MARKET DISCIPLINE IN THE EUROPEAN INSURANCE INDUSTRY: A PROPOSAL FOR A MODEL[1]

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Abstract

This paper investigates an important issue in financial markets: the market discipline. A theoretical model based on the option price theory is developed to verify if the spreads at launch of subordinated bonds could be used as a tool for the market discipline. It is worth emphasizing that insurance companies are greatly collecting capital in last years by using unsecured subordinated debt, due to their regulatory requirements and to the pressure on available capital from financial analysts. The model presented is also tested on a sample of subordinated issues in Europe by using both classical regressions and a newer method to deal simultaneously with categorical and quantitative variables, without the usual loss of information implicit in the statistical treatment of mixed predictors. The results are quite supportive of the predictions of the model. The findings could have significant implications in the assessment of the future solvency system in Europe, still in search of tools for increase the market discipline.

1. Introduction

The question of whether private investors can or cannot discriminate between different risk profiles of insurance companies is gaining importance in financial markets. This key issue is often indicated as "market monitoring" and it is included in the wider topic known as "market discipline" (see Bliss and Flannery 2001 and Bliss 2001). Market discipline is the process whereby financial markets participants produce value-relevant information able to discipline financial institution's management behaviour (see Lane 1993). On the other hand, market monitoring is the process whereby investors correctly understand changes in a firm's risk profile and incorporate those assessments into the firm's security prices.

In order to introduce or improve the market discipline process, it is relevant to identify which signals are able to differentiate between risk profiles.

What kind of signals financial market participants could use to investigate the risk profile of the insurance companies?

In these last years insurance companies are raising their regulatory capital by issuing unsecured subordinated debt, due to the pressure on available capital and on optimization form financial analysts

From a theoretical point of view subordinated debt prices (or their yields at launch) would give better information than other financial instruments (e.g. stock prices) mainly for two reasons. First, the payoff of structure of subordinated debt aligns the incentives of subordinated debtholders and the regulators. Second, several authors[2] found some evidence that yields include better information than usual accounting variables on the risk profile of the issuer.

Thus subordinated bonds have been deeply studied in the banking industry since "Market Discipline" represents the third pillar of the Basel II Accord.

However, two important weaknesses have been also indicated against their use as relevant indicators for market discipline. First, nowadays the market seems to be

[2] See below for an essential literature review on these authors.

illiquid and inefficient because of the small number of buyers and sellers relative to equity market. Second, subordinated bonds usually incorporate different and several option features, affecting the spreads at launch.

Yet, the market is quickly growing since financial institutions (banks and insurance companies) can use subordinated bonds for raising regulatory capital. Furthermore, option features tend to be more and more similar, greatly improving comparisons.

This paper investigates whether subordinated yield spreads at launch are sensitive to the insurer's risk profile. This issue will be analysed both for supervisory features and for investment management purposes.

Supervisors are interested in finding some tools to enhance the market discipline of financial institutions. Investors are in continuous search of relevant indicators to support their investment strategies, especially when they invest in complex institutions (e.g. insurance companies).

The question here investigated is whether the theoretical behaviour of subordinated yield spreads (the most common type of uninsured debt), well evident in a Merton model framework and deeply studied in the banking industry, could be extended to the insurance industry. Hence, the first question to be investigated is whether yield spreads are a meaningful forecast of the risk profile of insurance companies. Alternatively, the analysis focuses on market monitoring by examining whether private investors price European insurers' issues according to the risk profile of the issuer.

The risk sensitivity of spreads at launch is tested by analysing the statistical relationship between the primary market spreads of a sample of subordinated debts (issued during 1998-2004) and several measures of risk (externally provided, i.e. ratings, and internally calculated, i.e. financial ratios) of European insurance companies.

Such relationship, if significant, could be used by supervisors in their decision-taking processes.

A strong inter-relationship could be useful for policyholders as well. It would drive policyholders' decisions in the presence of riskier companies, for example raising elapsations (life) or reducing renewals (non-life).

Furthermore the significance of this relationship could be helpful in the presence of safety nets or guaranty funds. The contribution paid by the insurance companies could be linked to an indicator that sums up relevant information concerning the risk profile of the insurer.

It also worth emphasizing that the "Market Discipline theorem" could be viewed as an extension of the classical problem of agency costs, well studied since (Jensen and Meckling, 1976 and Jensen 1986). The issue of debt could be associated with time-inconsistent incentives and attendant increased risk-taking. In the presence of risk-sensitive lenders (deposit-holders or policyholders, shareholders bear the expected costs of these distorted incentives, thus motivating firms to accept risk-taking restrictions and otherwise reduce agency costs. In the case of banks or insurance companies, if the demand is risk-sensitive, thus financial institutions receive less favourable conditions on contracts (e.g. higher yields on bank deposits or lower prices on insurance contracts). An increase in the insolvency risk should hence produce a loss of customers (borrowers) and worse conditions on contracts. Those consequences should motivate managers to reduce risk-taking behaviours.

Furthermore if the customer demand is risk-sensitive, another factor should be taken into account. In case of deterioration of the soundness a potential loss of "franchise value" should motivate managers to preserve the investments made in building reputation and customer base.

The reminder of the paper is organized as follows. Section II provides a short literature review on subordinated debt, their risk sensitivity and their potential use to improve market discipline in the banking sector. Section III develops a financial framework for the valuation of subordinated debt. Section IV describes the data sources and summarizes sample characteristics. Section V discusses empirical results. Section VI concludes.

2. Literature Review

Some previous papers, even though referred to the banking industry, are here considered because they explain the payoffs of subordinated debts by using the Merton model (1974) and the contingent valuation framework developed by Black and Cox (1976).

Furthermore subordinated debt yield spreads of banks had been under investigation as a sufficient measure of default risk. Those studies can therefore be used as starting point, at least for their methodology. For banks, empirical evidence on this issue can be divided in two families:

1. authors who found significant relationship between yield spreads and risk profile (among others see Flannery and Sorescu 1999; Evanoff and Wall 2000 and 2003; Sironi 2001 and 2003).
2. researchers who found a weak relationship, too often affected by several external factors such as individual instrument characteristics, poor market, liquidity, investors' risk aversion and fluctuations in the market price of risk (Hancock and Kwast, 2000; Bliss and Flannery, 2000; Birchler and Hancock, 2003).

According to evidence of the first family, some authors advocated mandatory issuance of subordinated debt instruments by banks (for a review of proposals see Kwast et al. 1999); others would use such a spread as an early warning signal and as a trigger for prompt corrective actions. The second family proposed a composite system of signals to stimulate "good" decisions by management.

Nevertheless, no works have been presented in the insurance industry to test the relationship between risk profile and yield spreads. Thus, this would be the first one, encouraged also by the wide debate on market discipline in the insurance market developed around the new European solvency regime to be set up.

The Solvency II project includes a special section for market discipline, but the Board is still seeking significant indicators for investors and stakeholders in general. Researchers (see Harrington 2003) have already distinguished between *investors-driven market discipline* and *customer-driven market discipline*. The former has been primarily concentrated on the relationship between risk and reward, while the latter, deeply studied in the last decade, focuses on the relationship between demand of insurance and insolvency risk of the insurance company.

Investor-driven market discipline studies assumed an insurance company with equity and technical provisions as the only two sources of funds. Thus, the trade-off between risk and reward has been well studied only in the case of equityholders. Recently insurance companies have significantly raised their funds for regulatory purposes by increasing the issues of uninsured subordinated debt. What we can know from the prices (in particular yield spreads at launch) of these issues? Are they effectively sensitive to the insolvency risk? Are these spreads meaningful for the investor-driven market discipline?

