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The papers published in the 'Markets, Infrastructures, Payment Systems' series provide information and analysis on aspects regarding the institutional duties of the Bank of Italy in relation to the monitoring of financial markets and payment systems and the development and management of the corresponding infrastructures in order to foster a better understanding of these issues and stimulate discussion among institutions, economic actors and citizens.

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Printed copies can be requested from the Paolo Baffi Library: richieste.pubblicazioni@bancaditalia.it.

ISSN 2724-6418 (online)
ISSN 2724-640X (print)

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Designed and printing by the Printing and Publishing Division of the Bank of Italy

Rating the Raters. A Central Bank Perspective

by Francesco Columba*, Federica Orsini*, and Stefano Tranquillo*

Abstract

We use the Bank of Italy's credit assessment system for non-financial corporations as a benchmark to assess the ratings assigned by commercial banks through their own internal systems, which are also used for monetary policy purposes. We examine the distribution of ratings on bank loans pledged as collateral in monetary policy operations in Italy and test for underreporting of risk, which might generate unwarranted exposure for the central bank. The rating systems of commercial banks and of the central bank both show satisfactory discriminatory power and predictive ability, suggesting that they evaluate credit risk adequately. We find that banks' models are, on average, slightly less conservative than the central bank model for borrowers with loans eligible as collateral. We observe only some mild evidence of low economic significance that banks may strategically manage the credit risk assessment for borrowers whose loans are pledged. We find no evidence that banks using more central bank liquidity are more lenient in assigning default probabilities to their debtors.

JEL Classification: D82, G21, G24, G32, E52.

Keywords: Model-based ratings, Credit risk, Collateral, Central bank refinancing.

Sintesi

Utilizziamo il sistema di valutazione del merito creditizio delle imprese non finanziarie della Banca d'Italia per valutare i rating assegnati dalle banche commerciali italiane con i loro sistemi interni, usati anche a fini di politica monetaria. Analizzando la distribuzione dei rating delle due fonti per i prestiti stanziati come garanzia nelle operazioni di politica monetaria in Italia, verifichiamo l'esistenza di una eventuale sottostima del rischio da parte delle banche, che potrebbe esporre la banca centrale a rischi indesiderati. Entrambi i sistemi mostrano un potere discriminante e una capacità predittiva soddisfacenti, indicando una valutazione adeguata del rischio di credito. I modelli interni delle banche tendono a risultare leggermente meno prudenti rispetto al modello della Banca d'Italia per i prestiti idonei come garanzia. Per i prestiti stanziati, rileviamo evidenze deboli e di limitata rilevanza economica di una sottostima strategica del rischio. Non troviamo evidenze che le banche con maggiore utilizzo della liquidità di banca centrale siano più indulgenti verso i loro debitori.

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CONTENTS

1. Introduction[1]

Collateralized credit operations are a standard and widely used tool for monetary policy implementation. Central bank funding has been crucial for credit institutions' support to the real economy in the years following the financial crises and in the pandemic period, especially in the jurisdictions where the financial sector was more fragile. In 2020-21, during the Covid-19 pandemic, the average share of Eurosystem refinancing on total Italian bank liabilities was about 12 per cent.[2]

In this paper we employ a central bank credit assessment system for non-financial firms, the In-house Credit Assessment System (ICAS) of the Bank of Italy (BoI), which is part of the Eurosystem, as a benchmark to assess the ratings set by commercial banks with their internal ratings-based systems (IRBs) and used for monetary policy purposes. We examine the distribution of ratings on bank loans pledged as collateral in monetary policy in Italy and test for risk under-reporting, found by Behn *et al.* (2022) and Calza *et al.* (2021), which might generate an unwarranted exposure for the central bank. Our goal is to detect differences, if any, in ratings between Italian IRBs and the central bank's system, and investigate their determinants.

Credit claims are an essential source of collateral for banks. At the end of September 2023, bank loans were the main type of collateral in the Eurosystem, accounting for about one third of the total,[3] and the Eurosystem and the BoI employ several layers of protection against potential losses. To address the risk of counterparty default, banks accessing credit operations must be financially sound (first layer of protection). Credit risk is further mitigated by lending only against adequate collateral, which represents the second layer of protection.[4]

The accurate design of this system has ensured that the Eurosystem has never experienced losses in its credit operations so far.[5] To be accepted as collateral in Eurosystem monetary policy

[1] We thank for useful comments and suggestions an anonymous referee, Francesco Calise, Giorgio Donato, Davide Giammusso, Alessandra Iannamorelli, Riccardo Lo Conte, Francesco Monterisi, Gerardo Palazzo, Tommaso Perez, Andrea Polinici, Antonio Scalia, Stefano Siviero, Alberto Maria Sorrentino, seminar participants at Bank of Italy and at the 2024 International Risk Management Conference.

[2] For an in-depth analysis of the extent to which public guarantees in Italy created additional credit with respect to pre-existing levels, see Cascarino *et al.* (2022).

[3] The use of credit claims as collateral reached record volumes following the easing measures taken in response to the Covid-19 pandemic in 2020. See the press releases of 7 April 2020 and 22 April 2020 for the adoption of the package and the press release of 10 December 2020 for the extension of the collateral easing measures until June 2022. For an in-depth description of rules of the collateral framework see Antilici *et al.* (2023). The other types of collateral posted by banks in Eurosystem monetary policy operations, at the end of September 2023, are: covered bank bonds (25.4 per cent), asset-backed securities (20.4 per cent), government securities (11 per cent), unsecured bank bonds (4.5 per cent), corporate bonds (2.9 per cent), other marketable assets (2.1 per cent).

[4] Collateral is valued daily and is subject to haircuts. The daily valuation and the haircuts are further layers of risk protection. For a complete overview of the financial risk management of the Eurosystem's monetary policy operations see ECB (2015).

[5] Few cases of counterparty default events were offset by the proceedings deriving from the posted collateral. The main case of default concerned Lehman Brothers Bankhaus AG (LBB), the German subsidiary of Lehman Brothers Holdings

operations, bank loans must comply with some eligibility criteria, including a minimum credit quality threshold, assessed via a rating assigned by one of the following sources: i) the IRBs operated by banks; ii) the ICASs managed by some national central banks (NCBs);[6] iii) the external credit assessment institutions (ECAIs), or rating agencies. The rating is a key determinant of the haircut imposed on the collateral.[7]

To shed light on the consistency of the IRB ratings for non-financial firms with those produced by the Italian central bank, while we draw inspiration from Calza *et al.* (2021), we use a more recent and complete dataset and we employ a richer and more robust estimation strategy. The dataset includes all domestic IRBs used also for monetary policy purposes over the years 2015-2023,[8] providing a full characterization of banks' policies in this area over a full business cycle, while the ECB authors cover the 2014-2018 period. Additionally, while Calza *et al.* (2021) consider only credit claims pledged in the general collateral framework (known as the Eurosystem Credit Assessment Framework, ECAF), we take into account also those pledged in the temporary collateral framework (known as Additional Credit Claims, ACCs).[9] Considering the whole internal rating span enables us to avoid the sample selection bias that affects the analyses based only on the ratings accepted within the general collateral perimeter (i.e. IRB's PDs below 0.4 per cent), resulting in a potential overestimation of the average difference between IRB and ICAS ratings. Finally, as for the estimation approach, we test additional specifications to measure, if any, the degree of risk under-reporting by banks in the context of monetary policy operations.

Inc. whose liabilities vis-à-vis the Bundesbank from monetary policy operations stood at around €8.5 billion at the time of the insolvency of the bank. The Bundesbank eventually managed to recover all the amount of LBB exposure. For further details see the press release on the Bundesbank website.

[6] In the euro-area ICASs are currently adopted by Banca d'Italia, Banco de Espana, Banco de Portugal, Banque de France, Banka Slovenije, Bank of Greece, Deutsche Bundesbank, Oesterrichische Nationalbank. For a comprehensive overview of central banks' ICAS system in the euro area, see Auria *et al.* (2023).

[7] Collateral valuation haircuts are determined according to the credit risk assessment of the debtor, the residual maturity and the type of interest of the loan.

[8] The PDs reported by banks in the context of the annual ECAF exercise are those used to calculate prudential capital requirements under the European Banking Authority Common Reporting (CoRep) framework; as such, they comply both with the Capital Requirements Regulation (CRR) and any Single Supervision Mechanism bank-specific requirements.

[9] Additional credit claims (ACCs) are credit claims that do not fulfil all the eligibility criteria applicable under the general collateral framework; every national central bank is free to set up a country-specific ACC framework. The possibility of implementing ACC frameworks was introduced in December 2011, as part of the enhanced credit support measures to support bank lending during the financial crisis. BoI has made full use of this possibility from the beginning, accepting as collateral loans granted to debtors with lower creditworthiness and extending its ACC scheme several times. The ACC scheme was introduced in 2012 in the BoI collateral framework. Within the BoI ACC framework individual claims may be accepted if the one-year probability of default of the borrower is not higher than 1.5 per cent, while pools of credit claims may be considered with a probability of default not higher than 10 per cent. In the context of the pandemic collateral easing measures, from 25 May 2020 BoI has temporarily removed the 10 per cent PD threshold for pools of credit claims. Hence, in our analysis, differently than Calza *et al.* (2021), we use the full range of ICAS' PDs without censoring them.

The case of Italy is particularly fit to investigate the consistency across commercial and central banks' risk assessments systems, as a significant number of IRB systems are employed also for monetary policy purposes and a large number of non-financial corporations are rated by the BoI ICAS.[10] Banks that choose to use their IRB as a primary source in the collateral framework must use their IRB PDs for the mobilization of credit claims for all debtors rated by their IRB system.[11] The PDs are used both for the determination of the eligibility of the claim and for the calculation of the haircut.

The BoI ICAS performs an assessment of the borrower creditworthiness based on a statistical model that employs a large set of variables, yielding ICAS 'Statistical ratings'. For the largest exposures the model assessment is complemented by BoI financial analysts' evaluation, which yields the ICAS 'Full ratings'. ICAS Full ratings must be used for the sub-set of debtors whose claims can be accepted also by the Eurosystem in the general collateral framework, while ICAS Statistical ratings can only be used to assess debtors whose credit claims are accepted by BoI in the temporary collateral framework.

IRBs and ICAS have different primary purposes. The primary purpose of IRBs is to compute banks' capital requirements to cover credit risk; they must be authorized by the banking supervisors and abide to banking regulation.[12] Besides, to be used for monetary policy purposes, IRBs must also be specifically authorized by the Eurosystem. The primary purpose of ICAS is instead to assess the credit quality of eligible loans to be used as collateral in monetary policy operations and thus to determine the corresponding valuation haircuts. For the banks that do not manage an IRB, ICASs constitute an important tool for expanding the sources of liquidity, allowing the use of bank loans as collateral.

