadvantage when attempting to analyse financial stability issues. As the same ECB Special Feature on 'Measurement Challenges in Assessing Financial Stability', (ibid) put it, 'Financial stability assessment as currently practiced by central banks and international organisations probably compares with the way monetary policy assessment was practised by central banks three or four decades ago – before there was a widely accepted, rigorous framework."'

The authors proceed to argue as follows:

> "The point to note here is not so much the details [...] but that the crucial aspects of the impact of shocks on the banking system are contained in two variables, bank profitability and bank repayment rate, which in turn is equivalent to its probability of default (PD) ..." (page 8).

Another approach is based on the concept of the Value at Risk (VaR). For any random variable $\mathbb{X}$ with distribution function F and a given $\alpha \in (0, 1)$ we have: $\text{VaR} = \min\{y|F(y) \geq \alpha\} = \alpha$. If the distribution is continuous, $F(\text{VaR}) = \alpha$ so it is a particular quantile. For example, the Derivatives Policy Group in 2005 proposed a standard for over-the-counter derivatives broker-dealer reports to the Securities and Exchange Commission that would set a time horizon of two weeks and $\alpha = 0.01$. For more details see Basel Committee on Banking Supervision (2004).

This paper falls squarely within this literature. We focus on a concept of risk directly related to the performance of loans. Since this cannot be known in advance there is genuine uncertainty about the performance of financial institutions. This uncertainty must be taken formally into account in modeling properly the risk of financial institutions. In turn, this requires modeling the financial technology and embedding the problem in solid economic theory, provided by expected utility maximization. The framework of expected utility maximization goes, in fact, a long way in terms of measurement and assessment of risk, performance and stability. In this framework, we can provide explicit measures of Arrow-Pratt risk aversion as well as measures of downside risk aversion. Moreover, risk premia measures can be provided on a bank-specific basis. Hanschel and Monnin (2004) and Illing and Liu (2003) are examples of two papers that search for a metric of financial stability, without relying on an explicit structural model and focusing on the separate cases of Canada and Switzerland.

One problem with the widely used z-score is the volatility measure used in the denominator. For example, Lepetit and Strobel (2013) "compare the different existing approaches to the construction of time-varying z-score measures, plus an additional alternative one, using a panel of banks for the G20 group of countries covering the period 1992–2009." Their main finding is that the mean/standard deviation of ROA for the full sample with the current capital-asset ratio is the preferred measure. The use of the z-score as an indicator of bank stability has a long history, see for example de Nicolo (2000), Cihak (2007) and Maechler et al (2007). [14]

Boyd & Graham (1986) and Boyd et al. (1993) have pointed out that $1/z^2$ is an upper bound of the probability of insolvency (that is the probability of a bank having a negative capital asset ratio plus ROA) from which it follows that the z-score can be used in the wider context of insolvency, prudence and stability of financial institutions. Strobel (2015) made an excellent point in arguing that, in fact, $\frac{1}{1+z^2}$ provided a tighter bound on the probability of insolvency while $\frac{1}{z^2}$ provides a good upper bound on the odds of insolvency. The two concepts are closely related as they are functionally related through a simple mathematical transformation.

In Tables 1,2 and 3 we report estimates of risk aversion, downside risk aversion and the generalized risk measure for certain groups of countries over time for the period 2001 through 2011.

Table 1. Measures of risk aversion

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Overall excl. periphery	2.32	2.50	2.42	2.50	2.44	1.01	1.30	1.52	4.43	5.51	5.30
France	1.72	1.81	1.93	2.60	1.81	0.72	3.72	3.40	3.92	6.20	6.29
Germany	2.49	2.68	2.11	2.52	2.03	3.51	3.72	3.90	4.74	5.80	5.68
Periphery	0.73	1.11	0.82	0.93	1.10	1.21	1.35	4.78	5.11	6.55	5.39

Table 2. Measures of downside risk aversion

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Overall excl. periphery	2.30	2.58	2.51	2.11	2.50	2.98	3.31	3.50	3.41	4.22	4.32
France	1.97	2.51	1.87	2.42	2.20	2.71	3.68	4.41	4.32	4.20	4.31
Germany	2.71	2.92	2.70	2.91	3.11	3.49	3.72	4.93	4.70	4.82	5.13
Periphery	-0.70	-2.12	-2.80	-1.91	-1.10	-1.22	-0.032	0.21	0.52	0.51	1.50

