ON STATISTICAL ISSUES RAISED BY THE NEW BASEL CAPITAL ACCORD

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Abstract

Aiming at increasing the stability of the financial markets, the New Basel Capital Accord provides a set of rules for determining the minimum capital to cover the risks arising from three areas of the management: credit, operational and trading risks. It offers a great opportunity for statisticians to develop appropriate methods to accurately estimate the relevant risk components. In this paper we outline some of the issues that can be addressed via ad-hoc modifications of existing statistical methods. The focus is primarily on issues in measuring the credit risk components with particular attention to the probability of default.

Keywords: binary response models, credit scoring, internal rating, probability of default, selection models, skew link function.

1. INTRODUCTION

In 1988, the Basel Committee on Banking Supervision released a document, called Accord, with a supervisory regulation for determining the minimum capital requirements of internationally active banks. It exogenously imposed the banks to hold a minimum capital standard of 8% of the activities weighted by risk factors. The risk factors were determined on the basis of the type of credit exposures, and ranged from 0% for loans to OECD governments to 100% for retail exposures, i.e. exposures to an individual person or a small business. The document constituted the first attempt to set international standards for the determination of regulatory capital of banks and succeeded at raising capital levels in most countries (see Sironi, 2004, Ch. 18). However, it contained some limitations. One limitation lied on the fact that it focussed on credit risk only, i.e. the risk that a loan would go bad (the so called default event), so that the lender looses part or all of the amount. Moreover, it did not consider the length of the residual life of a loan. Furthermore, within each type of exposure, it was no sensitive to the quality of
the loans of a bank: banks with a portfolio of loans of good quality were given the
same risk weight as banks with a portfolio of loans of bad quality.

In response to these (and other) criticisms, the Basel Committee worked on
modifications of the document. The second release of 1996 included market risks,
i.e. risk that the prices of investments would fall, and allowed the banks to use
internal models to measure them. However, it took some more years to address the
criticism on the way the credit risk was assessed and to bring regulatory capital
requirements closer to the actual risk of a banks. A first extensive account is
contained in the document published in 1999, followed in 2004 by the so called
New Capital Accord (the latest version of it is dated November 2005\(^{(1)}\)). This
version introduces other forms of risk and is more flexible in the way that allows
the determination of banks’ regulatory capital requirements on the basis of risk
components that may be estimated and forecasted internally from the banks.

The New Capital Accord, which has to be enforced by the end of 2006,
is based on three pillars: Pillar 1 contains the minimum capital requirements;
Pillar 2 sets a supervisory review process, while Pillar 3 regulates the market
discipline and enhances transparency. With Pillar 2 it was therefore recognized
that, to be effective, the regulation on the minimum capital requirements has to be
complemented with a reviewing process involving close contacts between banks
and supervisory authorities.

Besides to credit and market risks, another source of risk is recognized:
operational risk, i.e. the risk of a loss resulting from inadequacy or failures
of internal processes, people or systems, or from external events. Each of the
three components contributes additively to the determination of the regulatory
capital. That is, letting \( T_C, T_O \) and \( T_M \) be the contribution coming from, in order,
credit, operational and market risks, the total value of the regulatory capital is:
\( T = T_C + T_O + T_M \). The Accord prescribes that the regulatory capital \( T_C \) should
be 8\% of the activity weighted with risks factors, the so called risk-weighted
assets. That is:

\[
T_C = 0.08 \sum_i RWA_i \tag{1}
\]

where \( RWA_i \) is the risk-weighted asset for the \( i \)-th exposure. We then have

\(^{(1)}\) Available at http://www.bis.org
\[ RWA_i = RW_i \times CE_i, \] with \( RW_i \) the risk weight and \( CE_i \) is the credit exposure. The way those terms are determined for each exposure is addressed in the next section.