On the other hand, the put default value (or the financial value of technical provisions) is the first candidate for customer-driven market discipline, since the riskier the insurance company (the higher the value of the put default option) is, the lower the demand of insurance coverage should be. This result about demand of insurance has been under investigation in numerous papers. Among others Cummins and Sommers (1996) introduced this relationship and provided empirical evidence on this issue by testing their theories on 142 US insurance companies between 1979 and 1990. Sommers (1996) analysed the relationship between prices of insurance contracts and firm's risk by using the same sample as in Cummins and Sommers (1996). He found a significant inverse relationship between prices and insolvency risk and advanced the evidence of customer-driven market discipline referred to prices. Phillips, Cummins and Allen (1998) achieved the same conclusion by testing the hypothesis of inverse relationship on ninety publicly traded insurance companies for the time period 1988-1992. These results are supportive of the hypothesis that prices of insurance contracts are inversely related to default risk and are therefore meaningful for policyholders. Rees, Gravelle e Wambach (1999), following these studies, proposed a wider disclosure of the risk profile of the insurance companies to improve the market discipline in the insurance industry. Nevertheless, these results seem to be more theoretical than empirical since policyholders are supposed to have all relevant information about the solvency of the insurance company. In the real world this is seldom the case and, for this reason, researchers are still searching significant signals for residual stakeholders. Ratings (provided by A.M. Best) have demonstrated to be good indicators for customer-driven market discipline (see Harrington and Epermanis 2000) because the growth rate of premiums increases following an upgrading and decreases following a downgrading. Thus, the demand of insurance seems to be risk-sensitive to the insolvency risk. The evidence of a customer-driven market discipline is also supported by the empirical evidence provided by Zanjani (2002) for life companies. He found a strong association between increases in company risk and increases in voluntary termination of policies. However, Zanjani investigated the effects of guaranty funds and found only weak evidence that policyholders' preferences are affected by the protection provided at the level of the state[3]. Nevertheless, researchers have also demonstrated that A.M. Best ratings are poor explanatory variables for insolvency predictions (among others see Ambrose and Seward 1988 and Ambrose and Carroll 1994). This result is against the hypothesis of customer-driven market discipline strictly related to the insurance ratings. Epermanis and Harrington in 2005 improved their previous work by including group variables. They found a decline in the written premiums in the year of and following rating changes. This decline is more evident in commercial lines than in personal lines due the lower level of guaranty protection, typical of the commercial business.

For all those reasons both investors and policyholders are continuously seeking new indicators to take into account in their decisions. As stated before, yield spreads have proved to be significantly correlated to the risk profile of banks. Do these spreads have the same explanatory power in the insurance industry? Is the relationship between spreads at launch and risk profile of insurance companies significant?

The statistical analysis in this paper will extend the existing literature in two directions. First, the empirical analysis will be aimed at testing whether primary yield spreads rationally differentiate among risks taken by insurance companies. Second, the empirical analysis is conducted by using a newer statistical method (namely CATREG) whose aim is to deal with categorical and quantitative variables at the same time, without affecting the explanatory power of these variables.

3. The Valuation of Subordinated Debt

Subordinated debt can be analysed as a special form of corporate liability, with final payoffs dependent upon the asset value. The model here developed is derived by Black and Cox (1976), based on the pricing of multiple classes of debt. However, the model introduces a capital structure with multiple debt claims by adding subordinated debt.

The capital structure of the insurance company consists of equity (E) and two types of liabilities: a) technical liabilities (TL); b) subordinated debt (S).

Debt claims are assumed to have the same maturity and to be differentiated only by their priorities. Thus, in the case of insolvency, technical liabilities are the first to be repaid (senior) whilst subordinated debt (junior) will be liquidated just before the equity. The payoffs of different claims depend on the asset value at the maturity of this claim.

Therefore, recovering the Merton model, three situations can be distinguished.

[3] Zanjani (2002) provided two explanation to this evidence: 1) the strength of the guarantee at the level of the state may be perceived as weak relative to the federal one offered by FDIC for banks; 2) guaranty funds for insurance companies were enacted within the past several decades, while FDIC appeared in the 1930's. It may take some time for include this protection in the decision-taking processes of policyholders.

1) if the asset value at maturity is greater than the sum of *TL* and *S* ($A > TL + S$), policyholders and debtholders get repaid in full and equityholders receive the residual (positive) amount;

2) if asset value at maturity is greater than technical liabilities *TL* but lower than the sum of technical liabilities and subordinated debt ($TL < A < S + TL$), then policyholders get repaid in full and subordinated debtholders receive the residual amount $(A – TL)$ suffering a loss $(S – (A – TL))$;

3) if asset value at maturity is lower than *TL* ($A < TL$), policyholders receive an amount smaller than the total outstanding technical liabilities with a substantial loss $(A – TL)$.

Clearly situations (2) and (3) indicate the insolvency status of the insurance company. Nonetheless situation (2) do not require an intervention provided by the guaranty fund since policyholders are repaid in full and subordinated debtholders suffer some losses, whilst situation (3) requires the intervention of the guaranty fund.

Assuming the limited liability, the value of equityholders' claims (E), subordinated debt claims (V_S) and policyholders claims (V_{TL}) can be therefore written as:

$$V_{TL} = min\ (\ A;\ TL\ ) = TL \cdot exp(-r \cdot \tau) - max[TL - A;\ 0] \qquad (1)$$

$$V_S = max\ [\ min\ (\ A - TL;\ S)\ ;\ 0\ ] \qquad (2)$$

$$E = max\ (\ A - (TL + S\ )\ ;\ 0\ ) \qquad (3)$$

Table 1 sums up the payoffs to different claimants for various asset values (*A*) at maturity.

Table 1: Contingent Payoffs for Different Asset Values at Maturity Date

	$A > TL + S$	**$TL < A < TL+S$**	**$A < TL$**
Technical Liabilities (*TL*)	*TL*	*TL*	*A*
Subordinated Debt (*S*)	*S*	*A – TL*	*0*
Equity (*E*)	*A – (TL + S)*	*0*	*0*

Equation (1) decomposes the value of the insurance liabilities in the present value of the nominal discounted insurance liabilities minus the well known put default (or insolvency) option.

Table 1 and equation (2) show that the payoff of the subordinated debt *S* is similar to the payoff of a bull spread and therefore it can be easily decomposed in a combination of two call options:

a) a call option (C_1) bought from policyholders on the asset value and exercise price equal to the value of technical liabilities (*TL*);
b) a call option (C_2) sold to equityholders on the value of assets with the exercise price equal to the financial value of total liabilities (*TL+S*).

$$V_S = C_1(A, TL, \sigma, \tau, r, r_L) - C_2(A, (TL+S), \sigma_S, \tau, r, r_L) \quad (4)$$

where *TL* is the nominal value of the technical provisions, *S* is the face value of the subordinated debt, *A* is the market value of the assets, *r* is the risk-free rate, r_L is liability growth rate, ($\tau = T - t$) is the time to expiration, σ is the insurer's risk parameter, σ_S is the insurer's risk parameter with subordinated debt[4].

The decomposition in two call options is very useful to understand some important relationships between variables. It is worth emphasizing that such relationships are verified if and only if the basic assumptions of the Black&Scholes Model (hereinafter BSM) hold. Particularly the BSM assumes that a) the price of the underlying assets moves in a continuous fashion; b) interest rates are known and constant; c) the variance of the underlying assets is constant and not time-varying; d) no market imperfections (no transaction costs, no taxes, short sales are allowed, therefore it is always possible to build up a replicating portfolio for the option under valuation).

