CASMEF Working Paper Series

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Working Paper No. 4
June 2015

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May, 2015

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ABSTRACT

Appropriate methodologies to assess interest rate risk contribute to the sound management of a credit institution and, given the systemic nature of this risk, help to pursue global financial stability. The regulatory models to estimate a bank's exposure to interest rate risk in the banking book are based on very coarse assumptions about the scenarios of interest rate changes. Consistent with the logic underlying the Basel Committee treatment, we develop more sophisticated methodologies to measure the sensitivity of a bank's economic value to changes in interest rates. Our methodologies are based on historical and Monte Carlo simulation and can be applied to publicly available data in a manner replicable by those outside the banking institutions.

The performance of both regulatory and more sophisticated methodologies is assessed through a backtesting analysis that allows to verify whether and to what extent their results are both consistent with actual bank exposure and adequate from a prudential perspective. Overall, our empirical evidence suggests that the latter perform better than the former. Based on some major drawbacks that we especially observe within a context of low market rates, the regulatory treatment of the interest rate risk in the banking book should not be considered conclusive: further efforts are required to both supervisors and banks in order to improve the current regulatory framework and to set more effective risk management policies, respectively.

JEL classification codes: G21, G28, G32.

Keywords: banks; interest rate risk; regulation; risk management; historical simulation; Monte Carlo simulation

1. Introduction

The U.S. savings and loan crisis in the 1980s and early 1990s showed that the interest rate risk in the banking book can undermine banks' earnings and lead credit institutions to bankruptcy . Therefore, appropriate methodologies to assess interest rate risk contribute both to significantly increase bank shareholders' wealth and, given the systemic nature of this risk, to pursue global financial stability. Banking international authorities have both developed models to estimate banks' exposure to interest rate risk and issued technical documents to provide credit institutions with guidelines to properly assess it. Right after the savings and loan crisis, the U.S. Federal Reserve introduced the Economic Value Model (EVM) in order to assess a bank's exposure to interest rate risk through the changes in its equity economic value, by providing a duration-based estimate of interest rate sensitivity based on accounting data [Houpt and Embersit (1991); Wright and Houpt (1996); Sierra and Yeager (2004) and Sierra (2009)]. In line with the EVM approach, the Basel Committee on Banking Supervision (BCBS) has adopted an accounting-based methodology according to which risk exposure is estimated by applying a "standardized" shock. The "standardized shock" can be given by a ± 200-basis point parallel shift in the yield curve, fixed for all maturities, 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 (BCBS, 2004). Banks estimate their exposure through a risk indicator which is the ratio of the change in their equity value, due to the interest rate shock, to their supervisory capital. The estimated risk indicator should not exceed a 20% critical threshold. In 2006, due to the considerable differences among banks in terms of both the nature of their exposure and their monitoring process, the Basel Committee decided to include the treatment of the interest rate risk in the banking book within the Pillar II "Supervisory review" of the New Basel Capital Accord (BCBS, 2006) and not to set any capital requirement. The Committee of European Banking Supervisors (CEBS) issued some guidelines to improve both the internal capital adequacy assessment process (ICAAP) and the supervisory review and evaluation process (CEBS, 2006). In a survey of the practices adopted at large banks to measure the economic capital, BCBS (2009) has highlighted the problems potentially arising from the assumption of a stress scenario based on parallel shifts of ± 200 basis points in the yield curve. More recently, the European Banking Authority (EBA) has issued a technical document for consultation that aims to revise and supplement the 2006 CEBS guidelines (EBA, 2013). Finally, the Basel Committee has initiated a fundamental review of the trading book regime to address shortcomings in its overall design (BCBS, 2012 and 2013). In particular, the Committee has expressed some concerns about the possibility of arbitrage across the banking book/trading book boundary. Different capital treatments for the same risks on either side of the boundary are one of the major contributors to arbitrage opportunities: interest rate risk is included under the Pillar 1 capital regime when referred to the trading book, whereas it is subject to Pillar 2 requirements when it concerns the banking book. The Committee has therefore undertaken some preliminary work on the key issues that would be associated with applying a Pillar 1 capital charge for interest rate risk in the banking book.

To the best of our knowledge, this research traces back to a scant list of previous studies testing the robustness of the main assumptions underlying the BCBS approach to assess banks' interest rate risk in the banking book: on the one hand, Entrop *et al.* (2008) and Entrop *et al.* (2009), who study interest rate risk exposure of the German banking sector, and, on the other hand, Fiori and Iannotti (2007) and Cocozza *et al.* (2015), whose empirical evidence is referred to Italian banks. By using time-series accounting-based data, Entrop *et al.* (2008) developed a model allowing to estimate the distribution of assets and liabilities' maturities within each regulatory time band. Therefore, interest rate risk estimates are more precise than those obtained by assuming the concentration of the maturities in the midpoints of the time bands, as the regulatory model does. Their model explains the cross-sectional variation of banks' interest rate risk better than the regulatory approach, its results are more in line with those obtained by banks' internal models. Entrop *et al.* (2009) analyze how a bank's risk exposure changes if the assumptions underlying the regulatory framework proposed by BCBS (2004) are modified. In particular, they refer to the allotment of non-maturity deposits into the time bands, to the allotment of assets and liabilities within the time bands, to the number and boundaries of the time bands, to the amortization rate of customer loans and to the spread between the coupon and the market interest rate used to calculate the modified duration associated with each time band. They warn to be cautious when using the results stemming from the regulatory framework for supervisory and risk management approaches because these results significantly depend on the assumptions underlying it. Fiori and Iannotti (2007) develop a methodology to estimate a bank's exposure to interest rate risk in the banking book that takes into account both asymmetry and kurtosis of the distribution of the changes in interest rates by applying a specific technique of local smoothing. Furthermore, their methodology, which is based on Monte Carlo simulations, accounts not only for the concept of duration but also for that of convexity and calibrates the sensitivity coefficients using market data. If the duration coefficients set by the Basel Committee are calibrated on the basis of current market data at the valuation date, their results are consistent with the estimates of risk exposure based on the ± 200-basis point parallel shift in the yield curve. Finally, Cocozza et al. (2015) focus on the allotment criterion of nonmaturity deposits within the time bands of the maturity ladder. They develop a methodology that considers deposits' actual behavior in terms of both price sensitivity to changes in market rates and volume stability over time, showing that the use of different allocation criteria affects not only the size of the risk estimate but also the nature of banks' risk exposure and determines the risk inversion phenomenon, that is, banks exposed to an increase in interest rates can experience a reduction in their equity economic value if interest rates decrease.

Relative to prior literature, this study is meant to highlight the importance of the scenarios of changes in interest rates adopted to estimate interest rate risk. The above mentioned regulatory specific scenarios would represent a fairly uncommon and stressful rate environment (BCBS, 2004) and aim at identifying the so called "outlier banks", whose risk indicator is higher than the 20% threshold. Based on the ICAAP set in BCBS (2006), though not formally required by supervisors, banks use to set aside an amount of internal capital corresponding to the numerator of the risk indicator. Therefore, misaligned estimates of interest rate risk would lead banks to set aside an amount of internal capital that might either underestimate or overestimate the appropriate one. In particular, errors in the estimates of interest rate risk might alternatively jeopardize banking system stability, in the former case, or charging banks with higher opportunity costs, in the case of overestimation. Furthermore, misaligned estimates of risk indicators also provide distorted indications for banks ALM strategies. By examining the risk exposure of a sample of 130 Italian commercial banks over the 2006 – 2013 period, we compare the results of the regulatory methodologies with two approaches where we adopt historical and Monte Carlo simulation techniques to model annual changes in interest rates, in line with the assumptions underlying the regulatory framework. Each methodology performance is assessed through a backtesting analysis that allows to assess whether and to what extent the estimated risk indicator is both consistent with actual bank exposure and adequate from a prudential perspective. Our main contribution consists in the proposal and implementation of well grounded methodologies to model annual changes in interest rates that are used to estimate banks' exposure to interest rate risk. These methodologies can be applied to publicly available data in a manner replicable by those outside the banking institution. Because of interest rate risk's systemic relevance, publicly available and transparent measures of it play a special role in global financial system functioning and stability and deserve greater attention from both academic research, banking industry, and regulatory supervisors. We analyze the Italian banking system because it has some features that make such an analysis especially interesting. In fact, Italian banks generally act as qualitative asset transformers, meaning that interest rate risk arises from the basic banking business, thus making the internal capital against this risk the second largest after that referred to credit risk. This evidence is common to those banking systems where intermediaries are mainly characterized by a commercial nature, and it makes our investigation relevant from a global perspective as well.

Our empirical evidence shows that the methodologies based on historical and Monte Carlo simulations perform better than regulatory methodologies in terms of both consistency with actual exposure and prudential adequacy. It is interesting to note that when market rates are quite low, as in the last part of the time period we analyze, the regulatory methodologies might lead to the risk neutrality phenomenon, according, by applying the ex ante scenario of changes in interest rates, a bank experiences an increase in its equity economic value. Therefore, the results obtained using the standardized framework in its current specification should be treated with caution if employed for supervisory and risk management purposes. Issues arising from the results of our empirical analysis would suggest a reconsideration of the standardized interest rate shocks that banks have to use and support the opportunity to develop and use methodologies that allow to better account for actual bank riskiness.

The rest of the paper is organized as follows: in section 2, we analyze the regulatory methodologies and develop our methodological proposals to implement the approach based on historical and Monte Carlo simulation; section 3 presents data and descriptive statistics for our empirical analysis; section 4 shows the results of the adoption of the different methodologies discussed in this study; in section 5 we show in details the backtesting procedure adopted to assess each methodology performance; section 6 concludes and provides some policy implications.

