Applying Credit Risk Models to Deposit Insurance Pricing: Empirical Evidence from the Italian Banking System

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Abstract

The Federal Deposit Insurance Corporation (FDIC) has recently tested credit risk measurement models used by large international banks to measure the risk of their credit portfolios in order to measure the risk of default of its portfolio of insured banks. Using both balance sheet and equity market data for a sample of 15 large Italian banks, this study applies a credit value at risk model to estimate both individual and portfolio default risks for the *Fondo Interbancario di Tutela dei Depositi* (FITD), the Italian deposit insurance fund. The empirical analysis allows us to estimate the loss probability distribution of the FITD exposures which in turn can be used to: (i) evaluate the FITD fund adequacy; (ii) estimate the marginal contribution to the whole portfolio risk of an individual insured bank; (iii) test an alternative risk-.adjusted deposit insurance pricing scheme to the more traditional one based on option pricing models. Two main results emerge from the empirical analysis. First, the estimated total risk-based premium for the sample banks is in line with the current practice of the FITD and with its available callable capital. Second, significant differences appear to exist in the pricing of the deposit insurance service for the different sample banks. Such differences reflect both differences in the banks' individual risk profiles and the higher impact that the exposures to larger banks present on the risk profile of the FITD portfolio.

Codes JEL: G21, G28, G11, G33

Key words: Credit risk, deposit insurance, value at risk, risk-based pricing

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1. INTRODUCTION

The measurement of risks faced by financial institutions has recently become a core topic widely discussed by both national and international supervisory authorities pursuing the objective of financial system stability through policy instruments such as risk-weighted capital ratios, deposit insurance, and lending of last resort. Banks are institutions subject to rigorous supervision and regulation aimed at avoiding that a systemic crisis might affect the general economic system. All over the world, banks are therefore accurately and constantly supervised through both off-site monitoring systems, and on-site systems use to analyse the organisational, informative and managerial adequacy of banks' risk management systems.

Banks are also subject to a safety net aimed at avoiding that single bank crisis episodes might generate systemic crisis undermining the financial system stability. In most of the economically advanced countries, such safety net is based on the lender of last resort function carried out by the central bank, restricted to liquidity crises, and on deposit insurance. The latter is typically justified by the need to overcome the asymmetry of information in the banking system and prevent bank runs (Diamond e Dybvig, 1983). While deposit insurance helps enhancing the stability of the financial system, it also creates moral hazard problems, by removing the incentives for bank creditors to monitor and price banks' risk profiles.

The delicate trade-off between the need to protect the stability of the financial system and the desire to avoid the moral hazard problem created by the safety net are typically addressed with three alternative instruments. One alternative is represented by risk-based capital requirements. The system of capital adequacy, firstly introduced in 1988 by the Basel Committee on Banking Supervision, plays a key role in preventing individual bank crisis and, at the same time, avoiding excessive risk-taking. At present, a radical reform process of the 1988 Capital Accord is in progress (Basel Committee on Banking Supervision, 2001).

A second alternative, recently emphasised by the Basel Committee as the "Third Pillar" of the new framework of capital adequacy, is market discipline. If banks' uninsured creditors are sufficiently risk-averse and are provided with an adequate amount of information to assess banks' risk profiles, then they can discipline the banks behaviour by pricing their liabilities accordingly. A large number of empirical studies found that yields charged by banks' subordinated bonds investors adequately reflect the issuing banks risk profiles (Flannery and Sorescu, 1996; Evanoff and Wall, 2000; De Young, Flannery, Lang and Sorescu, 2001; Sironi, 2003).

A third alternative instrument to provide banks with an incentive to reduce their risk-taking activities is represented by risk-adjusted deposit insurance pricing. The latter has always attracted a significant attention from financial economists and regulators. Merton (1977) was the first to apply options theory to deposit insurance pricing, pointing out that deposit insurance can be viewed as a loan guarantee and can be priced accordingly. A number of empirical studies has then been produced using the options theory approach to price deposit insurance (Markus and Shaked, 1984; Roon and Verma, 1986; Pennacchi, 1987).

More recently, an alternative approach based on the use of credit risk models has been proposed. Indeed, the U.S. Federal Deposit Insurance Corporation (FDIC, 2000) has recently started to investigate credit risk measurement models used by major international banks in order to test whether these models can be applied to quantify the risk of its portfolio of insured banks and price deposit insurance accordingly. As stated by the FDIC option paper, *"If deposit insurance is viewed as a service that banks use, the question is how this service should be priced. One answer is that the price should reflect the risk that the bank presents to the deposit insurance system. This expected loss approach to pricing is consistent with the best practices that have developed in the banking industry in recent years"*. A similar approach has recently been followed by Bennett (2001) and Kuritzkes, Schuermann and Weiner (2003).

Using both balance sheet and equity market data for a sample of 15 large Italian banks, this study applies a credit value at risk model to estimate both individual and portfolio default risks for the *Fondo Interbancario di Tutela dei Depositi* (FITD), the Italian deposit insurance fund. Established in 1987 as a voluntary consortium, the FITD is not a government agency but rather a mutual insurance fund. It therefore has no supervisory or regulatory power. Member banks[1] undertake to pay the contributions to the consortium and, upon request of the Fund, to make regular payments to cover the FITD operating expenses. The FITD capital is callable: in case of a bank insolvency, the member banks are required to pay a fixed percentage – ranging from 0.4% to 0.8% - of their insured deposits. These payments are partially risk-adjusted using a function of a set of banks' financial ratios.

The empirical analysis allows us to estimate the loss probability distribution of the FITD exposures which in turn can be used to: (i) evaluate the FITD capital adequacy; (ii) estimate the marginal contribution to the portfolio risk of a each individual insured bank; (iii) test an alternative risk-adjusted deposit insurance formula to the more traditional one based on option pricing models.

Two main results emerge from the empirical analysis. First, the estimated total risk-based premium for the sample banks is in line with the current practice of the FITD and with its callable capital. Second, significant differences appear to exist in the pricing of the deposit insurance service for the different sample banks. Such differences reflect both differences in the banks' individual risk profiles and the higher impact that the exposures to larger banks present on the risk profile of the FITD portfolio.