Table 3. Measures of generalized risk

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Overall excl. periphery	1.00	1.70	1.61	1.82	1.90	3.76	6.12	9.13	15.4	17.2	11.2
France	1.00	1.81	1.41	2.10	3.20	3.15	7.98	10.1	17.1	19.1	13.1
Germany	1.00	1.31	1.11	1.32	1.20	2.15	5.14	5.10	6.12	12.20	9.11
Periphery	1.00	6.50	7.12	9.31	9.50	10.42	16.73	15.30	22.11	25.32	33.24

Some interesting conclusions are as follows: (i) Risk aversion increases over time. (ii) Prudence increases for the periphery only after 2010 but increases considerably after 2008 for all other countries. (iii) Generalized risk continues to increase in the periphery even during 2011 but this is not so for all other countries. We have commented on some possible driving forces of these findings in the previous section. Here, we would like to compare and contrast these estimates with some alternative measures of risk. Based on the z-score we compute, directly from the data, the upper bound on the probability of insolvency $PI = \frac{1}{1+z^2}$ as argued by Strobel (2015)[15]. This measure is provided in Table 4.

[14]Its widespread use is evidenced by such papers as Bannier et al. (2010), Barry et al. (2011), Beck et al. (2010), Carbo-Valverde et al. (2011), Demirguc-Kunt & Detragiache (2011), Demirguc-Kunt & Huizinga (2010), Foos et al. (2010), Houston et al. (2010), Koetter et al. (2012), Laeven & Levine (2009) and Schaeck et al. (2012).

[15]To compute the Z score we have used ROE.

Table 4. Probability of insolvency

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Overall excl. periphery	0.008	0.007	0.007	0.007	0.008	0.005	0.005	0.005	0.006	0.007	0.008
France	0.009	0.009	0.008	0.009	0.009	0.006	0.007	0.006	0.009	0.009	0.009
Germany	0.007	0.005	0.006	0.006	0.007	0.003	0.003	0.004	0.003	0.005	0.007
Periphery	0.017	0.016	0.015	0.010	0.009	0.008	0.008	0.009	0.009	0.014	0.122
Italy	0.015	0.014	0.013	0.011	0.009	0.007	0.004	0.004	0.003	0.002	0.004
Greece	0.012	0.013	0.011	0.011	0.014	0.003	0.003	0.004	0.007	0.117	0.213
Spain	0.011	0.012	0.015	0.014	0.011	0.008	0.005	0.005	0.002	0.004	0.006

The comparison is interesting in the sense that both risk aversion measures and generalized risk start increasing even before the sub-prime crisis but the probability of default, in Greece for example, starts increasing considerably only after, roughly, 2009 or 2010 when the pressure on banking systems was already felt. In this sense, z-based measures are retrospective but both risk aversion measures and generalized risk are not, as they rely on more detailed (yet widely available) information on the price of loans.

5.2 Panel composition

As we noted in Section 3, there is an increase in the number of banks after 2005. These are not necessarily new market entrants, but rather successful banks that are added to the database over time. It is a possibility that the composition of the panel affects the results. To examine this possibility we re-estimate the econometric models using the same procedures -viz. CUE-GMM and factor analysis for the generalized measure of risk. Our results for the important parameters of the model are reported in Table 5. Since the estimates are obtained on a per country basis (using all banks and years available for the given country) it is sufficient to look at the results for the overall cases (excluding PIIGS, the periphery) to determine whether there are any differences.

Table 5. Results using the same banks since 2001

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Risk aversion, α	2.32	2.50	2.42	2.50	1.47	1.15	1.42	1.29	1.35	3.43	4.17
Downside risk, δ	2.30	2.58	2.51	2.11	1.57	1.05	1.22	1.43	2.52	2.57	4.45
Generalized Risk	1.00	1.70	1.61	1.82	3.22	4.88	7.25	11.45	17.2	21.1	15.32

A comparison of the results in Tables 5 and 1 through 3, shows that estimates of risk aversion and downside risk aversion are much larger when the new entrants in the data base are considered. Some differences in generalized risk show that the new entrants reduce the overall variance after 2010, so the successful banks helped in the stabilization of the banking system but in other respects they did not systematically affected risk during 2005-2009. Indeed, during 2005-2011 the generalized risk measures are 1.90, 3.76, 6.12, 9.13, 15.4, 17.2, 11.2when we use the same banks as in 2001, and 3.22, 4.88, 7.25, 11.45, 17.2, 21.1, 15.32, when we use the entire data set, thus allowing for the new entrants.

