

The Determinants of Systematic Risk in the Italian Banking System: A Cross-Sectional Time Series Analysis

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Abstract

This research provides an insight to the main determinants behind the systematic risk of banks. For this purpose, we use a number of regression models to test the statistical significance of a wide range of bank-specific risk factors. The results indicate that bank equity beta correlates positively with bank size and with the relative volume of loans and intangible assets, and negatively with bank profitability, liquidity levels and loan loss provisions. We find no evidence supporting the traditional hypothesis that lower leveraged banks may be exposed to lower systematic risk. The study refers to the Italian banking system. Our findings are of significance both to bank managers as well as investors, since they will enable them to fully assess the effects of different strategic choices on a bank's risk profile. We also discuss potential policy implications regarding the impact of the new capital requirements imposed by Basel III in light of the observed risk-leverage relationship.

Keywords: systematic risk, market beta, bank leverage, Modigliani-Miller, accounting indicators, Basel III

JEL Classification: C33; G12; G21; G32

1. Introduction

This paper analyzes the fundamental determinants of risk in the Italian banking sector. We refer to the most well known measure of risk, that is the systematic risk measured by equity beta. The equity beta, also known as "stock beta" or "market risk", is a measure of the sensitivity of a stock's returns to the returns of the overall financial market.

Systematic risk and its determinants have been widely discussed in financial literature and are considered one of the most interesting issues in banking studies. The classical Capital Asset Pricing Model (CAPM) suggests a positive linear relationship between the required rate of return of any stock and its beta (Sharpe, 1964). Since a stock required rate of return from the point of view of a company also constitutes the cost of equity capital, those factors which affect a firm's systematic risk at the same time indirectly influence the funding costs of the firm, as well as its market value. The importance of beta is also evident from the investor's point of view. Systematic risk estimation is useful for investors in order to analyze the nature of risk associated with different investment options and to recognize risk-return relationships within portfolio investment strategies. Given the importance of CAPM and beta in financial analysis, it is not surprising that the determinants of a company's systematic risk have been widely studied.

The current research aims at expanding the evidence arising from the existing literature by exploring the main accounting determinants of systematic risk in the banking sector. Our findings pertain to the Italian context. More specifically, our estimates are based on accounting and market panel data on Italian banks that were publicly traded on the Milan Stock Exchange from 1992 to 2011.

Seven financial indicators are explored as possible determinants of the systematic risk of banks: (1) book value of total assets, (2) book leverage, (3) loan to asset ratio, (4) liquidity ratio, (5) intangibles to assets ratio, (6) loan loss ratio and (7) earnings per share. In order to investigate their statistical significance in determining banks' systematic risk exposure, we tested five different regression approaches, so as to examine the best combination of bank and time specific effects. Through a sequence of statistical specification tests, we then isolated the two-way fixed effects model as the one which best fits our data.

Our results suggest that Italian banks' systematic risk is positively correlated with a bank's size and with the relative volume of loans and intangible assets in a bank's balance sheet. Also, we conclude that banks with high profitability and liquidity levels, as well as those with high relative levels of loan loss provisions, tend to have lower equity betas. Finally, contrary to most of the previous literature, our estimates do not support the traditional hypothesis that systematic risk exposure is negatively correlated with financial leverage.

We believe our findings provide a significant contribution to the understanding of the fundamental determinants behind the systematic risk of banks. Their empirical value is twofold. First, our estimates allow equity capital investors and bank managers to better assess the consequences of different strategic options on the risk profile of banks under their control (e.g. with regard to bank leverage, liquidity levels and revenue diversification). Second, this study may be of use to financial authorities, providing them with insights of the effects of their regulatory choices on bank risk profiles. This point is particularly noteworthy in light of the new capital requirements reform (Basel III). Policy implications of our findings will be discussed in the conclusion.

The structure of the paper is as follows: section 2 provides the literature review; in section 3 we introduce data and empirical methodology; in section 4 we evaluate the impact of accounting indicators on Italian banks' systematic risk; finally, section 5 summarizes the main results of the study.

2. Literature Review

Systematic risk and its determinants have been widely discussed in previous studies. The Capital Asset Pricing Model, developed by William Sharp in 1964, constituted a historic milestone in modern financial theory, being the first theoretical model to introduce a security's sensitivity to market risk, that is the systematic risk or beta, as a main determinant of its required rate of return in a well-diversified investment portfolio context.

A few years earlier, Modigliani and Miller (1958) had developed their general equilibrium model on corporate capital structure, which still affects modern financial thinking. The Modigliani and Miller (M-M) model states that, under idealized conditions, the market value of a company is determined by its earning power and the risk inherent in its underlying assets, while it is unaffected by how a company is financed. In other words, the debt-equity ratio does not affect a company's overall cost of funds (WACC - Weighted Average Cost of Capital) or its market value ("Capital structure irrelevance principle").