We contribute to the literature on credit risk assessment systems by bringing new evidence, including for the post Covid-19 recovery. We study some features that to our knowledge have not been explored yet, such as the use of credit rating systems within the ACC framework, which lends itself to the analysis of loans of a lower credit quality,[13] and of ratings produced from NCB internal models

[10] In 2023 eight out of ten Italian banks with IRB systems authorized for regulatory purposes had their IRBs approved also for monetary policy purposes. The number of Italian banks with IRB systems authorized for ECAF purposes ranges from seven in 2015 to eight in 2023, due to new authorizations and mergers. They were nine in 2020.

[11] Whenever a debtor is not covered by the IRB, the secondary source, namely the ICAS in our analysis, is used.

[12] The IRB approach to assign risk weights to exposures was introduced in 2004 by the Second Accord of the Basel Committee on Banking Supervision (Basel II) as an alternative to the standardized approach (SA). In Europe the use of the IRB approach for regulatory purposes was allowed since June 2006 by the Capital Requirements Directive; its adoption by banks started to spread from 2008 onwards. The use of IRB models is conditional on supervisory authorities' validation. In the euro area validation of the models used to be granted by national supervisors until the end of 2014, when the Single Supervisory Mechanism (SSM) established that IRB models of 'significant' banks must be validated by the European Central Bank.

[13] See note 9 for further details.

(ICAS Statistical) compared with those given by IRB quantitative models (IRB Statistical),[14] which significantly increase the sample size and provide more robust results.[15] Overall, the evidence and the analysis of the drivers of the small differences between the credit risk assessment provided by IRBs and ICAS lead us to conclude that the evidence of an economically significant strategic management of the IRB credit systems found by Behn *et al.* (2022) and Calza *et al.* (2021) is not supported by the data for Italy.

The remainder of this paper is organized as follows. Section 2 discusses the literature. Section 3 describes the data and stylized facts about the two credit assessment systems. Section 4 presents the results of the performance analysis of the rating systems. Section 5 presents the results of the empirical analysis. Section 6 discusses the robustness analysis. Section 7 concludes.

2. Literature review

With regard to the analysis of the framework of monetary operations, Calza *et al.* (2021) find that, based on data between 2014 and 2018 from Austria, Belgium, France, Germany, Italy, Portugal and Slovenia, for the set of debtors whose loans are eligible as collateral, banks' ratings are on average more conservative than NCB ratings, while the opposite occurs for the subset of borrowers whose loans are pledged with the Eurosystem. Banks' ratings become less conservative as loan size and the level of central bank liquidity utilization increase.[16] These results rely mainly on observations from France, Italy and Austria; in the authors' view, they support the hypothesis that banks strategically manage their IRBs to maximize access to central bank funding. As such, IRB leniency by banks might generate an unwarranted risk exposure for the central bank.

From the regulatory perspective, a set of studies investigate with pre-Basel II data the consistency of banks' IRBs to ascertain the role played by banks' policies within the debate on the merits of model-based capital regulation, with mixed results. Lenders may disagree on borrowers' riskiness reflecting different views on credit quality (Carey, 2002) and also because of different lending

[14] We group the IRB models which the banks use for ECAF purposes into Statistical (IRB Statistical) and Full (IRB Full) ones. In the first group PDs are calculated with statistical or econometric models, while in the second PDs are calculated complementing the models with the banks' financial analysts' assessment (potentially leading to so called override). We compare ICAS Full PDs with IRB Full PDs and ICAS Statistical PDs with IRB Statistical PDs.

[15] In 2023 ICAS Full ratings were in excess of 3,000 and ICAS Statistical ratings of 330,000.

[16] In contrast, the degree of capitalization of banks does not seem to have explanatory power for the difference between the ratings of the two systems for bank loans used as collateral.

or risk management styles (Jacobson *et al.*, 2006). Estimates of PDs can diverge significantly, but not systematically across banks.[17]

A second set of studies investigates the effect of the introduction of the model-based approach with post-Basel II data, focusing on the relation between the variability of PD estimates across IRBs and banks' characteristics. These works find that in Germany from 2008 to 2012 weakly capitalized banks may report lower PDs (Berg and Koziol, 2017) and some banks may systematically under-report risk to lower their capital requirements (Behn *et al.*, 2022). However, there is also evidence that validated IRB models are accurate and robust, and that the introduction of the IRB approach promotes the adoption of stronger risk management practices among Western European banks from 2008 to 2015 (Cucinelli *et al.*, 2018).[18]

3. The Italian banks' IRBs and the Bank of Italy ICAS features

General description - IRBs and ICASs are both designed to evaluate the probability of default associated with credit exposures.[19] However, they differ in their objectives, regulatory context, methodologies. In terms of objectives and regulatory context, IRBs' valuations are mainly used for the calculation of capital requirements and as important inputs in approving and pricing loans, and in managing the portfolio of a wide range of credit exposure which does not entail only the corporate ones; they are developed in line with the Basel framework. ICASs are instead specifically aimed at evaluating the creditworthiness of non-financial corporations whose credit claims are used as collateral in monetary policy operations; they are developed by central banks in line with the Eurosystem requirements.

As concerns the methodologies, both systems use statistical techniques and historical data to estimate the likelihood that a borrower will default within a specific time horizon, i.e. one year; however, the exact statistical methodology, the set of information taken into consideration and the length of the time series used in the models may differ among the systems.[20] Another important element

[17] A feature of the Basel rules is that banks can have differences in opinions and approaches to managing and measuring credit risk, that imply different risk parameters. Persistent differences in loss-given-default (LGD) may be attributed to banks' policies (Firestone and Rezende, 2016).

[18] From Austria, Belgium, Denmark, Finland, France, Germany, Great Britain, Ireland, Italy, Netherlands, Norway, Portugal, Spain, and Sweden.

[19] IRB models are also used for the estimation of other parameters apart from the PD, i.e. the Loss Given Default (LGD) and the Exposure at Default (EAD). For a detailed overview of the regulatory requirements that IRB models have to comply with see EBA (2017) and ECB (2024).

[20] These elements may of course also differ (for the same class of debtors) from one IRB bank to another. As concerns different ICASs, while all the ICASs developed within the Eurosystem are similar in their general characteristics and comply with Eurosystem requirements, some differences can be observed, either in the sources of information or in the methodology adopted in order to calculate the ratings.

which may differ among IRBs and ICASs is the rating "philosophy". In the context of rating systems, two approaches can be adopted, one that includes cyclical effects and one that does not. The two approaches generate different rating types, commonly known as point-in-time (PIT) and through-the-cycle (TTC).[21] While often models cannot be classified as purely PIT or TTC, but are rather a hybrid combination of the two approaches, it can be said that the rating philosophy of BoI ICAS is point-in-time, while it is expected to be more through-the-cycle oriented for IRBs.[22]

The BI-ICAS rating process is based on a two-stage procedure, which combines a statistical module assessment with a judgmental model. [23] Stage 1 (Statistical Module) consists of a system of logit models that determines a one-year default probability ("ICAS Statistical PDs"). [24] Stage 2 (Expert Assessment) involves the financial analysts' assessment through the use of a wider range of information sources.[25] The PDs output of this process are the "ICAS Full PDs".

Data - We use yearly data between 2015 and 2023 on ratings collected from ten Italian IRB systems and the BoI ICAS during the annual Eurosystem performance monitoring exercises and on credit claims used as collateral in credit operations with BoI. [26] In order to ensure consistency, accuracy, and comparability of the credit assessment systems used for monetary policy purposes, the Eurosystem established a framework to monitor their performance.[27] The managers of each NCB's credit assessment system are required to send to the ECB data on all firms whose bank loans are assessed to be eligible as collateral in the Eurosystem monetary policy operations. The data for ICASs and IRBs are reported to the respective NCB and include PDs assigned to debtors over a one-year horizon.[28]

Accepted credit assessment sources can use their own individual rating scales and grades. The Eurosystem maps these different grades into a harmonized rating scale to make the credit ratings comparable across systems and sources. The scale has a number of Credit Quality Steps (CQSs) linked

[21] PIT ratings aim at evaluating the current situation of an entity by taking into account both cyclical and permanent effects. In contrast, TTC ratings focus mainly on the permanent component of default risk and are essentially independent from cyclical changes in the entity's creditworthiness.
[22] See Paragraphs 105-106, Credit Risk Chapter of the ECB guide to internal models. Common statistical methods used by IRBs include traditional credit scoring models and machine learning algorithms. In particular, IRB models often use traditional credit scoring techniques which include discriminant analysis models and regression models (linear, logit, probit).
[23] See Giovannelli *et al.* (2020) for further details.
[24] The system exploits two sets of variables: indicators derived from the National Credit Register (NCR) and indicators based on financial statements data. Model parameters are estimated using the observed defaults derived from NCR as dependent variable. Rating levels are associated to estimated PDs according to a scale mapping
[25] The analysis can either confirm the rating derived from Stage 1 or modify it by notching the master score up or down.
[26] For the last performance exercise, conducted in 2022, the new ICAS statistical model (Narizzano *et al.*, 2024) was not yet available.
[27] The basic principles of the framework are included in Article 126 and Annex IX of the Guideline (EU) 2015/510 of the ECB of 19 December 2014 on the implementation of the Eurosystem's monetary policy framework (ECB/2014/60) (recast).
[28] See Appendix 1 for details on the variables employed.

to maximum PDs over a one-year horizon (Table 1). The CQSs are relevant for the eligibility of assets and to determine the valuation haircuts of the collateral.

The Eurosystem considers a PD over a one-year horizon of up to 0.1 per cent as equivalent to a credit assessment of CQS 1 and 2 in the Eurosystem harmonized rating scale, while a PD from 0.1 up to 0.4 per cent is equivalent to CQS 3. All assets accepted by the Eurosystem as collateral must meet the minimum requirement of a credit assessment of CQS 3. Probabilities of default from 0.4 up to 1 and from 1.0 to 1.5 per cent correspond to CQS 4 and 5, respectively, and are relevant for the acceptance by NCBs (among which BoI) of individual loans as collateral within temporary collateral frameworks. Similarly, NCBs may accept as collateral pools of ACCs up to CQS 8 (as in the BoI temporary collateral framework).

Data for ICAS and IRB systems transmitted for the annual Eurosystem monitoring exercise comprise PDs at the beginning and at the end of the year.[29] We focus on ratings assigned to non-financial corporates that are jointly rated by BoI ICAS and by at least one IRB system. We first consider the observations for all eligible loans from borrowers jointly rated by the BoI ICAS and by at least one IRB system; we then construct a narrower data set focusing only on those loans actually mobilized as collateral.[30] Table 2 shows the number of firms rated by at least one IRB, by BoI ICAS and jointly by both systems, with the detail of the number of firms whose credit claims are used as collateral by Italian banks.

Stylized facts - We compare the assessments of IRBs and BoI ICAS collected annually for the Eurosystem performance monitoring exercise.[31] IRB Full PDs have been slightly less conservative than ICAS Full ones for eligible borrowers since 2017 (Fig. 1A): the difference has been mildly larger for debtors with loans pledged as collateral. IRB Statistical PDs, instead, since 2016 have been overall more conservative than ICAS Statistical PDs (Fig. 1B), to a smaller extent for debtors with loans pledged as collateral. The differences between IRB PDs and BoI ICAS PDs are statistically significant, according to the Student's t-test and the Wilcoxon signed-rank test, in nearly all the years and samples.

