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Does prudential regulation contribute to effective measurement and management of interest rate risk? Evidence from Italian banks☆

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This paper contributes to prior literature and to the current debate concerning recent revisions of the regulatory approach to measuring bank exposure to interest rate risk in the banking book by focusing on assessment of the appropriate amount of capital banks should set aside against this specific risk. We first discuss how banks might develop internal measurement systems to model changes in interest rates and measure their exposure to interest rate risk that are more refined and effective than are regulatory methodologies. We then develop a backtesting framework to test the consistency of methodology results with actual bank risk exposure. Using a representative sample of Italian banks between 2006 and 2013, our empirical analysis supports the need to improve the standardized shock currently enforced by the Basel Committee on Banking Supervision. It also provides useful insights for properly measuring the amount of capital to cover interest rate risk that is sufficient to ensure both financial system functioning and banking stability.

1. Introduction

International banking authorities have recently developed models and issued guidelines to assess banks' exposure to interest rate risk in the banking book (IRRBB), because of its peculiar nature and systemic relevance. Following the savings and loan crisis of the 1980s and '90s, the U.S. Federal Reserve Bank (FED) developed the economic value model, which measures IRRBB through changes in a bank's economic value of equity (EVE) via a duration-based estimate of interest rate sensitivity (Houpt and Embersit, 1991; Sierra and Yeager, 2004; Sierra, 2009; Wright and Houpt, 1996 Sierra, 2009; Wright and Houpt, 1996). Subsequently, in 2004, the Basel Committee on Banking Supervision (BCBS) adopted an accounting-based duration model that estimates IRRBB by applying a standardized shock in interest rates. The standardized shock is alternatively given by a ± 200 bp parallel shift in the yield curve fixed for all maturities (the parallel shifts 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). These scenarios of changes in interest rates allow calculation of a risk indicator, which is given by the ratio of the change in a bank's EVE to its regulatory capital and whose alert threshold is set equal to 20 percent. Throughout the paper, we term the parallel shifts and percentiles methods as "regulatory methodologies."

The drawbacks of the BCBS framework have been pointed out not only by academic research, by mainly testing its underlying assumptions (Abdymomunov and Gerlach, 2014; Cocozza et al., 2015; Entrop et al., 2008; Entrop et al., 2009; Fiori and Iannotti, 2007), but also by the financial authorities (BCBS, 2009). In May 2015, the European Banking Authority (EBA, 2015) published a technical document to revise and supplement the guidelines proposed by the Committee of European Banking Supervisors (CEBS, 2006). Recently, BCBS (2016) issued new standards to revise the principles for IRRBB management and supervision set in 2004.

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These standards are intended to come into force in 2018 and should provide more extensive guidance on crucial areas, such as the development of interest rate shock scenarios and an updated standardized framework.

Within their internal capital adequacy assessment process (BCBS, 2006; CEBS, 2006), 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. Therefore, inaccurate estimates of IRRBB would lead banks to reserve an amount of internal capital that might either underestimate or overestimate a bank's actual riskiness, with potentially negative consequences in both cases: underestimation might jeopardize banking stability, whereas overestimation might charge banks higher opportunity costs and eventually reduce their credit supply to the economy.[1] A proper measurement of bank risk exposure is relevant from the perspective of supervisory authorities since, based on the results of this assessment, their actions may have a huge impact on bank activity.[2] Furthermore, inaccurate estimates of IRRBB would also provide poor indications for banks' asset and liability management (ALM) strategies: underestimation might drive managers to take excessive risk, whereas overestimation might prevent banks from implementing profitable ALM strategies. Overall, the output of the risk models embedded within the Basel regulations could have a tremendous impact on the real economy and, therefore, it is important to understand to what extent both banks and financial authorities can rely on them and when their use is not advisable (see Danielsson et al., 2016 for a general framework to quantify model risk).

Based on these issues and the current low-interest-rate environment, modeling interest rate changes and measuring their impact on the banking sector are still timely and key research areas. Recent papers have investigated how banks managed their interest rate risk during the crisis years, when unconventional monetary policy decisions drove interest rates to unprecedented low levels[3,4] (Esposito et al., 2015; Chaudron, 2016; Memmel et al., 2016). Our contribution to prior literature and to the current debate concerning recent revisions to the IRRBB regulatory treatment is twofold and centers on an assessment of the appropriate amount of the internal capital that banks should set aside against this specific risk.

First, consistent with important regulatory constraints commonly applied to quantify IRRBB-related internal capital, we show how banks might adopt simulation techniques to model changes in interest rates in a more refined and effective way than the regulatory standardized shock. Simulation techniques have been extensively examined by prior literature to estimate market risk (Jorion, 2007) and suggested by regulators to measure interest rate risk within banks' internal measurement systems (BCBS, 2004; BCBS, 2016; Comptroller of the Currency Administrator of National Banks, 2012). In the absence of specific previous contributions, we discuss the application of historical and Monte Carlo simulation techniques to model changes in interest rates to measure a bank's exposure to IRRBB in a low-interest-rate environment and henceforth term them "internal methodologies."

Second, we develop a backtesting framework to test the consistency of a methodology's results with actual bank risk exposure under ordinary operating business conditions. Our backtesting framework draws on the forecast evaluation methods developed by Lopez (1999) to test VaR models based on potential losses resulting from the underestimation of market risk. However, given the peculiarities of IRRBB measurement and management, we focus not only on its underestimation but also on the effects of overestimation. We compare the different methodologies by assessing their ability to avoid unnecessary reduction in bank lending activity and associated opportunity costs should the estimated risk indicator overestimate actual risk exposure, and to reduce the risk of undermining banking sector stability should underestimation occur.

This research examines exposure to IRRBB by collecting proprietary balance sheet information from a sample of 130 Italian commercial banks over the period from 2006 to 2013. Analysis of the Italian banking system is especially interesting because Italian banks generally act as qualitative asset transformers, meaning that IRRBB arises from basic banking business. Because of the crucial role played by commercial banks in modern financial systems, our investigation is also relevant from a global perspective.

Overall, Italian banks adequately manage IRRBB and their risk indicators are well below the alert level enforced by the regulator. In terms of the nature of their risk exposure, our sample intermediaries appear exposed to both raising (asset-sensitive banks) and, more frequently, decreasing (liability-sensitive banks) interest rates. We find that historical and Monte Carlo simulations (internal methodologies) produce estimates of internal capital that are more robust from a prudential adequacy perspective with regard to this specific aspect, when compared with regulatory methodologies. In fact, the internal methodologies avoid a specific issue that we term "risk neutrality." Based on this misleading result, some banks experience an increase in their EVE when the regulatory standardized shock is applied, whether the shock be up or down. Consistent with the overall decreasing trend in interest rates observed during the sample period, liability-sensitive banks use derivatives to offset their on-balance sheet risk exposure to IRRBB, whereas asset-sensitive banks use their off-balance sheet positions to enhance the gains associated with the same scenario. On average, derivatives have also allowed banks to reduce the distance between their estimated and actual risk exposure and thus optimize their amount of internal capital against IRRBB. Furthermore, the internal methodologies, and the Monte Carlo simulations in particular, perform better than the regulatory ones in terms of their consistency with actual bank riskiness, measured through the ex post changes in interest rates that actually occurred after the estimation date.

Our analysis improves upon the standardized shock treatment adopted in BCBS (2004) and provides new insights for properly measuring bank internal capital against IRRBB. The methodological framework we propose is applicable to publicly available data and can be replicated by those outside banking institutions. Such publicly available measures of IRRBB can provide a crucial contribution to the functioning and stability of the international banking system, thus calling for greater attention not only from regulators, supervisors and the overall banking industry, but also from academic researchers.

The rest of the paper is organized as follows. In order to position this research within the literature, in Section 2 we discuss three

[1] The risk indicator also provides useful information with regard to the equilibrium of banks' assets and liabilities structures in terms of their respective maturities and repricing dates. From this perspective, it complements the net stable funding ratio set by the BCBS to measure and manage banks' exposure to liquidity risk (for an analysis of the impact of the net stable funding ratio on financial stability see Ashraf et al., 2016).

