Interest rate risk and bank internal capital: what implications from the new supervisory framework?

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Abstract

This paper contributes to the prior literature and to the current debate concerning the revision of the prudential supervisory framework to measuring interest rate risk in the banking book (IRRBB). The objective of the paper is twofold. Firstly, we shed more light on the main innovation of the regulatory framework. Secondly, we address major issues in assessing the appropriate amount of capital that banks should set aside against this specific risk. Studying a sample of representative Italian less significant commercial banks between 2006 and 2019, we show that the greater prudential intensity of the new regulatory framework allows to avoid some drawbacks of previous simplified methodology and leads on average to a higher risk exposure measure. However, according to our back-testing approach, historial and Monte Carlo simulations seem to get an amount of internal capital more adequate than that obtained through the application of regulatory scenarios. Overall, our results provide useful insights for properly measuring the amount of internal capital to cover interest rate risk, suggesting the use of simulation techniques in ordinary condition and the criterion of the most penalizing scenario within a stress test environment.

1. Introduction

Since the '80s, Supervisory Authorities have been very concerned with interest rate risk in the banking book due to its systemic nature that can undermine the global financial stability. Bank's exposure to this type of risk depends on the maturity transformation activity that still lies at the heart of the modern commercial banking business. Right after the savings and loan crisis, the U.S. Federal Reserve (FED) developed the Economic Value Model (EVM), which measures IRRBB through the changes in a bank's economic value of equity (EVE) via a duration-based estimate of interest rate sensitivity [see Houpt and Embersit (1991); Sierra and Yeager (2004), Wright and Houpt, (1996) and Sierra (2009)]. Following the Fed's approach, BCBS (2004) had adopted an accounting-based duration model which requires: i) the allocation of both on and off-balance sheet interest rates sensitive items into 14 time bands to which are associated specific duration coefficients; ii) the application of standardized shock in interest rates given by a +/- 200 basis point parallel shift in the yield curve for all maturities (the parallel shift method) or by the 1st and 99th percentile of observed interest rate changes using a one-year holding period and a minimum five years of observations (the percentiles method); iii) the calculation of a risk indicators given by the ratio between the changes in bank's EVE following the application of the scenarios to the previous point ii) and the regulatory capital; and iv) the set of an alert threshold equal to 20% to identify the so-called outlier banks.

The methodological framework used also required the application of the non-negativity constraint according to which the negative changes in interest rates scenarios cannot drive the term structure of interest rates under the zero level. The drawbakcs of the BCBS (2004) framework have been pointed out non only by academic research by mainly testing its underlying assumptions [see Fiori and Iannotti (2007), Entrop et al. (2008), Entrop et al. (2009), Abdymomunov and Gerlach (2014), Cocozza et al. (2015) and Cerrone et al. (2017)] but also by the same regularors [see BCBS (2009)]. Particularly, the financial and macro-economic scenario characterized in the recent years by low, and in same case negatives, level of interest rates impacted on the risk indicator determining distorting effects that gave rise, due to the application of non-negative constraint, to the risk neutrality phenomenon as showed for the first time by Cocozza et al (2015). It is to say banks that experience an increase in their equity value in both the two scenarios of changes in interest rates considered within the parallel shift and/or the percentile method.

In April 2016 BCBS published an updated version of its standards on the management of IRRBB previously published in 2004 to reflect changes in markets and supervisory policy experienced over time. The BCBS standards confirmed the Pillar II approach to IRRBB given its heterogeneous nature and introduced some new elements in its measurement and management from a regulatory perspective among which the most important are: i) the new six scenarios of changes in interest rates represented, respectively, by parallel shock up and down, short rate shock up and down, steepener shock and flattener shock; and ii) a new methodology based on the criterion of the present value under continuous capitalization scheme to replace the duration coefficients. The other regulatory changes concern the number of time bands, the modeling of the optionality embedded in the balance sheet items and the reduction of the threshold within the SOT from 20% of Own Funds to 15% of Tier 1 Capital following the application of the scenarios referred to the previous point i).

BCSB (2016) standards will be implemented within the EU in two phases: first through the update of the EBA guidelines in July 2018 in those areas where the supervisor felt the need for a more practical approach; secondly following the revision of CRR and CRD approved in June 2019 that gives mandate to EBA to develop several Regylatory Tecnhincal Standards (RTS) and a further update of the guidelines to regulate in detail the whole new IRRBB methodological framework. Particularly, the update version of IRRBB guidelines in July 2018 introduce other specific elements compared to BSBC (2016) standards to calculate the impact on EVE under the SOT among which the most important is the removal of the non-negative constraint and the contextual introduction of a negative floor starting with -100 basis points for immediate maturieties within 1 year which gradually grows by 5 basis points per year up to zero level at the last time band of maturity ladder (the so-called lower bound EBA). The provisions set out in the EBA (2018) were implemented in Italy through the updating of Circular 285 by the Bank of Italy.

Recently, in decembre 2021 EBA published for consultation two different RTS. The former specifies the criteria to be used within the SOT for bot economic value (EVE) and net interest income (NII) approach as well as provide a definition and calibration of large decline for the SOT on NII. Particularly, this draft takes also into account the current low interest rate environment and consequentially propose to modify the above mentioned lower-bound EBA considering a negative floor starting with -150 basis points for immediate maturities within 1 year that increase by 3 basis points per year reaching the zero level for maturities of 50 years and more. The latter develop in detail the standardized methodology fro both EVE and NII approach as well as the simplified version for non-complex entities. In the same date, EBA also published for consultation an update version of guidelines in which are declined specific criteria for determining whether the internal systems implemented by banks for the purpose of evaluating IRRBB can be considered satisfactory and for the assessment and monitoring of credit spread risk arising from non trading book activities.

Within their Internal Capital Adequacy Assessment Process (ICAAP), banks use to set aside against IRRBB an amount of internal capital corresponding to the numerator of the previously mentioned risk indicator, i.e., the change in banks' EVE due to an interest rate shock. The evidence in terms of IRRBB are analyzed by supervisory authorities within the Supervisory Review and Evaluation Process (SREP) that lead to definition for each bank of the minimum regulatory requirements on solvency indicators. They are given by the sum of four components described in detail in EBA (2018) and represented, on the one hand, by the minimum capital requirement calculated on fist pillar risk and the combined buffer requirement that are exogenous from bank's perspective as they are defined by prudential regulations, and, on the other hand, by the additional requirements calculated on second pillar risk and the capital guidance that are instead functions of overall bank's risk profile to which contribute IRRBB too. It is important to underline that the minimum regulatory requirements on solvency indicators must be satisfied by banks taking into account only first pillar risks, but they are calculated by regulatory authorithies, as described above, also considering bank's exposure to second pillar risks. Therefore, a lower (higher) exposure to IRRBB deriving from the new regulatory framework could lead to a descrease (increase) in the minimum requirements defined by supervisoty authorities within SREP process and consequentially impact bank's business. This is of relevance especially for small and medium banks, which, according to the proportionality principle, underlying the prudenzial regulatory framework, should generally use the standardized methodology.

The issues above described imply that inappropriate estimates of IRRBB could lead banks to set aside an amount of internal capital that either underestimate or overestimate a bank's actual riskiness, with potentially negative consequences in both cases. Underestimation might provide poor indications in a assets and liabilities management perspective driving banks to take excessive risk through the implementation of new inappropriate operations and thus undermine global stability, whereas overestimation might reduce credit supply to the economy since the granting of new loans is function of the free capital available and so prevent bank from implementing profitable activities.

This paper is part of the research line that address the robustness of the methodology proposed by Basel (2004) and aims to analyze on a sample of 30 small and medium-sized Italian commercial banks in the period 2006-2019 the impact of the main changes introduced by the new regulatory framework represented, also according a comparison with practitiones, by the introduction of: i) the new six scenarios of changes in interest rates; ii) the methodological framework based on present value criterion under a continuous capitalization scheme and iii) the lower bound EBA. The long period allows us to analyze the application of new regulatory framework in different interest rate environment scenarios taking also into accout the evolution banks' maturity structures over time. Particularly, the monetary policy measures put in place by the European Central Bank (ECB) following the various crises that have occurred over the last decades have changed banks' asset & liability management strategies (ALM) determining, on the asset side, an increased of securities hold in portfolio and on the liabilities side a different composition of funding with higher recourse to financing from the ECB itself. The attention is intentionally focused on the main 30 small and medium-sized Italian commercial banks that, according to the proportionality principle, should use the standardized methodology within their capital adequacy process unliked large banks which instead generally use internal models.

We also further develop the back-testing procedure proposed by Cerrone et al (2017) that trace back to the loss function introduced by Lopez (1996) to compare the evidence deriving from the application of the regulatory methodologies and those obtained using more sophisticated tecniques such as historial and Monte Carlo simulation with the actual bank risk exposure calculated under the effective evolution of interest rates in a one-year time horizon starting the evaluation date. Since the results of a Monte Carlo simulation may depend on the specific sample of simulated scenarios, we also calculate the confidenze intervals according to the procedure proposed by Gupton, Finger and Bhatia (1997) to define a range of values in which, by carrying out the simulation several times, the results are placed with a certain level of confidence. In addition, we take into account the expected shortfall measure associated to the two simulation tecniquies used to capture the average of the values exceeding the chosen percentile.

Furthermore, we designed a new loss function which can assume various functional forms according to the different weight associated to regulators and industry concerns in estimating IRRBB represented by the need to ensure financial stability and at the same time to set aside an amont of internal capital consistent with the actual riskness and consequentiallty provide an adequate supply of credit to the economy. In this way we add a contribute to the existing literature concerning the development of alternatrive loss functions within back-testing procedures [see Sarma et al (2003), Caporin (2008), Sener et al (2012), Abad et al (2015), Cerrone et al (2017)]. Finally, given a specific functional form of the loss function designed, a non-parametric sign test is carried out to verify the superiority of one methodology over another.

To our knowledge this is the first paper that analyze in an integrated manner the implications deriving from the new IRRBB regulatory framework. Our results shows that the regulatory innovations lead to a greater prudential intensity due to the elimination of the risk neutrality phenomenon and the generally increase in average banks exposure. The empirical evidence obtained also raise the question about how methodology to be used by banks in assessing their capital adequacy given the relevant micro and macro implications described above as weel as the discretion margins provided by prudential regulations within Basel second pillar. In this context, two different approaches can be identified. The former which determines, in a prudential perspective, the internal capital in ordinary conditions by referring to the most penalizing scenario among the regulatory ones. The latter which calculates, in a managerial perspective, the internal capital in ordinary conditions according to a logic of plausibility with respect to the past and or the expected changes in interest rates taking also into account the related economic and financial outlook. Therefore, the use of regulatory scenarios as more severe than those deemed plausible would be more appropriate, according this second approach, within stress test framework.

The paper is organized as follow. Section 2 described the scant relate literature examining the hyphotheses underlying the previous regulatory framework proposed by BCBS (2004); section 3 provides an overview of the current regulatory framework, focusing attention on the evolution of regulatory framework, and backtesting methodogies used in our analysis; section 4 presents data about our sample banks and interest rate environment; section 5 provides empirical evidences concerning the the implication deriving the application of new regulatory framework and the back-tesitng results. Section 6 concludes with the related policy implications

2. Literature review

This research can be traced back to a scant stream of literature analyzing the main hypotheses underlying the regulatory framework proposed by Basel Committee on Banking Supervione on IRRBB. The previous literature showed the drawbaks of the regulatory framework proposed by BCSBS (2004) [see Fiori and Iannotti (2007), Entrop et al (2008), Entrop et al (2009), Cocozza et al (2015), Cerrone et al. (2017)] for different point of view. These works stimulated over time the activity of Supervisors to improve the existing regulation framework and, at the same time, the practitionars in adapting their risk management policies to the supervory guidelines. In addition, it is also provided a review of the literature relating to the works that have used the evidence of the regulatory methodologies within econometric framework to study the risk exposure determinants such ad Esposito et al (2015), Chauldron (2018) and Hoffmann et al (2019).