To assess this difference statistically, we use the bootstrap where all yearly observations of a bank are treated as a block and we implement the bootstrap on a per country basis (as our estimation technique is performed individually for each country). The results are reported in Table 6.

Table 6. Bootstrap p-values

Year⟶	2005	2006	2007	2008	2009	2010	2011
p-value, α	0.017	0.0016	0.0024	0.0015	0.000	0.000	0.000
p-value, δ	0.021	0.019	0.0016	0.000	0.000	0.000	0.000
p-value, GRM	0.003	0.001	0.001	0.000	0.000	0.000	0.000

The reported p-values test the significance of the generalized risk measure obtained from i) the entire sample, and ii) the sample that results when do not include new entrants in the data base.

For each of the 10,000 bootstrap replications the models are re-estimated under i) and ii) and the empirical distribution of generalized risk measures is obtained. From the p-values in Table 6 it is clear that the differences are statistically significant at conventional levels of statistical significance. The differences in risk and downside risk of the new entrants, which are successful banks, can probably be taken as responsible for the relative stabilization of the overall banking system after 2010 as well as the containment of overall volatility in the years of turmoil.

5.3 Allocative efficiency

Our specification in (15) allows to estimate price distortions and, in turn, allocative inefficiency. It is known that technical inefficiency results when a decision-making-unit does not produce maximum output given its inputs (Ruggiero, 2000). Allocative inefficiency results when the input or output mix is not optimal (Bogetoft, Fare, and Borge, 2006, Brissimis, Delis and Tsionas, 2010, Staub, Souza, and Tabak, 2010). Here, the notion of optimality refers to expected utility maximization. As we remarked in the discussion of (17) and (13) - (15), observed output prices are p_{mt} and virtual or shadow prices that would satisfy the first-order-conditions for expected utility maximization are $\tilde{p}_{mt}$ subject to some normalization. The differences $p_{mt} - \tilde{p}_{mt}$ are known as price distortions for all outputs $(m = 1, ..., M)$. Therefore, although the bank should use output prices $\tilde{p}_{mt}$, the bank uses the observed prices, p_{mt}. To determine the cost of this deviation from optimality we use the allocative inefficiency measure:

$$AI_{it} = \frac{|\mathbf{p}_{it} - \tilde{\mathbf{p}}_{it}|'\mathbf{y}_{it}}{\mathbf{p}'_{it}\mathbf{y}_{it}}, \tag{27}$$

where $\mathbf{p}_{it}, \tilde{\mathbf{p}}_{it}$ are the $M \times 1$ vectors of observed and virtual prices, and $\mathbf{y}_{it}$ is $M \times 1$ the vector of outputs.

Such estimates can be obtained easily from (15) which is estimated separately from (17) and (13). Given estimated parameters $\hat{\boldsymbol{\theta}}$ from (17) and (13), and estimated of the risk parameters from (14), equation (15) is estimated using a random-effects specification for $\gamma_{it} = [\gamma_{it,1}, ..., \gamma_{it,M}]'$. The model we estimate is:

$$\log p_{i,tm} = \gamma_{it,m} + \log \tilde{p}_{it,m} + \xi_{it,m}, m = 1, ..., M, \tag{28}$$

$$\xi_{it} = [\xi_{it,1}, ..., \xi_{it,M}]' \sim \text{i.i.d.}\mathcal{N}_M(0, \Omega_\xi), \tag{29}$$

$$\gamma_{it} = [\gamma_{it,1}, ..., \gamma_{it,M}]' = \delta_i + \lambda_t. \tag{30}$$

We use the normalizing restriction $\sum_{m'=1}^{M} (\mu_{m'} + \sigma_{m'}\Lambda_{m'}) = 1$, viz. output prices lie on the boundary of the unit simplex in $\Re^M$. In the specification (30) we decompose the systematic component γ_{it} into a bank specific component, δ_i, and a time-varying effect λ_t. The overall error term ξ_{it} can be interpreted as a bank-time effect. No assumption of independence between δ_i and λ_t is necessary nor assumptions of independence with ξ_{it}. The model can be estimated using GMM using the same instruments as the ones that were used in estimating (17) and (13). Our allocative efficiency estimates, defined as $AE_{it} = \exp(-AI_{it})$ are provided in Table 6.