More details on the two Accords can be found in Sironi (2005, Ch. 18-20). In this paper we focus on models for credit risk. The issues related with measurements of the other two components will not be addressed here. An overview may be found in Saindberg and Schuermann (2003), where it is stressed the importance of statistical methods for measuring all risk components, with particular attention to operational risks.

2. STANDARDIZED OR ADVANCED INTERNAL RATING

Within the Framework of the New Capital Accord, banks are allowed to choose on whether to use the Standardized approach or the Internal Rating-Based (IRB) approach to quantify their regulatory capital. The Standardized approach contains minor modifications of the first Accord, and is designed in view of a slow evolution of credit management practices. It allows to determine the risk-weights on the basis of a judgment provided by supervisory agencies (i.e. rating agencies) on the credit worthiness of the borrowers. These judgments range from AAA for an obligor with an extremely strong capacity to meet the financial commitments to B for a vulnerable obligor (in fact some more classes below B are also used). Plus (+) or minus (-) show relative standing within the rating category. Risk-weights are then determined with a rule that distinguishes among the type of the exposures (i.e. corporate, sovereign, bank). As an instance, an exposure to a corporate rated AAA is weighted 20%, while an exposure to a government with the same rate is weighted 0%. For exposures to non-rated corporate, the weight should be 100%, while exposures to an individual person or a small business are assigned a weight of 75%. Therefore, for a loan of 100 Euros to a non-rated corporate, the regulatory capital is 8 Euros.

The IRB approach introduces some novelty in the way the risks weights are determined. They are based on the following components:

1. \( PD \) i.e. the probability of default of a borrower over a one-year exposure;
2. \( EAD \) i.e. the exposure at default;
3. $LGD$ i.e. the loss given default (or 1 minus recovery rate) as a percentage of exposure at default;
4. $M$ i.e. the maturity;
5. $EL$ i.e. the expected loss.

For each exposure, the risk-weighted assets are determined as a function of the above components, i.e. $RWA = K(PD, LGD, M) \times 12.5 \times EAD$. To clarify the relationship with (1), the $EAD$ is the credit exposure, while $K(PD, LGD, M) \times 12.5$ is the risk weight (the index $i$ has been removed for brevity). Note that 12.5 is $0.08^{-1}$. The exact structure of the function $K$ varies with the type of the exposure (corporate, sovereign, bank, retail and equity). In the Appendix we give an instance of such a function. The distinction was introduced to take into account the different structure of correlation in the different exposures. Also, it was a response to the concern that banks with loans to small and medium sized enterprises may be penalized, as they are characterized in general by a probability of default higher than large businesses. Therefore, too large capital charges for exposures to those firms could reduce their capability to access to credit. We note that the maturity allows to determine the value of the exposure at default, and that, for a given maturity $M$, the value of $EL$ is so determined:

$$EL = PD \times LGD \times EAD.$$  

Therefore, the first four components constitute the important parameters to be estimated for the determination of the risk-weighed assets. The IRB allows for two variants: foundation and advanced. In the foundation approach only $PD$ may be determined internally by the bank, subject to supervisory review in compliance of Pillar 2, while the other risk components are externally assigned. In this case, for maturity, it is assumed a single averaged value of three years, while the other components are determined by the supervisory authority. In the advanced approach, all four components are determined internally by the banks, subject to supervisory review.

As an example of the possible gain in switching from the Standardized approach to the IRB approach, we calculate the capital requirement for an exposure of 100 Euros towards a non-rated corporate with an estimated probability of default of 0.005. In line with the values imposed by the supervisory authority, we pose the LGD equal to 0.5% and maturity of 3 years. Using the formula to
calculate the risk-weighted asset (see the Appendix) we find $RWA = 83.828$ and the regulatory capital drops to $6.706 \times 0.08 \times 83.828)$. This corresponds to a reduction of about 16%. The value of 8 would be achieved under the second approach, ceteris paribus, if the $PD$ were about 0.007.