Fiori and Iannotti (2007) developed a Value at Risk (VaR) methodology based on a principal component Monte Carlo simulation, taking into account: i) both symmetry and kurtosis of the interest rate distribution by applying a specific technique of local smooting; and ii) non only the concept of duration but also on that of convexity. By analizing a sample of the eighteen major Italian banks, they show that their results are consistent with the results obtained through the parallel scenario of +/- 200 bp if the regulatory duration coefficients are calibrated on the basis of current market data at the evaluation date.

Entrop et al (2008) developed the so-called times-series accounting based model (TAM) to estimate the distribution of bank's assets and liabilities within each time band of regulatory maturity ladder by using a time series' accounting-based data. Referring to a sample of German banks, the authors show that TAM is able to explain the cross-sectional variation in bank's interest rate risk better that the regulatory methodology proposed by BCBS (2014) based on point-in-time data and provides results that are more line with those obtained by banks' internal models.

Entrop et al (2009) analyzed how bank's risk exposure changes if some of main assumption underlying the regulatory model are modified. In details, they considered: i) the distribution of non-maturity deposits and into the time bands; ii) the allocation of assets and liabilities within the time band; iii) the number and boundaries of the time bands; iv) the amortization rate of customer loans and v) the spread between the coupon and the market interest rates used to calculate the modified duration associated with each time bands. By considering the aggregated German universal banking systems, the authors found that bank's risk exposure depends significantly on the assumption underlying the regulatory framework. Therefore, they warned that results coming fromt the regulatory framework should be treated with caution when used for supervisory and risk management purpose.

Abymomuvov and Gerlach (2014) proposed a new methodology for generating yield-curve scenarios for stress testing bank's exposure to interest rate risk based on Nielson-Siegel (1997) yield curve model. By considering an aggregated bank's balance sheet based on Call Report data from a sample of large United States banks, the authors show that their methodology produces scenarios with a wider variety of slopes and shapes than others generated by internal methods commonly used in industry and proposed in literature including the regulatory methodologies of +/-200bp parallel shift. the authors. Furthermore, the authors pointed out that their methodology is more appropriate in a stress test where the other method above mentioned can lead to ad underestimation of bank's exposure. Their methodology is also superior for conducting reserve stress tesing.

Cocozza et al (2015) develpoted a methodology to allote non-maturity deposits in the time bands of maturity ladder that consider their actual behaviour in terms of both price sensitivity to change in market rates and volume stability over time. By considering a sample of 30 italian commercial banks the authors show that different criteria to allocate non-maturity deposits could impact not only on the size of the risk indicator but also on the nature of risk exposure (asset sensitive vs liability sensitive). Their results confirm the importance of accurate modelling of non-maturity deposits for estimating interest rate risk in the banking book. Furthermore, in their analysis the authors discovered the presence of risk-neutral banks in a low interest rates environment. It is to say banks that appear to experience an increase in their equity economic value whether interest rates decrease or increase under the parallel shifts method.

Cerrone et al (2017) discuss how banks might adapt internal measurement systems based on simulation technique to face the risk-neutrality phenomen detected by Cocozza et al. (2015) and consequentially developed a back-testing procedure, modifying the original framework proposed by Lopez (1996) in the IRRBB perspective, to test the consistency of regulatory and simulation methodologies results with the actual bank risk exposure. By considering a representative sample of 130 Italian banks between 2006 and 2013 they showed that simulation teqniques performe better those regulatory methodologies. The results obtained supported the need to improve the standardized shocks currently in force and provide useful insight for proprerly measuring the amount of capital to cover interest rate risk that is sufficient to ensure both financial system functioning and banking stability.

Esposito et al. (2015) measure interest rate risk using the duration gap approach proposed by the BCBS. Based on a representative sample of 68 Italian intermediaries observed from the second half of 2008 to the first half of 2012, they show that Italian banking system has a limited exposure to interest rate risk. Italian banks have managed this risk by using changes in their balance-sheet exposure and interest rate derivatives as substitute. Their results suggest a substantial heterogeneity in banks' risk management practices. On the one hand, one third of the banks, namely the smaller ones and those characterized by a traditional business activity, follow an integrated risk management approach aiming at counterbalance interest rate risk and credit risk. On the other hand, most Italian banks tend to enhance the gains from an increase in interest rates also in the face of a widening of the funding gap.

Chaudron (2018) detects the interest-rate risk position of 42 Dutch banks during the 2008 – mid-2015. The author uses confidential quarterly data on interest rate risk in the banking book collected by the Dutch Central Bank and investigates how bank risk position changes over time, how much of banks' returns on assets and net interest margins depend on income from maturity transformation and which factors influence their interest-rate risk position. As far as the last issue is concerned, interest-rate risk positions are negatively related to on-balance sheet leverage, exhibit a U-shaped relation with solvability, and do not vary systematically with the size of the banks. Finally, banks that received government help during the crisis took on greater interest rate risk.

Hoffmann et al. (2019) focus their studies on interest rate risk by analyzing it with three different measures. The sample is made up of 104 banks from 18 Euro Area countries and supervised by the European Central Bank (ECB). Their work considers two important pieces of information provided by the supervisory authority. The first is represented by on balance-sheet exposures of all banks that provides a detailed breakdown of so-called repricing cash flows across 14 maturity buckets for key banking book items. The second provides transaction-level information on banks' positions in the interest rate derivatives market. The results reached by the authors, in part, are discordant with respect. On the contrary to what is stated by the traditional view, it is found that a higher interest rate has benefits in terms of equity and income.

Furthermore, they demonstrate what the possible determinants of banks' exposure to interest rate risk may be through the analysis of the mortgage market in which they detect, comparing the countries in which fixed-rate contracts prevail with those in which, at the on the contrary, they predominate at variable rates. Consistent with mortgage markets as a relevant channel, thet find that the change is driven by banks with a larger share of retail loans, which are predominantly mortgages. In further tests, they show that the systematic cross-country heterogeneity in asset-side exposures is due to loans, not securities, and is robust to control heterogeneity on the liability side. Finally, they show that only 25% of banks that use swap options to hedge against risk reduce their exposure. These results bring novelty compared to other studies in that the authors use a series of data made available by the European supervisory authority relating to the prices of cash flows deriving from the assets and liabilities of banks, and information on the level of transactions on the positions of the banks. banks. in the interest rate derivatives market.

3. Methodology

3.1. The regulatory framework

The standardized methodology declined by Bank of Italy (2013) on the basis on BCBS (2004) required banks to allocate on and off-balance sheet items into 14-time bands of a maturity ladder. Overall, floating rate assets and liabilities are slotted into the time bands based on their next repricing day, whereas fixed-rate accounts are assigned according to their residual maturity. As concern non-maturity the non-core component set equal to 25% of the total amount is allocated in the demande and revocable time band. The remaining amount, which can be considered the core component, is allotted to in the time bands from 1 months to 5 years in proportion the number of months included in each of them. By assuming that on and off-balance sheet accounts have a maturity exactely coinciding with the midpoint of each time band i to which thery are allotted, IRRBB is measured through predeterminated sensitivity coefficients, i.e. modified duration coefficients (MDi). Assets and liabilities are offset to calculate net positions (NPi), the corresponding MDi and the assumerd interest rate shock (Δr). The resulting net weighted positions are then summed up across the different time bands to calculate the change in a bank's EVE, which is finally divided by the bank Own Fund to obtain a risk indicator (RI) whose alert threshold is set equal to 20%.

$$RI = \frac{\sum_{i=1}^{14} NP_i \cdot DM_i \cdot \Delta r}{OF} \quad (1.)$$

Under the parallle shifts method, Δr is given by +-200 bp parallel shift for all the time bands of maturity ladder. According to the percentiles method, the interest rate shock is based on the 1st and 99th percentiles of the yearly interest rate change, obtained by using the overlapping data technique with a one year holding period and a minimum five years of observations (BCBS, 2004). Based on the so-called non-negativity constraint, negative shocks in interest rates cannot drive the term structure of the observed interest rates below the zero level. The correct application of the non-negativity constraint was subsequently regulated through the EBA FAQ published in July 2017.

The duration coefficients are calculated for the time bands up to 1 years as the modified duraton of a zero-coupon bond that expires in the mid-point of various time bands. For time bands greater that 1 years the duration coefficients is equal do the modified duration of a security that expire in the mid-point of various time bands with annual coupon set equal to 5%. In both cases, a costant discount rate equal to 5% for all the node of term structure is assumed. The duration coefficients used are not related to the term structure of interest rates observed at the valuation date.

The parallel shifts method is set regardless of actual changes in interest rates. In this respect, the two scenarios corresponding to the 1st and 99th percentiles are changes that occurred. Nevertheless, these changes might have occurred in different days and/or years. For example, the 1st percentile might refer to January 22nd, 2018 for the interest rate of a specific time band and to December 23rd, 2019 for the interest rate associated with another time band, etc. Therefore, just like the parallel shifts, the percentiles method does not account for the correlations observed among the annual changes in the interest rates.

According to the new Basel Regulatory Framework declined by BCBS (2016) and subsequently implemented by EBA (2018) banks should apply six interest rate shock scenarios for measuring their exposure to the IRRBB in the EVE perspective within the SOT. The six interest rate shock scenarios are: i) parallel shock up; ii) parallel shock down; iii) steepener shock; iv) flattener shock; v) short rate shock up; and vi) short rate shock down. The parallel shock up and down scenarios are characterized by costant change in interest rates across all time buckets of maturity ladder. It is interesting to highlight that for the euro currency the new parallel shock scenarios coincide with those already required by regulatory framework of +/-200 basis points. The short rates shock up and down are symmetric scenarios characterized by positive (negative) change which gradually decrease from 250 basis points in correspondence to demande and revocable time band to 0 basis point in correspondence more than 20 years time band. The steepener (flattener) shock are asymmetric scenarios characterized by negative (positive) change which gradually decrease from the demand and revocable to from 3 to 4 years (from 4 to 5 years) time band and positive (negative) change which gradually increase from 4 to 5 (from 5 to 7 years) untill more than 20 years time band.

Subsequently, EBA (2018) removed the non-negative constraint introducing a lower bound of -100 basis points for maturities of less than 1 year, which increases by 5 basis points each year until reaches 0% for maturities beyond 20 years. Recently, EBA (2021) propose to revise the above described lower bound by introducing a negative floor starting with -150 basis points for immediate maturities within 1 year that increase by 3 basis points per year reaching the zero level for maturities of 50 years and more. Generally, the application of the lower bound follows regardless the size of initial floor and annual changes, the same logic reported in the EBA FAQ pubblished in July 2017 as concern non-negative constraint. Finally, it is interesting to highlight that the new regulatory framework developed by BCBS (2016) and EBA (2018) no longer contemplates the percentile method which, instead, is still considered in Bank of Italy (2013). The following table 1 report the six new interest rate scenarios defined by BCBS (2016) before and after the application of the non-negativity constraint and the lower bound EBA calculated taking into account the term structure of interest rates in force at the reporting date of 31/12/2020.