2. Methodology

From a methodological point of view, in order to make risk exposure estimates based on the regulatory framework more realistic, the main objective of this paper is to build scenarios of changes in interest rates that can replace the interest rate shocks set by BCBS (2004). Therefore, as a necessary premise, the following section 2.1 shows in details the regulatory framework adopted by the Italian national supervisor. The above depicted international regulation has been introduced in the Italian banking system through the 2006 Bank of Italy's Circular 263, which has been modified in December 2010 and replaced by the 2013 Circular 285.

In developing models to assess interest rate risk we take into account a term structure of interest rates whose nodes correspond to the midpoints of the 14 time bands included in the maturity ladder adopted by the Italian national supervisor (see the first column of Table 1). These rates are our risk factors and are observed on T_0, that corresponds to the December 31st of each of the years included in the analyzed time period. T_0 is also the date in which we estimate our banks' risk exposure and which bank specific balance sheet data included in the maturity ladder are referred to.

We observe the key-rates on a daily frequency over a six-year period just ending in T_0. Therefore, we account for annual changes in our risk factors over a five-year period, as required by BCBS (2004). Key-rates referred to maturities not included in the market term structure are calculated through linear interpolation. We present in details our methodologies to improve estimates of banks' risk exposure in section 2.2; both of them are consistent with major assumptions of the current regulatory framework.

2.1. Regulatory framework

According to Bank of Italy (2013) banks must allocate on- and off-balance-sheet accounts into the 14 time bands of the maturity ladder shown in Table 1. Fixed-rate assets and liabilities are slotted into the time bands based on their residual maturity, while the next repricing date is considered to allot floating-rate accounts. Some accounts are allotted on the basis of specific criteria, which have also changed over time. For example, non-maturity deposits are currently treated as follows: 25% are allocated to the "demand and revocable" time band, whereas the remaining amount is allotted to the next eight time bands in proportion to the number of months included in each of them. According to the criterion in force until December 2010, non-maturity deposits up to the amount of current account assets were allotted to the "demand and revocable" time band, whereas the rest was distributed over the next four time bands in proportion of the number of months included in each of them. Coupon payments are not considered. On- and off-balance-sheet accounts are assumed to be characterized by a maturity exactly coinciding with the midpoint of each time band. Consequently, a bank's interest rate risk is measured on the basis of the proxy for modified duration just corresponding to this midpoint (second and third columns in Table 1).

Table 1. Regulatory maturity ladder for measuring interest rate risk

Time band	Midpoint of time band	Proxy of modified duration (in years) (a)	Assumed interest rate shock (in bps) (b)	Weighting factor (c) = (a) × (b)
Demand and revocable	0	0	+/–200	+/–0.00%
Up to 1 month	0.5 months	0.04	+/–200	+/–0.08%
From 1 month to 3 months	2 months	0.16	+/–200	+/–0.32%
From 3 months to 6 months	4.5 months	0.36	+/–200	+/–0.72%
From 6 months to 1 year	9 months	0.71	+/–200	+/–1.43%
From 1 year to 2 years	1.5 years	1.38	+/–200	+/–2.77%
From 2 years to 3 years	2.5 years	2.25	+/–200	+/–4.49%
From 3 years to 4 years	3.5 years	3.07	+/–200	+/–6.14%
From 4 years to 5 years	4.5 years	3.85	+/–200	+/–7.71%
From 5 years to 7 years	6 years	5.08	+/–200	+/–10.15%
From 7 years to 10 years	8.5 years	6.63	+/–200	+/–13.26%
From 10 years to 15 years	12.5 years	8.92	+/–200	+/–17.84%
From 15 years to 20 years	17.5 years	11.21	+/–200	+/–22.43%
More than 20 years	22.5 years	13.01	+/–200	+/–26.03%

Source: Bank of Italy (2013).

Assets and liabilities are offset to calculate a net position (NP_i) for the i-th time band (for i = 1, …, 14). Under a parallel shift scenario of ±200 bps, each NP_i is multiplied by the weighting factors shown in the fifth column of Table 1. These weighting coefficients are the product of proxies of modified durations (MD_i) and the assumed interest rate shock of ±200 bps (Δr). The change in the net position of the i-th time band (ΔNP_i), defined as "net weighted position", is:

$$\Delta NP_i = NP_i \cdot MD_i \cdot \Delta r \qquad (1)$$

As commonly known, equation (1) is the standard formula representing the relationship between the change in a fixed-rate security price and the change in the yield to maturity, without the minus sign. If the net position of the i-th time band is positive (negative) and interest rates increase (decrease), the resulting positive net weighted position expresses a reduction in the bank's equity value. Based on the so called "non-negativity constraint" set by the regulator, the –200-bp shock in interest rates cannot drive the term structure of the key rates observed in T_0 under the zero level. Consequently, if for a given node of the term structure the rate is lower than 2.00%, say 1.25%, the magnitude of the negative shock in absolute value corresponds to the interest rate itself: in this example, it equals –125 bps.

To obtain the change in the economic value of the net positions, for each significant currency j (j = 1, … k)—that is, currencies accounting for more than 5% of the total assets or liabilities in the banking book—and the aggregate of non-significant currencies, the net weighted positions of the different time bands are summed as follows:

$$\Delta EV_j = \sum_{i=1}^{14} \Delta NP_i \qquad (2)$$

The sum of the net weighted positions for each significant individual currency (ΔEV_j) and the aggregate of non-significant currencies (ΔEV_q) are summed, if positive, as described in equation (3):

$$\Delta EV_p = \sum_{j=1}^{k} \Delta EV_j + \Delta EV_q \quad (3) \qquad\qquad \textit{with} \quad \Delta EV_j > 0, \Delta EV_q > 0$$

where ΔEV_p represents the change in a bank's economic value. Finally, this amount is divided by supervisory capital (SC) to determine the risk indicator (RI), whose alert threshold is set equal to 20%. In symbols,

$$RI = \frac{\Delta EV_p}{SC} \leq 20\% \qquad (4)$$

The risk indicator provides an estimate of interest rate risk exposure in the banking book. Assuming the supervisory capital to be positive, the ratio cannot be negative for banks exposed to interest rate risk because for these banks the decrease in their economic value is expressed by a positive numerator. In particular, it is noteworthy to point out that, by construction, the numerator takes a positive sign whether a bank is exposed to an increase in interest rates or to a decrease.

The current regulatory framework proposes a second approach that we define as the "percentiles method" because the ±200-bp parallel shock in equation (1) is replaced by the 1^{st} and 99^{th} percentile of the distributions of annual changes in our key-rates. These distributions are obtained by using a one-year holding period and a minimum five years of observations. In particular, the 1^{st} and 99^{th} percentiles are associated with negative and positive changes in our key-rates, respectively. According to BCBS (2004), a one-year holding period was chosen both for practical purposes and in recognition that, on average, within one year banks are able to restructure or hedge their positions to mitigate further losses in economic value should rates be extraordinarily volatile. A five-year historical observation period (six years of data) allows to capture more recent and relevant interest rate cycles. Based on an overlapping approach, we calculate the time series of the key-rates annual changes by subtracting from the rates observed on a certain day of a given year those recorded one year before. These changes are then adjusted in order to meet the previously mentioned non-negativity constraint. In this way we get 14 distributions of the changes in our key-rates, one for each time band of the maturity ladder. Then, we use the changes associated with the 1^{st} and 99^{th} percentiles of each distribution to weight the net positions of the corresponding time band. Next, as for the parallel shift, we sum the net weighted positions to calculate the change in the economic value, which is finally divided by the supervisory capital to get the risk indicator.

2.2. Improving estimates of banks' exposure to interest rate risk

The parallel shift of ±200 basis points and the percentiles method show some major drawbacks. The former is set by the Basel Committee regardless of actual changes in interest rates. In this respect, the two scenarios corresponding to the 1st and the 99th percentile are changes actually occurred in our 14 key-rates. Nevertheless, these changes might have occurred on different days: for example, the 1st percentile of the risk factor annual changes distribution might refer to January 22nd, 2008 for the key-rate associated with the first time band, it might refer to December 23rd, 2010 for the key-rate associated with the second time band, etc. Therefore, this method does not allow to account for the correlations actually observed between the annual changes in the key-rates as well as the parallel shift approach.

Our first methodological proposal, which makes use of historical simulations, overcomes this limit because it calculates the risk indicator by using the joint annual changes in our key-rates that actually occurred in the past. In particular, it is based on as many scenarios as the days included in the five-year time horizon ending in T_o. Each scenario is represented by the joint annual changes in our key-rates, that are calculated on a given day through the overlapping technique suggested by the Committee, and replaces the ±200-bp parallel shift in equation (1). We apply those shocks to the net positions recorded in T_o and sum the net weighted positions to obtain the changes in a bank's economic value. By dividing a bank's economic value changes by its supervisory capital in T_o, we get an empirical distribution of the risk indicator. This distribution is then cut in correspondence of the percentile associated with the desired confidence level that we set equal to 99% following BCBS (2004). One final remark about this method is worth of consideration to us: during periods of low interest rates such as the current one, the non-negativity constraint might prevent this method from capturing the correlations as well. It would happen if annual changes in the key-rates were higher, in absolute value, than the key-rates observed in T_o.