In 1972, Robert S. Hamada combined the M-M theorem with the CAPM to develop a general model relating the beta of a company to its financial leverage (Hamada, 1972). Following Hamada's work, a number of studies have used the M-M proposition to establish the theoretical relationship between leverage and beta (Rubinstein, 1973; Bowman, 1979; Conine, 1980; Mandelker & Rhee, 1984, Fernandez, 2003), while several studies have extended and empirically investigated the validity of the theoretical model on leverage adjustments to market beta (Lev, 1974; Hill & Stone, 1980; Bhandari, 1988; Butler, Mohr, & Simmonds, 1991; Darrat & Mukherjee, 1995). Most of these studies support the theoretical leverage-beta relationship, while also observing the joint effects of operating and financial leverage on a company's systematic risk.

A different body of literature, mainly dating from the 70's, relates clusters of accounting variables to market measures of systematic risk (Beaver, Kettler, & Scholes, 1970; Rosenberg & McKibben, 1973; Lev & Kunitzky, 1974; Bildersee, 1975; Beaver & Manegold, 1975; Martikainen, 1991; Hong & Sarkar, 2007; Iqbal & Shah, 2012). Similarly, a number of researches explore the relationship between fundamental accounting indicators and stock returns (Chan, Hamao, & Lakonishok, 1991; Haugen, & Baker, 1996; Asl, Karimi, & Eghbali, 2012; Aldin, Dehnavi, Hajjighasemi, & Hajjighasemi, 2012). Most of these publications greatly differ in their selection of explanatory variables as well as in statistical model results. What these studies all seem to conclude is that accounting measures appear to be useful in predicting both market risk and stock performance.

In reference specifically to the banking industry, a considerable amount of studies have examined systematic risk and its determinants. Rosenberg and Perry (1981), based on data on U.S. bank holding companies (BHCs) between 1969 and 1977, build a large empirical model which relates both bank systematic and specific risk to a wide range of accounting variables. Their results show that the most important predictors of bank beta are size, dividend yield, equity capitalization and the asset to long-term liability ratio. In a similar study, Lee and Brewer (1985) confirm that bank market risk relates to leverage and dividend pay-out ratio. The dividend pay-out ratio also plays a role in the study of Jahankhani and Lynge (1980). The authors analyze the relationship between commonly used accounting ratios and market-based measures of risk for a sample of U.S. commercial banks and bank holding companies over the period from 1972 to 1976. Their results indicate that bank market beta is statistically related with the dividend pay-out ratio, the coefficient of variation of deposits, and the loan to deposits ratio.

Another strand of U.S. banking literature supports the view that systematic risk is strongly correlated with a bank's diversification level and/or with the composition of bank assets and liabilities. Templeton and Severiens (1992) find that diversification in non-bank activities has no effect on BHCs (Bank Holding Companies) systematic risk, although it can reduce risk as measured by stock return variance. Similar results are shown by Demsetz and Strahan (1997), who use data on the BHCs publicly traded over the period from 1980 to 1993 to investigate the relationship between size, diversification and risk. Their analysis indicates that BHCs assets size is positively correlated with bank systematic risk, although larger banks are more diversified than smaller ones. That is to say that for large BHCs the potential of diversification does not translate into reductions in risk. By analyzing bank-specific attributes to explain the positive size-risk relationship, the authors report that large BHCs engage in more commercial and industrial lending (C&I loans), are more active in derivatives and are more leveraged than small BHCs, thus offsetting their diversification advantage.

In the wake of the significant rise in defaults on mortgage lending post 2007, Bhattacharyya and Purnanandam (2011) analyze the evolution of U.S. commercial banks' risk profiles in the years leading up to the crisis. Their study shows, for the period from 2000 to 2006, a significant increase in the banking sector's systematic risk profile, which seems to be driven mostly by the effects of residential mortgage loans on both idiosyncratic and systematic risk levels. They conclude that the U.S. stock market was able to perceive increased mortgage lending activity (and securitizing of mortgages) as enhancing the systematic risk of banks' asset portfolios.

Although most existing literature has an overwhelming U.S. focus, a number of studies examined the determinants of bank systematic risk outside the United States. Vander Vennet, Baele and De Jonghe (2005) analyze the determinants of both systematic and idiosyncratic risk for European banking institutions. They provide evidence showing that capital levels and the proportion of loans and core deposits in total assets are negatively correlated with bank systematic risk, while higher levels of diversification and loan loss provisions tend to increase the market beta. Using empirical evidence on U.K. banking institutions, Miles, Yang and Marcheggiano (2011) explore the link between beta and a measure of leverage which is affected by regulatory rules on bank capital, that is a bank's total assets over its Tier 1 capital. Their estimates reveal a negative impact of leverage upon bank equity beta, although the results do not fully conform to the conditions implied by the joint hypothesis of M-M effects and the CAPM. In a recent inquiry, Yang and Tsatsaronis (2012) analyze the return-risk profile of bank stocks using data on 50 actively traded global banks located in 11 OECD countries from 1990 to 2009. They show that bank market beta is positively correlated with leverage and the ratio of book to market value of equity, while correlating negatively with bank profitability. They also find that the systematic risk of bank stocks differs across the stages of the business cycle: it is higher during recessions (when default rates on loans tend to decline, thus raising bank earnings) and lower in periods of economic expansion (when both loan values and bank earnings decrease). Agusman, Monroe, Gasbarro and Zumwalt (2008) investigate the relation between bank accounting and market measures of risk for a sample of 46 listed Asian banks during the period from 1998 to 2003. Their results show that the standard deviation of the return on assets (ROA) and the ratio of loan loss reserve to gross loans correlates significantly with total risk, while gross loans to total assets ratio and loan loss reserve to gross loans ratio are significantly related to specific risk. Eldomiaty, Al Dhahery and Al Shukri (2009) analyze the financial ratios that are statistically associated with market beta for different categories of companies - banking, insurance and nonfinancial institutions - in the Dubai financial market. With regard to banking companies, their results indicate that the fundamental determinants of systematic risk are financial leverage, measured by the assets to equity ratio, and the book value per share. More precisely, both the ratios exhibit a negative relationship with banks' market beta.

