CATCH THE HETEROGENEITY: THE NEW BANK TAILORED INTEGRATED RATING

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Abstract

We aim to develop a banks' specific integrated rating approach, tailored incorporating the various heterogeneity dimensions characterizing financial institutions, named "bank tailored integrated rating" (BTIR) able to catch the financial cycle and the ongoing change banking normative. The approach is inherently coherent with the challenging frontier of forecasting tail risk in financial markets (De Nicolò and Lucchetta, 2017) since it considers the downside risk in the theoretical framework. The innovation consists in using the integrated rating (IR) with the pre-selection of the variables through a statistical procedure that takes into account the characteristics of risk and greater heterogeneity of the banks, together with the forward-looking preselection requested by the new International Financial Reporting Standard (IFRS 9).

Keywords: Bank Tailored integrated rating, banks' heterogeneity, financial cycle.

JEL: G2, G21, G28.

I. INTRODUCTION

The capital regulatory policies imposed on banking institutions, increasingly reveal the need to consider the heterogeneity of regulated entities. At the same time, the regulating framework should contribute to avoid the common errors of over/under assessment of the risks inherent in the different business models recently applied by modern banks. Rating systems play a critical role. Unfortunately, a recent paper of Ongena et al (2017) suggests that the traditional ratings, based on risk rating agencies and homogeneous rating methodologies, are biased by the "too big to fail" phenomenon. Therefore, they are not completely reliable as the level of non-performing loans demonstrates. Two activities in banking management are critically related to the rating practices: (i) the firms' appraisal, as the root of a sound credit portfolio management; (ii) the financial reporting, as a key driver to protect the investors' wealth.

A. FIRMS' APPRAISAL

The corporate performance literature introduces the Lintner's model (1965) as an alternative approach to appraise firms and their performance, through the companies' asset-side capability of the management in the long term. The analysis is useful to understand whether there is an appropriate allocation of financial resources, in line with the goodness of the performance and it is important to assess company pay-out and managerial rents as in Lambrecht and Stewart (2012). The theoretical framework replaces the estimation of market risk premia for discounting rates with the use of the certainty equivalent approach. This substitution is possible, because the certainty equivalent of expected cash flows is discounted (at a free-risk rate) instead than the volatile expectations of cash flows (at a risky market rate). Furthermore, it requires a total risk-aversion input to estimate the confident equivalent, instead of the adoption of the systematic-risk-aversion, exactly as applied to a CAL-portfolio, used as benchmark. However, Leibowitz and Heriksson (1989) noted that it is important to consider a shortfall approach that looks more on a "confident equivalent", rather that the Lintner's "certainty equivalent", which is a minimum threshold that may be overpassed, according to a certain confidence percentage. Determining either the threshold and the confidence is up to the investor, even before choosing the investment. Indeed, in banking analysis the downside risk is particularly important since "tail risk" is considered an important component in financial market analysis as underlined in De Nicolò and Lucchetta (2017). Economic cycle may matter. The first to underline the importance of the cycle is Löffler (2004). This author proposes the Kalman filter procedure to distinguish between cyclical component and firm-specific component.

The cited current literature on risk assessment concentrates on corporate firms and the "tail risk" analysis is mainly oriented to macroeconomic risk measures. This paper fills these gaps and contributes to the identification of a synthetic indicator of company performance and long-term creditworthiness, which is also able to take into consideration the investor's risk

aversion and the downside risk component: the “bank tailored integrated rating” (BTIR). This need arises from studies on rating modelling in order to make easier the implementation and use of the results within banking organizations. Indeed, it must be ensured that the indicator has three characteristics: (i) scientifically reliable and (ii) comprehensible to customers, finally (iii) consistent with the credit policies adopted included the new International Financial Reporting Standard (IFRS 9).