As this example shows, the fact that internal determination of risk weights components is allowed pushes the banks to improve the quality of their portfolio and encourages risk managements to use systems which are well calibrated on the actual risk of their portfolio. The implications of this are twofold: (a) for the banks it requires the implementation of statistical tools to provide accurate estimates of the risk components and (b) for the supervisory authorities it requires the development of sophisticated techniques of validation.

3. **STATISTICAL MODELS FOR THE PROBABILITY OF DEFAULT**

To comply with the supervisory regulation for determining the minimum capital requirement, the probability of default of each borrower should be internally estimated under both the foundation and the advanced approach. We here focus on the statistical models that allow the estimation of the probability of default.

Since 1999, statistical models to estimate the $PD$ are applied successfully to estimate exposures in retail, both from bankers (see what reported in The Internal Rating-Based Approach, 2001, Consultative Document, Ch. 2 (2)) and academics (see e.g. Altman and Sabato, 2005). They are particularly used for modelling the retail exposures. From the methodological point of view, they range from parametric models, such as linear probability models, logistic regression, Probit models, discriminant analysis, to semi- or non-parametric techniques, such as neural networks, genetic algorithms, $k$-nearest-neighborhood, classification trees. The literature on the subject is vast. Here, just a relevant selection of papers will be recalled. An up-to-date list of references is available at [http://www.ma.ic.ac.uk/statistics/research/creditgroup/Financelist.html](http://www.ma.ic.ac.uk/statistics/research/creditgroup/Financelist.html).

We will refer to credit scoring models when those techniques are applied to measure the risks of an exposure to an individual person or a small business and internal rating models when they are applied to corporate exposures. Early use of credit scoring models are Myers and Forgy (1963). See Thomas et al. (2002, Available athttp://www.bis.org

2 Available athttp://www.bis.org
Ch. 1) for an historical review. A survey of most statistical methods is in Hand and Henley (1997). A critical comparison between neural networks, classification trees and logistic regression, in favor to the latter one, is in Arminger et al. (1997). Recently, as documented in Mester (1997), also option pricing theory models have started to be used in the context. For a recent account of credit scoring models see Mays (2004).

Early use of statistical techniques for the estimation of the default probability of firms are in Beaver (1966). Later, Altman (1968) initiated a series of paper based on discriminant analysis. An historical review is in Zavgren (1985). A more recent account is in Altman and Saunders (1998). In this context also models for forecasting the probability of default on the basis of their financial assets are used (see Gieseke, 2004, for a detailed review). These ones can be divided into two approaches (see e.g. Jarrow, 2001): the structural and the reduced form approach. Extensions of the reduced form approach are in Duffie and Garleanu (2001).

In this paper we will introduce a modification of the generalized linear model for a binary response. Therefore, the basic assumptions will be here recalled. Following Agresti, (2002, Ch. 4), generalized linear models for binary response variable can be so described. Let \( Y \) be a binary response variable. The expected value of \( Y \) depends on values \( x = (x_1, \ldots, x_p)^T \) of predictors and it is denoted by \( P(Y = 1 \mid x) = \pi(x) \). For simplicity we assume \( x_1 = 1 \). The variance of \( Y \) is therefore \( \pi(x)[1 - \pi(x)] \). Let

\[
P(Y = 1 \mid x) = \pi(x) = F(\beta^T x)
\]

with \( \beta \) a \( p \times 1 \) vector of unknown parameters. In the logistic model we \( F(\cdot) \) corresponds to standardized logistic distribution function, while in the Probit model it is the standardized normal distribution function. Both models are symmetric in the sense that the way \( \pi(x) \) approaches one is equal to the way it approaches zero, with the Probit model approaching its limit more rapidly than the logistic one. Details on the estimation of the models can be found in Agresti (2002, Ch. 4) or Amemya (1985, Ch. 9). In particular, by posing \( Y' = 1 \) whenever \( Y = 0 \), for the Probit model we have:

\[
P(Y' = 1 \mid x) = P(Y = 0 \mid x) = 1 - \Phi(\beta x) = \Phi(-\beta^T x) = P(Y = 1 \mid -x)
\]

where \( \Phi(\cdot) \) is the distribution function of a standardized normal variate. Therefore, \( P(Y = 1 \mid x) = 1 - P(Y = 1 \mid -x) \). Although symmetry is a
desirable assumption in many applications, when dealing with economic data it might not be satisfied. As an instance, when applied to modelling the probability of default of a firm, it is reasonable to assume that for an unhealthy firm, the negative effect induced by an unit increase in some indicator measuring the level of debts may outweigh the positive effect on a healthy one, induced by a unit decrease in the same indicator.

A generalization of the Probit model that allows asymmetry is proposed by Stanghellini and Stingo (2006) and makes use of the Extended Skew-Normal cumulative distribution (Capitanio et al., 2003) as a link function. That is:

$$ F(\beta^T x; \rho, \tau) = \frac{\Phi_2((\tau, \beta^T x); \rho)}{\Phi(\tau)} $$

in which $$ \Phi_2((\tau, \beta^T x); \rho) $$ denotes the distribution function of a bivariate Gaussian random variable with standardized marginals and correlation $$ \rho $$. An underlying model from which the previous link function may be derived is the following. Let $$ Y^* $$ be an unobserved variable such that:

$$ Y^* = -\beta^T x + \varepsilon. $$

The observable $$ Y $$ variable is so defined:

$$ Y = 1 \text{ se } Y^* \leq 0 $$
$$ Y = 0 \text{ se } Y^* > 0. $$

From (3) and (4), we then have:

$$ P(Y = 1) = P(\varepsilon \leq \beta^T x) = F(\beta^T x) $$

where $$ F(\beta^T x) $$ is the distribution function of the residuals evaluated at $$ (\beta^T x) $$. If we assume the residual $$ \varepsilon $$ to have an Extended Skew-Normal distribution with parameters $$ (0, 1, \alpha, \tau) $$ then model (2) is derived (see Stanghellini and Stingo, 2006, for more details). Note that in this case, the density function of the residuals is

$$ f(\varepsilon) = \frac{\phi(\varepsilon) \Phi(\alpha_0 + \alpha^T \varepsilon)}{\Phi(\tau)} $$

in which $$ \phi(\cdot) $$ is the density function of a univariate standard normal distribution and $$ \Phi(\cdot) $$ is its integral, $$ \alpha_0 = \tau(1 + \alpha^2)^{1/2} $$ with

$$ \alpha = \frac{\rho}{\sqrt{1 - \rho^2}}. $$
More details can be found in Azzalini (2005). In Figure 1 the link function for the univariate case is presented ($\beta > 0$). As the figure shows, the link is non-symmetric and by increasing $\rho$ the function becomes steeper, while by increasing $\tau$ the left tail becomes heavier. This effect becomes more evident with high values of $\rho$.

Several particular cases follow.

(a) If $\tau = 0$ then $\Phi(\tau) = 1/2$ and $\varepsilon$ is distributed as a Skew-Normal with parameter $\alpha$, that is $\varepsilon \sim SN(\alpha)$. This case has been considered in Chen et al. (1999) and Capobianco (2006). Note that in this case some symmetries are allowed, as if $Z \sim SN(\alpha)$ then $-Z \sim SN(-\alpha)$. Posing $Y' = 1$ whenever $Y = 0$, we then have:

$$P(Y' = 1 \mid x) = 1 - F(-\beta^T x; -\rho, 0).$$
The latter term is then equal to $P(Y = 1 \mid -x)$ in the model with $\varepsilon \sim SN(-\alpha)$.

(b) If $\tau = +\infty$ the residuals of model (3) have a Gaussian distribution. To see this notice that, in that case, $\Phi(\tau) = 1$ and $\Phi_2((\tau, \beta^T x); \rho) = \Phi(\beta^T x)$. Therefore, the model is a Probit model.