3. Data and Methodology

3.1 Data and Variable Definitions

As already observed, the present study explores bank-specific accounting measures which correlate significantly with stocks' market risk (*i.e.* equity beta) in the Italian banking sector. For this purpose, we collected from the Capital IQ database annual accounting and market data for Italian commercial banks and bank-holding companies which were listed on the Milan Stock Exchange from 1992 to 2011. We considered all kinds of banking institutions, from relatively small commercial banks to larger financial conglomerates.

For each bank, key accounting ratios are obtained from the annually consolidated income statements and balance sheets, while equity betas are estimated by regressing banks' daily stock returns on the daily returns of the FTSE MIB index over discrete periods of one year.

A number of banks have been excluded due to the lack of data. We also imposed a minimum limit of at least three years available data in order to include banks in the study. Our final sample consists of 38 companies and 350 bank-year observations. Table 1 shows our final sample composition.

Table 1. Sample composition

N. Bank	Obs.	N. Bank	Obs.
1 Banca Antonveneta	3	20 Banca Popolare di Spoleto	10
2 Banca Carige	14	21 Banca Popolare Italiana	7
3 Banca Commerciale Italiana	6	22 Banca Profilo	8
4 Banca CR Firenze	7	23 Banca Toscana	4
5 Banca Fideuram	11	24 Banco di Desio e della Brianza	12
6 Banca Fimnat Euramerica	14	25 Banco Popolare	8
7 Banca Generali	5	26 Capitalia	8
8 Banca Ifis	10	27 Credito Artigiano	12
9 Banca Lombarda e Piemontese	8	28 Credito Bergamasco	18
10 Banca Monte dei Paschi di Siena	12	29 Credito Emiliano	11
11 Banca Nazionale del Lavoro	6	30 Credito Valtellinese	12
12 Banca Popolare Commercio e Industria	3	31 Fineco Group	4
13 Banca Popolare dell'Etruria e del Lazio	10	32 Intesa Sanpaolo	18
14 Banca Popolare dell'Emilia Romagna	10	33 IW Bank	3
15 Banca Popolare di Cremona	5	34 Mediobanca	8
16 Banca Popolare di Intra	8	35 Meliorbanca	6
17 Banca Popolare di Milano	14	36 SanPaolo IMI	8
18 Banca Popolare di Novara	8	37 UniCredit	18
19 Banca Popolare di Sondrio	13	38 Unione di Banche Italiane	8

Based on theory and previous banking literature evidence, we tested a wide range of accounting predictors as possible determinants of Italian banks' systematic risk. Through a stepwise regression process, we finally limited our analysis to the following seven indicators: (1) book value of total assets, (2) leverage ratio, (3) loan to asset ratio, (4) liquidity ratio, (5) intangibles ratio, (6) loan loss ratio, and (7) earnings per share.

Each indicator serves as a proxy for a bank-specific attribute which we expect affects market risk exposure. Those attributes are: (1) size, (2) financial leverage, (3) degree of diversification, (4) liquidity, (5) volume of intangible resources, (6) loan portfolio quality and (7) profitability. Table 2 presents the explanatory variables used in our regression analysis and their measurement.

Table 2. Explanatory variables tested in the study

Symbol	Indicator	Measurement
SIZE	Total Assets	Book value of total assets (in billions of euro)
LEV	Leverage ratio	Book value of debt / Book value of equity
LTA	Loan to asset ratio	Gross loans / Total assets
LIQ	Liquidity ratio	Cash / Total Assets
INTA	Intangibles ratio	Intangibles / Total assets
LLR	Loan Loss Ratio	Provision for Loan Losses / Gross Loans
EPS	Earnings per Share	Net Income / Nr. of shares outstanding

The first accounting predictor is the book value of a bank's total assets, which we use as a proxy for bank size. Although previous studies show that firm size is a key determinant of market risk, the theoretical size-risk relationship is somehow ambiguous. On the one hand, a negative relationship is to be expected since larger banking institutions have a scale competitive advantage over smaller ones, are more diversified and benefit from the implicit government guarantees provided by the too-big-to-fail (TBTF) principle. On the other hand, the size effect may have a positive impact on a bank's risk assessment given that larger institutions are often more exposed to certain bank-specific risk profiles, such as credit and operating risk, exchange rate risk and systematic risk resulting from common shocks to the financial system (Rosenberg & Perry, 1981; Vander Venet et al.,

2005). Thus, the sign of correlation between bank size and equity beta in the case of Italian banks remains an empirical question.