Our second method is based on Monte Carlo simulations and allows to generate scenarios that both take into account the correlations between the annual changes in our risk factors and meet the non-negativity constraint. We carry out as many simulations as those required to obtain the desired number N of scenarios and reject simulations leading the term-structure of our key-rates observed in T_0 under the zero level in one or more nodes. In this way we get a distribution of the risk indicator which is cut at the percentile corresponding to the desired confidence level of 99%. Particularly, our methodological proposal 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 our 14 key-rates. The application of the overlapping data technique makes well grounded the use of a normal joint probability density function which has been already used by Fiori and Iannotti (2007);

ii) estimating means and variances of the distributions of the annual changes in our key-rates, as well as their variance-covariance matrix, denoted by 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 risk factors;

iii) generating a random number u_i (i=1,...14) ranging from 0 to 1 at each node of our key-rates term structure;

iv) converting each u_i obtained in the previous point iii) into a value z_i (i=1,...14) distributed according to a standard normal. In symbols:

$z_i = F^{-1}(u_i)$

where F^{-1} is the inverse of the distribution function of the probability density function of the annual changes of the *i-th* key-rate;

v) using the algorithm of Cholesky in order to decompose the matrix of variances and covariances of the previous point ii), in two matrices Q and Q' such that:

$$Q' \cdot Q = \Omega \quad (5.)$$

vi) calculating the vector x, whose elements are the joint simulated annual changes in our 14 key-rates through the following formula:

$$x = Q' \cdot z + \mu \quad (6.)$$

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 risk factors annual changes. 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 N of scenarios that meet the non-negativity constraint. In fact, we only take into account those scenarios meeting the non-negativity constraint for each node of our key-rates term structure;

viii) the N simulated changes defined in point vii) replace the ± 200 basis points parallel shift in equation (1) and are applied to the net positions recorded in T_0. Then, the net weighted positions are summed in order to calculate the change in a bank's economic value, which is finally divided by its supervisory capital referred to date T_0. In this way we obtain an empirical distribution of the risk indicator, from which we can identify the percentile associated with the 99% confidence level.

The level of the risk indicator obtained in step viii) depends on the N simulated scenarios. Running the simulation a second time would generate other N different scenarios, which would lead to a different level of the risk indicator. Based on Gupton *et al.* (1997) we propose a method to define a range of values within which the risk indicator has to fall if the simulation is run more than a single time. Given the number of scenarios N, which also corresponds to the number of observations of the risk indicator distribution, and p the chosen confidence level, the casual number $n_p = Np$ follows the binomial distribution with mean and variance equal, respectively, to Np and $Np(1 - p)$. For high values of N, it can be proved that n_p follows a normal distribution. Under this hypothesis it is possible to construct a confidence interval for n_p, with lower bound and upper bound, respectively, equal to:

$$\text{lower bound} = Np - \alpha\sqrt{Np(1-p)} \quad (7.)$$

$$\text{upper bound} = Np + \alpha\sqrt{Np(1-p)} \quad (8.)$$

where α depends on the desired confidence level. If the upper and lower bound are not integers, they are rounded, respectively, downwards and upwards. For example, for the estimate of the 99th percentile of a 10,000-observation distribution, given a confidence interval of 99% (α = 2.576), there is a 99% probability that the true value of the 99th percentile is comprised between 9,874 and 9,926:

$$\Pr(9{,}874 \leq N_p \leq 9{,}926) = 99\%$$

The levels of risk indicator associated to these observations allows us to obtain a range of values within which the internal capital estimate can be placed.

Within the historical and Monte Carlo simulations framework, we also calculate a risk measure based on the Expected Shortfall (ES) in order to estimate the size of the decreases in a bank's economic value that are higher than the 99th percentile of the risk indicator distribution. In this context the risk indicator (RI_{ES}) is the ratio between the expected value of all the reductions in economic value in excess to the one corresponding to the 99th percentile of the distribution of the risk indicator ($\Delta EV_{P,99^{th}}$) and the bank's supervisory capital. In symbols:

$$RI_{ES} = \frac{E\left\lfloor \Delta EV_P \middle| \Delta EV_P > \Delta EV_{P,99^{th}} \right\rfloor}{SC} \qquad (9.)$$

From a prudential perspective, by adopting this approach, the risk indicator synthesizes a bank's exposure to a set of scenarios more adverse than that associated with the 99th percentile and reduces the probability to underestimate its actual risk.

3. Data and descriptive statistics

We estimate our banks' risk indicators as of December 31st of each of the eight years included in the sample period by using key-rates annual changes calculated over a six-year period which just ends in the evaluation date. In line with the current industry practice, we use the EONIA (Euro Overnight Index Average) rate for the "*Demand and revocable*" time band, the Euribor rate for maturities shorter than 12 months, and IRS rates for maturities longer than, or equal to, 1 year. Table 2 shows the term structure of our key-rates observed as of December 31st of each of the years included in the 2006-2013 period. Its characteristics and dynamics over time do have a strong impact on banks' risk exposure. In general, we observe that the term structure becomes steeper and, what's more interesting to us, it experiences a downward shift over time. In fact, starting from 2009 all the short-term (up to 1 year) key-rates are lower than 2%, and since 2011 the downward move takes even some long-term rates below the 2% threshold. Therefore, due to the changes observed in our key-rates, it is more likely for the non-negativity constraint to come into effect during the last years of the time horizon analyzed in this research.

Table 2: Key-rates term structure as of December 31st (2006 – 2013)

T_0	Demand and revocable	Up to 1 month	From 1 month to 3 months	From 3 months to 6 months	From 6 months to 1 year	From 1 year to 2 years	From 2 year to 3 years	From 3 year to 4 years	From 4 year to 5 years	From 5 year to 7 years	From 7 year to 10 years	From 10 year to 15 years	From 15 year to 20 years	Over 20 years
December 31st 2006	3.69%	3.62%	3.66%	3.79%	3.95%	4.10%	4.13%	4.13%	4.13%	4.14%	4.17%	4.24%	4.29%	4.31%
December 31st 2007	3.92%	4.18%	4.49%	4.70%	4.73%	4.63%	4.54%	4.53%	4.54%	4.58%	4.67%	4.80%	4.89%	4.91%
December 31st 2008	2.35%	2.45%	2.79%	2.93%	3.02%	2.72%	2.86%	3.04%	3.18%	3.36%	3.61%	3.85%	3.88%	3.76%
December 31st 2009	0.41%	0.40%	0.56%	0.84%	1.13%	1.59%	2.06%	2.41%	2.68%	2.99%	3.43%	3.82%	4.02%	4.05%
December 31st 2010	0.82%	0.65%	0.89%	1.10%	1.37%	1.45%	1.75%	2.08%	2.34%	2.70%	3.12%	3.50%	3.67%	3.68%
December 31st 2011	0.63%	0.76%	1.18%	1.48%	1.79%	1.37%	1.35%	1.45%	1.63%	1.91%	2.24%	2.57%	2.68%	2.65%
December 31st 2012	0.13%	0.09%	0.15%	0.25%	0.43%	0.35%	0.42%	0.54%	0.69%	0.95%	1.37%	1.83%	2.09%	2.20%
December 31st 2013	0.45%	0.20%	0.26%	0.34%	0.48%	0.48%	0.66%	0.89%	1.13%	1.49%	1.95%	2.41%	2.65%	2.73%

Source: Datastream™.

The following Table 3 shows main descriptive statistics of the distributions of the key-rates annual changes that we obtain when the term structure is observed in December 31st, 2013. Following BCBS (2004), these distributions are generated by using five years of observations, back to December 31st, 2008. Overall, the evidence we find can be summarized as follows: i) since kurtosis coefficients are negative the adoption of a normal joint probability density function in running our Monte Carlo simulations allows us to take into account extreme events; ii) short-term key-rates are more volatile than long-term ones; iii) positive changes in key-rates are wider than negative ones. We get similar results (available upon request) if we repeat the descriptive analysis by setting as estimation date the last day of each of the seven years included in the 2006-2012 time horizon.

Table 3. Annual changes in key-rates over the period December 31st, 2008 – December 31st, 2013, with December 31st, 2013 set as evaluation date

	Demand and revocable	Up to 1 month	From 1 month to 3 months	From 3 months to 6 months	From 6 months to 1 year	From 1 year to 2 years	From 2 years to 3 years	From 3 years to 4 years	From 4 years to 5 years	From 5 years to 7 years	From 7 years to 10 years	From 10 years to 15 years	From 15 years to 20 years	Over 20 years
Mean	-0.76	-0.80	-0.86	-0.88	-0.87	-0.79	-0.74	-0.70	-0.67	-0.61	-0.55	-0.49	-0.45	-0.43
Std. Deviation	1.32	1.41	1.45	1.41	1.38	1.16	0.97	0.86	0.79	0.71	0.61	0.56	0.56	0.57
Max.	1.22	0.94	0.85	0.77	0.83	1.00	1.09	1.05	0.93	0.78	0.59	0.60	0.62	0.66
Min.	-4.27	-4.67	-4.67	-4.54	-4.34	-3.89	-3.41	-2.94	-2.60	-2.14	-1.69	-1.76	-1.86	-1.91
Kurtosis	0.29	0.16	0.08	0.11	0.07	0.41	0.16	-0.33	-0.68	-0.99	-1.13	-1.07	-0.92	-0.93
Asimmetry	-1.21	-1.12	-1.07	-1.05	-0.99	-1.00	-0.67	-0.30	-0.08	0.11	0.17	0.12	-0.02	-0.11
Shapiro-Wilks normality test	0.83172***	0.85722***	0.86439***	0.87277***	0.88889***	0.90614***	0.95645***	0.98275***	0.98518***	0.97020***	0.95502***	0.96304***	0.97112***	0.97028***

Source: Datastream™. *** denotes significance at the 1% level.

The methodologies described above are used to measure the interest rate risk exposure of a sample of 130 Italian commercial, savings and cooperative banks during the period 2006-2013. The sample represents approximately 70% of the total assets of the Italian banking system and includes major banking groups and independent banks which have systematically published the above mentioned maturity ladder over the analyzed time period. Our data is taken from the maturity ladder which Italian banks can discretionally publish in Section E of the Notes to the Financial Statements, dealing with risks and hedging policies, according to the 2005 Bank of Italy's Circular 262. Based on that information, and focusing on different maturities and repricing dates that balance sheet accounts are characterized by, we group them into the following classes: i) current or non-maturity accounts, such as non-maturity deposits and demand loans; ii) accounts with maturities up to one year (short-term maturities); iii) accounts with maturities comprised between one year and five years (medium-term maturities); and iv) accounts with maturities longer than five years (long-term maturities). The following Table 4 shows the average values of our sample banks' cash assets and liabilities in panel A and panel B, respectively. Our banks are characterized by a large share of customer loans, equal to circa 86% of total cash assets. 70% of them are slotted in short-term time bands, ie, lower than one year, due to relevance of floating-rate loans. From a liability perspective, non-maturity deposits are 42.49% of total cash liabilities, confirming the relevance of the maturity transformation function at our sample banks and the associated importance from a risk management standpoint. Overall, debt securities issued by our sample banks constitute circa 32% of total cash liabilities: in particular, securities with a maturity shorter than one year are 22.84% of total cash liabilities and consist mainly of floating-rate securities.