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[29] In our analysis we use beginning-of-year PDs. Calza *et al.* (2021) use end-of-year PDs, in order to benefit from greater rating variability, because beginning-of-year data are bounded by the ex-ante eligibility threshold (while end-of-year PDs may also refer to debtors that have lost eligibility throughout the year). However, in jurisdictions (like Italy) in which pools of credit claims are accepted, the credit assessment sources are requested to report debtors belonging to the full rating spectrum also at the beginning of the year; therefore, we are able to use beginning-of-year PDs without incurring in the problem of losing rating variability.

[30] All the Italian banks with IRBs authorized for monetary policy purposes have chosen to use the PDs calculated by their IRB systems when pledging their loans to the ECAF.

[31] In our analysis firms rated by more than one IRB are considered as different debtors, i.e. if a firm is rated by two different IRBs and by the BoI ICAS it is considered twice in the sample of debtors rated in common.

The circumstance that IRB Full PDs are only slightly less conservative than ICAS Full ones for both eligible borrowers and those with loans mobilized as collateral, indicates the absence of a relevant underestimation of credit risk by the banks in the use of IRB to maximize the pledgeability of their loans. Moreover, the differences between the ratings of the IRBs and BoI ICAS, which are more pronounced for the debtors with mobilized loans, may reflect the selection made by banks when assembling the collateral portfolio, contrary to the negative effect associated to the hypothesis of a strategic management of collateral. Banks may have in the first place an incentive to pledge loans with higher credit quality according to their genuine assessment to secure lower haircuts and more stable central bank liquidity. [32]

To appreciate how a sub-sample with a higher share of debtors with lower PDs may affect the difference between IRB and ICAS PDs, we focus on the three sub-samples of the general collateral framework, of the individual claims and of the pools of credit claims in the temporary collateral framework of Additional Credit Claims (ACC).[33]

Within the general collateral framework sub-sample of pledged debtors (Fig. 2) the differences between IRBs and ICAS Full PDs are negative, as in the full sample of pledged debtors; this is in line with the finding of Calza *et al.* (2021). However, when considering individual ACC claims, IRB ratings are on average less conservative than ICAS ratings only in half of the years analyzed and IRB ratings are on average more conservative than ICAS ones for ACC pools.[34] The comparison between IRBs and ICAS Statistical ratings provides a similar result, with larger differences for the ACC pools (Fig.

[32]A collateral valuation haircut is the deduction of a certain percentage from the valuation of an asset for the purpose of calculating the amount of liquidity that can be backed by the asset in case of counterparty default. The calibration of haircuts aims to ensure the equivalence of risk across different types of collateral assets. The loss in value of collateral that the Eurosystem expects to incur – with low probability – in an adverse scenario should be the same for the different assets and asset types. An adverse, but still reasonable scenario, is defined by the Eurosystem as the average loss occurring within the worst percentile of the loss distribution. For calibration purposes, an adverse scenario is set to correspond to the average loss in the worst one per cent of the cases, i.e. to expected shortfall at a 99 per cent confidence level (ES[99%]). An important risk component for the haircut calibration is represented by default risk, which is embedded in rating assessments, even though it is not the only one. Market and liquidity risk are also other modelled sources of risk. For more detail on haircut calibration see ECB (2015) and, with specific reference to marketable assets, Adler *et al*. (2023).

[33] We proxy the three frameworks (ECAF, ACC single claims and pool of ACCs) splitting the sample into three subsamples based on IRB PD ranges; this is due to the fact that debtors can overlap between the three frameworks, especially for ACC pools, where there is not a lower PD boundary and PDs can also assume values below 1.5 per cent. Therefore, in this paragraph when we refer to ECAF, ACC single claims and pool of ACCs we intend, respectively, credit claims with PD values: i) up to 0.4 per cent; ii) from 0.4 to 1.5 per cent; iii) greater than 1.5 per cent.

[34] In the context of the collateral easing measures introduced in 2020 to cope with the effects of the Covid-19 pandemic, the 10 per cent upper limit has been removed in the Italian ACC framework. This means that banks can pledge loans in the ACC pools with debtors' PDs greater than 10 per cent, provided that such loans are performing. This measure is supposed to be in place until March 2024, when the ECB should, to this moment, phase-out all the pandemic collateral easing measures, following a comprehensive review of the ACC frameworks.

2). The fact that IRB PDs are less or more conservative than ICAS PDs is mainly an effect of the considered sub-sample's selection criteria, which is based on the variable of analysis (i.e. the PD).[35]

The selection induced by the criteria of the collateral frameworks arguably leads to observed differences between the ratings of the two systems that are more pronounced in the sub-sample of pledged debtors than in the sample of eligible debtors (Fig. 3).[36] Indeed we find that the share of IRB banks' loans in CQSs 1, 2 and 3 in the sample of borrowers assessed with full ratings is 48 per cent for pledged debtors and 36 for eligible debtors (Fig. 3, left graph). As for the sample of borrowers assessed with statistical rating, the share of banks' loans in CQSs 1, 2 and 3 is 29 per cent for pledged debtors and 22 per cent for eligible debtors (Fig. 3, right graph). These figures suggest to control for IRB credit quality rating in the empirical analysis since the credit quality distribution is more skewed towards higher CQSs for pledged firms than for eligible firms.

4. The performance of the credit assessment systems

AUROC curve – One of the most widely used metric to test the performance of the credit assessment system is the Area Under the Receiver Operating Characteristic (AUROC) curve.[37] The ROC curve shows the trade-off between the true positive rate (TPR) and the false positive rate (FPR) across different decision thresholds, where:

$$TPR = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)}$$

and

$$FPR = \frac{False\ Positives\ (FP)}{False\ Positives\ (FP) + True\ Negatives\ (TN)}$$

The calculation of the area under the ROC curve is a popular way of testing the discriminatory power of the rating systems, which measures the degree with which the system is capable of assigning every entity to the correct class (in our case, the system performs a binary classification between

[35] The PDs of borrowers whose loans are pledged by IRB banks have to be lower than 0.4 per cent, while ICAS PDs are not upper-bounded. As for the ACC individual claims sample and the ACC pool sample, instead, a censoring of lower IRB PDs occurs, since IRB PDs cannot be lower than 0.4 and 1.5 per cent, respectively, while ICAS PDs are not lower-bounded, contributing to the circumstance that IRBs are more conservative than ICAS in this sample.
[36] Eligible debtors are those whose loans are eligible as collateral in monetary policy operations; pledged debtors are those whose loans are pledged as collateral in such operations.
[37] See Engelmann (2006) and Tasche (2006) for further details.

defaulted and non-defaulted debtors).[38] The area under the curve ranges from 1, corresponding to perfect discrimination, to 0.5, corresponding to a model with no discrimination ability (naïve model). Figure 4 shows the ROC curves relative to the Italian IRB systems accepted for monetary policy purposes (considered as a whole) and to BoI Full ICAS.

The AUROC is quite high for both the IRBs and the ICAS Full, with IRBs showing a steeper ROC curve (0.87 and 0.83 in Fig. 4A and 4B, respectively). The good results in terms of AUROC are confirmed also considering smaller samples of data for individual banks, years, and for debtors with loans pledged in monetary policy operations. Similar evidence can be detected also regarding the AUROC of IRBs and ICAS Statistical (0.87 for both systems in Fig. 4C and 5D). This is another element which confirms that the ability of the two credit assessment sources to properly evaluate the credit risk of the debtors they rate is satisfactory and that it does not raise concerns with respect to underestimation of credit risk.

Back-testing - In the previous sections we have verified that ICAS and IRB ratings are dissimilar to a certain extent, especially for pledged loans and in the more recent period. However, it is rather normal that ratings issued by two different credit assessment sources are not identical (Firestone and Rezende, 2016), as this may be due to different information sets, diverse statistical models, divergences in the expert assessment of the analysts. The true PD of a debtor is an unobservable variable; therefore, it is not possible to establish ex-ante whether a credit assessment system is correct in assigning a certain rating to a debtor, but it can be verified ex-post. From the perspective of a central bank, which receives bank loans as collateral in monetary policy operations, the satisfactory performance of the credit assessment systems evaluating these loans is of the utmost importance.

We performed a back-testing exercise with the purpose to confirm that the two credit assessment systems under investigation do not underestimate the defaults in the sample of the debtors with bank loans pledged as collateral in monetary policy operations, as for the AUROC, we focus on the full rating sample in line with the goal of the paper. [39] The methodology we use follows a 'traffic-light approach' (TLA) with a green zone, a yellow ('monitoring') zone and a red ('trigger') zone. These zones indicate different levels of significance of the deviations of the number of defaulted entities and

[38] A system with a very high discriminatory power has a ROC curve which goes closer to the top left hand corner of the plot, whereas a model performing poorly (naïve model) has a ROC curve close to a 45 degree line.
[39] The results of the tests are not reported due to confidentiality reasons.

of the corresponding default rates from the PD thresholds of the respective Eurosystem CQSs as defined in Table 1.[40]

We first calculated the back-testing on eligible debtors, as if we had a whole static pool which includes all the static pools of each IRB system. We then repeated the test only on the sub-sample of debtors in common with ICAS with loans pledged in monetary policy operations. The results indicate that, apart from some performance issues between 2015 and 2017, due to the unsatisfactory performance of some IRBs, in the last five years the IRB systems in aggregate showed a satisfactory performance both for the whole perimeter of eligible debtors and for the sample of debtors with pledged loans, which is the most relevant from a central bank risk management perspective.

We repeated the performance monitoring exercise for ICAS ratings on the whole sample of eligible debtors and then we focused on the sample of debtors in common with IRB banks with loans pledged as collateral; we detected some performance issues in the first years under analysis, the start-up phase of the ICAS system, which were solved from 2018 onwards.

In addition, we conducted the performance monitoring exercise also for IRB and ICAS Statistical ratings. The results for IRBs indicate that, apart from some performance issues in 2015, IRB Statistical systems show a good predictive capacity both on the universe of eligible debtors and on the sample of pledged debtors in common with ICAS Statistical. The performance is satisfactory also for ICAS Statistical ratings for almost the whole period; the model had some minor performance issues only in 2022,[41] then overcome with a new statistical model, developed and implemented also to address these issues, as explained in Narizzano *et al.* (2024). In the development of the new statistical model features of traditional models (i.e. the logit regression) and machine learning components for some variables are combined, in the attempt to solve the trade-off between predictability and transparency.

In conclusion, despite some issues emerging mainly in the first years of the analysis, in the more recent period both IRBs and ICAS systems show a good performance, even when tested on bank loans pledged as collateral.

[40] The trigger zone indicates that the deviation is considered very significant, i.e. the probability that the credit assessment system is mis-calibrated is very high. The monitoring zone, in turn, indicates a degree of deviation that is significant, i.e. the probability that the credit assessment system is mis-calibrated is high, but not large enough for classifying this situation as a breach of good performance by the system. The green, yellow and red zones are determined on the basis of a statistical binomial test: for further insights see Coppens *et al.* (2007).