[2] Kupiec et al. (2016) have recently highlighted the importance of bank examination by supervisory authorities with regard to U.S. credit institutions. Their evidence suggests that the bank supervision process successfully constrains the lending activities of banks operating in an unsafe and unsound manner.

[3] Cukierman (2013) describes the changes that occurred in the conduct and instruments of monetary policy used by major central banks when the crisis hit. He also discusses the consequent new tradeoffs and controversies and speculates about additional likely future changes in monetary policy and institutions.

[4] The extremely low level of interest rates has raised many issues in terms of financial intermediaries' profitability and overall financial system stability. According to Barnea et al. (2015), monetary policy and financial stability policy are highly interrelated. They show that the monetary policy transmission mechanism depends on financial stability policy tools as well as on regulatory and institutional constraints. In particular, they find policy tradeoffs in trying to accomplish both monetary and financial stability targets that central banks must take into account.

papers that examine banks' exposure to and management of interest rate risk during the financial crisis and measure IRRBB through the economic value approach adopted in this paper. Section 3 provides an overview of the current regulatory IRRBB framework and discusses previous literature testing the robustness of its main assumptions. In Section 4, we describe the two methodologies that banks might internally develop to model interest rate changes based on historical and Monte Carlo simulation techniques. Section 5 presents a backtesting framework to test the effectiveness of both internal and regulatory methodologies. Section 6 presents the results of our empirical analysis, in which we measure the IRRBB of a sample of Italian banks based on both regulatory and internal methodologies and implement our backtesting procedure. Section 7 concludes the paper.

2. The exposure and management of interest rate risk during the financial crisis

After the collapse of Lehman Brothers in 2008, interest-rate risk management became more important than ever for both European and U.S. banks, as a result of unprecedented monetary policy decisions taken by both the European Central Bank (ECB) and the U.S. FED.[5] The previously unheard of reduction in official policy rates and unconventional measures adopted by the two central banks had a strong impact on the term structure of market interest rates and reduced them to an extremely low level. As shown by Borio et al. (2015) and Busch and Memmel (2015), current low interest rates and the flat yield curve have also driven down bank profitability. Major issues, therefore, especially for bank supervisors and policy makers, are whether or not the current low-interest-rate environment has created incentives to take more risk, and how banks managed their risk exposure under extraordinary financial and economic conditions during the crisis. Recent literature has investigated the exposure to and management of interest rate risk during the crisis years. We examine below three papers that refer to the Italian, German and Dutch banking sectors, respectively, all using an economic value approach to measure IRRBB.

Esposito et al. (2015) measure the IRRBB exposure of a sample of 68 Italian banks over the period ranging between the second half of 2008 and the first half of 2012. In particular, they assess how intermediaries managed IRRBB either modifying the duration mismatch between on-balance sheet assets and liabilities (on-balance sheet restructuring) or relying on interest rate derivatives (off-balance sheet adjustment). Overall, by adopting the duration gap approach of the simplified methodology introduced by Bank of Italy (2006), and by using a unique dataset of semi-annual observations, they find that Italian banks' exposure was well below the previously mentioned alert threshold. Furthermore, they observe that banks used their on-balance sheet interest rate risk and their off-balance sheet exposure to offset each other, rather than to pursue a strategy aiming to enhance the potential gains that might have occurred in the case of a rise in interest rates.

Memmel et al. (2016), examine a sample of German banks during the period from 2005 to 2014, in order to study the relationship between banks' expected returns from term transformation and their exposure to the corresponding interest rate risk. According to this research, decreasing interest rates not only drive down bank profit margins but, if the low-interest-rate scenario persists, bank managers have the incentive to act as if they are risk prone, which is extremely dangerous from a financial stability perspective. The authors find that the relationship between interest rate risk and bank risk taking is, as expected, usually positive, but becomes weaker when a bank's operating income decreases. They then show that the relationship changes its sign and banks start to increase their exposure to interest rate risk, even if the expected returns from term transformation decrease, when operating income falls below a certain threshold.

By investigating how banks have managed their IRRBB exposure under a scenario of decreasing interest rates and a flattening yield curve, Chaudron (2016) detects the interest-rate risk position of 42 Dutch banks, representing roughly 90 percent of the entire balance sheet of the Dutch banking sector during the investigation period from 2008 until the middle of 2015. The author investigates how bank risk position changes over time, how much of their returns on assets and net interest margins depend on income from maturity transformation and which factors influence their interest-rate risk position. Interest rate risk is measured through the basis point value, which is the change in the economic value of equity due to a change in the interest rate by one hundredth of a percent (0.01%). Dutch banks show rather small interest rate risk positions, are active in maturity transformation only to a limited degree, and do not maintain a constant interest rate risk position, but adjust it to changes in the economic environment. Based on a panel model estimation, interest-rate risk positions are negatively related to on-balance sheet leverage, exhibit a U-shaped relation with solvability, and, contrary to the evidence reported in other studies, 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.

3. Regulatory methodologies to estimate interest rate risk in the banking sector: overview and related literature

Based on BCBS (2004), Bank of Italy (2013) requires banks to allocate on- and off-balance sheet accounts into the following 14 time bands of a maturity ladder: i) demand and revocable, ii) up to 1 month, iii) 1–3 months, iv) 3–6 months, v) 6–12 months, vi) 1–2 years, vii) 2–3 years, viii) 3–4 years, ix) 4–5 years, x) 5–7 years, xi) 7–10 years, xii) 10–15 years, xiii) 15–20 years, xiv) more than 20 years. 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.

By assuming that on- and off-balance sheet accounts have a maturity exactly coinciding with the midpoint of each time band i to which they are allotted, IRRBB is measured through predetermined sensitivity coefficients, i.e., modified duration coefficients (MD_i). Assets and liabilities are offset to calculate net positions (NP_i), which are weighted by the corresponding MD_i and the assumed 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 regulatory capital (RC) to obtain a risk indicator (RI), whose alert threshold is set equal to 20%:

$$RI = \frac{\sum_{i=1}^{14} NP_i \cdot MD_i \cdot \Delta r}{RC} \leq 20\% \tag{1}$$

Under the parallel shifts method, Δr is given by a ±200 bp parallel shift in the yield curve. 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.

Within the BCBS framework, accounting-based data are used to obtain the cash flow structure of a bank's on- and off-balance posi-

[5] See ECB (2011) for a discussion of the effectiveness of unconventional monetary policy measures adopted by the two central banks.

tions. Therefore, a bank's exposure to IRRBB depends, among the other things, on assumptions concerning the distribution of asset and liability maturities and repricing dates within the time bands of the maturity ladder. By using time-series accounting-based data, Entrop et al. (2008) develop a model to estimate the distribution of the maturities of a bank's assets and liabilities within each time band. Their estimates are more in line with those internally obtained by banks, and their model explains the cross-sectional variation in bank interest rate risk better than the BCBS approach.

As far as interest rate shocks and predetermined sensitivity coefficients are concerned, Fiori and Iannotti (2007) develop a Value at Risk (VaR) methodology to model interest rate changes that takes into account both asymmetry and kurtosis of the interest-rate distribution. Their methodology, based on a principal component Monte Carlo simulation, accounts not only for the concept of duration but also for that of convexity, and calibrates the sensitivity coefficients using market data. By analyzing the 18 major large- and medium-sized Italian banks, they show that their results are consistent with the risk exposure estimated via the ±200 bp parallel shift if the regulatory sensitivity coefficients are calibrated on the basis of current market data at the evaluation date.