This paper is organized as follows. Section 2 provides a short review and description of credit risk models and shows how such models can be used by deposit insurance agencies to measure the risk of default of their portfolios of insured deposits. Section 3 reports the methodology applied in the empirical analysis. A detailed description of the model inputs is provided by separately estimating the individual bank default probability and the risk of the whole portfolio. Section 4 highlights the main empirical results and shows how such results can be used both for the evaluation of the deposit insurance fund capital adequacy and for deposit insurance pricing. Finally, section 5 reports the main conclusions and implications.

[1] All Italian banks (about 300) are members of the Fund, except for "mutual banks" (*banche di credito cooperativo*), which are members of the Deposit Guarantee System of Mutual Banks (*Garanzia dei Depositanti del Credito Cooperativo*).

2. CREDIT RISK MODELS

Credit risk measurement models can be gathered in two main categories: 1) Default Mode models (DM) and 2) Mark-to-Market (MTM) models. In the former, credit risk is identified with default risk and a binomial approach is adopted. Therefore, only two possible events are taken into account: default and survival. The latter takes into account all possible changes of the borrower creditworthiness, technically called “credit migrations”. In DM models credit losses only arise when a default occurs. On the other side, MTM models are multinomial, in that losses arise also when credit migrations occur. The two approaches basically differ for the amount of data necessary to feed them: limited in the case of default mode models, much wider in the case of mark-to-market ones.

The main output of a credit risk model is the density function of the portfolio credit loss probability (probability density function – PDF). From the analysis of such loss distribution, a financial institution can estimate both the expected loss and the unexpected loss of its credit portfolio. The expected loss equals the (unconditional) mean of the loss distribution; it represents the amount the bank can expect to loose within a specific period of time (usually one year). On the other side, the unexpected loss represents the average “deviation” from expected loss and measures the actual portfolio risk. This can in turn be measured as the standard deviation of the loss distribution. Such measure is relevant only in the case of a normal distribution and is therefore hardly useful for credit risk measurement: indeed, the distribution of credit losses is usually highly asymmetrical and fat-tailed. This implies that the probability of large losses is higher than the one that would be associated with a normal distribution.

The main features of credit risk models applied by major international banks are reported in technical documents[2]. Two such documents, *CreditMetricsô* (Gupton & others, 1997) and *CreditRisk+ô* (Wilde, 1997) are publicly available. Starting from the analysis of such technical documents, academic research has focused on two main issues. The first one concerns the model-related differences, both from a theoretical and empirical point of view. As for the former, a distinction is made (Frey e McNeil, 2001) between latent variable

[2] See Crouhy, Galai and Mark (2000) for a comparative descriptive analysis.

models, such as *CreditMetrics*™ and *KMV Portfolio Manager*™, and mixture models, such as *CreditRisk+*™ and *CreditPortfolioView*™. In the first group, a borrower default depends on prevailing unobserved variables (latent): common risk factors "governing" latent variables give rise to interdependent defaults. In the second group, according to the values of common economic factors, a borrower default is rather conditionally independent.

In spite of this formal distinction, various authors found remarkable similarities among such models. Gordy (2000) carried out a comparative analysis of the *CreditMetrics*™ and *CreditRisk+*™ models: apart from some differences in the assumptions concerning the loss distribution function, the two approaches present similar methodological structures. The simulations revealed similar results if applied to average loan portfolios, besides being particularly receptive to default correlation coefficients and to the assumptions on the distributions of systematic risk factors. Koylouglu and Hickman (1998) compared the *CreditMetrics*™, *CreditRisk+*™ and *CreditPortfolioView*™ approaches showing how their methodologies were theoretically equivalent. According to these empirical studies, one of the main differentiating factor is the approach adopted for the measurement of correlation between different portfolio exposures: correlation among default events, also called default correlation, versus correlation among asset returns, also called asset correlation.

Financial institutions apply credit risk models to evaluate the "economic capital" necessary to face the risk associated with their credit portfolios. In such a framework, provisions for credit losses should cover expected losses[3], while economic capital is seen as a cushion for unexpected losses. Similarly, the logic behind this approach can be applied to the credit exposures of deposit insurance agencies. In the case of a bank credit portfolio, a loss occurs if a borrower defaults. In the case of a deposit insurance fund, a loss occurs if an insured institution fails, thereby triggering a payout on the part of the fund.

Following this approach, a deposit insurance fund can be compared to a bank measuring its counterparts' default risk. While for banks counterparts are borrowers, for deposit insurance agencies they are rather the same banks, with exposures equal to the

[3] As discussed in Jones and Mingo (1998), reserves are used to cover expected losses..

insured deposits. The deposit insurance fund is indeed managing a portfolio of contingent credit exposures to the banks it insures.

In the same way as a bank's capital adequacy is evaluated based on its portfolio unexpected loss, a deposit insurance fund adequacy can be evaluated on the basis of the unexpected loss associated with its portfolio of insured institutions. Credit risk models can also be used to determine deposit insurance pricing as an alternative to the more traditional approaches based on option pricing.

Credit portfolio loss empirical distributions are usually asymmetrical towards high loss values: the probability to incur into extreme losses is higher than that implied in a normal distribution. A deposit insurance fund is therefore facing a similar situation: within a certain period of time, a relatively high probability of relatively low losses due to the default of small banks, counterbalanced by a very low probability of large losses in case of default of one or more large banks. As the distribution is asymmetrical, the precise evaluation of the distribution extreme quantiles is a fundamental factor.

Despite these similarities between the two types of default risks, the two types of default events are quite different. A loan default is actually the credit borrower inability to afford targeted payments. Even though the borrower default might lead to the bank default, credit risk is not the only crisis threatening banks as it usually depends on a combination of risks: credit, market and operational risks.

We should also further distinguish between the default of a bank's borrower and the one of a bank itself, being the latter an exceptional event: only supervisory authorities have the power to "close down" a bank. From this point of view, a technically insolvent bank might be kept alive by the supervisory authorities if bail-out policies such as *too big to fail* ones are adopted.

3. RESEARCH METHODOLOGY

This section describes the approach that we used to evaluate the portfolio loss distribution of the FITD. Such distribution is useful to identify the appropriate level of resources necessary to face the potential losses coming from future bank crisis and to define a pricing system for risk-based deposit insurance.