If the BSM assumptions are verified it is easy to derive a *risk-neutral* valuation of the subordinated debt. If such assumptions are not verified, relationships hold only asymptotically.

Using this decomposition and assuming that the basic assumptions of the BSM hold, the *risk-neutral* value of the subordinated debt (V_S) can be written as follows:

$$V_S = \left[A \cdot N(d_1) - TL \cdot exp(-(r - r_L) \cdot \tau) \cdot N(d_2)\right] - \left[A \cdot N(d_1^S) - (TL+S) \cdot exp(-(r - r_L) \cdot \tau) \cdot N(d_2^S)\right] \quad (5)$$

where

$$d_1 = \frac{\left[\ln\left(\frac{A}{TL}\right) + \left(r - r_L + \frac{\sigma^2}{2}\right) \cdot \tau\right]}{\sigma \cdot \sqrt{\tau}} \qquad d_2 = d_1 - \sigma \cdot \sqrt{\tau}$$

$$d_1^S = \frac{\left[\ln\left(\frac{A}{(TL+S)}\right) + \left(r - r_L + \frac{\sigma_S^2}{2}\right) \cdot \tau\right]}{\sigma_S \cdot \sqrt{\tau}} \qquad d_2^S = d_1^S - \sigma_S \cdot \sqrt{\tau}$$

[4] See below for a detailed description of the risk parameters.

and σ^2 is the insurer's risk parameter (Euro-value denominated) without subordinate debt ($\sigma^2 = \sigma_A^2 + \sigma_{TL}^2 - 2\sigma_A\sigma_{TL}\rho$)[5], σ_S^2 is the insurer's risk parameter with unsecured subordinated debt ($\sigma_S^2 = \sigma_A^2 + \sigma_{TL}^2 + \sigma_S^2 - 2\sigma_A\sigma_{TL}\rho_{A,TL} - 2\sigma_A\sigma_S\rho_{A,S} + 2\sigma_S\sigma_{TL}\rho_{S,TL}$), τ is the time to maturity of the two call options, *N(.)* is the univariate cumulative normal distribution and *r* is the risk-free rate (held constant) and r_L is the liability and subordinated debt growth rate[6].

After some algebra, equation (5) can be rewritten in terms of spread between the yield to maturity on S (r^*) and the risk free rate *(r)*. Dividing equation (5) by the nominal value of the subordinate debt discounted using the risk-free rate $(S \cdot \exp(-r\tau))$ and assuming that V_S is equal to the face value of S discounted using a proper rate $\left(V_S = S \cdot \exp(-r^*\tau)\right)$, the spread at launch can be written as follows.

$$r^* - r = -\frac{\ln\left\{\frac{A}{S}\cdot\exp((r-r_L))\cdot\tau\cdot N(d_1) - \frac{TL}{S}\cdot N(d_2) - \left[\frac{A}{S}\cdot\exp((r-r_L)\cdot\tau)\cdot N(d_1^S) - \frac{(TL+S)}{S}\cdot N(d_2^S)\right]\right\}}{\tau} \qquad (6)$$

If the subordinated debt is valuated at launch, the time to maturity (τ) can be replaced by *T* and the spread ($r^* - r$) is the primary spread.

Equation (6) is useful to highlight important relationships between spreads at launch (if $\tau = T$) and assets, technical provisions, nominal amount of subordinated debt issued and volatility[7] of the firm, with and without the issue of subordinated debt.

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[5] The risk parameter (σ) used is derived by Sommer (1996) and Cummins and Sommer (1996). In this notation σ_A, σ_{TL} and σ_S are the instantaneous standard deviations of assets, technical liabilities and subordinated debt, and $\rho_{A,TL}$, $\rho_{A,S}$ and $\rho_{S,TL}$ are the instantaneous correlation coefficients between growth rates of assets and technical liabilities, between assets and subordinated debt and between subordinated debt and technical liabilities.

[6] Notice that in this model the growth rate is the same for the two different types of liabilities. A more structured model could involve different growth rates. This is a field for future research.

[7] Notice that the in the standard Merton model the volatility (σ) in equation (5) is referred to assets and not to the overall firm, as in this model, or to the equity, as in the standard Black & Scholes formula. In the real world the volatility of the equity is observable and the volatility of assets can be obtained by using hedging arguments. Defining Δ as the *hedge ratio*, the volatility of assets is $\sigma_A = \sigma_E \cdot \frac{E}{A \cdot \Delta}$. Recovering the Δ of a call option from the option theory, the volatility of the assets is expressed as $\sigma_A = \sigma_E \cdot \frac{E}{A \cdot N(d_1)}$.

Spreads are inversely related to the asset value. The higher the assets the lower the spreads to be paid to debtholders at launch.

It is straightforward to verify that spreads are directly related to the amount of the issued subordinated debt and to the amount of technical liabilities. This evidence is consistent with the financial theory since the higher the amount of the outstanding subordinated debt is, the riskier this type of uninsured debt should be. Moreover the riskier the subordinated debt, the higher the yield to maturity (and therefore larger spreads at launch) requested by financial market participants. Nonetheless this theoretical rule could be not so strong because of the liquidity effect. A bigger issue of subordinated debt can reduce the liquidity premium requested by investors.

Finally there is a direct and strong relationship between the insurer's risk parameters (σ, σ_S) and the spreads to be paid. Highly volatile investments require significant increase in the spreads to be paid to debtholders[8]. Similarly, an insurance company deeply concentrated on volatile business lines (e.g. commercial liability) is perceived riskier than a property insurance company. Yet, the issue of particularly volatile subordinated bonds, for example due to the presence of callable options in an increasing interest rates environment, can greatly affect the spreads at launch.

4. Data, Research Methodology and Models

4.1 Description of Data

According to the Merton theory, spreads at issuance are a function of:

1) characteristics of the issues (listed below);

2) risk profile of the insurance company (issuer);

Characteristics of the issues, included in the dataset are:

- amounts which affect secondary market liquidity (measured as the log of the euro value);
- years to maturity;
- the presence of callable options;

The risk profile of the issuers has been investigated by including the following explanatory ratios:

- capital ratio in the year of issuance (Surplus/ Net Written Premiums);
- technical profitability measured as: Balance on General Technical Account divided by Net Written Premiums;
- ROE, identified as a proxy measure of profitability.
- Ratings of the issuers provided by S&P and Moody's .

[8] As noted by Phillips, Cummins and Allen (1998) – pg. 7 – this is an effect of the limited liability. With the unlimited liability assumption, policyholders always receive the full value of their claims. Thus, the investment strategy does not affect the value of the technical provisions. They noted that this result is a type of insurance Modigliani-Miller theorem.

These ratios are used since insurance economists, supervisors, and financial analysts believe them important in predicting the likelihood of insolvency of an insurance company, even though they are not fully risk sensitive (see Dickinson et al. 2001 and more recently Natale 2003).

The log of the total firm assets is also added to test if the size effect can improve the explanatory power. The rationale for this effect is basically due to two factors:

1. more information is usually available for bigger insurance companies;
2. the technical profitability is more stable due to the law of large numbers.

S&P and Moody's issue ratings and A.M. Best's Ratings, even though well diffused in the insurance industry, has not been used since they are available only for some issues.