(c) If $\alpha = 0$ then $\rho = 0$ (and viceversa). From (6), the density function of the residuals is Gaussian and therefore, also in this case, the model is a Probit model.

The unknown parameters of the model are $\tau$, $\alpha$ and $\beta$. For $\tau$ and $\alpha$ known, the model is an instance of generalized linear model for binary response. This suggests the use of a profile log-likelihood (see e.g. Azzalini, 1996, Ch. 4). More details on inference and estimation of the proposed models can be found in Stanghellini and Stingo (2006).

4. RESEARCH QUESTIONS

Although flexible and easy to be implemented, statistical models for the probability of default do contain some limitations. Here we outline some of them. We distinguish between credit scoring and internal rating models, as the two contexts are necessarily different and raise different research questions.

4.1 ISSUES IN CREDIT SCORING MODELS

In the context of credit scoring, lending institutions base their estimates of the default probability solely on credit histories of individuals coming from credit bureaus. Sometimes, these information are integrated with those contained in the application form. However, issues concerning omitted variables and the completeness and representativeness of the bureau files arise. Furthermore, default events tend to be rare, thereby affecting the accuracy of the estimates. Also, problems regarding sample selection bias arise. These issues raise concerns on the accuracy of the estimate of the default probability. Besides having negative effects on the bank’s ability to discriminate between good and bad costumers, with public-policy concerns, from a regulatory perspective, the cumulative effects of these biases may raise doubts on the adequacy of the regulatory capital. In particular those are:
Adjustments for geographic and macro-economic effects. No adjustment is usually made for local economic conditions, such as employment rate, regional growth or other macro-economic factors. Avery et al. (2000 and 2003) empirically show that failure to take into account geographic variables can lead to a substantial bias in the estimate of the probability of default. Possible solutions involve the construction of more sophisticated statistical models, such as generalized multilevel models (see e.g. Hox, 2002, Ch. 6, or Skrondal and Rabe-Hesketh, 2004, Ch. 9).

The omission of the true explanatory variables. The explanatory variables included in the models are usually recorded at the time the loan was granted and may not be representative of the real credit worthiness of the customer. This might be due to the fact that the true determinants (a) are not recorded, or (b) change over the time. These issues might be addressed by including latent variables or by implementing models with time-dependent covariates, such as models for longitudinal data (see e.g. Skrondal and Rabe-Hesketh, 2004, Ch. 3, or the book of Diggle et al., 1994).

Rare events. As the probability of default tends to be quite small, random samples drawn from the population of borrowers are heavily unbalanced. As shown by several authors (see e.g. King and Zeng, 2001), this reduces the capability of a model to capture the determinants of the default event. In credit scoring the issue is usually addressed by retrospective sampling. The usual assumption made in this situation is that samples of the same size are drawn randomly within the population of defaulting and of non-defaulting obligors. The issue of estimating the probability of default with rare events has been addressed for the logistic model by Prentice and Pyke (1971) who showed how to correct the maximum likelihood estimates in retrospective studies. Outside the logistic model, very few attempts are made to address the issue. New techniques, such as boosting or bagging (see Azzalini and Scarpa, 2004, Ch. 5) may usefully be applied in the context. See also Estabrooks et al. (2004).
Sample selection. In building credit scoring models banks use historical data on loan performance. However, historical data are only present if an applicant has already been granted a loan (or has already given access to other credit means, such as credit cards). There is therefore a potential flaw in the model, due to possible unobserved factors that may induce a bias in the estimate of the probability of default in the second loan. In fact, if there are unmeasured factors that influenced the grantor’s first decision, then they are likely to influence the performance of the second loan. This problem is known as sample selection and has been addressed by Greene (1998) by specification of the Heckman (1979) model. The Heckman’s model has also been used by Banasik et al. (2003) and a related approach, which makes use of a Tobit model (see e.g. Amemya, 1985, Ch. 10), is in Rozbach (2003). The model presented here can be viewed as another attempt to address the issue. In fact, as shown by e.g. Arnold and Beaver (2002), the Extended Skew-Normal distribution may arise from hidden truncation or selective reporting.