B. IFRS 9

The need of a different internal banking rating is consistent with the introduction of IFRS 9, which brought major changes either to firms and banks. The main elements introduced by the principle concern credit risk and forward-looking information.
First, the introduction of the principle influences the credit cycle, by increasing the quantity and quality of information necessary for the appraisal of the application of funds.
Second, IFRS 9 needs historical data, which are an important source of information about credit risk drivers and cash flow. Third, forward looking events that influence the credit risk drivers and should reflect possible differences in the future cash-flows. All information lead to an efficient assessment of credit risk. Beyond micro-level data, IFRS 9 needs to incorporate in the valuation also macroeconomic elements. Taking into account forward-looking information, including macroeconomic factors, is one of the main innovative elements considered in the valuation of credit risk. Indeed, the macroeconomic framework in not only an element of the competitiveness of the environment in which the bank is set, but it becomes a fundamental influence of merit of credit.
The forward-looking approach introduced a certain discontinuity in the already established banking-system frameworks. For this and the above listed reasons, the Bank Tailored Integrated Rating purposely manages to incorporate the characteristics of the principle.

The Integrated Rating (IR, Mantovani et Al., 2015) indicator provides a comparison between the permanent-ROI of a given company indexed by “i” (used as a proxy for company performance) and a benchmark value, called threshold-ROI, computed for the same company according to the confident-equivalent framework. The ROI threshold is calculated through panel regressions, which consider 25 indicators calculated on company balance sheets, which include the income, risk, economic performance, financial management and technological status of the company. The difference between permanent-ROI and threshold-ROI shows how the company performs better (worse) than its target. The target considers the company indicators and the weights of the reference market, that is, the coefficients of the regressions.

To use IR method, the degree of confidence to adopt is required. This leads to investigate its relationship with the risk tolerance of the specific financial institution. The bank specific integrate rating project, here detailed, focus on the development of a mathematical / econometric method that allows us to identify the best algorithm, to determine a fair degree

of convexity and concavity (consequently, the correct degree of risk aversion of the investor), which can be dynamic and adaptable, consequently to heterogeneous banks.
To take into account the characteristics of risk and greater heterogeneity of the banks, we propose a challenge procedure that cluster banks by risk. This further step allows us to design our "bank tailored integrated rating" (BTIR). The approach is inherently coherent with the challenging frontier of forecasting tail risk in financial markets.

The rest of the paper introduces at section II the basic model and the statistical procedure adopted. Section III extends the IR model to the challenging definition of BTIR that better fits risk and heterogeneity of the banking sector. Section IV discusses further developments to better catch the financial cycle. In our example, we show how heterogeneity is important in banks' rating, but the systemic risk is considered implicitly. Therefore, section IV proposes a methodology to deal explicitly with the common factors (for instance using as explanatory variables the Factors of a VAR). Finally, section V concludes.

II. THE BASIC MODEL

In Integrated Rating (Mantovani et Al. 2015), determining either the threshold and the confidence, is up to the investor, even before choosing the investment. Equation (1) explains the relationship between the expected return for a specific investment (i-th) and the confident equivalent return (Rce), supposing a 10% confidence for the overall market:

$$Rce = E(R_i) - Z\sigma_i \qquad (1)$$
$$E(R_i) = Rce + Z\sigma_i$$

Where $Z = \int_{-\infty}^{10\%} f(x)\,dx$

Equation (1) indicates that the investor's risk aversion makes her accept an ex-post return below Rce only once each 10 cases for the entire investment's holding period. The confidence level adopted to estimate Rce relates to the specific investor's risk aversion. This equation is indeed a Shortfall Line according to Leibowitz and Hericksson (1989)

The Capital Allocation Line can be seen as an original case of a Shortfall Line if:

a. The confidence is higher than 50%, since the Sharpe ratio is positive to back investors' risk aversion;
b. A bottom threshold determined at the risk-free rate.

If a risk-free investment is not found, Fisher Black's zero-beta model must be considered to identify the market portfolio through the CAL (Black, 1972). With this methodology, the zero-beta return is seen as a confident equivalent return identified between the market portfolios lying on the efficient frontier; consequently, the slope of the CAL is linked directly

to a probability. In Black's model, in order to determine the downside threshold-return without leading an analytical estimation of the investors' risk aversion, it is adopted a market replicability of zero-beta return through the efficient frontier.