BCBS (2004) and Bank of Italy (2013) set specific criteria to allot specific accounts whose legal maturity differs from the behavioral one. With regard to non-maturity deposits, Cocozza et al. (2015) develop a methodology that considers their actual behavior in terms of both price sensitivity to changes in market rates and volume stability over time. According to their results from a sample of 30 Italian commercial banks, the use of different allocation criteria affects not only the size of the risk estimate but also the nature of bank risk exposure. Allotment criteria may also determine the so-called risk inversion phenomenon, i.e., banks formerly exposed to an increase in interest rates can also become exposed to a reduction in interest rates. Furthermore, they show that, when market rates are low, some banks, defined as risk-neutral banks, appear to experience an increase in their equity economic value whether interest rates decrease or increase under the parallel shifts method.

Abdymomunov and Gerlach (2014) show that, when market rates are low, the methods used by banks and supervisors to assess interest rate risk under stressed conditions can understate banks' exposure and propose a new method for generating yield-curve scenarios. Their evidence from a large U.S. bank shows that their model generates yield-curve scenarios with a wider variety of slopes and shapes than alternative historical and hypothetical scenario-generation methods, including the regulatory methodologies.

By considering the aggregated German universal banking system, Entrop et al. (2009) analyze how a bank's risk exposure changes if some major assumptions of the regulatory model are modified. In particular, they consider the allotment of non-maturity deposits into the time bands, the allotment of assets and liabilities within the time bands, the number and boundaries of the time bands, the amortization rate of customer loans, and the spread between the coupon and the market interest rate used to calculate the modified duration associated with each time band. They prove that the results of the regulatory framework significantly depend on the underlying assumptions and must be considered with caution for both supervisory and risk-management purposes, since they cannot be assumed to be above the level of real bank riskiness.

4. Internal methodologies to estimate IRRBB

Within their internal capital adequacy-assessment process, Italian banks measure IRRBB, under both ordinary and stressed conditions, by applying different techniques, *ceteris paribus*, to model interest rate changes. Therefore, in line with banking practice, here we take the rest of the regulatory assumptions as given and focus on modeling interest rate changes, in order to address the limits of the BCBS (2004) parallel shifts and percentiles methods. In particular, 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 of the percentiles method are changes that actually occurred. Nevertheless, these changes might have occurred on different days. For example, the 1st percentile might refer to January 22nd, 2008 for the interest rate of the first time band, to December 23rd, 2010 for the interest rate associated with the second time band, etc. Therefore, as with parallel shifts, the percentiles method does not account for the correlations actually observed among the annual changes in interest rates.

In this section, we present two methods that banks can internally develop by making use of historical and Monte Carlo simulation techniques, respectively. The shocks are applied to a term structure of interest rates (henceforth, our key rates) whose nodes correspond to the midpoints of the 14 time bands of the regulatory maturity ladder.

The historical simulation method can account for correlations among the annual changes in key rates because the risk indicator is based on scenarios of changes in interest rates that are represented by the joint annual changes in our key rates that have actually occurred over the past five years. These scenarios are calculated on a given day through the overlapping technique, as suggested by BCBS (2004), and are applied to the net positions to obtain the net weighted positions. We then sum the net weighted positions to calculate the change in a bank's EVE and divide this sum by the regulatory capital to obtain an empirical distribution of the risk indicator. This distribution is cut in correspondence with the percentile associated with the desired confidence level, which is set equal to 99% following BCBS (2004). However, it is possible that the non-negativity constraint might prevent this method from capturing the correlations when interest rates are very low.

The Monte Carlo simulation method allows us to generate scenarios that both take into account the correlations between the annual changes in our key rates and meet the non-negativity constraint. We carry out as many simulations as are 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 zero level in one or more nodes. In this way, we obtain a distribution of the risk indicator that is cut at the percentile corresponding to a 99 percent confidence level. Specifically, we develop the method as follows:

i) Select the joint probability density function that guarantees the best approximation of the actual distributions of annual changes in the key rates. The application of the overlapping data technique supports the use of a normal joint probability density function, already adopted by Fiori and Iannotti (2007).

ii) Estimate 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) Generate a random number u_i (i = 1,. . .14) ranging from 0 to 1 at each node of our key rates term structure.

iv) Convert each u_i into a value z_i (i = 1,. . .14) distributed according to a standard normal. In symbols:

$$z_i = F^{-1}(u_i) \tag{2}$$

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

$$Q' \cdot Q = \Omega \tag{3}$$

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

$$x = Q' \cdot z + \mu \tag{4}$$

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) Repeat steps iii)-vi) until we reach a number K of scenarios that meet the non-negativity constraint.

viii) Apply the K simulated scenarios to the net positions to calculate the net weighted positions. For each scenario, the net weighted positions are summed in order 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 99th percentile.

From a methodological perspective, it is interesting to note that, under the parallel shifts and percentiles methods, the risk indicator is obtained by assuming that all the key rates move together in the same direction. Under both the internal methodologies presented here, however, key rates are allowed to move in different directions and the only restriction applied to the changes in the key rates is the non-negativity constraint set by BCBS. We allow the key rates to change because episodes in the recent and more distant past, such as the measures of monetary policy that have driven market rates to extremely low levels and the U.S. savings and loan crisis, have shown that their term structure can actually assume characteristics and dynamics which, ex ante, would have been judged unrealistic.

5. A backtesting framework

Based on the related literature (for a review, see Campbell, 2006), mainly two approaches have been employed to implement a backtesting procedure. A backtest could be based either on a hit function (see, for example, the backtests developed by Kupiec, 1995; Christoffersen, 1998; Christoffersen and Pelletier, 2004) or on a loss function (Lopez, 1999). Regarding the former, backtesting procedures based on a loss function have greater flexibility, since the loss function can be tailored to address specific concerns, even if the increased flexibility generates a substantial increase in the informational burden associated with assessing the accuracy of a certain model under consideration. In fact, in order to assess whether the average loss is "too large relative to what would be expected," it is necessary to understand the stochastic behavior of the loss function. Therefore, backtesting procedures based on a loss function approach require an explicit assumption about the distribution of profits and losses.

Given our objective of comparing the performance of the different methodologies used to measure IRRBB, however, we decide to adopt a loss-function-based approach, since prior literature recognizes that loss-function-based backtests may be very useful for determining whether one model provides a better risk assessment than a competing model. From this perspective, loss-function-based backtests may be more suited to discriminating among competing models rather than judging the accuracy of a single model, which is exactly the aim of our backtesting framework.

To set up our backtesting framework, we adopt the logic underlying the forecast evaluation methods proposed by Lopez (1999), which tests VaR models by focusing on the potential losses associated with the underestimation of market risk and gives to each

Table 1
Key rate term structures.

t (evaluation date)	Demand and revocable	Up to 1 month	From 1 to 3 months	From 3 to 6 months	From 6 months 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
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%

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 the 2006–2008 period. We use data from Datastream, and, in particular, we use the EONIA (Euro Overnight Index Average) rate for the maturity corresponding to the demand and revocable time band, the Euribor rates for maturities shorter than 12 months, and interest rate swap (IRS) rates for maturities longer than, or equal to, 1 year. Key rates referred to maturities not included in the market term structure are calculated through linear interpolation.

Table 2
Descriptive statistics of the annual changes in the key rates observed over the 2009–2013 period with December 31st, 2013 as the evaluation date.

	Demand and revocable	Up to 1 month	From 1 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
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. Dev.	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

We use data from Datastream, and, in particular, we use the EONIA (Euro Overnight Index Average) rate for the maturity corresponding to the demand and revocable time band, the Euribor rates for maturities shorter than 12 months, and interest rate swap (IRS) rates for maturities longer than, or equal to, 1 year. Key rates referred to maturities not included in the market term structure are calculated through linear interpolation.

methodology a score based on a certain loss function: The lower the score, the better is the methodology performance. Forecast evaluation methods are particularly suitable for backtesting with datasets as small as ours because they do not suffer from the low power of a standard test since they are not frequency-based statistical tests. Furthermore, as mentioned above, forecast evaluation methods allow us to tailor the loss function to the specific objectives of the backtesting analysis. Therefore, given the peculiarities of IRRBB, we adapt Lopez's (1999) backtesting framework to specifically account for both regulator and industry concerns in estimating IRRBB, especially in terms of banking stability and credit supply to the economy.