3.1. Estimating the default probability of individual banks

The evaluation of individual default probability is based on both market (stock prices) and accounting information (balance sheets data). This approach uses the theoretical relation between the market value of a company's assets and its default probability, as originally developed by Merton (1974). In such a framework, the default process of a company is driven by the value of the company's assets and the risk of a firm's default is therefore explicitly linked to the variability in the firm's asset value. The basic intuition behind the Merton model is relatively simple: default occurs when the value of a firm's assets (the market value of the firm) is lower than that of its liabilities. The payment to the debt-holders at the maturity of the debt is therefore the smaller of two quantities: the face value of the debt or the market value of the firm's assets. Assuming that the company's debt is entirely represented by a zero-coupon bond, if the value of the firm at maturity is greater than the face value of the bond, then the bondholder gets back the face value of the bond. However, if the value of the firm is less than the face value of the bond, the equity-holders get nothing and the bondholder gets back the market value of the firm. The payoff at maturity to the bondholder is therefore equivalent to the face value of the bond minus a put option on the value of the firm, with a strike price equal to the face value of the bond and a maturity equal to the maturity of the bond. Following this basic intuition, Merton derived an explicit formula for default risky bonds which can be used both to estimate the PD of a firm and to estimate the yield differential between a risky bond and a default-free bond.

In our empirical analysis, we use a modified version of the Merton model, as originally proposed by KMV (Crosbie, 1999). Restricting the empirical analysis to listed banks, for which market data is available, we can apply an approach similar to the CreditMonitor™ model of KMV to evaluate individual default probabilities. More precisely, this approach is based on two theoretical relations: (i) the equivalence between the value of equity capital and that of a call option on the corporate asset value, and (ii) the link between the (observed) volatility of equity capital returns and the (unobserved) volatility of assets returns. The estimate of the default probability is based on three steps: (1) evaluation of the market value of assets and its related volatility, (2) calculation of the distance to default, equal to the number of the standard deviations of the asset value from the default point, (3) identification of the default probability corresponding to the distance-to-default.

The asset market value and its related volatility come from an option *pricing* model. Following the evaluation of the asset market value, the CreditMonitor™ approach evaluates whether such asset value is higher or lower than the default point (DPT). The default point, i.e. the asset value under which liabilities exceed assets bearing the company to default, is equal to the total amount of short term liabilities plus half that of long term liabilities. The distance-to-default (DTD) measures the number of standard deviations of the corporate asset from the default point. Finally, the distance-to-default is turned into default probability based on the empirical evidence of default rates per classes of DTD.

As far as this last step is concerned, a problem arises when banks defaults are involved. Indeed, the limited number of bank default events makes critical any statistical approach to risk measurement. A really uncommon exception is the large number of bank crisis occurred in the US system during the Savings and Loans crisis. In general, some approaches, such as the KMV's one, use the US system data to evaluate the default historical frequencies of the banking industry. In the Italian banking system, the lack of data definitely prevents the comparison with the historical frequency of the outputs resulting from the application of a Merton model. We therefore estimate bank default probabilities (expected default frequency – EDF) using theoretical rather than empirical probabilities.

3.2. A portfolio approach to estimate expected loss and marginal risk

In a default-mode model, where only default and survival events are taken into account, the portfolio expected loss (EL_P) is equal to the product of the individual exposures to each one of the n banks (EXP_i), the default probabilities (EDF_i) of each bank, and the loss rates in case of default (LGD_i).

(1) $$EL_P = \sum_{i=1}^{n} EXP_i \cdot EDF_i \cdot LGD_i$$

The unexpected loss evaluation implies two phases: in the first one we calculate the unexpected loss related to each individual portfolio exposure i (UL_i), equal to the loss standard deviation. Assuming LGD as a deterministic variable, we obtain the following formula:

(2) $$UL_i = EXP_i \cdot LGD_i \cdot \sqrt{EDF_i \cdot (1 - EDF_i)}$$

In the second phase, the individual exposures loss volatilities are combined in the loss volatility of the whole portfolio, using the correlations between defaults (*default correlations*) of the various exposures, $r_{i,j}$[4]:

(3) $$UL_P = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} r_{i,j} \cdot UL_i \cdot UL_j}$$

This simple model emphasises the importance of the correct evaluation of all relevant parameters (EDF_i, EXP_i, LGD_i and $r_{i,j}$) to define portfolio risk measures. The quality of such estimations can strongly impact the outputs of credit risk models.

The unexpected portfolio loss, UL_P, can also be expressed as the sum of marginal unexpected losses, ULC_i, attributable to each individual portfolio exposure:

(4) $$UL_P = \sum_{i=1}^{N} ULC_i$$

where:

(5) $$ULC_i = \frac{\partial UL_P}{\partial UL_i} \cdot UL_i$$

4 For further details on the derivation of this volatility formula see Ong (1999).

In this way, the marginal unexpected loss of exposure *i* is the result of the partial derivative of the portfolio unexpected loss with respect to the unexpected loss of the same exposure. As Ong (1999) proved, by solving this partial derivative one gets the following "closed" formula to calculate the marginal unexpected loss of each individual exposure:

$$(6) \qquad ULC_i = \frac{UL_i \cdot \sum_{j=1}^{n} \left(UL_j \cdot \rho_{i,j} \right)}{UL_P}$$

The contribution to the risk of the deposit insurance agency portfolio given by the *i-th* bank does not actually depend on its expected loss, but rather on its "unexpected" loss. In particular, the contribution to portfolio risk of the *i-th* bank, ULC_i, is a function of two variables: 1) the unexpected loss of the *i-th* bank, that, on its turn, is a function of the default probability of the *i-th* bank and of the exposure of the insurance fund to the same bank; 2) the correlation rate of such loss with the rest of the portfolio. As it will be shown, the contribution to portfolio risk is a fundamental parameter to define a pricing system for a risk-based deposit insurance (see paragraph 3.4).

3.3. Generating the empirical distribution of portfolio losses

The "mean-variance" approach cannot be applied to define the entire loss distribution for a deposit insurance fund. The distribution of credit losses is indeed non-normal and this prevents the application of a simple multiplier to the portfolio standard deviation (UL_P) in order to get a measure of potential maximum loss (and consequently the portfolio value at risk or VaR[5]) within a certain confidence interval. For this reason, a Monte Carlo simulation can be used in order to generate the empirical distribution of losses and to get the analytical scenarios of losses related to different levels of probability. This output also provides an empirical multiplier to be applied to the standard deviation (called capital multiplier), in order to use the "closed" formulas described in paragraph 3.2.