Indeed, as with Linter's certainty equivalent of a specific investment which moves towards the equilibrium as proposed in classic CAPM, similarly the explained confident equivalent for a specific investor directs to the equilibrium as shown in Black's Zero-beta model.

The strong points of this methodology are:

1. Risk aversion is not a punctual data;
2. The estimation of the confident equivalent for a specific investment is sufficient with an ex-ante probability;

These are the fundamentals of change of the original integrated rating and developing our new bank tailored integrated rating, dedicated to the financial institutions combining the expectations of the IFRS 9 legislation.

The methodology considers different characteristics of the financial institution. Although our final aim is to introduce a preselection of variables, our starting point is identifying which are the ratios that do impact the banks' performance and trying to understand whether it is possible to cluster the selected banks, according to their risk level, which we have proxied through two ratios, that will be introduced later.

We have started with a simple panel regression that considers

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \cdots + \beta_n X_{nit} + \epsilon_i$$

Where Y_{it} is a banks' performance indicator and βs are banks' health characteristics.

The explanatory variable that has been chosen to conduct the analysis is a different computation of the Return on Equity. Indeed, ROE is the classic measurement of performance for banks. However, to compute the panel regression, we use a decomposed ROE measure, which considers four different drivers (as suggest by the ECB, 2010): non-recurring assets, leverage, recurring revenues and cost efficiency through the formula:

$$ROE = \frac{Pre - Tax\ Profit}{Op.Income} * \frac{Tot.Assets}{Equity} * \frac{Net\ Revenue}{Tot.Assets} * \frac{Op.Income}{Net\ Revenue}$$

The decomposed ROE considers difference characteristics of performance. For this reason, it is more suitable for the specific purposes of the analysis.
The independent variables are made up of indexes that inform about different characteristics of the bank. In particular, there are 26 indexes concerning: asset quality, capital, operations, liquidity and structure.

ASSET QUALITY

In order to measure the asset quality of banks, we consider:

- Loan loss reserves on Gross Loans (%);
- Loan Loss Provisions on Net Int. Rev. (%);
- Loan Loss Reserves on NPLs (%);
- NPLs on Gross Loans (%);
- NCO on Average Gross Loans (%);
- NCO on Net Income before Loan Loss Provision (%);
- Impaired Loans on Equity (%).

CAPITAL RATIOS

- Total Capital Ratio (%);
- Equity on Total Assets (%);
- Equity on Net Loans (%);
- Equity on Liabilities (%).

OPERATIONS RATIOS

- Profit Margin (%);
- Net Interest Margin (%);
- Net Interest Rev. on Avg Assets (%);
- Non Int. Exp. On Avg Assets (%);
- Pre-Tax Op. Inc. on Avg Assets (%);
- ROA using Net Income (%);
- Cost to Income Ratio (%);
- Recurring Earning Power (%);

LIQUIDITY RATIOS

- Interbank Ratio (%);
- Net Loans on Total Assets (%);
- Net Loans on Dep. & ST Funding (%);
- Liquid Assets on Dep. & ST Funding (%).

STRUCTURE RATIO

- Solvency Ratio (asset-based) (%).

III. THE CLUSTERING

After leading the regression, banks needed to be clustered according to their risk level and their BTIR level.

First, in order to rank banks according to the bank tailored integrated rating, we consider the results from the panel which give us a Threshold ROE $[T(ROE)]$, that must be compared to a Permanent ROE $[P(ROE)]$, an average of the ROE ratio through years. The positive $[\mathrm{P(ROE)} > \mathrm{T(ROE)}]$ and negative $[\mathrm{P(ROE)} < \mathrm{T(ROE)}]$ ratings are then compared to risk

ratios, proxied by “Non-Performing Loans on Gross Loans” and “Non-Performing Loans on Total Assets”.

In order to get a more comprehensible reading of the results, a transformation is needed for the difference between the Permanent and the Threshold ROE to make it usable even to non-academic individuals. We state the following proposition.