[41] The performance issue in 2022 was related to the micro firms class, due to the fact that a number of such firms disclosed a simplified version of the financial statements, without the breakdown required for a complete model estimation.

5. Empirical analysis

Empirical approach - In this section we investigate the factors driving the differences between the ratings provided by banks' IRB systems and those provided by BoI ICASs in the collateral framework. First, we estimate the following equation in a panel setting:

$$\log\left(\frac{PD_{IRBijt}}{PD_{ICASit}}\right) = \alpha_i + \alpha_j + \beta_t \cdot D_t + \beta \quad \cdot Dpledge_{ijt} + \varepsilon_{ijt} \tag{1}$$

where *i* indicates the individual firm, *j* the bank and *t* the year examined, $\log\left(\frac{PD_{IRBijt}}{PD_{ICASit}}\right)$ is the log ratio between PD_{IRB} and PD_{ICAS}, $Dpledge_{ijt}$ is a dummy that is active when the loan is pledged in either of the general collateral, individual or pool temporary collateral frameworks. We include year (D_t), firm and bank fixed effects, to control for business cycle, structural changes, businesses' and banks' unobservable characteristics and we use the log ratio between the PDs of the IRBs and that of BoI ICAS to address the non-linearity in the absolute differences between PDs.

As in Calza *et al.* (2021), we assume as a benchmark for the risk assessment of the borrower the PD assigned to the debtor by the NCB, since it has no incentive to manage strategically its rating models parameters, while commercial banks may have an incentive to optimize them to save on capital requirements (this would be the primary goal of a hypothetical strategic behaviour in the management of the internal rating systems), or to save on the collateral posted. According to this hypothesis, banks could underestimate the credit risk of the debtors whose loans are pledged to the NCB to save on the haircuts imposed on the value of the collateral in the monetary policy operation to maximize the liquidity obtained. The effect of this behaviour would materialize in a lower credit risk assessed by IRBs, with respect to ICAS, for the borrowers whose loans are pledged, while it would not alter the creditworthiness assigned by banks to the other borrowers, relative to that calculated by ICAS.

In our analysis, thanks to the richness of the data set received from the banks and used to monitor the compliance with the collateral frameworks, we can also differentiate the IRB models of banks among Statistical ones, that do not entail a credit analysts' judgment before issuance of the rating, and Full ones where analysts' judgment is layered on the outcome of the statistical model. We also have the benefit of being able to match those data with the respective ratings produced by the BoI ICAS Statistical and Full (which include BoI analysts' judgment) models. This wealth of data allows us to differentiate the models among those theoretically amenable to some strategic management of the risk assessment via the intervention of the analysts' judgment, the Full ones, and those who are not, the Statistical ones. IRB models are validated and supervised by the Single Supervision Mechanism (SSM) both for supervisory purposes and for the use in the Eurosystem monetary policy purposes and their parameters are rigorously calibrated excluding the possibility that they systematically underestimate the credit risk.

Our analysis thus differs from that of Calza *et al.* (2021), who only consider ICAS Full models in comparison with undistinguished Full and Statistical IRBs and interpret as strategic underestimation of the credit risk any observation of a debtor to which an IRB assigns a PD lower than the one assigned by the ICAS. [42]

We also argue that to ascertain a hypothetical strategic behavior of banks on the basis of the comparison between IRB and ICAS PDs for the firms whose loans are pledged (pledged firms) and for those whose loans are not (eligible firms), the effects of the criteria for acceptance of loans in the collateral frameworks on the credit quality composition of the sample of pledged loans have to be duly considered. Indeed, when we compare IRB and ICAS assessments of eligible debtors the observed borrowers are not selected and represent the universe of the debtors assessed.[43] Differently, when we consider the assessments of pledged debtors the observed sample is filtered by the selection made by the banks and, presumably, the pledged debtors are those with the best IRB rating available responding to the incentive to secure the lowest haircuts for the loans.[44]

Hence, in order to correctly measure the effect of the pledging of a loan on the difference between IRB PDs and ICAS PDs (which proxies the degree of relative conservativeness in credit risk assessment of IRB banks with respect to the NCB) the credit quality of the pledged loan has to be controlled for. In equation (2) we therefore control also for the credit quality of the loans, where *k* indicates one of the eight CQSs in which loans are classified according to the ECAF rating scale (Table 1).

$$\log\left(\frac{PD_{IRBijt}}{PD_{ICASit}}\right) = \alpha_i + \alpha_j + \alpha_k + \beta_t \cdot D_t + \beta \quad \cdot Dpledge_{ijt} + \varepsilon_{ijt} \tag{2}$$

[42] Before the introduction of the pandemic easing measures, BoI ICAS was the only ICAS in the euro area to use both a Full and a statistical model (the latter only in the ACC framework). Therefore, in Calza *et al.* (2021) only ICAS Full models are considered. Since 2020, Statistical ICAS have been also used in the ACC framework by Oesterreichische Nationalbank, Banco de España, Banco de Portugal and Banca Slovenije.

[43] We considered all the debtors jointly assessed by at least one of the IRB systems of the banks and the ICAS system.

[44] The effects of the selection can be seen in Fig. 3, which shows that the CQS distribution is more skewed to the left in the pledged sample with respect to the distribution for all eligible borrowers.

We then aim to investigate what drives the differences among the IRBs and ICAS ratings for pledged debtors. In particular, we analyze the characteristics of the debtors rated by IRBs and ICAS and of the banks which rate them estimating equation (3) for debtors with loans pledged as collateral.

$$\log\left(\frac{PD_{IRBijt}}{PD_{ICASit}}\right) = \alpha_i + \alpha_j + \alpha_k + \alpha_t + \alpha_i.\alpha_t + \beta_1 \cdot REV_{it-2} + \beta_2 \cdot DEB_{ijt} + \beta_3 \cdot CVAH_{ijt} + \beta_4 \cdot CET1R_{jt} + \beta_5 \cdot LTC_{jt} + \varepsilon_{ijt} \tag{3}$$

where REV is the log of the borrower's net revenues, that proxies the size of the borrower,[45] and DEB denotes the share of the loans received by the company from bank *j*, to proxy the relationship lending intensity. CVAH is the collateral value after haircuts of the loans of the company *i* pledged by the bank *j* in monetary policy operations. CET1R is the bank Common Equity Tier 1 Ratio of bank *j*, and LTC is the loan-to-collateral ratio for bank *j*, i.e. the ratio of the central bank liquidity received in the monetary policy operation and the collateral posted by the bank.[46] We also include time, bank and firm fixed effects.

Results - The results for equation 1 indicate that IRB Full PDs are lower than ICAS Full PDs for the eligible debtors, as the coefficients of the time dummies are negative (Table 3a),[47] also controlling for firm fixed effects, indicating that IRB models are less conservative than ICAS in credit risk assessment.[48] The (negative) difference between IRB and ICAS PDs increases when a loan is pledged, also controlling for firm fixed effects. Calza *et al.* (2021) find a different result for the eligible debtors, since IRB Full PDs are higher than ICAS Full ones, while their results for pledged debtors are in line with our evidence , i.e. a negative difference between IRBs and ICAS Full PDs; they argue that this large decrease (comparing results on eligible debtors and pledged debtors) in the difference between IRB and ICAS PDs indicates a strategic underestimation of the credit risk by commercial banks to increase the pledgeability of loans and banks' access to central bank liquidity.

The results are different for the sample of Statistical ratings (Table 3b). The positive coefficients of the year dummies, with the exception of 2015, indicate that for eligible debtors IRBs are more

[45] The variable is used with a two-year lag with reference to the PDs to conform to the data available when ratings are assigned.

[46] The rationale behind the introduction of this covariate is to test for the hypothesis that banks with a higher level of central bank liquidity utilization are more keen to strategically underestimate credit risk when pledging credit claims.

[47] The results are discussed using the same metric of Calza *et al.* (2021).

[48] The only exception is the 2016 coefficient for eligible loans.

conservative than ICAS, and, similarly to what observed for Full ratings, the (positive) difference decreases when considering pledged debtors.

The coefficients estimated for the dummy pledged indicate to what extent the circumstance that a debtor is pledged affects the difference between IRB PDs and ICAS PDs. The estimated effect for Full ratings is -0.40 and, controlling for bank fixed effects, it is halved, to -0.23. The inclusion of credit quality steps in equation 2 yields a significant reduction by a factor of 10, to -0.027 (Table 4) for Full ratings, and from -0.18 to -0.08 for Statistical ratings, in both cases with an improvement in the explanatory power of the model.

This evidence further indicates that the hypothesis of Calza *et al.* (2021) of a sizeable strategic management behaviour of banks is not supported by the data as the coefficient of the dummy for pledged debtors significantly decreases controlling for bank fixed effects and CQS by a factor of almost 20. Indeed, the small change (i.e. -0.027) in the gap between IRB and ICAS PD associated to the pledging of a loan contrasts with the sensibly larger variation in Calza *et al.* (2021), who find that IRB PDs double the ICAS PDs for eligible debtors,[49] and amounts to two-thirds of ICAS PDs for pledged debtors.

The analysis of the drivers of the difference between the assessments of IRBs and ICAS can be beneficial to the calibration of the credit risk models and it can also shed light on how the features of the rating systems interact with banks' and firms' characteristics that influence the transmission of the monetary policy.

We find that rating disagreements become less likely the larger the borrower (Tables 5a, 5b), as the coefficient of REV is positive, reducing the negative gap between the IRB and the ICAS PDs: this result is in line with the fact that public information is more easily available for larger firms, inducing a likely convergence of the ratings from different CASs, as found by Carey (2002). The results indicate also that the intensity of the lending relationship, proxied by the variable DEB, affects differently the two kinds of assessment to a very limited extent and only in the Statistical ratings sample, possibly as the use of loans as collateral is not perceived relevant enough to activate banks' behavior aimed at protecting their relationships by increasing the pledgeability of the loans via a more favorable credit assessment.

We also find that more capitalized banks tend to assign more conservative ratings to their debtors, as the Common Equity Tier 1 coefficient is positive in the Full ratings sample, where assessments are constituted of the banks' analysts' judgment overlaid on the statistical models'

[49] With positive average log-differences ranging from 0.8 to 0.95.

outcome, while it is mostly not significant in the statistical ratings sample, that relies only on models' ratings. This finding suggests that, correspondingly, banks with less capital and more limited balance sheet capacity are incentivized to be less conservative in credit risk assessment to strengthen primarily their capital base, and, secondarily, their access to central bank funding, in line with Calza *et al.* (2021) and the literature on regulatory capital and credit risk (Berg and Koziol, 2017, Behn *et al.*, 2022).

On the contrary, an increase in the amount of the pledged loan, proxied by the variable CVAH, increases the negative difference between the ratings of the IRBs and ICAS in the Full ratings sample, in line with the results found by Calza *et al.* (2021).[50] This result could suggest a strategic behaviour of the banks in managing the collateral.