The correlation of bank assets returns are used as parameters of a multivariate normal distribution. As in the case of the Merton model, we assume that: (i) an individual

[5] The portfolio VaR, with a certain confidence interval, corresponds to the difference between maximum potential loss and expected loss.

bank goes into default when its asset value decreases under a certain threshold level, (ii) the asset value of each individual bank follows a normal distribution; (iii) the asset values of different banks follow a multivariate normal distribution.

We obtain some correlated random values[6] to be compared to the default threshold rate, equal to the inverse standard normal distribution of the default probability. In this way, if the correlated random number is higher than the default-point threshold, then the bank does not default and gets a 0 value of the Bernoullian random variable; on the contrary, if the correlated random value is lower than the default threshold, then the bank goes into default and gets a 1. For every bank that incurs into default during the simulation, the model calculates the expected loss for the deposit insurance fund (EL_i) as the product of the exposure (EXP_i) by the loss in case of default (LGD_i)[7].

Finally, all individual expected losses are summed up to get the expected loss for a specific simulation. By repeating the Monte Carlo simulation a large number of times (in our case, 30,000) we get the empirical distribution of portfolio losses. This allows us to calculate the loss rate for every possible confidence level and a multiplier to apply to the standard deviation already calculated (UL_i) to directly obtain the loss corresponding to the desired confidence interval.

3.4. The Risk-based pricing model of deposit insurance

In the case of deposit insurance, the methodology described allows an immediate application to the quantification of the risk-based premium that should be associated to each individual insured bank. This premium should cover the expected loss rate, just as the spread between the interest rate charged by a bank to a borrower and the risk-free rate covers the expected loss of the loan to this borrower. This deposit insurance pricing based on the expected loss has two main advantages. First, establishing an insurance price for each bank equal to the expected loss allows the insurance premia to cover average losses over a relatively long period of time. Second, this pricing system based on individual risk

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[6] In the numerical application (section 4), in order to get correlated random numbers we factorised the *asset return correlation* matrix applying the Cholesky method.
7 In our case the LGD is fixed and equal to 50%.

discourages the moral hazard phenomenon: the most risky banks are subject to higher insurance costs.

While the expected loss-based *pricing* allows to monitor risks at the individual level, it does not take into account the actual contribution of each individual exposure to portfolio risk. Every bank exposure contribution to the portfolio unexpected loss (ULC_P) is a function of expected loss, correlation and exposure. Indeed, the pricing for an individual bank *i* (P_i) should be equal to the expected loss component (EL_i) plus the contribution to the insurance fund portfolio unexpected loss (ULC_i) multiplied by a market risk premium, estimated as the difference between the market portfolio return (R_M) and the risk-free rate (R_F)[8]:

$$P_i = EL_i + (R_M - R_F) \cdot ULC_i \tag{7}$$

The empirical estimate of ULC_i can be of difficult computation, especially if carried out within a simulation framework. In this case, the calculation of the contribution of the *i-th* exposure to the unexpected loss requires the comparison of the unexpected loss (at a certain confidence interval) estimated for the whole portfolio with the one resulting from the removal of the *i-th* exposure[9]. As an alternative, we can apply the "closed" formula previously described, $ULC_i = \frac{UL_i \cdot \sum_{j=1}^{n} UL_j \cdot r_{i,j}}{UL_P}$, which requires a multiplying factor (estimated through simulations) to be applied to the standard deviation of the loss distribution, in order to get the targeted confidence level.

In general, exposures to larger banks present a lower cost for the expected loss component, as they tend to be less risky, but a higher one for the unexpected loss

[8] The logic applied to this analysis is similar to the one used by a bank when defining the spread between the interest rate charged to a loan and its funding cost. The *pricing* method applied by banks adopting credit risk models is based on the sum of two main elements: the expected loss rate and the product of the amount of risk – a VaR estimate – and the price of risk – roughly given by the difference between the cost of equity and the *risk-free* rate. In the case of a mutual insurance fund, such as the FITD, where every member bank is committed to provide the funds necessary to reimburse the deposits of defaulted banks, every single bank assumes the risk related to the possible defaults of the other joining banks. They therefore need to be remunerated on the basis of a market risk-based premium.

[9] This method, called "leave-one-out", requires a number of simulations corresponding to the number of the portfolio exposures.

component, as they provide a high contribution to the loss volatility of the deposit insurance fund portfolio.

4. AN APPLICATION TO ITALIAN LISTED BANKS

This section reports the results of an empirical analysis based on a sample of Italian listed banks. According to the CreditMonitor™ model of KMV, it is possible to evaluate the theoretical default probabilities of individual banks using both balance sheet and stock market data. Following this model, we obtain the correlation matrix between the asset returns of the sample banks (asset return correlations). The asset market values are on their turn evaluated on the basis of the Merton model. Then, the correlation matrix between asset returns is used to estimate the corresponding correlation matrix between bank defaults (default correlations), using the relation between these two variables[10]. Such information allows us to:

1) obtain the empirical distribution of portfolio losses and evaluate both expected and unexpected losses of the deposit insurance fund portfolio due to future defaults of the Italian listed banks;
2) estimate the deposit insurance price, based on both the expected loss and the contribution to the portfolio risk of every individual exposure;
3) evaluate the adequacy of the deposit insurance fund.

4.1. Exposure at default risk and recovery rate

As shown in Table 1, the banks included in the analysis are the 15 largest Italian institutions in terms of total assets and represent more then 60% of the total assets of the Italian commercial banks. These banks are rated by one or more of the main international rating agencies (Moody's, Standard and Poor's, FitchIBCA). Table 2 reports their long term ratings. The exposure (*EXP*) of the deposit insurance fund (FITD) is represented by customers' deposits (mostly current account deposits). This value is a proxy of the amount of the deposits the insurance fund is to reimburse in case of a bank default[11]. The FITD

[10] For further details on this calculation method, see Zazzara (2002).