Table 4: Average cash assets and liabilities term structure (data as of December 31st; % of total; standard deviation into brackets)

Panel A: cash assets								
	2006	2007	2008	2009	2010	2011	2012	2013
Debt securities with maturity shorter than 1 year	9.34% (9.13%)	9.13% (8.27%)	11.79% (7.34%)	12.13% (8.28%)	12.04% (7.31%)	11.65% (7.13%)	13.54% (7.51%)	16.06% (9.12%)
Debt securities with maturity between 1 year and 5 years	3.59% (5.91%)	2.66% (4.39%)	1.32% (3.02%)	1.85% (2.98%)	1.84% (2.84%)	2.97% (2.90%)	6.24% (4.98%)	7.69% (5.96%)
Debt securities with maturity longer than 5 years	1.36% (23.81%)	1.12% (2.40%)	0.63% (1.36%)	1.31% (3.11%)	1.59% (2.56%)	1.95% (2.62%)	3.68% (3.58%)	4.74% (4.80%)
Demand loan	51.83% (19.37%)	53.32% (23.30%)	51.46% (21.38%)	44.55% (20.54%)	42.36% (21.43%)	41.33% (20.32%)	41.55% (17.22%)	38.63% (17.10%)
Loans with maturity shorter than 1 year	21.05% (7.38%)	25.51% (21.50%)	25.39% (19.70%)	27.76% (19.90%)	32.72% (20.84%)	30.23% (19.56%)	25.41% (17.95%)	22.86% (16.78%)
Loans with maturity between 1 year and 5 years	6.72% (8.84%)	4.22% (4.49%)	4.48% (4.34%)	6.08% (5.37%)	5.50% (3.76%)	7.11% (5.38%)	6.26% (3.79%)	6.83% (3.79%)
Loans with maturity longer than 5 years	6.11% (8.84%)	4.04% (5.26%)	4.93% (5.17%)	6.32% (6.80%)	3.95% (3.25%)	4.75% (5.18%)	3.32% (2.88%)	3.19% (2.94%)
Panel B: cash liabilities								
	2006	2007	2008	2009	2010	2011	2012	2013
Non-maturity deposits	42.49% (10.87%)	40.68% (10.31%)	40.25% (9.48%)	43.61% (9.11%)	43.40% (8.76%)	40.47% (8.27%)	36.08% (8.41%)	37.83% (8.41%)
Other current accounts	9.48% (8.52%)	9.08% (7.88%)	8.23% (7.52%)	8.67% (7.14%)	9.81% (7.35%)	9.65% (6.90%)	10.85% (8.13%)	8.32% (6.90%)
Term deposits and other funds with maturity shorter than 1 year	13.37% (11.55%)	10.96% (9.76%)	8.20% (5.65%)	5.41% (5.92%)	6.32% (5.14%)	9.80% (7.56%)	17.02% (9.58%)	20.50% (9.96%)
Term deposits and other funds with maturity between 1 year and 5 years	2.26% (5.06%)	1.32% (3.98%)	0.49% (2.62%)	0.40% (2.06%)	0.38% (1.79%)	1.65% (3.16%)	1.84% (4.43%)	2.29% (3.97%)
Term deposits and other funds with maturity longer than 5 years	0.40% (1.27%)	0.22% (0.84%)	0.20% (0.99%)	0.19% (1.12%)	0.24% (1.14%)	0.20% (0.93%)	0.19% (1.03%)	0.19% (1.07%)
Debt securities with maturity shorter than 1 year	22.84% (13.55%)	28.40% (13.24%)	32.59% (12.61%)	30.80% (11.43%)	24.42% (8.90%)	22.06% (9.19%)	17.23% (7.40%)	15.62% (6.37%)
Debt securities with maturity between 1 year and 5 years	8.40% (8.72%)	8.72% (8.31%)	9.60% (7.80%)	10.40% (7.67%)	14.50% (7.42%)	15.28% (7.63%)	16.01% (7.84%)	14.48% (7.00%)
Debt securities with maturity longer than 5 years	0.75% (1.80%)	0.61% (1.57%)	0.45% (1.02%)	0.52% (1.08%)	0.93% (1.53%)	0.89% (1.37%)	0.78% (1.30%)	0.77% (1.24%)

Source: our elaborations on banks' balance sheet data.

Finally, Table 13 shows the average figures and the standard deviation of some ratios used to analyze our sample banks' performance, leverage, capital adequacy and cost efficiency. Overall, the net interest income ranges from a minimum of 1.96% of total assets in 2013 to a maximum of 2.86% in 2008, whereas the average ratio of net fees and commissions to total assets stands at 0.70% over the 2006-2013 time horizon, which confirms our institutions' commercial nature. Profitability for our sample banks has experienced a tremendous decline whether we measure it in terms of return on assets or return on equity. This result stems mainly from the effect of the financial crisis on the real economy and the consequent huge increase in loan loss provisions, which negatively affected the sample banks' income statements. Furthermore, we observe a strong reduction in the leverage ratio (equity to total assets), which shows a 20% decline over the analyzed time horizon even if it remains far above the 3.33% threshold imposed by the reform of the Basel capital accord known as Basel III. Finally, our sample banks are well capitalized from a prudential regulation perspective: the average solvency ratio is 14.61% on an annual basis, by far higher than the threshold set in Basel III.

Table 5: Sample banks' key ratios (data as of December 31st)

		2006	2007	2008	2009	2010	2011	2012	2013
Net interest revenue/total assets	Average	2.67%	2.84%	2.86%	2.35%	2.15%	2.29%	2.17%	1.96%
	Std. Dev.	0.79%	0.81%	0.75%	0.45%	0.41%	0.40%	0.43%	0.45%
Net fees and commission/total assets	Average	0.67%	0.65%	0.65%	0.69%	0.76%	0.76%	0.69%	0.64%
	Std. Dev.	0.30%	0.27%	0.23%	0.24%	0.26%	0.26%	0.26%	0.30%
Cost-income ratio	Average	60.58%	61.06%	63.54%	66.18%	71.64%	67.68%	59.92%	58.96%
	Std. Dev.	16.84%	8.20%	8.63%	8.66%	13.28%	8.47%	9.31%	11.98%
Leverage Ratio (equity to total assets)	Average	9.69%	9.06%	9.05%	9.26%	9.09%	8.98%	8.31%	7.70%
	Std. Dev.	3.88%	3.83%	3.41%	2.73%	2.86%	2.56%	2.49%	2.93%
Return on Assets	Average	0.83%	0.94%	0.69%	0.44%	0.25%	0.20%	0.14%	-0.06%
	Std. Dev.	0.50%	0.34%	0.36%	0.33%	0.35%	0.39%	0.60%	0.78%
Return on Equity	Average	7.81%	8.91%	6.44%	4.22%	2.36%	2.05%	0.95%	-1.51%
	Std. Dev.	4.94%	2.66%	3.20%	3.36%	4.17%	4.69%	8.73%	12.86%
Solvency Ratio	Average	13.40%	14.58%	14.62%	14.82%	14.89%	14.88%	14.71%	15.00%
	Std. Dev.	6.68%	5.04%	4.84%	4.83%	4.82%	4.60%	4.53%	5.04%

Source: our elaborations on banks' balance sheet data.

4. Results

Italian commercial banks typically fund long-term assets with short- and medium-term liabilities. Therefore, they are expected to be exposed to an increase in interest rates because, *ceteris paribus*, when interest rates move up, the reduction in the economic value of long-term assets should be greater, in absolute value, than that observed for the short- and medium-term liabilities. On the contrary, when interest rates decrease, these banks should experience a larger increase in their assets' economic value relative to that of their liabilities. Nevertheless, we also find banks that are exposed to decreasing interest rates and, what is more interesting to us, we find that some institutions do not appear to suffer from changes in interest rates. We define these institutions "risk-neutral", as we can see in the following Table 6. Overall, the heterogeneity in terms of risk exposure can be explained by the two following groups of factors: first, the adoption of both regulatory allocation criteria and hedging strategies through derivatives, which modify the contractual maturity of balance sheet accounts; second, the scenarios of changes in the key-rates and the duration coefficients associated with the time bands of the regulatory maturity ladder.

Table 6. Sample banks' types of interest rate risk exposure: breakdown by measurement methodology (2006 – 2013)

Evaluation date (*t*)	# of banks	Parallel shift			Percentiles method			Historical simulations		Monte Carlo simulations	
		I	D	N	I	D	N	I	D	I	D
December 31st 2006	130	47	83	0	41	87	2	39	91	40	90
December 31st 2007	130	32	98	0	24	105	1	25	105	23	107
December 31st 2008	130	23	107	0	15	107	8	20	110	23	107
December 31st 2009	130	31	94	5	18	111	1	17	113	43	87
December 31st 2010	130	21	105	4	11	119	0	10	120	20	110
December 31st 2011	130	38	78	14	27	96	7	18	112	35	95
December 31st 2012	130	54	25	51 [50]	27	26	77 [50]	35	95	73	57
December 31st 2013	130	71	25	34 [31]	36	28	66 [31]	42	88	77	53
Average # of banks per year	130	39.63	76.88	13.50	24.88	84.88	20.25	25.75	104.25	41.75	88.25

Source: our elaborations on Datastream™ and balance sheet data.
t is the evaluation date.
I = number of banks exposed to increasing interest rates; D = number of banks exposed to decreasing interest rates; N = number of risk-neutral banks.
[#] number of risk-neutral banks under both parallel shift and percentiles method.
Note: non-maturity deposits have been allotted using the criterion introduced in December 2010 also for the 2006-2009 period.