Proposition 1. *Consider the bank (firm)“i”, it is possible to design its integrated rating IR based on a robust model ranking firms’ performance.*

Proof. The logistic function spread in Mathematics and Statistics is a useful instrument, in order to apply the transformation. The function is defined as:

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

For all the real values of x with codomain $[0, L > 0]$, with inflection point in x_0 and with slope $k > 0$.
The simplest case is the logistic function defined as in the codomain [0,1], with inflection in $x = 0$:

$$f(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{e^x + 1}$$

Graphically, it is represented as:

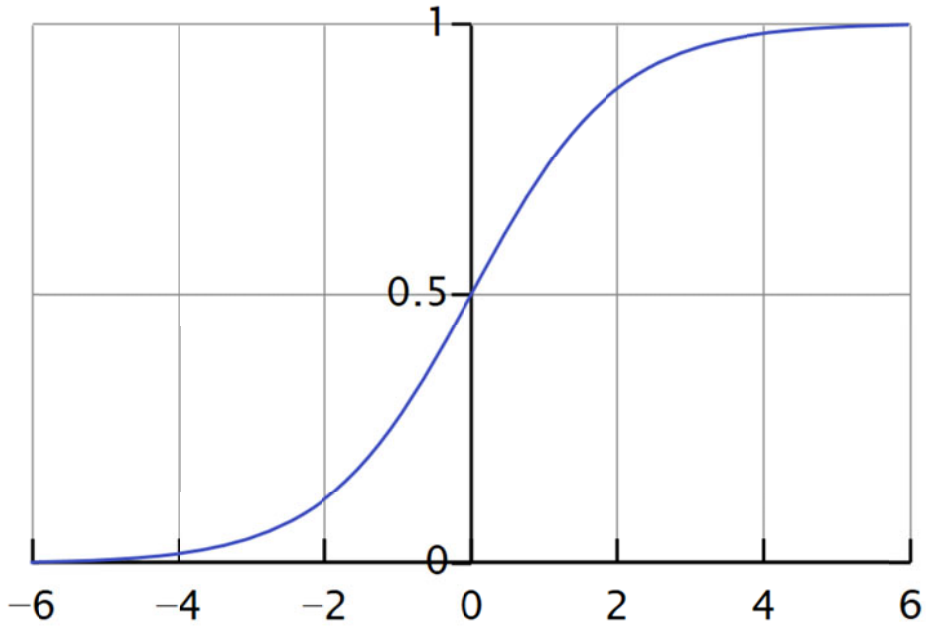

Figure 1: Graphic representation of the logistic function

In the case of integrated rating, the variable X is the difference between Permanent ROE and Threshold ROE, in a way that $f(x)$ becomes an indicator in a close and limited interval, with a clear interpretation.

The transformation belongs to the interval $[-1,1]$ and the preserving of the algebraic difference. A useful modification of the logistic function might be the following:

$$f(x) = \frac{2}{1 + e^{-x}} - 1$$

In this case, $f(x)$ is in the interval $[-1,1]$ with a unitary curve. A multiplying constant in the exponential component (e.g., e^{-2x}) change the degree of the function slope, changing the way in which the data might be discriminated, comparing them to more extreme values.

Then, it is straightforward to hypothesise the following distribution for the rating indicator:

- BTIR $\in \left[-1, -\frac{1}{2}\right]$ the bank has performed very bad, and the rating leads to a negative merit of credit valuation
- BTIR $\in (-\frac{1}{2}, 0]$ the bank has performed bad, but it is not the only one in the sample.
- BTIR $\in (0, \frac{1}{2}]$ the bank has performed in a good way, but it has not overpassed the expectations
- BTIR $\in (\frac{1}{2}, 1]$ the bank has over-performed, compared to the benchmark.

IV. EXTENDING RI TO THE BANK TAILORED INTEGRATED RATING BY CLUSTER OF BANKS: BTIR

This section shows how to cluster banks and illustrates a first simple procedure to deal with banks' heterogeneity. We would like to point out that systemic risk is implicitly considered, and clustering concerns the effective diversity of banks. Next, we explain how to insert, for example through the factors of a VAR, the systemic component. Actually, our purpose is to demonstrate that the subset procedures are needed to consider the inevitable difference between banks.