[11] The total amount of the refundable deposits is lower than this amount as it refers to the deposits subject to protection up to a value amounting to approximately 103.000 euro per depositor. Indeed, while the EU Directive on deposit insurance calls for

exposure to the risk of default of these insured banks is adjusted assuming a constant recovery rate of 50%, obtaining the values reported in the last column of Table 1.

Note that some banks (BNL, BPT and BDR), in spite of an investment grade rating (A2 in the Moody's scale or BBB+ in the FitchIBCA's and S&P's ones), present a very low FitchIBCA Individual[12] rating; this means that, while presenting poor financial and economic conditions, these banks are perceived by the rating agencies to benefit from an external support from either the supervisory authority or the Government in case of default (conjectural guarantee).

4.2. Evaluation of individual default probabilities

The evaluation of the theoretical default probability is carried out according to the *CreditMonitor*™ model of KMV, that enables to obtain this variable based on both balance sheet data and stock prices. Using the equity value of each bank (market capitalization) and its volatility (standard deviation of stock returns), it is possible to evaluate both the market value of each bank assets and the standard deviation of such variable.

Table 3 reports the descriptive statistics related to the logarithmic returns of the *equity* monthly value of the sample banks, for the period March 1997 - March 2002[13]. All data estimated on a monthly basis have been annualised by multiplying the mean by 12 and the standard deviation by $\sqrt{12}$, therefore assuming serial independence of returns. These annual volatility estimates are used as inputs of the *CreditMonitor*™ model, necessary to evaluate the default probability (EDF) of each bank.

In order to define the Default Point, following the KMV model assumptions, we consider half of the long term liabilities plus the short term ones. We therefore assume that a single bank can survive, within the targeted period of time (1 year), even if the assets cannot cover the total liabilities. Table 4 reports both balance sheet and market values

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a minimum level of guarantee of 20,000 Euro per depositor, the Italian legislator has increased this amount to 103,291.38 Euro, which is currently the maximum level of compensation per depositor.

[12] The FitchIBCA Individual ratings focus on banks economic and financial conditions and do not take into account any external support from banks' owners, state authorities or other official institutions. The scale used by FitchIBCA for this rating includes five classes (A, B, C, D, E) plus four intermediate classes or notches (A/B, B/C, C/D, D/E).

[13] In some cases the evaluation refers to a shorter period of time, depending on when the bank has been listed on the Stock Exchange. We take this aspect into account for the following evaluation of the correlations coefficients.

necessary to estimate the EDF of the 15 sample banks. The equity market value refers to March 2002, while the bank liabilities and their related Default Points refer to the balance sheet as at December 31st 2000.

Using both market value and equity volatility data we obtain both asset market value and asset volatility. In order to estimate the EDF of each individual bank, the analysis has been based on data directly provided by KMV. This is because our results expressed in terms of "distance to default" are then converted into EDFs based on the historical default frequencies of those companies with a similar distance to default. In this case, the EDF are based on empirical defaults of foreign banks and financial companies (especially American and Asian)[14]. Table 5 reports the results.

4.3. Portfolio risk and deposit insurance pricing

Once the evaluation of the risk variables on an individual basis has been completed, the insurance fund portfolio risk can be estimated. At the portfolio level, correlation becomes the key variable. The estimate of risk dimensions reported in paragraphs 3.2 and 3.3 requires the evaluation of two different correlation data: default correlations and asset return correlations.

The default correlation coefficients are used to estimate the insurance fund portfolio unexpected loss (UL_P), while the asset return correlation coefficients are used to generate the empirical distribution of portfolio losses, obtained through a Monte Carlo simulation. Having both equity and asset market values, evaluated according to the CreditMonitor approach of KMV, we can estimate the asset return correlation matrix. Table 6 reports the correlation matrix of the equity monthly logarithmic returns, estimated on the basis of the data pertaining to the period March '97- March 2002. The last column of the matrix also reports the correlation coefficients of the equity returns of every bank with the returns of a market index of the Milan Stock Exchange[15] (the so called "MKT"). The data show quite high correlations both between bank stock returns and between the latter and the market index, with coefficients ranging between a minimum of 8% and a maximum of 81%, with

[14] In Italy "real" defaults (technically defined "*compulsory administrative liquidations*") of commercial banks hardly ever occur. The actual default probability of a bank would therefore be zero for any *distance-to-default* level.

an average value of 52%[16]. This is quite a normal trend for the share prices of companies belonging to the same industry. The corresponding default correlation matrix is reported in Table 7.

The correlation coefficients are in this case much lower than the asset returns ones, ranging from a minimum of 0% to a maximum value of 27%, with an average value of 8%. The ratio between the average coefficients of asset return correlation and default correlation is nearly 7[17].

4.3.1. Portfolio standard deviation

Using the default correlation coefficients we can estimate the portfolio standard deviation and obtain:

$$UL_P = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{n} r_{i,j} \cdot UL_i \cdot UL_j} = 2{,}766{,}000{,}000 \; euro$$

Applying the equations reported in paragraph 3.2, we can then estimate the portfolio expected loss (EL_P), its standard deviation (UL_i) and the marginal unexpected loss of each individual exposure (ULC_i). The sum of these marginal unexpected losses should equal the portfolio standard deviation. Table 8 reports such evaluation outputs.

The total insurance fund exposure amounts to 172,136 ml euro, while the expected loss amounts to 218 ml euro, a relatively small amount. This is equal to the sum of the expected losses of each exposure (corresponding to the product of the exposures by their respective EDFs). The sum of all unexpected losses, corresponding to 1 standard deviation around the expected value, is equal to 5,735 ml euro. This value is higher than the whole portfolio standard deviation, as it does not include the diversification benefit related to the imperfect correlations between the exposures. The sum of the marginal contributions to the marginal portfolio standard deviation ($\sum_i ULC_i$) is equal to 2,766 ml euro, precisely the portfolio unexpected loss (UL_P).

[15] Such index is provided by Datastream and covers nearly all companies listed in the Italian stock market.
[16] This value was calculated as the average between the correlation coefficients not included in the main diagonal.