The effect of the loan-to-collateral ratio in the monetary policy operations in the Full rating sample is positive, when also bank fixed effects are introduced, indicating that higher NCB liquidity utilization by banks makes the banks produce more conservative ratings.[51] This evidence contrasts with the negative effect of high liquidity utilization of banks on banks' conservativeness in the assessment of credit risk found by Calza *et al.* (2021), who infer that banks interested to save on their capacity to access central bank's liquidity underestimate the credit risk of the collateral.

We then introduce among the regressors the classes of credit quality steps to control also for the effect of the criteria for acceptance of loans in the collateral framework. Such approach represents an innovation with respect to previous works, making our results not directly comparable with them. In the Full rating sample, the effect of net revenues remains positive and that of the intensity of the banking relation is not significant (Table 6a). The effect of bank capital remains positive, confirming that more capitalized banks tend to assign more conservative ratings to their debtors. The effects of the collateral value after haircuts and of the LTC ratio, instead, turn out to be not significant, when all unobservable effects are accounted for, confirming the absence of a strategic behaviour of banks.[52] The results for the Statistical rating sample (Table 6b) confirm those commented above.

The residual differences between IRB and ICAS PDs not explained by the abovementioned factors could be driven also by diversity across rating models along the following dimensions: i) the

[50] In the Statistical rating sample, the effect, statistically weaker, is of a reduction of the positive difference between IRB and ICAS ratings; we do not view this as a sign of strategic management of collateral either since banks' analysts cannot override the ratings produced by the models.

[51] The effect of higher liquidity utilization in the Statistical rating sample, statistically weaker, is of a reduction of the positive difference between IRB and ICAS ratings; we do not view this as a sign of strategic management of collateral either since banks' analysts cannot modify the ratings produced by the models. We also note that higher values of loan-to-collateral ratio do not necessarily indicate more liquidity-constrained banks, instead they can be linked to the liquidity management practices or to the specific business models of the banks under analysis.

[52] Finally, we explore whether the disagreements could be lower if a debtor is rated by many banks (i.e. by three or more banks). The results suggest that this variable is not significant and therefore it seems not to have a role in explaining the differences among IRB and ICAS ratings.

rating quantification approach, i.e. the assignment of PD values to different rating classes; ii) the set of information and statistical methodology used for the rating assignment; iii) the length of the time-series used for PD calibration; iv) the rating "philosophy", which is more through-the-cycle oriented for IRBs and point-in-time for ICAS, as explained in Section 2.

6. Robustness analysis

In order to allay the concern on the dependence of the comparison between eligible and pledged debtors on the IRB PD distribution in the two samples we estimate equation (2) separately, for both Full and Statistical ratings, on the seven sub-samples of eligible debtors grouped by credit quality step class according to their IRB PD, which allows also for controlling more accurately for the effects of the different distribution of loans across lower and higher credit quality classes. The results confirm those found controlling directly for credit quality steps in equation (2) (Tables 7, 8).

As a further robustness check, we run equations (1), (2) and (3) using the absolute differences between IRB PDs and ICAS PDs as the dependent variable. The results (tables 9a, 9b, 10, 11a, 11b) broadly confirm the main evidence found when running the same equations with log PD ratios as the dependent variable.

Finally, we test the differences between the IRBs and ICAS in terms of ranking of borrowers' creditworthiness using proximity indicators (Appendix 2). Since the relative ordering of the debtors' assessments is similar and the statistics indicate an agreement of the two kinds of systems, the evidence supports the assessment that the differences between the IRB and ICAS systems are quite low.

7. Conclusions

This work aims at understanding whether there are systematic differences in the ratings issued by Italian IRB systems accepted for monetary policy purposes and by the internal rating system (ICAS) developed by BoI. The data indicate that small differences exist and that IRBs tend to be less conservative than ICAS when considering the Full models, i.e. those that include banks' financial analysts' assessment, while the opposite occurs when considering the purely statistical models. The difference between IRB and NCB PDs mildly increases for firms with loans pledged as collateral.

We bring new evidence on credit risk assessment systems, including for the post Covid-19 recovery. We claim to contribute to the literature with the study of features of the internal rating models not yet explored to our knowledge, such as the pandemic related extension of the Eurosystem collateral framework, which allows to analyze loans of lower credit quality, and ratings produced by the NCB internal models and by IRB purely quantitative models, extending the analysis to a vast number of small non-financial corporates that account for a large part of the Italian economy.

We observe that IRB and BoI systems show an overall satisfactory predictive capacity and a good discriminatory power.

We find that, for borrowers whose corporate loans are eligible as collateral, IRB Full PDs are slightly less conservative than those assigned by ICAS, especially in the more recent years. We also find that the difference between IRB and ICAS Full PDs increases very modestly when restricting the sample to the debtors with loans mobilized as collateral and fully accounting for borrowers' creditworthiness. This evidence suggests that, when taking into account banks' common liquidity management practices in the context of the collateral framework, a strategic management of the rating of the collateral, if any, is negligible and of low economic significance. Furthermore, ratings produced by quantitative models without the judgment of analysts, IRBs Statistical PDs, are often more conservative than ICAS Statistical PDs, but to a lesser extent when considering the borrowers whose loans have been pledged.

We also characterize the factors driving the differences between the ratings issued by IRBs and by BoI ICAS. We find that the difference between PDs issued by IRBs and by ICAS decreases with the size of the borrower. We view this finding as reflecting the consideration that for larger companies and for those accessing market financing the availability of public information is larger, contributing to align the assessment of rating systems. In addition, we find that the difference between PDs is not affected by the size of the loan pledged and by the levels of central bank liquidity utilization, allowing us to conclude that IRB banks do not underestimate the PDs assigned to borrowers to mobilize strategically the largest amount of collateral. Residual differences between IRB and ICAS PDs may be ascribed also to methodological diversity across rating systems.

We also evaluate the ratings produced by the banks and NCB systems as similar according to proximity measures.

Overall, the evidence discussed above and the analysis of the drivers of the small differences between the credit risk assessment provided by IRBs and ICAS leads us to conclude that the hypothesis of an economically significant strategic management of the IRB credit systems is not supported by the data for Italy and that, while IRBs in some instances appear less conservative than ICAS, both IRBs and ICAS evaluate credit risk adequately, in this way contributing to minimize the risks borne by the Eurosystem and Bank of Italy within the monetary policy collateral frameworks.

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Tables and Figures

Table 1

Mapping between Eurosystem Credit Quality Steps (CQSs) and probabilities of default (PDs) over one-year horizon

CQS	**1 & 2**	**3**	**4**	**5**	**6**	**7**	**8**
PD	≤0.1%	≤0.4%	≤1%	≤1.5%	≤3%	≤5%	>5%
Employed for	ECAF; individual loans and pools of ACCs		individual loans and pools of ACCs		pools of ACCs		

Table 2

Distribution of firms rated by IRBs and BoI ICAS

(2015-2023)

Year	No. of firms rated by at least an IRB	No. of firms rated by BoI ICAS Full	No. of firms rated by BoI ICAS Stat	No. of firms rated by BoI ICAS Full and by at least 1 IRB: Total assessed	With mobilised credit claims: Total	*ECAF*	*ACC single claims*	*ACC pools*	No. of firms rated by BoI ICAS Stat and by at least 1 IRB: Total assessed	With mobilised credit claims: Total	*ECAF*	*ACC single claims*	*ACC pools*
2015	776 480	1 192	256 452	4 616	668	*425*	*202*	*41*	278 813	8 649	*3 988*	*2 464*	*2 197*
2016	738 471	2 057	275 096	7 935	1 658	*801*	*522*	*335*	322 472	22 486	*7 837*	*4 563*	*10 086*
2017	725 815	2 357	290 300	9 386	2 628	*1 306*	*429*	*893*	330 590	47 531	*17 842*	*4 382*	*25 307*
2018	722 134	2 374	284 526	10 463	3 376	*1 253*	*497*	*1 626*	329 697	46 709	*14 734*	*2 792*	*29 183*
2019	792 090	2 444	285 349	12 103	4 247	*1 611*	*604*	*2 032*	361 700	57 431	*16 232*	*3 400*	*37 799*
2020	803 290	2 850	268 943	14 239	4 571	*1 714*	*623*	*2 234*	353 908	54 038	*16 034*	*3 055*	*34 949*
2021	832 210	2 991	273 100	14 634	5 506	*1 655*	*717*	*3 134*	349 799	65 113	*12 278*	*4 474*	*48 361*
2022	721 533	2 925	309 889	12 849	4 400	*1 328*	*582*	*2 490*	330 549	74 248	*11 987*	*3 411*	*58 850*
2023	695 785	3 036	334 370	12 568	3 832	*1 080*	*431*	*2 321*	329 872	62 476	*9 547*	*3 087*	*49 842*
Total	**6 807 808**	**22 226**	**2 578 025**	**98 793**	**30 886**	***11 173***	***4 607***	***15 106***	**2 987 400**	**438 681**	***110 479***	***31 628***	***296 574***

Note: firms rated by more than one IRB are considered as different debtors, i.e. if a firm is rated by two different IRBs and by the BoI ICASs it is considered twice in the sample of debtors rated in common (this explains why the figures in the fourth column exceed those in the second column).

Table 3a

Estimation of equation (1) – Full ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
Year:				
2015	-0.021	0.007 ***		
	(0.018)	(0.021)		
2016	-0.055 ***	0.045 ***	0.068 *	0.044 *
	(0.015)	(0.018)	(0.021)	(0.019)
2017	-0.271 ***	-0.178 ***	-0.124 ***	-0.163 ***
	(0.014)	(0.017)	(0.021)	(0.019)
2018	-0.149 ***	-0.107 ***	-0.032 ***	-0.083 ***
	(0.012)	(0.016)	(0.022)	(0.020)
2019	-0.181 ***	-0.180 ***	-0.095 ***	-0.115 ***
	(0.011)	(0.015)	(0.021)	(0.019)
2020	-0.218 ***	-0.253 ***	-0.179 ***	-0.195 ***
	(0.010)	(0.013)	(0.021)	(0.019)
2021	-0.391 ***	-0.404 ***	-0.307 ***	-0.333 ***
	(0.010)	(0.013)	(0.021)	(0.019)
2022	-0.341 ***	-0.396 ***	-0.307 ***	-0.333 ***
	(0.010)	(0.013)	(0.021)	(0.020)
2023	-0.275 ***	-0.322 ***	-0.244 ***	-0.282 ***
	(0.010)	(0.010)	(0.021)	(0.020)
dummy_pledged			-0.396 ***	-0.231 ***
			(0.008)	(0.007)
Fixed - Effects	-------------	-------------	-------------	-------------
Firm FE	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes
Observations	90,015	89,748	89,748	89,748
R-sqr	0.05	0.34	0.36	0.45
R-sqr_adj	0.05	0.30	0.32	0.41