In line with classical theory, our second predictor of systematic risk is financial leverage (*LEV*). According to the joint hypothesis of the M-M theory and CAPM, we expect a positive relationship between equity beta and leverage. That is to say that highly-leveraged banks should exhibit greater systematic risk given that, as leverage intensifies (decreases), earnings volatility and default probability increase (decrease) as well and, as a consequence, equity becomes more (less) risky. Here, we estimate the leverage ratio as the ratio of book value of debt to book value of equity (book leverage).

The third explanatory variable included in our model is the loan to assets ratio (*LTA*), that is the ratio of gross loans to total assets. *LTA* is assumed as a proxy for a bank's degree of diversification in activities beyond traditional intermediation. Theoretically, to the extent that the cash flows generated by different bank activities are not perfectly correlated, diversification should increase revenue stability, thus reducing bank systematic risk exposure. However, banking empirical literature shows that the impact of diversification on bank risk profile is somewhat uncertain. A number of studies show that diversification in non-bank activities does not affect bank systematic risk exposure (Templeton & Severiens, 1992; Demsetz & Strahan, 1997), while others show that the effect of diversification on banks' market beta, contrary to what one might expect, is predominantly positive (Vander Vennet et al., 2005).

We also investigate whether the liquidity ratio (*LIQ*), that is the ratio of cash and equivalents to total assets, acts as a proxy for bank systematic risk. We suppose that the higher the liquidity of a bank the lower the risk of financial distress should be, which implies a negative effect of the liquidity ratio on the market risk of a bank.

The fifth explanatory variable is the intangibles ratio (*INTA*), *i.e.* the ratio of intangible assets to bank total assets. We suspect that goodwill and other intangible assets may have a critical role in explaining banks' risk exposure, given their relatively low loss-absorbing capacity, their link with bank growth opportunities and their effect on transparency of banks' balance sheets.

In addition, bank betas are likely to vary with the overall quality of the loan portfolio, here expressed by the loan loss ratio (*LLR*), *i.e.* the ratio of provisions for loan losses to gross loans. Given the pivotal role played by interest margin in Italian banks' income statements, we expect to find a negative relationship between the bank loan portfolio quality and bank equity beta.

Finally, we investigated whether or not high profitability levels provide banks with a structural hedge against deterioration in financial market conditions. Specifically, we assume a negative relationship between a bank's overall profitability and its systematic risk, since banks with higher margin capacity should have less volatile profits. Profitability is here measured by the earnings per share indicator (*EPS*).

Table 3 provides summary statistics for the explanatory variables. Banks' mean equity beta is 0.674 (*i.e.* bank stocks are less volatile than the market index), while the mean value of total assets is about 67.3 billion Euros. The sample displays considerable cross-section heterogeneity: the largest bank is more than 29,000 times the size of the smallest one. Debt to equity ratio has a mean value of about 13.5 and loans are roughly 64.2% of total assets, which confirms that Italian banks are typically focused on more traditional forms of intermediation, where both the lending portfolio and the interest margin play a key role. On average, cash and intangible assets are, respectively, 1% and 1.1% of total assets, while annual loan loss provisions are 0.6% of gross loans. Finally, mean value of banks' earnings is about 0.4 euro per share.

Table 3. Summary statistics of the explanatory variables

Variable	Mean	Min	Max	Std. Dev.
BETA	0.674	-0.547	1.767	0.408
SIZE	67.285	0.036	1,045.61	145.51
LEV	13.520	0.235	48.311	5.866
LTA	0.642	0.033	0.965	0.174
LIQ	0.010	0.000	0.130	0.014
INTA	0.011	0.000	0.056	0.012
LLR	0.006	-0.004	0.064	0.008
EPS	0.434	-2.923	4.451	0.714

Table 4 presents pair-wise correlations among the variables involved in the study. Equity beta is positively correlated with size, leverage, intangibles ratio and earnings per share, while correlating negatively with loan to asset ratio, liquidity ratio and loan loss ratio. The correlation matrix provides a first indication of possible multicollinearity issues: correlation values between two explanatory variables close to +/- 1 indicate that the given couple of predictors is multicollinear. Table 4 shows that there is no problem of multicollinearity, given that the higher correlation value is 0.354 (size-earning per shares correlation). However, the pair-wise correlation method is not able to detect more complex linear relationships between more than two variables at a time. For this reason, we also used the Variance Inflation Factor (VIF) to better assess potential multicollinearity problems in our estimations¹.