For each sample bank, we compare the ex ante risk indicators with a measure of actual bank risk exposure, termed the ex post risk indicator. The ex post risk indicator is obtained by setting Δr in Eq. (1) equal to the joint annual changes in the key rates that actually occurred over the one-year time horizon following the evaluation date t. For any evaluation date t, we assign to each methodology m a score, calculated through a score function, $S_{m,t}$, taking as inputs the results of an accuracy function, $A_{i,t}$, that is applied to each bank i ($i = 1, 2, \ldots N$, with $N = 130$) at each evaluation date t. The generic score function, for a methodology m and an evaluation date t, is formalized as follows:

$$S_{m,t} = \frac{\sum_{i=1}^{N} A_{i,t}}{N^{*}} \tag{5}$$

where:

- $A_{i,t}$ is defined such 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:

$$A_{i,t} = \begin{cases} f\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) & if \quad RI_{i,t}^{post} > RI_{i,t}^{ante} \\ g\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) & if \quad RI_{i,t}^{post} \leq RI_{i,t}^{ante} \end{cases} \tag{6}$$

- where: $RI_{i,t}^{ante}$ and $RI_{i,t}^{post}$ are the ex ante and ex post risk indicators, 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.
- f and g define the values of the accuracy function if the ex post risk indicator is higher or lower than (equal to) the ex ante one.

The first two specifications of the accuracy function refer to the case of an underestimation of actual risk exposure, when the ex post risk indicator is higher than (equal to) the ex ante one. Therefore, consistently with Lopez (1999), the first and second specifications both satisfy the following condition:

$$f\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) \geq g\left(RI_{i,t}^{post}, RI_{i,t}^{ante}\right) \tag{7}$$

In particular, according to the first specification shown in the following Eq. (8), the accuracy function equals 1 if the ex post is higher than the ex ante risk indicator, and 0 otherwise:

$$A_{i,t} = \begin{cases} 1 & if \quad RI_{i,t}^{post} > RI_{i,t}^{ante} \\ 0 & if \quad RI_{i,t}^{post} \leq RI_{i,t}^{ante} \end{cases} \tag{8}$$

By setting N^{*} equal to 1 in the score function (5), the final score is the number of times in which an underestimation occurs, for a given methodology m at an evaluation date t, and is defined as a frequency score. Under the second specification of Eq. (9), the accuracy function provides a measure of the severity of the underestimation error since it equals the difference between the ex post and the ex ante risk indicators, if the former is higher than the latter, and 0 otherwise. The larger the difference, the greater is the underestimation of actual risk exposure and the greater is the potential threat to banking stability. In symbols we have:

$$A_{i,t} = \begin{cases} RI_{i,t}^{post} - RI_{i,t}^{ante} & if \quad RI_{i,t}^{post} > RI_{i,t}^{ante} \\ 0 & if \quad RI_{i,t}^{post} \leq RI_{i,t}^{ante} \end{cases} \tag{9}$$

In this case, N* in the score function (6) is set equal to the number of banks for which $RI_{i,t}^{post} > RI_{i,t}^{ante}$ and the score function captures the average magnitude of the measurement error for each methodology m on a certain evaluation date t, providing what we term a severity score for the underestimation case.

By removing the constraint of Eq. (7), the third specification of the accuracy function, shown in Eq. (10), accounts for an overestimation of actual risk exposure. In particular, it equals the absolute value of the difference between the ex post and the ex ante risk indicators, when the former is lower than the latter, and 0 otherwise. The larger the difference, the greater is the potential reduction of the credit supply to the economy, since the amount of internal capital that a bank unnecessarily sets aside is higher. In symbols we have:

$$A_{i,t} = \begin{cases} 0 \quad if \quad RI_{i,t}^{post} \geq RI_{i,t}^{ante} \\ |RI_{i,t}^{post} - RI_{i,t}^{ante}| if \quad RI_{i,t}^{post} < RI_{i,t}^{ante} \end{cases} \tag{10}$$

In this case, N^* in the score function (5) is the number of banks for which $RI_{i,t}^{post} < RI_{i,t}^{ante}$ and the final score captures the average difference between them for a given methodology m and an evaluation date t, providing a measure of the average error, i.e., a severity score for the overestimation case.

Finally, we adopt a fourth specification of the accuracy function, which is given by the combination of the previous accuracy functions (9) and (10), thus considering the distance between the ex ante and the ex post risk indicators in both cases of underestimation and overestimation. In symbols:

$$A_{i,t} = \begin{cases} RI_{i,t}^{post} - RI_{i,t}^{ante} & if \quad RI_{i,t}^{post} > RI_{i,t}^{ante} \\ |RI_{i,t}^{post} - RI_{i,t}^{ante}| & if \quad RI_{i,t}^{post} < RI_{i,t}^{ante} \end{cases} \tag{11}$$

In this case, N^* of the score function (5) is the total number of banks and the final score is a measure of the overall proximity of the ex ante to the ex post risk indicator, and is defined simply as a proximity score. The accuracy function (11) makes no distinction between cases of underestimation and overestimation. In any event, in order to set a specific order of priority, Eq. (11) can be easily adjusted to take the key issues associated with overestimation and underestimation of IRRBB into account by differently weighting the two cases.

6. Empirical evidence

6.1. Data

We estimate our sample banks' risk indicators as of December 31st for each of the years included in the 2006–2013 period. December 31st is also the date on which we estimate IRRBB and to which bank specific balance sheet data refer. In consistency with the previous section, these evaluation dates are indicated with t (*t* = *December 31st, 2006, December 31st, 2007, ... December 31st, 2013*). Key rates are observed on December 31st for each of the years 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 current banking practices.

The characteristics and dynamics of the key rate term structure over time have a strong impact on bank risk exposure. Table 1 shows that the term structure of our key rates becomes steeper and experiences a downward shift over time, which makes the application of the non-negativity constraint more likely to occur.

Table 2 shows the main descriptive statistics of the key rates annual changes observed over the 2009–2013 period, with December 31st, 2013 as evaluation date t. As expected, short-term are more volatile than long-term key rates. Furthermore, the negative kurtosis coefficients confirm that the distributions of interest rate changes generated through the overlapping technique do not suffer from the fat tail issue. These results are confirmed for the rest of the evaluation dates and are available upon request.

We use both regulatory and internal methodologies to measure IRRBB of 130 Italian commercial, savings, and cooperative banks. On average, our sample includes both banking groups and independent banks. Table 3 shows the average values of our sample banks' cash assets and off-balance sheet long positions in Panel A and cash liabilities and off-balance sheet short positions in panel B, respectively. It is worth considering that the off-balance sheet positions include hedging derivatives, such as interest rate swaps, and the optionalities embedded in some financial contracts, namely the floors and caps associated with floating-rate loans.

Average customer loans represent approximately 75 percent of total on- and off-balance sheet positions; a large proportion of these loans, equal to 65 percent of total on- and off-balance sheet positions, are floating-rate loans and are slotted in short-term time bands because, following the regulatory allotment criteria, they are treated as short-term loans. Non-maturity deposits represent around 37 percent of total on- and off-balance sheet positions, confirming their importance from a risk-management standpoint and the relevance of the Italian bank maturity transformation function. Overall, debt securities constitute about 33 percent of total on- and off-balance sheet positions. Specifically, securities with a maturity shorter than one year represent almost 22 percent of total on- and off-balance sheet positions and mainly consist of floating-rate securities. Over the entire investigation period, both long and short on- and off-balance sheet positions account on average for less than 10 percent of the total, being equal to 9.35 percent and 9.85 percent, respectively.