By adopting the jargon used within the BCBS framework, banks are defined exposed to raising interest rates when, due to an increase (decrease) of interest rates, the sum of the positive net weighted positions is higher (lower) than the absolute value of the negative ones, thus determining a reduction (increase) in banks' economic value. Typically, if a bank is exposed to an increase in interest rates, the reduction in its economic value can be attributed to the positive net positions of long-term time bands (from the time band "*From 5 years to 7 years*" to "*More than 20 years*" of Table 1), which are mainly fed by the allotment of capital repayments of fixed-rate loans and of the book value of fixed-rate securities. For banks exposed to rising interest rates, the level of the risk indicators is positively (negatively) correlated with: i) the amount of positive (negative) net positions; and ii) the size of the changes in key-rates associated with the time bands characterized by positive (negative) net positions. Previous Table 6 shows that, on average, during the 8-year time horizon we take into account, out of 130 institutions, circa 40 banks per year are exposed to raising interest rates under the parallel shift approach and circa 42 if we measure interest rate risk through the Monte Carlo simulations. The number of banks whose economic value drops if interest rates increase is circa 25 and 26 if the percentiles method and historical simulations approaches are adopted, respectively.

As concerns institutions exposed to decreasing interest rates, the average number per year goes from a minimum of circa 77, observed when the parallel shift is applied, to a maximum of circa 104 for the historical simulations. For these banks, a negative interest rate shock causes an increase in their assets' economic value which is lower, in absolute value, than the increase of their liabilities, whereas an increase in interest rates determines a reduction in their asset economic value which is lower than the decrease of their liabilities. Should interest rates decrease (increase), the sum of the positive net weighted positions would be higher (lower) than the absolute value of the negative ones, determining an overall decrease (increase) in banks' equity economic value. In particular, the reduction in the economic value mainly depends on the negative net positions observed in the medium-term time bands (from the time band "*From 1 year to 2 years*" to "*From 4 years to 5 years*") stemming from both the allotment of non-maturity deposits and the allocation of fixed-rate issued bonds. For banks exposed to decreasing interest rates, the level of the risk indicators is positively (negatively) correlated with: i) the amount of negative (positive) net positions; and ii) the size of the changes in key-rates associated with the time bands characterized by negative (positive) net positions.

It is interesting to note that, under both the parallel shifts approach and percentiles method, a bank's risk indicator is obtained by assuming that all the key-rates move together in the same direction. Key-rates are allowed to move in different directions if we adopt more sophisticated methodologies, such as those based on historical and Monte Carlo simulations, respectively. In this case, positive net weighted positions can be obtained by either multiplying positive net positions by positive changes in interest rates, or negative net positions by negative changes in interest rates. If those obtained in the first case are larger (smaller) than the latter, a bank is exposed to raising (decreasing) interest rates. Therefore, a bank would be classified as exposed to an increase (decrease) in interest rates if its risk exposure is mainly driven by positive (negative) changes in interest rates.

Beyond the two categories described above, in assessing risk exposure through the parallel shift scenario of ±200 bps and percentiles method, some banks experience an increase in their economic value under both the positive and negative change in the key-rates imposed by the supervisor. On average, circa 11 and 14 banks per year are risk-neutral under the parallel shift and percentiles method, respectively. For this particular type of banks, the sum of the positive net weighted positions is lower, in absolute value, than that of the negative ones, whether interest rates increase or decrease. The decrease (increase) in their asset economic value is lower (higher), in absolute value, than the decrease (increase) of their liabilities if interest rates raise (decrease). The main reason underlying the risk neutrality phenomenon is the application of the non-negativity constraint, that weakens the reduction in a bank's equity economic value associated with negative net positions of the medium-term time bands under a scenario of decreasing interest rates. This interpretation is confirmed by the significant increase in the number of risk-neutral banks over the last two years of our sample period, when interest rates are lower than before. In fact, analyzing only the results referred to the years 2012 and 2013, 51 and 34 banks are risk-neutral under the parallel shift approach and 77 and 66 if interest rate risk is measured through the percentiles method. These values are much higher than the average number per year, which is 13.50 and 20.25 under the parallel shift and the percentiles method, respectively. From 2006 to 2011 banks resulting risk-neutral under the parallel shift show a different type of risk exposure under the percentiles method, and, viceversa, risk-neutral banks under the percentiles method appear to be exposed to specific changes in interest rates if their exposure is measured through the parallel shift approach. Finally, in 2012 and 2013, 50 and 31 banks are risk-neutral under both the approaches, respectively.

If the non-negativity constraint were not applied to adjust a -200-bp parallel shift, these banks would be exposed to decreasing interest rates and the reduction in their equity economic value would be equal, in absolute value, to the increase associated with the case of a +200-bp parallel shift. Due to the low level of the key-rates term structure as of some evaluation dates, the non-negativity constraint prevents these banks from having, in the medium-term time bands, positive net weighted positions larger, in absolute value, than the negative ones that are associated with long-term time bands. Under the percentiles method, the 1st percentile of the distribution of the annual changes in the key-rates would not show the same change in a banks' equity, in absolute value but with opposite sign, as the 99th percentile. In some evaluation dates, such as December 31st of the years 2006 – 2008, particular scenarios of changes in the key-rates, combined with the term structure of some banks' net positions and the regulatory duration coefficients gave rise to the risk neutrality phenomenon even if the non-negativity constraint did not come into force.

Table 7 reports, for each year included in the sample period, the average values of the risk indicator obtained under the different methodologies. Interest rate risk is adequately managed by our sample banks: on average, the 20% critical threshold set by the BCBS is quite far from the risk indicators shown in Table 7, whose highest value is 15.2%, and is observed for the parallel shift adopting December 31st, 2006 as evaluation date. Banks exposed to increasing interest rates are characterized by higher risk indicators under the parallel shift approach because of the impact of a +200-bp interest rate shock on long-term positive net positions. The average value of the risk indicator for banks exposed to increasing interest rates is 10.32% under the parallel shift, versus a

6.87% for the Monte Carlo simulations, 4.73% for the percentiles method and 5.93% for the historical simulations. The distance among the different methods shrinks if we examine banks exposed to decreasing interest rates. Banks exposed to decreasing interest rates show risk indicators that, on average, go from the 5.32% for the Monte Carlo simulations to 7.58% for the historical simulations.

Furthermore, for both historical and Monte Carlo simulations, we also estimate the risk indicator based on the expected shortfall. For banks exposed to an increase in interest rates, its annual average is 6.30% in the case of historical simulations and 8.05% in the case of Monte Carlo simulations. Banks exposed to decreasing interest rates show an average risk indicator based on the expected shortfall which is 7.86% for historical simulations and 6.13% for Monte Carlo simulations. Because of the differences in the key-rates annual changes distributions, the distance between the risk indicator based on the 99th percentile and that associated with the expected shortfall is larger for the Monte Carlo simulations, under both decreasing and increasing interest rates scenarios. In fact, since Monte Carlo simulations are built assuming a normal joint probability density function, they are better able to capture tail events relative to historical simulations. Finally, Table 7 also reports the average level of the risk indicator estimated based on the technique proposed by Gupton et al. (1997) which has been described in previous equations (7) and (8) of paragraph 2.2.

Table 7. Sample banks' average risk indicators: breakdown by measurement approach (2006 – 2012)

Evaluation date (*t*)	Parallel shift		Percentiles method		Historical simulations				Monte Carlo simulations							
	RI_I	RI_D	RI_I	RI_D	RI_I	RI_{ES-I}	RI_D	RI_{ES-D}	RI_I	$RI_{I-Lower}$	$RI_{I-Upper}$	RI_{ES-I}	RI_D	$RI_{D-Lower}$	$RI_{D-Upper}$	RI_{ES-D}
December 31st, 2006	15.20%	9.46%	7.17%	9.79%	7.04%	7.40%	9.72%	9.99%	8.56%	8.15%	9.07%	10.15%	9.43%	9.10%	9.91%	10.75%
December 31st, 2007	10.94%	8.28%	5.04%	8.64%	5.77%	6.06%	8.73%	9.01%	10.17%	9.77%	10.63%	11.77%	7.92%	7.61%	8.29%	9.06%
December 31st, 2008	10.04%	7.47%	4.06%	5.32%	5.16%	5.39%	5.90%	6.32%	6.95%	6.62%	7.34%	8.23%	5.03%	4.75%	5.35%	5.99%
December 31st, 2009	13.26%	7.67%	8.51%	9.91%	9.53%	10.08%	10.53%	10.74%	8.16%	7.83%	8.57%	9.43%	3.91%	3.69%	4.20%	4.77%
December 31st, 2010	6.81%	8.66%	3.78%	10.50%	6.26%	6.74%	10.96%	11.12%	6.01%	5.76%	6.31%	6.91%	5.69%	5.38%	6.05%	6.70%
December 31st, 2011	10.56%	5.45%	4.65%	6.23%	6.59%	6.98%	7.33%	7.62%	7.27%	6.96%	7.65%	8.36%	5.24%	5.05%	5.45%	5.84%
December 31st, 2012	8.01%	2.48%	2.33%	2.69%	3.31%	3.68%	3.18%	3.43%	3.83%	3.62%	4.10%	4.66%	2.03%	1.94%	2.13%	2.33%
December 31st, 2013	7.78%	3.38%	2.26%	3.61%	3.76%	4.09%	4.31%	4.65%	4.01%	3.79%	4.28%	4.85%	3.24%	3.13%	3.38%	3.62%
Average risk indicator per year	10.32%	6.60%	4.73%	7.09%	5.93%	6.30%	7.58%	7.86%	6.87%	6.56%	7.24%	8.05%	5.32%	5.09%	5.60%	6.13%

Source: our elaborations on Datastream™ and balance sheet data.