Several datasets of spreads, ratings and accounting measures of insurance risk have been used to set up a unique sample of subordinated notes issued during the 1998/Q1 – 2004/Q3 period and related characteristics of the issuers. In particular, four main sources provided essential data to explain the variability of spreads:

1. Bondware provides data for subordinated debt issues (spreads at issuance, ratings, amounts, issuer, issuer specific industry, debt type, currency, dollar value, offer date, maturity date, years to maturity, yield to maturity, detailed report text). Moody's Issuer Ratings and S&P Issuer Ratings, which omit the influence of government (if any) and other external support (e.g. guaranty fund for debt holders) are used as insurance risk proxies jointly with accounting variables.

2. A.M. Best's Insight Global and ISIS are the natural sources for accounting variables. A. M. Best's Insight Global is a detailed database of all insurance companies worldwide (10,333 insurance companies). It provides balance sheet data for the insurers with subordinated debt. Unfortunately it is deeply concentrated on the US insurance industry (5,365 insurance companies) and thus, the lack of data is filled by using ISIS. The latter is another database of all insurance companies worldwide (over 5,400 insurance companies).

3. DataStream is the source for national and European yields of risk-free bonds (i.e. government debt). Risk-free rates are the yields to maturity of government bonds with a similar maturity denominated in the same currency. For maturities longer than 30 years, including perpetual issues, the 30-year bond is considered[9].

A total of 68 issues met the above criteria. Nevertheless seven issues have been eliminated since they were issued with a convertible option. This call option on the equity of the issuer greatly affects the spreads at launch, therefore the comparisons become no longer suitable. Other six issues have been eliminated because the issuers presented anomalous values for the financial ratios (outliers) or "not available" data in the required fields.

Table 2 summarizes the main statistics of the dataset. The distribution for each class of rating is reported in Fig 1. Notice that each issue is rated by S&P rating,

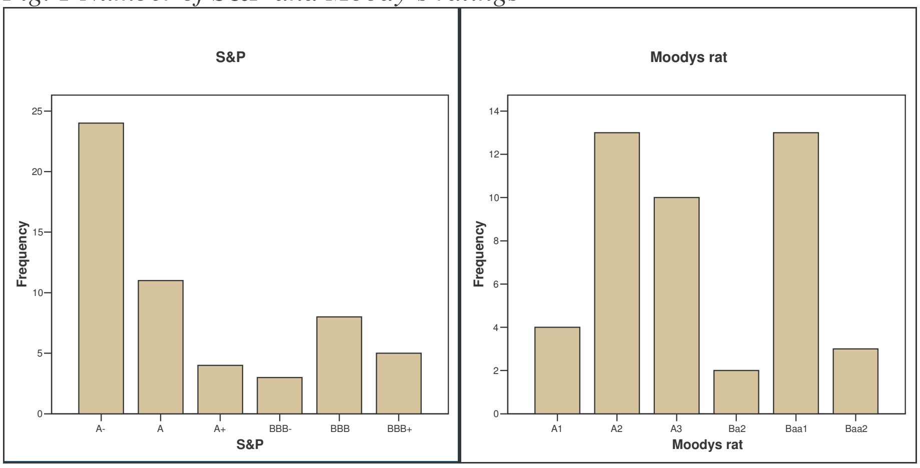
[9] In most European countries the maturity of 30 years is the longest available and therefore the 30-year bond is the natural term of comparison even for longer maturities.

while it is not the same for Moody's. Thus, a lack of information in the use of Moody's rating should affect regression results.

Table 2: Summary Statistics

Variables	*N*	*Mean*	*Std. Dev*	*Min*	*25%*	*Median*	*75%*	*Max*
SPREAD	55	0,015	0,006	0,004	0,010	0,014	0,018	0,032
Log_Subordinated_Issue (Amount)	55	13,042	0,808	10,127	12,559	13,122	13,528	14,914
Maturity (Matu)	55	24,691	5,398	10,000	20,000	22,000	30,000	35,000
Log_Assets (Size)	55	18,303	1,474	15,137	16,919	18,395	19,386	20,664
Capital_ratio	55	0,815	1,002	0,195	0,280	0,605	0,910	5,561
Technical_Result	55	0,015	0,273	-0,751	-0,088	-0,018	0,054	1,154
ROE	55	-0,003	0,310	-1,315	-0,037	0,062	0,126	0,871

Fig. 1 Number of S&P and Moody's ratings



4.2 Research Methodology

The empirical analysis involves regressions of the form:

$$Spr_i=f(Amount_i;\ Matu_i;\ Call_i;\ Issuer\_Rat_i;\ Issuer\_R_i;\ Size_i)+\varepsilon_i \quad (7)$$

Table 3 summarizes the definitions of the variables in regressions and the predicted signs.

Table 3: Definition and Predicted Signs of Variables in Equation (7)

Variable	Definition	Predicted Sign
Spread (numerical)	Spreads at issuance are defined as the difference between the yield to maturity at launch and the yield to maturity of a correspondent government bond with a similar maturity denominated in the same currency.	
Amount (numerical)	The log of the euro amount of the issue *I*	-/+
Matu (numerical)	The time to maturity (in years) of the issue*;*	+
Call (nominal)	A dummy variable for the presence of a callable option	+
Issuer_Rat (ordinal)	Moody's Issuer Ratings and S&P Issuer Ratings for each issue	-
Issuer_R (numerical)	Different quantitative measures of the insolvency risk of the issuer (see below for further details)	+/-
Size (numerical)	The natural logarithm of the total firm assets	-

The amount of the issue (*Amount*) can greatly affects the spread at launch in two different ways. The first is related to the liquidity premium. The market of subordinated bonds is characterized by an high level of illiquidity and therefore larger amount of issues could imply lower spread because of the higher level of liquidity of these bonds (see Sironi 2003). On the other side larger amount of issue also means an higher leveraged insurance company and this can greatly improve the risk profile of this debt, requiring thus an higher spread at launch. However this effect is controlled in the regression with a specific risk variable.

The maturity (*Matu*) should be positive related to the spread at launch. This result comes from the theoretical model, but also from the common wisdom.

Risk variable for the issuer (*Issuer_R*) used in equation (7) has several specifications.

The first one is based on the capital ratio (*cap_ratio*) in the year of issuance. This is consistent with both the regulatory and the financial view. The lower the capital available, the riskier the insurance company, all else being equal.

In the second equation the technical profitability (*Tech_Res*) ratio is inserted as a proxy for the technical risk profile. This ratio has demonstrated to be significant in the insolvency prediction[10] and it is also included because it is easily observable.

[10] For Europe, the Müller Group Report (1997) analysed the causes of insolvencies and identified technical losses (imprudent underwriting policies) as one of the main. For US a larger number of insolvencies allowed for several more structured studies. For example

Thus it is likely this information is taken into account by the financial market participants in assessing the spreads at launch.

The third model inserts the profitability ratio (*ROE*) in equation (7) since it is common wisdom to perceive as riskier an insurance company with large losses and safer a firm with high return on equity.

Finally the log of assets (*Size*) has been inserted in the regression to test if a dimensional factor affects the spreads at launch. Larger insurance companies could be perceived safer due to the greater level of diversification both on the asset side (e.g. more diversified equity portfolio) and on the liability side (e.g. a higher degree of geographical and business line diversification on the business book).

Regressions for testing significant relationships are performed by using two versions of LS methods: the standard OLS method and the categorical regression (also known as CATREG).