*** p<.001, ** p<.01, * p<.05

Table 3b

Estimation of equation (1) – Statistical ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
Year:				
2015	-0.228 ***	-0.195 ***		
	(0.003)	(0.005)		
2016	0.051 ***	0.075 ***	0.277 ***	-0.213 ***
	(0.003)	(0.005)	(0.004)	(0.012)
2017	0.274 ***	0.284 ***	0.495 ***	-0.017 *
	(0.003)	(0.004)	(0.004)	(0.008)
2018	0.346 ***	0.346 ***	0.556 ***	0.111 ***
	(0.003)	(0.004)	(0.004)	(0.008)
2019	0.393 ***	0.376 ***	0.587 ***	0.128 ***
	(0.003)	(0.004)	(0.004)	(0.008)
2020	0.387 ***	0.354 ***	0.567 ***	0.130 ***
	(0.003)	(0.004)	(0.004)	(0.008)
2021	0.261 ***	0.216 ***	0.433 ***	-0.058 ***
	(0.003)	(0.004)	(0.004)	(0.008)
2022	0.607 ***	0.541	0.761 ***	0.285 ***
	(0.004)	(0.004)	(0.005)	(0.009)
2023	0.601 ***	0.545 ***	0.766 ***	0.446 ***
	(0.004)	(0.004)	(0.005)	(0.009)
dummy_pledged			-0.149 ***	-0.178 ***
			(0.004)	(0.004)
Fixed - Effects	-----------------	------------------	--------------	--------------
Firm FE	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes
Observations	1,201,177	1,141,556	1,141,556	1,141,556
R-sqr	0.09	0.54	0.54	0.55
R-sqr_adj	0.09	0.44	0.44	0.45

*** p<.001, ** p<.01, * p<.05

Table 4

Estimation of equation (2)

	FULL (1)	STAT (2)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
Year:		
2016	-0.029 *	0.241 ***
	(0.013)	(0.003)
2017	-0.240 ***	0.426 ***
	(0.014)	(0.003)
2018	-0.287 ***	0.482 ***
	(0.015)	(0.003)
2019	-0.286 ***	0.534 ***
	(0.014)	(0.003)
2020	-0.353 ***	0.537 ***
	(0.014)	(0.003)
2021	-0.525 ***	0.475 ***
	(0.014)	(0.003)
2022	-0.522 ***	0.665 ***
	(0.014)	(0.004)
2023	-0.401 ***	0.670 ***
	(0.014)	(0.004)
dummy_pledged	-0.027 ***	-0.081 ***
	(0.005)	(0.003)
Fixed - Effects	------------	------------
Firm FE	Yes	Yes
Bank FE	Yes	Yes
CQS FE	Yes	Yes
Observations	89,748	1,141,556
R-sqr	0.72	0.70
R-sqr_adj	0.70	0.64

*** p<.001, ** p<.01, * p<.05

Table 5a

Estimates of equation (3) with different sets of fixed effects – Full ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
REV	0.146 ***	0.217 ***		0.224 ***
	(0.040)	(0.045)		(0.044)
DEB	0.002 *	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
CVAH	-0.106 ***	-0.091 ***	-0.091 ***	-0.101 ***
	(0.008)	(0.008)	(0.010)	(0.008)
CET1R_Q4	0.033 ***	0.033 ***	0.037 ***	0.018 ***
	(0.001)	(0.001)	(0.002)	(0.003)
Q4_LTC	-0.009 ***	-0.006 ***	-0.008 ***	0.009 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Fixed - Effects	------------	--------------	--------------	--------------
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
Observations	23,350	23,350	18,588	23,350
R-sqr	0.40	0.41	0.57	0.50
R-sqr_adj	0.31	0.31	0.33	0.42

*** p<.001, ** p<.01, * p<.05

Table 5b

Estimates of equation (3) with different sets of fixed effects – Statistical ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
REV	0.044 ***	0.056 ***		0.060 ***
	(0.010)	(0.010)		(0.010)
DEB	0.000	0.001 ***	-0.003	0.001 ***
	(0.000)	(0.000)	(0.002)	(0.000)
CVAH	-0.129 ***	-0.092 ***	-0.023	-0.082 ***
	(0.006)	(0.006)	(0.030)	(0.006)
CET1R_Q4	0.001	-0.022 ***	-0.071 ***	-0.003
	(0.001)	(0.001)	(0.004)	(0.001)
Q4_LTC	0.005 ***	-0.010 ***	-0.002	-0.006 ***
	(0.000)	(0.001)	(0.002)	(0.001)
Fixed - Effects	------------	--------------	--------------	--------------
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
Observations	93,355	93,355	2,475	93,355
R-sqr	0.71	0.72	0.72	0.73
R-sqr_adj	0.56	0.59	0.44	0.60

*** p<.001, ** p<.01, * p<.05

Table 6a

Estimates of equation (3) with different sets of fixed effects – Full ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
REV	0.423 ***	0.583 ***	0.000	0.565 ***
	(0.031)	(0.035)	(0.000)	(0.035)
DEB	0.002 **	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
CVAH	-0.027 ***	-0.005	-0.006	-0.009
	(0.005)	(0.005)	(0.004)	(0.005)
CET1R_Q4	0.011 ***	0.012 ***	0.008 ***	0.010 ***
	(0.001)	(0.001)	(0.001)	(0.002)
Q4_LTC	-0.009 ***	-0.005 ***	-0.003 ***	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
Fixed - Effects	--------------	--------------	--------------	--------------
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
CQS FE	Yes	Yes	Yes	Yes
Observations	23,350	23,350	18,588	23,350
R-sqr	0.73	0.74	0.94	0.74
R-sqr_adj	0.69	0.70	0.90	0.70

*** p<.001, ** p<.01, * p<.05

Table 6b

Estimates of equation (3) with different sets of fixed effects – Statistical ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
REV	0.139 ***	0.133 ***		0.133 ***
	(0.008)	(0.008)		(0.008)
DEB	0.002 ***	0.002 ***	0.000	0.002 ***
	(0.000)	(0.000)	(0.001)	(0.000)
CVAH	-0.081 ***	-0.063 ***	-0.017	-0.061 ***
	(0.005)	(0.005)	(0.011)	(0.005)
CET1R_Q4	0.007 ***	-0.006 ***	-0.003 *	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Q4_LTC	0.002 ***	-0.006 ***	-0.005 ***	-0.004 ***
	(0.000)	(0.001)	(0.001)	(0.001)
Fixed - Effects				
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	93,355	93,355	2,475	93,355
R-sqr	0.81	0.81	0.97	0.81
R-sqr_adj	0.72	0.72	0.94	0.72

*** p<.001, ** p<.01, * p<.05

Table 7

Estimation of equation (2) on split samples – Full ratings

	CQS 1&2	CQS 3	CQS 4	CQS 5	CQS 6	CQS 7	CQS 8
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
Year							
2016	-0.006	-0.029	-0.016	0.050	-0.053	-0.152 *	-0.378 *
	(0.031)	(0.021)	(0.027)	(0.059)	(0.040)	(0.069)	(0.158)
2017	-0.032	-0.132 ***	-0.304 ***	-0.198 ***	-0.366 ***	-0.536 ***	-0.831 ***
	(0.036)	(0.022)	(0.029)	(0.059)	(0.044)	(0.077)	(0.162)
2018	0.004	-0.061 *	-0.315 ***	-0.159 **	-0.434 ***	-0.738 ***	-1.121 ***
	(0.048)	(0.025)	(0.030)	(0.059)	(0.048)	(0.080)	(0.164)
2019	0.002	-0.075 **	-0.305 ***	-0.233 ***	-0.482 ***	-0.783 ***	-1.118 ***
	(0.049)	(0.023)	(0.028)	(0.058)	(0.046)	(0.081)	(0.165)
2020	0.048	-0.106 ***	-0.393 ***	-0.308 ***	-0.608 ***	-0.890 ***	-1.321 ***
	(0.047)	(0.023)	(0.028)	(0.057)	(0.047)	(0.080)	(0.165)
2021	-0.034	-0.294 ***	-0.557 ***	-0.440 ***	-0.760 ***	-1.125 ***	-1.681 ***
	(0.048)	(0.023)	(0.028)	(0.057)	(0.050)	(0.083)	(0.168)
2022	-0.101 *	-0.273 ***	-0.535 ***	-0.424 ***	-0.808 ***	-1.117 ***	-1.563 ***
	(0.048)	(0.024)	(0.028)	(0.057)	(0.050)	(0.082)	(0.169)
2023	0.100	-0.168 ***	-0.384 ***	-0.376 ***	-0.673 ***	-0.965 ***	-1.479 ***
	(0.052)	(0.024)	(0.029)	(0.058)	(0.049)	(0.085)	(0.171)
dummy_pledged	-0.057 *	-0.021 *	-0.012	-0.038 *	0.023	-0.075	-0.065
	(0.024)	(0.009)	(0.010)	(0.017)	(0.022)	(0.039)	(0.058)
Fixed - Effects	------------	--------------	-------------	-------------	--------------	--------------	--------------
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,627	25,097	22,527	10,642	10,288	5,336	3,637
R-sqr	0.71	0.70	0.70	0.73	0.73	0.72	0.72
R-sqr_adj	0.62	0.65	0.64	0.65	0.65	0.63	0.61

*** p<.001, ** p<.01, * p<.05

Table 8

Estimation of equation (2) on split samples – Statistical ratings

	CQS 1&2	CQS 3	CQS 4	CQS 5	CQS 6	CQS 7	CQS 8
Dependent Var:	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$	$\ln\frac{PD_{IRB}}{PD_{ICAS}}$
Year							
2016	0.335 ***	0.315 ***	0.292 ***	0.228 ***	0.327 ***	0.316 ***	0.072 ***
	(0.020)	(0.007)	(0.008)	(0.010)	(0.008)	(0.017)	(0.009)
2017	0.527 ***	0.491 ***	0.434 ***	0.397 ***	0.482 ***	0.506 ***	0.350 ***
	(0.024)	(0.007)	(0.008)	(0.011)	(0.009)	(0.017)	(0.010)
2018	0.814 ***	0.530 ***	0.455 ***	0.367 ***	0.464 ***	0.553 ***	0.587 ***
	(0.028)	(0.007)	(0.008)	(0.012)	(0.009)	(0.016)	(0.011)
2019	0.918 ***	0.579 ***	0.492 ***	0.436 ***	0.509 ***	0.592 ***	0.652 ***
	(0.028)	(0.007)	(0.008)	(0.013)	(0.009)	(0.017)	(0.011)
2020	0.919 ***	0.510 ***	0.475 ***	0.431 ***	0.507 ***	0.580 ***	0.742 ***
	(0.026)	(0.007)	(0.008)	(0.013)	(0.009)	(0.017)	(0.012)
2021	0.815 ***	0.423 ***	0.420 ***	0.395 ***	0.470 ***	0.580 ***	0.657 ***
	(0.028)	(0.008)	(0.009)	(0.014)	(0.010)	(0.018)	(0.013)
2022	0.795 ***	0.916 ***	0.628 ***	0.482 ***	0.620 ***	0.729 ***	0.829 ***
	(0.043)	(0.010)	(0.009)	(0.016)	(0.011)	(0.019)	(0.013)
2023	0.830 ***	1.271 ***	0.702 ***	0.516 ***	0.647 ***	0.628 ***	0.571 ***
	(0.052)	(0.010)	(0.010)	(0.018)	(0.012)	(0.020)	(0.014)
dummy_pledged	-0.115 ***	-0.060 ***	-0.035 ***	-0.056 ***	-0.083 ***	-0.074 ***	-0.173 ***
	(0.032)	(0.007)	(0.007)	(0.013)	(0.008)	(0.015)	(0.013)
Fixed - Effects	--------------	--------------	--------------	--------------	--------------	--------------	--------------
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,599	193,446	212,096	76,656	169,486	68,558	173,287
R-sqr	0.83	0.77	0.77	0.80	0.73	0.73	0.64
R-sqr_adj	0.74	0.69	0.67	0.67	0.60	0.56	0.49