4.3.2. Capital multiplier, VaR and deposit insurance pricing

Given the asymmetrical nature of the portfolio loss distribution, the standard deviation measure obtained through the mean-variance approach described in the previous paragraph cannot be used to estimate a portfolio value at risk measure. We therefore apply a Monte Carlo simulation to obtain the alternative loss scenarios and related confidence levels. This is in turn based on the following main steps:

1. Evaluation of default probabilities (EDFs)
2. Evaluation of the asset return correlation matrix
3. Generation of correlated random numbers (by factorising the asset return correlation matrix – Cholesky factorisation)
4. Definition of the default threshold for every bank, equal to the reciprocal normal standard of the default probability
5. Assignment of the values 0 or 1 of the Bernoullian random variable (Di), according to the following criterium:

   Correlated random number >default threshold = 0 (Di)

   Correlated random number < default threshold = 1 (Di)
6. Estimate of the total amount of losses occurred during the cycle
7. Creation of a frequency histogram to sum up the simulation outputs.

Following this procedure and using the asset return correlation matrix reported in Table 6, we obtain the results reported in Table 9. A confidence level of 99.50%, corresponding approximately to a BBB- rating, gives rise to a maximum loss amount of 17,530 ml euro: subtracting the expected loss (218 ml) we obtain a portfolio VaR of 17,312 ml euro.

In order to avoid heavy calculations to measure the marginal unexpected loss of each individual exposure (and its marginal VaR) used in the pricing formula of deposit insurance, we opt for the capital multiplier method rather than the "leave-one-out"[18] one.

[17] Crouhy et al. (2000) report a value of approximately 10 for this ratio in the United States for asset correlations ranging from 20% to 60%.

[18] According to such method, the marginal VaR of an individual exposure *i* is evaluated as the difference between the whole portfolio VaR and the portfolio VaR obtained excluding the *i*-th exposure. In case of a large number of exposures, this method takes a long time to compute marginal VaR.

For this reason we estimate the multiplier to apply to the portfolio standard deviation (UL_P) in order to obtain the maximum loss associated to the desired confidence interval. The "empirical" multipliers are reported in Table 10.

Applying these multipliers to the marginal unexpected losses (ULC_i) previously calculated, we obtain the "empirical" marginal unexpected losses. The pricing corresponds to the sum of the expected loss (*EL*) and the product of the marginal VaR of each exposure - equal to the difference between ULC_i and EL_i[19] - and a market risk premium, as provided by (7). The risk premium applied in the empirical analysis is equal to 5%. Empirical results are reported in Table 11.

While the most risky banks (not necessarily the largest ones in terms of customer deposits) present a relatively higher expected loss component, the largest ones generally present a greater unexpected loss component. As reported in the last column of Table 11, the difference between an insurance premium exclusively based on expected losses and the one based on portfolio risk is higher for banks representing larger exposures.

Finally, comparing the estimated total risk-based premium for the 15 banks (1,083 ml Euro) with the total amount of exposures (172,136 ml Euro), we get the theoretical value of the deposit insurance fund intervention. This value is 0.63% of the total amount of exposures, therefore falling within the 0.4%-0.8% range stated by the charter of FITD. We can therefore conclude that the amount of callable capital available to the FITD is consistent with the risk profile of its portfolio.

5. CONCLUSIONS

In Italy, as well as in other European countries, the deposit insurance fund intervenes in case of a bank default but has no supervisory power on the banks with insured deposits. This situation, that might be called "powerless responsibility", calls for the FITD to cover the losses emerging from banks defaults without having any policy instrument to control banks' risk taking policies. In such a framework, the moral hazard problem is greatly emphasised. Due to the mutual nature of the FITD, a free-riding problem also

[19] If the relative expected loss (ELi) was not subtracted from $ULCi$, the EL would be calculated twice in the *pricing* formula.

exists. Indeed, shareholders of member banks would greatly benefit from aggressive risk-taking policies, well-aware of the negative consequences that these policies might produce for the other member banks.

The FITD has only one tool to address these problems: an effective insurance pricing scheme based on the actual risk contribution that every insured bank represents for the Fund itself. Following this logic, this study applied an approach similar to the one adopted by credit VaR models to measure the risk faced by the deposit insurance agency. In particular, we used both balance sheet and market data for a sample of 15 major Italian listed banks. We estimated both default risk on an individual basis and portfolio risk for the deposit insurance fund. Using a Monte Carlo simulation, we estimated the FITD loss probability distribution. We also showed how the latter can be used to: (i) evaluate the adequacy of the financial resources of a deposit insurance agency, (ii) estimate the marginal contribution to the whole portfolio risk for a single bank, (iii) test a pricing formula for deposit insurance which represents an alternative to the more traditional one based on option pricing models.

Our empirical analysis showed that the estimated total risk-based premium for the sample banks is in line with the current practice of the FITD and with its available callable capital. However, while a total amount of insurance premium complying with the current engagement of the FITD has been obtained, results showed significant differences in the pricing of the insurance deposit protection for the different sample banks. Such differences reflect both differences in their individual risk profiles and the higher impact that the exposures to larger banks present on the risk profile of the FITD portfolio. These significant differences make it even more important the introduction of a risk-based pricing system for deposit insurance in Italy.

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Table 1 – *The sample banks (data in EUR ml as at December 31st, 2000)*

	Acronym	Name	Total Assets	Customer Deposits	Adjusted Exposure
1	IBC	IntesaBci	331,364	76,162	38,081
2	UCT	UniCredito Italiano	202,649	48,503	24,252
3	SIM	San Paolo IMI	172,101	64,718	32,359
4	BDR	Banca di Roma	132,729	31,081	15,541
5	MPS	Banca Monte dei Paschi di Siena	108,033	31,759	15,880
6	BNL	Banca Nazionale del Lavoro	87,940	23,650	11,825
7	RLB	Rolo Banca 1473	47,044	11,784	5,892
8	BPC	Banca Popolare di Bergamo - Credito Varesino	37,579	10,726	5,363
9	BPM	Banca Popolare di Milano	28,282	8,828	4,414
10	BPV	Banca Popolare di Verona	27,633	7,610	3,805
11	BPE	Banca popolare dell'Emilia Romagna	21,528	8,708	4,354
12	BPN	Banca Popolare di Novara	20,959	5,859	2,929
13	CRF	Cassa di Risparmio di Firenze	15,251	5,332	2,666
14	CRE	Credito Emiliano	15,148	4,074	2,037
15	BTS	Banca Toscana	14,512	5,478	2,739
		Total adjusted exposure			172,136

Source: estimates based on BankScope data, April 2002 (Bureau Van Dijk and Fitch-IBCA).