We analyze a sample of 227 Italian banks extracted by ORBIS database (edited by Bureau Van Dijck). This basic example is the origin of what the Bank Tailored Integrated Rating is. The selected banks have as last year of accounts 2016; the banks do show details of their balance sheets for 6 years, in particular, 2016, 2015, 2014, 2013, 2012 and 2011. The estimations are performing using a panel regression, whose coefficients will be used to compute the measure of the rating.

The following table shows the main estimation results.

Table 1: Panel regression with decomposed ROE as dependent variable and ratios describing the major characteristics of the banks as independent variables.

	Coefficients
Intercept	21,1780 *** 1,5268
NPL/Gross Loans	-0,1550 *** 0,0353
NPL/Tot. Assets	1,1367 *** 0,0707
NCO/Avg Gross Loans	0,2954 *** 0,0872
NCO/Net Inc. bef. Ln Lss Prov.	-0,0028 *** 0,0008
Impaired Loans/Equity	-0,0789 *** 0,0038
Equity/Net Loans	-0,0625 *** 0,0176
Equity/Tot. Liab.	4,5427 *** 0,3062
Profit Marg.	0,1510 *** 0,0115
Net Int. Rev. /Avg Ass.	-0,3912 * 0,1613
Non Int. Exp. Avg Ass.	1,2895 *** 0,2909
Pre-Tax Op. Inc./Avg Ass.	3,2931 *** 0,4963
ROA	6,9032 *** 0,5271
Cost to Inc.	-0,0355 . 0,0196
Recurr. Earn. Power	-1,3532 * 0,6156
Net Loans/Tot. Ass.	-0,0544 *** 0,0107
Solvency	-6,8087 *** 0,4127
Signif. codes: 0 ‘***’ 0,001 ‘**’ 0,01 ‘*’ 0,05 ‘.’ 0,1 ‘ ’ 1	
Total Sum of Squares: 90259	
Residual Sum of Squares: 6964,1	
R-Squared: 0,92284	
Adj. R-Squared: 0,92193	
F-statistic: 1005,44 on 16 and 1345 DF, p-value: < 2,22e-16	

The panel regression conveys that all the independent variables are significative, with a significance level of 0,1%, apart from Net Int. Rev. on Avg Assets (5%), Recurring Earning Power (5%), Cost to Income (10%) and Loan loss reserves on Gross Loans, Loan Loss Provisions on Net Int. Rev, Loan Loss Reserves on NPLs, Total Capital Ratio, Equity on Total Assets, Net Interest Margin, Interbank Ratio, Net Loans on Dep. & ST Funding and Liquid Assets on Dep. & ST Funding which are not significant and, consequently, their coefficients will not be used in the computation of the "Threshold ROE".

In order to investigate the goodness of the banks, we have considered two measures and we have created four different clusters of banks for each indicator: (i) Non-Performing Loans/Gross Loans, where the four clusters are: "good", for the interval [0 to 7%); "not so good", for [8% to 15%); "bad", for [16% to 23%); "very bad", for [24% to 30%]; (ii) Non-Performing Loans/Tot. Assets where the four clusters are: "good", for the interval [0 to 6%); "not so good", for [7% to 13%); "bad", for [14% to 20%); "very bad", for [21% to 25%].

The following schemes show the results for the two indicators taken as benchmark. The two matrixes give a very small result of the first version of the Integrated Rating on banks. With the original version proposed in the paper the methodology used is quite different.