Our sample mostly includes banks active at provincial, interprovincial, and regional levels. Consistent with their limited geographical scopes of activity, Table 4 shows that the average total assets of our sample intermediaries, calculated over the entire investigation period, amount to almost €2,378 million, with a clear increasing trend from €1,661 million in 2006 to €2,909 million in 2013. Furthermore, it is interesting to note that, on average, about 88 percent of the intermediaries that we examine (115 banks out of 130) have total assets lower than €3.5 billion, which is the threshold below which they are identified by prudential supervision as so-called "minor intermediaries." In terms of regulatory capital, we also find evidence of a growing path, even if at a slower pace relative to total assets, from a value of €179 million as of December 2006 to approximately €254 million at the end of 2013. Finally, despite their overall small size, our banks make heavy use of derivatives; on average, over the entire sample period, almost 87 percent (114 banks out of 130) are derivative users. Nevertheless, most likely because of their limited size, their hedging practices appear to be relatively homogeneous, consisting mainly in using interest rate swaps against the risk associated with issued bonds and amortizing interest rate swaps specifically to hedge the risk potentially arising from fixed-rate mortgage loans.

Table 3
Cash assets and liabilities term structure and off-balance sheet positions.

Panel A: cash assets term structure and off-balance sheet long positions									
	2006	2007	2008	2009	2010	2011	2012	2013	Avg. per year
Debt securities with maturity shorter than 1 year	8.56%	8.28%	10.95%	11.45%	10.99%	10.48%	12.10%	14.81%	10.95%
Debt securities with maturity between 1 year and 5 years	3.32%	2.48%	1.23%	1.74%	1.67%	2.61%	5.55%	7.06%	3.21%
Debt securities with maturity longer than 5 years	1.24%	1.04%	0.60%	1.23%	1.46%	1.77%	3.32%	4.43%	1.89%
Loans with maturity shorter than 1 year	65.58%	70.76%	70.64%	66.93%	67.07%	63.47%	59.54%	56.17%	65.02%
Loans with maturity between 1 year and 5 years	6.15%	3.86%	4.15%	5.64%	4.93%	6.34%	5.61%	6.27%	5.37%
Loans with maturity longer than 5 years	5.52%	3.66%	4.53%	5.76%	3.47%	4.20%	2.93%	2.92%	4.12%
Total cash assets	90.37%	90.80%	92.10%	92.75%	89.59%	88.87%	89.05%	91.66%	90.65%
Off-balance sheet long positions	9.63%	9.20%	7.90%	7.25%	10.41%	11.13%	10.95%	8.34%	9.35%
Panel B: cash liabilities term structure and off-balance sheet short positions									
	2006	2007	2008	2009	2010	2011	2012	2013	Avg. per year
Non-maturity deposits	38.38%	37.02%	37.18%	40.36%	38.84%	36.07%	32.12%	34.21%	36.77%
Other current accounts	8.70%	8.40%	7.77%	8.20%	8.97%	8.79%	9.84%	7.85%	8.56%
Term deposits and other funds with maturity shorter than 1 year	11.86%	9.92%	7.52%	4.99%	5.52%	8.61%	14.99%	18.45%	10.23%
Term deposits and other funds with maturity between 1 year and 5 years	1.93%	1.14%	0.43%	0.37%	0.34%	1.39%	1.65%	2.17%	1.18%
Term deposits and other funds with maturity longer than 5 years	0.35%	0.20%	0.17%	0.17%	0.22%	0.18%	0.18%	0.19%	0.21%
Debt securities with maturity shorter than 1 year	20.47%	25.47%	29.74%	28.33%	21.69%	19.40%	15.17%	13.96%	21.78%
Debt securities with maturity between 1 year and 5 years	7.40%	7.64%	8.60%	9.46%	12.81%	13.39%	14.07%	12.96%	10.79%
Debt securities with maturity longer than 5 years	0.66%	0.53%	0.39%	0.45%	0.78%	0.76%	0.67%	0.72%	0.62%
Total cash liabilities	89.76%	90.32%	91.81%	92.33%	89.18%	88.59%	88.69%	90.51%	90.15%
Off-balance sheet short positions	10.24%	9.68%	8.19%	7.67%	10.82%	11.41%	11.31%	9.49%	9.85%

This table shows the average values of our sample banks' cash assets and off-balance sheet long positions in Panel A and cash liabilities and off-balance sheet short positions in Panel B, respectively. Data are taken from banks' balance sheets, and refer to December 31st of each year included in the 2006–2013 period. Results are expressed in percentage of total on- and off-balance sheet positions.

Table 4
Sample banks' size and derivatives usage.

	2006	2007	2008	2009	2010	2011	2012	2013	Avg. per year
Avg. total assets (€ million)	1,660.98	1,999.51	2,044.52	2,209.73	2,505.39	2,704.34	2,994.21	2,908.90	2,378.45
Avg. regulatory capital (€ million)	179.03	195.12	218.82	234.42	247.18	262.35	266.62	254.23	232.22
% of banks with total assets ≤€3.5 bn.	91.54%	90.00%	90.00%	87.69%	87.69%	87.69%	86.15%	86.15%	88.37%
% of derivative users banks	79.23%	84.62%	85.38%	85.38%	87.69%	91.54%	92.31%	93.08%	87.40%

In the first and second rows, this table shows the average total assets and regulatory capital of our sample banks, respectively (both denoted in million euros). In the third and fourth rows, the table shows the percentage of banks with total assets lower than €3.5 billion and the percentage of banks using derivatives. Data refer to December 31st of each year included in the 2006–2013 period and are taken from banks' balance sheets.

6.2. The nature of banks' interest rate risk exposure

Italian commercial banks typically fund long-term assets with short- and medium-term liabilities. Therefore, if interest rates move up (down), their economic value should decrease (increase) because, *ceteris paribus*, the reduction (increase) in the economic value of their long-term assets should be larger, in absolute value, than the decrease observed for their short- and medium-term liabilities. Adopting BCBS terminology, if interest rates increase (decrease), the sum of the positive net weighted positions is higher (lower) than the absolute value of the negative net weighted positions. We define intermediaries characterized by this type of exposure as asset-sensitive banks.

Nevertheless, bank risk exposure derives from the interaction of: i) the term structure of the net positions, which is the result of banks' ALM and commercial strategies; ii) the regulatory allotment criteria, and iii) the actually applied scenario of annual changes in the key rates, which depends on the adopted methodology and on the application of the non-negativity constraint. Therefore, we also find banks exposed to decreasing interest rates (also termed "liability-sensitive") and risk-neutral banks, i.e., those that experience an increase in their economic value whether the current standardized shock is applied up or down.

If interest rates decrease (increase), liability-sensitive banks experience a decrease (growth) in their economic value because, *ceteris paribus*, the increase (decrease) in the economic value of their long-term assets is lower, in absolute value, than the increase (decrease) observed for their short- and medium-term 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 net weighted positions.

Based on the calculation mechanism of the risk indicator, a bank is risk neutral if, in the case of a positive (negative) interest rate shock, the decrease (increase) in its assets economic value is lower (higher), in absolute value, than the decrease (increase) in its liabilities, thus determining an overall increase in EVE. In other words, using BCBS terminology, whether interest rates increase or decrease, the sum of the positive net weighted positions is lower than that of the negative net weighted positions taken in absolute value.

Table 5 shows that, during our investigation period, out of 130 institutions, on average 40 banks per year are asset-sensitive under the parallel shifts method and that number increases to 42 if we measure IRRBB through the Monte Carlo simulations. If we use the percentiles method and historical simulations, the number of banks exposed to an increase in interest rates is around 25 and 27, respectively. As far as exposure to decreasing interest rates is concerned, the average number of banks per year goes from approximately 76 under the parallel shifts method, to around 103 for historical simulations. Roughly 13 and 21 banks per year are risk-neutral under the parallel shifts and percentiles methods, respectively; however, we find no instance of risk-neutrality for either the Monte Carlo or the historical simulations.