Table 2 – *Sample Banks Ratings*

Bank	Fitch Long Term	Fitch Support Rating	Fitch Individual Rating	Moody's Long Term	S&P's Long Term
IBC	A+	2	C	A1	A
UCT	AA-	2	B	Aa3	A+
SIM	AA-	2	B/C	Aa3	A+
BDR	BBB+	2	D/E	A2	
MPS	A+	2	C	A1	A
BNL	BBB+	2	C/D	A2	BBB+
RLB	AA-	3	A/B	Aa3	A+
BPC		4		A2	A
BPM	A-	4	C	A2	A-
BPV	A+	4	B	A2	A
BPE	BBB+	4	C		BBB+
BPN	BBB+	4	D		
CRF	A-	4	C	A2	
CRE	A	4	B/C		
BTS				A2	A

Source: BankScope™, April 2002 (Bureau Van Dijk and Fitch-IBCA).

Table 3 – *Descriptive statistics of equity returns (3/97-3/02)*

Bank	Mean	Standard Deviation
IBC	2.10%	39.84%
UCT	8.40%	21.13%
SIM	-5.82%	27.50%
BDR	11.19%	39.00%
MPS	9.58%	33.87%
BNL	-3.24%	32.17%
RLB	5.50%	20.90%
BPC	20.26%	17.34%
BPM	-0.44%	36.91%
BPV	2.05%	27.16%
BPE	20.92%	18.42%
BPN	26.73%	36.18%
CRF	10.83%	21.15%
CRE	12.46%	42.15%
BTS	20.40%	26.26%

Source: calculations based on Datastream™ data.

Table 4 – *Inputs to the CreditMonitorÔ pattern (balance sheet values in ml of Euro)*

Bank	Equity Market Value (EVL)	Equity Return Volatility (ERV)	Liabilities (LBS)	Default Point (DPT)
IBC	21,326	39.83%	297,060	238,622
UCT	23,964	21.13%	178,977	149,291
SIM	17,744	27.50%	153,963	128,484
BDR	3,480	39.00%	120,202	100,458
MPS	8,233	33.87%	95,708	78,964
BNL	5,178	32.17%	81,382	68,270
RLB	8,274	20.90%	41,110	35,137
BPC	2,629	17.34%	33,370	27,922
BPM	1,649	36.91%	24,850	20,360
BPV	2,881	27.16%	23,994	20,984
BPE	2,132	18.42%	18,697	15,703
BPN	2,100	36.18%	18,652	14,621
CRF	1,409	21.15%	13,322	11,375
CRE	1,807	42.15%	13,446	10,838
BTS	1,259	26.26%	12,513	10,964

Source: Authors calculations based on both BankScope™ and Datastream™ data.

Table 5 – *Individual Default probability of the sample banks (03/2002)*

Bank	Asset Value (AVL)	Asset Volatility (AVOL)	EDF
IBC	317,547	4%	0.14%
UCT	205,100	3%	0.02%
SIM	171,798	4%	0.12%
BDR	121,875	3%	0.23%
MPS	104,825	3%	0.04%
BNL	86,276	3%	0.16%
RLB	49,125	6%	0.45%
BPC	36,189	3%	0.04%
BPM	26,250	4%	0.18%
BPV	26,976	3%	0.13%
BPE	20,996	3%	0.06%
BPN	20,989	4%	0.06%
CRF	14,803	3%	0.09%
CRE	15,197	6%	0.39%
BTS	13,823	3%	0.14%

Source: calculations based on BankScope™ and Creditmonitor™ data.

Table 6 – *The "asset return correlations" matrix (March 1997- March 2002)*

	IBC	UCT	SIM	BDR	MPS	BNL	RLB	BPC	BPM	BPV	BPE	BPN	CRF	CRE	BTS	MKT
IBC	**100%**	72%	70%	61%	61%	53%	62%	47%	23%	57%	49%	58%	75%	61%	43%	75%
UCT	72%	**100%**	77%	46%	66%	38%	63%	38%	21%	62%	50%	57%	80%	66%	43%	76%
SIM	70%	77%	**100%**	62%	74%	41%	81%	45%	20%	49%	66%	53%	68%	52%	33%	77%
BDR	61%	46%	62%	**100%**	65%	73%	75%	69%	20%	57%	71%	65%	59%	60%	23%	74%
MPS	61%	66%	74%	65%	**100%**	61%	74%	48%	14%	48%	34%	69%	60%	56%	34%	63%
BNL	53%	38%	41%	73%	61%	**100%**	45%	59%	25%	49%	48%	58%	47%	67%	20%	62%
RLB	62%	63%	81%	75%	74%	45%	**100%**	53%	10%	50%	54%	64%	77%	61%	26%	84%
BPC	47%	38%	45%	69%	48%	59%	53%	**100%**	25%	59%	50%	60%	52%	61%	41%	55%
BPM	23%	21%	20%	20%	14%	25%	10%	25%	**100%**	30%	27%	23%	19%	34%	43%	22%
BPV	57%	62%	49%	57%	48%	49%	50%	59%	30%	**100%**	64%	78%	76%	74%	36%	52%
BPE	49%	50%	66%	71%	34%	48%	54%	50%	27%	64%	**100%**	49%	61%	49%	8%	58%
BPN	58%	57%	53%	65%	69%	58%	64%	60%	23%	78%	49%	**100%**	73%	77%	42%	56%
CRF	75%	80%	68%	59%	60%	47%	77%	52%	19%	76%	61%	73%	**100%**	78%	51%	76%
CRE	61%	66%	52%	60%	56%	67%	61%	61%	34%	74%	49%	77%	78%	**100%**	41%	67%
BTS	43%	43%	33%	23%	34%	20%	26%	41%	43%	36%	8%	42%	51%	41%	**100%**	38%
MKT	75%	76%	77%	74%	63%	62%	84%	55%	22%	52%	58%	56%	76%	67%	38%	**100%**

Source: Estimates based on Datastream™ data.