Models for the Expected Loss. In the regulation for retail exposure, the New Capital accord seems to abolish the distinction on foundation and standardized approach (see the Internal Ratings-Based Approach, Consultative Document, Ch. 3). In this segment, the expected loss is defined as simply $PD \times LGD$ and banks are expected to provide one or the other of the following, subject to meeting supervisory rules: (a) separate estimates of $PD$ and $LGD$ or (b) estimate of the $EL$. To comply with the supervisory regulation in the segment, models for the other two components are then required. Issues concerning the independence assumption of the two components then arise. They can be addressed using a censored Probit model as in Boyes at al. (1982), or a truncated Poisson model as in Dionne at al. (1996). In the context of large corporate credit risk models, a Tobit model is also used by Tarashev (2005), while Jarrow (2001) uses reduced form models that incorporate equity prices to estimate both the probability of default and the recovery rate.

4.2 ISSUES WITH INTERNAL RATING MODELS

When applied to middle or large corporate exposures, statistical methods tend to be complemented by a qualitative judgment of experts to form the so called internal rating. In fact, differently from the retail segment in which the $PD$ of
an exposure is almost automatically determined, in this context the qualitative assessment coming from the expertise of the risk manager is as important as the quantitative one derived by statistical methods. Nevertheless, statistical models play a crucial role also in this context, as remarked in Ch. 2 of the Consultative Document, explaining the Internal Rating-Based Approach.

Many of the criticisms outlined in the above section also apply to internal rating models, with some more due to the different nature of the borrowers. As noted in the Consultative Document, while defaults of individuals or small businesses tend to be driven heavily by factors idiosyncratic to the borrowers, large business or corporate exposures tend to be more interrelated. Therefore, the issue of correlation between exposures in this segment of the portfolio should be carefully addressed. Moreover, classical statistical models, by simply concentrating on a binary event (default or non default) on a fixed time horizon, are unable to provide a measurement of credit risks due to the deterioration of the credit worthiness of the borrower. Issues of adverse selection should also be addressed, as one of the feared effect of the Second Accord is to push firms with poor capacity to meet financial commitments towards lending institutions without internal rating systems. They are methodologically similar to the sample bias problem recalled in the previous section. Finally, the issue of validation is the great challenge of the Framework. In more details those are:

**Joint defaults and Correlation.** The issue of correlation is of crucial importance in credit risk models. As noted in Jarrow and Turnbull (2000), two types of correlation should be recognized: default and event correlation. The first one is the correlation between default events induced by common factors of the economy; the second is the variation of firm’s default probabilities due to default events of other firms. The first type of correlation may be addressed by introducing observed or unobserved factors related to the state of the economy, both in the structural and the reduced approach (for a review, see Schoenbucher, 2003, Ch. 10). Related to this, is the problem of reducing the dimension of a portfolio of loans. This makes use of the so called *diversity score*, that is the minimum number of independent exposures that is necessary to construct a theoretical portfolio with similar characteristics of the actual one. The second type of correlation is usually addressed by the use of copula models (see e.g. Joe, 1997, Ch. 1, or Schoenbucher and Schubert, 2001). Also, contagious models are
used (see e.g. Davis and Lo, 2001). As noted in Jarrow and Turnbull (2000), the crucial difficulty is in distinguishing between the two kind of correlation. Also, the statistical aspects related to the estimation of those models are still to be investigated.