Table 6. Allocative Efficiency

Year⟶	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Overall excl. periphery	0.816	0.810	0.781	0.774	0.732	0.710	0.688	0.631	0.716	0.812	0.893
France	0.811	0.814	0.794	0.782	0.744	0.722	0.655	0.620	0.628	0.833	0.902
Germany	0.891	0.932	0.871	0.844	0.831	0.806	0.733	0.710	0.724	0.876	0.923
Periphery	0.744	0.762	0.744	0.710	0.681	0.645	0.610	0.554	0.617	0.773	0.885
Greece	0.826	0.856	0.713	0.684	0.643	0.610	0.564	0.553	0.545	0.512	0.515

There is an interesting pattern emerging from the estimates in Table 6. First, there is a decline in allocative efficiency of the banking system in the Eurozone excluding the peripheral countries from 2001-2002 and the trend reverses only after 2009. This decline followed by a recovery is evident also in France and Germany. Second, the same is true for the peripheral countries but not in Greece whose allocative efficiency declined from 82.6% in 2001 to nearly 51.5% in 2010 and 2011. The banking system in the periphery as a whole, however, increased its efficiency from 74.4% in 2001 to 88.5% in 2011. The (almost) general increase in allocative efficiency after 2010 can, probably, be attributed to the bail-out plans of the EU but also the re-orientation of the banking system towards more sound investments along the lines of expected utility maximization. In this sense, recapitalization of European banks through the intervention of the ECB resulted in better performance with the exception of Greece, whose problems of the banking sector can be attributed to structural weaknesses in its economy.

The important evidence is, additionally, the decline in allocative efficiency throughout 2001-2009. It is not entirely out of line to attribute this development to the policies of expanding credit and low interest rates of the ECB. Artificially "cheap money", quite naturally made many investments appear more profitable than they truly were (in view of differential information between banks and investors seeking funding of their projects) and, in that way, they magnified the wedge between actual and virtual loan prices or costs. In turn, this is responsible for lower allocative efficiency over time. The liquidation of unprofitable projects resulted in capitalization problems of the banking system that were resolved only after the bail-out policies of the ECB and the exercise of more prudence by the banks. As as saw, this resulted in higher risk aversion as well as downside risk aversion or prudence.

Concluding remarks

This paper has developed a new model of expected utility of profit maximization for financial institutions, subject to the neoclassical production possibility restrictions. The essential feature of the model is loan-price uncertainty in a multivariate context, an issue that has not been considered so far in the literature. The model can be estimated using standard econometric techniques: GMM for dynamic panel data along with latent factor analysis for the estimation of covariance matrices. An explicit functional form for the utility function is not needed and we show how measures of risk aversion and prudence (downside risk aversion) can be derived and estimated from the model. The model is estimated using data for Eurozone countries and we focus particularly on: (i) the use of the modeling approach as an "early warning mechanism"; (ii) the bank- and country-specific estimates of risk aversion and prudence (downside risk aversion); and (iii) the derivation of a generalized measure of risk that relies on loan-price uncertainty. The empirical results show that prudential behavior and risk aversion differ substantially among the periphery and the rest of the Eurozone, as well as compared to French and German banks. Risk aversion in the French and German began to increase well in advance of the sub-prime crisis. The same is true for the Eurozone excluding the periphery. For the periphery, risk aversion followed the sub-prime crisis and started increasing only after 2008. Our generalized measure of risk shows that risk has been building up in the Eurozone since the early 2000s and is still at high levels although it has already begun to decrease for the large financial sectors of France and Germany. Moreover, the model provides estimates of loan price distortions and thus, allocative efficiency in the banking sector. Estimates of allocative efficiency and their pattern over time, provides corroborating evidence to risk aversion, prudence, and our generalized risk measure.