The first method is the standard OLS with some adjustments to deal with both ordinal variables (ratings) and dummies variables (presence of a callable option). Nonetheless categorical variables (ratings and the presence of callable) in the predictors deserve particular care in dealing with. In standard regression methods categorical variables should be recoded as indicator variables. In this approach the model contains a separate intercept and slopes for each combination of the levels of the categorical variables. This results in a large number of parameters to be tested and to interpret. Obviously the small sample size represents a natural drawback for the use of this method[11].

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recent studies (see Ryan et al. 2001) identified underwriting risk as responsible for 42% of 683 insolvencies analysed from 1969 to 1998. Yet, Kim et al. (1995) used dynamic statistical models (i.e. event history analysis) to analyse and predict insolvencies. The authors concluded that underwriting result is one of the most important driver in predicting insolvencies. For another review of US solvency experiences see the Reports by A.M.Best.

[11] When using indicator variables to represent a set of categories, the number of these variables is the number of categories less one. For example, in the case of S&P ratings (a categorical variable with six categories) we create five indicator variables to be tested. In both cases (Moody's and S&P ratings) we chose the lowest categories as the base categories. The other five indicator variables are treated as dummy variables. For instance, in prior studies on insurance ratings, such categorical variables have been treated as dummy variables. Ambrose and Seward (1988) used multivariate stepwise discriminant analysis to analyze if Best's ratings are good predictors for the solvency/insolvency status. In their study Best's ratings have been considered as vector of independent observations. This technique significantly amplifies the number of variables to be tested with a corresponding loss in degrees of freedom. For example in their work a vector of 001000 indicated an insurance company rated B+ (one of the six possible ratings). Notice that in a previous version of this paper we tested the method introduced by Ambrose and Seward, but results were inconsistent due to the small size sample. Although in the field of logit regression, Ambrose and Carroll (1994) ran multivariate discriminant analysis to examine how effectively Best's ratings identify financially distressed life insurers. The dummy variable (Best's recommendation status) took the value of one if the insurer was recommended in a particular year, zero if not. This method reduce the information included in the analysis

CATREG is a regression family variant which can be used when there is a combination of nominal, ordinal, and interval-level (or numerical) independent variables[12]. This procedure introduces a transformation that quantifies categorical variables (of ordinal-nominal-scale) by assigning numerical scores to their levels (including applying non-linear transformations - e.g. splines with two or more degrees and two or more knots) in order to produce an optimal linear regression equation for the transformed variables. Unlike the original labels of the nominal or ordinal variables in the analysis, these scale values have metric properties.

The optimality criterion is the maximisation of the squared correlation (r-squared, goodness of fit statistic) between the transformed dependent variable and the weighted combination of the transformed independent variables.

CATREG was introduced by Meulman (see Meulman 2000, 2004) and has been already applied in other fields of research. For example Angelis et al. (2001) ran categorical regression on a data set provided by ISBSG[13] to analyze relationships between costs of developing a software and some categorical variables. Androulidakis S. (2001) employed CATREG in the agricultural science on qualitative and quantitative data collected using questionnaires administered to 337 women in Greece. Haber et al. (2001) applied CATREG to the evaluation of acute inhalation toxicity data. To our knowledge CATREG has never been applied to financial studies.

Another advantage of CATREG should be emphasized. The data sample is internally biased because it includes issuers subject to different national accounting standards[14]. In the case of relevant differences and without any transformation or control variable such analysis could be biased. To overcame the paucity of data and the internal bias, the transformation introduced by CATREG can significantly reduce the potential error on the results.

Operationally, the CATREG algorithm minimizes a least squares function using alternating least squares (ALS) to find optimal quantifications for categorical variables, while simultaneously optimizing the squared multiple regression coefficient.

CATREG is deeply suggested if models and datasets are affected by the following problems:

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since it does not consider the changes in the ratings, but only the 'recommended' status. Obviously the interpretation of the regression results is difficult when the number of categorical predictors is large.

[12] Noticeably the combination of different types of variables is the most difficult situation to deal with. For example the detection of multicollinearity among data is greatly difficult due to the presence of many binary variables. CATREG allows to overcame most of the previous difficulties. This method uses optimal scaling to analyze categorical data that are difficult for standard statistical procedures to analyze. In this way categorical data and quantitative data (even though transformed) can be included in the same regression.

[13] ISBSG stands for International Software Benchmarking Standards Groups.

[14] For example Italian accounting standards require not-discounted technical reserves, while in other countries (e.g. Denmark, Sweden) the discount of the provisions is the rule.

a) too few observations;
b) too many variables;
c) too many values per variable.

In our study the dataset is composed by 55[15] observations and 11 variables (four numerical predictors, one dummy, and two categorical predictors, alternatively tested, with five indicator variables for each one). The situation described met the above conditions and thus categorical regression seems to be the optimal solution.

It is worth emphasizing that CATREG has advantages and drawbacks as well. As advantage, linear and non-linear transformations of variables reduce the dependencies among the predictors. However, as drawback, it is also obvious that there are certain risks which have their sources either in the quantification of the categorical variables or in the regression procedure itself. CATREG can be seriously affected by the presence of outliers and the transformations of the obtained data as solutions under an optimality criterion are not necessarily optimal under other criteria (for further details on the advantages and risks of CATREG see Angelis et al. 2001).

4.3 Models

Several models have been tested in order to identify significant variables. Models differ each other for the rating of the issuer and for the risk variable of the issuer. For the former, both ratings from S&P and Moody's have been alternatively used, while for the latter the three financial ratios discussed above have been included. The remaining variables (namely *Amount*, *Size*, *Call*, *Matu)* have been included in all models.

Thus, twelve models (models named from #1 to #12) have been built-in in the regressions.

Models tested are summarized below in table 4.

[15] Notice that we have Moody's Ratings only for 45 issues, while S&P Ratings are complete.

Table 4: Description of the different variables included in the tested models

Method	*Rating*	*Financial ratios*		
		Capital ratio (Cap_ratio)	*Technical profitability ratio (Tech_Res)*	*Profitability ratio (ROE)*
OLS with indicator variables	*S&P Rating*	Model #1		
			Model #2	
				Model #3
	Moody's Rating	Model #4		
			Model #5	
				Model #6
CATREG	*S&P Rating*	Model #7		
			Model #8	
				Model #9
	Moody's Rating	Model #10		
			Model #11	
				Model #12

As stated before OLS method with indicator variables has been performed in the relative form. We are interested in explaining if a change in the rating affects the spread at launch, all else being equal, or otherwise if ratings are good risk proxies for the *investor-driven market discipline.* In order to correctly run such regression we chose the lowest rating in the sample as the base category (not included in the output) and then we created five variables to try to explain the effect of changing in the ratings on the spread. For example an issuer rated BBB- by S&P is inserted as 00000, while an issuer rated A+ is inserted as 10000. Notice that each of these numbers represents a predictor to be tested with obvious implications on the degrees of freedom. The presence of a callable option has been treated as a dummy variable.

In order to use CATREG method two steps are required. The first step is the discretization of variables. This step allows to deal with all types of variables at same time. The quantitative variables have been discretized according to default choice. Only *Matu* has been grouped in three categories due to its original data distribution[16].

The second step is the optimal scaling of the discretized variables. We scaled the quantitative variables by using an ordinal spline function of second degree and two knots. We left out from this scaling only *Matu*[17]. The particular distribution of this variable suggests a numeric optimal scaling level. Categorical variables, namely *Issuer_Rat* and *Call*, has been considered as follows. The former received

[16] Obviously the qualitative predictors *Call* and *Issue_Rat* have not been discretized.
[17] This predictor is considerably grouped around 20 years and 30 years

an ordinal optimal scaling level while the latter has been scaled by using the nominal transformation.