Table 7 – *The "default correlations" matrix (03/1997-03/2002)*

	IBC	UCT	SIM	BDR	MPS	BNL	RLB	BPC	BPM	BPV	BPE	BPN	CRF	CRE	BTS
IBC	100%	14%	17%	12%	9%	7%	13%	4%	1%	9%	5%	8%	20%	12%	4%
UCT	14%	100%	17%	3%	9%	2%	8%	1%	0%	8%	3%	6%	20%	9%	2%
SIM	17%	17%	100%	12%	17%	3%	27%	3%	1%	6%	12%	6%	14%	8%	2%
BDR	12%	3%	12%	100%	11%	21%	25%	13%	1%	9%	16%	12%	9%	13%	1%
MPS	9%	9%	17%	11%	100%	9%	16%	3%	0%	4%	1%	13%	8%	7%	2%
BNL	7%	2%	3%	21%	9%	100%	6%	8%	1%	6%	5%	8%	5%	16%	1%
RLB	13%	8%	27%	25%	16%	6%	100%	6%	0%	7%	7%	12%	22%	14%	2%
BPC	4%	1%	3%	13%	3%	8%	6%	100%	1%	8%	4%	8%	5%	9%	3%
BPM	1%	0%	1%	1%	0%	1%	0%	1%	100%	2%	1%	1%	1%	3%	4%
BPV	9%	8%	6%	9%	4%	6%	7%	8%	2%	100%	11%	22%	22%	21%	3%
BPE	5%	3%	12%	16%	1%	5%	7%	4%	1%	11%	100%	4%	9%	5%	0%
BPN	8%	6%	6%	12%	13%	8%	12%	8%	1%	22%	4%	100%	17%	20%	3%
CRF	20%	20%	14%	9%	8%	5%	22%	5%	1%	22%	9%	17%	100%	24%	6%
CRE	12%	9%	8%	13%	7%	16%	14%	9%	3%	21%	5%	20%	24%	100%	4%
BTS	4%	2%	2%	1%	2%	1%	2%	3%	4%	3%	0%	3%	6%	4%	100%

Source: estimates based on Datastream™ data.

Table 8 – *Expected loss, unexpected loss and marginal contribution to portfolio risk*

Bank	Exposure (EUR ml)	EDF	EL	UL	ULC_i
IBC	38,081	0.14%	53	1,424	990.495
UCT	24,252	0.02%	5	343	108.412
SIM	32,359	0.12%	39	1,120	704.276
BDR	15,541	0.23%	36	744	366.616
MPS	15,880	0.04%	6	318	102.145
BNL	11,825	0.16%	19	473	150.181
RLB	5,892	0.45%	27	394	178.026
BPC	5,363	0.04%	2	107	16.042
BPM	4,414	0.18%	8	187	16.248
BPV	3,805	0.13%	5	137	28.545
BPE	4,354	0.06%	3	107	20.783
BPN	2,929	0.06%	2	72	14.836
CRF	2,666	0.09%	2	80	26.062
CRE	2,037	0.39%	8	127	34.614
BTS	2,739	0.14%	4	102	8.907
Total	*172,136*		*218*	*5,735*	*2,766*

Source: estimates based on BankScope™ and Creditmonitor™ data.

Table 9 – *Monte Carlo Simulation output synthesis (50.000 scenarios)*

Expected Loss		218
Confidence Level	*Maximum Loss (EUR ml)*	*VaR (EUR ml)*
99.00%	8,607	8,389
99.50%	17,530	17,312
99.90%	52,295	52,077
99.95%	66,866	66,648
99.99%	87,165	86,947

Source: estimates based on BankScope™ and Creditmonitor™ data.

Table 10 - *Capital Multiplier Evaluation*

Expected Loss		218		
Confidence Level	*Maximum Loss (EUR ml)*	*VaR (EUR ml)*	*ULp (EUR ml)*	*Capital Multiplier*
99.00%	8,607	8,389	2,766	3.11
99.50%	17,530	17,312	2,766	6.34
99.90%	52,295	52,077	2,766	18.90
99.95%	66,866	66,648	2,766	24.17
99.99%	87,165	86,947	2,766	31.51

Source: estimates based on BankScope™ and Creditmonitor™ data.

Table 11 – *Deposit Insurance Pricing based on Value at Risk (99.5% confidence level)*

Bank	Adjusted Exposure (EUR ml) (1)	EDF (2)	EL (3)=(2)*(1) (EUR ml)	UL (4) (EUR ml)	ULC_i (5) (EUR ml)	ULC_i* capital multiplier (6)=(5)*6.34	VaR_i (99,5%) (7)=(6)-(3)	Pricing (8)=(3)+5%*(7) (EUR ml)	Pricing (9)=(7)/(1)	Change in risk premium with respect to EL (10)=(9)/(2)-1
IBC	38,081	0.14%	53	1,424	990.5	6,277	6,224	364.50	0.96%	584%
UCT	24,252	0.02%	5	343	108.4	687	682	38.96	0.16%	703%
SIM	32,359	0.12%	39	1,120	704.3	4,463	4,424	260.05	0.80%	570%
BDR	15,541	0.23%	36	744	366.6	2,323	2,288	150.12	0.97%	320%
MPS	15,880	0.04%	6	318	102.1	647	641	38.40	0.24%	505%
BNL	11,825	0.16%	19	473	150.2	952	933	65.56	0.55%	247%
RLB	5,892	0.45%	27	394	178.0	1,128	1,102	81.60	1.38%	208%
BPC	5,363	0.04%	2	107	16.0	102	100	7.12	0.13%	232%
BPM	4,414	0.18%	8	187	16.2	103	95	12.70	0.29%	60%
BPV	3,805	0.13%	5	137	28.5	181	176	13.74	0.36%	178%
BPE	4,354	0.06%	3	107	20.7	132	129	9.07	0.21%	247%
BPN	2,929	0.06%	2	72	14.8	94	92	6.37	0.22%	262%
CRF	2,666	0.09%	2	80	26.1	165	163	10.54	0.40%	339%
CRE	2,037	0.39%	8	127	34.6	219	211	18.51	0.91%	133%
BTS	2,739	0.14%	4	102	8.9	56	53	6.47	0.24%	69%
Total	*172,136*		*218*	*5,735*	*2,766*	*17,530*		*1,083.72*		

Source: estimates based on BankScope™ and Creditmonitor™ data.