Table 4. Correlation matrix

	BETA	SIZE	LEV	LTA	LIQ	INTA	LLR	EPS
BETA	1							
SIZE	0.529	1						
LEV	0.208	0.151	1					
LTA	-0.036	0.040	-0.075	1				
LIQ	-0.034	-0.033	0.035	0.043	1			
INTA	0.250	0.255	-0.251	-0.012	-0.103	1		
LLR	-0.119	-0.023	0.016	-0.185	-0.138	0.127	1	
EPS	0.076	0.354	-0.082	0.089	-0.091	-0.047	-0.348	1

3.2 Regression Models

The methodology presented in this study compares five different regression models between the selected financial fundamentals (the predictor variables) and bank systematic risk (the response variable): (1) a simple pooled OLS model (POLS), (2) a one-way fixed effect model (FE1), (3) a one-way random effect model (RE1), (4) a two-way fixed effect model (FE2), and (5) a two-way random effect model (RE2).

In the simple pooled OLS regression we do not consider unobserved heterogeneity across units (banks) or time (years). Under this assumption, each observation is viewed as independent and the regression model takes the following form:

$$\beta_{i,t} = a + x'_{i,t-1} b + \varepsilon_{i,t} \quad (1)$$

where β (that is the equity beta) is the dependent variable, a is the intercept, x' is the row vector of (lagged) explanatory variables, b is the column vector of parameters (regression coefficients), ε is the random error term, i and t are indices for observation units (banks) and time (years). Since the POLS estimator ignores the panel structure of the data, it provides consistent and efficient estimates only if there is no unit-specific and time-specific heterogeneity across observations (*i.e.* the error term is uncorrelated with regressors).

If this is not the case, a one-way fixed or random effects transformation may be a better choice, since it allows the impact of unobserved and time-invariant factors (effects) that are specific to each bank (e.g. effects relating to the geographical localization, management competence, etc.) to be assessed.

In the (one-way) fixed and random effects approach the error term (ε_{it}) is divided into two components: a unit-specific error (λ_i), which does not change over time (*i.e.* the individual effect), and an idiosyncratic error (μ_{it}) which is observation-specific (*i.e.* varies over units and time).

The key difference of the fixed and random effects estimator is in the assumptions about λ_i . In the FE1 model we assume each unit (bank) to have a constant individual-specific effect shifting the dependent variable up or down by a fixed amount; that is, λ_i is now part of the constant term and the regression line turns out to be as follows:

$$\beta_{i,t} = (a + \lambda_i) + x'_{i,t-1} b + \mu_{i,t} \quad (2)$$

where the constant term is now the sum of a constant (a) plus an individual effect which varies across banks (λ_i). This way, we permit each unit (bank) to have a different intercept term, though all regression coefficient (slopes) are the same.

While the fixed effects model treats the individual-specific effects (λ_i) as a variable that is allowed to be correlated with the observed regressors, in the RE1 approach we assume any unobserved individual heterogeneity (λ_i) to be a random variable which is distributed independently of the explanatory variables. As a consequence, individual effects are treated as a part of the composite error term and the model can be written as follows:

$$\beta_{i,t} = a + x'_{i,t-1} b + (\mu_{i,t} + \lambda_i) \quad (3)$$

Given that the one-way fixed and the random effects specification do not fully eliminate the possibility of omitted-variable bias, we also performed a two-way fixed and random effects model, which allow to estimate both bank-specific and time-specific effects. In the two-ways approach the error term (ε_{it}) is divided into three components: an individual effect (λ_i), which is time-invariant and bank-specific, a time-specific effect (δ_t), which affects all banks in the same way for each time period (e.g. effects relating to the economical cycle, the stock exchange market conditions, etc.), and an observation-specific idiosyncratic error (μ_{it}).

In the FE2 model both individual and time effects are assumed to be constant, respectively, across banks (individual effect) and across years (time effect), and the regression model takes the following form:

$$\beta_{i,t} = (a + \lambda_i + \delta_t) + x'_{i,t-1} b + \mu_{i,t} \quad (4)$$

Contrastingly, in the RE2 model the individual and time effects are included in the composite error term, being assumed to be both random and uncorrelated to the regressors. The model can be expressed as follows:

$$\beta_{i,t} = a + x'_{i,t-1} b + (\mu_{i,t} + \lambda_i + \delta_t) \quad (5)$$

For each of the regression equations above, we corrected potential heteroskedastic and autocorrelation effects using an HAC (Heteroskedasticity Autocorrelated Consistent) estimator of standard errors, so to improve the significance of estimates.

We also used the Box-Cox technique to identify a suitable power transformation for the data in order to reduce anomalies such as non-normality and heteroscedasticity. In any case, Box-Cox results suggest that, for our panel data, no transformation of the response and predictors is required to improve the fit of regressions.

3.3 Model Selection

Table 5 presents the results of the five different regression models. *SIZE* and *INTA* variables are positively related with equity beta for all the regression equations and their estimated regression coefficients turn out to be statistically significant. *EPS*, *LIQ* and *LLR* predictors exhibit a negative regression coefficient which is highly significant for most of the regression models. *LTA* predictor has a negative but statistically insignificant coefficient in the POLS model; once controlling for differences across banks and years, *LTA* became significant and positively correlated with the dependent variable. Finally, the regression coefficient between leverage and bank systematic risk is positive but statistically significant only for the POLS and the RE2 specifications.