(Insert Table 1)

The new methodology proposed by BCSB (2016) requires the use of speficic continuously compuded discount factors $DF_{0,c}$ and $DF_{i,c}$ calculated, rispectively, on the basis of currently term structures of interest rates ($R_{0,c}$) and of the currently term structures of interest rates modified to take into account the changes in interest rates taken into account by the various scenarios i considered ($R_{i,c}$). In formulas:

$$DF_{0,c}(t_k) = exp\left(-R_{0,c}(t_k) * t_k\right) \quad (2.)$$

$$DF_{i,c}(t_k) = exp\left(-R_{i,c}(t_k) * t_k\right) \quad (3.)$$

Where t_k is the time bucket mid-point. It is important to note that discount factor used are related to the term structure of interest rates observed at the valuation date compared to the duration coefficients used in the previous framework and explained in the previous paragrafh 3.1. For a given currency c, the net positions (NPi) in each time bucket are weighted by a the discount factors of previous formulas in order to calculate the net present value of banking book portafolio on the basis of the currently term structures of interest rates ($EVE_{0,c}$) and subsequentely the application of the specific scenario i ($EVE_{i,c}$). In formulas:

$$EVE_{0,c} = \sum_{k=1}^{K} NP_{0,c}(k) * DF_{0,c}(t_k) \quad (4.)$$

$$EVE_{i,c} = \sum_{k=1}^{K} NP_{i,c}(k) * DF_{i,c}(t_k) \quad (5.)$$

Then the change in economic value in currency c associated with scenario i is obtained by subtracting equation (10.) to equation (9.). A positive difference represents a reduction in economic value of equity. Thas is because the net present value calculated according to the term structures if interest rates pre-shock is greater than that calculated after the application of specific scenario i.

Finally, is importanto to highlight that according BCBS (2016) that automatic interest rate options, as for example cap and floor emedded in banking products are excluded from the above calculation of formulas (9.) and (10.) and taken into account separately. This issue, however, will be defined by EBA through the the technical standards that will published later and supposedly, according to proportionality principle, will concerne mainly large banks those adope internal models. For these reasons, we consider items characterized by automatic and other option in linea with the previous framework.

Finally, it is important to underline, in fact, that following the adoption of new methodology proposed by BCBS (2016), the impact of the scenario of +/- 200 basis points is no longer, in the absence of a regulatory floor, symmetrical as it happens under the application of duration coefficients. That is given the exponential nature of the discount factor which, all other conditions being equal, leads to higher values of the post-shock discount factor in correspondence with negative changes in interest rates. This also means that the application of the regulatory floor is no longer a necessary condition for the phenomenon of neutrality.

3.2. Historical and Monte Carlo simulation

In this section, we present two methodologies based on historical and Monte Carlo simulation techniques that banks can internally develop to measure their exposure to IRRBB. In line with the best industry practices consolidated over time the historical simulation methodology is based on the joint annual changes in our key rates that occurred over the past five years. These scenarios are calculated on a given day through the overlapping technique, as also suggested by BCBS (2004), and are applied to the net positions to obtain the net weighted positions. Then, we sum the net weighted positions to calculate the change in a bank's EVE and divide this sum by the regulatory capital to get an empirical distribution of the risk indicator. This distribution is cut in correspondence of the percentile associated with the desired confidence level, which is set equal to 99% following BCBS (2004). The historical simulation methodology allows to capture the implicit correlation observed in previous five years among the annual changes in key-rates. Hovever, when interest rates at the evavaltuaion date are low, the application of non-negativity constraint or the lower bound EBA might prevent this methodology from capturing the correlations.

Monte Carlo simulation allows us to generate scenarios that take into account the correlations between the changes in interest rates and soddisfy the presence of a regulatory floor. As for the historical simulation methodology we consider as input the annual changes in interest rates that occurred over the past five years the evaluation date calculated through the overlapping tecnique. We carry out as many simulations as those required to obtain the desired number K of scenarios, which we set equal to 10,000, and reject those simulations leading the term structure of our key rates under the regulatory floor. Thus, allows us to capture the correlation among annual changes in interest rates observed in the past five years regardless the application of the regulatory floor. In this way, we get a distribution of the risk indicator which is cut at the desiderate percentile. In particular, the method is developed along the following steps:

i) selecting the joint probability density function that guarantees the best approximation of the actual distributions of the annual changes in the key rates. The application of the overlapping data technique supports the use of a normal joint probability density function, which has been already adopted by Fiori and Iannotti (2007);
ii) estimating means and variances of the distributions of the annual changes in the key rates and their variance-covariance matrix (Ω). Distributions of annual changes are not adjusted on the basis of the non-negativity constraint in order to account for actual correlations among the annual changes in key rates;
iii) generating a random number ui (i=1, …14) ranging from 0 to 1 at each node of our key rates term structure;
iv) converting each ui into a value zi (i=1 ,..14) distributed according to a standard normal. In symbols:

$$z_i = F^{-1}(u_i) \quad (6.)$$

where F-1 is the inverse of the distribution function of the probability density function of the annual changes of the ith key rate;

v) using the algorithm of Cholesky in order to decompose the matrix Ω in two matrices Q and Q' such that:

$$Q' \cdot Q = \Omega \quad (7.)$$

vi) calculating the vector x, whose elements are the joint simulated annual changes in the key rates through the following formula:

$$x = Q' \cdot z + \mu \quad (8.)$$

where z is the vector of the values calculated in step iv) and μ is the vector of the 14 means of the distributions of the key rates annual changes calculated in step ii). Each vector x represents a simulated scenario that will be used to calculate the risk indicator.

vii) repeating steps from iii) to vi) until reaching a number K of scenarios that meet the regulatory floor;

viii) the K simulated scenarios are applied to the net positions to calculate the net weighted positions. For each scenario, the net weighted positions are summed to calculate the change in a bank's economic value, which is finally divided by the regulatory capital. The empirical distribution of the risk indicator is finally cut to identify the desiderate percentile.

We don’t set, in line with Cerrone et al (2017) any further restrictions to changes in interest rate in addition to regulatory floor since both past and recent episodes, such as the U.S. savings and loan crisis and the measures of monetary policy that drove market rates to extremely low levels, have shown that their term structure can assume characteristics and dynamics which, ex ante, would have been judged unrealistic.

The results obtained throght the step from i) to viii) above described may, however, depend on the specific sample of simulated scenarios. In other words, if the simulation is repeated several times the final value of the risk indicator associated to the desired percentile may be different. To address this issue, we use the procedure developed by Gupton, Finger e Bathia (1997) that allows us to construct apposite confidence interval in which the risk indicator obtained trought the simulation The authors highlighted that if the results of a simulation are reported in ascending order, the percentile np associated with the confidence level p should coincide with the observation p*N. However, Monte Carlo simulations are affected by sampling errors consequently the number of values below the desidered percentile could be less or higher that p*N. it is possible to prove that np is distributed according to a normal with mean N*P and variance $\sqrt{Np(1-p)}$. Consequently, it is possible to define the following confince interval:

$$pr\left(pN - |z_\alpha|\sqrt{Np(1-p)} < np < pN + |z_\alpha|\sqrt{Np(1-p)}\right) \ (9.)$$

For example, wit N set equal to 10000 and a desidere percentile of 99%, if the true percentile may not be the one obtained through the simulation, there is at least a probability of 98% that it falls within the confidence interval calculated accordint the previous formula (9.).

Finally, in our analysis, we also take into account the Expected Shortfall (ES) measure associate both to historical and Monte Carlo simulation to capture the average of the risk indicators (IR) values exceeding the chosen percentile (99p) calculated as follows:

$$EL = E\left[IR|IR > IR_{99p}\right] \quad (10.)$$

This is because the simulation technique reported above does not provide us any information about the size of the risk indicator in the extreme tail of the distribution.

3.3. The back-testing procedure

According to the existing literarature the backtesting procedures can be classified in two differet approaches based respectively on a hit function or on a loss function. The former is designed to test wheter a single VaR model provides accurate estimates. The statical tests developed by Kupiec (1995) and Christoffersen (1998) are still the most popular ones within this approach among practioners and academics. The latter allows us to rank the different available VaR models. Given our objective of comparing the performance of the different methodologies used to measure IRRBB we adopt a loss function-based approach. The logic underlying this approach trace back to the pioneer work by Lopez (1996) that, in a market risk perspective, tests VaR models by focusing on the potential losses associated with underestimation case and gives to each methodology a score function based on a certain loss function. The lower is the score, the better is the methodology performance. Furthermore, this approach gives us greater flexibility to address both regulator and industry concerns since the loss function can be tailored to take into account the implications related to the financial stability and credit supply to the economy.

In detail Lopez (1996) developed three different loss functions represented, respectively, by: i) the loss function implied in the binomial method that assigns the value 1 when VaR estimates exceeded its loss and 0 otherwise; ii) the zone loss function based on the adjustment schedule for the multiplier factor used in the regulatory framework; and iii) the magnitude loss function that assign a quadratic numerical score when VaR estimates exceeded its loss and 0 otherwise. Subsequently, always staying in a market risk perspective, alternative loss functions were proposed by literature to assess non only the case of underestimation already addressed by Lopez (1999) but also the case of overestimation that could lead to set aside much more capital than necessary thus imposing to banks an opportunity cost. These two differet types of functions were named, respectively, regulators loss function (RLF) and firm loss function (FLF).

Sarma et al (2003) developed a RLF based on a quadratic functional form substantially similarity to that provided by Lopez (1996) and a FLS, which, in addition to penalizing the underestimation cases in the same way of the RLF, imposes in the cases of overestimation a penalty based on the opportunity cost of capital held by firm. Caporin (2008) developed three different regulators loss function taking into account in two of them the relative size of the losses and suggested to apply the same loss functions non only to the expections but also to the entire observations. Sener et al (2012) provided a firm loss function named penalization measure that considers not only the magnitude of the errors between realized and predicted losses but also the dependence among errors. The model proposed also penalize excessive capital allocations. Finally, Abad et al (2015) further developed of the firm loss function proposed by Sarma et al (2003) modelling the no-exceptions cases through the excess of capital held by firm.

In a IRRBB perspective, we further develop the back-testing procedure declined by Cerrone et al (2017) to valuate the consistency of results deriving to the application of regulatory methodologies and internal models based on simulation tecniquies with the actual banks risk exposure. In detail, we compare the ex-ante risk indicators obtained through the application of regulatory methodologies and internal models with the ex-post risk indicator that measure the actual bank risk exposure. The ex-post risk indicator is obtained by setting Δr in equation (1.) equal to the joint annual changes in key-rates that actuallyu occurred over the one-year time horizon following the evaluation date t. The back-testing procedure used in based at each valuation date t on a score function $S_{m,t}$ that allows to assign to each methodology m a score taking as input the results of an accuracy function $A_{i,t}$ that is applied to each single bank. The generic score function for a methodology m and an evaluation date t is formalized as follows:

$$S_{m,t} = \frac{\sum_{i=1}^{N} A_{i,t}}{N^*} \qquad (11.)$$

where:

- $A_{i,t}$ is defined in such a way that the outputs of the score function cannot take negative values and better methodologies are characterized by lower scores;
- N* is an integer whose value depends on the specification of the accuracy function.

The generic accuracy function can be written as follows:

$$A_{i,t} = \begin{cases} f\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) & if\ RI_{i,t}^{post} > RI_{i,t}^{ante} \\ g\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) & if\ RI_{i,t}^{post} \leq RI_{i,t}^{ante} \end{cases} \qquad (12.)$$

where: $RI_{i,t}^{ante}$ and $RI_{i,t}^{post}$ are the ex-ante and ex-post risk indicator, respectively. Both $RI_{i,t}^{ante}$ and $RI_{i,t}^{post}$ refer to the term structure of the i^{th} bank's net positions observed in the evaluation date *t*. The function *f* and *g* define the values of the accuracy function if the ex-post risk indicator is higher or lower (equal) than the ex-ante one.

The specificiation of the above-described accuracy functions allows to obtain measures referring, respectively, the case of underestimation and overestimation of actual risk exposure, it is to say when the ex-ante risk indicator is lower or higher than the ex-post one, or a combination of the two cases considered. Cerrrone et al (2017) developed in a IRRBB perspective four different specifications of the accuracy function represented, respectively, by i) a frequency score, based on the number of times in which an underestimation occurs; ii) a severity score calculated separately in the underestimation and overestimation cases, that capture the magnitude of the measurement error for each methodology; and iii) a proximity score that represents a combination of the two case in the previous point ii) taking into account simultaneously the distance between the ex-ante and ex-post in both cases of underestimation and overestimation. In their analysis, Cerrone et al (2017) gave the same wheight to the cases of underestimation and overestimation considering of equal importance the different needs of regulatory and industry in terms, respectively, of banking stability and credit supply to the economy.