Term structure of individual default probabilities. One of the criticism of the traditional credit scoring models is that, due to the fact that they are static, they are unable to capture the changes over time of the probability that an individual would default (see e.g. Shumway, 2001). By allowing multiple responses, graphical models may be a useful tool (for an application in a different, though related, context see Stanghellini, 2003). To that end, also statistical models for survival data (see e.g. Kalbfleish and Prentice, 2002, or Lando, 2004, Ch. 4-5) might be of great use and several papers document their implementation to forecast the failure of banks (see e.g. Henebry, 1996) or loans (see e.g. Rozbach, 2003). The interesting advances from the methodological point of view (see Van Deventer and Imai, 2003, Ch. 13) concern making use of statistical models in the context of the reduced form credit risk models, such as proportional hazards model (Cox, 1972) and its extensions (see Therneau and Grambsch, 2000), or the doubly stochastic Poisson model. Examples are in Chava and Jarrow (2004) and Duffie et al. (2006).

Validation measures. One of the greatest challenge of the New Basel Accord (see the Basel Committee Newsletter n. 4 issued on January 2005) is ”the need to validate the systems used to generate the parameters that serve as inputs into the IRB approach”. This applies to both banks and supervisors. For validation it should be intended ”the process and activities that contribute to an assessment of whether ratings adequately differentiate risks and estimates the risk components”. Validation therefore involves both assessment of the model power and its calibration. The first refers to the capacity of a model to discriminate between defaulting and non-defaulting obligors, whereas the second describes how well a model’s predicted probabilities agree with the actual outcome. To assess the power of a rating system, methods based on the ROC or CAP curve (see e.g. Stein, 2002) are suggested, whereas calibration may be assessed by dynamic approaches of benchmarking. As outlined in the Working Paper N. 14 of B.I.S. issued on May 2005, the major obstacle to a proper validation system is, however, the scarcity of default events and the impact of default correlation, which lead to interesting research questions.
5. CONCLUSION

As this note suggests, the New Basel Capital Accord opens to new statistical methodologies and raises interesting research questions. Instead of supervisory ruling how to determine the minimum capital requirements, as in the first Accord, within the framework of the New Capital Accord, a forward-looking approach has been adopted, that seeks for the interaction between academics and industry. It therefore encourages the evolution of new techniques and the implementation of modern practices in credit risk managements.

APPENDIX

The function $K$ to determine the risk-weighted asset varies with the type of the exposure. For corporate, sovereign and bank exposures is the following:

\[
K = \begin{cases} 
LGD \times \Phi \left[ \frac{\Phi^{-1}(PD)}{\sqrt{1-\rho}} + \sqrt{\frac{\rho}{1-\rho}} \times \Phi^{-1}(0.999) \right] - PD \times LGD \\
1 + (M - 2.5) b \\
1 - 1.5 b
\end{cases}
\]

\[
\rho = 0.12 \times \lambda + 0.24 \times (1 - \lambda)
\]

\[
\lambda = \frac{1 - \exp(-50PD)}{1 - \exp(PD)}
\]

\[
b = [0.11852 - 0.05478 \log(PD)]^2
\]

where $\Phi(\cdot)$ is the standard normal distribution function. The maturity $M$ allows to determine the value of the exposure at default. Note that this determination derives from the Merton approach.

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**SULLE IMPLICAZIONI STATISTICHE DEL NUOVO ACCORDO DI BASILEA SUL CAPITALE**

*Riassunto*

Il Nuovo Accordo di Basilea sul Capitale formula un insieme di regole per la quantificazione del capitale di vigilanza, ovvero il capitale minimo posto a copertura dei rischi che originano dalle tre aree della attività della banca: il rischio di credito, operativo e di mercato. L’accordo, che ha lo scopo di incrementare la stabilità dei mercati finanziari, offre interessanti spunti di ricerca per gli statistici e costituisce una importante opportunità per la formulazione di metodi appropriati di stima delle componenti del rischio. L’articolo descrive alcuni dei problemi che originano in questo ambito e che possono essere affrontati con modifiche ad-hoc di tecniche statistiche esistenti. L’attenzione è qui rivolta ai problemi di stima delle componenti del rischio di credito, con particolare riferimento alla stima della probabilità di default.