Table 5. Determinants of bank equity beta: regression results

	POLS	FE1	RE1	FE2	RE2
SIZE	0.0014 *** (5.852)	0.0007 *** (9.062)	0.0009 *** (5.898)	0.0005 *** (5.533)	0.0007 *** (4.802)
LEV	0.011 * (1.863)	0.0004 (0.088)	0.006 (1.558)	0.004 (1.038)	0.008 ** (2.233)
LTA	-0.146 (-1.111)	0.557 *** (3.84)	0.313 *** (2.629)	0.446 *** (3.466)	0.296 ** (2.511)
LIQ	-1.241 (-0.826)	-3.109 *** (-2.917)	-2.82 *** (-2.603)	-2.919 *** (-3.154)	-3.041 ** (-2.239)
INTA	5.863 ** (2.248)	3.859 ** (2.197)	4.668 *** (2.821)	3.407 ** (2.298)	4.088 ** (2.531)
LLR	-10.939 *** (-2.889)	-1.947 (-0.793)	-4.274 ** (-1.972)	-3.486 ** (-2.199)	-5.442 *** (-2.663)
EPS	-0.086 *** (-2.802)	-0.057 *** (-2.665)	-0.062 ** (-2.19)	-0.066 *** (-3.182)	-0.064 ** (-2.299)
Constant	0.573 *** (3.775)	0.289 (2.682)	0.373 *** (3.39)	0.06 (0.475)	0.177 (0.774)
Standard error	0.329	0.238	0.352	0.216	0.351
R ² overall	0.363	0.705	-	0.770	-
R ² between	-	-	0.049	-	0.049
R ² within	-	-	0.056	-	0.047
Adj R ²	0.350	0.662	-	0.721	-
F-test	27.90	16.53	-	15.53	-
Prob. >F	2.72E-30	7.09E-58	-	3.34E-62	-
B.I.C.	253.87	202	302.96	219.16	387.31
Bank effect	No	Yes	Yes	Yes	Yes
Year effect	No	No	No	Yes	Yes

Notes: (1) * denotes significance at 10% ($p < 0.1$), ** denotes significance at 5% ($p < 0.05$), *** denotes significance at 1% ($p < 0.01$); (2) Numbers in parentheses below each coefficient show t-statistics; (3) B.I.C. = Bayesian Information Criterion.

In order to select the most appropriate estimator, we implemented a sequential choice process which relies on various specification tests (see table 6). First, to choose between the pooled OLS regression and one-way fixed effects model, we used an F-Test, where the null hypothesis implies that the POLS model is the appropriate specification (no significant difference across units).

Second, to examine whether the pooled OLS model is more appropriate than the one-way random effects model, we performed a Breusch-Pagan LM (Lagrange Multiplier) test, where the null hypothesis is that the pooled OLS estimator is adequate against the random effects model (no error variance across units). In our case, the null hypothesis is rejected for both tests and thus the one-way fixed and random effects model turns out to be the optimal specification.

In a third step, to verify whether time dummies are needed when running the fixed and random effects models, we implemented a Wald specification test. Under the null hypothesis all year coefficients are jointly equal to zero (no time effects are needed). For our data, the test goes in favour of the two-way specifications.

Finally, to compare the two-way fixed and random effects estimators, we performed a Hausman test, which investigates the null hypothesis that the random effects estimator is adequate against the fixed effects alternative (no correlation between effects and regressors). Given the results obtained by the Hausman test, the two-way fixed effects model is taken as our central estimate, and the regression equation assumes the following structural form:

$$\beta_{i,t} = (a + \lambda_i + \delta_t) + b_1 SIZE_{i,t-1} + b_2 LEV_{i,t-1} + b_3 LTA_{i,t-1} + b_4 LIQ_{i,t-1} + b_5 INTA_{i,t-1} + b_6 LLR_{i,t-1} + b_7 EPS_{i,t-1} + \mu_{i,t} \quad (6)$$

Table 6. Results of the model selection process

	Specification Test	Null hypothesis	Alternative hypothesis	Test Statistics	p-value
Test I	F-Test	POLS	FE1	F = 9.51	8.86E-33 ***
Test II	Breusch-Pagan	POLS	RE1	$\chi^2 = 199.21$	3.10E-45 ***
Test III	Wald	FE1	FE2	$\chi^2 = 233.23$	2.06E-39 ***
Test IV	Wald	RE1	RE2	$\chi^2 = 76.26$	3.84E-09 ***
Test V	Hausman	RE2	FE2	$\chi^2 = 56.73$	0.0003 ***

By fully considering the panel structure of the data, the FE2 specification enables us to analyze systematic risk exposures of a bank both over space (cross-sectional analysis) and time (time series analysis), thus allowing to account for unobserved heterogeneity across banks and years that may be related with banks' equity betas.