5.Empirical Results

As shown in table 5 the goodness of fit is greatly different according to the model tested.

Table 5: Estimation Results SPREAD=dependent variable with OLS methods

Variable	**Model 1**	**Model 2**	**Model 3**	Variable	**Model 4**	**Model 5**	**Model 6**
Intercept	0.0301 (2.0764)	0.0284 (2.0996)	0.025 (1.911)	*Intercept*	0.030 (1.491)	0.032 (1.638)	0.029 (1.438)
Amount	0.0024 (1.297)	0.002 (1.419)	0.002 (1.525)	*Amount*	0.001 (0.793)	0.001 (0.735)	-0.001 (-0.912)
Matu	-0.0008 (-0.619)	-0.0008 (-0.653)	-0.0008 (-0.643)	*Matu*	0.0001 (0.658)	-0.00069 (-0.467)	0.0001 (0.662)
Call	-0.002 (-0.0787)	-0.003 (-0.929)	-0.002 (-0.774)	*Call*	-0.0001 (-0.111)	-0.001 (-0.313)	-0.001 (-0.139)
Size	-0.001 (-1.301)	-0.001 (-1.263)	-0.001 (-1.239)	*Size*	-0.002 (-1.592)	-0.002 (-1.803)	-0.002 (-1.770)
Cap_ratio	0.002 (0.694)			*Cap_ratio*	-0.00005 (-0.014)		
Tech_Res		-0.007 (-0.907)		*Tech_Res*		-0.018 (-1.935)	
ROE			0.004 (0.502)	*ROE*			0.006 (0.617)
AA-	-0.016 (-3.757)	-0.0152 (-3.567)	-0.016 (-3.718)	*Aa3*	0.0001 (0.057)	0.002 (0.375)	-0.001 (-0.181)
A+	-0.018 (-4.971)	-0.017 (-4.695)	-0.018 (-4.945)	*A1*	-0.001 (-0.241)	-0.001 (-0.161)	-0.001 (-0.234)
A	-0.015 (-4.489)	-0.014 (-3.951)	-0.015 (-4.348)	*A2*	0.003 (0.867)	0.004 (1.093)	0.003 (0.904)
A-	-0.014 (-2.942)	-0.012 (-2.856)	-0.013 (-2.907)	*A3*	0.002 (0.634)	0.003 (1.188)	-0.002 (-0.769)
BBB+	-0.016 (-3.6367)	-0.012 (-3.465)	-0.012 (-3.496)	*Baa1*	0.005 (1.148)	0.005 (1.168)	0.005 (1.287)
R^2	0.461	0.465	0.458	R^2	0.211	0.272	0.217
R^2*-Adjusted*	0.338	0.343	0.335	R^{2-}*Adjusted*	0.031	0.107	0.039
F	3.761	3.824	3.719	*F*	1.173	1.647	1.221
p- value	0.001	0.001	0.001	*p- value*	0.334	0.125	0.304

Note: t-statistics are in parenthesis. Variables are defined in table 2

With reference to models #1,#2,#3, we can observe a quite low Adjusted-R^2, as it varies from 0,343 to 0,335. Model #1, R^2 indicates that 46.1% of the variability of the Spread is explained by the 10 variables under study, but only variables linked to the rating are significant and have the expected signs.

The second model shows both a Adjusted-R^2 similar to the previous one and the same situation among the coefficients. Coefficients are different from zero but only the rating variables are significant. Model #3 presents an Adjusted-R^2 slightly lower than the other two models, nonetheless also in this case only ratings are significant. Instead, if we compare the three models altogether, we notice that model #2 better explains the phenomenon under study.

The results for models from #4 to #6 are extremely different. All the three models show a very low Adjusted-R^2 and such a result allows us to accept the hypothesis of coefficients not different from zero, that is they are inadequate in explaining the model (F statistics ranges from 1.173 to 1.647).

Appendix A shows empirical results with CATREG method. For the models #7, #8, #9 the CATREG procedure yields an Adjusted-R^2 from 0.783 to 0.773 indicating that almost 78% of the variance in the transformed spread is explained by the regression on the optimally transformed predictors. Transforming the predictors improves the fit over the OLS approach. The models #7, #8, #9 and #12 have a p-value for the F-statistics less than 0.001 indicating that these models are performing quite well, while models 10 and 11 have relative large p-values of 0.035 and 0.0259 respectively. However some care should be taken in interpreting the results of CATREG. CATREG also reports standardized regression coefficients (Standardized Beta) and F value for each variable. However, the regression coefficients cannot fully describe the impact of the predictors since the original variables have been transformed. For example, a change in the quantification of the predictor could not correspond to a change in the original variable. This implies that these tests must be interpreted conservatively. Appendix A displays the standardized coefficients and the importance of each variable for the six models. Alternative statistics, used to fully explore predictor effects, are the relative importance of each variable. To interpret the contributions of the predictors to the regression, an inspection of the correlations, partial correlations[18] and Pratt's measure of relative importance (Pratt, 1987) is required.

The intercorrelations of the predictors for both the untransformed and transformed predictors is measured by the tolerance coefficients indicated in Appendix A. Notice that tolerance reflects how much the independent variables are linearly related to one another. This measure is the proportion of a variable's variance not accounted for by other independent variables in the equation. If the other predictors can explain a large amount of a predictor's variance, that predictor is not needed in the model. A tolerance value near 1 indicates that the variable cannot be predicted very well from the other predictors. In contrast, a variable with a very low tolerance contributes little information to the model, and can cause computational problems.

Pratt's measure of relative importance aids in interpreting predictor contributions to the regression. CATREG reports each predictor's importance with

[18] Correlations and partial correlations for Models from #7 to #12 are reported in Appendix B.

a sum of one[19]. Importance values are calculated for each variable, but the two most important variables for each model have been reported in Table 6.

Table 6 Two most important variables per model

Models	***First Important Variable***	***Second Important Variable***
#7	Issuer_Rat (S&P) (0.997)	Size and Matu (0.028)
#8	Issuer_Rat (S&P) (0.989)	Tech_res (0.033)
#9	Issuer_Rat (S&P) (1.006)	Matu (0.026)
#10	Issuer_Rat (Moody's) (0.446)	Size (0.300)
#11	Issuer_Rat (Moody's) (0.312)	Size (0.273)
#12	Roe (0.461)	Issuer_Rat (Moody's) (0.299)

It is worth highlighting that S&P ratings (Models form #7 to #9) of the issuers are very important in explaining the spread at issuance. Moody's ratings are substantially less important in predicting the spread at issuance, and they are not always the first variable to consider.

6. Conclusion

The above results support the valuation's framework implied by the option model of the corporate bonds adapted to the subordinated debts issued by insurance companies. Yields at issuance are positively related to risk variables of the issuers, even though significance of the financial rations is not so strong as expected. The poor explanation power of some variables could be explained in two ways: 1) the small number (but increasing) of the issues in the last decades, 2) the paucity of variables included which try to explain complex relationships amongst assets, liabilities and subordinated debt. Unfortunately, the two problems are strictly connected since the small sample size does not allow to test a greater number of financial predictors.

CATREG provides an helpful solution for this kind of problems, but care should be taken on interpreting the results. CATREG implies a mathematical transformation which can affect results, and some punctual information can be lost in discrediting quantitative variables.