RI_I = risk indicators of banks exposed to increasing interest rates; RI_D = risk indicators of banks exposed to decreasing interest rates; RI_{ES-I} = risk indicators of banks exposed to increasing interest rates.

Note: non-maturity deposits have been allotted using the criterion introduced in December 2010 also for the 2006-2009 period.

5. Backtesting

The objective of this section is to assess whether and to what extent risk indicators estimated through the methodologies presented before are both consistent with actual bank risk exposure and adequate from a prudential point of view. Consistency with actual bank riskiness is measured by comparing the estimated risk indicators with ex post risk indicators that are obtained by replacing the ± 200 bps of equation (1.) with the joint annual changes actually occurred over the one-year time horizon following the evaluation date t (t = *December 31st, 2006, December 31st, 2007, ... December 31st, 2013*). In line with the logic underlying Basel capital requirements, we assume that estimated risk indicators are adequate from a prudential perspective when the internal capital corresponding to their numerator protects the bank against a reasonably wide set of adverse scenarios of changes in the key-rates. In particular, we assume that prudential adequacy is met if the estimated risk indicator is higher than a minimum threshold, which is unique for all banks, is based on empirically observed riskiness and consequently allows to ensure the financial system stability. Within the debate about the opportunity to apply a Pillar 1 capital charge for interest rate risk in the banking book, our approach is therefore very different from that currently adopted by the regulator, whose main objective is to identify institutions reporting estimated risk indicators higher than 20% in order to promptly take corrective actions.

5.1 Methodology and results

In essence, our backtesting procedure consists in the comparison of the estimated risk indicator with a benchmark that takes into account ex post, actual riskiness from both a bank-specific and a systemic perspective. In particular, for each of our sample banks and for each evaluation date t, we prudentially set the benchmark ($B_{i,t}$) as the highest value between the ex post risk indicator of the i^{th} bank ($RI^*_{i,t}$) and its mean value for those banks that ex post turn out to be actually risk-exposed.

$$B_{i,t} = \max\left(RI^*_{i,t}; \frac{\sum_{i=1}^{n} RI^*_{i,t}}{n} \right) \qquad (10.)$$

Three main cases have to be carefully considered. First, when the estimated risk indicator is lower than the benchmark, it can alternatively be: i) both inconsistent with actual riskiness and prudentially inadequate; ii) either prudentially adequate but inconsistent with actual risk exposure or consistent but not adequate from a prudential perspective. Second, and even more threatening from a banking stability perspective, should the scenarios set by the regulator not be comprised among those that can reduce a bank's equity value, this institution would erroneously result as not exposed to interest rate risk, which is a clearly unrealistic result. Third, when the estimated risk indicator is higher than the benchmark, the associated measure of internal capital is higher than the appropriate one. In this case, since within the current regulatory framework the potential amount of loans a bank can issue is a multiple of its internal capital, the institution would unnecessarily reduce its lending activity, thus bearing the associated opportunity costs. In assessing the performance of the different methodologies,

The estimated risk indicator could either be higher (overestimation) or lower (underestimation) than the benchmark. In both cases the lower is the distance between the former and the latter, the more effective is the methodology. In the case of overestimation, we will rank methodologies based on the extent to which they minimize the reduction in the lending activity; in the case of underestimation, methodologies will be classified based on the extent to which they minimize the negative effects on the overall sample financial stability.

From a methodology perspective, some further considerations are noteworthy. First, banks are exposed to many adverse scenarios of annual changes in the key-rates, which differ not only for the size but also for the sign of the changes. Under the prudential perspective we follow, we assess a methodology results by comparing them with the previously defined benchmark. Therefore, the potential discordance of signs between the ex ante changes in the key-rates and the ex post ones is not an issue because a methodology performance only depends on the sign and the size of the difference between the estimated risk indicator and the benchmark. Second, the ex ante scenario of changes in the key-rates identified by the methodology and the scenario actually occurred could be included or not within the set of the adverse scenarios. In the former case, we would have a case of ex ante risk neutrality, which is a clearly unrealistic result; in the second case, the backtesting result would be biased. The benchmark described above allows to address these risk-neutrality issues.

The following Table 8 shows in panel A ex post key-rates annual changes, which are the main driver of our banks' actual risk exposure, given their balance sheet structure, and in panel B both the average risk indicators for each year of the sample period and the number of risk-exposed banks. Ex post changes in the key-rates referred to the medium- and long-term time bands of the maturity ladder (from "*From 1 year to 2 years*" to "*From 10 years to 15 years*") were negative for most of the years included in the sample period, with the exception of the years 2007 and 2013. Italian banks' risk exposure appears to be far below the 20% threshold set by the Basel Committee: the average ex post risk indicator ranges from 5.41% in 2008 to 0.04% in 2014.

Table 8: Sample banks' actual risk exposure

	2007	2008	2009	2010	2011	2012	2013	2014
	Panel A: Ex post key-rates annual changes							
Demand and revocable	0.23%	-1.56%	-1.94%	0.41%	-0.19%	-0.50%	0.32%	-0.30%
Up to 1 month	0.55%	-1.72%	-2.06%	0.26%	0.11%	-0.68%	0.11%	-0.20%
From 1 month to 3 months	0.83%	-1.71%	-2.23%	0.33%	0.29%	-1.03%	0.11%	-0.21%
From 3 months to 6 months	0.91%	-1.77%	-2.09%	0.26%	0.38%	-1.22%	0.09%	-0.21%
From 6 months to 1 year	0.77%	-1.71%	-1.89%	0.25%	0.42%	-1.36%	0.05%	-0.24%
From 1 year to 2 years	0.53%	-1.91%	-1.13%	-0.14%	-0.08%	-1.02%	0.13%	-0.31%
From 2 year to 3 years	0.41%	-1.68%	-0.80%	-0.31%	-0.41%	-0.93%	0.24%	-0.46%
From 3 year to 4 years	0.40%	-1.49%	-0.63%	-0.33%	-0.62%	-0.92%	0.35%	-0.63%
From 4 year to 5 years	0.42%	-1.37%	-0.50%	-0.34%	-0.72%	-0.94%	0.45%	-0.81%
From 5 year to 7 years	0.45%	-1.23%	-0.36%	-0.29%	-0.79%	-0.97%	0.54%	-1.04%
From 7 year to 10 years	0.49%	-1.05%	-0.19%	-0.31%	-0.88%	-0.87%	0.58%	-1.27%
From 10 year to 15 years	0.56%	-0.95%	-0.04%	-0.32%	-0.93%	-0.73%	0.57%	-1.40%
From 15 year to 20 years	0.59%	-1.01%	0.14%	-0.35%	-0.99%	-0.58%	0.56%	-1.41%
Over 20 years	0.60%	-1.15%	0.28%	-0.36%	-1.03%	-0.46%	0.53%	-1.36%
	Panel B: Ex post average risk exposure							
Ex post average risk indicator	1.54%	5.41%	4.51%	0.77%	1.37%	3.34%	1.56%	0.04%
# of ex post risk exposed banks	47	106	128	88	77	102	84	3

Source: our elaborations on Datastream™ and balance sheet data.
Note: non-maturity deposits have been allotted using the criterion introduced in December 2010 also for the years 2006-2009.
Annual changes in key rates are calculated based on data referred to December 31st of each year. For example, the annual changes shown in column 2007 are given by each key-rate observed on December 31st, 2007 minus the corresponding key-rate observed on December 31st, 2006.

5.2 Methodology and results

We are not just interested in how individual methodologies perform but also in how different methodologies compare to each other. The logic underlying our backtesting approach draws on the forecast evaluation methods to backtesting (Lopez, 1999), which give each methodology a score in terms of some loss function. The scores are used to rank the methodologies: in particular, the lower the score, the better the methodology performance. Forecast evaluation methods do not suffer from the low power of a standard test because they are not frequency-based statistical tests . That makes them attractive for backtesting with small datasets such as our sample of Italian banks. Finally, these methods allow to tailor the loss function according to the specific objectives of the backtesting analysis.

In assessing the overall performance of the methodologies in terms of both prudential adequacy and consistency with actual bank riskiness, we specifically account for particular concerns, such as those associated with the measurement of interest rate risk from both regulators' and industry's perspective. In particular, we refer to issues arising from inaccurate estimates of internal capital , in terms of both banking stability, credit supply to the economy and bank managers' decisions about ALM strategies. Compared to Lopez (1999), who tests VaR models within a market risk environment, given the peculiarities of the interest rate risk in the banking book, we focus not only on the potential losses resulting from its underestimation, but also on the implications of its overestimation.

In particular, for any evaluation date t (t = *December 31st, 2006, December 31st, 2007, ... December 31st, 2013*), we assign to each methodology m a score calculated on the basis of a score function ($S_{m,t}$) which takes as its inputs the results of some accuracy functions $A_{i,t}$ applied to each bank i (*i=1, 2, ... n*) within our sample. The generic score function is obtained as follows:

$$S_{m,t} = \sum_{i=1}^{n} A_{i,t} \qquad (12.)$$

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. In particular, the generic accuracy function can be written as follows:

$$A_{i,t} = \begin{cases} f\left(B_{i,t}, RI_{i,t}\right) & if \ B_{i,t} > RI_{i,t} \\ g\left(B_{i,t}, RI_{i,t}\right) & if \ B_{i,t} \le RI_{i,t} \end{cases} \qquad (13.)$$

where $RI_{i,t}$ and $B_{i,t}$ are the estimated risk indicator and the benchmark defined in the previous paragraph, respectively. Both $RI_{i,t}$ and $B_{i,t}$ refer to the term structure of the i^{th} bank's net positions observed in t.