We propose the following specification of accuracy functions that equals 1 plus the difference in absolute value between the ex-post and ex-ante risk indicator raised to a coefficient (α or β) that reflects the different weight assigned to the case of underestimation and overestimation. In symbols:

$$A_{i,t} = \begin{cases} (1 + DIFF)^{\propto} & if\ RI_{i,t}^{post} > RI_{i,t}^{ante} \\ (1 + DIFF)^{\beta} & if\ RI_{i,t}^{post} \leq RI_{i,t}^{ante} \end{cases} \qquad (13.)$$

where: $DIFF = \left| RI_{i,t}^{post} - RI_{i,t}^{ante} \right|$

The accuracy function declined in the previous equation (13.) allows to build a combination of functions according to the different value assigned to α and β. As for example if we set α=2 and β=1 we assign a quadratic function to the underestimation case and a linear function to the overestimation case, giving greater importance to the underestimation case. Furthermore, by construction, as the difference in absolute value between the ex-ante and ex-post risk indicator increases, the score assigned to the case of underestimation augments to a greater extent than that assigned to the case of overestimation. As for underestimation case the larger is the difference, the greater is the underestimation of actual risk exposure and the greater is the potential threat to the banking stability. As for overestimation case the larger is the difference, the greater is the potential reduction of the credit supply to the economy, since the higher is the amount of internal capital that a bank unnecessarily sets aside.

Finally, in line with Sarma et al (2013) we also use the sign test to compare the different methodologies analyzed two by two. In other words, the above-mentioned statistical test allows us to verify the superiority of one methodology over another given a specific loss function. In detail, we test the null hypothesis $H_0 : (\theta = 0)$ against the one-side alternative hypothesis $H_1 : (\theta < 0)$ where ϴ is the median of the distribution Z_t defined as follows:

$$Z_t = S_{i,t} - S_{j,t} \quad (14.)$$

and $S_{i,t}$ and $S_{j,t}$ are the values obtained by applying a specific loss function respectively to methodology i and j for the evaluation date t. Given thee following varable

$$\phi(t) = \begin{cases} 1, & Z_t \geq 0 \\ 0, & Z_t < 0 \end{cases} \quad (15.)$$

the sign statistic S_{ij} in the number of non-negative values of Z_t. In symbols:

$$S_{i,j} = \sum_{i=1}^{T} \phi(t) \quad (16.)$$

Under the null hypotesis H_0 if Z_t is iid the exact distribtuons of sign statistic $S_{i,j}$ is binomial with parameters T and 0,5, while for large sample t the asymptotic distribution is given by

$$S_{i,j} = \frac{S_{i,j} - 0{,}5T}{\sqrt{0{,}25T}} \sim N(0{,}1) \quad (17.)$$

If the null hypothesis H_0 is rejected, the methodology i is significantly better than methodology j for the chosen loss function.

4. Data

In our analysis, we consider the main 30 italian commercial banks of small and medium size that use, according to the proportionality principle, the standardized methodology to calculate their exposure to IRRBB within their capital adeguacy valuation. We estimate our sample bank's risk indicator as of December 31st for each of years included in the 2006-2020 period through the regulatory and simulation methodologies described in the previous paragraph 3 by considering: i) the old methodology based on duration coeffiicents proposed by BCSB (2004) with both the application of non-negativity constraint and the lower bound EBA; and ii) the new methodology based on the criterion of present value under the scheme of continuous capitalization proposed by BCBS (2016) with the only application of lower bound EBA. December 31st is also the date on which bank specific balance sheet data refer. The data used are available in Section E of the Note to Financial Statements "Information on risk and related hedging policies". Italian banks can draw up a maturily ladder that presents eight-time bands that are wider than those required by Supervisory Authorities are. Therefore, we hypothesize that our bank's balanche sheet accounts are slotted in proportion to the number of months included in each of the regulatory time bands

The following Table 2 shows the average values of our sample banks' cash assets and liabilities sheet long position (in Panel A) and cash liabilities and off-balance sheet short position (in Panel B), respectively. It is worth considering that the off-balance sheet positions include hedging derivatives, such as amortizing interest rate swaps and the optionalities embedded in some financial contracts, namely the floors and caps associated with floaring rates loans. it is interesting to highlight, on the asset side, the increase in the weight of securities hold in portfolio by banks, which goes from 7.93% in 2006 to 18.01% in 2012 following the sovereign debt crisis, reaching above 30% in 2020 during the crisis linked to the spread of Covid-19. At the same time, there has been a simultaneous reduction in the weight on total asstes of the loans granted in the period under analysis ranging from 86.08% to 62.15%. On the liabilities side, however, there has beeen an increase in the share of the demand deposit component from 42.35% to 54.69% and in the other deposits component, which includes that towards the ECB, from 14.52% to 28.56%. Finally, it is interesting to note the reduction in the weight of bonds issued from 28.78% to 5.22%

(Insert Table 2)

Given the italian banks balance sheet composition above described, the allocation criteria defined by the regulatory framework generally lead to a term structure of bank's net positions, over the entire period 2006-2020, characterized by negative net positions in the middle term time bands (from from 1 to 2 years to from 4 to 5 years) mainly attributable to the demand and revocable deposits that are distributed over a 5-year time horizon and by positive net positions in the long term time bands (from 5 to 7 years to more than 20 years) mainly attributable to the capital repayment of fixed rate loans and fixed rate securities.

Following an increase (decrease) in interest rates negative net positions lead to a negative (positive) weighted net positions and therefore to an increase (decrease) of economic value. On the contrary, following an increase (decrease) in interest rates positive net positions lead to a positive (negative) weighted net positions and therefore to a decrease (increase) of economic value. The impact of net positions (positive or negative) in the short-term time bands is, generally, marginal given the related low duration coefficients. These latter include include floating rate mortgages and in general all the balance sheet items characterized by a floating rate, the balance sheet items characterized by a fixed rate maturing within 1 year and the part of demand and revocable deposits distributed over 1 year. The same logic applies to the methodology proposed by BCBS (2016). An increase (decrease) in interest rates results in a lower (higher) discount factor, which when multiplied by the negative net positions determines a greater (lower) bank's economic value than that obtained using the term structure of interest rates at the valuation date. On the contrary, if multiplied by the positive net positions, it leads to a lower (higher) bank's economic value of own funds than that calculated based on the level of interest rates at the valuation date.

We calculate the risk indicator by referring to a term structure on interest rates consisting of 14 nodes (the so-called key rates) each associated to a single time band of the regulatory maturity ladder. In details, key rates are observed on december 31st for each year included in the investigation period. To build the term structure of the key rates we use the EONIA (Euro Overnight Index Average) rate for the node corresponding to the demand and revocable time band, the Euribor rate for maturities shorter than 12 months and interest rate swap (IRS) rates for maturities longer than, or equal to, 1 year, in line with the current banking practices. The characteristics and dynamic of the key rates term structure over time have a strong impacct on bank risk exposure.

The following Table 3 shows that the term structure of our key rates become steeper and experiences a downward shift over time, which makes the application of non-negativity constraint more likely to occur. Particuparly, starting from 2009 the level of interest rares on the short- and medium-term bands falls below 200 basis points and subsequently placed in negative territory from 2015. The number of time bands characterized by negative key rates increase from year to year until to reach that from 10 to 15 years at the evaluation date of 31/12/2020.

(Insert Table 3)

Finally, it is important to underline that the dynamics of the key-rates impacts on the risk exposure of banks calculated using the methodology defined by BCBS (2016) due not only to the possible application of the lower bound EBA but also through the value changes of the discount factor. The reduction in interest rates determines, in fact, a higher value of the discount factors given its exponential functional form, that impacts on the difference between the post-shock and ante-ante shock economic values. This phenomenon is noted, in particularly, on the long-term maturities in the hypothesis of an incresing key-rates term structure. However, it can be mitigated for the scenarios characterized by negative changes by the progressive application of the lower bound EBA as observed in the period analyzed.

5. Empirical evidence

This paragraph analyzes the implications deriving from the application of the new regulatory scenarios proposed by BCBS (2016) and the historical and simulation tecniques. The assessment is carried out first of all using the previous methodological framework based on the duration coefficients with the application of both the non-negativity constraint (referred in the following as OLD_NNC hypothesis) and the lower bound EBA introduced in 2018 (OLD_LB_EBA_2018). Subsequently, we take into account the transition to the new methodology based on present value criterion under the scheme of continuous capitalization proposed by BCBS (2016) with the application of lower bound EBA in force (NEW_LB_EBA_2018) e that proposed in the recent RTS in consultation (NEW_LB_EBA_2021). Finally, we address the issues of the adequate amount of internal capital to set aside IRRRB thorugh the implementation of a backtesting procedure based on differet declination of the loss function and specific inferential statistic tests. The analysis is carried out for the entire period taking into accout: i) a maturity ladder of 14-time bands; ii) a non-core component of deposits equals to 25% and the distribution of the core component in the following 5 years according to the months of each time band; iii) the own funds as the denominator of the risk indicator; iv) the automatic options within the time bands according to the delta value associated. These above-mentioned hypotheses from i) to iv) don't alter the evidence reported in the following concerning those we retain, following a comparison with different risk management departments, the main changes in the IRRBB regulatory framework.

5.1. Implications deriving from the application of new regulatory scenarios

The following Table 4 reports on average over the entire period 2006-2019 the number of banks exposed to each individual regulatory scenario and the value of related risk indicator. Table 4 also reports for each regulatory methods the number of banks characterized by risk-neutrality and double-exposure phenomena. It is to say banks that, respectively, are not exposed to either of the two scenarios considered in each regulatory method or that are exposed to both scenarios.

(Insert Table 4)

Given maturity transformation function, according to which Italian commercial banks tipically fund long-term assets with short- and medium-term liabilities, we expect banks to be exposed to rising interest rates. In fact, if interest rates increase, the reduction in the economic value of long-term assets should be greater in absolute value than the decrease in the economic value of the short- and medium-term liabilities, thus determining an overall reduction of their economic value. Because both the application of the regulatory allocation criteria and the adoption of hedging strategies modify the contractual maturities of assets and liabilities, we find that banks not only are exposed to an increase in interest rates but also experience a reduction in their economic value if interest rates decrease.

Infact, with reference to the parallel method (Panel A of Table 4), the evidence obtained shows on average, under the hypothesis OLD_NNC, a greater number of banks exposed to decreasing in interest rates (11.54) than those exposed to increasing in interest rates (9.93). This is due to a greater share of floating rate mortgages, which are allocated in the short-term time bands according to their repricing date, than fixed rate mortgages in bank's loan portfoglio and a high amount of demand deposits distribuited according to the regulatory criterion within 5 years. Furthermore, banks exposed to +200 basis points have on average a higher level of risk indicator (11.54%) than that observed for banks exposed to -200 basis points (4.69%). This is attributable to the net positive positions in the long-term bands where are allocated fixed rate mortgage and securities to which are applied higher duration coefficients than those refereed to the short- and medium-term time bands.

The number of risk neutral banks are on average 8.80 per year. It is interesting to note (data available upon request) a significant higher number of cases from 2012 owing to the low level of interest rates. In the first three years of our investigation period (2006-2008) there are not any risk neutral banks. This is due to the level of interest rates higher of 200 basis point across the term structure which dit not lead to the application of non-negativity constraint. The significant increase in the number of of risk-neutral banks in the last years of our sample when interest rates are lower or negative than before confirms this interpretation. In the absence of the non-negativity constraint with regard to the parallel shift, by applying a -200 bp parallel shock, a bank, formerly exposed to decreasing interest rates, would experience a reduction in its economic value equal, in absolute value, to the increase associated with a +200-basis point parallel shock. Nevertheless, due to the non-negativity constraint, the magnitude of the reduction in the bank economic value associated with a negative net position would be lower and not enough to offset the increase in the economic value generated by the positive net positions. In other words, they are banks, which, in the absence of the non-negativity constraint, would be exposed to a decrease in interest rates.