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Figure 1. Sample distributions of measures of risk aversion

The figure presents the sample distribution of bank-specific and time-varying estimates of the risk aversion parameter, α. i) We estimate jointly (17) and (14) by GMM to estimate the technology parameters, $\boldsymbol{\theta}$. ii) Given estimates $\hat{\boldsymbol{\theta}}$we recover $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ from (13). iii) In turn, given $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ we solve the expressions in (7) and (9) in terms of α, δ of a nonlinear system of equations given the data, for bank-specific and time-varying estimates of α_{it}, δ_{it} . Parameters μ and $\Sigma$are assumed the same for all banks and years in the same country but different across countries and are estimated using their sample counterparts from (1).

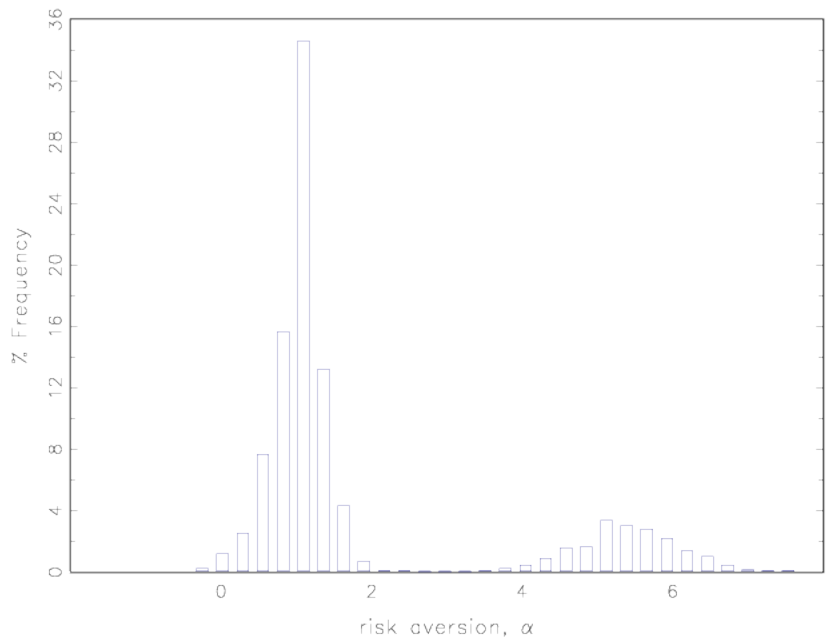


Figure 2. Sample distributions of measures of downside risk aversion

The figure presents the sample distribution of bank-specific and time-varying estimates of the downside risk aversion parameter, δ. i) We estimate jointly (17) and (14) by GMM to estimate the technology parameters, $\boldsymbol{\theta}$. ii) Given estimates $\hat{\boldsymbol{\theta}}$we recover $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$

from (13). iii) In turn, given log $\frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ we solve the expressions in (7) and (9) in terms of α, δ of a nonlinear system of equations given the data, for bank-specific and time-varying estimates of α_{it}, δ_{it} . Parameters μ and $\Sigma$are assumed the same for all banks and years in the same country but different across countries and are estimated using their sample counterparts from (1).