NON-PERFOMING LOANS ON GROSS LOANS

	GOOD	NOT SO GOOD	BAD	VERY BAD	
POSITVE RATING	17	38	38	5	98
NEGATIVE RATING	25	61	39	4	129
	42	99	77	9	227

	GOOD	NOT SO GOOD	BAD	VERY BAD	
POSITVE RATING	7,49%	16,74%	16,74%	2,20%	43,17%
NEGATIVE RATING	11,01%	26,87%	17,18%	1,76%	56,83%
	18,50%	43,61%	33,92%	3,96%	100,00%

NON-PERFORMING LOANS ON TOTAL ASSETS

	GOOD	NOT SO GOOD	BAD	VERY BAD	
POSITVE RATING	21	65	12	0	98
NEGATIVE RATING	42	72	14	1	129
	63	137	26	1	226

	GOOD	NOT SO GOOD	BAD	VERY BAD	
POSITVE RATING	9,29%	28,76%	5,31%	0,00%	43,36%
NEGATIVE RATING	18,58%	31,86%	6,19%	0,44%	57,08%
	27,88%	60,62%	11,50%	0,44%	100,00%

V. FUTURE DEVELOPMENTS TO BETTER CATCH THE FINANCIAL CYCLE

Through this procedure we adapt the Integrated Rating according to the banks' characteristics, which allows us to apply the RI tailored on bank's selected variables. In particular, riskiness is a crucial element that needs to be considered; indeed, banks are extremely riskier and more heterogeneous, comparing them to normal enterprises. Past researches already considered these special characteristics belonging to banks and they tried to select banks ex-ante, through a quantile regression, which provides an endogenous risk index (Koenker and Hallock, 2001). Furthermore, more recent researches preselected banks' default risk in two different ways: (i) through a CoVAR to analyse which banks are riskier (Tobias and Brunnermeier, 2016) (ii) through a measure of tail risk, which indicates that banks are different from enterprises, because of this excessive risk, named "tail risk" (De Nicolò and Lucchetta, 2017).

The model that we may chose, in order to conduct a further bank pre-selection is the VAR model that allows to extract the common factors, called Factor VAR. The VAR model is a powerful instrument to preselect the important xs and it is not a usual instrument in this field, indeed it is usually applied in researches about financial markets or corporate finance.

The BTIR is an important innovation which allows through the factor VAR model to consider the diversities across banks and the condition of global risk, by selecting the xs through VAR factors.

Proposition 2. *Consider the bank "i", it is possible to design its BTIR based on the robust model that extends the RI preselecting the variables though a factor VAR methodology.*

Proposition 2 underlines a challenging framework that consist in pre-selecting or clustering the relevant banks' variables though a simple factor VAR model.

VI. CONCLUSION

The current development of ever-increasing banking regulations requires the study and the development of rating methods that take into account the increasing heterogeneity of banks while facing the presence of systemic risk, in addition to the ongoing contagion relations between financial institutions. This leads to more effective financial reporting in the foreground the new IFRS 9, as well. Also, the traditional and simple capital regulatory policies imposed on banking institutions, increasingly reveal the need to consider the heterogeneity of regulated entities and, at the same time, to avoid obvious errors above or under assessment of the risks inherent in the various business models of modern banks.

Our work considers the extension of the integrated rating (IR) procedure (Mantovani et Al., 2015), used primarily for non-financial companies, developing the "bank tailored integrated rating" (BTIR). The approach is inherently coherent with the challenging frontier of forecasting tail risk in financial markets (De Nicolò and Lucchetta, 2017) since it considers the downside risk in the theoretical framework. The innovation consists in a clustering of banks according to their risk level and rating's ranking, through a statistical procedure that takes into account the characteristics of risk and greater heterogeneity of the banks.

In this first proposal, we use a simple panel regression that clusters bank by heterogeneity and considers systemic risk implicitly. Moreover, we consider that using balance sheets might bring to a slight loss in the quality of data, due to the potential errors in the balance sheets. However, our innovative procedure may include, in the future, more sophisticated pre-selection of variables such as Factor VAR (FAVAR). This work requires testing whether a more sophisticated pre-selection model is better than a traditional VAR. In fact, for simplicity, we believe that starting with a simple methodology is the first step of research.

BTIR makes possible to adapt the rating procedures to all banks, even that showing very different characteristics. In fact, the VAR allows to pre-select and to evaluate markets with high systemic risk, avoiding errors due to general market conditions that may differ from country to country.

In conclusion, BTIR opens the door to a new research line to innovative ideas for the development of increasingly accurate ratings for banks embedding the needs of macro- and micro-prudential policies.

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