The generic accuracy function of equation (13.) can be specified in different ways. In the rest of the paragraph we focus on four main specifications. The first two provide evidence on the potential losses arising from an underestimation of the benchmark and correspond to the loss function defined in Lopez (1999) because they satisfy the following condition:

$$f\left(B_{i,t}, RI_{i,t}\right) \geq g\left(B_{i,t}, RI_{i,t}\right) \quad (14.)$$

In the third and fourth specification we remove the constraint presented in equation (14.) . The third specification accounts for the case of an overestimation of interest rate risk, providing evidence on the distance between the estimated risk indicator and the benchmark when the former is higher than the latter. By combining the second and third specifications, the fourth one assigns to each methodology a final score that takes into account both the overestimation and underestimation cases.

The first specification of equation (13.) is based on the binomial loss function proposed by Lopez (1999), which takes a value of 1 when the benchmark is higher than the estimated risk indicator estimated ex ante, and a value of 0 otherwise:

$$A_{i,t} = \begin{cases} 1 & if \ B_{i,t} > RI_{i,t} \\ 0 & if \ B_{i,t} \leq RI_{i,t} \end{cases} \quad (15.)$$

Table 9 reports the scores obtained through the application of equations (12.) and (15.) for each of the years included in the analyzed time period. These scores equal the number of exceptions typical of the statistical tests used for market risk backtesting, such as those proposed by Kupiec (1995) and Christoffersen (1998). In our analysis, the “exception” is the case in which the benchmark is higher than the estimated risk indicator and the loss function takes a value of 1. Therefore, the score corresponds to the number of banks that underestimate interest rate risk.

At the bottom of Table 9, we provide the average number of exceptions per year. For the historical and Monte Carlo simulations we also calculate the number of exceptions referred to the expected shortfall-based risk indicator, i.e., the number of banks for which the risk indicator estimated according to equation (9.) is lower than the benchmark (see columns 5 and 9 of Table 9). In columns 7 and 8 we also show the number of exceptions associated with the lower and upper bound of the confidence interval based on the technique proposed by Gupton et al. (1997). In particular, we have an exception when the risk indicator corresponding to the lower and upper bound of the confidence interval calculated according to equations (7.) and (8.) is lower than the benchmark.

If the risk indicator is estimated on the basis of the 99th percentile, the historical and Monte Carlo simulations show a lower average annual score relative to the parallel shift and percentiles method. In fact, it is 32.25 and 41.50 for the historical and Monte Carlo simulations, respectively, whereas it is 45.38 for the parallel shift and 56.88 for the percentiles method. By focusing on the Monte Carlo simulations, we also calculate the average annual scores obtained when the ex ante risk indicator is alternatively the lower and upper bound of the confidence interval described in equations (7.) and (8.). In particular, the former (45.50) almost coincides with risk indicator resulting from the adoption of the parallel shift, and the average annual score of the percentiles method is higher than both the former and the latter (36.63). The average annual scores obtained for the historical simulation when the estimate of the risk indicator is alternatively based on the 99th percentile or the expected shortfall of the distribution are lower than those estimated on the basis of the lower and upper bound of the confidence interval defined by equations (7.) and (8.). Nevertheless, the Monte Carlo simulation shows a slightly higher average score per year, compared to the historical simulations, when the ex ante risk indicator is calculated based on the expected shortfall measure: 30.50 for the former and 28.88 for the latter.

Table n. 9: Outputs of the score function based on equation (15)

Evaluation date (*t*)	Regulatory methodologies		Historical simulations		Monte Carlo simulations			
	Parallel Shift	Percentiles Method	99th [(a)]	ES [(b)]	99th [(a)]	Lower [(c)]	Upper [(d)]	ES [(b)]
December 31st, 2006	23	35	33	33	28	31	25	24
December 31st, 2007	56	64	62	58	60	62	55	47
December 31st, 2008	43	75	55	51	76	80	70	58
December 31st, 2009	16	5	0	0	2	2	2	0
December 31st, 2010	19	8	2	0	4	7	2	1
December 31st, 2011	71	61	30	23	60	69	47	36
December 31st, 2012	80	115	62	56	74	82	69	62
December 31st, 2013	55	92	14	10	28	31	23	16
Avg. per year	45.38	56.88	32.25	28.88	41.50	45.50	36.63	30.50

[a] The score is calculated by comparing the 99th percentile of the risk indicators distribution with the benchmark.
[b] The score is calculated by comparing the expected shortfall of the risk indicators distribution with the benchmark.
[c] The score is calculated by comparing the risk indicator corresponding to the lower extreme of the confidence interval described in equations (7.) and (8.)
[d] The score is calculated by comparing the risk indicator corresponding to the upper extreme of the confidence interval described in equations (7.) and (8.)

Equation (15.) ignores the magnitude of the difference between the benchmark and the estimated risk indicator – the larger this difference, the more significant the potential threat to the overall banking stability. To address this issue we adopt a new specification of equation (13.) which equals the difference between the benchmark and the estimated risk indicator when the former is higher than the latter (i.e., when an exception occurs), and 0 otherwise:

$$A_{i,t} = \begin{cases} B_{i,t} - RI_{i,t} & \text{if } B_{i,t} > RI_{i,t} \\ 0 & \text{if } B_{i,t} \leq RI_{i,t} \end{cases} \qquad (16)$$

By adopting this specification, equation (12) is slightly modified as follows:

$$S_{m,t} = \frac{\sum_{i=1}^{n} A_{i,t}}{N} \qquad (17.)$$

where N is the number of banks for which the benchmark is higher than the estimated risk indicator. The outputs of the score function (17.) allow to capture the average distance of the ex ante risk indicator from the benchmark at our sample banks. The annual scores obtained through the application of equations (16.) and (17.) are presented in the following Table 10. By examining the average annual scores, which are reported at the bottom of the table, we find that: i) when the estimated risk indicator is based on the 99th percentile of the risk indicators distribution, the two advanced methodologies show the same performance (1.12%) and have lower scores than the parallel shift (2.07%) and percentiles method (2.05%); ii) the average annual score of the historical simulations is comprised between those estimated on the basis of the risk indicators corresponding to the upper (1.11%) and lower (1.15%) bounds of the confidence interval proposed by Gupton et al. (1997) [see equations (7.) and (8.)], whereas the risk indicator estimated, whereas the score obtained when the risk indicator is estimated through the expected shortfall measure (1.06%) falls outside the range; iii) the average annual score associated with the lower extreme of the confidence interval of equation (7.) (1.15%) is lower than those of the two regulatory methodologies; iv) the average annual score based on the expected shortfall measure for the Monte Carlo simulation (1.07%) is slightly higher than that estimated for the historical simulation. Overall, relative to the results referred to the number of exceptions, the performance of Monte Carlo simulations improves if compared to historical simulations.

Table 10: Outputs of the score function based on equation (16)

Evaluation date (t)	Regulatory methodologies		Historical simulations		Monte Carlo simulations			
	Parallel Shift	Percentiles Method	99th [(a)]	ES [(b)]	99th [(a)]	Lower [(c)]	Upper [(d)]	ES [(b)]
December 31st, 2006	2.25%	2.34%	2.14%	2.02%	1.79%	1.73%	1.86%	1.68%
December 31st, 2007	3.47%	3.13%	2.77%	2.82%	2.63%	2.72%	2.65%	2.69%
December 31st, 2008	2.71%	2.37%	1.53%	1.48%	1.61%	1.72%	1.49%	1.30%
December 31st, 2009	0.68%	0.61%	0.00%	0.00%	0.12%	0.18%	0.04%	0.00%
December 31st, 2010	1.53%	1.78%	0.14%	0.00%	0.41%	0.40%	0.39%	0.55%
December 31st, 2011	2.38%	2.26%	1.10%	1.11%	0.94%	0.95%	1.02%	1.07%
December 31st, 2012	2.06%	2.36%	1.03%	0.89%	0.97%	0.98%	0.91%	0.78%
December 31st, 2013	1.46%	1.52%	0.24%	0.19%	0.48%	0.51%	0.49%	0.51%
Avg. per year	2.07%	2.05%	1.12%	1.06%	1.12%	1.15%	1.11%	1.07%

[a] The score is calculated by comparing the 99th percentile of the risk indicators distribution with the benchmark.
[b] The score is calculated by comparing the expected shortfall of the risk indicators distribution with the benchmark.
[c] The score is calculated by comparing the risk indicator corresponding to the lower extreme of the confidence interval described in equations (7.) and (8.)
[d] The score is calculated by comparing the risk indicator corresponding to the upper extreme of the confidence interval described in equations (7.) and (8.)

Equations (15.) and (16.) aim at assessing the potential threat to the overall stability of the banking system because they capture the cases in which the estimate of the risk indicator is lower than the benchmark, by focusing on their frequency and size, respectively. Nevertheless, from both a macro and micro perspective, it is important to shed some light also on the cases in which the estimated risk indicator is higher than the benchmark. Should that happen, on the one hand, miscalculated risk indicators would require an excessive capital absorption leading to an unnecessary reduction in a bank lending capacity; on the other hand, overestimated risk indicators might provide distorted indications for risk managers' decisions about ALM-referred strategies.