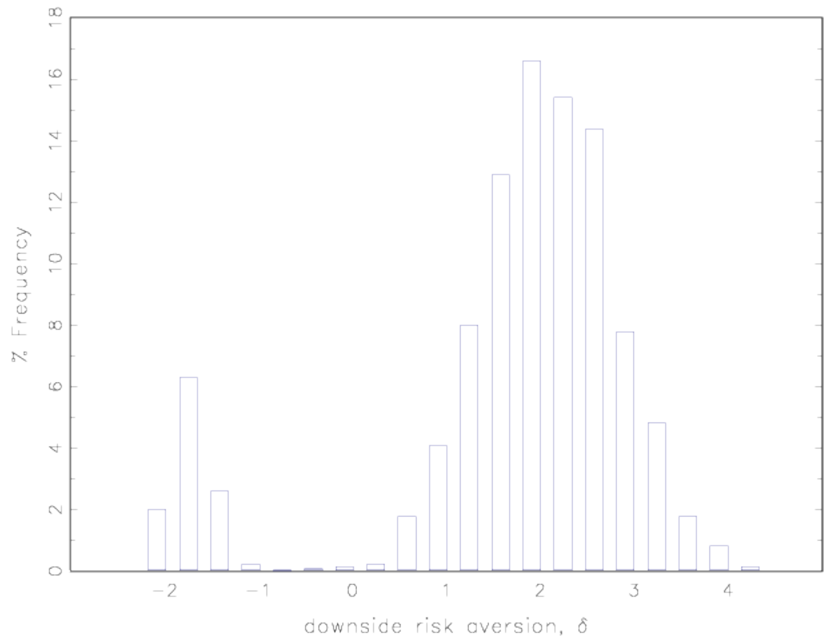


Figure 3. Risk aversion measures over time

The figure presents estimates of risk aversion parameter, α, over time. The estimates are yearly averages across banks for different grouping (PIIGS etc). i) We estimate jointly (17) and (14) by GMM to estimate the technology parameters, $\boldsymbol{\theta}$. ii) Given estimates $\hat{\boldsymbol{\theta}}$we recover log $\frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ from (13). iii) In turn, given log $\frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ we solve the expressions in (7) and (9) in terms of α, δ of a nonlinear system of equations given the data, for bank-specific and time-varying estimates of α_{it}, δ_{it} . Parameters μ and $\Sigma$are assumed the same for all banks and years in the same country but different across countries and are estimated using their sample counterparts from (1).

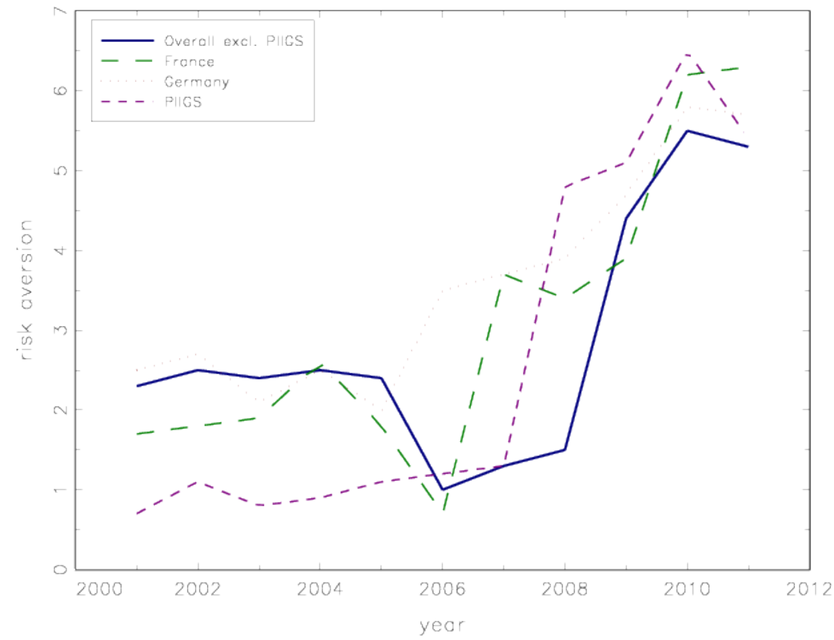


Figure 4. Downside risk aversion measures over time

The figure presents estimates of downside risk aversion parameter, δ, over time. The estimates are yearly averages across banks for different grouping (PIIGS etc). i) We estimate jointly (17) and (14) by GMM to estimate the technology parameters, $\boldsymbol{\theta}$. ii) Given estimates $\hat{\boldsymbol{\theta}}$we recover $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ from (13). iii) In turn, given $\log \frac{\tilde{p}_{m,it}}{\tilde{p}_{1,it}}$ we solve the expressions in (7) and (9) in terms of α, δ of a nonlinear system of equations given the data, for bank-specific and time-varying estimates of α_{it}, δ_{it} . Parameters μ and $\Sigma$are assumed the same for all banks and years in the same country but different across countries and are estimated using their sample counterparts from (1).