Furthermore, based on table 5 data, the statistical properties of the FE2 specification meet statistical standards for reliability. The chosen model is also the one associated with the lowest standard error and the highest R-squared (the equation accounts for more than three-quarters of the variability in bank equity betas).

4. Results and Discussion

Some of the evidence for a bank systematic risk drivers shown by the FE2 model fully meet expectations. Both the profitability (*EPS*) and liquidity (*LIQ*) coefficients are negative and statistically significant at 1%, providing evidence that higher profitability and liquidity levels lower a bank's systematic risk. Those results are not surprising since high performing and liquid institutions are generally perceived, *ceteris paribus*, as less risky than banks with bad economic performance and/or low liquidity level.

We also established a strong positive link, statistically significant at the 1% level, between a bank's equity beta and its loan to asset ratio (*LTA*). The loan to asset ratio is assumed, in the current study, as a proxy for bank diversification level: the larger the loan portfolio relative to total assets (*LTA*), the lower the degree of diversification in non-interest generating activities. Thus, our regression model indirectly confirms a negative relationship between bank systematic risk and the degree of revenue diversification. This evidence, contrary to previous empirical studies (Templeton & Severiens, 1992; Demsetz & Strahan, 1997; Vander Vennet et al., 2005), is consistent with the theoretical model on diversification benefits, according to which a higher degree of diversification reduces revenue and earnings volatility (since earnings from activities beyond intermediation are more stable than loan-based earnings) as well as bankruptcy risk (since non-interest income is less affected by a possible deterioration in credit market conditions), while expanding income sources and cross-selling opportunities.

A positive and highly significant (1% level of statistical significance) correlation is also found between systematic risk and bank size, indicating that, despite the higher diversification opportunities and the implicit public protection against failure, larger banks tend to have higher market risk exposure. A number of factors may explain the observed size-risk relationship. First, as observed, large banks are more exposed to the risk of common shocks because of the higher interconnectivity among large institutions, as recent financial crises have clearly illustrated. They are also more exposed to other bank-specific risk profiles, such as operating risk, exchange rate risk and credit risk. Vander Vennet et al. (2005) find that differences in systematic risk between small and large banking institutions may also reflect a different lending behavior, given that small banks' loan portfolio appears to be, on average, safer than those of large banks². Finally, large and complex banking organizations seem to be harder to evaluate and are likely to be perceived as more opaque, which may result in investors perceiving a higher risk exposure.

Sound and transparent financial accounting information may also have a role in explaining the observed intangible-risk relationship, as well as the association between bank equity beta and loan portfolio quality. The FE2 specification shows, with a level of significance of 5%, that bank equity betas vary with the relative volume of investments in intangibles assets. We suspect that goodwill and other intangibles increase banks' perceived opacity because of the complex accounting rules and the difficulty in auditing the valuation of intangible assets, which makes bank risk profiles harder to quantify. Furthermore, many intangibles have a relatively low loss-absorbing capacity as their book value can hardly be monetized in the event of lack of liquidity and financial distress.

Regarding the loan portfolio quality, our model assumes the loan loss ratio, that is the ratio of loan loss provisions (income statement item) to gross loans (balance sheet item), as a proxy for the overall quality of a

lending portfolio: given a certain level of loans (the denominator of the *LLR*), the higher the allowance a bank sets aside for bad loans (the numerator of the *LLR*), the lower the loan portfolio quality should be. Thus, we would expect to obtain a positively-correlated regressor, while table 5 shows a negative regression coefficient, which is statistically significant at the 5% level.

Discretionary practices over bank loan loss provisioning and opportunistic accounting behavior by bank managers provide a potential explanation for our finding. Indeed, in accordance with sound accounting principles, loan loss provisions should reflect a bank management's assessment of the real quality (that is, inherent credit risk) of the loan portfolio. However, a number of studies find evidence that bank managers use the discretionary component of *LLP* (sometimes, jointly with other discretionary accounting variables) to smooth bank earnings (Kanagaretnam, Lobo, & Mathieu, 2003; Rivard, Bland, & Hatfield Morris, 2003; Taktak, Shabou, & Dumontier, 2010) or to signal their banks' future prospects (Wahlen, 1994). According to these studies, discretionary use of loan loss provisions allows bank managers to reduce time variation in reported earnings by saving income for the future (by reducing current income through *LLP*) in times of good current performance, while borrowing income from the future (by increasing current income through *LLP*) in bad times. Also, the signaling hypothesis states that managers may use *LLP* to signal their private information about their banks' current health and future prospects, setting aside a larger provision when current and/or future expected earnings before loan losses are high. The observed *LLR*-risk relationship may result from such opportunistic *LLP* management, since an increase in loan loss provisions (and, as a consequence, in the *LLR*) may be interpreted by investors as a sign of confidence in the bank's future returns, thus reducing the perceived systematic risk.

Finally, one of the main results of our empirical test concerns the correlation between leverage and bank market risk. Our central estimate (FE2 regression) indicates that the regression coefficient of leverage, as predicted, is positive, but the coefficient itself is very low and statistically not significant. Therefore, financial leverage may not be regarded as a key determinant of Italian banks' systematic risk, which contradicts the traditional corporate finance theories.