Nonetheless, results are interesting. Spreads at launch are greatly explained by S&P ratings and the explanatory power increases if other non collinear variables are added. Thus, financial market participants could capture some information about the soundness of the issuer by analysing, among the other variables, the spreads at launch. It is worth emphasizing that US investors and policyholders deeply use AM Best Ratings to have an initial indication of the risk profile of the insurance company, even though ratings are not precise (see Epermanis and Harrington 2005). In the absence

[19] Notice that negative values of Pratt's importance measure indicate multicollinearity.

of rigorous studies on the solvency prediction of EU Insurance Financial Strength Rating (shortly EU-IFRS) European market participants are continuously seeking signals to use in their decision-taking process. Tested methods demonstrated an higher explanatory power than ratings of the issuers. Thus signals like spreads, publicly disclosed or easily calculated, can be a helpful variable to use for market discipline purposes.

These results have some important implications for policymakers as well.

A form of market discipline exists in the insurance industry. Risk-taking insurance companies raise their regulatory capital with subordinated debt issued with higher spreads. This is important first and obviously for investors (*investor-driven market discipline*), since they can easily make a comparison amongst issuers by analysing spreads at launch for different companies, and second for policyholders as well (*customer-driven market discipline*), since they can allocate their savings (life insurance) or buying protections (non-life insurance) from safer insurance companies by including the spreads in their decisions.

In conclusion some questions for further researches arise:

1. Can insurance companies be more innovative than banks in the assessment of their system of market discipline?

2. Does the safety net have implications on the spreads at launch? In the case of complete protection the shift of the insolvency risk is from policyholders to the guaranty fund and, in case of financial distress, to the subordinated debtholders. What we can derive from this reallocation of the insolvency risk?

REFERENCES

1. S. ANDROULIDAKIS *Leadership Ability Dimensions in Relation to Rural Women's Personal Characteristics: a Methodological Model For Further Considerations*, in Journal of International Agricultural and Extension Education, Volume 8 n.1, Spring 2001.
2. J.M AMBROSE, A.M. CARROL. *Using Best's Ratings in Life Insurer Insolvency Prediction*, in Journal of Risk and Insurance, vol. 61, pagg. 317-327, 1994.
3. J.M AMBROSE, A. SEWARD. *Best's Ratings, Financial Ratios and Prior Probabilities in Insolvency Prediction,* in Journal of Risk and Insurance, vol. 55, pagg. 229-244, 1988.
4. L. ANGELIS, I. STAMELOS, M. MORISIO. *Building a Software Cost Estimation Model Based on Categorical Data*, Proceedings of the 7th International Symposium on Software Metrics, 2001.
5. F. BLACK, J. C. COX, *Valuing Corporate Securities: Some Effects of Bond Indenture Provisions.* The Journal of Finance, vol. 31, pagg. 351-367, 1976.
6. R. R. BLISS. *Market Discipline and Subordinated Debt: A Review of Some Salient Issues*, in Mishkin F. S. "Prudential Supervision: What Works and What Doesn't. Federal Reserve Bank of Chicago Economic Review, pagg. 24-45, 2001.
7. R. R. BLISS, FLANNERY M. J. *Market Discipline in Governance of US Bank Holding Companies: Monitoring vs. Influencing*, in Mishkin F. S. "Prudential Supervision: What Works and What Doesn't. Chicago, IL, The University of Chicago Press, 2001.
8. J. D. CUMMINS, *Risk-Based Premiums for Insurance Guaranty Funds,* in Journal of Finance n.43, pagg. 823-839, 1988.
9. J. D. CUMMINS, D. W. SOMMER, *Capital and risk in property-liability insurance markets*, in Journal of Banking & Finance n.20, pagg. 1069-1092, 1996.
10. J. D. CUMMINS, R. PHILLIPS, *Estimating the Cost of Equity Capital for Property-Liability Insurer*. The Journal of Risk and Insurance, forthcoming, 2005.
11. G. M. DICKINSON, E. DINENIS, V. SIOKIS, *Rethinking the Solvency Margin System in Europe*, in Insurance Research and Practice vol. 16, 2001.
12. K. EPERMANIS, S. E. HARRINGTON. *Financial Rating Changes and Market Discipline in Property-Liability Insurance*, America Risk and Insurance Association, 2001.
13. K. EPERMANIS, S. E. HARRINGTON. *Market Discipline in Property/Casualty Insurance: Evidence from Premium Growth Surrounding Changes in Financial Strength Ratings*, America Risk and Insurance Association, 2005.
14. D. D. EVANOFF, L. D. WALL. *Subordinated Debt and Prompt Corrective Regulatory Action*. Government of the United States of America - Federal Reserve Bank of Chicago and Federal Reserve Bank of Atlanta - Research Department. Working Papers Series, 2000.

15. D. D. EVANOFF, L. D. WALL. *Subordinated Debt and Bank Capital Reform.* Government of the United States of America - Federal Reserve Bank of Chicago and Federal Reserve Bank of Atlanta - Research Department. Working Papers Series, 2003.

16. M. J. FLANNERY, S. M. SORESCU**.** *Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983-1991.* The Journal of Finance, vol. 51, pagg. 1347-1377, 1996.

17. HABER L., STRICKLAND J.A., GUTH D.J., *Categorical Regression Analysis of Toxicity Data*, Comments on Toxicology, Vol. 7 n. 5-6, pp.437-452, 2001.

18. D. HANCOCK, M. L. KWAST. *Using Subordinated Debt to Monitor Bank Holding Companies: Is It Feasible?* Federal Reserve Board - Division of Research and Statistics and Government of the United States of America - Division of Research and Statistics. Working Papers Series, 2000.

19. D. HANCOCK, U. BIRCHLER. *What Does the Yield on Subordinated Bank Debt Measure?* Federal Reserve Board - Division of Research and Statistics and Swiss National Bank. Working Papers Series, 2003.

20. S. E. HARRINGTON. *Market Discipline in Insurance and Reinsurance Industry,* Federal reserve Bank of Chicago, 2003.

21. M. C. JENSEN, W. H. MECKLING, *Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure,* Journal of Financial Economics, vol. 13, pg. 305-360, October 1976.

22. M. C. JENSEN, *Agency Costs of Free Cash Flow, Corporate Finance and Takeovers,* American Economic Review, vol. 76, pg. 73, May 1986.

23. Y.D. KIM, D.R. ANDERSON, T.L. AMBURGEY, J.C. HICKMAN, *The Use of Event History Analysis to Examine Insurer Insolvencies*. The Journal of Risk and Insurance, vol. 62 n.1, pp. 94-110. 1995.

24. M. L. KWAST. *Using Subordinated Debt as an Instruments of Market Discipline.* Report of a Study Group on Subordinated Notes and Debentures, M. Kwast, Chair. Board of Governors of the Federal Reserve System, Staff Study n. 172, December 1999.

25. T. D. LANE. *Market Discipline*. IMF Staff Paper, n. 40, pagg. 53-88, 1993.

26. R. C. MERTON, *On the Pricing of Corporate Debt: The Risk Structure of Interest Rates.* The Journal of Finance, vol. 29, pagg. 449-470, 1974.

27. MEULMAN, J. J., A. J. VAN DER KOOIJ, A. BABINEC. *New features of categorical principal components analysis for complicated data sets, including data mining*, in: *Classification, Automation and New Media,* W. Gaul, and G. Ritter, eds. Berlin: Springer-Verlag, 207–217, 2000.