*** p<.001, ** p<.01, * p<.05

Table 9a

Estimation of equation (1) on absolute PD differences – Full ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$
Year:				
2015	-11,124 *	-2,708 ***		
	(4.356)	(4.366)		
2016	-48,671 ***	-1,438 ***	4,143	1,723 ***
	(4.574)	(4.076)	(3.883)	(3.846)
2017	-97,255 ***	-47,318 ***	-38,793 ***	-42,332 ***
	(4.643)	(4.177)	(4.278)	(4.250)
2018	-84,468 ***	-65,672	-55,262 ***	-59,620 ***
	(4.058)	(4.316)	(4.772)	(4.753)
2019	-52,467 ***	-60,625	-49,213 ***	-49,511 ***
	(3.069)	(3.671)	(4.409)	(4.396)
2020	-56,614 ***	-68,932	-58,656 ***	-58,812 ***
	(2.836)	(3.383)	(4.251)	(4.239)
2021	-91,108 ***	-99,500 ***	-86,999 ***	-87,918 ***
	(3.166)	(3.344)	(4.380)	(4.375)
2022	-60,829 ***	-85,165 ***	-73,393 ***	-74,519 ***
	(2.842)	(3.147)	(4.359)	(4.355)
2023	-44,510 ***	-63,813	-53,042 ***	-56,618 ***
	(2.613)	(2.464)	(4.386)	(4.378)
dummy_pledged			-37,089 ***	-27,033 ***
			(1.799)	(1.838)
Fixed - Effects	------------	--------------	--------------	--------------
Firm FE	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes
Observations	90.015	89.748	89.748	89.748
R-sqr	0,04	0,53	0,54	0,54
R-sqr_adj	0,04	0,50	0,50	0,51

*** p<.001, ** p<.01, * p<.05

Table 9b

Estimation of equation (1) on absolute PD differences – Statistical ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$
Year:				
2015	-61,540 ***	-59,066 ***		
	(1.862)	(2.326)		
2016	-7,112 ***	-9,446 ***	53,312 ***	55,679 ***
	(1.636)	(2.116)	(2.128)	(2.128)
2017	79,486 ***	69,231 ***	136,088 ***	138,613 ***
	(1.580)	(2.032)	(2.143)	(2.144)
2018	116,983 ***	107,263 **	173,826 ***	176,360 ***
	(1.478)	(1.965)	(2.126)	(2.128)
2019	118,929 ***	112,450	179,864 ***	181,451 ***
	(1.364)	(1.902)	(2.098)	(2.099)
2020	135,379 ***	130,342 ***	198,428 ***	199,889 ***
	(1.431)	(1.916)	(2.147)	(2.149)
2021	83,084 ***	81,008 ***	151,248 ***	153,333 ***
	(1.337)	(1.879)	(2.146)	(2.147)
2022	149,710 ***	134,343 ***	206,351 ***	211,461 ***
	(1.557)	(1.863)	(2.283)	(2.300)
2023	132,277 ***	112,927 ***	185,158 ***	190,906 ***
	(1.603)	(1.533)	(2.372)	(2.389)
dummy_pledged			-73,662 ***	-76,242 ***
			(1.401)	(1.434)
Fixed - Effects	--------------	--------------	--------------	--------------
Firm FE	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes
Observations	1.201.177	1.141.556	1.141.556	1.141.556
R-sqr	0,03	0,43	0,43	0,43
R-sqr_adj	0,03	0,31	0,31	0,31

*** p<.001, ** p<.01, * p<.05

Table 10

Estimation of equation (2) on absolute PD differences

	FULL	STAT
	(1)	(2)
Dependent Var:	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$
Year:		
2016	-7.034 *	26.521 ***
	(3.485)	(2.027)
2017	-53.520 ***	95.584 ***
	(3.895)	(2.022)
2018	-84.142 ***	147.183 ***
	(4.438)	(1.984)
2019	-68.808 ***	155.149 ***
	(4.077)	(1.950)
2020	-80.005 ***	168.869 ***
	(3.907)	(1.976)
2021	-111.502 ***	142.602 ***
	(4.050)	(1.991)
2022	-100.384 ***	164.230 ***
	(4.006)	(2.126)
2023	-74.220 ***	138.601 ***
	(4.048)	(2.228)
dummy_pledged	-4.448 *	-36.876 ***
	(1.749)	(1.263)
Fixed - Effects	------------	------------
Firm FE	Yes	Yes
Bank FE	Yes	Yes
CQS FE	Yes	Yes
Observations	89,748	1,141,556
R-sqr	0.61	0.53
R-sqr_adj	0.58	0.43

*** p<.001, ** p<.01, * p<.05

Table 11a

Estimates of equation (3) on absolute PD differences with different sets of fixed effects – Full ratings

	(1)	(2)	(3)	(4)
Dependent Var:	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$
REV	103.675 ***	131.023 ***		128.632 ***
	(11.731)	(13.958)		(13.941)
DEB	0.150	-0.010	0.007	-0.001
	(0.153)	(0.154)	(0.030)	(0.157)
CVAH	-3.109	0.146	-0.668 *	-0.159
	(1.700)	(1.689)	(0.321)	(1.707)
CET1R_Q4	0.682 *	0.892 **	0.282 ***	1.634 **
	(0.290)	(0.287)	(0.056)	(0.605)
Q4_LTC	-1.002 ***	-0.292 **	-0.305 ***	0.464 **
	(0.102)	(0.110)	(0.019)	(0.152)
Fixed - Effects	------------	--------------	--------------	--------------
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
CQS FE	Yes	Yes	Yes	Yes
Observations	23,350	23,350	18,588	23,350
R-sqr	0.60	0.61	0.99	0.61
R-sqr_adj	0.54	0.54	0.98	0.55

*** p<.001, ** p<.01, * p<.05

Table 11b

Estimates of equation (3) on absolute PD differences with different sets of fixed effects – Full ratings

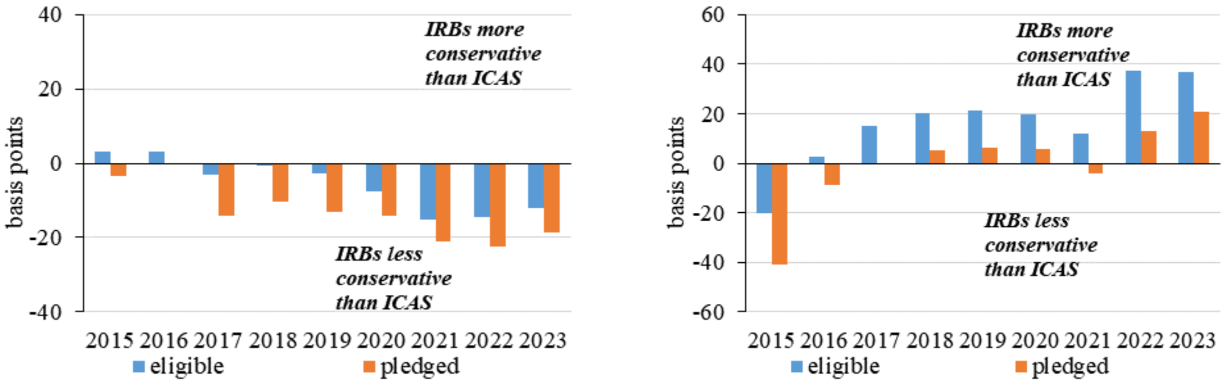
	(1)	(2)	(3)	(4)
Dependent Var:	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$	$PD_{IRB} - PD_{ICAS}$
REV	17.049 ***	17.773 ***		17.802 ***
	(2.054)	(2.153)		(2.152)
DEB	0.105 **	0.125 ***	-0.005	0.135 ***
	(0.035)	(0.036)	(0.103)	(0.036)
CVAH	-2.661 **	-1.306	-1.273	-0.965
	(0.925)	(0.964)	(2.207)	(0.967)
CET1R_Q4	0.013	-0.822 ***	-1.042 **	-0.120
	(0.182)	(0.211)	(0.396)	(0.252)
Q4_LTC	-0.057	-0.863 ***	-0.476 ***	-0.828 ***
	(0.071)	(0.108)	(0.115)	(0.156)
Fixed - Effects	------------	--------------	--------------	--------------
Firm FE	Yes	Yes	No	Yes
Year FE	No	Yes	No	Yes
FirmxYear FE	No	No	Yes	No
Bank FE	No	No	No	Yes
CQS FE				
Observations	93,355	93,355	2,475	93,355
R-sqr	0.76	0.76	0.96	0.76
R-sqr_adj	0.64	0.64	0.93	0.64

*** p<.001, ** p<.01, * p<.05

Figure 1

IRB and ICAS assessments: eligible debtors and with pledged loans

A) ICAS Full vs IRB Full PDs *B) ICAS vs IRB Statistical PDs*

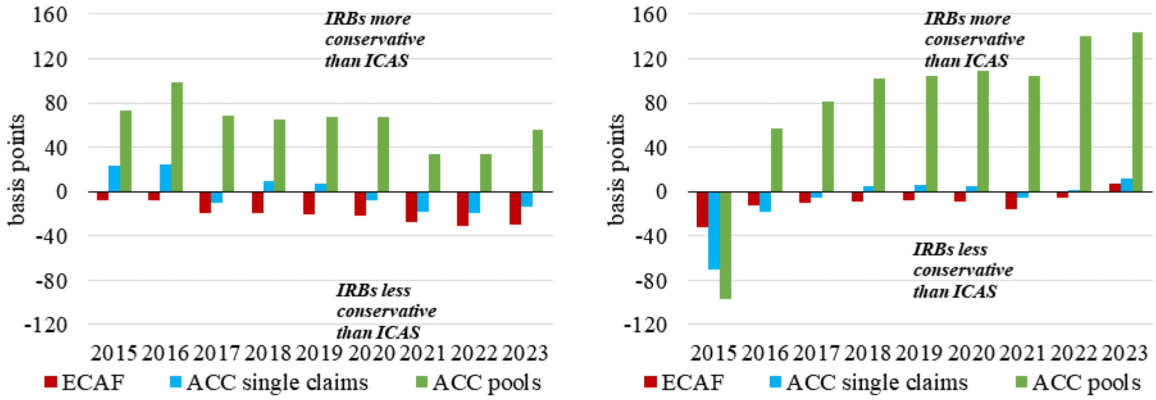


Note: for each debtor is reported the median difference between the IRB PD and the ICAS PD.