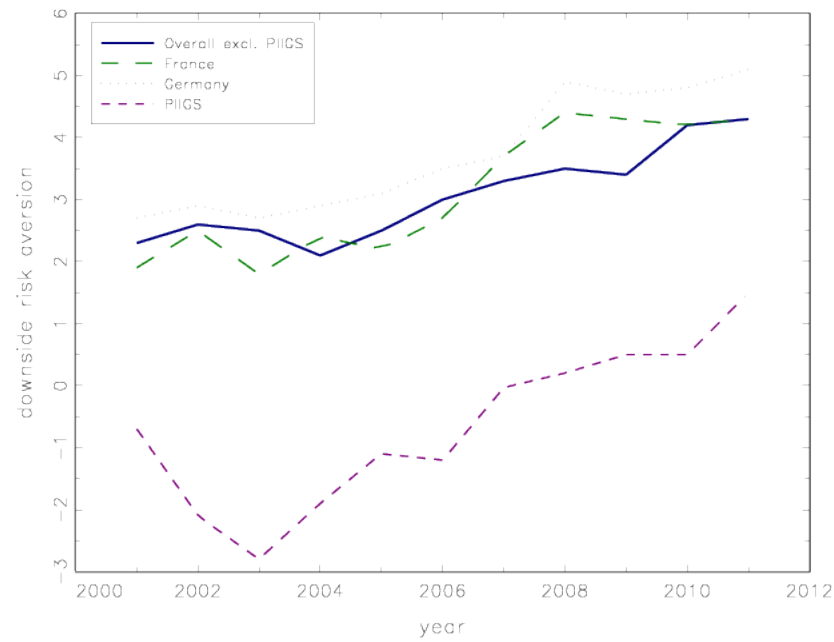


Figure 5. Generalized risk measures over time

In the figure shown are measures of generalized risk, $\det(\hat{\mathbf{\Sigma}}_t)$ over time. The measures are normalized to 1.000 for 2001. Generalized risk measures are estimated using the factor model (22), (25) and (26).

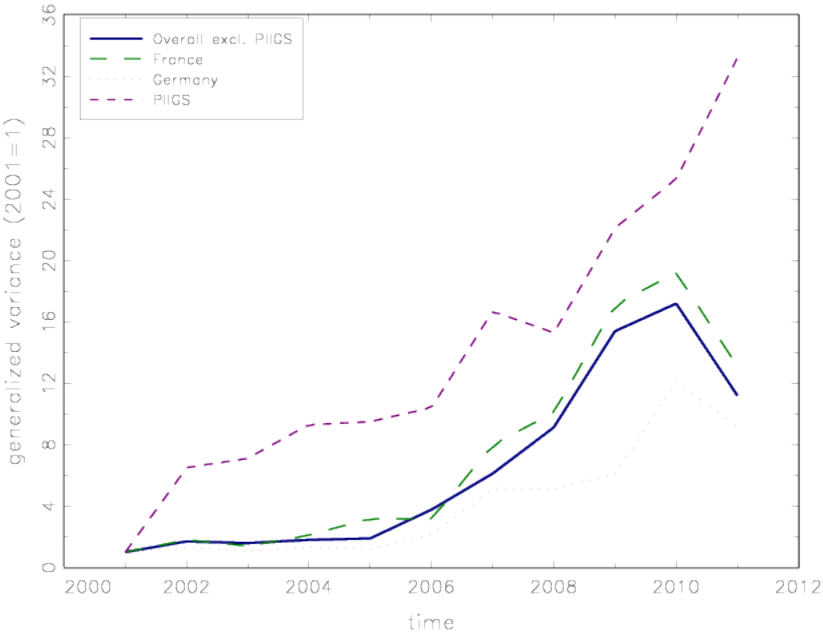
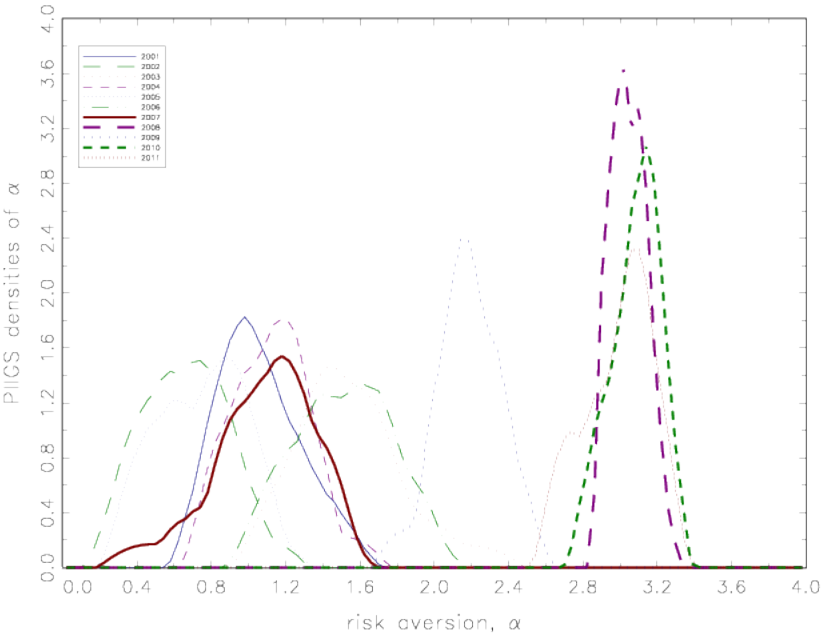