28. MEULMAN, J. J., A. J. VAN DER KOOIJ, W. J. HEISER. *Principal components analysis with nonlinear optimal scaling transformations for ordinal and nominal data*, in: *Handbook of Quantitative Methodology for the Social Sciences,* D. Kaplan, ed. Thousand Oaks, California: Sage Publications, Inc, 49–70, 2004.

29. THE MÜLLER GROUP REPORT. *Solvency of Insurance Undertakings*. Conference of insurance Supervisory Authorities of the Member States of the European Union, 1997.

30. F. P. NATALE, *I nuovi requisiti di solvibilità individuale delle imprese di assicurazione*, WP n. 29 CERAP, Università Commerciale "Luigi Bocconi", Milano, marzo 2003.

31. E. NIVOROZHKIN. *Subordinated Debt and Equity: Complements or Substitutes?*
Goeteborg University - School of Economics & Commercial Law, 2002.

32. R. D. PHILLIPS, J. D. CUMMINS, F. ALLEN. *Financial Pricing of Insurance in the Multiple Line Insurance Companies,* in Journal of Risk and Insurance, vol. 95 pagg. 597-636, 1998.

33. R. REES, H. GRAVELLE, A. WAMBACH, *Regulation of Insurance Markets*, in The Geneva Paper of Risk and Insurance Theory n.24, pagg. 55-68, 1999.

34. J.P. RYAN, P.R. ARCHER-LOCK, A.J. CZERNUSZEWICZ, N.R. GILLOTT, P.H. HINTON, D. IBESON, S.A. MALDEN, D. PAUL, N. SHAH, *Financial Condition Assessment*. Institute of Actuaries, London, March 2001.

35. A. SIRONI. *An Analysis of European Banks SND Issues and Its Implications for the Design of a Mandatory Subordinated Debt Policy,* in Journal of Financial Services Research, vol. 20, pagg. 233-266, 2001.

36. A. SIRONI. *Testing for Market Discipline in the European Banking Industry: Evidence from Subordinated Debt Issues,* in Journal of Money, Credit and Banking, vol. 35 pagg. 443-472, 2003.

37. D. W. SOMMER, *The Impact of Firm Risk on Property - Liability Insurance Prices*, in The Journal of Risk and Insurance vol. 63, pagg. 501-514, 1996.

38. G. ZANJANI, *Market Discipline and Government Guarantees in Life Insurance*, Federal Reserve Bank of New York, 2002.

APPENDIX A

Estimation Results SPREAD=dependent variable with CATREG methods

Variable	Model 7 *Coeff.*	Imp.	Model 8 *Coeff.*	Imp.	Model 9 *Coeff.*	Imp.	Variable	Model 10 *Coeff.*	Imp.	Model 11 *Coeff.*	Imp.	Model 12 *Coeff.*	Imp.
Amount	0.212	-0.05	-0.035	0.004	-0.015	0.002	*Amount*	0.261	-0.18	-0.035	0.018	-0.078	0.038
Matu	0.143	0.028	0.122	0.024	0.132)	0.026	*Matu*	0.282	0.155	0.278	0.164	0.197)	0.099
Call	-0.001	0.000	-0.004	0.000	-0.001	0.000	*Call*	-0.021	-0.01	-0.058	0.001	-0.080	0.002
Size	-0.001	0.028	0.129	-0.05	0.143	-0.05	*Size*	-0.406	0.300	-0.338	0.273	-0.139	0.100
S&P	0.909	0.997	0.891	0.989	0.904	1.006	*Moody's*	0.472	0.446	0.350	0.312	0.409	0.299
Cap_ratio	0.004	0.001					*Cap_ratio*	0.356	0.279				
Tech_Res			-0.088	0.033			*Tech_Res*			-0.287	0.233		
ROE					-0.029	0.020	*ROE*					-0.449	0.461
R^2	0.783		0.777		0.773		R^2	0.455		0.446		0.502	
Adjusted-R^2	0.734		0.727		0.721		*Adjusted-*R^2	0.250		0.262		0.391	
F	15.902		15.352		14.968		*F*	2.225		2.419		4.537	
p-value	0.000		0.000		0.000		*p-value*	0.035		0.025		0.001	

APPENDIX B

Model #7: Correlations and Tolerances

	Correlations			Importance	Tolerance	
	Zero-Order	Partial	Part*		After trasformation	Before trasformation
Call	-.031	-.003	-.001	.000	.953	.924
Issuer_Rat(S&P)	.859	.848	.746	.997	.675	.652
Amount	-.197	.295	.144	-.054	.457	.399
Matu	.152	.286	.139	.028	.942	.975
Log_Assets	-.305	-.095	-.045	.028	.389	.395
Cap_ratio	.221	.007	.003	.001	.765	.777

Model #8: Correlations and Tolerances

	Correlations			Importance	Tolerance	
	Zero Order	Partial	Part*		After trasformation	Before trasformation
Call	.031	-.008	-.004	.000	.981	.922
Issuer_Rat(S&P)	.862	.849	.758	.989	.723	.712
Amount	-.100	-.069	-.033	.004	.882	.395
Matu	.152	.245	.119	.024	.959	.983
Log_Assets	-.303	.228	.111	-.050	.740	.384
Tech_Pre	-.293	-.173	-.083	.033	.879	.876

Model #9: Correlations and Tolerances

	Correlations			Importance	Tolerance	
	Zero Order	Partial	Part*		After trasformation	Before trasformation
Call	-.031	-.021	-.010	.000	.980	.951
Issuer_Rat(S&P)	.860	.820	.683	1.006	.571	.566
Amount	-.094	-.028	-.014	.002	.861	.364
Matu	.152	.261	.129	.026	.959	.970
Log_Assets	-.294	.242	.119	-.054	.692	.373
ROE	-.527	-.048	-.023	.020	.606	.648

Model #10: Correlations and Tolerances

	Correlation			Importance	Tolerance	
	Zero Order	Partial	Part*		After trasformation	Before trasformation
Call	.015	-.027	-.020	-.001	.947	.922
Amount	-.312	.194	.146	-.179	.313	.415
Matu	.250	.351	.276	.155	.962	.966
Log_Assets	-.336	-.334	-.262	.300	.417	.444
Cap_ratio	.356	.392	.314	.279	.779	.815
Issuer_Rat (Moody's)	.430	.491	.416	.446	.780	.638

Model #11: Correlations and Tolerances

	Correlation			Importance	Tolerance	
	Zero Order	Partial	Part*		After trasformation	Before trasformation
Call	-.005	-.076	-.056	.001	.952	.926
Amount	-.235	-.040	-.030	.018	.739	.435
Matu	.262	.347	.276	.164	.981	.967
Log_Assets	-.360	-.368	-.294	.273	.758	.424
Issuer_Rat (Moody's)	.398	.417	.342	.312	.954	.633
Tech_Pre	-.362	-.350	-.278	.233	.942	.917

Model #12: Correlations and Tolerances

	Correlation			Importance	Tolerance	
	Zero Order	Partial	Part*		After trasformation	Before trasformation
Call	-.012	-.110	-.078	.002	.957	.942
Amount	-.245	-.096	-.068	.038	.748	.436
Matu	.253	.259	.189	.099	.927	.923
Log_Assets	-.363	-.147	-.105	.100	.573	.415
Issuer_Rat (Moody's)	.367	.496	.403	.299	.972	.619
ROE	-.516	-.467	-.373	.461	.689	.739

*)*The correlation between the response and the residuals from regressing a predictor on the other predictors is the part correlation. Squaring this value yields a measure of the proportion of variance explained relative to the total variance of response.*