The application of the non-negativity constraint, which is more likely when interest rates are low, is the main factor underlying the risk-neutrality phenomenon for both parallel shifts and percentiles methods. Because of the non-negativity constraint, under a scenario of decreasing interest rates, the reduction in a bank's EVE associated with the negative net positions of medium-term time bands is not sufficient to offset the increase in the EVE attributable to the positive net positions of long-term time bands.[6] The significant increase in the number of risk-neutral banks in the last two years of our sample period, when interest rates are lower than before, confirms this interpretation. Nevertheless, under the percentiles method, the few cases of risk neutrality observed on December 31st of the years 2006–2008 do not result from application of the non-negativity constraint, which does not come into play. In those cases, risk neutrality stems from the combined effect of peculiar scenarios of changes in the key rates, on the one hand, and specific term structures of banks' net positions across the time bands of the regulatory maturity ladder, on the other hand.

Regarding historical and Monte Carlo simulations, we do not observe risk-neutrality cases. These simulations make use of multiple scenarios, namely around 1200 scenarios for the historical simulations, given by the sum of the approximately 240 scenarios per year observed over the 5-year period across which, based on the current regulatory framework, annual changes in the key rates have to be measured, and 10,000 scenarios for the Monte Carlo simulations. With regard to the latter, the process to generate the 10,000 scenarios of changes in the key rates requires us to select scenarios from those that do not drive the key rate term structure below zero, thus fulfilling the non-negativity constraint by construction. In the historical simulations, despite application of the non-negativity constraint, contrary to what occurs with the regulatory methodologies, the key rates of the term structure are free to move in different directions within the same scenario. The high number and the different nature, in terms of sign and magnitude of interest rate changes, of the scenarios used to generate the distributions of the risk indicators minimizes the probability that a bank will be risk neutral.

6.3. The on- and off-balance sheet components of bank interest rate risk exposure

Our sample banks carry out a homogeneous hedging activity through basic interest rate derivatives, such as interest rate swaps. Based on the approach of Esposito et al. (2015), in order to detect whether and to what extent Italian banks use derivatives to manage IRRBB, we have decomposed the risk indicator obtained through Eq. (1) into two components, based on the on- and off-balance sheet items, respectively. However, it is important to point out that, as highlighted above in Section 6.1, the off-balance sheet component includes not only hedging derivatives, but also floors and caps embedded in floating-rate loans.

Based on the current regulatory treatment of these off-balance sheet items, their effect on bank risk exposure is as follows. Amortizing interest rate swaps transform a fixed-rate mortgage into a floating-rate mortgage. Therefore, *ceteris paribus*, they reduce the average maturity of a bank's assets and accordingly decrease (increase) the exposure of an originally asset-sensitive (liability-sensitive) credit institution. Interest rate swaps change a fixed-rate issued bond into a floating-rate bond and, therefore, reduce the average maturity of a bank's liabilities. Consequently, they decrease (increase) the exposure of a credit institution formerly exposed to decreasing (increasing) interest rates. Finally, concerning the caps and floors embedded into floating-rate mortgage loans, a portion of these loans, based on the option's delta, becomes fixed-rate and an increase in the average asset maturity occurs. Thus, *ceteris paribus*, the risk exposure of a formerly asset-sensitive (liability-sensitive) bank increases (decreases).

For each of the four methodologies discussed above, Table 6 shows our sample banks' average overall risk exposure (see columns labeled "Overall"), measured through the risk indicator of Eq. (1), and its breakdown in the on- and off-balance sheet components (see the columns labeled "On" and "Off," respectively). Overall, IRRBB is adequately managed by Italian banks. Table 6 shows that the 20 percent critical threshold set by the BCBS is, on average, by far higher than our sample banks' risk indicators.[7] The average risk indicator calculated over the entire sample period for asset-sensitive banks is 10.37 percent under the parallel shifts method, versus 6.87 percent for the Monte Carlo simulations, 4.73 percent for the percentiles method and 5.98 percent for the historical simulations. Banks exposed to increasing interest rates show higher risk indicators under the parallel shifts method because of the impact of the +200-bp shock on the net positions of long-term time bands. The distance in terms of risk indicators among the different methods shrinks for banks exposed to decreasing interest rates, whose average risk indicators go from 5.32 percent for the Monte Carlo simulations to 7.54 percent for the historical simulations.

When we consider the breakdown of the overall risk exposure between the on- and off-balance sheet components, we find evidence of different behavior by our sample banks, depending on the

[6] 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 bp parallel shock. Nevertheless, due to the non-negativity constraint, the magnitude of the reduction in the bank economic value associated with negative net positions would be lower and not enough to offset the increase in the economic value generated by the positive net positions. Under the percentiles method, we would not have a symmetric risk exposure by applying the 1st and 99th percentiles in absence of the non-negativity constraint, but, in essence, its final effect would be the same as that just described for the parallel shifts method.

[7] The highest single value (not shown in the Table) is 15.20%, which is observed on December 31st, 2006 for the parallel shifts method and refers to asset-sensitive banks. Data referring to each single year are available upon request.

Table 5
Sample banks' types of interest rate risk exposure: number of banks by measurement methodology.

	Parallel shifts method			Percentiles method			Historical simulations		Monte Carlo simulations	
t (evaluation date)	A	L	RN	A	L	RN	A	L	A	L
December 31st 2006	47	83	0	41	87	2	40	90	40	90
December 31st 2007	32	98	0	23	105	2	25	105	23	107
December 31st 2008	23	107	0	15	107	8	20	110	23	107
December 31st 2009	31	94	5	18	111	1	17	113	43	87
December 31st 2010	21	105	4	11	119	0	10	120	20	110
December 31st 2011	38	78	14	27	96	7	18	112	35	95
December 31st 2012	60	20	50	32	20	78	43	87	73	57
December 31st 2013	71	25	34	36	27	67	42	88	77	53
Average n. of banks per year	40.38	76.25	13.38	25.38	84.00	20.63	26.88	103.13	41.75	88.25

This table shows our sample banks' type of risk exposure based on the methodology used to model interest rate shocks. Columns 1–3 refer to the parallel shifts method, columns 4–6 to the percentiles method, columns 7–8 to the historical simulations and columns 9–11 to the Monte Carlo simulations. For a description of the parallel shifts and percentiles approaches, see Section 3. For a description of the historical and Monte Carlo simulations approaches, see Section 4.
A indicates banks exposed to increasing interest rates (asset-sensitive banks), *L* indicates banks exposed to decreasing interest rates (liability-sensitive banks) and *RN* indicates risk-neutral credit institutions.
Interest rate risk exposure is calculated according to the Bank of Italy's duration gap approach and is expressed as percentage of regulatory capital, as shown in Eq. (1). Non-maturity deposits have been allotted within 5 years according to the criterion defined in Bank of Italy (2013) and data are taken from Datastream and banks' balance sheets.

Table 6
Sample banks' average risk indicators: breakdown by measurement methodology and type of interest rate risk exposure.

	Parallel shifts method			Percentiles method			Historical simulations			Monte Carlo simulations		
	Overall	On	Off	Overall	On	Off	Overall	On	Off	Overall	On	Off
A	10.37%	6.82%	3.55%	4.73%	2.95%	1.78%	5.98%	4.66%	1.32%	6.87%	5.38%	1.49%
L	6.62%	7.93%	−1.31%	7.11%	8.61%	−1.51%	7.54%	8.93%	−1.39%	5.32%	6.22%	−0.91%

This table shows the average risk indicators of our sample banks over the 2006–2013 period, based on the methodology used to model interest rate shocks.
Columns 1–3 refer to the parallel shifts method, columns 4–6 to the percentiles method, columns 7–9 to the historical simulations and columns 10–12 to the Monte Carlo simulations. For a description of the parallel shifts and percentiles methods, see Section 3. For a description of the historical and Monte Carlo simulation approaches, see Section 4.
A indicates banks exposed to increasing interest rates (asset-sensitive banks) and *L* indicates banks exposed to decreasing interest rates (liability-sensitive banks). *Overall* indicates the overall risk indicator based on both the on- and off-balance sheet items, *On* indicates the risk indicator based on the only on-balance sheet items, and *Off* indicates the risk indicator based on the only off-balance sheet items. Overall risk indicators have been decomposed in the on- and off-balance sheet components following Esposito et al. (2015).
Interest rate risk exposure is calculated according to the Bank of Italy's duration gap approach and is expressed as percentage of regulatory capital, as shown in Eq. (1). Non-maturity deposits have been allotted within 5 years according to the criterion defined in Bank of Italy (2013) and data are taken from Datastream and banks' balance sheets.