The application of the lower bound EBA to replace the non-negativity constraint (OLD_LB_EBA_2018) reduces the phenomena of risk neutrality. The number of bank risk-neutral descrease from 8.80 to 3.07 leading at the same time to an increase in the number of banks exposed to decreasing in interest rates from 11.17 to 17.00. We also observe an increase of the associated risk indicator from 4.69% to 7.28% attributable to the greater magnitude of the negative changes in interest rates used in the calculation, particularly referred to the medium-term time bands. By construction, we have similar values in terms of the number of banks and the level of the risk indicator for the scenario of +200 basis points. The transition from the old to new methodology (NEW_LB_EBA_2018) does not show substantial changes compared with the previously hypothesis considered (OLD_LB_EBA_2018).

The percentiles method (Panel B of Table 4) shows evidence substantially similar to those of the parallel method. In fact, under the hypothesis OLD_NCC there is in average a prevalence of banks exposed to decreasing interest rates (1st percentile) compared to increasing ones (99th percentile) equals respectively 11.00 and 12.00. The number of risk neutral banks is equal to 7.00. The application of the lower bound EBA (OLD_LB_EBA_2018) leads to a reduction of the number of neutral banks from 7.00 to 2.33 and a contestually increase in the number of banks exposed to the 1st percentile scenario from 12.00 to 16.67. We also observe an increase of related level of the risk indicator from 5.02% to 7.78%. The transition from the old methodology to the new methodology (NEW_LB_EBA_2018) does not bring substantial changes. Respect to the parallel method, it should be noted the lower level of the risk indicator for the 99th percentile compared to the 1st percentile (4.42% vs 5.02%) due to the lesser extent of the changes in interest rates in the 99th percentile scenario compared to that of +200 basis points on the long-term bands where net positive positions are recorded.

Since the 1st and 99th percentile scenarios are not symmetrical, the application of the non-negativity constraint is not a necessary condition for the neutrality phenomenon under the old methodology. As observed in our investigation period (data available upon request) under the hypotheses OLD_NNC and OLD_LB_EBA the dynamics of interest rates observed in the previous 6 years the evaluation date could lead to scenarios related to the 1st and 99th percentiles, which combined to the term structure of the net positions, generate the phenomenon of neutrality regardless of whether the regulatory floor is applied. This is confirmed in the case of the new methodology where also the functional form of discount factor contributes to the asymmetry of the risk exposure between increasing and decreasing interest rates scenarios.

The specific term structure of bank's net positions means that Italian banks are not particularly exposed to short rates shock up. This is because the higher positive change on the medium-term time bands where there are negative net positions lead to an increase in economic value higher, in absolute value, than the reduction recorded on the long-term time bands where there are positive net positions. On the contrary, italian banks are exposed to the short rates shock down. This is because the higher negative change on the medium-term time bans where there are negative net positions lead to a decrease in economic value higher, in absolute value, than the increase recorded on the long-term time bands where there re positive net positions. The empirical evidence (Panel C of Table 4) confirms, during the whole investigation period, our interpretation.

Under the hypothesis OLD_NCC, the number of banks exposed on average to short rates shock up under are only 1.53 per year while the banks exposed to short rates shock down are 19.80 per year. Risk neutral banks are equal to 8,67 per year attributable, given the symmetry among the two scenarios considered, to the application of non-negative constraint. Infact, the smaller changes in interest rates dampens the impact of net negative positions on the medium-term time band making some banks risk netural. Since without the application of non-negative constraint the two scenarios (short rates shock up and down) are characterized by changes of opposite sign and same size we can apply simular considerations to those made for the parallel shock scenarios in terms of link between risk-neutrality and the application of non negativity constraint. The average value of the risk indicator for banks exposed to short rates shock down is 3.72% and is lower than that observed for both -200 basis points (4.69%) and the 1st percentile scenarios (5.02%)

The application of the lower bound EBA (OLD_LB_EBA_2018) in place of the non-negativity constraint (OLD_NNC) significantly reduces, respect to what observed for the scenario of -200 basis points and the 1st percentile, the phenomena of risk neutrality that pass in average over the entire period from 8.67 to 0.07, causing almost all of the sample to be exposed to short rates shock down (from 19.80 to 28.40). In line with the two previously regulatory methods considered we observe a reduction in the related risk indicator (from 3.72% to 6.48%). The transition to new methodology (NEW_LB_EBA_2018) does not provide additional significant elements with respect to the previous discussion (OLD_LB_EBA_2018). Almost all of the sample remains exposed to the short rates shock down rate (from 28.40 to 28.07) with a further increase in the relative risk indicator (from 6.48% to 6.90%). The average level of the indicator remains, however, both under the hypotheses OLD_LB_EBA and NEW_LB_EBA below the values observed for the -200 basis points and 1st percentile scenarios.

The specific term structure of bank's net positions means that Italian banks are not particularly exposed to flattener scenario. This is because the positive change on the medium-term time bands and negative on the long temr time bands lead to an increase in economic value given the related net positions, respectively, negative, and positive. In other words, the application of this scenario lead to an increase in economic value on all the medium and long-term time bands. On the contrary, Italian banks are exposed to steepener scenarios. This is because the particular term structure of bank's net positions leads to reduction in economic value boh on the medium-term time bands, given the application of negative change (with the excpetion of from 4 to 5 years time band) to negative net positions and on long-term time bands, given the application of positive changes to positive net positions.

The empirical evidence reported Panel D of Table 4 confirm, during the whole investigation period, our interpretation. Under the hypothesis OLD_NNC, the number of banks exposed to steepener are on average 29.67 per year with a value of risks indicator equals to 5.27%, while the banks exposed to flattener are on only 0.07 per year, with an average value of the risk indicators equals to 0.15%. Besides, we observe a very low number of banks risk neutral set equal on average to 0.20 per year. As for the percentile method, the application of non-negativity constraint is not a necessary condition for the occurrence of the neutrality phenomenon. It is interesting to note that steepener scenario is characterized by negative changes in the short- and medium-term time bands. Therefore, the application of non-negative constraint in a period of low or negative interest rates reduces the impact of negative net positions in the middle-term time bands consequently reducing the overall risk exposure, determined in such cases mainly on the long-term time bands. The flattener scenario is, in general, not characterized by the application of non-negative constraint given the positive change in the short and middle time bands.

The application of the lower bound EBA (OLD_LB_EBA_2018) does not substantially change the number of banks exposed to the steepener scenario (from 29.67 to 29.73) determining an increase in the risk indicator from 5.27% to 6, 10%. This is attributable to the wider negative changes applied in the medium-term time bands where net negative positions are recorded which led to a higher reduction in economic value. The evidences relating to the transition to new methodology (NEW_LB_EBA_2018) confirms the exposure of almost the entire sample to the steepener scenario (from 29.73 to 29.80) with a further increase in the average level of the indicator risk from 6.10% to 6.64%.

5.2. Assessing an adequate amount of internal capital

The banking practices consolidated in the recent years led to consider the most penalizing regulatory scenario within the assessement of capital adequacy. However, in the past whether the risk neutrality phenomenon characterized both the parallel and percentile method this criterion led to calculate an amount of internal capital equal to zero not coherent with a prudential perspective. It is important to highlight that the use of this criteria was required in the consultation document by BCBS (2015) for the purpose of calculating the capital requirement in the hypothesis of inclusion of the IRRBB within the first pillar of Basel II accord. The final document published in April 2016 no longer contemplated the above-mentioned criteria given the maintainance of IRRBB under the second pillar. In the whole regulatory framework, referred to BCSB (2016), EBA (2018) and to the 32° update of Circular 285/2013, the most penalizing scenario is, in fact, required only in terms of identifying outlier banks within SOT. The analysis of the above-mentioned documents does not reveal specific references to support the thesis of an internal capital based on the the most penalizing scenario.

Table 5 reports the evidence on average over the whole period considered concerning: i) the number of banks exposed to each regulatory method and the associated level of the risk indicators (Panel A); ii) the number of banks exposed at least to one of the four scenarios previously in force and the new six scenarios as wee lase the related risk indicators corresponding to the most penalizing scenarios indicated, respectively, with MAX_4 ad MAX_6 (Panel A); iii) the number of banks exposed to historical and Monte Carlo simulations and the associated level of the risk indicators (Panel B). The analysis is carried out taking into account all the three hypotheses given by the combination between regulatory floors and methodologies considered in the previous paragraph.

(Insert Table 5)

The evidence reported in the Panel A of Table 5 referred to the whole period 2006-2020 show that the introduction of the lower bound EBA (OLD_LB_EBA) to repleace non-negative constraint (OLD_NNC) reduces the phenomenon of risk neutrality as concerns previously scenarios represente by parallel and percentiles methods determining, at the same, time a higher risk exposure. This is true both considering each regulatory methods and the criterion of most penalizing scenario. The average number of banks exposed to at least one of the four previously in force scenarios (MAX_4) increase from 24.53 to 28.93 with a consequent higher level of the associated risk indicator from 7.54% to 9.84%. The new set of regulatory scenarios that include the short rates shock up and down and the steepener / flattener in addition to the parallel scenario of + / 200 basis points resets the jointly cases of nentral-banks (it is to say banks not exposed to at least one of the new six scenarios) even in the hypothesis of application of the non-negativity constraint. In both the hypotheshes we observe a numer of bank exposed equals to 30. That is mainly attributable to the introduction of steepener scenario to which almost all the sample is exposed due to the particular term structure of the net positions of Italian banks. The transition to the new methodology does not make substantial changes to the aforementioned evidence (Panel A).

The average level of the risk indicator relating to the max_6 criterion is always greater than that obtained with the max_2 criterion under the all three working hypotheses considered. The adoption of the lower bound EBA (OLD_LB_EBA_2018) replacing the non-negativity constraint (OLD_NNC) leads over the entire period considered to an increase in the average level of the risk indicator from 7.54% to 9.84% (MAX_4) and from 9.09% to 10.88% (MAX_6). The transition to new methodology (NEW_LB_EBA_2018) leads to a further increase in the average level of exposure which stands, respectively, to 9.83% and 11.50% under the MAX_4 and MAX_6 criteria. The regulatory changes proposed by BCBS (2016) and EBA (2018) taken into account in our analysis lead, therefore, to a greater prudential intensity of the supervisory regulatory framework due to the simultaneous elimination of the neutrality phenomenon and to the average increase exposure to IRRBB (Panel A).

The evidence reported in the Panel B of Table 5 referred to the application of historical and Monte Carlo simulations referred to the 99-percentile of the distribution of risk indicators and the associated level of expected shortfall. As concern Monte Carlo simulation we also take into account the evidence associated to the confidence intervals calculated according to the procedure proposed by Gupton et al (1997). On average across the entire period considered, the results obtained show that the phenomenon of neutrality is marginal and occurs for a few banks only in the case of OLD_NNC in specific years characterized by negative interest rates. In this context the simulated scenarios are characterized by only positive changes for short- and medium-term time bands, that combinated with particular term structure of net positions could lead to the neutrality phenomenon. Furthermore, Monte Carlo simulations leads to a value of the risk indicators, calculated according the 99° percentile, lower than those calculated with the historical simulations for all three hypotheses considered (5,95% vs 6,56% in the OLD_NNC; 7,34% vs 8,20% in the OLD_LB_EBA and 7,77% vs 8,23% in the NEW_LB_EBA). That is true also if we consider the upper bound of the related confidence interval. As concern Excepted shortfall related to the 99° percentile, Monte Carlo simulation leads to higher values of the risk indicators thant those obtained trough historical simulation in correspondence of the hypothesis OLD_NNC (6.90% vs 6.56%) and NEW_LB_EBA_2018 (8.88% vs 8.68%) and viceversa according to the hypothesis OLD_LB_EBA_2018 (8.42% vs 8.66%).