Figure 2

IRB and ICAS assessments: debtors with pledged loans

A) ICAS Full vs IRB Full PDs *B) ICAS Statistical vs IRB Statistical PDs*



Note: for each debtor is reported the median difference between the IRB PD and the ICAS PD.

Figure 3

IRBs CQS distribution: comparison between eligible and pledged debtors commonly rated by IRBs and ICASs

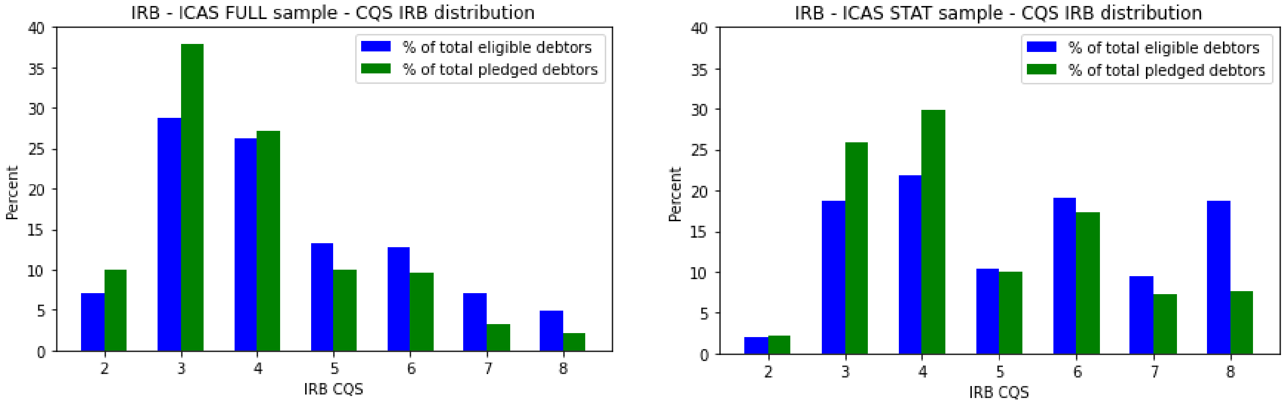
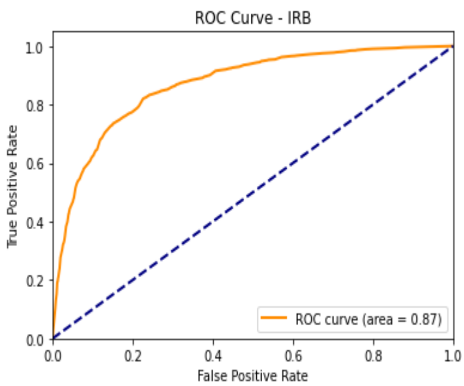


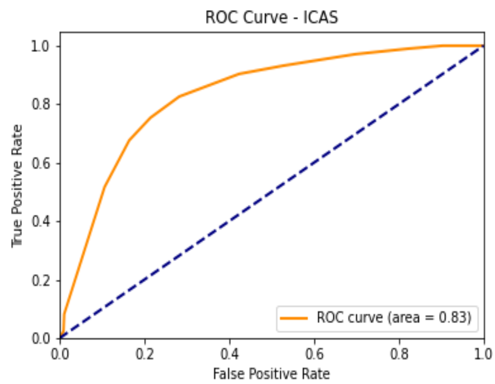
Figure 4

ROC curves

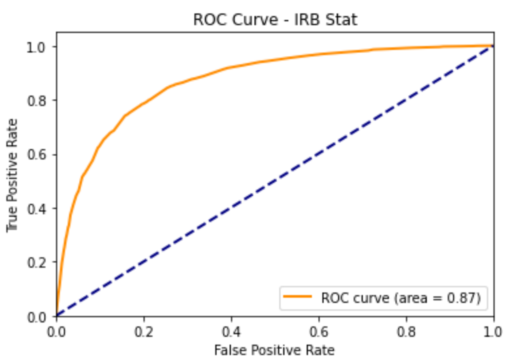
IRBs Full



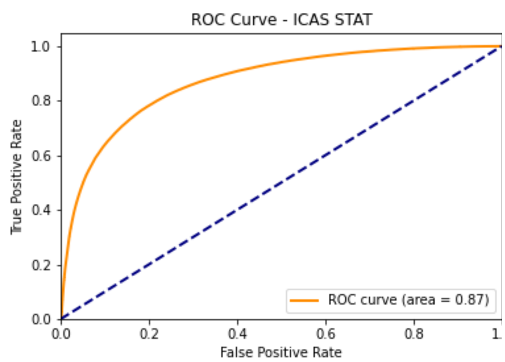
BoI ICAS Full



IRBs Statistical



BoI ICAS Statistical



Appendix 1. Dataset

Variable	*Description*	*Unit*	*Source*
Firm information			
ICAS PD	Probability of default (PD) over a 1-year horizon, provided by BoI ICAS Full or by BoI ICAS statistical to an individual firm.	Basis points	Bank of Italy
REV	Net revenues of a firm. In the regressions the variable is used with a two years lag with reference to the PDs to conform to the data available when ratings are assigned. The logarithmic transformation has been used.	EUR million	Cerved
DEB	Share of the loans received by the firm *i* from bank *j* on its total bank loans.	Percentage	Cerved
Bank information			
CET 1	Common Equity Tier 1 ratio at the end of each year.	Percentage	Bank of Italy
LTC	Loan-to-Collateral ratio (ratio between the central bank credit provided by the bank and collateral mobilized by the bank) at the end of each year.	Percentage	Bank of Italy
Firm-bank information			
IRB PD	PD over 1-year horizon assigned by IRB banks to firms.	Basis points	Bank of Italy
CVAH	Collateral value after haircut (outstanding amount of the loan mobilized by bank *j* to a firm *i*, net of haircuts applied on the basis of the Eurosystem collateral framework rules); logarithmic transformation.	EUR million	Bank of Italy

Appendix 2. Proximity statistics

The ratings of two credit assessment systems can be compared via the use of proximity measures calculated on the basis of the pairs of ratings for a sample of commonly rated entities. In order to obtain an indication of the degree of proximity between the IRB and BoI ICAS Full ratings,[53] we follow Hornik *et al.* (2006) and use the following two measures of proximity: Association and Agreement.[54] In addition, we perform the Wilcoxon signed rank test in order to test whether the median rating difference between the two systems is significantly different from zero. The proximity statistics are calculated on the Credit Quality Steps (CQS) used by the Eurosystem.

The Association indicator measures to what extent the relative pair-wise ordering produced by one credit assessment system (CAS) matches that of the other CAS. The Association indicator is also known as the Kendall Tau distance or the Kemeny-Snell τ_x. This measure is scaled so that it can take values in the interval [0, 1], with 1 corresponding to identical orderings.

The Agreement is another measure for the proximity of two rating systems. While the Association only measures whether the rank-ordering is similar, the Agreement also depends on the rating distance between the two systems. The measure can take positive values up to 1, but is not limited by zero on the lower end. A value of 1 corresponds to a perfect agreement between the CASs, a value of 0 corresponds to the expected agreement as if the ratings were independent, and a negative value corresponds to disagreement.

Finally, as far as the Wilcoxon test is concerned, it can be used to test whether the median rating difference between the two CASs is zero.[55]

The main advantage of the Wilcoxon test is that it is non-parametric and therefore the individual distributions of both samples can be left undetermined. The test, however, requires that both samples to be tested originate from the same population, and that both systems use an ordinal scale for measurement (Table A2.1).

[53] We do not show the results for IRB and ICAS Statistical ratings for brevity, since our main focus for these additional statistics is on the IRB judgmental systems, which proved to be less conservative than ICAS Full

[54] Hornik *et al.* use a third proximity measure, i.e. the “rating bias”, which measures, for every debtor rated by two credit assessment sources, the deviation between the two rating classes, subsequently scaled to the interval [-1, +1]. We do not present here the rating bias because this measure is very similar to the one calculated in par.3.1

[55] The hypothesis to be tested using the Wilcoxon test is the following: $H_0: m_A = m_B$; $H_1: m_A \neq m_B$, where m_A and m_B are the median rating grades for CAS A and B, respectively.

Table A2.1

Comparison between IRBs and ICAS Full ratings according to a set of proximity statistics

Year	Kendall-Tau (Association)		Cohen's coefficient (Agreement)		Wilcoxon test (p-values)	
	IRB-ICAS Full eligible	*IRB-ICAS Full pledged*	*IRB-ICAS Full eligible*	*IRB-ICAS Full pledged*	*IRB-ICAS Full eligible*	*IRB-ICAS Full pledged*
2015	0.69	0.70	0.33	0.29	0.0%	0.0%
2016	0.70	0.72	0.41	0.42	0.0%	0.1%
2017	0.71	0.71	0.48	0.45	14.8%	0.0%
2018	0.72	0.71	0.57	0.53	0.1%	0.0%
2019	0.71	0.71	0.55	0.53	12.2%	0.0%
2020	0.73	0.72	0.61	0.58	0.0%	0.0%
2021	0.72	0.71	0.57	0.52	0.0%	0.0%
2022	0.71	0.71	0.57	0.53	0.0%	0.0%
2023	0.72	0.72	0.58	0.58	0.0%	0.0%

According to the Association measure, in the time span under investigation the pair-wise ordering for both CASs matches in between 65 and 73 percent of the cases, i.e. the internal relative ordering of the rated debtors was the same (100 per cent is a perfect match).

The Agreement measure suggests that, at least in the more recent period, around 55 percent of the IRBs and ICAS Full provide equivalent or very close to equivalent rating assessments (a value of 100 percent would mean a perfect agreement) for the samples of eligible debtors. Agreement measures tend to be higher in the more recent period. Evidences are similar for the samples of pledged debtors, though on slightly lower levels, which look consistent with the results of section 3.

The Wilcoxon p-values are instead very low (with a few exceptions), meaning that the null hypothesis $H_0: m_A = m_B$ is rejected at the 5 percent level, and therefore that the median rating grades assigned by IRBs and ICAS do not coincide, in line with the findings of section 3.

To sum up, the analysis of the proximity measures confirms that there are some differences in the way BoI ICAS and IRBs rate debtors, as evidenced by the results of the Wilcoxon test. However, the relative ordering of the debtors' assessments is similar and the level of agreement is sufficient. A reliable benchmark to assess the level of the indicators is represented by the outcome of a cross-comparison of ICAS ratings with other credit assessment systems ECAF-accepted conducted by the ECB in the context of the works related to the prioritization of ICAS ratings. The ECB concludes, on the basis of proximity measures with levels in line with those showed above (or even lower), that the cross-comparison of ICAS ratings with IRB systems shows limited average differences overall. This evidence thus further supports the assessment that the differences between the IRB and ICAS systems are quite low.

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