A number of factors can affect bank capital structure choices, causing a misalignment with the M-M model. Apart from the impact of the debt tax shield³, leverage-risk relationship is affected by the fact that banks are, by nature, more leveraged than most non-financial institutions, and that banks' capital structure is highly regulated by the capital requirements addressed by the Basel Committee. Furthermore, bank debts benefit from government guarantees. In the case of deposits, an explicit guarantee exists in the form of the deposit insurance system itself. At the same time, a banks' non-deposit liabilities benefit from an implicit government guarantee, since investors assume that the government will not let the banking system default on its debt (especially in the case of large banking institutions). These government guarantees, whether explicit or implicit, make banks' debt (partially) free from systematic risk, thus substantially reducing debt cost and providing bank managers with an incentive to prefer debt funding to equity funding.

5. Conclusion

Our contribution to existing banking literature is the use of a set of statistically robust regression models and an updated data set, to assess the ability of a range of accounting indicators to predict market risk within the Italian banking system.

After running a sequence of specification tests, a regression estimator including both bank and year fixed effects has been selected as our reference model. Evidence from this model indicates that bank equity beta is significantly and positively associated with (1) bank size (book value of total assets) and with the relative volume of (2) loans and (3) intangibles in bank total assets (loan to asset ratio and intangibles to asset ratio, respectively). Also, we find that bank systematic risk is significantly and negatively correlated with (1) a bank's profitability, as measured by earnings per share, (2) liquidity levels, *i.e.* the cash to assets ratio, and (3) loan loss ratio, that is the ratio of provision for loan losses to gross loans.

As discussed, some of these findings, namely the effects of intangibles and loan loss provisions on banks' systematic risk, indirectly outline the role of financial disclosure and opportunistic accounting behavior in explaining the stock market perceptions about a bank's systematic risk. At the same time, the positive association between systematic risk and the loan to asset ratio indirectly confirms diversification benefits. It is also noteworthy that there is a leverage-risk relationship in the Italian banking system. Indeed, we find no statistically robust evidence in favour of the traditional hypothesis that less-leveraged banks are perceived by investors to be less risky. This finding implies the relatively small importance of capital adequacy as a proxy for bank creditworthiness.

This study entails a number of strategic implications at different levels. First, for Italian bank managers it seems advisable, from a systematic risk perspective, to increase revenue diversification and to maintain high levels of liquidity and profitability. Also, Italian listed banks would seem to have significant incentives to increase the level of voluntary disclosures regarding loan loss provisions and intangible assets accounting rules. Indeed, our results indirectly demonstrate that full accounting disclosure may help the financial market to better assess a bank's risk profile.

At the same time, our findings are worthy of particular consideration in light of the new capital requirements imposed under Basel III. By requiring banks to increase their capital ratios, the new capital rules will involve lower levels of financial leverage, since banks are called upon to hold a larger amount of equity for a given amount of assets. Under the M-M framework, if a bank raises equity capital by issuing stock and/or selling debt, the increase in the portion of equity, which is more expensive than debt, is offset by a decrease in the required rate of return on both debt and equity, because of the lower risk premium investors demand. This would happen in such a way that the overall impact of higher equity capital (and less debt) on the funding cost is zero. However, to the extent that lower leverage levels do not affect equity beta, *i.e.* the M-M model does not hold true for banks, an increase of equity capital, which is more expensive than debt, will not be offset by a decrease in the required rate of return on both bank debt and equity. Thus, given that our estimates do not confirm the assumptions underlying the M-M theorem, the Basel III reform could result in potentially higher bank funding costs which might, in turn, lead Italian banks to raise loan prices and/or reduce their lending portfolio.

Given the positive link between the cost of capital and equity beta, our findings also suggest that the increase in funding costs should be, on average, higher for large Italian banks with relatively low performance, liquidity levels and revenue diversification and/or with high volumes of intangible assets. However, this conclusion needs to be further investigated in order to confirm its accuracy.

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Notes

Note 1. We initially tested a wide range of indicators which were likely to affect a bank systemic risk, such as bank market capitalization, market leverage (debt / market value of equity), book value per share, book to market value, operating efficiency indicators (total revenue to total assets ratio and cost/income ratio) and standards profitability indicators (ROA and ROE). Those indicators have not been included in our final regression models because of the multicollinearity problems revealed by the VIF test ($VIF \geq 5$).

Note 2. It is an open question whether small banks tend to have a lower credit risk exposure because they simply require more collateral from each borrower or because their loan decision model benefits from the superior knowledge arising from closer lender-borrower relationships.

Note 3. As a result of their different tax treatment (interest payments are tax-deductible for companies while dividends are not), a higher proportion of equity reduces the impact of the debt tax shield, thereby increasing funding costs. The same Modigliani and Miller made a correction to their original model by incorporating the impact of the tax advantage arising from debt financing into their model (Modigliani and Miller, 1963).