Finally, the values of the risk indicators referred to 99° percentile of both historical and Monte Carlo simulation are always lower than those obtained by applying the criteria MAX_4 and MAX_6 referred to previous table 4 under the three different hypotheses considered. That is also valid even if we consider the expected shortafall. The simulation tecniquies taken into account therefore lead to a lower amount of internal capitale to set aside against IRRBB than that calculated according to the most-penalizing scenario criterion, leaving to banks a greater amount of free capital functional to the lending activity and, generally, to be able to implement new profitable businesses opportunities. It is therefore crucial to understand whether these simulation tecniques provide at the same time also adequate values in a prudential perspective in order to ensure financial stability. This is what we will be analyzed in the following paragraph by the application of the back-testing procedures designed in the prevuoius paragraph 4.2.

5.3. Backtesting results

The following Table 6 and 7 report the evidence concerning the application of back-testing procedure. Table 6 reports the average number of expections (Panel A) and the average severity scores in the case of underestimation calculated according to the accuracy function of equation (13.) with different calibration of the coefficient α (Panel B). Particularly, we consider the cases in which the loss function assumes in the case of underestimation a linear (α=1) or quadratic (α=2) representation. Table 7 reports the average proximity scores calculated through the accuracty function of equation (13) with different calibration of coefficients α and β. Particulary we firstly assign to underestimation and overestiman case the same linear functional form (α= β = 1). Secondly, we set a quadratic functional form for the underestimation (a=2) firstly manteining a linear functional form for the overestimation case (β =1) and then replaicing this latter through a square root functional form (β =0,5). In this way we firstly give the same importance to regulatory and industry concerns. Then we gradually assign an increasing importance to regulatory issues compared with industry ones.

(Insert Table 6)

(Insert Table 7)

The analysis is carried out by taking into account: i) the four regulatory method represented by parallel shift method (indicated with 1); percentile method (2), short rates shock up and down (3) and steepener and flattener (4); ii) the two-criteria concerning the most penalizing scenarios referred to the previously (MAX_2) and new (MAX_6) regulatory framework; iii) the historial and Montecarlo simulation referred both to the 99° percentile (99_HS and 99MC) and related expected shortfall (ES_HS and MC_HS). As concern Monte Carlo simulation we also verify the evidence associate do the extremes of confidence interval (INF and SUP) calculated according to Gupta et al (1997). The analysis is also carried out takking into accout the four hypotheses related to the combination between regulatory methodologies and floors.

The comparison between the single regulatory methodologies taken individually shows mixed results. The higher number of expetions is recored following the application of the parallel shift method under the hypothesis OLD_NNC and of the steepener/flattener under the other two remaining hypotheses (OLD_LB_EBA_2018 and NEW_LB_EBA_2018). At the same time, steepener/flattener is also the method that leads to the lower number of exeptions within the first hypothesis (OLD_NCC). The short rates shock up and down method provide the lower numer of the exeptions under the two remaining hypotheses (OLD_LB_EBA_2018 and NEW_LB_EBA_2018). As concern the severity score in case of underestimation the steepener/flattener method leads to the higher values of scores for all three hypotheses considered. The lower scores are, instead, recorded by the percentile and parallel method respectively for α=1 and α=2. As concern proximity score, parallel shift method leads to the higher scores under the hypothesis OLD_NNC while steepener and flattener under the remaining two hypotheses OLD_LB_EBA and NEW_LB_EBA. The lower scores are observed regardless the coeffiicents calibration. The heterogeneous results obtained attest the necessity to consider in a jointly form the single regulatory method as also suggested by supervisory regulatory framework within the SOT thorugh the us of the most penalizing scenario criterion. In oder to identify the most adequate methodology to use to calculate internal capital to set aside IRRBB, the above resuts suggest limiting our analysis to the comparison between the most penalizing scenario MAX_6 and and the historical and Monte Calro simulations.

The results reported in the PANEL A of Table 6 show that MAX_6 criterion leads always to lower number of expetions under the different three hyphotheses considered. Particularly, under the hypotheses OLD_LB_EBA and NEW_LB_EBA there is no expetions during the whole period considered. The number of expetions recorded for the criterion MAX_2 is higher and respectively equals to 6.29, 1.71 and 2.36 under the three different hypotheses considered. Monte Carlo simulation is the second methodology in terms of lower number of expections that are on average equals to 3,50 under the hypothesis OLD_NNC and 1,00 for both OLD_LB_EBA and NEW_LB_EBA. By construction, the lowest values are recorded for the ES, which shows for the three hypotheses considered values, respectively, equals to 2.50, 0.50 and 0.43. The number of exepetions related to historical simulation for both 99 percentile and expected shortfall are equals higher under the OLD_NNC (2.36 and 1.79) than those observed under the other two hypotheses OLD_LB_EBA_2018 (1.57 and 1.14) and NEW_LB_EBA_2018 (1.47 and 1.15). The number of exeptions observed for both the two simulations tecniques are always lower than that observed for the MAX_2 criterion and the regulatory methods taken individually. The regulatory methods taken individually also lead to a higher number of exceptions than that observed for the MAX_2 criterion. Finally, it is interesting to note that the introduction of the lower bound EBA (OLD_LB_EBA_2018) in replace of non-negative constraint (OLD_NNC) always results in a reduction in the number of exceptions for all regulatory method and criteria as weel as simulation tecniques. The transiction from old (OLD_LB_EBA_2018) to new methodology (NEW_LB_EBA_2018) confirms, in general, the results obtained, with a moderate reduction in the number of exeptions for simulation tecniquies.

The results reported in PANEL B of Table 6 concerning the severity scores in the case of underestimation, generally, confirm the evidence obtained in terms of the number of exceptions within the comparison between the different regulatory methods and criteria as weel as simulation tecniques. The different calibration of the coefficient α does not make any changes to the following considerations. Criterion MAX_6 lead on average to lower scores under the three different htphothesis considered. The scores associated to Monte Carlo simulation for both 99 percentile and expected shortfall are higher than those obtained through historial simulation in the case of OLD_VNN and lower under the other two hypotheses take into consideration (OLD_LB_EBA_2018 and NEW_LB_EBA_2018). MAX2 criterion leads to scores on average higher than the above-mentioned MAX_6 criterion and simulations tecquiques. Finally, the regulatory methodologies taken individually always leads to higher scores than that obtained through the two different criteria based on the most penalizing scenarios and simulation tecquiques. The same considerations apply to the application of the lower bound EBA (OLD_LB_EBA_2018) with respect to the non-negative constraint (OLD_NNC).

The results reported in table 7 show that under the first calibration of coefficients α=β MAX_6 criterion leads to highest values of scores with respect to all regulatory methods, criterion MAX_4 and simulation techniques under all three hypotheses considered. If we assign a higher weight to underestimation cases setting α=2, the the highet are provided by MAX_4 criterion under the first hypothesis (OLD_VNN) and by MAX_6 criterion under the remaining two hypoteses (OLD_LB_EBA_2018 and NEW_LB_EBA_2018). If we penalize the overestimation case by assigning it a square root function form (β=0.5) we find that criterion MAX_2 leads to the highest score values for all the three hypotheses considered. Referred to the criterion MAX_6 we can observe that the lower number of exceptions and the best in terms of severity scores were achieved through higher levels of the risk indicator and, therefore, a greater allocation of capital. That ensures an adequate level of financial stability from a supervisory prudential perspective but, at the same time, could excessively penalize the supply of credit to the economy and, in general, new business opportunities for banks.

Monte Carlo simulation is the methodology that referred to the 99 percentile leads, generally, to lower value of scores compared both the two criteria based on the most penalizing scenario and the historical simulation regardless the different calibration of coefficient α and β the three hypotheses taken into account. The score calculated according to the historial simulation are, in turn, always lower than that referred to the two criteria MAX_4 and MAX_6. In general, with refered to the 99° percentile Monte Carlo simulation can be therefore considered on average better than historical simulations as it shows lower number of exceptions and at the same time lower values of the loss function with regards to the different calibration coefficients considered. As concern expected shortfall, we found in the comparison between Monte Carlo and historical simulations different result depending on the calibration of the loss function and the hypotheses under consideration. Further evidence to support our results can be obtained by applying the signs statistical test that allows us to compare the different methodologies two by two. The following Table 8 report the evidence refereed to the comparison between the two simulation tecquiques with the criterion MAX_6. We also compare Monte Carlo simulation with historial simulation. The comparison is made with reference both to 99° percentile and the related expected shortall of the two simulation tecquiques. The analysis is also carried out under the loss function that consider underestimation that overestiman case in the three different hypotheses considered.

(Insert Table 8)

The results obtained confirms the superiorty of Monte Carlo and historial simulation with respect to MAX_6 criterion and thus the significance of the differences between the scores obtained in corresponde of each calibration of the loss function. With referred to the 99° percentile, the related coefficients are always significant at 1% level for both Monte Carlo and historial simulation. This is also true referring to the expected shortfall calculated according the 99° percentile of historial simulations. As regards instead the expected shortfall calculated according the 99° percentile of Monte Carlo simulation, we find a significant at 1% level only in the first two hypotheses (OLD_NNC and NEW_LB_EBA_2018). Finally, Monte Carlo simulation is superior to historial simulation with a significant at 1% level for all the three different calibration of loss function under the first two hypotheses considered (OLD_NNC and NEW_LB_EBA_2018).

6. Conclusions and policy implications

The decision circa the criterion to use to calcunate the amount of internal capital to set aside against IRRBB within ICAAP represents a crucial issue both in a business and prudential perspective given the micro and macro implications impied in the underestimation and overestiman cases as previously described. EBA (2018) provides several indications on this issue, suggesting banks to evaluate in ordinary conditions the impact of both the new six regulatory scenarios that those based on the historial movements and behaviour of interest rates as well as simulation of future interest rates. It is important to underline that the SOT declined by EBA (2018) requires that all the new six regulatory scenarios must be below the alert threshold. In other words, the SOT is carried out with reference to the most penalizing scenario. In terms of capital adequacy, EBA (2018) do not require an amount of internal capital corresponding to the most penalizing scenario, leaving discretion margins to the banks to identify the most appropriate scenario within a set of general indications.

Using a sample of 30 italian banks between 2006 and 2019 rappresentative of the main less significant institutions that referred to simplified methodologies to calculate their exposure to IRRBB we firstly we sheed more light on the implications deriving from the recent main regulatory changes represented by the introduction of i) the new six scenarios of changes in interest rates; ii) the methodological framework based on present value criterion under a continuous capitalization scheme that replace the duration coefficients and iii) the removal of the non-negative constraint and the contextual introduction of a negative floor. Secondly, we address the issue concerning the appropriate amount of capital banks should set aside against this specific risk, by developing a back-testing procedure that allow us to compare the evidence of regulatory methods and in particulary the above-mentioned criterion based on the most penalizing scenario with that obtained through more sophisticated methodologies such as historical and Monte Carlo simulations.

Our results show the greater prudential intensity of the new regulatory framework that allows to avoid some distorting effects such as the risk neutrality phenomenon and at the same time leads to a higher risk exposure. However, the regulatory scenarios do not seem to lead to adequate internal capital both taken individually and jointly through the application of the most penalizing scenario criterion. According to our back-testing procedures, infact, historical and simulation methodologies lead to lower values of different calibration of the loss functions adopted that capture with different weight underestimation and overestimation cases, thus taking into account, respectively, both regulatory and industry concernes. These results are also confirmed by the application of a specific inferential statistic tecquiques.