Figure 6. Risk aversion sample distributions over time (Periphery)

The figure presents, for each year (2001-2011), the distribution across banks of the risk aversion parameter, α. The densities are produced using a kernel technique using an Epanechnikov kernel. See the captions to Figure 2.



APPENDIX. DESCRIPTIVE STATISTICS

VARIABLE	OBS	MEAN	STD. DEV.	MIN	MAX	MEDIAN
TOTALCOST	27187	251051.5	2118596	400	9.69E+07	25600
WL	27187	1.372345	0.5482313	0.0045845	9.957204	1.363636
WD	27187	2.925444	1.45002	0.0402936	19.9481	2.734338
WC	27187	119.1985	192.7809	3.355705	1991.667	67.75956
PLO	27187	8.638201	6.323479	0.4840662	145.7831	7.648243
POEA	27187	3.552788	5.039146	-27.71947	145	2.542373
RLO	27187	0.9944931	0.153318	0.016129	2.53605	0.995283
ROEA	27187	0.2045313	0.1332156	-2.666667	2.146497	0.1826402
LNTOTALASSETS	27187	13.40506	1.60163	8.219057	21.51282	13.22058
LIQUIDITYRATIO	27187	16.85366	13.35406	0.0131752	95.89972	13.36217
CASHRATIO	27187	2.00879	1.835655	0.0002079	64.43212	1.938426
OBSRATIO	27187	8.738165	32.31466	0.0006494	3396.91	5.522683
FUNDINGRATIO	27187	80.05762	17.08493	0.0319489	100	83.66225
FUNDINGRATIOBROADER	27187	72.61329	18.14847	0.0319489	100	76.67171
ZSCORE_BANKSPEC	27187	0.8829516	3.173709	-0.0342153	168.4996	0.4555166
EQUITYTOTALASSETS	27187	7.251305	4.135922	0	86.35	6.24
NIM	27187	2.622199	0.8642883	-2.22	15.61	2.63
ROAA	27187	0.3435572	0.7718211	-46.27	11.21	0.27
ROAE	27187	4.824281	11.60493	-458.17	775.51	4.37
COM	27187	0.1410968	0.3481278	0	1	0
INV	27187	0.0068415	0.0824315	0	1	0
EST	27187	0.0111083	0.1048106	0	1	0
SAV	27187	0.2644279	0.4410362	0	1	0
COOP	27187	0.5765255	0.4941182	0	1	1
COUNTR_ZSCORE	27187	17.99962	11.85795	2.03641	65.577	12.9567
COUNTR_BANKCREDTOBANKDEP	27187	113.3285	22.67743	15.0084	206.223	114.537
TOTALASSETS	27187	6534709	6.05E+07	3711	2.20E+09	551600
EQUITY	27187	315604.9	2360113	200	8.56E+07	36000
DEPOSITSSHORTTERMFUNDING	27187	3891900	2.92E+07	3157	1.21E+09	454100
Y1	27187	3155331	2.28E+07	1306.5	7.51E+08	321400
Y2	27187	3024273	3.71E+07	940	1.76E+09	177500
PROFITBEFORETAX	27187	23406.14	371818.7	-1.85E+07	1.30E+07	2400