nature of their risk exposure. On average, for the liability-sensitive banks, the on- and off-balance sheet components show a positive and a negative sign, respectively, whereas, the two components have the same positive sign for the asset-sensitive banks. Based on these results, liability-sensitive banks seem to use derivatives as a hedging tool to offset on-balance sheet interest rate risk, which is consistent with the overall decreasing trend experienced by market interest rates over the investigation period. On the other hand, asset-sensitive banks seem to use their off-balance sheet positions to enhance the gains associated with the decreasing interest-rate trend.[8]

This preliminary evidence disregards a substantial degree of heterogeneity among intermediaries concerning their exposure to IRRBB. Therefore, in Table 7 we split our sample into three groups, according to the sign of their risk exposure over the entire 2006–2013 sample period: i) banks that were always asset-sensitive; ii) banks continuously exposed to decreasing interest rates; iii) banks that varied the sign of their exposure at least once, also termed "other banks."

Overall, Table 7 shows that the vast majority of our 130 sample banks experienced a change in the nature of their interest rate risk exposure at least once over the time horizon we consider. If IRRBB is measured through the historical and Monte Carlo simulations, we observe a higher number of liability-sensitive banks, i.e., 41 for the former and 20 for the latter, both higher than the figure observed for the parallel shifts and percentiles methods. Concerning the breakdown of the overall risk exposure into the on- and off-balance sheet components, on average, the results reported in Table 7 are consistent with those shown in Table 6; the on- and off-balance sheet components have the same positive sign for the asset-sensitive banks and an opposite sign for the intermediaries exposed to decreasing interest rates.

7. Backtesting results

Table 8 shows the average results across the whole sample period of our backtesting framework applied to the regulatory and internal methodologies. Panel A reports the average frequency scores based on the accuracy function (8), whereas Panels B and C show the average severity scores in the case of underestimation and overestimation of the actual ex post risk exposure, that are calculated through the accuracy functions (9) and (10), respectively. Finally, Panel D presents the average proximity scores based on the accuracy function (11). The ex ante risk exposure is alternatively assessed through the parallel shifts method (Columns 2 and 3), the percentiles method (Columns 4 and 5), the historical simulations (Columns 6 and 7) and the Monte Carlo simulations (Columns 8 and 9). In each panel, our results separately refer to the whole sample and to the two sub-groups of asset-sensitive and liability-sensitive banks. Table 8 also distinguishes between the scores based

[8] It is worth underlining that, to some extent, the treatment of the caps and floors options embedded into floating-rate loans can help explain the evidence referring to the asset-sensitive intermediaries, since it determines greater sensitivity to increasing interest rates.

Table 7
Sample banks' average risk indicators: breakdown by methodology and constant type of interest rate risk exposure.

	Parallel shifts method				Percentiles method				Historical simulations				Monte Carlo simulations			
	N. of banks	Overall	On	Off	N. of banks	Overall	On	Off	N. of banks	Overall	On	Off	N. of banks	Overall	On	Off
A*	6	13.22%	11.35%	1.87%	3	5.58%	5.47%	0.11%	2	5.97%	5.83%	0.14%	5	8.21%	7.00%	1.21%
L*	9	10.13%	10.83%	−0.70%	9	11.05%	11.95%	−0.90%	41	8.22%	9.48%	−1.25%	20	6.18%	7.09%	−0.91%
O	115	7.12%	6.78%	0.34%	118	5.77%	6.57%	−0.80%	87	6.87%	7.61%	−0.74%	105	5.62%	5.73%	−0.10%

This table shows the average risk indicators of our sample banks over the 2006–2013 period, based on the methodology used to model interest rate shocks.
Columns 2–4 refer to the parallel shifts method, columns 6–8 to the percentiles method, columns 10–12 to the historical simulations and columns 14–16 to the Monte Carlo simulations. For a description of the parallel shifts and percentiles methods, see Section 3. For a description of the historical and Monte Carlo simulation approaches, see Section 4.
*A** indicates banks exposed to increasing interest rates (asset-sensitive banks), over the entire sample period, *L** indicates banks exposed to decreasing interest rates (liability-sensitive banks) over the entire sample period, and *O* indicates banks whose nature of interest rate risk exposure changed at least once over the sample period.
Overall indicates the overall risk indicator based on both the on- and off-balance sheet items, *On* indicates the risk indicator based on the only on-balance sheet items, and *Off* indicates the risk indicator based on the only off-balance sheet items. Overall risk indicators have been decomposed in the on- and off-balance sheet components following Esposito et al. (2015).
Interest rate risk exposure is calculated according to the Bank of Italy's duration gap approach and is expressed as percentage of regulatory capital, as shown in Eq. (1). Non-maturity deposits have been allotted within 5 years according to the criterion defined in Bank of Italy (2013) and data are taken from Datastream and banks' balance sheets.

Table 8
Backtesting results.

	Parallel Shifts		Percentiles method		Historical simulations[a]		Monte Carlo simulations[a]	
Panel A: average frequency scores[b]								
	Overall	On	Overall	On	Overall	On	Overall	On
W	19.75	17.50	22.50	18.63	11.13	8.38	11.00	10.13
A	3.25	5.75	5.75	7.13	6.50	5.25	3.25	3.38
L	10.88	7.38	7.25	5.13	4.63	3.13	7.75	6.50
Panel B: average severity scores in the underestimation case[c]								
	Overall	On	Overall	On	Overall	On	Overall	On
W	0.68%	0.76%	0.76%	0.83%	0.42%	0.50%	0.27%	0.23%
A	0.70%	0.89%	0.89%	0.82%	0.46%	0.38%	0.25%	0.29%
L	0.53%	0.59%	0.53%	0.64%	0.31%	0.34%	0.24%	0.19%
Panel C: average severity scores in the overestimation case[d]								
	Overall	On	Overall	On	Overall	On	Overall	On
W	6.60%	6.73%	4.72%	5.41%	5.22%	6.06%	3.67%	3.93%
A	9.73%	9.54%	3.82%	4.23%	4.78%	4.86%	5.47%	5.19%
L	4.34%	5.39%	4.81%	5.79%	5.34%	6.35%	3.06%	3.59%
Panel D: average proximity scores[e]								
	Overall	On	Overall	On	Overall	On	Overall	On
W	6.02%	6.29%	4.62%	5.28%	5.17%	5.96%	3.55%	3.82%
A	9.08%	8.28%	4.07%	3.98%	4.65%	4.57%	5.28%	4.93%
L	4.19%	5.22%	4.74%	5.72%	5.27%	6.31%	3.01%	3.55%

This table shows the average results over the 2006–2013 sample period of our backtesting procedure applied to the methodologies used to model interest rate shocks.
Columns 2–3 refer to the parallel shifts method, columns 4–5 to the percentiles method, columns 6–7 to the historical simulations and columns 8–9 to the Monte Carlo simulations. For a description of the parallel shifts and percentiles methods, see Section 3. For a description of the historical and Monte Carlo simulation approaches, see Section 4.
W indicates whole sample banks, *A* indicates banks exposed to increasing interest rates (asset-sensitive banks), and *L* indicates banks exposed to decreasing interest rates (liability-sensitive banks).
Overall indicates the overall risk indicator based on both the on- and off-balance sheet items, *On* indicates the risk indicator based on the only on-balance sheet items, and *Off* indicates the risk indicator based on the only off-balance sheet items. Overall risk indicators have been decomposed in the on- and off-balance sheet components following Esposito et al. (2015).
Interest rate risk exposure is calculated according to the Bank of Italy's duration gap approach and is expressed as percentage of regulatory capital, as shown in Eq. (1). Non-maturity deposits have been allotted within 5 years according to the criterion defined in Bank of Italy (2013) and data are taken from Datastream and banks' balance sheets.
[a] The score is calculated by comparing the 99th percentile of the ex ante risk indicator distribution with the ex post risk indicator.
[b] Scores are calculated by applying the score function (5) and the accuracy function (8).
[c] Scores are calculated by applying the score function (5) and the accuracy function (10).
[d] Scores are calculated by applying the score function (5) and the accuracy function (11).
[e] Scores are calculated by applying the score function (5) and the accuracy function (12).

on overall risk exposure and those associated with risk exposure based on only the on-balance sheet components. In this way, we can capture the effect of derivatives on bank risk exposure within our backtesting framework.