From an operational perspective, managers can use such a framework to support their choise of a certain methodology that, based on the backtesting results, better estimates actual risk exposure. Supervisor can test the appropriateness of the deterministi shock and make them more consistent with the levels and dynamic of market interest rates. Generally, our results provide useful insight for properly measuring the amount of internal capital to cover interest rate risk suggesting the use of simulation techniques in ordinary condition and the criterion of most penalizing scenario withim a stress test environment, guiding in this way the transposition of supervisory guidelines in the banking sector practices.

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Table 1. Interest rate scenarios

Time bands	31/12/ 2019	Parallel method +/- 200 basis points				Short rates shock up/down				Steepener/Flattener					
		PSU	PSD	NNC	LB_EBA	SRU	SRD	NNC	LB_EBA	STEEP	NNC	LB_EBA	FLAT	NNC	LB_EBA
Demand and revocable	-0.50	2.00	-2.00	0.00	-0.50	2.50	-2.50	-2.50	-0.50	-1.63	0.00	-0.50	2.00	2.00	2.00
Up to 1m	-0.55	2.00	-2.00	0.00	-0.45	2.47	-2.47	-2.47	-0.45	-1.60	0.00	-0.45	1.97	1.97	1.97
From 1 to 3 mounths	-0.54	2.00	-2.00	0.00	-0.46	2.40	-2.40	-2.40	-0.46	-1.52	0.00	-0.46	1.89	1.89	1.89
From 3 to 6 months	-0.53	2.00	-2.00	0.00	-0.47	2.28	-2.28	-2.28	-0.47	-1.40	0.00	-0.47	1.77	1.77	1.77
From 6 months to 1 years	-0.52	2.00	-2.00	0.00	-0.48	2.07	-2.07	-2.07	-0.48	-1.19	0.00	-0.48	1.56	1.56	1.56
From 1 to 2 years	-0.52	2.00	-2.00	0.00	-0.43	1.72	-1.72	-1.72	-0.43	-0.84	0.00	-0.43	1.19	1.19	1.19
From 2 to 3 years	-0.51	2.00	-2.00	0.00	-0.39	1.34	-1.34	-1.34	-0.39	-0.45	0.00	-0.39	0.79	0.79	0.79
From 3 to 4 years	-0.49	2.00	-2.00	0.00	-0.36	1.04	-1.04	-1.04	-0.36	-0.15	0.00	-0.15	0.48	0.48	0.48
From 4 to 5 years	-0.46	2.00	-2.00	0.00	-0.34	0.81	-0.81	-0.81	-0.34	0.08	0.08	0.08	0.24	0.24	0.24
From 5 to 7 years	-0.38	2.00	-2.00	0.00	-0.32	0.56	-0.56	-0.56	-0.32	0.34	0.34	0.34	-0.02	0.00	-0.02
From 7 to 10 years	-0.27	2.00	-2.00	0.00	-0.29	0.30	-0.30	-0.30	-0.29	0.60	0.60	0.60	-0.29	0.00	-0.29
From 10 to 15 years	-0.07	2.00	-2.00	0.00	-0.23	0.11	-0.11	-0.11	-0.11	0.79	0.79	0.79	-0.49	0.00	-0.23
From 15 to 20 years	0.01	2.00	-2.00	-0.01	-0.06	0.03	-0.03	-0.03	-0.03	0.87	0.87	0.87	-0.57	-0.01	-0.06
0ver 20 years	0.01	2.00	-2.00	-0.01	-0.01	0.00	0.00	0.00	0.00	0.90	0.90	0.90	-0.59	-0.01	-0.01

Note: PSU = parallel shock up +200 basis points; PSD = parallel shock down -200 basis poitns; SRU = short rates shock up; SRD = short rates shock down; STEEP = steepener; FLAT = flattener. NNC and LB_EBA refers, respectively, the application of non-negative constraint and the lower bound EBA taking into account the term structure of interest rates as 31/12/2019. Data are expressed in percentage.

Table 2. Cash assets and liabilities term structure and off-balance sheet positions

Panel A: cash assets term structure and off-balance sheet positions	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Debt securities with maturity shorter that 1 year	5.91	7.20	8.66	9.07	9.20	7.99	10.61	13.71	15.72	16.33	16.27	15.69	12.63	13.04
Debt securities with maturity between 1 year and 5 years	1.33	1.61	1.36	1.62	1.79	2.42	4.56	6.12	5.61	5.24	6.67	6.34	11.05	10.04
Debt securities with maturity longer than 5 years	0.69	0.36	0.42	0.74	1.54	1.52	2.84	3.12	3.35	4.51	5.01	3.52	5.31	6.03
Loans with maturity shorter that 1 years	71.02	76.30	73.04	68.75	67.55	69.42	64.84	57.57	55.51	55.71	53.88	54.67	52.47	52.24
Loanss with maturity between 1 year and 5 years	27.09	28.79	29.52	39.09	41.47	43.25	40.46	36.24	35.97	37.14	36.22	37.49	35.09	35.22
Loans with maturity longer than 5 years	15.07	8.92	11.18	14.46	9.23	9.93	8.56	9.75	10.10	10.42	11.45	13.64	12.69	12.73
Off-balance sheet long positions	5.97	5.61	5.33	5.37	10.70	8.71	8.58	9.73	9.70	7.79	6.72	6.14	5.84	5.93
Panel B: cash liabilites term structure and off-balance sheetr positions	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**
Non-maturity deposits	42.35	42.35	43.20	46.83	43.61	41.50	37.73	37.49	41.45	46.36	49.85	51.69	52.57	54.16
Other current accounts	8.20	10.67	8.86	8.86	9.65	10.46	11.84	7.43	7.30	7.83	6.38	8.74	6.34	6.30
Term deposits and other funds with maturity shorter than 1 year	13.46	10.44	7.92	4.90	5.69	7.93	14.22	19.92	16.69	14.40	13.01	7.94	12.90	18.49
Term deposits and other funds with maturity between 1 year and 5 years	0.88	0.08	0.36	0.29	0.13	0.44	1.31	1.63	2.38	4.19	9.62	13.18	13.60	7.91
Term deposits and other funds with maturity longer than 5 years	0.09	0.06	0.01	0.06	0.07	0.06	0.08	0.20	0.45	0.55	0.70	0.87	1.07	1.14
Debt securities with maturity shorter than 1 year	22.10	24.08	27.69	26.19	19.77	17.59	14.12	12.79	10.31	8.81	6.69	5.73	4.21	2.96
Debt securities with maturity between 1 year and 5 years	6.18	6.18	6.36	6.92	9.24	12.52	11.45	10.49	11.03	9.05	6.34	4.17	3.07	2.63
Debt securities with matyriuty longer than 5 years.	0.42	0.38	0.33	0.54	0.81	0.65	0.43	0.49	0.65	0.87	0.68	0.60	0.59	0.65
Off-balance sheet short positions	6.33	5.76	5.27	5.42	11.03	8.83	8.82	9.56	9.73	7.94	6.74	7.10	5.65	5.75

The table shows the average value of our sample bans' cash and off-balance sheet long position in Panel A and cash liabilities and off-balance sheet positions in Panel B, respectively. Data are taken from bank's balance sheet and refer to December 31st of each year included in the 2006-2019 period. Data are expressed in percentage of total on-and-off balance sheet positions.

Table 3. key rates term structure

	Demande and revocable	Up to 1 month	From1 to 3 months	From 3 to 6 months	From 6 to 1 year	From 1 to 2 years	From 2 to 3 years	From 3 to 4 years	From 4 to 5 years	From 5 to 7 years	From 7 to 10 years	From 10 to 15 years	From 15 to 20 years	Over 20 years
31/12/2006	3.69	3.63	3.73	3.85	3.84	4.13	4.13	4.13	4.13	4.15	4.20	4.27	4.31	4.31
31/12/2007	3.92	4.29	4.68	4.71	4.72	4.55	4.53	4.53	4.56	4.61	4.72	4.86	4.91	4.91
31/12/2008	2.35	2.60	2.89	2.97	2.68	2.76	2.96	3.12	3.24	3.46	3.74	3.90	3.86	3.67
31/12/2009	0.41	0.45	0.70	0.99	1.32	1.86	2.26	2.56	2.81	3.21	3.60	3.96	4.07	4.02
31/12/2010	0.82	0.78	1.01	1.23	1.33	1.56	1.95	2.21	2.48	2.89	3.31	3.64	3.70	3.67
31/12/2011	0.63	1.02	1.36	1.62	1.42	1.32	1.38	1.53	1.73	2.07	2.37	2.67	2.69	2.62
31/12/2012	0.13	0.11	0.19	0.32	0.33	0.37	0.46	0.61	0.77	1.13	1.57	2.02	2.17	2.22
31/12/2013	0.45	0.22	0.29	0.39	0.41	0.54	0.77	1.00	1.26	1.68	2.16	2.59	2.71	2.74
31/12/2014	0.14	0.02	0.08	0.17	0.16	0.18	0.22	0.29	0.36	0.53	0.82	1.15	1.33	1.42
31/12/2015	-0.13	-0.21	-0.13	-0.04	-0.06	-0.03	0.06	0.19	0.33	0.62	1.00	1.40	1.57	1.60
31/12/2016	-0.33	-0.37	-0.32	-0.22	-0.20	-0.16	-0.10	-0.03	0.08	0.31	0.66	1.03	1.18	1.22
31/12/2017	-0.35	-0.37	-0.33	-0.27	-0.26	-0.15	0.01	0.17	0.31	0.57	0.90	1.25	1.42	1.48
31/12/2018	-0.36	-0.36	-0.31	-0.24	-0.23	-0.17	-0.07	0.07	0.21	0.47	0.82	1.17	1.35	1.37
31/12/2019	-0.45	-0.44	-0.38	-0.32	-0.32	-0.29	-0.24	-0.17	-0.12	0.02	0.21	0.47	0.60	0.64

This table shows the term structure of the key rates referred to each time band of the regulatory maturity ladder observed at the end of the years included in 2006-2019 period. Particularly, we use data from Datastream and the EONIA (Euro Overnight Index Average) for the maturity corresponding to the demand and revocable time bandm the Euribor rates for maturities shorter than 12 months, and interest rate swaps (IRS) rates for maturities longer or equal than 1 years. Data are expressed in percentage.

Table 4. Regulatory scenarios

	Panel A: Parallel method +/- 200 basis points						Panel B: Percentile Method					
	PSU		PSD		N	D	99_PERC		1_PERC		N	D
	n.	RI	n.	RI	n.	n.	n.	RI	n.	RI	n.	n.
OLD_NNC	9.93	11.54	11.27	4.69	8.80	0.00	11.00	4.42	12.00	5.02	7.00	0.00
OLD_LB_EBA_2018	8.93	11.54	17.00	7.28	3.07	1.00	8.80	4.42	16.67	7.78	2.33	2.20
NEW_LB_EBA_2018	8.67	10.76	15.33	7.99	4.73	1.27	8.93	4.72	16.33	8.22	2.87	1.87
	Panel C: Short rates shock up / down						**Panel D: Steepener / Flattener**					
	SRU		SRD		N	D	STEEP		FLATT		N	D
	n.	RI	n.	RI	n.	n.	n.	RI	n.	RI	n.	n.
OLD_NNC	1.53	4.43	19.80	3.72	8.67	0.00	29.67	5.27	0.07	0.15	0.20	0.07
OLD_LB_EBA_2018	1.53	4.43	28.40	6.48	0.07	0.00	29.73	6.10	0.07	0.07	0.13	0.07
NEW_LB_EBA_2018	1.53	4.93	28.07	6.90	0.40	0.00	29.80	6.64	0.07	0.03	0.13	0.00

This table shows on average the numer of banks exposed to each regulatory scenarios and the value of the related risk indicators over the period 2006-2019. It is also reported for each regulatory method the number of risk-neutral banks and of double-exposed banks.