In order to take into account these issues, we introduce the following, third specification of equation (13), which equals the absolute value of the difference between the benchmark and the estimated risk indicator when the former is lower than the latter, and 0 otherwise:

$$A_{i,t} = \begin{cases} 0 \quad if \ B_{i,t} > RI_{i,t} \\ | \ B_{i,t} - RI_{i,t} \ | \quad if \ B_{i,t} \leq RI_{i,t} \end{cases} \qquad (18)$$

Results from the application of equations (17) and (18) are reported in Table 11. Relative to the results obtained through equations (16.) and (17.) , while the Monte Carlo simulations show the best performance among the methodologies investigated in this research, with an average annual score equal to 3.08%, the percentiles method (4.30%) performs slightly better than the historical simulations (4.41%). The average annual scores obtained when the risk indicator is estimated on the basis of the lower and upper bounds of the confidence interval defined in equations (7) and (8) are 2.90% and 3.30%, respectively, being both lower than the scores associated with the risk indicators corresponding to the 99th percentile and expected shortfall of the historical simulation. The average annual score based on the expected shortfall measure for the Monte Carlo simulation (3.85%) is lower than that estimated for the historical simulations (4.64%).

Table 11. Outputs of the score function based on equation (18)

Evaluation date (t)	Regulatory methodologies		Historical simulations		Monte Carlo simulations			
	Parallel Shift	Percentiles Method	99th [(a)]	ES [(b)]	99th [(a)]	Lower [(c)]	Upper [(d)]	ES [(b)]
December 31st, 2006	8.66%	6.35%	6.24%	6.60%	6.04%	5.80%	6.45%	7.45%
December 31st, 2007	4.25%	2.84%	2.81%	3.05%	2.83%	2.45%	3.15%	3.91%
December 31st, 2008	5.22%	2.11%	1.93%	2.36%	2.37%	2.12%	2.55%	2.96%
December 31st, 2009	8.51%	8.67%	9.07%	9.32%	4.09%	3.82%	4.41%	4.95%
December 31st, 2010	6.47%	7.72%	7.93%	7.99%	3.05%	2.82%	3.36%	3.98%
December 31st, 2011	5.83%	3.05%	3.21%	3.30%	2.24%	2.25%	2.19%	2.49%
December 31st, 2012	5.49%	1.33%	1.42%	1.56%	1.46%	1.47%	1.61%	2.01%
December 31st, 2013	6.49%	2.35%	2.68%	2.94%	2.58%	2.45%	2.70%	3.01%
Avg. per year	6.37%	4.30%	4.41%	4.64%	3.08%	2.90%	3.30%	3.85%

[a] The score is calculated by comparing the 99th percentile of the risk indicators distribution with the benchmark.
[b] The score is calculated by comparing the expected shortfall of the risk indicators distribution with the benchmark.
[c] The score is calculated by comparing the risk indicator corresponding to the lower extreme of the confidence interval described in equations (7.) and (8.)
[d] The score is calculated by comparing the risk indicator corresponding to the upper extreme of the confidence interval described in equations (7.) and (8.)

Equations (16) and (18) examine the cases in which the estimated risk indicators are lower and higher than the benchmark, respectively. Overall, our empirical evidence suggests that the advanced methodologies developed in this research provide a better performance relative to the parallel shift and percentiles method. In particular, the historical simulation is the best approach in terms of frequency of exceptions, they show the same performance when the estimated risk indicator is lower than the benchmark, whereas Monte Carlo simulations minimize the distance between the estimates of the risk indicator and the benchmark when the former is higher than the latter. Therefore, from a micro perspective, by adopting Monte Carlo simulations, bank managers are less likely to assume unnecessary ALM hedging strategies; from a macro perspective, bank lending capacity is less likely to be unreasonably constrained and global financial stability is better pursued.

Finally, we adopt an accuracy function which is given by the combination of equations (16.) and (18.), thus considering the distance between the estimated risk indicator and the benchmark in both cases of underestimation and overestimation. In symbols:

$$C_{i,t} = \begin{cases} BI_{i,t} - RI_{i,t} & \text{if } BI_{i,t} > RI_{i,t} \\ | BI_{i,t} - RI_{i,t} | & \text{if } BI_{i,t} < RI_{i,t} \end{cases} \quad (19)$$

Table 12 shows the results of the application of equation (19.) which confirm the evidence obtained through equation (18.). It is noteworthy that, in the form it has been proposed, equation (19.) does not make any distinction based on the positive or negative sign of the difference between the estimated risk indicator and the benchmark, i.e., whether the former is higher or lower than the latter. Anyway, in order to set a specific order of priority between the key issues associated with the overestimation and underestimation of the interest rate risk in the banking book, equation (19.) can be adjusted to account in a different way for those issues.

Table 12. Outputs of the score function based on equation (18)

Evaluation date (t)	Regulatory methodologies		Historical simulations		Monte Carlo simulations			
	Parallel Shift	Percentiles Method	99th [(a)]	ES [(b)]	99th [(a)]	Lower [(c)]	Upper [(d)]	ES [(b)]
December 31st, 2006	7.53%	5.27%	5.20%	5.43%	5.13%	4.83%	5.57%	6.38%
December 31st, 2007	3.91%	2.98%	2.79%	2.94%	2.74%	2.58%	2.94%	3.47%
December 31st, 2008	4.39%	2.26%	1.76%	2.02%	1.92%	1.87%	1.98%	2.22%
December 31st, 2009	7.55%	8.36%	9.07%	9.32%	4.03%	3.76%	4.35%	4.95%
December 31st, 2010	5.75%	7.35%	7.81%	7.99%	2.97%	2.69%	3.31%	3.95%
December 31st, 2011	5.09%	3.24%	4.73%	5.03%	1.64%	1.56%	1.77%	2.10%
December 31st, 2012	3.38%	2.24%	1.24%	1.28%	1.18%	1.16%	1.24%	1.43%
December 31st, 2013	4.36%	1.77%	2.41%	2.73%	2.13%	1.99%	2.31%	2.70%
Avg. per year	5.24%	4.19%	4.38%	4.59%	2.72%	2.56%	2.93%	3.40%

[a] The score is calculated by comparing the 99th percentile of the risk indicators distribution with the benchmark.
[b] The score is calculated by comparing the expected shortfall of the risk indicators distribution with the benchmark.
[c] The score is calculated by comparing the risk indicator corresponding to the lower extreme of the confidence interval described in equations (7.) and (8.)
[d] The score is calculated by comparing the risk indicator corresponding to the upper extreme of the confidence interval described in equations (7.) and (8.)

7. Conclusions

This paper aims to evaluate the robustness of the regulatory framework set by the Basel Committee to estimate a bank's exposure to the interest rate risk in the banking book. We focus on the strict assumptions about the interest rate shock used to assess a bank's equity sensitivity and to determine the corresponding measure of internal capital. In particular, the regulators introduced two simplified methodologies based, on the one hand, on a ±200bp parallel shock in interest rates and, on the other hand, on the 1st and 99th percentile of observed interest rate changes using a one-year holding period and a minimum five years of observations, respectively (BCBS, 2004).

Testing whether and to what extent the estimates of internal capital obtained through the regulatory methodologies are accurate and adequate from a prudential perspective is crucial for banking supervisors, credit institutions and the economic system as a whole. In fact, an underestimation of interest rate risk would represent a serious threat to the banking stability, since this is still the second whereas an overestimation would lead to a reduction of banks' credit supply, due to an excessive absorption of internal capital. In general, measurement errors would undermine banks' ALM strategies and prevent supervisors from identifying banks characterized by an excessive risk exposure.

Based on the main assumptions of the current regulatory framework and adopting historical and Monte Carlo simulations techniques, respectively, we contribute to previous literature by developing two methods to model annual changes in interest rates and a backtesting procedure to assess the results of the different methodologies. By examining a sample of 130 Italian commercial banks over the 2006 – 2013 period, we compare our methods with the regulatory methodologies and show that the latter might lead to somewhat inaccurate results. In particular, each methodology performance is assessed through a backtesting analysis according to which the estimated risk exposure is compared with a benchmark that allows us to assess a methodology results based on their prudential adequacy and consistency with the ex post, actual riskiness. Overall, the advanced methodologies we present in this research provide a better performance. This entails that, from a micro perspective, by adopting the historical and Monte Carlo simulations, bank managers are less likely to assume unfounded ALM strategies and to lose lending opportunities; from a macro perspective credit supply to the economy is less likely to be unreasonably constrained and global financial stability is more effectively pursued. According to the evidence reported in this research, the Monte Carlo and historical simulations are the best-suited methodologies from a prudential perspective and address some shortcomings of the regulatory approaches, such as the phenomenon of the ex ante risk neutrality, that we observe especially with low term structures of interest rates, and the inability to account for the correlations of interest rates changes. Therefore, the adoption of more sophisticated methodologies, like those proposed here, can help supervisors to correctly identify *outlier banks* (i.e., banks whose interest rate risk leads to an economic value decline of more than 20% of supervisory capital), and to promptly take corrective actions.

The regulatory treatment of the interest rate risk in the banking book should not be considered conclusive, because this research casts some doubt about its effectiveness, especially within a context of low market interest rates. Based on our empirical evidence, it would be appropriate to spend further efforts into the analysis of the current drawbacks and the development of more adequate approaches. Some careful considerations should be done about the following issues. First, the current set of scenarios of changes in interest rates used by the regulator to assess the sensitivity of a bank's equity might be replaced by adaptive and forward-looking scenarios that are able to capture interest rates dynamics over time and to consequently adjust the shock applied to evaluate a bank risk exposure. Second, well-equipped banks might also consider the opportunity to develop a backtesting procedure to identify the best-suited methodology to assess their exposure to interest rate risk, given the current and past characteristics of the term structure of their balance sheet. Third, following the logic underlying our backtesting procedure, a minimum capital requirement against interest rate risk in the banking book might be beneficial from a twofold perspective: on the one hand, it would address the issue of the ex ante risk neutrality, should the changes in the key-rates not be included among the set of adverse scenarios; on the other hand, it would provide a system-wide protection mechanism. With this regard, this research contributes to the current debate about the opportunity to introduce a capital charge for the interest rate risk in the banking book. Further developments of this research might just investigate how to define the threshold and grant its ongoing calibration to both make it promptly reactive to different market conditions and able to ensure the banking system stability.

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