If we focus on the results of the backtesting for the whole sample, the main findings are as follows. In terms of the overall risk indicator, taking all scores into account, the Monte Carlo simulations perform better than the other methodologies. They show a better performance even if we focus on the scores based only on on-balance sheet risk exposure, with the exception of the frequency scores, where the historical simulations perform better. Furthermore, it is worth noting that, for all the methodologies, and based only on the on-balance sheet risk indicator, the frequency scores reported in Panel A are lower than the corresponding scores based on the overall risk indicator. The use of derivatives leads to an increase in the number of times an underestimation of ex post risk exposure occurs. Thus, for a certain number of banks where the ex ante formerly overestimated the ex post on-balance sheet exposure, due to the derivatives use, both the ex ante and ex post exposures changed in such a way that the former finally underestimates the latter. Nevertheless, in Panel D, we find that the proximity scores based on overall risk exposure are lower than those associated with only the on-balance sheet risk exposure, indicating that, on average, our sample intermediaries have been able to reduce the overall distance between the estimated and actual risk exposure and have optimized their amount of internal capital against IRRBB.

When we examine the two samples of liability- and asset-sensitive banks separately, the results that we have just discussed for the whole sample are confirmed for the former, but not for the latter. For banks exposed to decreasing interest rates, the Monte Carlo simulations perform better than all the other methodologies, in terms of all the scores reported in Table 8, with the only exception being the frequency scores, where the historical simulations show better performance. Even for the comparison between the overall and the on-balance sheet risk indicators, the results confirm the evidence already discussed for the whole sample. In fact, on the one hand, the number of cases corresponding to an underestimation of ex post risk increases when moving from the scores associated with only the on-balance sheet risk indicator to those based on the overall risk indicators. On the other hand, the distance shrinks between the ex ante and the ex post risk exposures, i.e., the impact of the errors in measuring ex post risk exposure in terms of internal capital decreases.

The results for banks exposed to increasing interest rates must be read with caution because of the peculiar dynamics reported by market interest rates during the examined time horizon. Over the eight-year investigation period, we observe positive changes in interest rates, i.e., the interest rate shock scenarios to which asset-sensitive banks are potentially exposed, in only two years (2007 and 2013). We assess the performance of the methodologies for the asset-sensitive banks by comparing ex ante positive shocks of interest rates with ex post scenarios where interest rates actually decrease most of the time. This procedure may help explain the good performance of the parallel shifts method in terms of frequency scores. In fact, the application of positive ex ante interest rate shocks, such as the +200 bp parallel shift, leads generally to an overestimation of the ex post risk exposure and to a small number of cases in which an underestimation occurs. Regarding the severity scores calculated in the case of an overestimation of actual risk exposure, due to the above-mentioned dynamics of market rates, as expected, methodologies based on historical changes in interest rates (in our case the percentiles method and historical simulations) perform better than the others. The Monte Carlo simulations perform better than the other methodologies in terms of severity scores calculated in the case of an underestimation of ex post risk exposure. Finally, regarding the comparison between the overall and the on-balance sheet risk indicators, the frequency scores become lower when derivatives are taken into account, with the exception of the historical simulations, whereas the proximity scores tend to increase, thus providing opposite evidence to that referring to the sample as a whole and to liability-sensitive banks.

Memmel et al. (2016) propose to normalize a bank's change in EVE with its total assets, rather than with its regulatory capital, because the Basel risk indicator includes both risk exposure and risk-bearing capacity. As a robustness check for the results discussed in this and the previous section, we change the denominator of the risk indicator to bank total assets and we find our results qualitatively unchanged. The only difference seen is that, because of the larger scale of total assets relative to that of regulatory capital (the former are almost ten times the latter), the risk indicators are much smaller by normalizing with total assets than by regulatory capital.

8. Conclusions

The use of historical and, especially, Monte Carlo simulations to model interest rates shocks produces estimates of bank exposure to IRRBB that are more consistent with actual riskiness than the current standardized shocks, and these methods do not produce the unrealistic and misleading result of banks not exposed to interest rate risk (i.e., risk neutrality). Overall, simulation techniques overcome the limits of the current deterministic scenarios since they allow estimating a bank's equity sensitivity to a wider set of adverse scenarios and capturing interest rates dynamics over time, which enables us to consistently update the shock applied to assess a bank's risk exposure.

Given their methodological robustness and superior empirical performance, regulators might consider the opportunity to allow banks to model scenarios of changes in interest rates by using simulation techniques within their internal measurement systems. However, giving banks the opportunity to choose among deterministic regulatory shocks and more refined, simulation-based ones might create incentives for them to choose a certain methodology simply because it minimizes the amount of internal capital required to hedge against IRRBB.

In order to avoid such opportunistic behaviors, therefore, regulators might allow the use of simulations only if banks fulfill certain, predetermined conditions, for example, using a minimum number of scenarios to create the distribution of the risk indicator. They might also introduce constraints other than the current non-negativity restriction in order to simulate interest rates shocks that are more in line with market conditions and their reasonable evolution, such as setting a negative lower bound for post-shock interest rates, which is consistent with BCBS (2016). Toward the same purpose of making the simulated shock scenarios more consistent with interest rate levels and dynamics, regulators might also impose the use of a joint probability density function that guarantees the best approximation of actual distributions of annual changes in key rates for Monte Carlo simulations. A backtesting framework similar to that developed here can help to make both bank managers' and supervisors' activities better grounded and their interactions more constructive. From an operational perspective, managers can use such a framework to support their choice of a certain methodology that, based on the backtesting results, better estimates actual risk exposure. Supervisors can test the appropriateness of the deterministic shocks and make them more consistent with the levels and dynamics of market interest rates.

Based on our results, identifying interest-rate-change scenarios that are significant for business and consistent with market conditions is crucial to properly assess and manage IRRBB. According to the new standards set in BCBS (2016), banks should apply six interest rate shock scenarios to measure their risk exposure: 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. When compared to the current standardized shocks, these new scenarios can effectively contribute to a better measurement of banks' interest rate risk exposure despite their deterministic nature, since they account for its main drivers more accurately. Some of the scenarios proposed in the new framework allow for the possibility of a change in the slope of the yield curve and take into consideration the higher volatility of short- relative to long-term rates. This is important because banks are exposed to a wide set of adverse scenarios that can be characterized by changes of both sign and magnitude across the nodes of the key rate term structure.

The multiple shocks of the new framework, together with the condition that banks have to identify their EVE risk measure with the potential maximum loss across all interest rate shock scenarios, helps reduce the probability of observing the risk-neutrality phenomenon. Nevertheless, in an extremely low interest-rate environment, the application of a zero percent floor can significantly weaken the differences among the above-mentioned six scenarios and lead to a miscalculation of interest rate risk exposure, similar to the manner in which the parallel shifts and percentiles methods function in the current low-interest-rate scenario.

Possible development of this research should take into account the implications of the increasing prevalence of negative interest rates. Because of the application of the non-negativity constraint, negative interest rates make the deterministic scenarios to measure IRRBB even less effective from a technical perspective than in the case of low, but still positive, interest rates. Future research might further test the effects of the non-negativity constraint under low/negative interest rates and contribute to the development of approaches for generating scenarios that better account for the actual conditions of market interest rates.

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