Note: PSU = parallel shock up +200 basis points; PSD = parallel shock down -200 basis poitns; 99_PER= scenario associated to the 99° percentile; 1_PER= scenario associated to the 1° percentile; SRU = short rates shock up; SRD = short rates shock down; STEEP = steepener; FLAT = flattener; N = risk neutral banks; D= double esposed banks; n.= number of banks; IR = value of the risk indicator expressed in percentage and calculated taking into account the only banks exposed to the related scenario; OLD_NNC = application of old methodology based on duration coefficients and of non-negative constraint; OLD_LB_EBA = application of old methodology based on duration coefficients and of the lower bound EBA; EBA; NEW_LB_EBA = application of new methodology based on the present value criterion under a continuous capitalization scheme and of the lower bound EBA.

Table 5. Regutory method and simulation tecquiques

Panel A: regulatory method

	PSU and PSD		99_PER and 1_PER		SRU and SRD		STEEP and FLATT		MAX_4		MAX_6	
	n.	RI	n.	RI	n.	RI	n.	RI	n.	RI	n.	RI
OLD_NNC	21.57	6.99%	22.86	5.21%	22.79	3.84%	29.79	5.07%	24.50	7.54%	30.00	9.09%
OLD_LB_EBA_2018	26.71	8.47%	27.50	7.10%	29.93	6.63%	29.86	5.80%	28.86	9.84%	30.00	10.88%
NEW_LB_EBA_2018	24.93	8.29%	26.93	7.48%	29.64	7.03%	29.86	6.15%	28.21	9.83%	30.00	11.29%

Panel B: simulation techniques

	HS				MCS							
	99_HS		ES_HS		99_MC		INF		SUP		ES_MCS	
	n.	RI	n.	RI	n.	RI	n.	RI	n.	RI	n.	RI
OLD_NNC	30.00	6.15%	30.00	6.56%	29.64	5.95%	29.64	5.77%	29.71	6.15%	29.86	6.90%
OLD_LB_EBA_2018	30.00	8.20%	30.00	8.66%	30.00	7.34%	30.00	7.15%	30.00	7.56%	30.00	8.42%
NEW_LB_EBA_2018	30.00	8.23%	30.00	8.68%	30.00	7.77%	30.00	7.57%	30.00	8.01%	30.00	8.88%

This table shows on average the numer of banks exposed to each regulatory method and simulation techniques and the value of the related risk indicators over the period 2006-2019.

Note: PSU = parallel shock up +200 basis points; PSD = parallel shock down -200 basis poitns; 99_PER= scenario associated to the 99° percentile; 1_PER= scenario associated to the 1° percentile; SRU = short rates shock up; SRD = short rates shock down; STEEP = steepener; FLAT = flattener; MAX_4 and MAX_6 value of the risk indicator calculated according to the most penalizing scenario under previous four regulatory scenarios and the new six regulatory scenarios. n= number of banks; IR = value of the risk indicator expressed in percentage and calculated taking into account the only banks exposed to the related method; HS= historical simulations; MCS = Monte Carlo simulations; 99_HS and 99_MCS = scenario associated to the 99° percentile respectively to the application of historical and Monte Carlo simulations; ES_HS and ES_MCS = expected shortfall calculated on the basis of 99° percentile of historical and Monte Carlo simulations: INF and SUP = lower and upper bound associated with the 99 percentile of the Monte Carlo simulation and calculated according to the methodology proposed by Gupta et al (1997); OLD_NNC = application of old methodology based on duration coefficients and of non-negative constraint; OLD_LB_EBA = application of old methodology based on duration coefficients and of the lower bound EBA; EBA; NEW_LB_EBA = application of new methodology based on the present value criterion under a continuous capitalization scheme and of the lower bound EBA.

Table 6. backtesting results in terms of number of exceptions and severity scores in case of underestimation

Panel A: Numer of exceptions												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	7.29	6.29	5.86	5.79	6.29	0.50	2.36	1.79	3.50	3.71	3.36	2.50
OLD_LB_EBA_2018	3.29	3.00	2.64	5.18	1.71	0.00	1.57	1.14	1.00	1.14	0.93	0.50
NEW_LB_EBA_2018	4.36	3.29	2.36	6.00	2.36	0.00	1.29	1.07	1.00	1.14	0.86	0.43
Panel B: Severiy scores in case of underestimation (α=1)												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	1.65	1.61	2.06	2.29	1.84	0.39	0.96	0.80	1.34	1.47	1.27	1.01
OLD_LB_EBA_2018	0.97	0.85	1.33	1.81	0.66	0.00	0.49	0.45	0.33	0.35	0.29	0.13
NEW_LB_EBA_2018	1.13	0.97	1.39	1.61	0.94	0.00	0.52	0.46	0.35	0.46	0.34	0.14
Panel B: Severiy scores in case of underestimation (α=2)												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	4.26	5.00	7.14	10.43	6.56	0.82	2.60	2.10	3.18	3.45	2.93	2.55
OLD_LB_EBA_2018	2.36	3.07	4.82	9.07	1.88	0.00	1.34	1.04	0.61	0.67	0.48	0.27
NEW_LB_EBA_2018	3.00	3.55	5.02	8.11	3.36	0.00	1.47	1.15	0.66	0.85	0.59	0.29

This table shows on average the number of exceptions and the scores of loss function in terms of severity scores in case of underestimation described in equation (xx) for each regulatory methods, criterion based on the most penalizing scenario and simulation tecniques.

Note: 1= parallel shift method; 2 = percentile method; 3 = method based on short rates up and down scenarios; 4 = method based on steepener and flattener scenarios; MAX_4 and MAX_6 value of the risk indicator calculated according to the most penalizing scenario under previous four regulatory scenarios (methods 1 and 2) and the new six regulatory scenarios (methods 1, 3 and 4); 99_HS and 99_MCS = scenario associated to the 99° percentile respectively to the application of historical and Monte Carlo simulations; ES_HS and ES_MCS = expected shortfall calculated on the basis of 99° percentile of historical and Monte Carlo simulations: INF and SUP = lower and upper bound associated with the 99 percentile of the Monte Carlo simulation and calculated according to the methodology proposed by Gupta et al (1997); OLD_NNC = application of old methodology based on duration coefficients and of non-negative constraint; OLD_LB_EBA_2018 = application of old methodology based on duration coefficients and of the lower bound EBA; EBA; NEW_LB_EBA_2018 = application of new methodology based on the present value criterion under a continuous capitalization scheme and of the lower bound EBA.

Table 7. Baktesting results in terms of proximity scores

Panel A: α=β=1												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	7.98	6.36	4.96	6.71	8.93	9.63	6.85	7.21	6.68	6.52	6.86	7.56
OLD_LB_EBA_2018	9.16	8.01	7.50	7.40	10.49	11.38	8.83	9.25	7.91	7.73	8.12	8.95
NEW_LB_EBA_2018	9.35	8.70	8.14	8.07	11.52	12.67	9.63	10.05	9.13	8.94	9.36	10.21
Panel B: α=2; β=1												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	8.66	7.53	6.22	10.53	10.75	9.67	7.14	7.41	6.99	6.87	7.14	7.77
OLD_LB_EBA_2018	9.43	8.86	8.30	11.16	10.72	11.38	9.02	9.35	8.00	7.83	8.19	8.99
NEW_LB_EBA_2018	9.81	9.66	8.83	11.87	12.15	12.67	9.86	10.19	9.21	9.03	9.42	10.24
Panel C: α=2; β=0.5												
	1	**2**	**3**	**4**	**MAX_4**	**MAX_6**	**99_HS**	**ES_HS**	**99_MC**	**INF**	**SUP**	**ES_MC**
OLD_NNC	3.28	3.67	3.52	6.63	4.78	2.90	2.76	2.73	2.67	2.68	2.66	2.72
OLD_LB_EBA_2018	3.04	3.60	3.54	6.69	3.23	3.17	3.03	3.00	2.73	2.72	2.74	2.85
NEW_LB_EBA_2018	3.27	3.81	3.51	6.82	3.83	3.36	3.18	3.16	2.91	2.90	2.93	3.03

This table shows on average the scores of loss function in terms of proximity scores described in equation (xx) for each regulatory methods, criterion based on the most penalizing scenario and simulation tecniques. Note: 1= parallel shift method; 2 = percentile method; 3 = method based on short rates up and down scenarios; 4 = method based on steepener and flattener scenarios; MAX_4 and MAX_6 value of the risk indicator calculated according to the most penalizing scenario under previous four regulatory scenarios (methods 1 and 2) and the new six regulatory scenarios (methods 1, 3 and 4); 99_HS and 99_MCS = scenario associated to the 99° percentile respectively to the application of historical and Monte Carlo simulations; ES_HS and ES_MCS = expected shortfall calculated on the basis of 99° percentile of historical and Monte Carlo simulations: INF and SUP = lower and upper bound associated with the 99 percentile of the Monte Carlo simulation and calculated according to the methodology proposed by Gupta et al (1997); OLD_NNC = application of old methodology based on duration coefficients and of non-negative constraint; OLD_LB_EBA_2018 = application of old methodology based on duration coefficients and of the lower bound EBA; EBA; NEW_LB_EBA_2018 = application of new methodology based on the present value criterion under a continuous capitalization scheme and of the lower bound EBA.

Table 8. Comparison between regulatory criteria and simulation methodologies according to the sign statistical test

	99_MC_VS_MAX_6	ES_MC_VS_MAX_6	99_MC_VS_99HS	ES_MC_VS_ES_HS	99_HS_vs_MAX_6	ES_HS_vs_MAX_6
			Panel A: α=β=1			
OLD_NNC	-14.541***	-3.123***	-3.025***	-2.635***	-9.271***	-7.807***
OLD_LB_EBA_2018	-19.518***	-5.758***	-5.465***	-3.318***	-7.807***	-5.855***
NEW_LB_EBA_2018	-19.030***	-1.366***	-1.171	-0.488	-8.198***	-6.343***
			Panel B: α=2; β=1			
OLD_NNC	-13.467***	-3.318***	-3.220***	-2.440***	-8.978***	-7.612***
OLD_LB_EBA_2018	-19.030***	-5.953***	-5.660***	-3.708***	-7.514***	-5.660***
NEW_LB_EBA_2018	-18.640***	-1.366*	-1.171	-0.878	-7.612***	-5.953***
			Panel C: α=2; β=0,5			
OLD_NNC	-12.199***	-2.830***	-2.830***	-2.245***	-7.710***	-6.636***
OLD_LB_EBA_2018	-18.542***	-5.953***	-5.660***	-3.806***	-6.441***	-4.977***
NEW_LB_EBA_2018	-18.347***	-1.269***	-1.073	-1.269	-7.026***	-5.465***

This table shows the results concerning the application on the whole period 2006-2019 of the sign statistical test. The analysis is carried out by taking into account the different methodologies two by two and for the loss function of equation (xx) in terms of proximity scores. The different specifications of the loss function are declined accordint the different calibration of α and β coefficients.

Note: 1 MAX_6 value of the risk indicator calculated according to the most penalizing scenario under the new six regulatory scenarios; 99_HS and 99_MCS = scenario associated to the 99° percentile respectively to the application of historical and Monte Carlo simulations; ES_HS and ES_MCS = expected shortfall calculated on the basis of 99° percentile of historical and Monte Carlo simulations:; OLD_NNC = application of old methodology based on duration coefficients and of non-negative constraint; OLD_LB_EBA_2018 = application of old methodology based on duration coefficients and of the lower bound EBA; EBA; NEW_LB_EBA_2018 = application of new methodology based on the present value criterion under a continuous capitalization scheme and of the lower bound EBA.

*** significance at 1% level, ** significance at 5% level, * significance at 10% level.